FINAL REPORT

Modeling Income in the Near Term: Revised Projections of Retirement Income Through 2020 for the 1931-1960 Birth Cohorts

by

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PREFACE

This report was prepared by The Urban Institute for the Social Security Administration, Office of Research, Evaluation, and Statistics, Division of Policy Evaluation (SSA/ORES/DPE) under Task Order 0440-00-39422, pursuant to contact No. 600-96-27332 and by The Brookings Institution, under subcontract to The Urban Institute.

Many people, both at The Urban Institute and The Brookings Institution, contributed to this report. Eric Toder and Lawrence Thompson directed the day to day research on the project and contributed to writing several of the chapters. Principal authors of the main chapters in the report are:

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Karen Smith was a technical leader on the project, developing the infrastructure for the iterative (year-by-year) processing that distinguishes MINT3 from the prior version of the model. Jillian Berk and Benjamin Keys also made major contributions to preparing and programming the basic data files used in the report. Others who performed programming and research assistance for various tasks were Todor Stavrev and Romina Woldemariam.

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Howard Iams and the late Steven Sandell developed the original design for a model that would project retirement incomes through 2020. Howard Iams has continued to provide extensive guidance for the project. The Urban/Brookings team also benefited from collaboration with others at the Social Security Administration, including Lee Cohen, Joyce Manchester, James Moore, Tom Solomon, Paul Van de Water, and Mikki Waid. In addition, Jason Schultz in the Office of the Chief Actuary (OCACT) at the Social Security Administration was helpful in providing the OCACT projections of beneficiaries and benefit levels in 2020.

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CHAPTER 1

INTRODUCTION

The Division of Policy Evaluation (DPE) of the Social Security Administration (SSA) has entered into two contracts with the Urban Institute to help it develop a new tool for analyzing the distributional consequences of Social Security reform proposals. The first, awarded in 1998, led to the development of Modeling Income in the Near Term (MINT), a tool for simulating the retirement incomes of members of the Baby Boom and neighboring cohorts. The second, awarded in 2000, was to expand and improve on the first version of MINT. In all phases of the project, members of the research staff at SSA/DPE collaborated closely with the contractors. The Brookings Institution served as a subcontractor to the Urban Institute under both contracts and the RAND Corporation participated in the development of the initial version of MINT under a separate contract. This report describes the work of the researchers at Urban and Brookings under the second contract.

The MINT data system begins with household data from the 1990 through 1993 panels of the Survey of Income and Program Participation (SIPP) that have been matched to the administrative records of the Social Security Administration pertaining to earnings, benefit receipt, and date of death. MINT's core population consists of individuals from the 1931 to 1960 birth cohorts.

The version of MINT described in this report extends the earlier version of MINT by incorporating a more sophisticated representation of retirement, more elaborate models of pension and non-pension wealth accruals, and detailed earnings and retirement behavior of recipients of Disability Insurance (DI) benefits. It also adds new modules simulating health and work limitations, living arrangements, and eligibility and participation in the Supplemental Security Income (SSI) program. The new version is also more interactive than the first version of the model, with retirement and wealth depending recursively upon one another. The version described in this report is called MINT3, and the initial version is called MINT1.[1]

The primary purpose of the MINT effort is to develop a tool for projecting the distribution of income in retirement for the 1931 to 1960 birth cohorts. MINT3 can produce projections of economic and demographic characteristics in the year 2020, at the time of retirement, and for other years (from 1999 through 2032) and ages (between age 50 and death, or 2032, whichever comes first). It can be used both to construct a baseline using alternative economic and demographic assumptions and to analyze the distributional consequences of a variety of Social Security policy changes. The types of policy changes that MINT3 can help to analyze are discussed in greater detail in Chapter 11.

[1] As will be noted shortly, an intermediate step in the process of improving MINT was called MINT2. The changes introduced in MINT2 are also in MINT3.

I. SEQUENCING OF TASKS

The various forecasts that comprise MINT3 proceed sequentially. As in other dynamic microsimulation modeling efforts, outcomes in each stage depend on outcomes in previous stages. Further, time-varying predictors (for example, earnings or marital status) are limited to those elements that are themselves predicted elsewhere in MINT. Fixed (i.e., unchanging) parameters, like place of birth, must be available on the SIPP or the administrative records, or else must be imputed to the starting file.

The structure of MINT1 consisted of a number of blocks that were almost completely recursive.[2] Figure 1-1 illustrates the MINT1 processing sequence. In MINT1, many life events such as marriage transitions, earnings through age 67, and death were projected for the entire lifetime at one time for each individual in the sample. The first step was marriage and mortality, followed by a spouse imputation for those marrying or remarrying after the last SIPP interview, followed by earnings, and a Disability Insurance receipt hazard. Next, several important outcomes, such as pensions and the size of non-pension wealth, were projected as of ages 62, the early eligibility age for Social Security, and 67, the age for full benefits (the "normal retirement age"). MINT1 then predicted the age at which each person would take-up Social Security benefits, the rate at which the person would spend down his or her assets during Social Security benefit receipt, and any earnings the individual would have after first receipt of benefits.

MINT2 extended MINT1 to incorporate a new method of projecting earnings (see Chapter 2), but otherwise retained the overall structure and parameter estimates of MINT1. This version of the model was used to produce several conference papers (Cohen and Steuerle 2001; Smith, Toder, and Iams 2001).

MINT3 is better classified as having a dynamically recursive block structure. Instead of processing each outcome for an individual's entire lifetime, the model now processes a significant fraction of outcomes for one year at a time. While the modules of marriage and mortality and earnings to age 50 retain the block recursive features, the retirement, wealth, and earnings have become dynamically recursive. An advantage of this approach is that it allows additional feedbacks between processes. For example, earnings choices influence wealth accumulation, and subsequent shocks to wealth influence retirement decisions.

Figure 1-2 presents the overall structure of MINT3. The first step in the projection process is the generation of the estimates of earnings to age 67. As described in Chapter 2, this step implements a fundamentally different methodology than was employed in MINT1 and one that appears to produce much greater individual variation in lifetime earnings patterns. The process also produces revised estimates of mortality through age 67 and selects the records that will be projected to claim disability benefits.

The next steps involve applying the modules to generate demographic projections of mortality and changes in marital status for each record. Following this, spouses are found from other individuals in the SIPP panels for those who reported previous marriages or who are projected to marry subsequently.

[2] For a discussion of the distinction between completely and dynamically recursive blocks, see Sabelhaus, 1999.

Figure 1-1.
Original Mint Structure

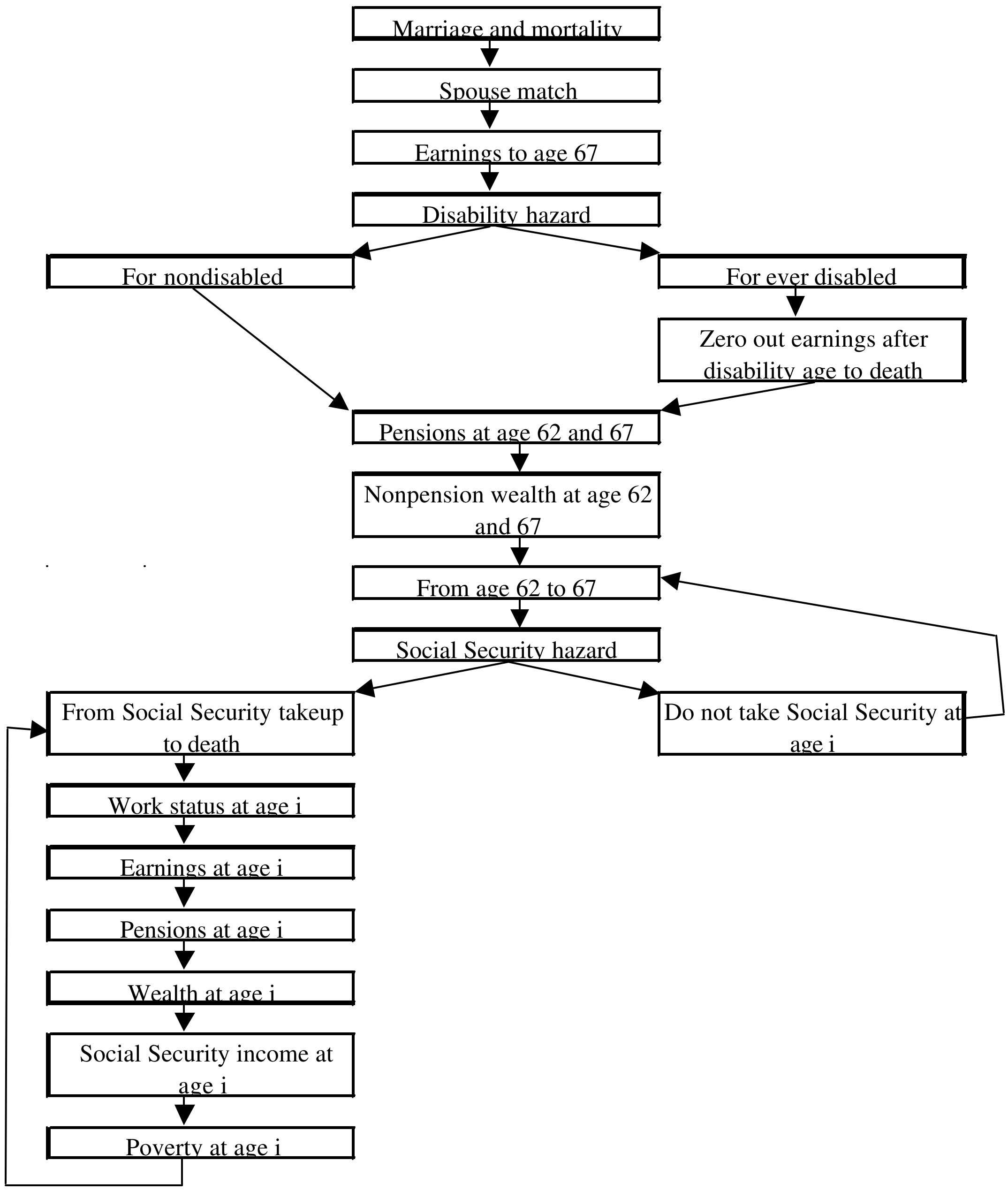
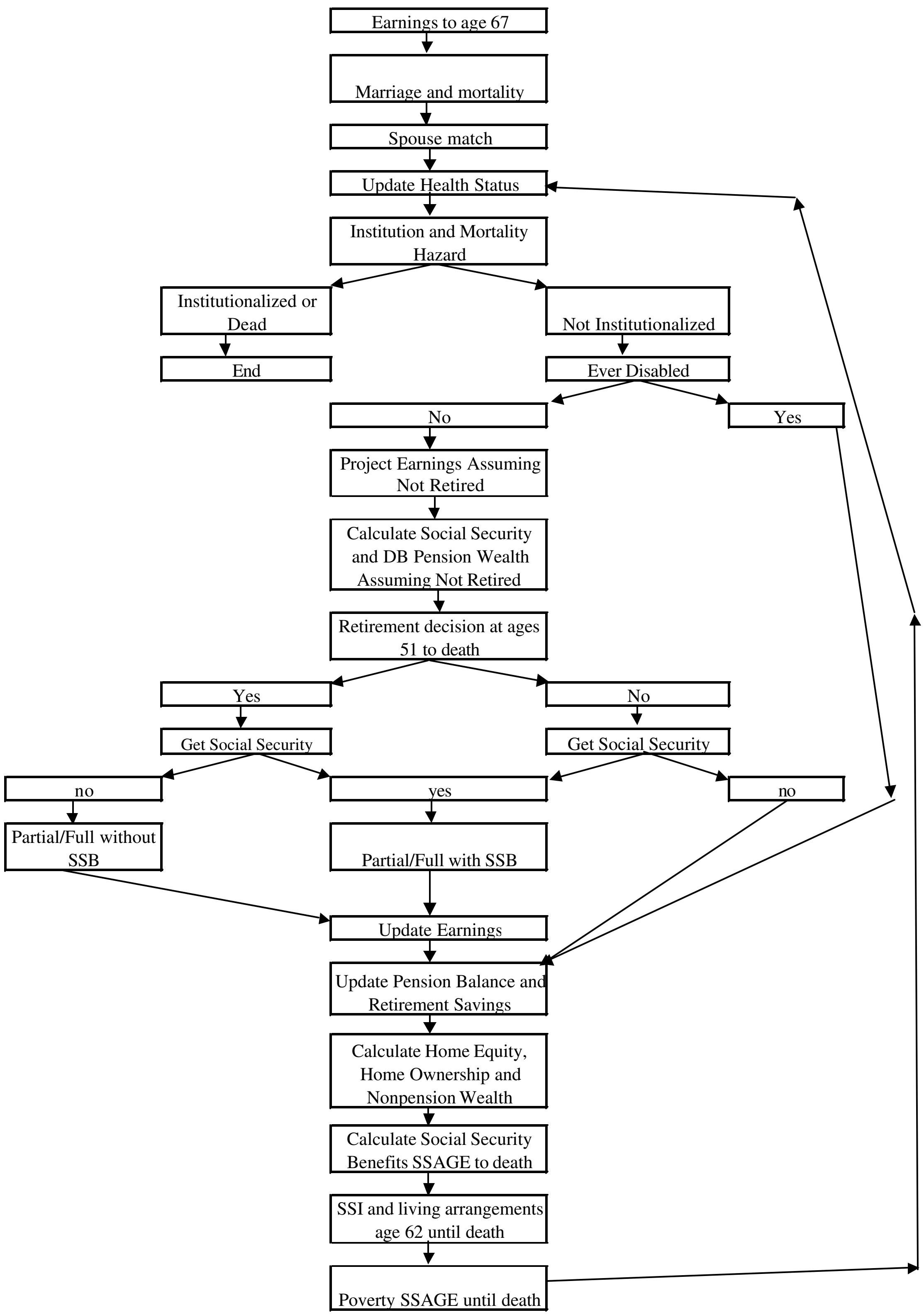


Figure 1-2. MINT 3 Program Structure



The next step is to update the health status. Health status influences the retirement decision prior to age 67 and the probability of institutionalization after age 62. The simulation stops for individuals at death or institutionalization. For survivors, the record is then checked to see if the individual has claimed disability benefits. Ever-disabled beneficiaries bypass the retirement loop retaining their step one earnings, while never-disabled individuals move into the retirement model where earnings may be updated.

The next two steps in the process provide the never-disabled, working population information that will be used to project retirement behavior from age 51 on. One involves projecting the individual's earnings should the individual not retire. The other involves projecting the Social Security and defined benefit pension wealth to which the individual would be entitled if he or she continued to work one more year. Each year, separate determinations are made as to whether non-disabled workers retire and whether they file for Social Security benefits. Once their retirement and beneficiary status has been determined, their earnings are updated for an additional year.

After the retirement and benefit status has been determined, all individuals are then exposed to a hazard function to update their home ownership status. After that, their home equity value is updated, and their pension wealth, non-pension wealth, and Social Security benefits (if any) are calculated. The last step in the cycle is to check for eligibility for SSI benefits. Those ages 62 to 64 may be eligible for disability benefits if their health status limits their ability to work, while those 65 and over are potentially eligible for SSI aged benefits. For those found to be eligible for benefits, the model simulates whether any SSI benefit is taken, and calculates the SSI benefit they receive. It then sums up the total income of the household and establishes whether the family income is above or below the poverty line. When this sequence has been completed, the program loops back to repeat the process for another year, beginning with update to health status.

II. ORGANIZATION OF THE CHAPTERS

The next six chapters of this report detail the specifications of each of the MINT3 modules. Chapter 2 discusses the method for projecting earnings through age 50, prevalence of Disability Insurance receipt, and earnings of the disabled through age 67. Because the Social Security Administration requested that MINT users have the capacity to calibrate disability prevalence rates to rates produced by the Office of the Chief Actuary (OCACT), these projections interact with the mortality forecasts originally produced by the RAND Corporation. Chapter 3 describes the model’s treatment of job demands, work limitations, and health status. In Chapter 4, we discuss the models of retirement, Social Security take-up, and earnings after age 50 for the non-disabled. Chapter 5 focuses on forecasts for retirement income from both defined benefit and defined contribution pensions. Chapter 6 outlines the models of asset accumulation and spend down. Chapter 7 describes the models of Supplemental Security Income program eligibility and participation and living arrangements.[3]

[3] These processes are considered together because of regulations that reduce SSI benefits for certain recipients who are living in another’s household.

Many of the individual chapters report the results of analyses to test the sensitivity of the baseline projections to changes in projection methodologies. One such test focused on the impact of substituting the mortality rates used in the Trustees' Report projections for those developed by RAND and used in the baseline projections. These results are reported in Chapter 8.

The final chapters pull together results from the preceding chapters to provide an overview of MINT3 projections. Chapter 9 traces the patterns in outcomes that the interacting MINT modules produce, focusing on the cohorts as they reach age 62 and age 67, respectively, and on the entire model population still alive in 2020. These patterns are disaggregated along many different dimensions, with specific consideration given to outcomes by sex and cohort. Separate tables examine labor force participation rates, retirement and Social Security take-up ages, earnings, living arrangements, and housing and non-housing wealth. Summary tables aggregate these sources of income (and SSI) to show total family incomes. Chapter 10 focuses on the MINT3 projections of poverty in 2020 and on the changes in family income and poverty between the 1990 and 2020 retirement populations. Chapter 11 discusses the policy changes that MINT3 can help analyze and contains some concluding observations.

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CHAPTER 2

PROJECTIONS OF EARNINGS AND PREVALENCE OF DISABILITY ENTITLEMENT

I. INTRODUCTION

This chapter describes the revised methodology used in MINT to predict the future prevalence of Social Security disabled workers and the level and distribution of Social-Security-covered-earnings for respondents in the 1990-93 Survey of Income and Program Participation (SIPP). It also describes the disability and earnings predictions produced by the most recent implementation of the methodology. Because our predictions of future disability prevalence depend on knowing the identities of MINT sample members who will survive in future years, we have also developed a method for predicting mortality up through age 67 for SIPP respondents in our sample. Our method integrates prediction of a respondent's future earnings and disability experience with the prediction of his or her mortality experience. Our method for predicting future deaths is described and documented in this report.

We have made predictions of earnings for years after 1999 for SIPP respondents born between 1931 and 1965. For all workers in our sample, we have made final or preliminary earnings predictions for the period beginning in 2000 and ending when a worker attains the Normal Retirement Age (NRA). An earlier version of our earnings predictions was incorporated in one version of MINT (MINT 2.0) that was used in recent research by Iams, Smith, and Toder (2001) and Cohen and Steuerle (2001), who examined the effects of OASI on the lifetime income distribution. Our earnings predictions after age 50, for most workers, will in turn be superseded by earnings predictions produced by an econometric model of retirement behavior. This model of retirement, described in Chapter 4, links annual earnings amounts to workers' transitions from long-term or full-time jobs to retirement. The retirement model produces a second set of earnings predictions, starting at age 51, for workers who do not become entitled to disability pensions according to the predictions generated in this chapter.

II. BACKGROUND

Most respondents to the 1990, 1991, 1992, and 1993 SIPP interviews provided Social Security numbers to the Census interviewer. The Social Security numbers were used to match SIPP interview records with respondents' Summary Earnings Records (SER) and Master Beneficiary Records (MBR). The SER provides administrative estimates of Social-Security-covered earnings up to the maximum taxable earnings amount in each calendar year after 1950. In earlier work, we used an adjustment procedure to convert the maximum amount into a consistent percentage of the economy-wide average wage. (See Toder *et. al*, 1999, for details.) The extract of administrative SER records available to us provided information on workers' earnings up through 1999. The MBR contains administrative data on Social Security benefit payments and spells of Social Security disability. The most recent extract from the MBR provides Social Security benefits information up through early 2000. The goal of our research is to predict Social Security covered earnings up through age 67 and to predict future spells of Social Security Disability Insurance (DI) entitlement in the MINT sample. We have used the prediction methodology described below to make disability and earnings forecasts for SIPP respondents born between 1926 and 1965 who have full-panel weights in the SIPP. We make predictions for all SIPP respondents in these birth cohorts, including those respondents who failed to provide a valid Social Security number.[1]

The predictions described in this chapter do not constitute final projections for most workers in the sample. For the SIPP respondents whom we predict will not become DI entitled, the final MINT model will use our earnings predictions only up through the year the worker attains age 50. A procedure described in Chapter 4 predicts earnings, retirement ages, and pension coverage at ages 51 and higher for those workers who never become DI entitled.

1. Earnings and Disability Projections in MINT 1.0

The first version of the MINT model, MINT 1.0, used a fixed-effects statistical model to estimate and forecast the earnings of workers born between 1926 and 1965. The parameter estimates in MINT 1.0 were based on observed Social-Security-covered earnings for workers who were in the matched SIPP-SER sample in calendar years from 1987 through 1996. The predictions of earnings after 1996 were obtained using a sample that included nondisabled workers as well as workers who ultimately became entitled to DI benefits or who were predicted to collect DI after 1996. After parameter estimates for the model were obtained, earnings after 1996 and up through age 66 were predicted for members of the sample who were 65 years old or younger in 1996. The procedure for predicting earnings after 1996 included a method for imputing a time-varying error term to the expected earnings of each worker in each year.

2. Problems with the Projections in MINT 1.0

The approach used in MINT 1.0 may have produced acceptable estimates of career-average earnings (average indexed monthly earnings), but its predictions of annual earnings and of the sequence of employment and non-employment status were deficient. The approach was designed to estimate the determinants of unconditional earnings, that is, average earnings not conditioned on a person's employment status. The approach therefore produced unreliable forecasts of employment status and of annual earnings conditional on a sample member's employment status.

[1] In a small number of cases, researchers have discovered major discrepancies between the SIPP demographic information and demographic information available in the Social Security Administration records of the supposed SIPP respondent. The discrepancies probably mean that a small number of SIPP records were incorrectly matched to Social Security records. These discrepancies were discovered after we made the tabulations described in this chapter. The discrepancies were taken into account by re-running the earnings, disability, and mortality prediction programs described below. Because only a small number of records was affected by this problem, the tabulations we describe here would match very closely – but not exactly – identical tabulations of the final MINT 2.1 data base.

The earnings predictions in the MINT 1.0 model were deemed unsatisfactory for a number of other reasons. They did not produce reliable predictions of the sequence of employment and nonemployment, and for that reason they cannot be directly used to predict future retirement patterns. They did not produce large enough variation in workers' lifetime earnings patterns at the end of workers' careers. This is because they were based on a structural model in which lifetime earnings profiles were assumed to center around a common humped-shaped pattern, whereas in fact lifetime earnings patterns are much more diverse. Finally, they did not generate enough predictions of the distinctive earnings patterns that are characteristic of workers who become disabled. Disabled workers usually experience sharp and relatively permanent earnings reductions around the time of their disabilities. Such earnings patterns were rare in the post-1996 earnings predictions of MINT 1.0.

The last problem of the earnings predictions was addressed in MINT 1.0 by using forecasts of future health limitations to modify the predicted pattern of earnings after the onset of a health limit. If a worker was predicted to develop a health limit, the DI entitlement model in MINT 1.0 predicted that the worker would face a sharply elevated risk of becoming DI entitled. Workers who were predicted to become DI entitled were then predicted to have no Social Security covered earnings after the entitlement occurred. In MINT 1.0, health limit predictions were produced by a model developed by Rand analysts based on information on historical health problems reported by SIPP respondents. Because respondents' reports of past health limitations were reliable predictors of past spells of DI entitlement, we believed that the predictions of future health limitations could be used to predict future spells of DI entitlement. Unfortunately, careful examination of the health limit predictions showed that they implied far too many future spells of health limitation, thus biasing the predictions of the future DI prevalence.

Rather than develop better predictions of future health limitation, we have chosen to develop better predictions of earnings patterns and sequences of employment and nonemployment. Because the earnings patterns of DI-entitled workers are quite distinctive in comparison with those of non-disabled workers, especially in the years leading up to disability and immediately following disability, improved predictions of future earnings patterns can help us identify those workers most likely to become disabled. At the same time, improved earnings predictions can help us produce a more realistic distribution of Old-Age Insurance (OAI) benefit entitlements as well as a more plausible distribution of retirement ages.

III. PROJECTIONS OF EARNINGS, DISABILTY AND MORTALITY

To predict earnings, disability and mortality over the remainder of a worker's career, we have developed a forecasting method that we refer to as "earnings splicing."[2] Rather than estimate a structural model of lifetime earnings, we use the observed earnings patterns of individual workers in older birth cohorts to predict future earnings of individual workers in younger cohorts. In order to duplicate the exact statistical properties of the observed earnings patterns of older birth cohorts, we use a hot deck statistical imputation procedure to splice part of the earnings record of an older worker to that of a younger worker. This also provides a

[2] In the MINT data set, disability is defined as entitlement to a Social Security Disability Insurance (DI) benefit for a primary worker beneficiary.

straightforward method to integrate earnings, disability entitlements, and mortality experience into our projections. We apply this technique repeatedly in 5-year intervals to build up the full lifetime work histories of persons who had not yet completed their careers by the last year of the SER (1999).

Survey statisticians frequently use the hot deck procedure to impute missing data in the case of interview non-response. This type of problem arises when a participant fails to give a valid answer to a survey question. In a typical hot deck imputation, non-respondents and those with valid survey responses are stratified into cells defined by several categorical variables (not including the variable to be imputed). Within each cell, a "donor" (that is, a responding person) is randomly selected to represent a person who failed to give a valid response. In some cases, the procedure is carried out with the limitation that the same donor cannot be selected twice, a practice known as "hot decking without replacement." (We did not impose this constraint in our implementation.) Once a donor and nonrespondent are matched, the valid responses of the donor are copied over to the nonrespondent while leaving the valid responses of the nonrespondent unchanged. It might be the case that, with a given set of matching variables, a non-respondent is a member of a cell containing no suitable donors. The chances of a match can be increased by reducing the number of cells or by using fewer variables or broader categories to define the cells. The hot deck procedure requires decisions about the matching variables to use, as well as the order in which they should be relaxed.

We used the hot deck procedure to select older workers' earnings records to splice to the end of incomplete earnings records of younger workers. First, we created a historical record covering the period through 1999 for each person in the MINT file. This record combines information on the worker's annual covered earnings (from the Summary Earnings Record or SER), disability entitlements (from the Master Beneficiary Record or MBR), and mortality (from both the Numident file and the MBR).[3] Information on gender, race and educational attainment was also included from SIPP. We define an "incomplete record" as one in which the MINT sample member had not yet attained age 67 by 1999, the last year covered by the SSA earnings record. We then used the splicing methodology to predict covered earnings, disability entitlements, and mortality experience for all persons with incomplete records. However, rather than splice the entire completed earnings record of an older donor onto the record of a worker with an incomplete earnings record, we performed successive imputations in 5-year time segments at the end of each incomplete record. Different donors from successively older cohorts provided the earnings information that is spliced to the end of each incomplete earnings record.

Our splicing method can be illustrated with reference to a specific worker. Suppose a target male worker attains age 44 in 1999. To predict his earnings from ages 45 to 49, we match him to a donor for whom we observe the *actual* earnings sequence in this age interval. Thus, the potential donor pool for this target worker can only contain men who were at least 49 years old

[3] Persons who did not provide a valid Social Security number or whose reported number could not be matched to Social Security records were also included in the earnings splicing procedure. However, to implement the splicing procedure for these cases we first had to impute an earnings, disability, and mortality record up through 1999 for each SIPP respondent who failed to provide a valid Social Security number. Earnings records up through 1999 were imputed to these persons with a hot deck procedure developed by John Coder for MINT 1.0 (see below). After this first imputation was completed, we followed the earnings splicing methodology to generate a complete earnings, disability, and mortality record through age 67.

in 1999. In addition, we restricted the years of spliced earnings records to the period 1993-1999. In this case, men in the 1948-1950 birth cohorts comprised the donor pool, since they attained age 49 in 1997-1999, respectively.[4] In order to select an appropriate donor for this target worker, we compared the experience of donor and target workers in the five-year period immediately before age 45. For this matching interval (ages 40 to 44), we defined a number of categorical variables. These variables were used to match the target worker to a donor with similar earnings and disability experience. The actual donor is selected at random from among the candidate donors. We then spliced the relevant information from the donor's record to the target worker's incomplete record. At this point, the target worker has a complete record through 2004 or age 49. The projections continue in 5-year segments for ages 50-54, 55-59, 60-64, and 65-69. In each iteration, the selection of a donor follows the same procedure, so a sequence of donors is selected from successively older birth cohorts. In the last step of the splicing procedure, our target worker is matched to a similar worker drawn from the 1928-1930 birth cohorts.

1. Earnings and Disability Projections for Non-Disabled Workers

While the splicing procedure is similar for all our projections, we developed separate matching variables and donor restrictions for disabled and non-disabled workers. This was done because of the important differences in the earnings patterns and mortality experience of these two groups. To be included in the splicing procedure for non-disabled workers, neither target nor donor worker could have been entitled to DI benefits before the end of the matching period. We selected the following categorical variables to match non-disabled target workers to donors:

(1) Age:
Age at the end of the matching interval. For the target worker, this is the age attained in the last year of the incomplete earnings record.

(2) Gender:
1=Male;
2=Female.

(3) Years of earnings in 5-year matching period (workers must have earnings equal to at least 2.7% of the economy-wide average age – or one quarter of Social Security earnings credit – to be credited with positive earnings in any year[5]):

[4] For potential donors who are 6 or 7 years older than the target worker, there may be a problem of including them in the donor pool. If a candidate donor was enrolled in the SIPP sample in 1993, there is no possibility the candidate can die in either 1991 or 1992. Including this observation in the donor pool would bias our predictions of mortality by understating the probability that the target worker could die in the first year or two of the projection period. To eliminate this bias we only included potential donors in the donor pool if every year of the projection period occurred after the candidate donor was selected in the SIPP sample.

[5] Workers were classified as non-earners in a particular year if they earned less than 2.7% of the economy-wide average wage. To be more precise, the threshold was calculated as 2.7% of the economy-wide average wage two years before the indicated year. This is approximately the threshold presently used to obtain one quarter of earnings credit for gaining eligibility for OASI and DI benefits. This measure of non-zero earnings is used throughout the imputation process. Within each matching period, a large percentage of workers has 5 years of positive earnings. To make a further distinction between high and low earners with 5 years of steady earnings, we sub-divided this category into two equal groups. First we calculated the median earnings over the 5-year interval for

0=Zero; 1=One; 2=Two; 3=Three; 4=Four;
5=Five years and earnings below median for age-gender-years of work group;
6= Five years and earnings above median for age-gender-years of work group.

(4) Average earnings in 5-year matching period:
0=Zero;
1=Bottom one-fifth of earners in age-gender-years of work group;
2=Second one-fifth of earners in age-gender-years of work group;
3=Middle one-fifth of earners in age-gender-years of work group;
4=Fourth one-fifth of earners in age-gender-years of work group;
5= Top one-fifth of earners in age-gender-years of work group.

(5) Earnings in fifth year:
0=No;
1=Yes.

(6) Earnings in fourth year of matching period:
0=No;
1=Yes.

(7) Average earnings before 5-year matching period:
1= Bottom one-fifth of age-gender group;
2= Second one-fifth of age-gender group;
3= Middle one-fifth of age-gender group;
4= Fourth one-fifth of age-gender group;
5= Top one-fifth of age-gender group.

(8) Race and ethnicity:
1=White, non-Hispanic;
2=White, Hispanic;
3=Black;
4=Other race.

(9) Educational attainment group:
1=Less than high school diploma;
2=High school diploma;
3=Some college;
4=College graduate or post-graduate.

both men and women separately, who had worked 5 full years. If a person's earnings exceeded her gender group's median, she was coded as "6." Otherwise she continued to be coded as having 5 years of earnings in the 5-year interval.

We first attempted to find a donor who shared a target worker's values for all nine variables. If no such person existed, we relaxed the categorical constraint in the reverse sequence of that shown above. Experimentation with alternative definitions of the key variables revealed that it was often difficult to find candidate donors for younger workers who worked just two or three years in a 5-year matching period. Such earnings sequences are relatively uncommon among prime-age workers. If we failed to find a match on the earnings variable (key variable #4 above), we started the matching process over using an alternative earnings variable:

(4a) Earnings level:
0=No earnings in 5-year matching period;
1=Bottom one-fourth of earnings in the target worker's age-gender group;
2=Second one-fourth of earnings in the target worker's age-gender group;
3=Third one-fourth of earnings in the target worker's age-gender group;
4=Top one-fourth of earnings in the target worker's age-gender group.

Although it was not always possible to find donors who matched target workers on all nine key variables, we always successfully matched non-disabled workers on age, gender, a measure of average earnings during the match period, and number of years worked during the matching interval. Our success in obtaining good matches for non-disabled target workers is indicated in Appendix Tables A2-1 and A2-2. These tables show the percentage of target workers whose donor was found at each of 9 matching levels, where level one represents a match on all of our key variables. With access to an exceptionally large sample of candidate donors, we were able to match over three-quarters of the target workers to donors on this first level.

Before imputing a donor's earnings data to the target worker's post-1999 earnings record, we modified the earnings record of the donor worker to provide a slightly better prediction. The donor's annual earnings were first multiplied by W_T / W_D, where W_T is the target worker's average wage and W_D is the donor's average wage during the matching period. If the target worker earned 5% less earnings in the matching interval than the selected donor worker, for example, the donor's average earnings in the projection interval would be reduced 5% before final imputation to the target worker. This modification preserves the relative age-earnings pattern observed for the donor worker. (We did not follow this procedure for earnings records where the donor's or target worker's average earnings during the five-year matching period were less than 10% of the average economy-wide wage. In that case, we imputed the donor's earnings record without any modification. If instead we had multiplied the donor's earnings by W_T / W_D, some of the resulting imputations for target workers would have been absurdly large or small, because the ratio W_T / W_D can easily take extreme values when W_T or W_D is very small.)

We used the identical splicing procedure to project disability and mortality of the target worker. In fact, the donor selected for purposes of predicting earnings was used to predict the target worker's disability and mortality experience during the five-year imputation period. If the selected donor worker became entitled to DI benefits during the five years following the matching interval, then we predicted that the target worker would become disabled at the same age. Likewise, the donor's death, if it occurred within the 5-year imputation period, was also imputed to the target worker. Any target worker predicted to die or become disabled was then removed from the non-disabled splicing procedure. The splicing methodology thus offers a natural way to link projections of DI receipt and mortality to earnings patterns. For workers who are predicted to die, no further earnings projections are necessary. In the case of a worker who is predicted to become disabled during a 5-year imputation period, earnings records for 5-year intervals after the predicted disability were selected from candidate donors who had experienced a previous spell of disability.

2. Projections of Earnings and Entitlement Patterns for Disabled Workers

A different set of characteristics was used to identify candidate donor records for target workers who had ever been disability-entitled before the beginning of a five-year imputation period. Other than new matching variables and the restriction that donors and target be disabled workers, the splicing procedure was the same as the one for non-disabled workers. The key variables for disabled workers are defined as follows:

(1) Age:
Age at the end of the matching interval.

(2) Gender:
1=Male;
2=Female.

(3) Mental Condition
0=Disabling condition is not a mental disability;
1=Disabling condition is a mental disability.

(4) DI entitlement ended due to recovery:
0=Has not recovered before end of matching period;
1=Recovered from disability before end of matching period.

(5) Disability entitlement has lasted more than 5 years:
0=No;
1=Yes.

(6) Duration of DI entitlement:
1=DI entitlement 5 years or less;
2=DI entitlement between 6 and 10 years;
3=DI entitlement greater than 10 years.

(7a) Average earnings since DI entitlement (for those entitled to DI more than 5 years):
1=Zero earnings;
2=Earnings less than the median of the non-zero averages of age-gender group;
3=Earnings greater than or equal to the non-zero averages of age-gender group.

(7b) Average earnings prior to DI entitlement (for those entitled to DI 5 years or less):
1=Zero earnings;
2=Earnings less than the median of the non-zero averages of age-gender group;
3=Earnings greater than or equal to the non-zero averages of age-gender group.

(8) Educational attainment group:
1=Less than high school diploma;
2=High school diploma;
3=Some college;
4=College graduate.

The indicator variables were relaxed in the reverse sequence of that shown above. Appendix Tables A2-3 and A2-4 present the quality of our matches for disabled workers. Because workers who become disabled only rarely have much earned income, we did not multiply the donor's earnings by W_T / W_D as we did in the case of never-disabled workers. In addition, disabled worker's earnings cannot exceed an absolute level defined by "substantial gainful activity," so it does not make sense to make any adjustment in the observed earnings of donor workers.

As in the non-disabled procedure if a donor died in the five-year projection age interval, the target worker was predicted to die at the same age. Additional DI information was passed from donor to target. Specifically, if the donor worker exited the DI rolls via recovery or conversion to an OAI benefit, this experience was also imputed to the target worker.[6] Even if a target worker was no longer entitled to DI benefits due to medical recovery, he remained in the disabled splicing procedure. However, he was matched to other disabled workers, who had also recovered. It was possible for a recovered target worker to receive a new DI entitlement. We tracked up to three spells of DI benefit receipt.

3. Imputed Records for Persons Without Matched Social Security Records

Workers who did not report a valid Social Security number during the SIPP survey could not be matched to their SER, MBR or Numident records. This group represents slightly more than 8% of the MINT sample with positive full panel weights. We used the hot-deck imputation program developed by John Coder for MINT 1.0 to provide earnings, disability, and mortality records up through 1999 for those persons in the MINT sample who lacked matched records.

In this imputation process, the donor pool included workers from a target worker's cohort, who had matched Social Security records. (This imputation was done before both the non-disabled and disabled splicing procedures described above.) Donors and target workers were

[6] Obviously, we delayed conversion to an OAI benefit to a later age than indicated in the donor's records for a target worker who has a higher NRA than the donor. Age 65 was the NRA for all older workers converted to an OAI pension in the late 1990s, but members of younger cohorts face a NRA that will be gradually increased until it reaches age 67 for members of the youngest MINT cohorts.

matched according to sex, age, race, marital status, education, monthly earnings, and class of worker as recorded in the SIPP survey. In contrast to the splicing procedure, the entire donor record up through 1999 was imputed to the target worker. This included all of the donor's earnings as well as any disability experience or mortality.

4. Advantages of the Splicing Method

The splicing imputation method has some crucial advantages compared with the individual fixed-effects panel model used in MINT 1.0. Perhaps the most important one is that it does not require us to make prior assumptions about the functional form of the age-earnings profile or about the time series structure of the sequence of employment/no employment states. Workers are imputed a much wider variety of age-earning profiles than are predicted when a standard earnings profile is estimated or assumed. If our procedure yields good matches, the sequence of earnings and of employment statuses that we predict for an individual worker will mirror those actually observed for a very similar worker during the five years between 1995 and 1999 (or between 1993-1997 or between 1994-1998).

A further benefit of earnings splicing is that the imputations only use data from the most recent available years in the SSA earnings records. The procedure does not impute earnings data drawn from workers' records in any year before 1993. It seems reasonable to believe that future earnings patterns will be more similar to those observed in the 1990s than those observed in the 1970s or 1980s. Of course, earnings patterns will probably change in the future compared with those observed in the 1990s, and some of the changes will not be reflected in our earnings forecasts. Earnings inequality may continue to increase among workers who have the same education and work experience, for example. The wage premium for higher skill and greater educational attainment may also continue to rise, and this trend will not be captured in our projections.

This does not mean, however, that our forecasts imply a static distribution of future earnings. The educational and other characteristics of younger MINT cohorts differ from those of the older cohorts. Because younger workers are only matched to observationally equivalent older workers, our forecast of future wage patterns is crucially affected by the changing pattern of observational characteristics in successive cohorts. One of the most important changes in characteristics has been the steady rise in employment rates and relative wages of American women. Women with incomplete earnings records are matched to older workers who have had similar earnings profiles up through the beginning of the splicing period. The increase in women's employment rates means that younger women are matched to women in the older cohorts who had unusually persistent employment or high earnings when they were young. Thus, the earnings splicing procedure yields a forecast of future employment and earnings that tends to reproduce the experiences of women in the older cohorts who remained steadily employed and earned good wages. The result is a forecast that predicts continued increases in female employment rates and improvements in women's wages, although at a slower pace than was observed in the 1980s and early 1990s.

IV. ADJUSTMENTS OF FORECASTS TO REPRODUCE THE DISABILTIY AND MORTALITY PROJECTIONS IN THE 2001 TRUSTEES' REPORT

In our discussion so far, we have outlined the basic splicing method used to select donors' records for purposes of predicting target workers' earnings, disability, and mortality in 2000 and later years. If our first-round predictions had been used without any modification, they would necessarily imply that the mortality and disability onset rates observed in the MINT sample during the 1990s would persist during the entire forecast period. However, the Social Security Actuary predicts that mortality rates will decline and disability rates increase over the next three decades. We obtained forecasts of disability prevalence and Social-Security-area mortality from the Office of the Chief Actuary (OCACT). These forecasts were used by the Actuary to produce the intermediate-cost projections in the 2001 *OASDI Trustees' Report.* In a modification of our basic splicing procedure, we then calibrated our predictions to match the intermediate projections of the Social Security Actuary.

1. Benchmarking the Disability and Mortality Predictions

The OCACT prepares detailed estimates of future rates of mortality and disability prevalence to support its predictions of OASDI revenues and outlays. These estimates show the precise mortality rate and disability prevalence rate by year of age for future years under three sets of assumptions about mortality and disability trends. The three sets of assumptions are commonly referred to as "high cost," "intermediate," and "low cost" assumptions, because each set of assumptions is associated with a pessimistic, intermediate, and optimistic projection of future Social Security revenues and outlays. We devised our imputation procedure so that our projections of future mortality and disability prevalence could match a variety of forecasts of future morality and disability, including the forecasts under the high-, intermediate-, and low-cost projections of the OCACT.

Mortality. The first step of our procedure was to calculate "benchmark" mortality and disability prevalence rates for designated groups of MINT sample members in specific future years. The goal of our benchmarking procedure was to make forecasts of mortality or disability prevalence for these groups of sample members in future years that match a particular set of benchmark rates implied by a particular OCACT forecast. We first divided MINT respondents into two gender groups and then into seven birth-year cohorts: Persons born 1931-35, 1936-40, 1941-45, 1946-50, 1951-55, 1956-60, and 1961-65. For each of these 14 groups we then calculated the mortality rate and disability prevalence rate implied by the OCACT forecast for seven different five-year periods: 2000-04, 2005-09, 2010-14, 2015-19, 2020-24, 2025-29, and 2030-34. These are the benchmark rates that we attempted to match with our forecasts of future disability and mortality.

The next step of our analysis was to modify our basic splicing method so that our forecasts of future mortality and disability prevalence would match the benchmark rates. To accomplish this, we selected "back-up" donors for a fraction of the target workers in the MINT sample. If our first-round donors produced forecasts of future mortality or disability that failed to duplicate the benchmark mortality or disability, we substituted back-up donors for first-round donors until the predicted mortality or disability rate matched the benchmark rate.

Consider our procedure for matching the benchmark mortality rate of women born between 1946-50 in the calendar years 2005-09. We selected first-round donor records for each target worker in this sample using the procedure described in Section III above. We then selected a candidate back-up donor for each target worker. If the candidate back-up donor had the same mortality outcome as the first-round donor, the candidate record was discarded and no back-up donor was selected for the target worker. If instead the candidate back-up donor had the opposite mortality outcome as the first-round donor, the candidate donor record was accepted as a valid back-up donor. This procedure produces two kinds of back-up donors. For target workers with a first-round donor who *dies*, the selected back-up donor must *survive* the five-year period from 2005-09. For target workers with a first-round donor who *survives*, the back-up donor must *die* during the five years from 2005 and 2009. Only a subset of target workers is assigned a back-up donor.[7]

With back-up donor records for many target workers, it is straightforward to make a mortality forecast for 2005-09 that matches the OCACT benchmark mortality forecast. Suppose the first-round donor records produce a mortality forecast that is higher than the rate implied by the OCACT forecast. In that case, our benchmarking procedure replaces some first-round donor records in which the donors die with back-up donor records in which the donors survive. The back-up donor records were selected at random from among all surviving back-up donors available in the sub-sample. We developed an iterative procedure in which larger or smaller numbers of first-round donor records are replaced by back-up donor records until the benchmark mortality rate is matched by our mortality forecast.[8]

This method for selecting donor records treats death as a random event which has a probability that depends on the key variables in the hot-deck matching procedure. Workers who have key variables associated with an elevated risk of death, such as below-average education or earnings, will face an above-average risk of being selected for a premature death. Our procedure for selecting back-up donor records preserves this relationship between the key variables and the risk of death.

Disability prevalence. The procedure we used to duplicate the OCACT disability forecast was essentially the same as the procedure we used to match the benchmark mortality

[7] Our software was written to allow for the selection of multiple back-up donors if the selection of only a single back-up donor was insufficient to duplicate the benchmark mortality rate. The selection of multiple back-up donors is needed when the target mortality rate is far above the rate observed in the MINT sample between 1993 and 1999. This might easily be true when we are trying to duplicate the mortality rate implied by the OCACT's low-cost projection.

[8] The selection criteria that we used to select back-up records were somewhat more complicated than the criteria described in the text. In particular, in selecting back-up records for adjusting our mortality forecast we required that included back-up records satisfy two conditions. First, the mortality status of the back-up donor record had to be the opposite of the mortality status of the first-round donor record. Second, the disability status of the back-up record had to be the *same* as that of the first-round donor record.

forecast. We selected a candidate back-up "disability donor" for each of the target workers. If the candidate back-up donor had the same disability outcome as the first-round donor, the candidate record was discarded and no back-up disability donor was selected for that target worker. If instead the candidate back-up donor had the opposite disability outcome as the first-round donor, the candidate donor record was accepted as a valid back-up donor. This procedure produces two kinds of back-up disability donors. For target workers with a first-round donor who becomes *disabled* during the five-year imputation period, the selected back-up donor *cannot* become disabled during the five-year period. For target workers with a first-round donor who *does not* become disabled, the back-up donor *must* become disabled during the five-year period.[9]

Using back-up donor records for some of the target workers, we could produce a disability forecast for each five-year period that closely matches the OCACT benchmark disability forecast. Suppose the first-round donor records produce a disability forecast that is below the rate implied by the OCACT forecast. In that case, our benchmarking procedure replaces some first-round donor records in which the donors do not become disabled with back-up donor records in which the donors become disabled. We developed an iterative procedure in which larger or smaller numbers of first-round donor records are replaced by back-up donor records until the benchmark disability rate is matched by our disability forecast.

2. Comparison with OCACT Mortality Predictions

Table 2-1 shows benchmark mortality rates for each birth cohort in successive periods through 2034. Rates for males are displayed in the first column; rates for females are shown in the fourth column. For example, the top entry in the first column shows the 2000-2004 mortality rate for males born between 1931 and 1935. We derived this estimate from the OCACT's intermediate-cost predictions of annual mortality in the Social-Security-area population, by year of age, during the period from 2000-2004. In the second and fifth columns we show the initial prediction of mortality for the same birth cohorts in the same years using the splicing methodology described in Section III above. The third and sixth columns contain our final predictions of mortality for each birth cohort in each five-year period. In each case the final predicted mortality rate is very close to corresponding benchmark rate, indicating that our benchmarking procedure was able to duplicate the OCACT's intermediate-cost mortality projection.

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[9] Again, the actual selection criteria that we used to identify back-up donor records were a little more complicated than described in the text. In selecting back-up records for adjusting our disability forecast we required that included back-up records satisfy two conditions. First, the disability status of the back-up donor record had to be the opposite of the disability status of the first-round donor record. Second, the mortality status of the back-up record had to be the *same* as that of the first-round donor record. By imposing the latter criterion, we ensured that the mortality rate remained unchanged even if we used the back-up donor record instead of the first-round donor record.

Table 2-1
Mortality Rate by Sex and Birth Cohort in Successive Five-Year Periods, Benchmark Rates and Rates in MINT 2.1 Data Set

	Men			Women		
Cohort	Benchmark Rate	Initial MINT Rate	Final MINT Rate	Benchmark Rate	Initial MINT Rate	Final MINT Rate
Years 2000-04						
1931-35	2.44%	2.51%	2.43%	1.51%	1.75%	1.51%
1936-40	1.87%	1.86%	1.86%	1.18%	1.01%	1.18%
1941-45	1.15%	0.99%	1.16%	0.73%	0.74%	0.73%
1946-50	0.73%	0.64%	0.74%	0.45%	0.37%	0.45%
1951-55	0.48%	0.43%	0.48%	0.28%	0.23%	0.28%
1956-60	0.33%	0.25%	0.33%	0.18%	0.14%	0.18%
1961-65	0.23%	0.19%	0.23%	0.12%	0.15%	0.12%
Years 2005-09						
1936-40	2.31%	2.81%	2.27%	1.50%	1.23%	1.51%
1941-45	1.76%	1.66%	1.75%	1.17%	1.18%	1.17%
1946-50	1.06%	1.14%	1.07%	0.70%	0.56%	0.71%
1951-55	0.66%	0.63%	0.65%	0.43%	0.42%	0.42%
1956-60	0.43%	0.47%	0.43%	0.26%	0.23%	0.26%
1961-65	0.30%	0.29%	0.30%	0.16%	0.15%	0.16%
Years 2010-14						
1941-45	2.21%	2.39%	2.20%	1.50%	1.16%	1.50%
1946-50	1.66%	1.48%	1.65%	1.15%	1.00%	1.15%
1951-55	0.99%	1.11%	0.99%	0.68%	0.64%	0.68%
1956-60	0.61%	0.61%	0.61%	0.40%	0.38%	0.41%
1961-65	0.40%	0.42%	0.40%	0.24%	0.24%	0.23%
Years 2015-19						
1946-50	2.11%	2.72%	2.10%	1.47%	1.63%	1.46%
1951-55	1.58%	1.59%	1.59%	1.12%	1.00%	1.11%
1956-60	0.93%	1.18%	0.94%	0.66%	0.62%	0.65%
1961-65	0.58%	0.69%	0.57%	0.39%	0.33%	0.39%
Years 2020-24						
1951-55	2.03%	2.57%	2.02%	1.43%	1.21%	1.44%
1956-60	1.52%	1.62%	1.51%	1.08%	1.09%	1.09%
1961-65	0.90%	1.27%	0.89%	0.64%	0.63%	0.64%
Years 2025-29						
1956-60	1.95%	2.45%	1.94%	1.38%	1.17%	1.37%
1961-65	1.47%	1.73%	1.47%	1.05%	1.04%	1.04%
Years 2030-34						
1961-65	1.88%	2.87%	1.88%	1.33%	1.40%	1.34%

Note: Benchmark mortality rates are calculated using the OCACT intermediate-cost assumptions for the 2001 *Annual Trustees' Report*. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C.

We also display the correspondence between the final MINT 2.1 mortality projections and the forecast of the OCACT using an alternative set of calculations. The top panel in Table 2-2 shows the historical and OCACT-projected mortality rate, by gender and age group, in 1994-1998 and future five-year periods. The second panel shows the mortality rates in the MINT 2.1 data set for the same age and gender groups in the same set of years. The bottom panel shows the ratio of the MINT forecast to the OCACT forecast for the same age and gender groups. Because we are only examining the experiences of MINT sample members who were born between 1926-65, the table contains many blank entries. There are not enough people in the MINT sample to estimate mortality rates in the blank cells reliably.

The tabulations in Table 2-2 show larger discrepancies between mortality rates predicted in the MINT 2.1 sample and mortality rates predicted under the intermediate-cost assumptions embedded in the 2001 *OASDI Trustees' Report*. For example, the predicted mortality rate for 50-54 year-old men is about 7% - 8% higher in the MINT 2.1 sample than it is in the OCACT forecast. On the other hand, mortality rates of older men in the MINT 2.1 sample are somewhat lower than those in the OCACT forecast. The discrepancies appear larger in Table 2-2 than Table 2-1 because mortality rates are calculated over somewhat different populations in the two tables. In Table 2-1, we calculate morality rates for precisely the same populations, defined by birth-year cohorts, that were used to benchmark the MINT 2.1 mortality predictions. In Table 2-2, we calculate mortality rates for populations defined by workers' age in a year rather than by their birth year. If 52-year-old men in the SIPP sample had an unusually high death rate during the late 1990s, our splicing methodology will produce high predictions of death among 52-year-old men throughout the projection period. The benchmarking procedure attempts to minimize the difference between entries in columns 1 and 3 in Table 2-1. This does not necessarily eliminate differences between entries in the top and middle panels in Table 2-2. On the whole, we believe our mortality predictions are reasonably close to the OCACT forecast.

Note that we do not make any adjustments in our estimates of mortality during the historical period. As it happens, male mortality rates in the MINT 2.1 sample were approximately the same between 1994 and 1998 as the rates suggested by national vital statistics data. However, the female mortality rate in the MINT 2.1 sample was somewhat lower than indicated in the vital statistics data, especially before age 55. The mortality rates found in the Numident and MBR data sets for the MINT 2.1 sample were left unchanged in our final data set.

3. Comparison with OCACT Disability Predictions

To measure DI prevalence using statistics provided by the OCACT, we divide the number of disabled workers in current payment status on the first day of a year by the total number of workers in the Social-Security area on the first day of the year.

With information available to us from the MBR it is difficult to determine precisely the identity of workers in the MINT sample who are disabled and in current pay status at a given point in time. It is easier to determine whether a worker is "DI entitled." Unfortunately, not all DI-entitled workers are in current pay status. In some cases, workers who will later be

Table 2-2
Benchmark Mortality Rates in Social-Security-Area Population and MINT 2.1 Sample, 1994-2024

	Men					Women				
Year	40-44	45-49	50-54	55-59	60-66 *	40-44	45-49	50-54	55-59	60-66 *
Office of the Chief Actuary										
1994-98	0.34%	0.47%	0.70%	1.08%	1.73%	0.17%	0.25%	0.40%	0.64%	1.03%
2000-04	0.31%	0.44%	0.67%	1.04%	1.84%	0.17%	0.25%	0.41%	0.66%	1.17%
2005-09		0.40%	0.61%	0.96%	1.73%		0.23%	0.38%	0.63%	1.15%
2010-14			0.55%	0.89%	1.64%			0.36%	0.61%	1.13%
2015-19				0.84%	1.56%				0.59%	1.10%
2020-24					1.50%					1.07%
MINT 2.1										
1994-98	0.26%	0.49%	0.72%	1.01%	1.72%	0.15%	0.20%	0.32%	0.62%	0.97%
2000-04	0.26%	0.49%	0.72%	1.01%	1.80%	0.18%	0.25%	0.43%	0.65%	1.29%
2005-09		0.40%	0.65%	0.99%	1.62%		0.26%	0.38%	0.64%	1.18%
2010-14			0.59%	0.88%	1.54%			0.40%	0.62%	1.23%
2015-19				0.80%	1.56%				0.62%	1.16%
2020-24					1.54%					1.11%
Ratio MINT / OACT										
1994-98	0.77	1.05	1.03	0.93	1.00	0.88	0.80	0.81	0.98	0.94
2000-04	0.85	1.11	1.08	0.96	0.98	1.11	0.99	1.05	0.98	1.10
2005-09		1.00	1.08	1.03	0.94		1.13	0.99	1.01	1.03
2010-14			1.07	0.99	0.94			1.10	1.01	1.09
2015-19				0.94	1.00				1.05	1.05
2020-24					1.03					1.04

* Ages 60-64 in 1994-98.
Sources: Office of the Chief Actuary and authors' tabulations of MINT 2.1 sample.

determined to be DI-entitled have not yet been awarded their first monthly benefit check. In such cases, the worker is entitled to DI even though he or she has not yet received a DI check. In other cases, workers who are entitled to benefits may be suspended from current pay status because they have substantial earnings that temporarily exclude them from receiving a monthly check. We measure DI prevalence in the MINT sample in a given year by dividing the number of workers who are DI entitled on the first day of the year by the total MINT population in the indicated age group on the first day of the year.

Table 2-3 shows benchmark disability rates for each birth cohort in successive periods through 2034. Rates for males are displayed in the first column; rates for females are shown in the fourth column. For example, the top entry in the first column shows the 2000-2004 disability rate for males born between 1931 and 1935. We derived this estimate from the

Table 2-3
Disability Prevalence by Sex and Birth Cohort in Successive Five-Year Periods, Benchmark Rates and Rates in MINT 2.1 Data Set

	Men			Women		
Cohort	**Benchmark Rate**	**Initial MINT Rate**	**Final MINT Rate**	**Benchmark Rate**	**Initial MINT Rate**	**Final MINT Rate**
Years 2000-04						
1936-40	12.83%	14.41%	12.85%	8.72%	8.92%	8.77%
1941-45	10.06%	11.85%	10.08%	7.65%	10.59%	7.74%
1946-50	6.53%	7.98%	6.54%	5.25%	6.96%	5.29%
1951-55	4.46%	4.57%	4.47%	3.67%	4.56%	3.66%
1956-60	3.19%	3.01%	3.19%	2.58%	3.08%	2.58%
1961-65	2.21%	3.33%	2.19%	1.80%	2.24%	1.79%
Years 2005-09						
1941-45	13.06%	11.14%	13.09%	9.77%	8.70%	9.80%
1946-50	10.06%	10.76%	10.09%	8.29%	9.77%	8.27%
1951-55	6.78%	7.74%	6.75%	6.05%	6.39%	6.01%
1956-60	4.62%	5.00%	4.62%	4.09%	4.52%	4.09%
1961-65	3.26%	3.12%	3.23%	2.91%	3.15%	2.89%
Years 2010-14						
1946-50	13.19%	12.25%	13.06%	10.58%	9.14%	10.44%
1951-55	10.57%	10.35%	10.65%	9.37%	9.52%	9.37%
1956-60	7.11%	8.14%	7.13%	6.64%	7.69%	6.65%
1961-65	4.85%	5.23%	4.81%	4.57%	5.23%	4.61%
Years 2015-19						
1951-55	14.01%	12.64%	14.08%	11.69%	10.49%	11.75%
1956-60	11.44%	11.05%	11.40%	10.20%	10.33%	10.24%
1961-65	7.78%	7.53%	7.77%	7.33%	8.41%	7.33%
Years 2020-24						
1956-60	15.06%	12.95%	15.13%	**12.50%**	10.97%	**12.17%** *
1961-65	12.38%	11.97%	12.33%	10.93%	10.99%	10.99%
Years 2025-29						
1961-65	16.31%	14.47%	16.33%	**13.33%**	11.78%	**12.88%** *

Note: Benchmark rates of disability prevalence are calculated using the OCACT intermediate-cost assumptions for the 2001 *Annual Trustees' Report*. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C.

* Final MINT rate differs from benchmark rate by at least 2% of the benchmark rate.

OCACT's intermediate-cost predictions of disability prevalence in the Social-Security-area population, by year of age, during the period from 2000-2004. In the second and fifth columns we show the initial prediction of disability for the same birth cohorts in the same years using the splicing methodology described in Section III above. The third and sixth columns contain our final predictions of disability prevalence for each birth cohort in each five-year period. In almost all cases the final predicted disability rate is very close to corresponding benchmark rate, indicating that our benchmarking procedure was usually able to duplicate the OCACT's intermediate-cost disability projection. The two exceptions are indicated in bold and with an asterisk. We were unable to match exactly the OCACT forecast of disability prevalence for the two youngest female birth cohorts, 1956-60 and 1961-65, when they approached the normal retirement age (NRA). Our final prediction of DI prevalence falls about 3% short of the OCACT forecast of disability prevalence.

We also display the correspondence between the final MINT 2.1 disability projections and the forecast of the OCACT using an alternative set of calculations. The top panel in Table 2-4 shows the historical and OCACT-projected disability rate, by gender and age group, in 1994-1998 and future five-year periods. The second panel shows the disability rates in the MINT 2.1 data set for the same age and gender groups in the same set of years. The bottom panel shows the ratio of the MINT forecast to the OCACT forecast for the same age and gender groups. Because we are only examining the experiences of MINT sample members who were born between 1926-65, the table contains many blank entries. There are not enough people in the MINT sample to estimate disability rates in the blank cells reliably.

As noted earlier, the OCACT predicts a higher rate of DI prevalence in the future than was observed in the 1990s. The top panel in Tables 2-4 shows male and female DI prevalence rates under the intermediate assumptions of the Social Security Trustees. (The average historical rates shown for the period 1994-1998 are taken from the *Annual Statistical Supplement* rather than the OCACT projections.) Note that the Actuarial forecast implies DI prevalence will climb substantially after 1999, especially among women.

The differences between our projections and the forecasts of the OCACT are shown in the bottom panel of Tables 2-4. In the historical period (1994-1998) our estimates are reasonably close to those of the Social Security Administration for men under the age of 60 and most women under age 50. Our estimates of DI prevalence are lower than SSA's for older age groups. One reason for the difference is that we use a somewhat different definition of DI prevalence than the OCACT. The OCACT definition uses the number of disabled workers *in current pay status* in estimating prevalence, but we use the number of *DI-entitled* workers. Because many workers become DI-entitled before they are in current pay status, the resulting difference between the estimates seems plausible.

V. ANALYSIS OF PROJECTIONS: VALIDATION TESTS

We have performed a variety of tabulations to determine whether the earnings imputations for the MINT sample seem valid or reasonable.

1. Average Age-Earnings Profile across Birth Cohorts and Pattern of Standard Deviation of Annual Earnings

Our first set of tabulations, which show the projected trend in age-earnings profiles across successive birth cohorts, are displayed in Figures 2-1 through 2-14. Figures 2-1 through 2-7 contain information on the historical and projected age-earnings profiles of men; Figures 2-8 through 2-14 show information on the age profiles of women. Unless otherwise noted, the tabulations cover all members of the MINT 2.1 sample who are alive or are projected to be alive at the age indicated on the horizontal axis in the graphs. This includes sample members who die before attaining the Early Entitlement Age (EEA) or the NRA, as well as sample members who become disabled before attaining the NRA.

Table 2-4
Disability Prevalence by Sex and Birth Cohort in Successive Five-Year Periods, Benchmark Rates and Rates in MINT 2.1 Data Set

	Men: Age group						Women: Age group					
Year	35-39	40-44	45-49	50-54	55-59	60-64	35-39	40-44	45-49	50-54	55-59	60-64
Office of the Chief Actuary												
1994-98	1.9%	3.2%	4.3%	6.1%	9.8%	15.1%	1.5%	2.5%	3.4%	5.1%	8.1%	12.0%
2000-04	1.9%	2.8%	3.9%	5.6%	8.6%	12.5%	1.6%	2.2%	3.1%	4.5%	6.7%	8.8%
2005-09		2.9%	4.0%	5.8%	8.8%	12.6%		2.6%	3.5%	5.2%	7.5%	9.6%
2010-14			4.3%	6.0%	9.1%	13.1%			4.0%	5.7%	8.3%	10.7%
2015-19				6.8%	9.8%	13.9%				6.4%	9.0%	11.7%
2020-24					11.0%	14.9%					9.9%	12.5%
2025-29						16.3%						13.3%
MINT 2.1												
1994-98	2.3%	2.9%	4.2%	5.4%	9.3%	13.3%	1.6%	1.9%	3.0%	4.4%	6.4%	8.1%
2000-04	2.3%	2.9%	4.1%	5.3%	7.4%	12.0%	1.7%	2.2%	2.9%	4.5%	6.1%	8.1%
2005-09		2.7%	4.1%	5.8%	7.8%	10.9%		2.2%	3.4%	4.9%	6.6%	8.4%
2010-14			4.2%	6.1%	9.3%	13.0%			3.6%	5.6%	7.8%	11.2%
2015-19				6.7%	9.5%	13.2%				6.1%	8.4%	10.9%
2020-24					10.2%	14.3%					9.3%	12.2%
2025-29						16.5%						13.5%
Ratio MINT / OACT												
1994-98	1.17	0.92	0.97	0.88	0.95	0.88	1.07	0.76	0.89	0.86	0.78	0.68
2000-04	1.17	1.06	1.07	0.95	0.86	0.96	1.07	0.98	0.92	0.98	0.90	0.92
2005-09		0.94	1.03	1.00	0.89	0.87		0.85	0.96	0.95	0.87	0.87
2010-14			0.99	1.01	1.03	1.00			0.91	0.98	0.93	1.05
2015-19				0.99	0.97	0.94				0.95	0.93	0.93
2020-24					0.93	0.96					0.93	0.97
2025-29						1.01						1.01

Sources: Office of the Chief Actuary and authors' tabulations of MINT 2.1 sample.

This inclusive sample presents a challenge for comparing the age-earnings profiles of older and younger cohorts. The oldest cohorts include only those potential members of the SIPP sample who survived to be interviewed in the SIPP. Since the MINT 2.1 sample is further restricted to SIPP sample members with full panel weights, nearly all members of the sample are also required to respond to all or most of the SIPP interviews. This basic sample criterion means that older and younger birth cohorts will contain a somewhat different mix of sample respondents. The older cohorts will exclude members of the birth cohort who died young. Since the young disabled have an unusually high mortality rate, this means the older cohorts will exclude many more of the workers who become disabled at a young age than will be the case in the younger cohorts. On the other hand, the younger cohorts exclude potential members of the cohort who have not yet immigrated to the United States, but who will immigrate sometime before late middle age. Most or all of these immigrants are represented in the older birth cohorts.

Figures 2-1 and 2-8: These figures show the average age-earnings profiles of all persons in the sample, including both earners and surviving persons with zero earnings in a given year. The top panel in the figure shows the average age-earnings profiles for members of four birth-year cohorts – persons born between 1926-1930, between 1936-1940, between 1946-1950, and between 1956-1960. The lower panel shows the age-earnings profiles of the other birth-year cohorts – persons born between 1931-1935, between 1941-1945, between 1951-1955, and between 1961-1965. For men in successive cohorts, the age-earnings profile does not change very much. Younger cohorts generally have lower relative earnings than older cohorts, in large measure because of the rapid progress of women in closing the earnings gap with men, a trend which in turn must depress the mean earnings of men relative to the economy-wide average wage. For women in successive cohorts the lifetime pattern of earnings changes dramatically, in part because younger cohorts have enjoyed higher relative earnings when they are employed, but also because women in younger cohorts are remaining steadily employed, whereas women in older cohorts were more likely to withdraw from the work force in their twenties, shortly after they married or had their first children.

Figures 2-2 and 2-9: These figures show average age-earnings profiles of all persons in the sample who have positive earnings in a given year, that is, who earn at least 2.7% of the economy-wide wage.[10]

Figures 2-3 and 2-10: These figures show the average age profile of employment-population ratios for all persons in the sample. A worker who earns at least 2.7% of the economy-wide wage is treated as employed in a given year. The shift in the age profile of employment is not very interesting for men. Aside from the increase in covered employment at the youngest ages, there is very little trend in the percentage of men who earn positive Social-Security-covered labor income at successive ages. (The apparent increase of male employment at younger ages is almost certainly attributable to the gradual increase in the percentage of employment covered by the Social Security system, a factor that will depress the measured employment rates of 22-35 year-old men in the oldest birth cohorts.) For women, the historical data and our projections show a much more interesting shift over time. Employment rates at a given age are progressively higher for women in the younger cohorts, although the difference is quite modest by the time women reach age 65.

Figures 2-4 and 2-11: These figures show the age profile of the standard deviation of earnings for persons who earn at least 2.7% of the economy-wide wage in a given year. In the top panel we show the trend, by year of age, of the standard deviation of earnings for persons in the 1926-1930, 1936-1940, 1946-1950, and 1956-1960 birth-year cohorts. The lower panel shows the standard deviations for workers in the other four birth-year cohorts. Among both men

[10] More precisely, we calculate a threshold level of earnings that is 2.7% of the economy-wide wage two years before the indicated year. This threshold is the amount now needed to obtain credit for one quarter of earnings credit. In the past, the minimum threshold was sometimes higher and sometimes lower than this. However, in order to make our definition of "zero earnings" more or less consistent over time, we have adopted this uniform definition of "zero earnings."

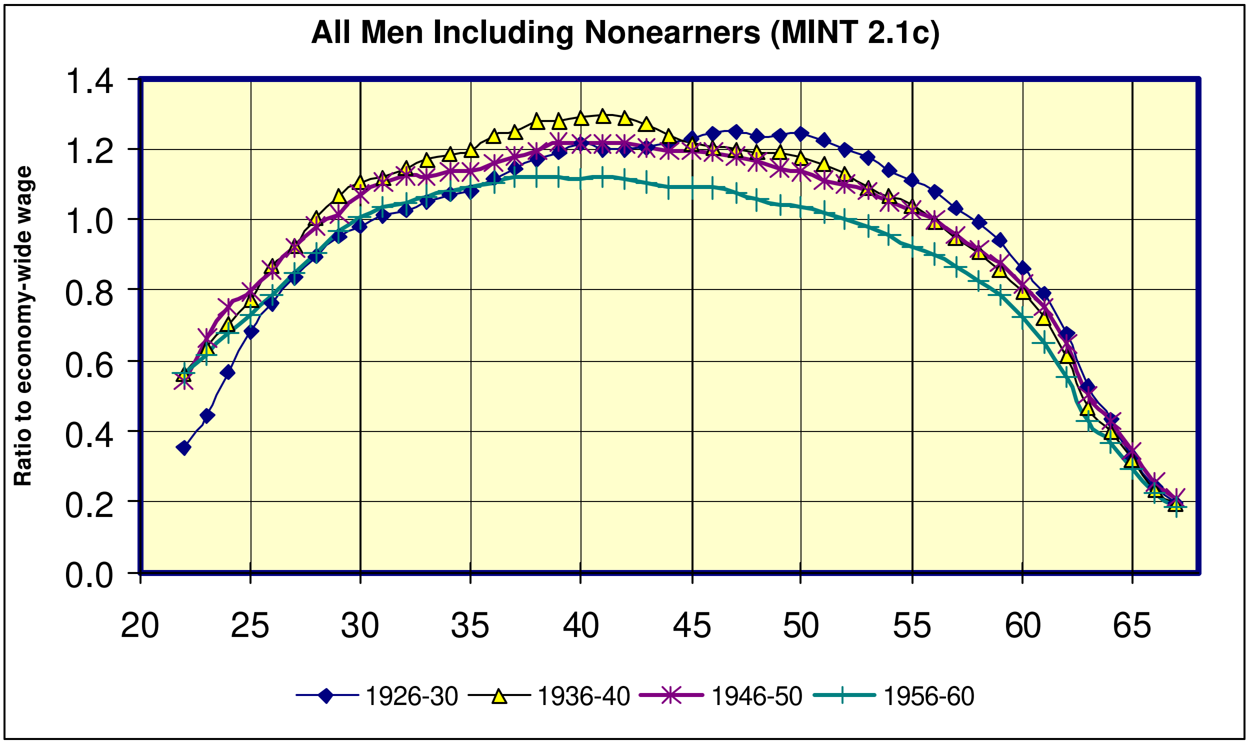
and women, workers in the younger cohorts have a substantially higher standard deviation of covered earnings at younger ages compared with workers in the oldest cohorts. This trend is apparent in the historical data and is not a by-product of our projection methodology. At the oldest ages, we project that younger female cohorts will have a somewhat higher standard deviation of earnings compared with the older cohorts. For men, however, the standard deviation of earned income at older ages is predicted to decline somewhat in the younger cohorts compared with the older ones.

Figures 2-5, 2-6 , 2-12, and 2-13: The age profile of earners differs significantly depending on the level of a worker's educational attainment. Workers who have more schooling typically achieve much higher peak career earnings, and the peak of the career earnings profile is usually attained later in life. The next set of figures shows average age-earnings profiles of all persons in the sample, including both earners and surviving persons with zero earnings in a given year, separately for each educational attainment group and selected birth-year cohort. The top panel in Figures 2-5 and 2-12 shows profiles for persons who failed to graduate from high school; the lower panel shows profiles for workers who graduated from high school but did not receive further post-secondary education. The top panel in Figures 2-6 and 2-13 shows profiles for persons with some college; the lower panel shows profiles for persons who completed college.

The largest shift in the age-earnings profile has occurred among men with the *least* schooling and among women with the *highest* educational attainment. Men who have completed college show only a comparatively small change in their age-earnings profile. In contrast, men with less schooling have experienced a sizable decline in their relative earnings. This decline is apparent at younger ages, where the comparison is based on observed earnings data, and it is projected to continue through workers' careers. Women with little education have not experienced a notable shift in their age earnings profile, but women who have attained a high school or college diploma have enjoyed sizable earnings gains at successive ages. These gains are especially pronounced among women who have college degrees. We predict that these gains will continue until women reach their early and middle 60s, when the gains become quite modest. This prediction seems consistent with the historical trend in female labor force participation at successive ages. The historical gains have been much larger among women under age 50 than among women past age 60.

Figures 2-7 and 2-14: The age-earnings profile also differs significantly depending on a worker's race. Figures 2-7 and 2-14 show shifts over time in the average age-earnings profiles of successive birth cohorts of men and women in three major groups defined by race or ethnicity: White non-Hispanics; African Americans (regardless of Hispanic ancestry); and non-black Hispanics. (We do not display our results for Asian or Native Americans or other groups defined by race and ethnicity because the number of people in these groups is so small.)

Figure 2-1
Age-Earnings Profiles: Males



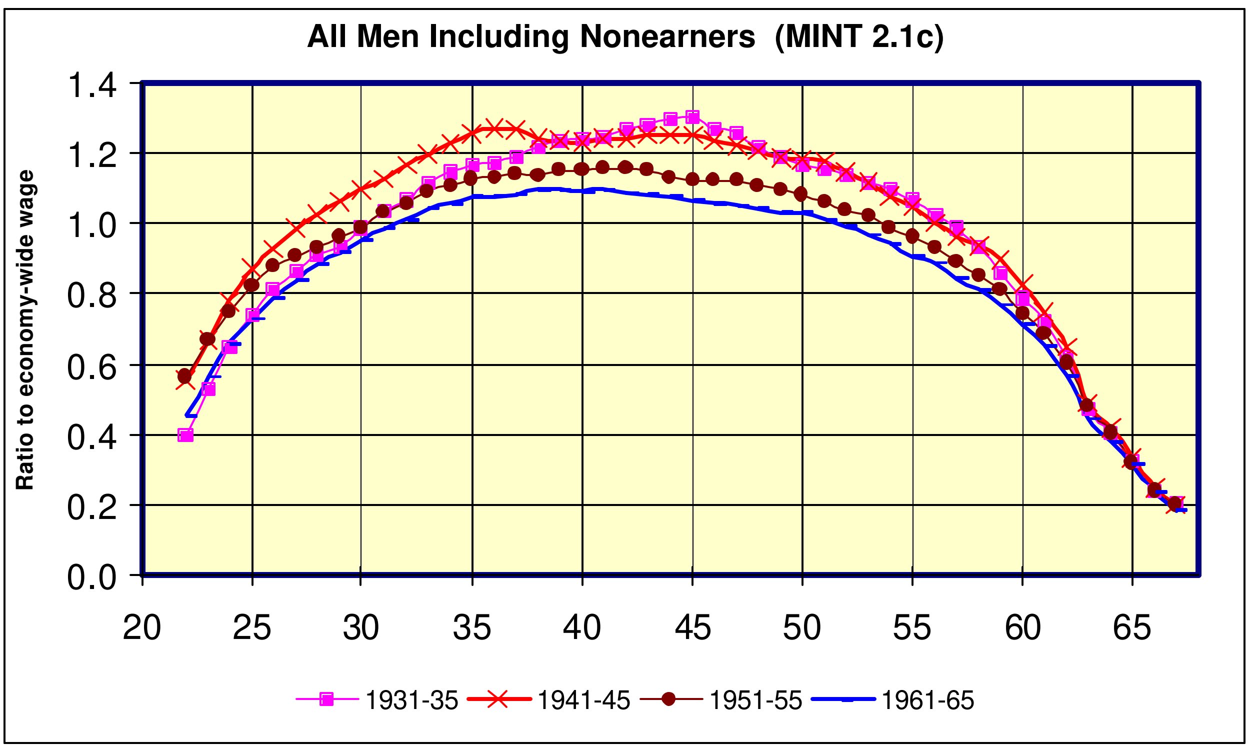
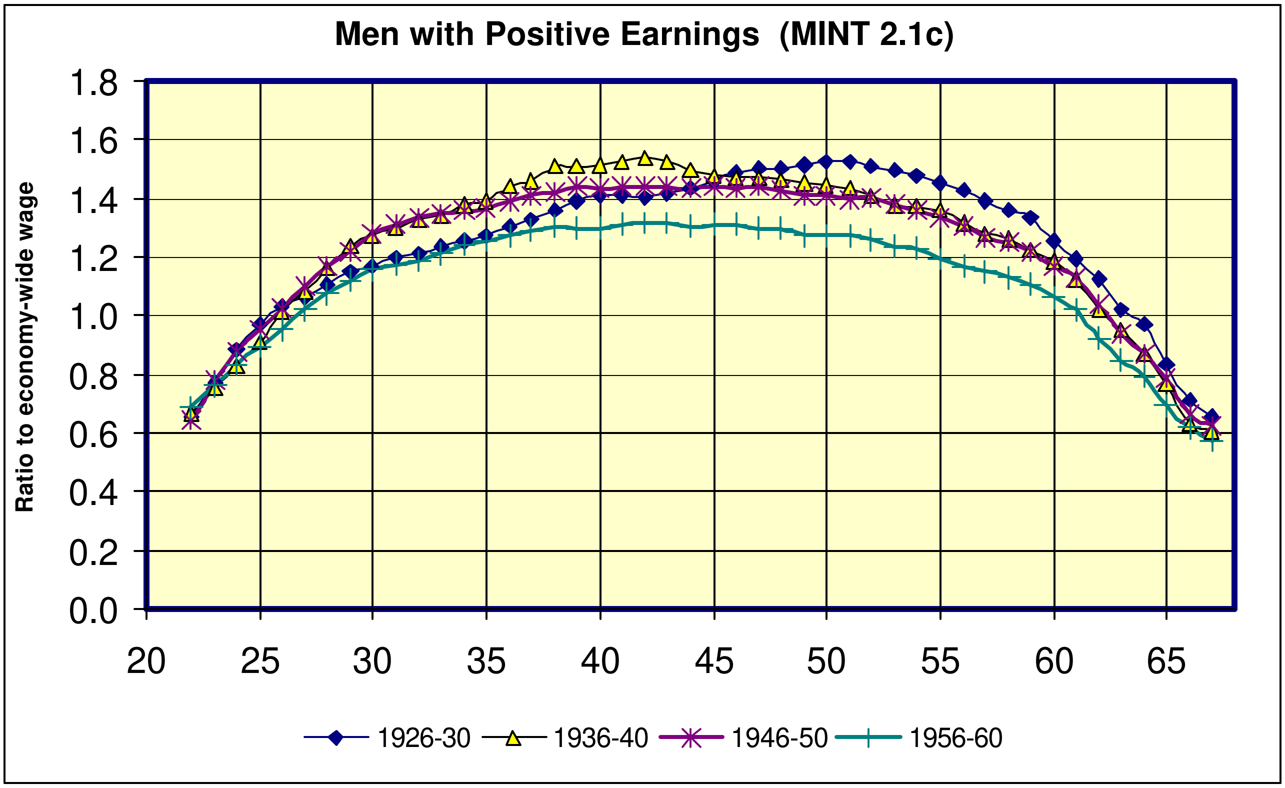


Figure 2-2
Age-Earnings Profiles: Males With Positive Earnings



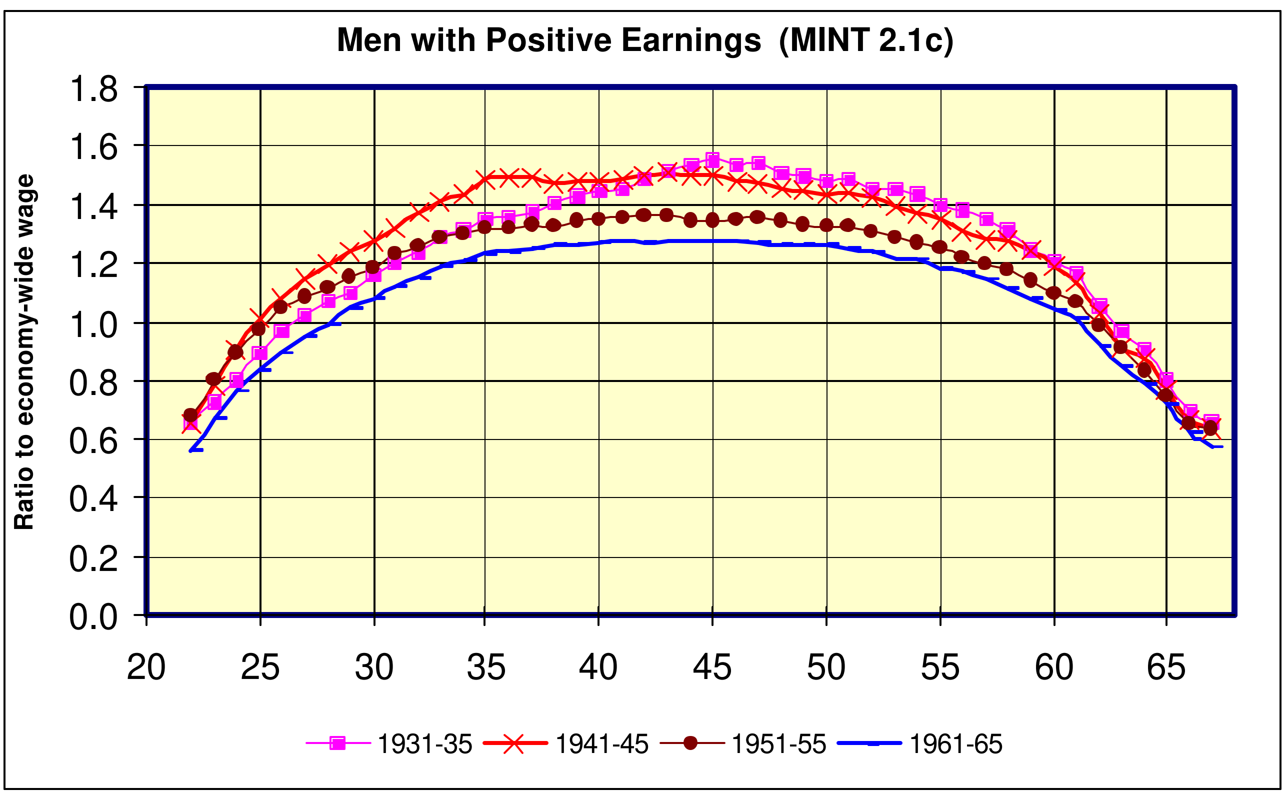
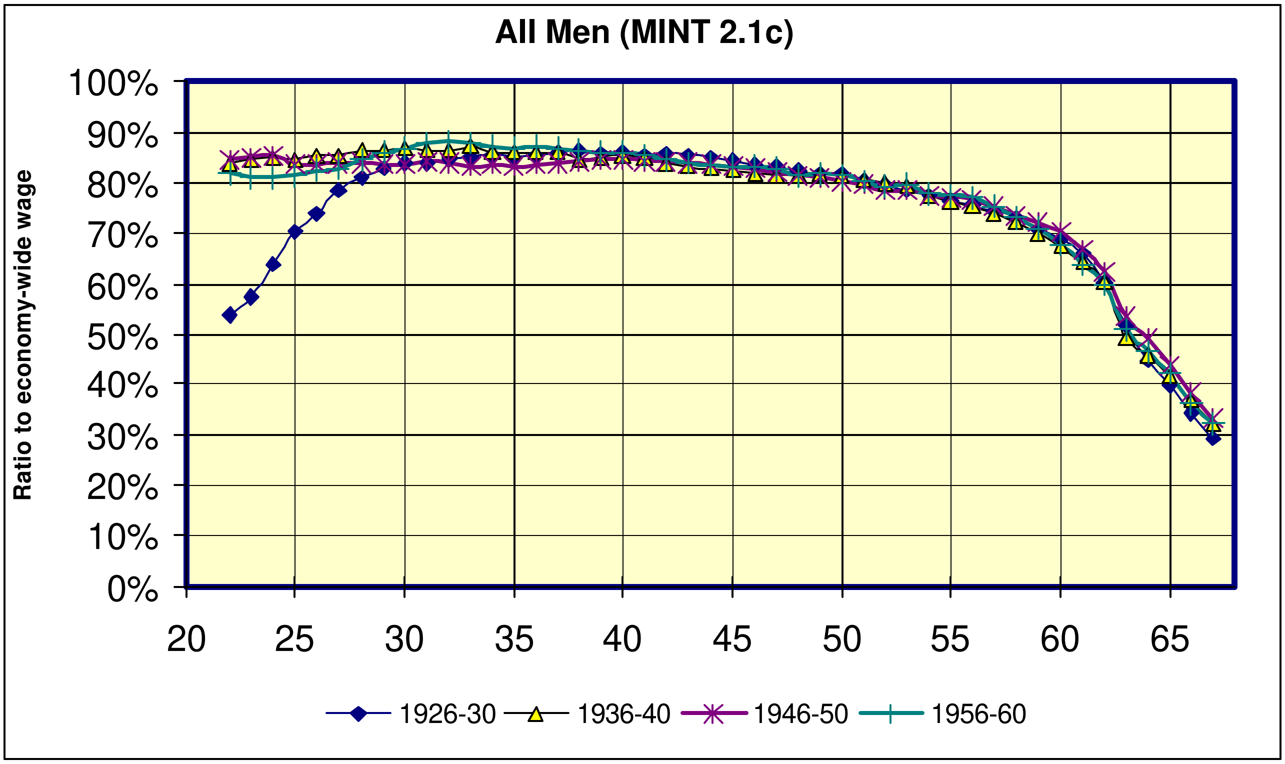


Figure 2-3
Employment Population Ratios: Males



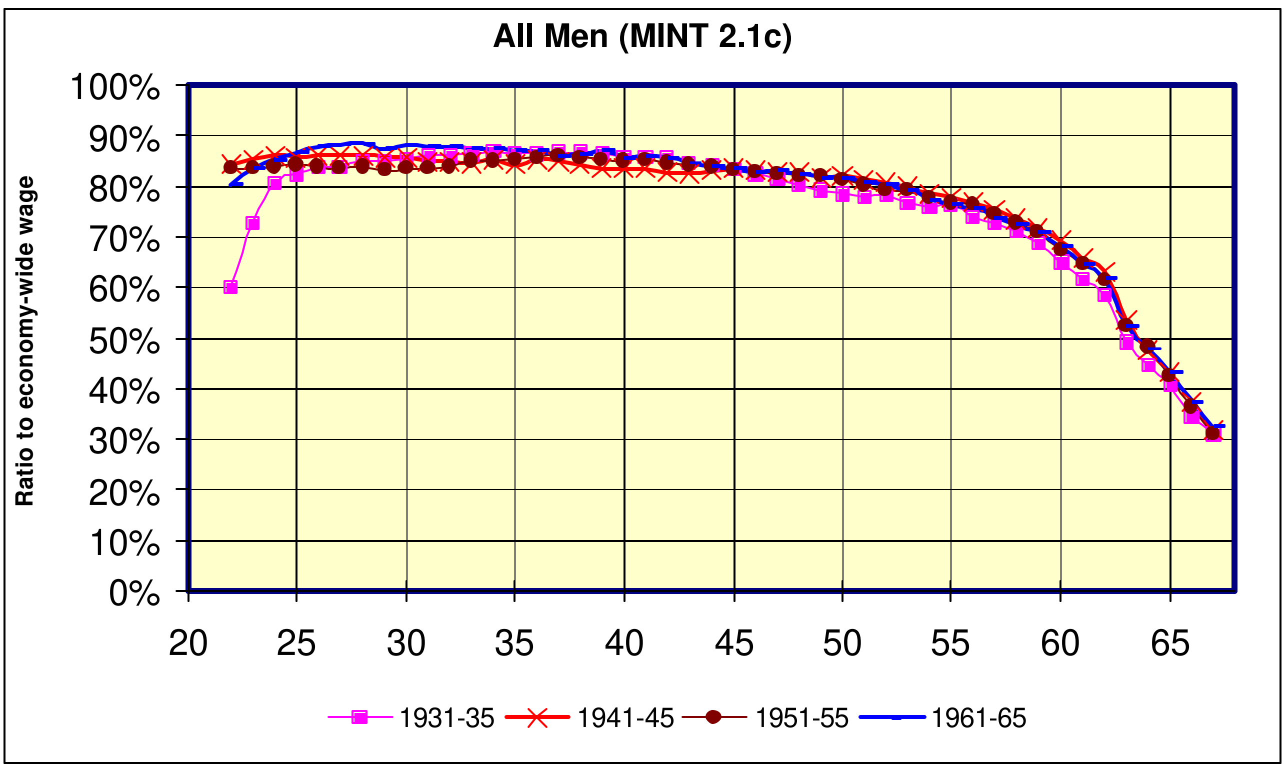
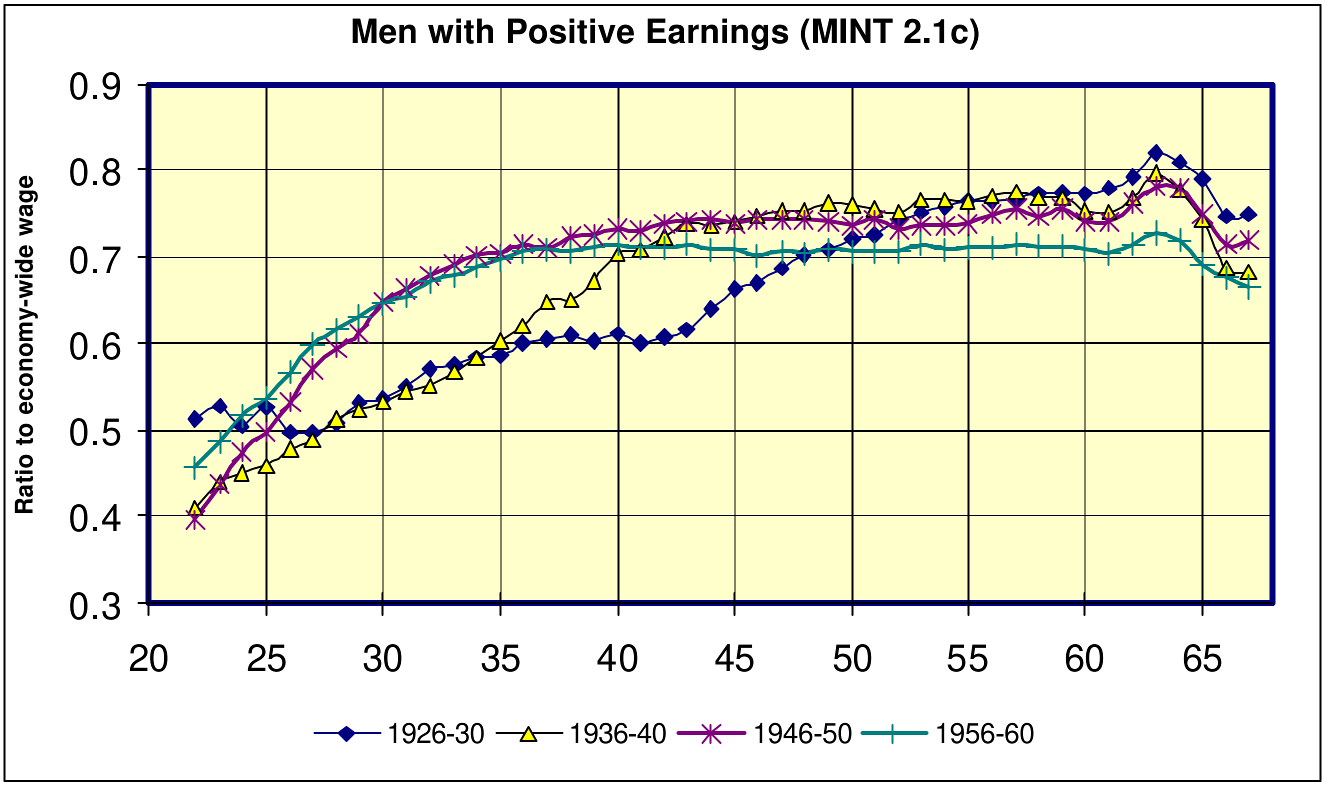


Figure 2-4
Standard Deviation of Age-Earnings Profiles: Males With Positive Earnings



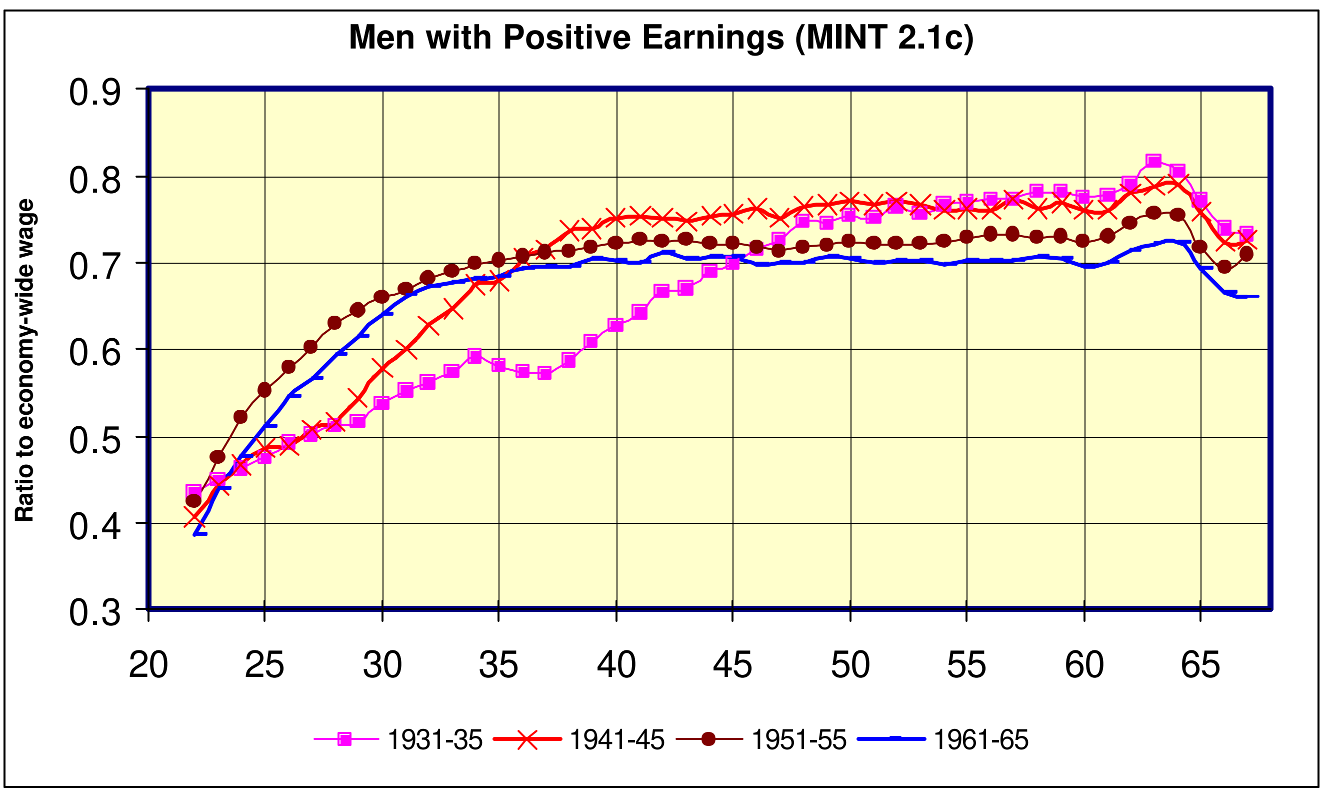


Figure 2-5
Age-Earnings Profiles: Males with Lower Educational Attainment

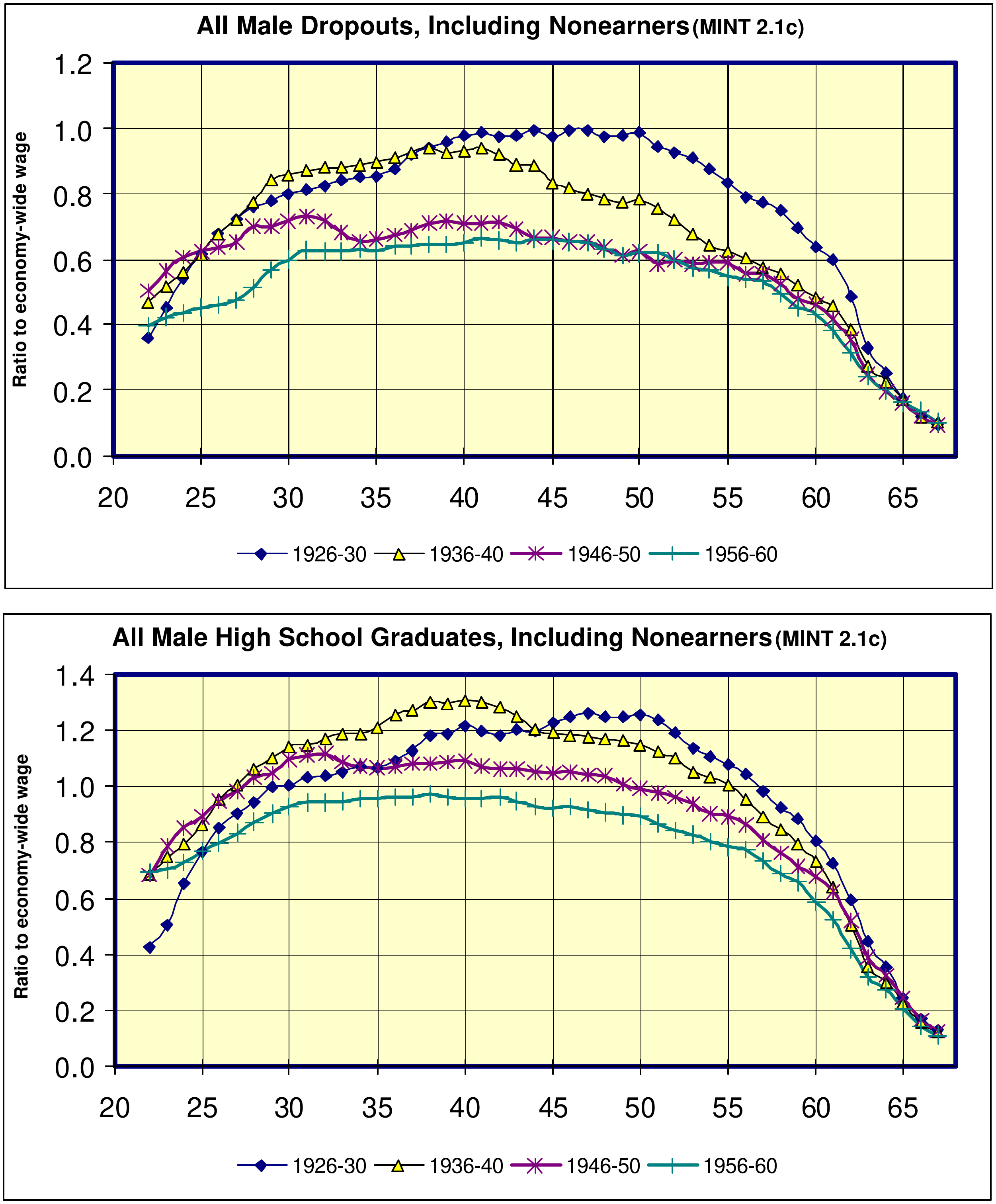
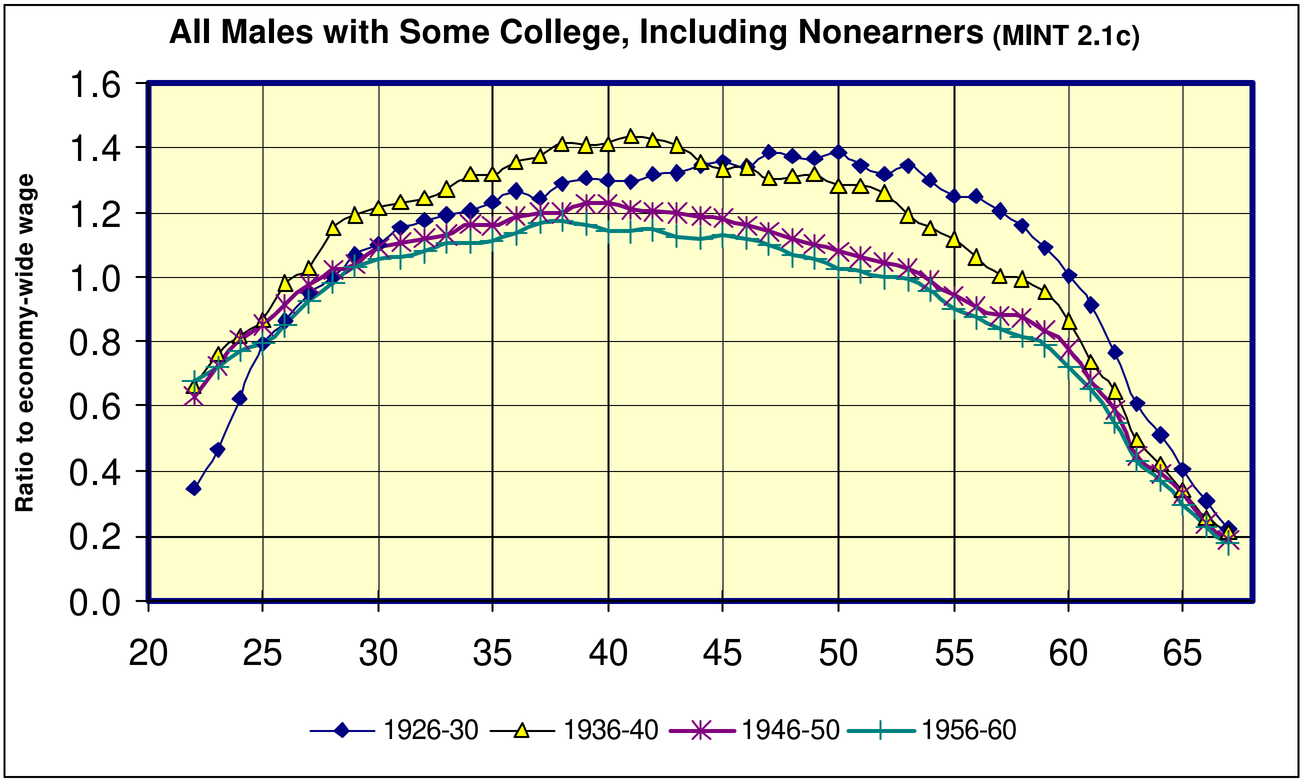


Figure 2-6
Age-Earnings Profiles: Males with Higher Educational Attainment



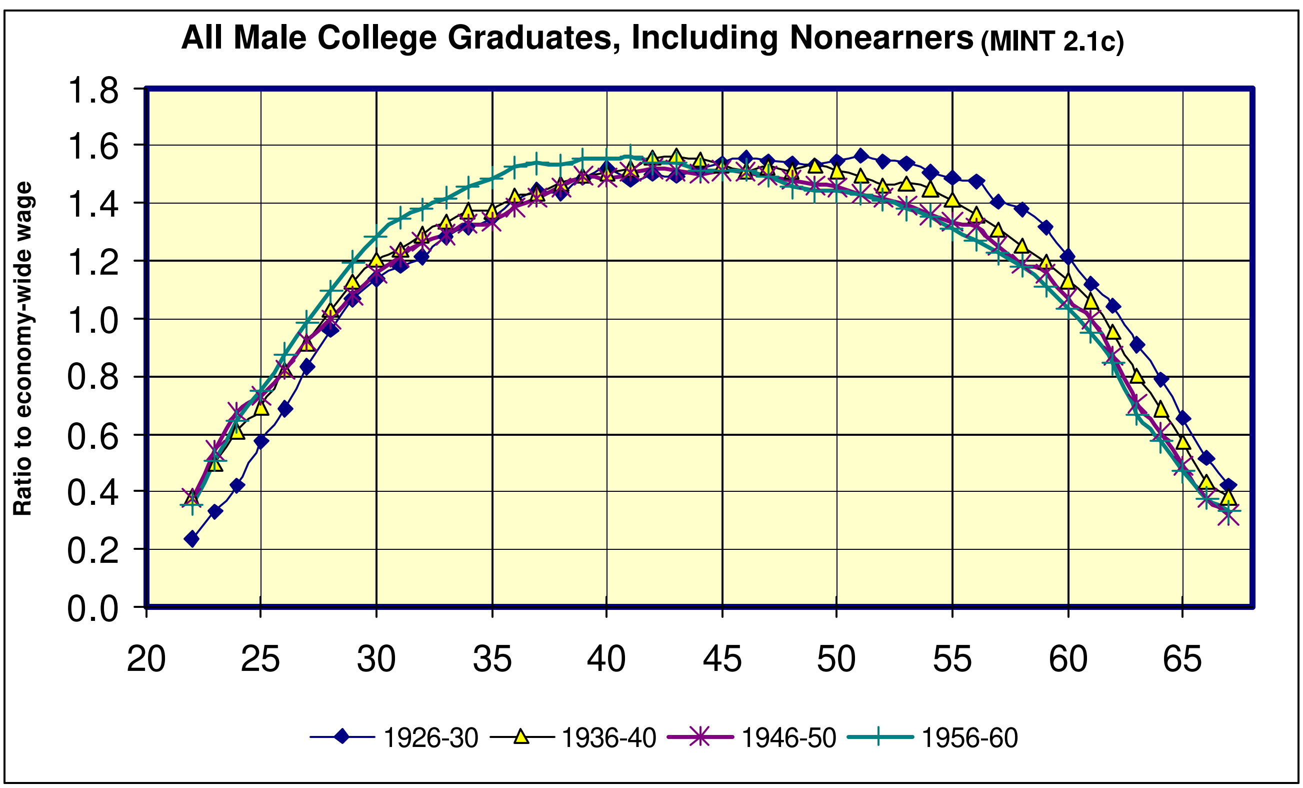


Figure 2-7
Age-Earnings Profiles of Males, by Race and Ethnicity

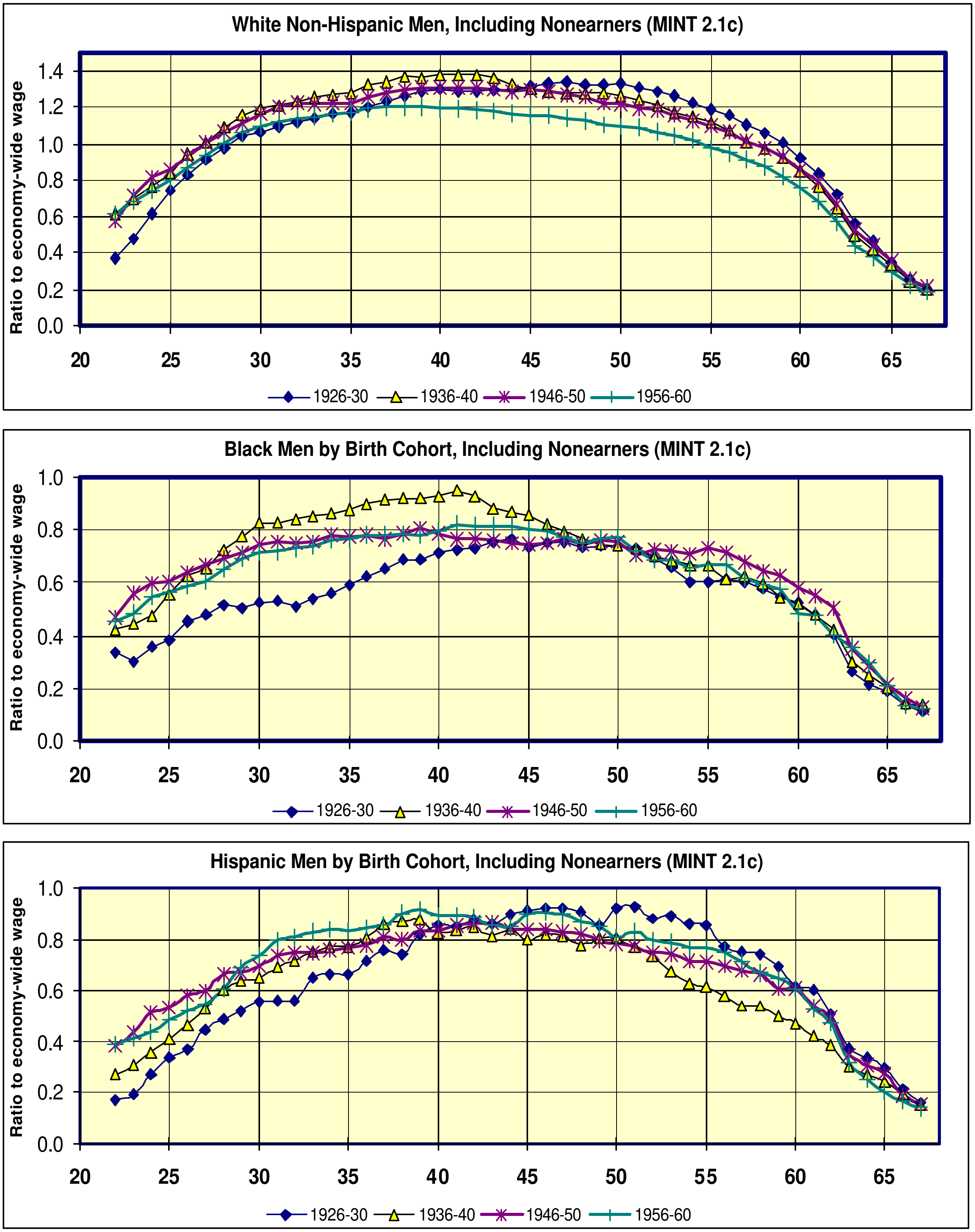
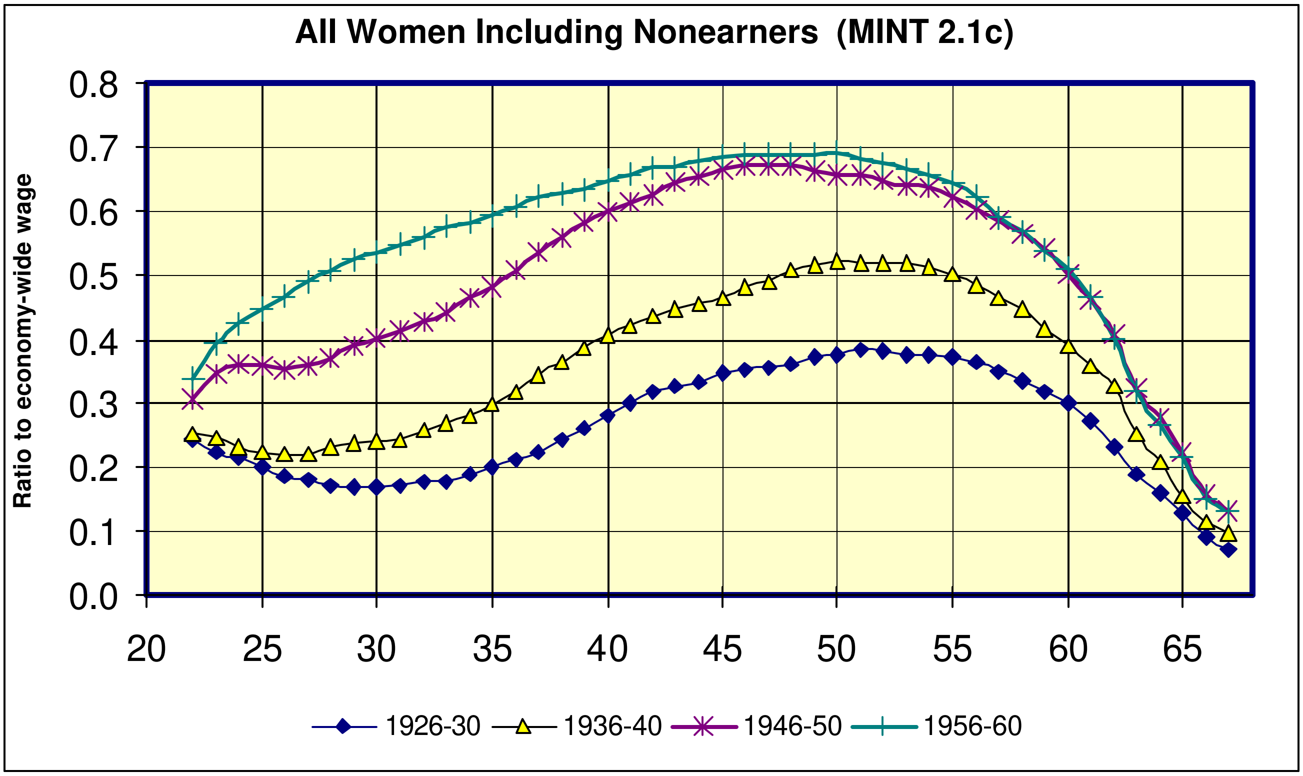


Figure 2-8
Age-Earnings Profiles: Women



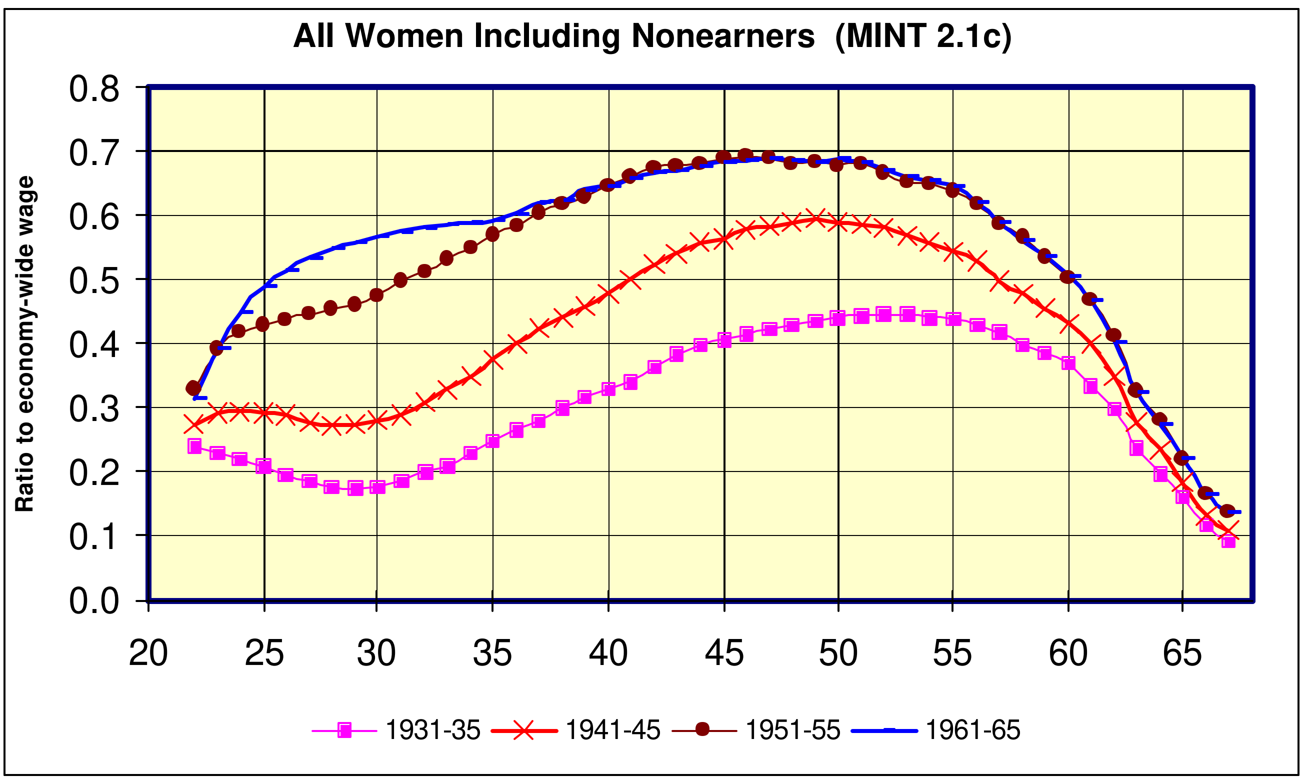
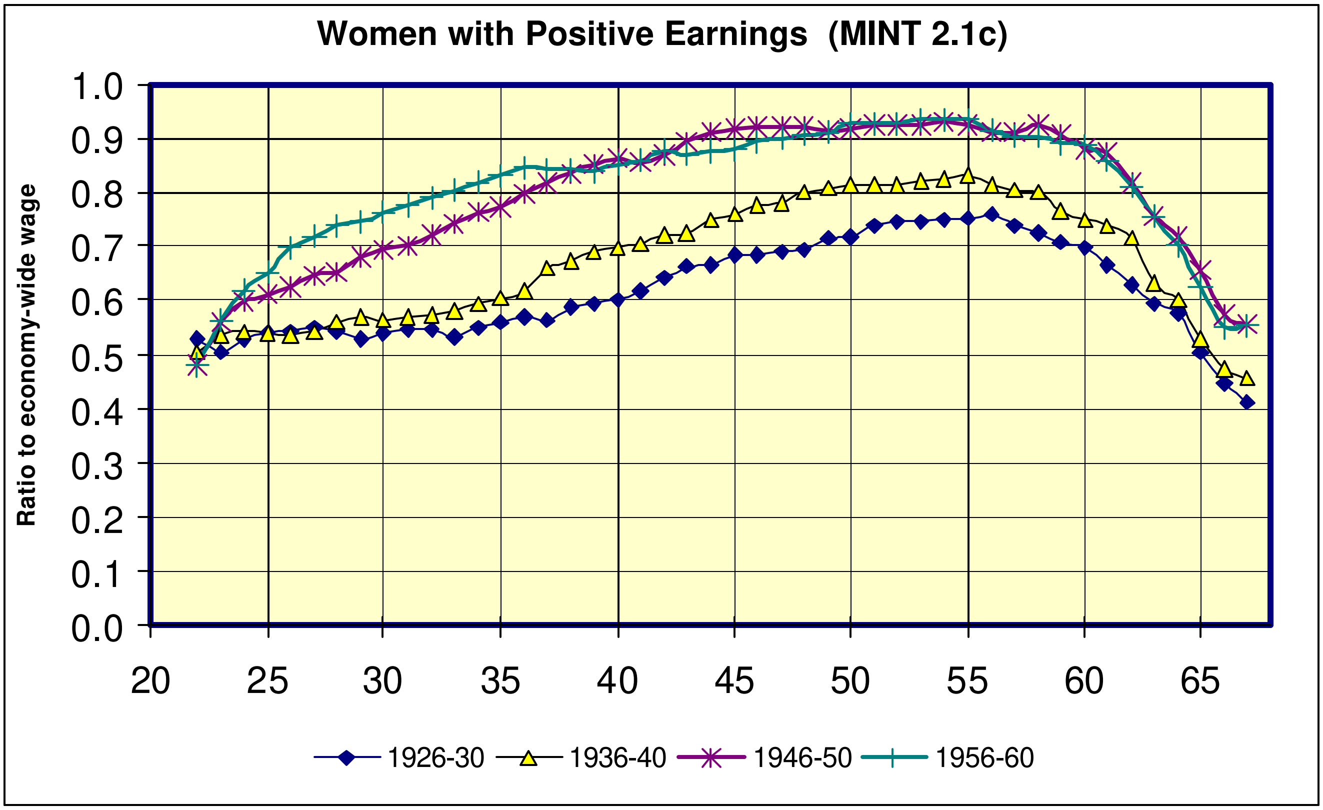


Figure 2-9
Age-Earnings Profiles: Women With Positive Earnings



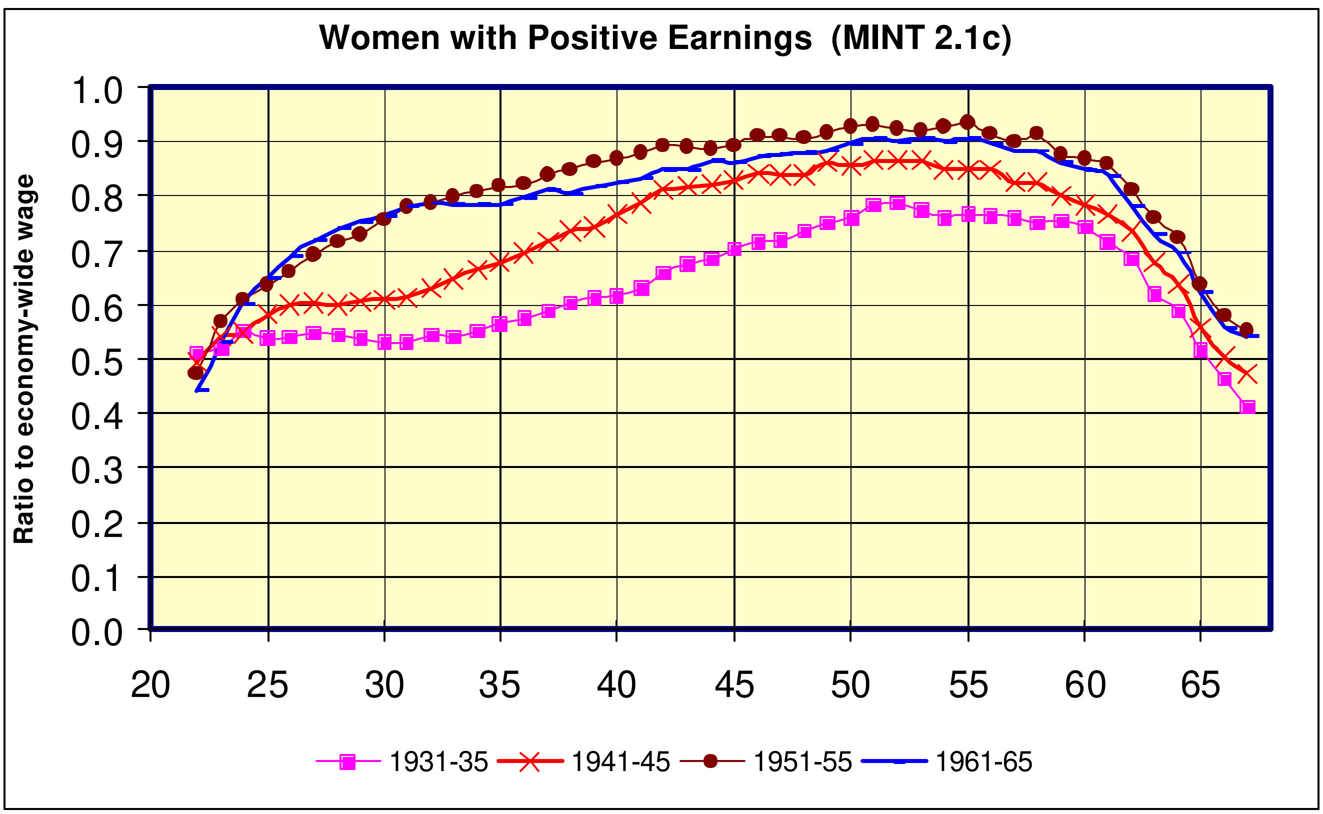
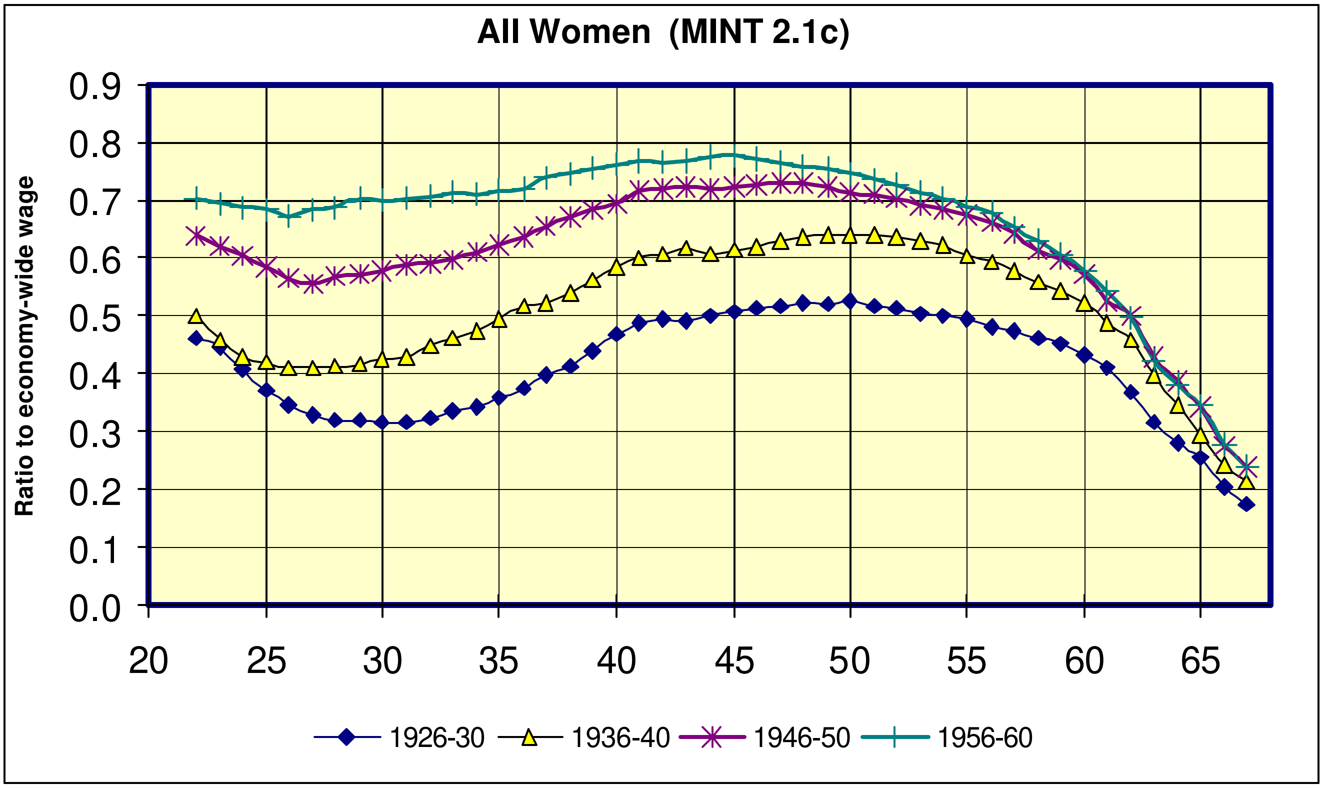


Figure 2-10
Employment Population Ratios: Women



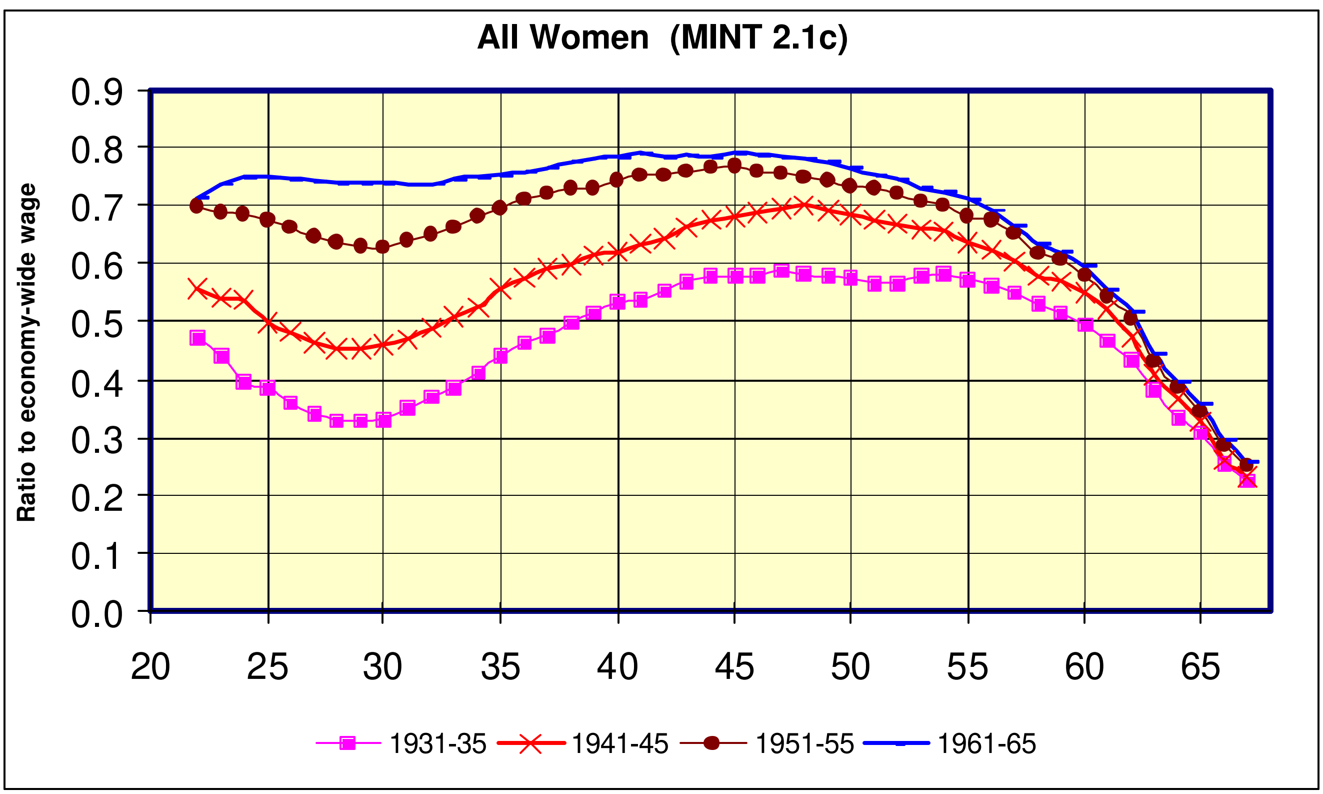
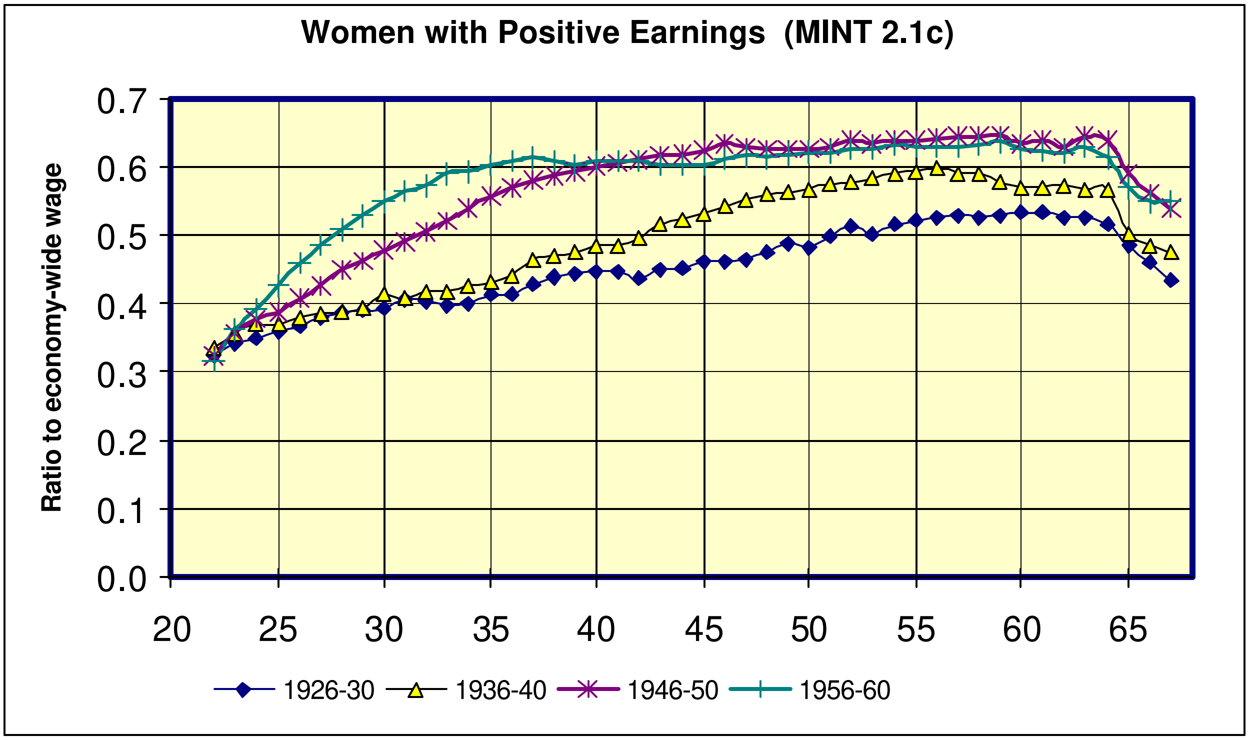


Figure 2-11
Standard Deviation of Age-Earnings Profiles: Women



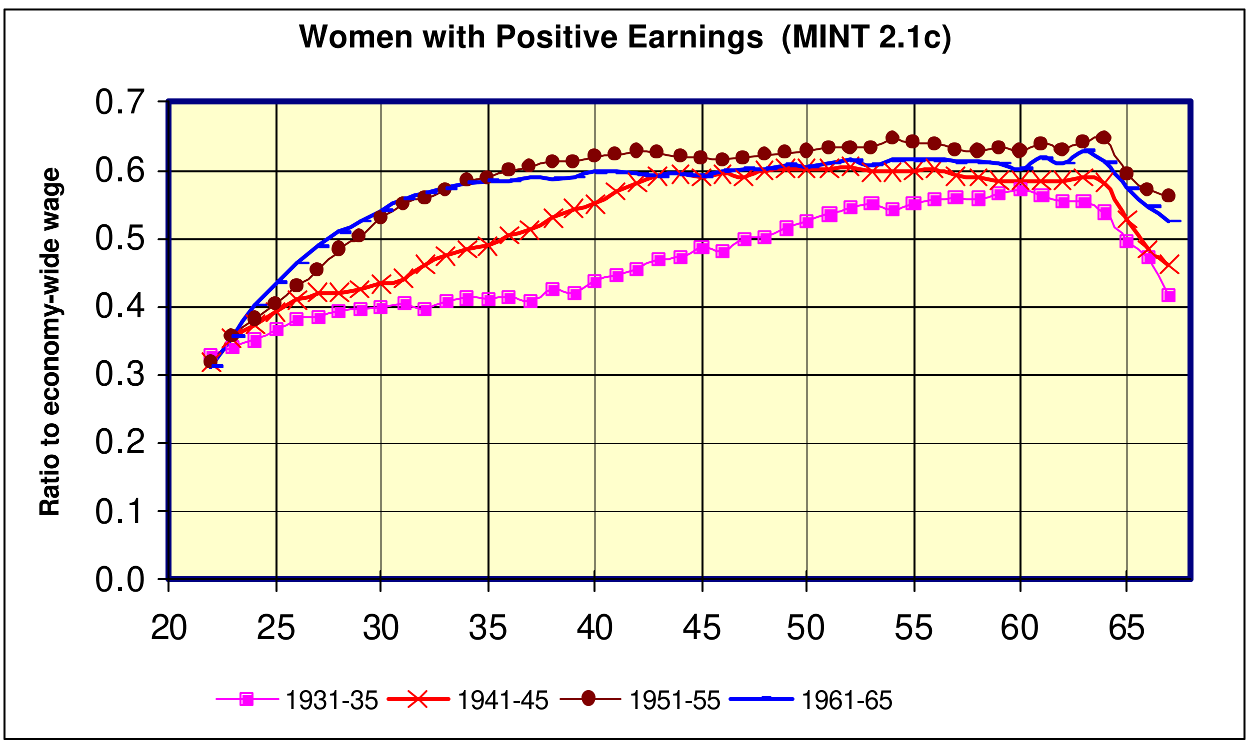
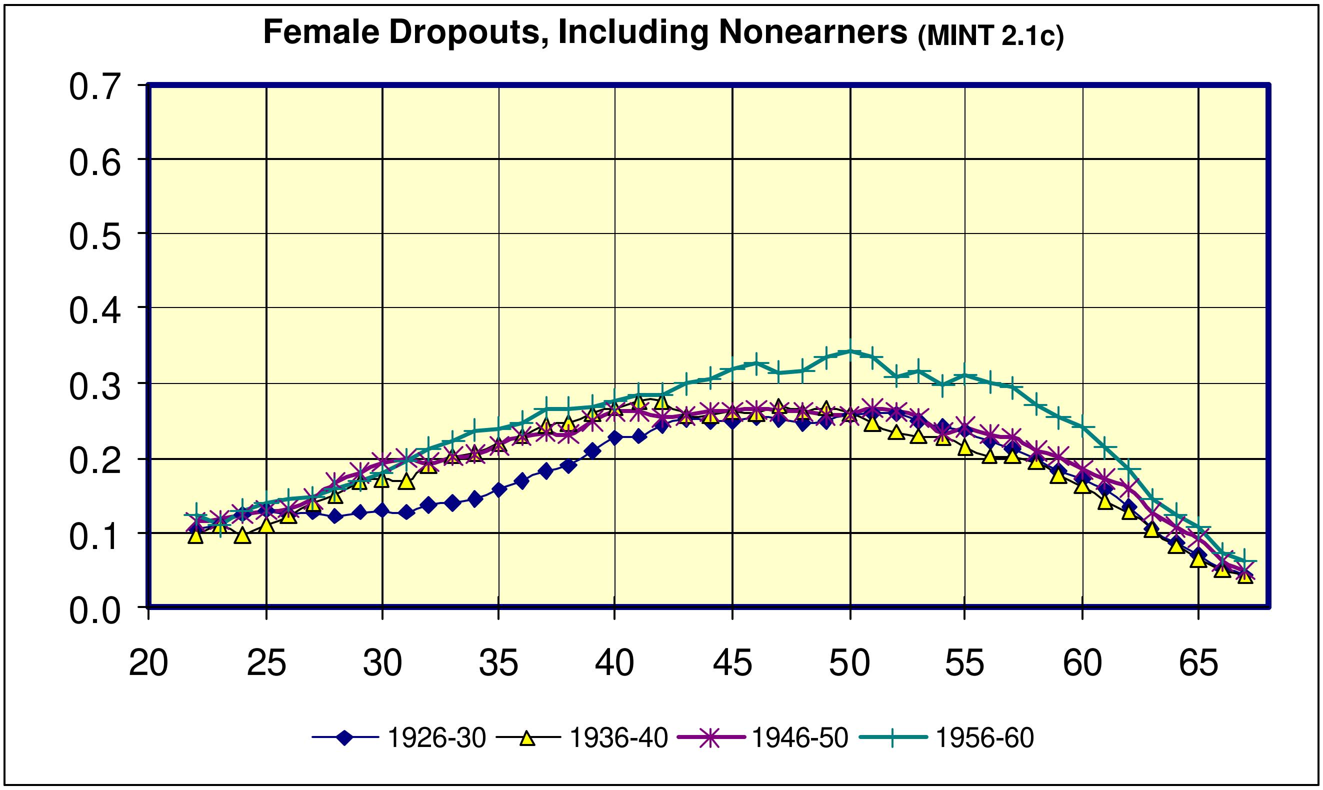


Figure 2-12
Age-Earnings Profiles: Females with Lower Educational Attainment



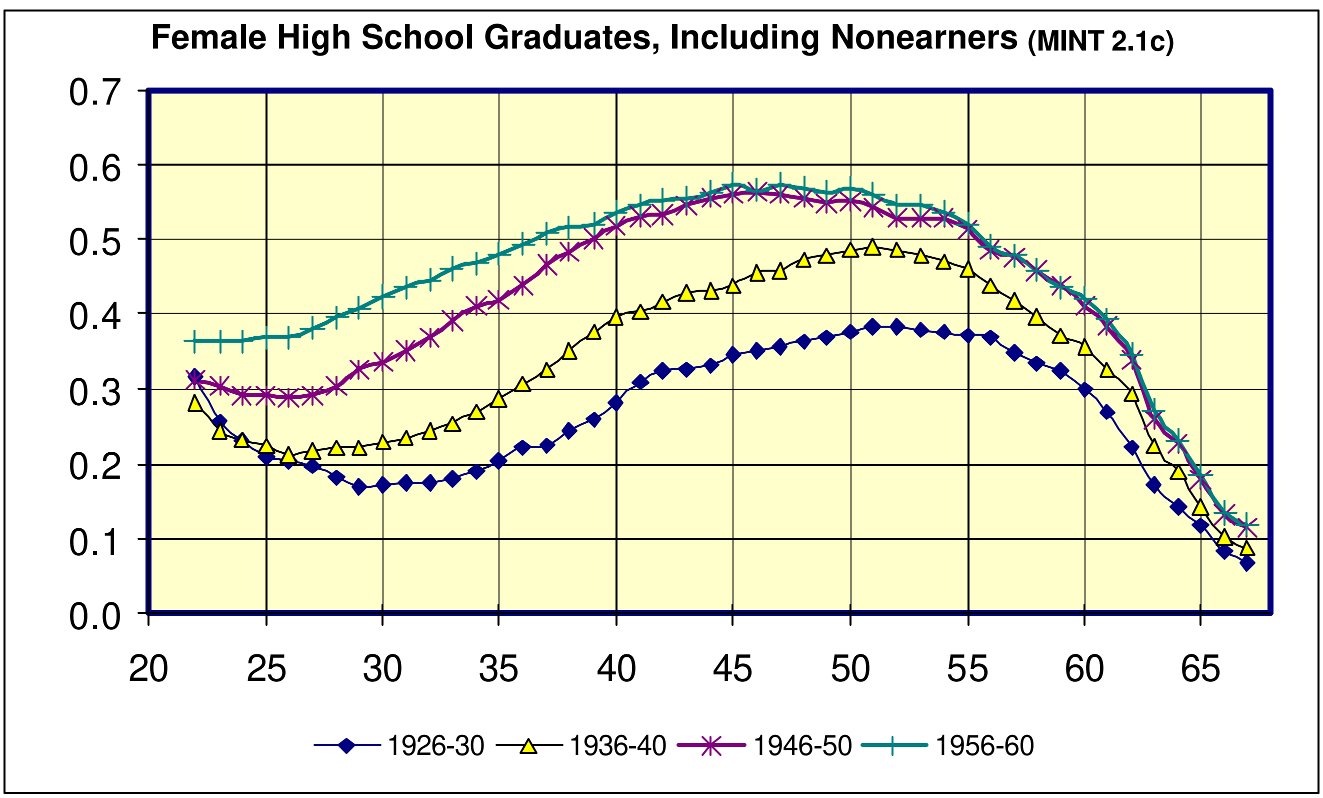
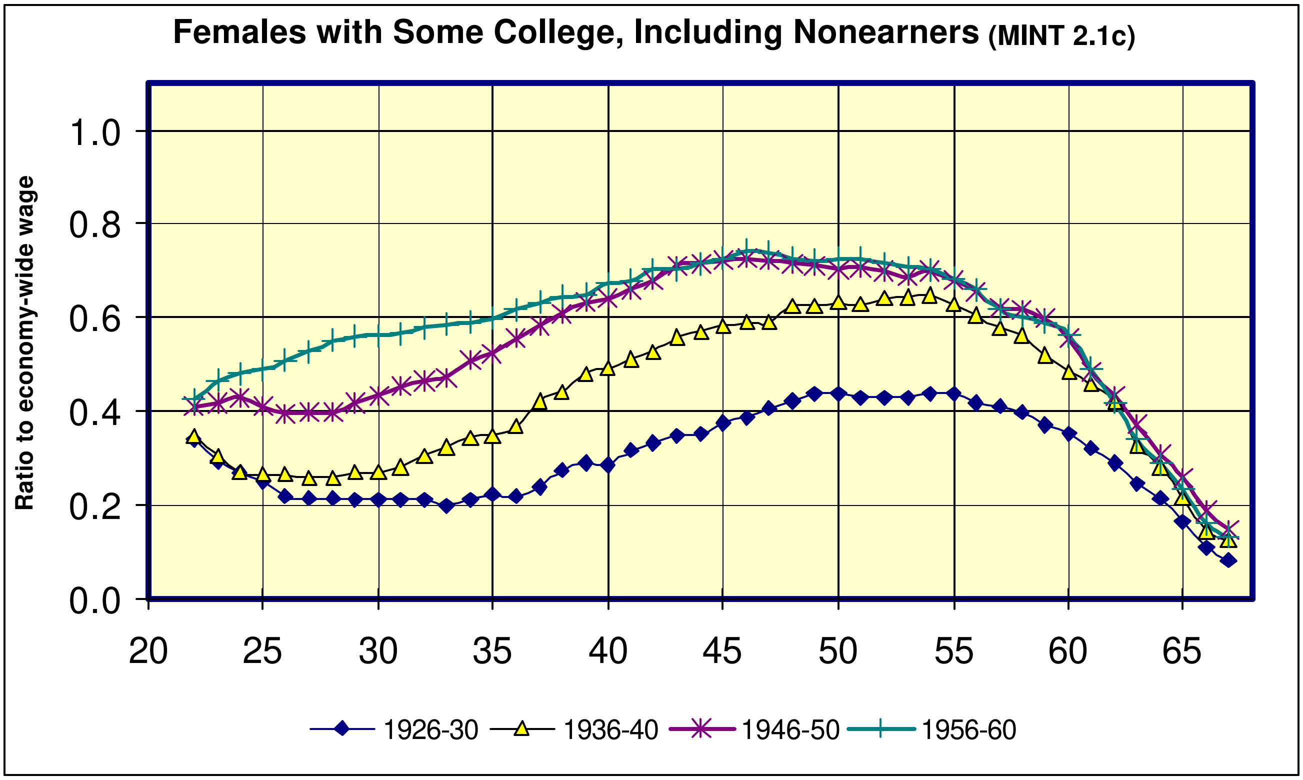


Figure 2-13
Age-Earnings Profiles: Females with Higher Educational Attainment



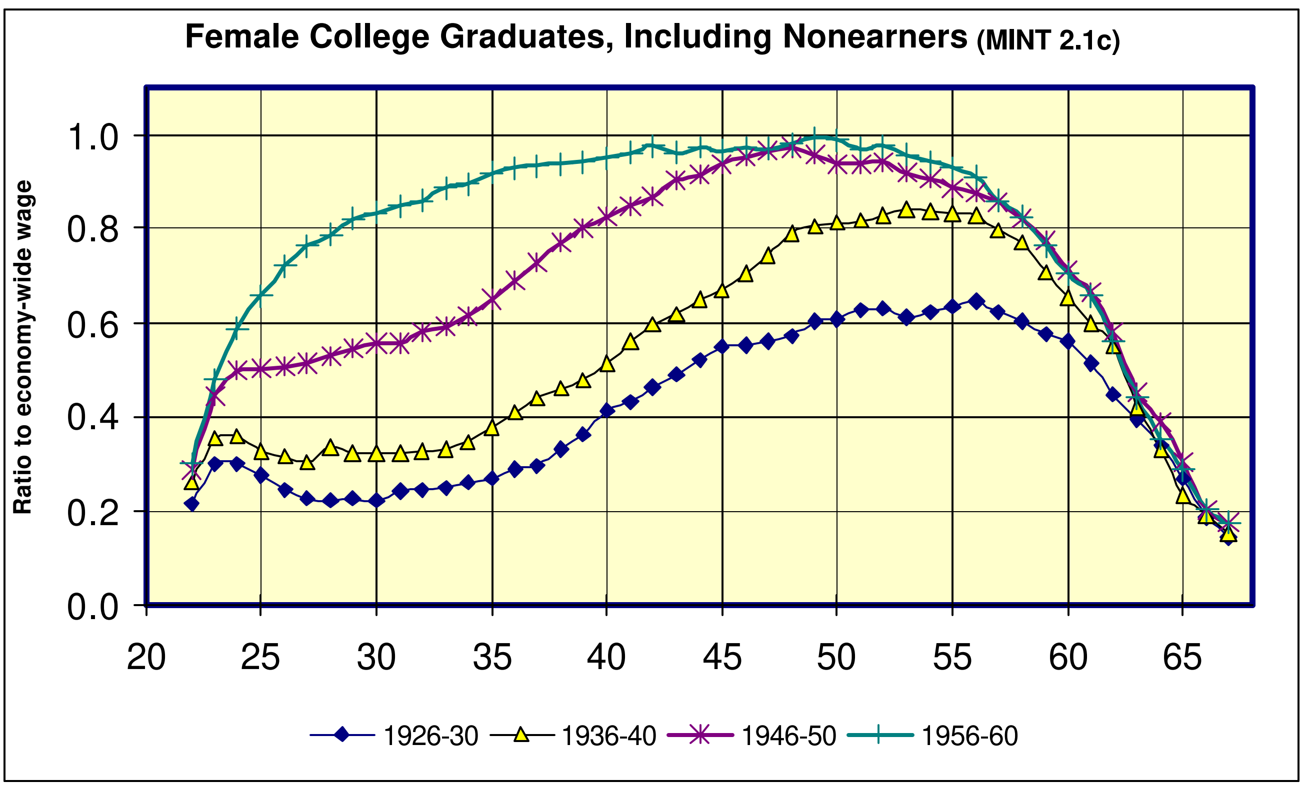
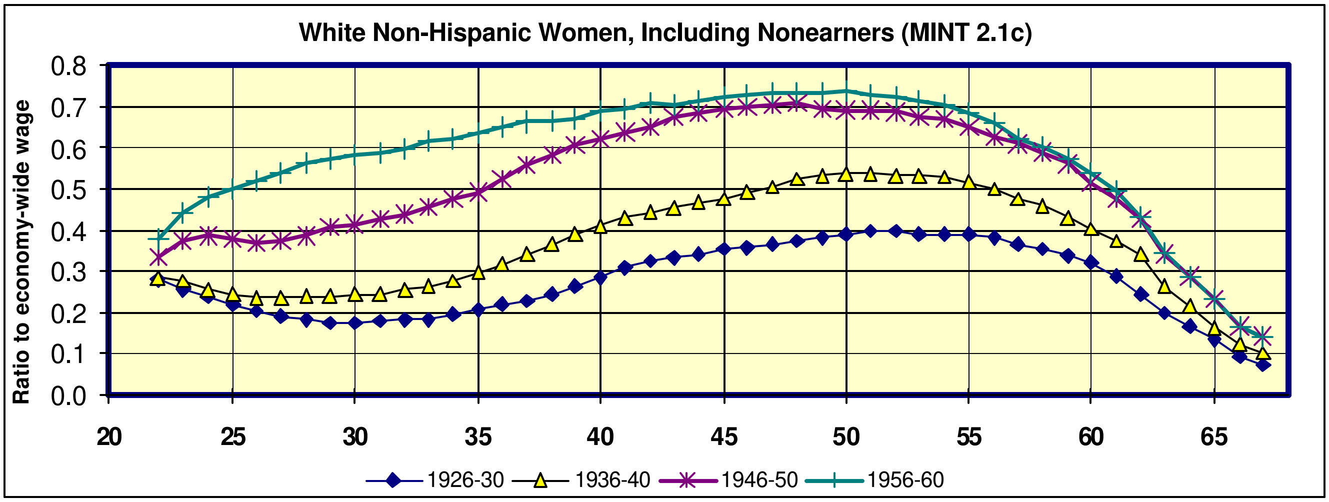
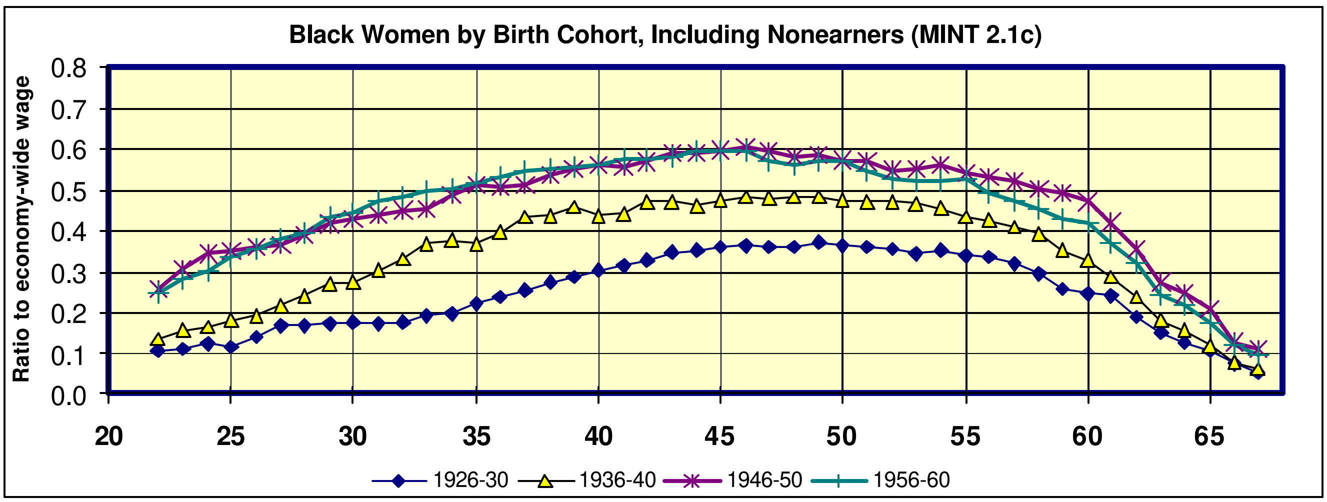
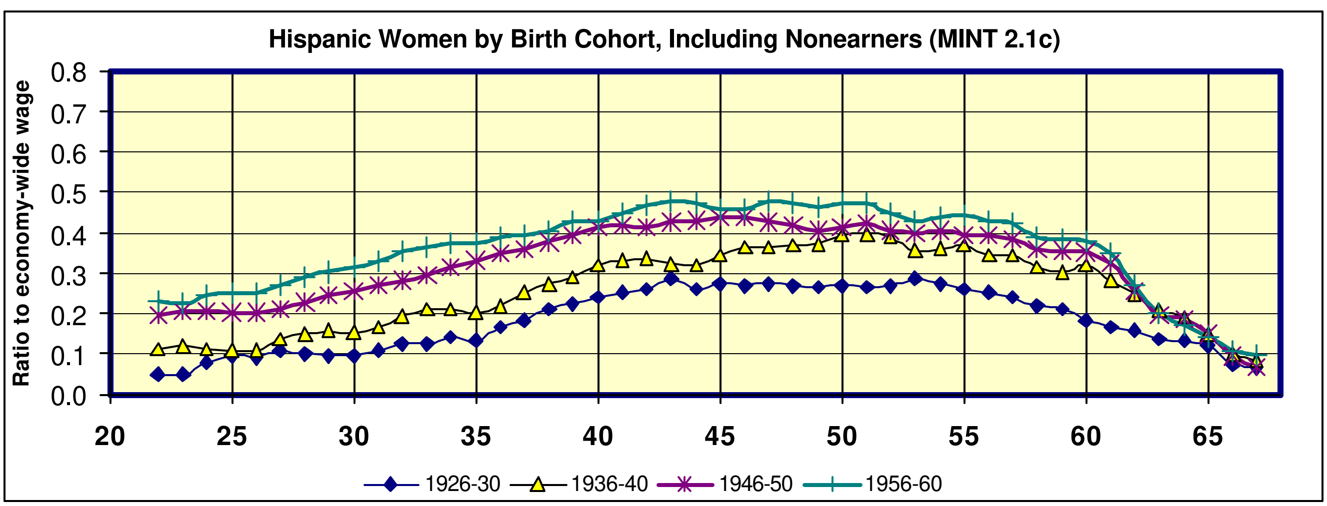


Figure 2-14
Age-Earnings Profiles of Females, by Race and Ethnicity







2. Trends Over Time in the Prevalence Stylized Earnings Patterns

By defining a small number of characteristic earnings patterns, we have tried to capture the diversity of individual earnings on the MINT 2.1 file. The trends in stylized earnings profiles across cohorts highlight the improvements in our earnings projections. While MINT 1.0 predicted reasonable average career earnings, it did not yield a plausible prediction of the future trend in stylized earnings patterns.

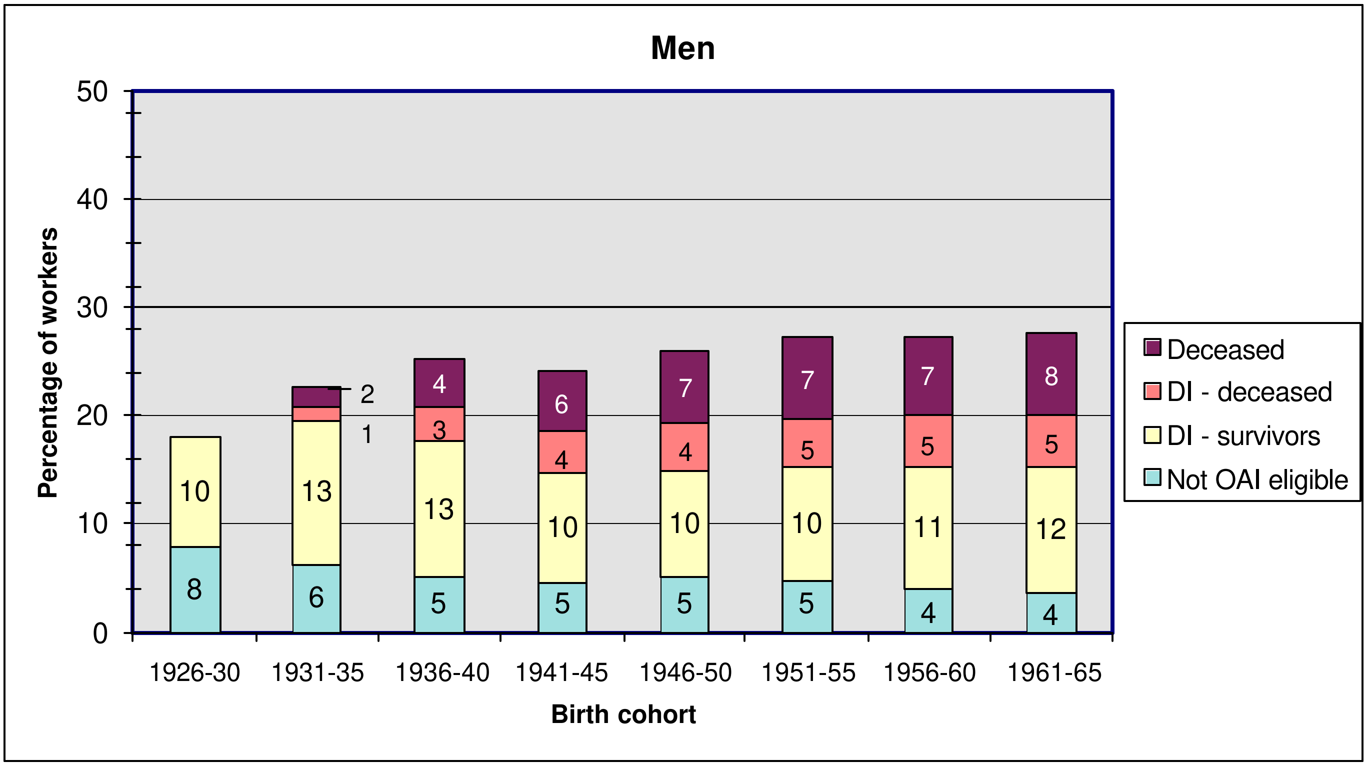
Assignment of workers to stylized profiles. Full panel respondents to the SIPP survey, who were born between 1926-65, are assigned to one of 13 groups depending on the pattern of their observed and predicted earnings over the course of their careers. The first nine groups correspond to level-trend categories in the original MINT analysis. However, in the current implementation of our stylized earnings profiles, we only assign persons who survive until 62 and are not disabled before they attain age 61 to one of these nine basic profiles. To make an assignment to these nine basic earnings pattern, we also require that the worker must have worked at least one year between ages 32 and 61 and be entitled to their own OAI benefits.[11]

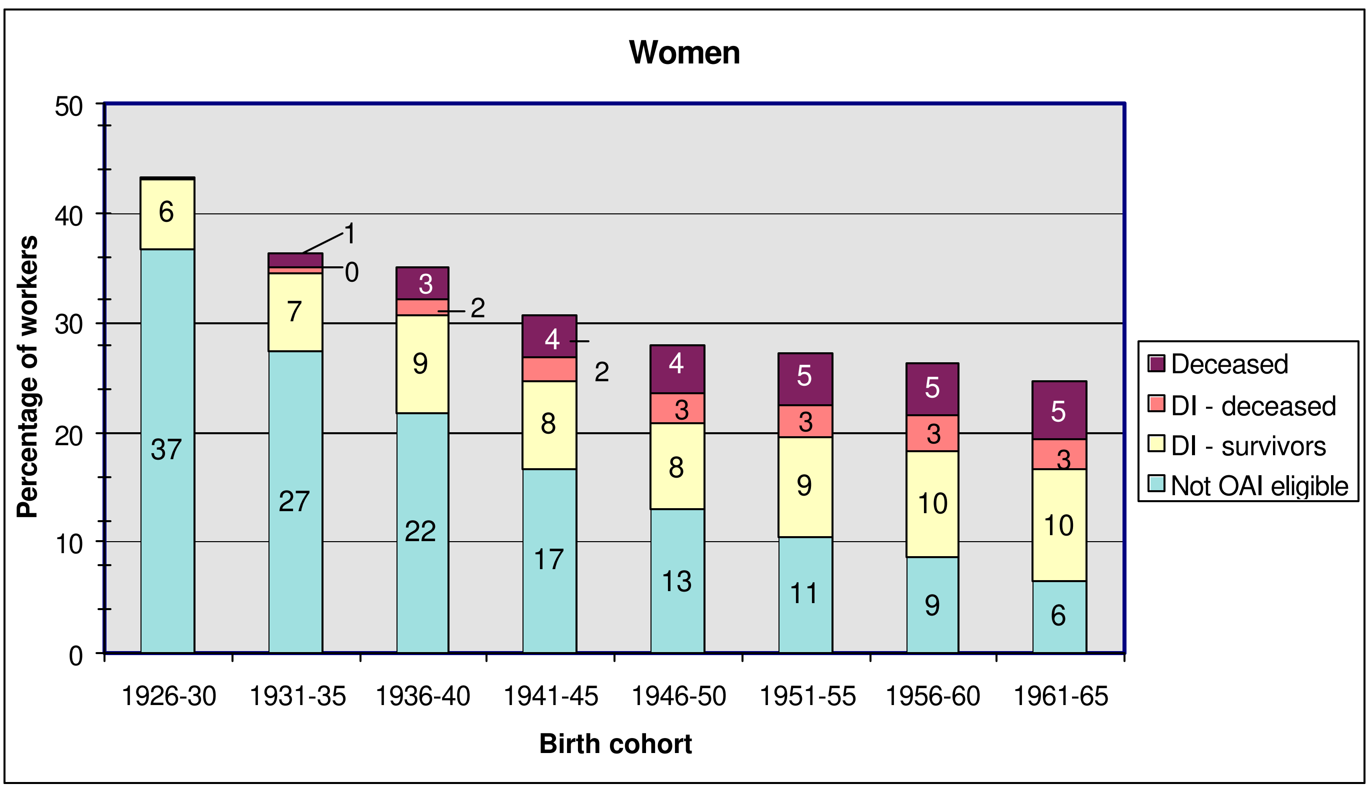
Individuals who do not fulfill these criteria are assigned to one of the four remaining groups: (1) OAI ineligible workers and non-workers who survive to age 62; (2) non-disabled workers who die before age 62; (3) disabled workers who survive until age 62; and (4) disabled workers who die before age 62. As shown in Figure 2-15, a significant portion of the MINT sample does not have a complete earnings career under our definition. A comparison across cohorts also highlights important changes in the careers of men and women. The percentage of women who are not entitled to their own OAI benefits has declined dramatically over time. With increases in female attachment to the workforce and male disability rates, a slightly larger proportion of women than men fit our definition of a standard career by the latest cohorts, 1956-65. It should be noted, however, that the upward trend in mortality is a result of sample selection bias in the MINT sample. Only workers who survived until the 1990-93 SIPP surveys are included in our analysis. Thus, we do not have a representative sample of workers from the earliest cohorts. By excluding workers with incomplete earnings histories from the level and trend analysis, we can derive our stylized earnings patterns from a relatively comparable sample in successive cohorts.

The classification of the remaining workers is based on their relative earnings for the 30-year period prior to the early retirement age of 62. Our analysis focuses on two characteristics of the time path of earnings: the average earnings *level* and the *trend* in earnings over a worker's career. The average earnings level is simply the 30-year average of the worker's relative earnings. The trend in earnings captures the direction and magnitude of change in relative earnings between the early and late periods of the worker's career. Specifically, it compares

[11] There are two possible standards for including individuals in this category. One could use the actual record of whether the individual earned the required income in each calendar year. However, the legal standard has varied over time. Thus, we have adopted the current standard, where one quarter of coverage requires 2.7 percent of the Social Security economy-wide wage (two years lagged) and applied that rule consistently over the entire interval. To be OAI entitled, a worker must have accrued 40 quarters of coverage from age 22 to 61.

Figure 2-15
Percent of Sample Without a Full or Regular Career - MINT 2.1





average earnings from ages 32-41 (A) to those from ages 52-61 (B).[12] The trend is calculated as:

$$t = (B-A) / (B+A).$$

In Table 2-5 we show the critical parameter values that determine whether a worker is assigned to the "declining," "level," or "rising" trend categories and to the "low," "average," or "high" lifetime earnings categories. The column to the left shows the crucial parameter values in the MINT 1.0 data set; the column to the right shows critical values in the MINT 2.1 data set.

Table 2-5
Comparison of Trend and Lifetime Earnings Thresholds in MINT 1.0 and MINT 2.1 Data Sets

	MINT 1.0	MINT 2.1
Trend = (B-A) / (B+A)		
"Declining" trend in career earnings	t < -0.11	t < -0.16
"Level" trend in career earnings	-0.11 < t < 0.11	-0.16 < t < 0.17
"Rising" trend in career earnings	t > 0.11	t > 0.17
Level = (Total earnings ages 32-61) / 30		
"Low" lifetime earnings category	a < 0.37	a < 0.50
"Average" lifetime earnings category	0.37 < a < 1.04	0.50 < a < 1.19
"High" lifetime earnings category	a > 1.04	a > 1.19

Source: Authors' tabulations of MINT 1.0 and MINT 2.1_c data sets.

Table 2-6 shows basic statistics of the level and trend values by 5-year cohort groups with men and women analyzed both together and separately. Clearly there are important differences between men and women in the mean level and trend of career earnings. For men, the average level of earnings remains relatively constant until the 1941-45 cohorts and then begins to decline moderately. In contrast, the average level of women's earnings rises almost 50 percent from the oldest to youngest cohorts. Nonetheless the career earnings of women in the latest cohorts represents only two-thirds of male earnings. The average trend of men is consistently negative and increasing in magnitude across cohorts. This suggests that the declining trend in male earnings over their career is becoming more pronounced. In the earliest cohorts, women's earnings exhibit a strong positive trend. The value steadily declines over time, so that the earnings of the latest female cohorts also decline over their careers.

For both characteristics of the career earnings path, we then divide workers into three mutually exclusive groups. The final four columns of Table 2-6 display the level and trend values that divide various groupings into thirds. Individuals are assigned to stylized profiles based on consistent cutoff points across cohorts and gender. The benchmark cohorts for the

[12] The methodology is adapted from work by Herman Grundman and Barry Bye of the Social Security Administration as reported in Committee on Finance (1976).

Table 2-6
Level and Trend Statistics for Workers with Complete Careers

Cohorts	Average		Standard Deviation		Level Quantiles		Trend Quantiles	
	Level	Trend	Level	Trend	1/3	2/3	1/3	2/3
Men and Women								
1926-30	0.928	0.048	0.648	0.551	0.494	1.217	-0.111	0.209
1931-35	0.917	0.020	0.654	0.560	0.475	1.171	-0.148	0.182
1936-40	0.945	0.007	0.657	0.543	0.517	1.207	-0.175	0.148
1941-45	0.962	0.007	0.664	0.527	0.534	1.218	-0.163	0.155
1946-50	0.990	-0.025	0.650	0.508	0.585	1.246	-0.181	0.135
1951-55	0.961	-0.073	0.633	0.494	0.569	1.186	-0.212	0.095
1956-60	0.932	-0.088	0.622	0.497	0.555	1.139	-0.232	0.088
1961-65	0.912	-0.090	0.614	0.489	0.539	1.109	-0.224	0.082
1926-65	0.945	-0.039	0.639	0.516	0.542	1.179	-0.192	0.121
1931-40 (1)	0.932	0.013	0.655	0.551	0.496	1.189	-0.162	0.165
Men								
1926-30	1.277	-0.083	0.608	0.410	0.998	1.605	-0.154	0.085
1931-35	1.279	-0.132	0.631	0.419	0.982	1.630	-0.210	0.051
1936-40	1.279	-0.137	0.647	0.427	0.970	1.618	-0.236	0.020
1941-45	1.283	-0.118	0.669	0.432	0.930	1.641	-0.223	0.020
1946-50	1.259	-0.107	0.652	0.425	0.926	1.587	-0.205	0.032
1951-55	1.196	-0.134	0.641	0.418	0.854	1.499	-0.225	0.021
1956-60	1.141	-0.143	0.637	0.421	0.787	1.414	-0.249	0.017
1961-65	1.125	-0.146	0.635	0.415	0.775	1.400	-0.232	0.011
Women								
1926-30	0.486	0.213	0.366	0.652	0.263	0.572	0.013	0.624
1931-35	0.512	0.191	0.387	0.643	0.267	0.605	0.001	0.582
1936-40	0.575	0.166	0.431	0.609	0.300	0.704	-0.038	0.489
1941-45	0.630	0.136	0.468	0.582	0.340	0.757	-0.064	0.422
1946-50	0.716	0.057	0.520	0.569	0.398	0.853	-0.131	0.300
1951-55	0.729	-0.012	0.531	0.553	0.404	0.884	-0.193	0.215
1956-60	0.729	-0.034	0.534	0.555	0.400	0.868	-0.209	0.191
1961-65	0.717	-0.040	0.523	0.544	0.399	0.840	-0.213	0.189

Note: These calculations only include OAI entitled workers with at least some earnings from ages 32-61. They must also survive to age 61 and be non-disabled.

(1) Quantile cutoffs used to categorize nondisabled workers into 9 profiles groups.

Source: Authors' tabulations of MINT 2.1_c data set.

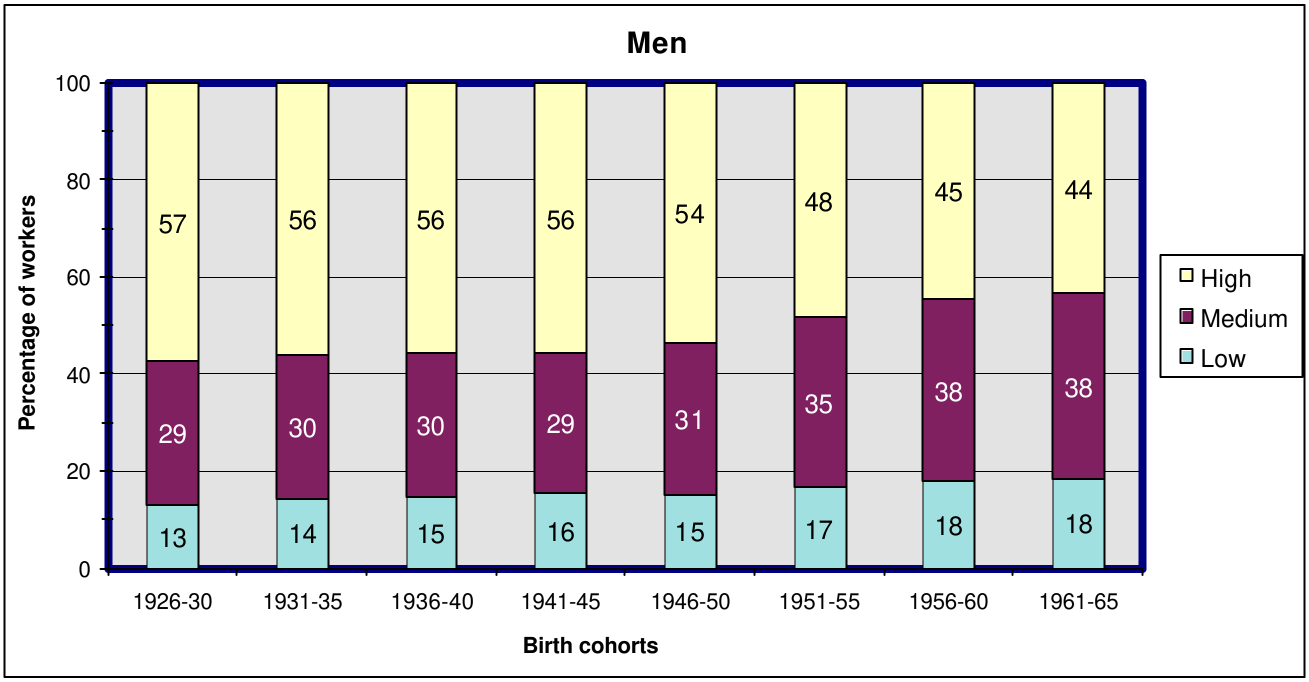
current analysis are the 1931-40 cohorts because their earnings are largely based on historical data. By comparing the average earnings level to the benchmark quantiles, workers are categorized as “low,” “average,” and “high” earners. The percentage of men and women in each level category is shown in Figure 2-16. A smaller percentage of men are high earners in the later than in the earlier cohorts. In contrast, the share of women who are high earners increases sharply between the earlier and later cohorts. However, a gender difference remains - over 40 percent of men are in this top-level category in the most recent cohort, compared to 20 percent of women.

In Figure 2-17, we further divide workers into those with “declining,” “level,” and “rising” trends in career earnings. On this dimension, the male distribution is fairly stable, although a slightly larger share of men in the later than in the earlier cohorts are characterized by a declining trend in earnings. For women, the relative shares have been altered significantly over time. In the 1926-30 cohorts, 58 percent of women had a rising earnings trend, whereas only 35 percent in the 1961-65 cohorts were in this category. In the 1961-65 cohorts, women are more equally distributed across the three trend types than are men.

The demographic characteristics and educational attainment of persons in these level and trend categories can also be evaluated. A higher share of both white, non-Hispanics and Asians are in the high earnings level categories, compared with other racial and ethnic groups. In addition, there is a strong relationship between educational attainment and earnings level. In the trend distributions, there are fewer differences across the demographic groups. A higher proportion of women and Asians exhibit a rising trend, while most other gender and racial groups are concentrated in the level or declining trends. A level trend also describes a higher portion of career earnings for college graduates relative to those with less schooling.

We then assign workers to one of nine stylized profile groups based on the level and trend categories. The mean of male and female earnings in each group is presented in Figure 2-18. The proportion of the MINT sample in each category is listed above its chart. The most notable feature is the wide disparity of earnings profiles. Less than half of the workers have the rising pattern on earnings over their work life that is considered typical, and the pattern of declining earnings is more common for men than for women. These differences reflect variations in both nonzero earnings and rates of employment to population. However, most of the variation can be traced to variations in nonzero earnings. For example, variation in the employment to population rate accounts for only 20 percent of the difference in the 30-year average of earnings between the top and bottom thirds of the distribution for both men and women. Also, the age profiles of nonzero earnings are very similar to the corresponding profile of all earnings with a displacement in level. In addition, the shape of the earnings profiles change little when examining different cohort subgroups. However, the distribution of the nine stylized profiles changes considerably across cohorts. As shown in Table 2-7, the proportion of men and women with a declining trend increases with successive cohorts regardless of earnings level. Compared with earlier cohorts, a smaller percentage of male workers in later cohorts have either high and rising earnings or high and level earnings. In contrast, an increasing percentage of women in later cohorts are categorized as high earners.

Figure 2-16
Distribution of Average Career Earnings By Level - MINT 2.1



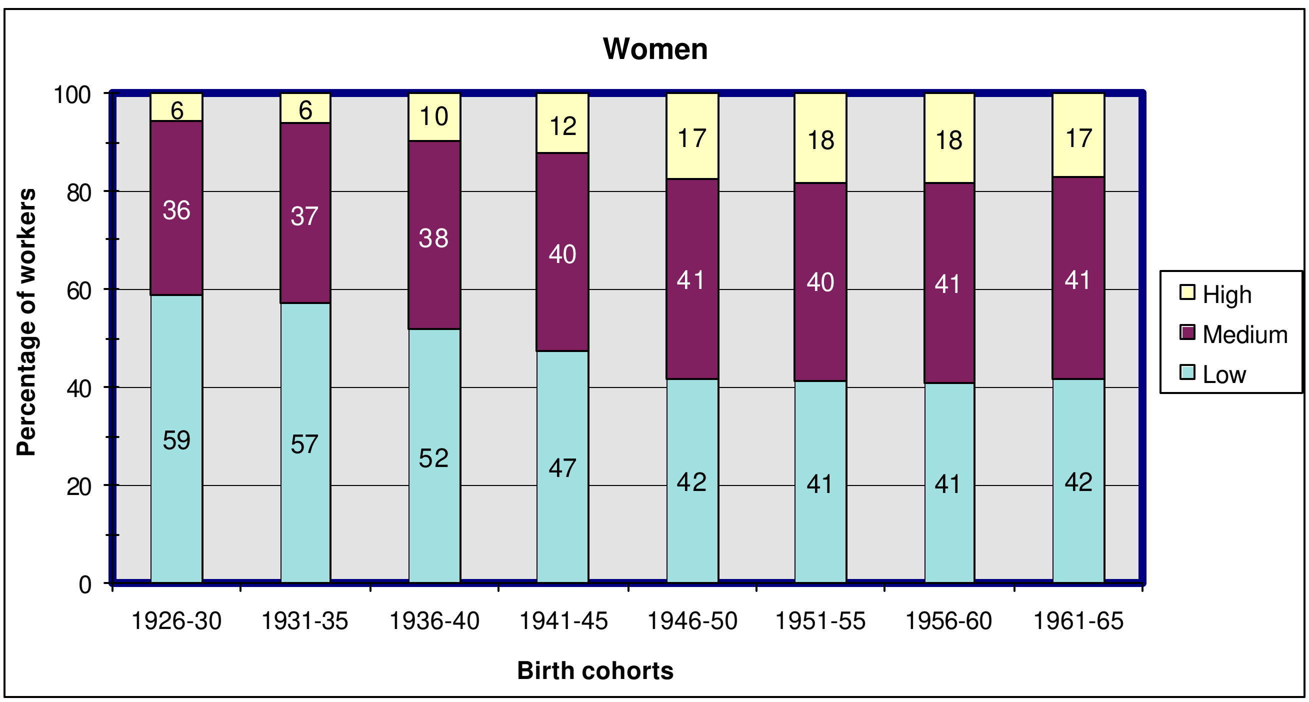
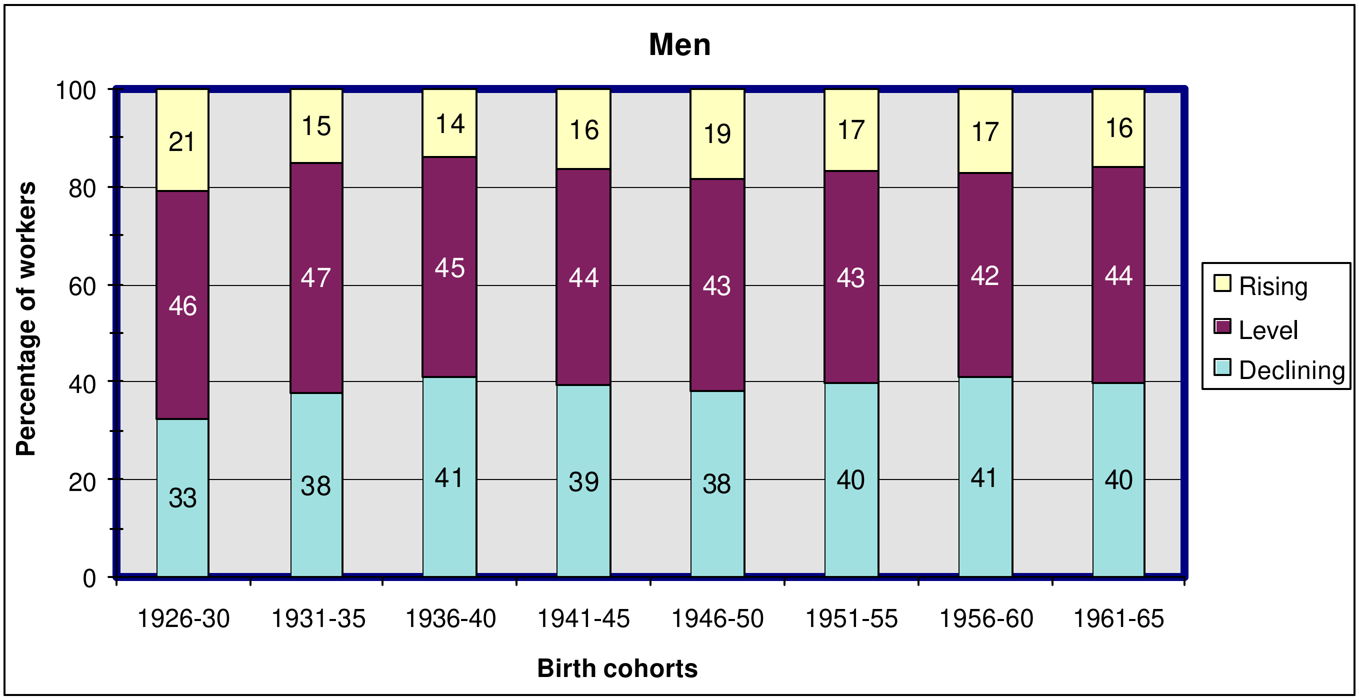


Figure 2-17
Distribution of Average Career Earnings By Trend - MINT 2.1



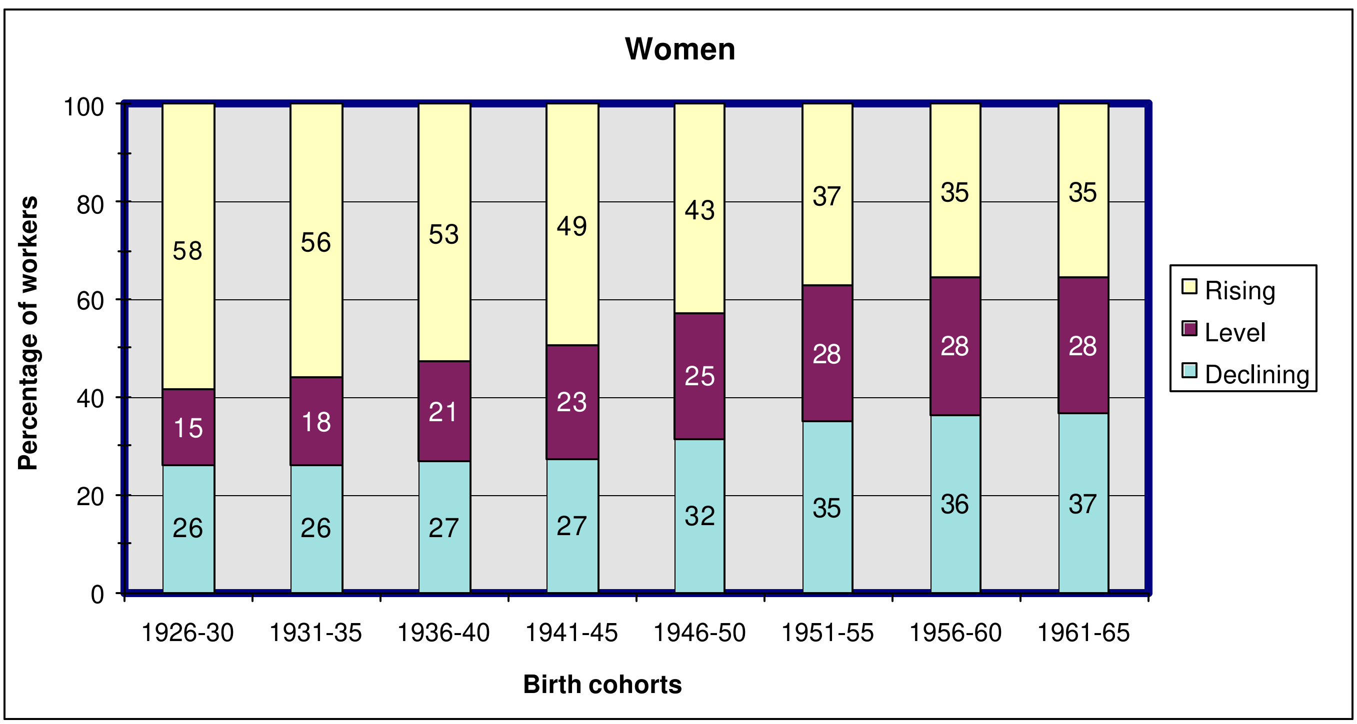
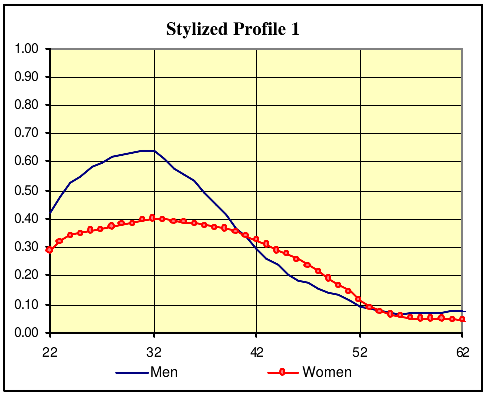


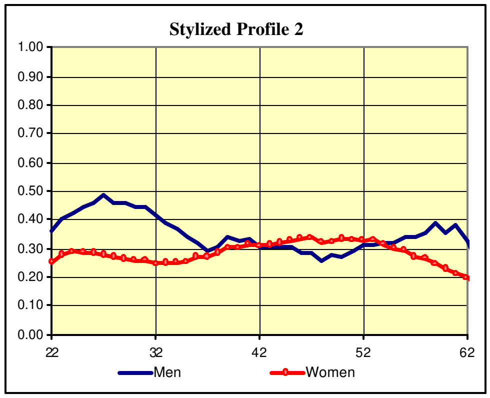
Figure 2-18
Stylized Age-Earnings Profiles for Men and Women, 1926-1965 Birth Cohorts
(All Earnings)

Low Income Level

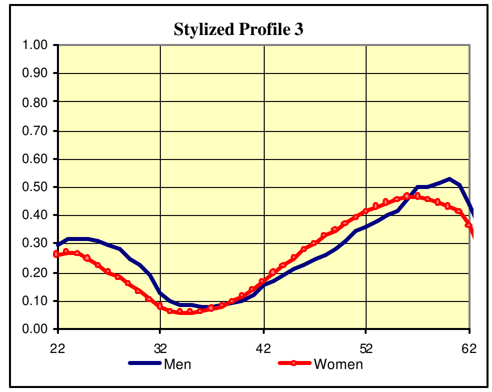
Men 7.1% *Declining Trend* 13.3% Women



Men 1.4% *Level Trend* 3.7% Women

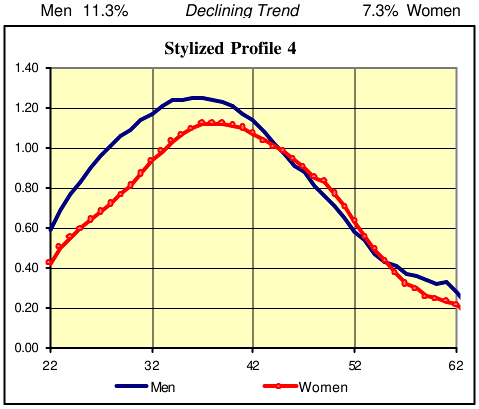


Men 3.5% *Rising Trend* 14.8% Women

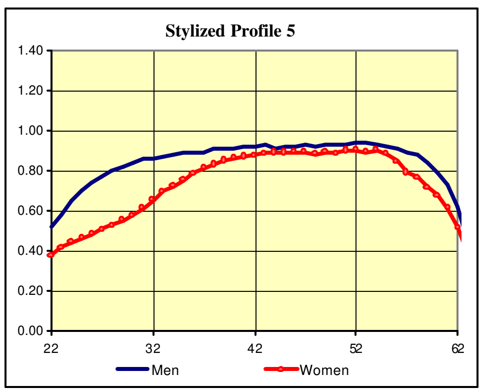


Medium Income Level

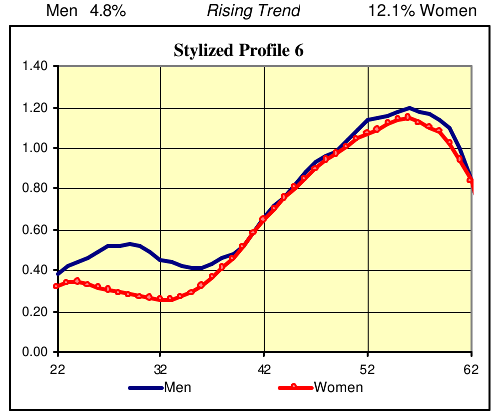
Men 11.3% *Declining Trend* 7.3% Women



Men 8.6% *Level Trend* 8.6% Women

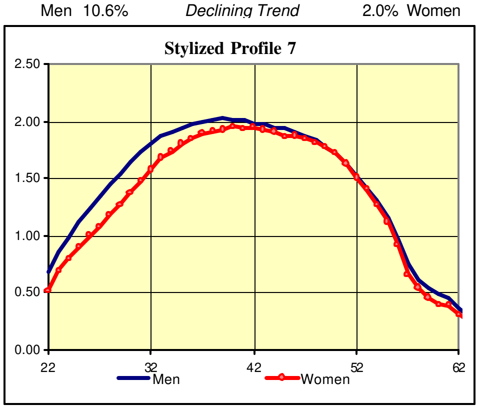


Men 4.8% *Rising Trend* 12.1% Women

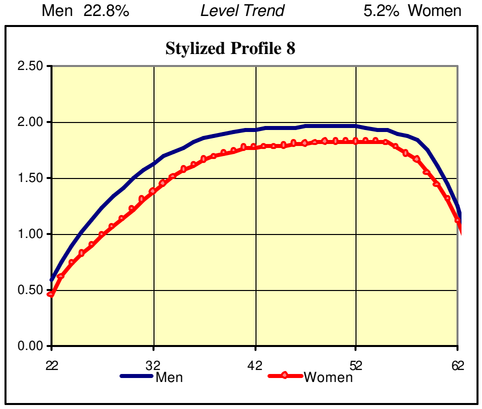


High Income Level

Men 10.6% *Declining Trend* 2.0% Women



Men 22.8% *Level Trend* 5.2% Women



Men 4.3% *Rising Trend* 3.1% Women

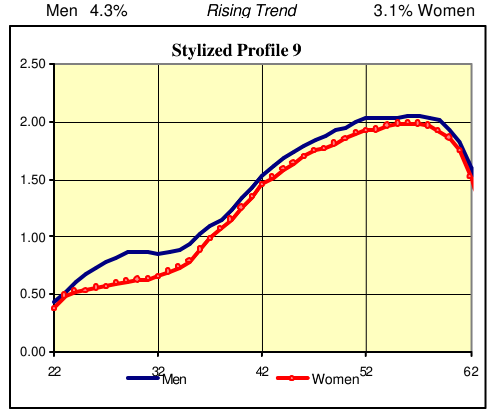


Table 2-7
Distribution of Workers in Stylized Profiles by Cohort

Percent

	Birth cohort								
	1926-30	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	1961-65	All cohorts
Men									
Low, declining	8.1	9.8	8.7	8.8	8.0	9.7	10.7	11.2	9.5
Low, level	1.5	1.1	1.4	2.1	1.9	2.1	2.4	2.2	1.9
Low, rising	3.6	3.4	4.4	4.7	5.2	4.9	4.8	5.1	4.7
Average, declining	13.8	15.8	15.9	13.4	13.5	15.2	16.4	16.6	15.2
Average, level	9.9	9.6	8.8	9.0	10.8	12.7	13.4	14.5	11.6
Average, rising	5.8	4.2	4.7	6.2	6.8	7.0	7.8	6.8	6.5
High, declining	10.6	12.2	16.2	17.1	16.6	15.0	13.8	11.9	14.3
High, level	35.1	36.1	35.0	33.3	30.4	28.6	26.2	27.7	30.6
High, rising	11.7	7.8	4.7	5.4	6.7	4.9	4.6	4.0	5.8
Total	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*
Women									
Low, declining	19.7	19.8	18.0	16.4	17.0	18.9	20.3	20.9	19.0
Low, level	5.1	6.5	5.7	5.9	5.1	5.0	4.9	4.8	5.2
Low, rising	34.1	30.9	28.0	25.1	19.8	17.6	15.8	15.9	21.1
Average, declining	6.1	5.9	7.5	8.8	11.5	12.5	12.1	12.0	10.4
Average, level	8.1	9.0	11.4	11.9	12.0	13.0	13.3	14.0	12.2
Average, rising	21.4	21.8	19.5	19.5	17.4	14.9	15.3	15.2	17.2
High, declining	0.5	0.6	1.3	2.3	3.1	3.8	4.0	3.7	2.9
High, level	2.2	2.4	3.5	5.5	8.4	9.7	10.0	9.3	7.5
High, rising	2.9	3.2	5.0	4.6	5.9	4.7	4.2	4.1	4.5
Total	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*

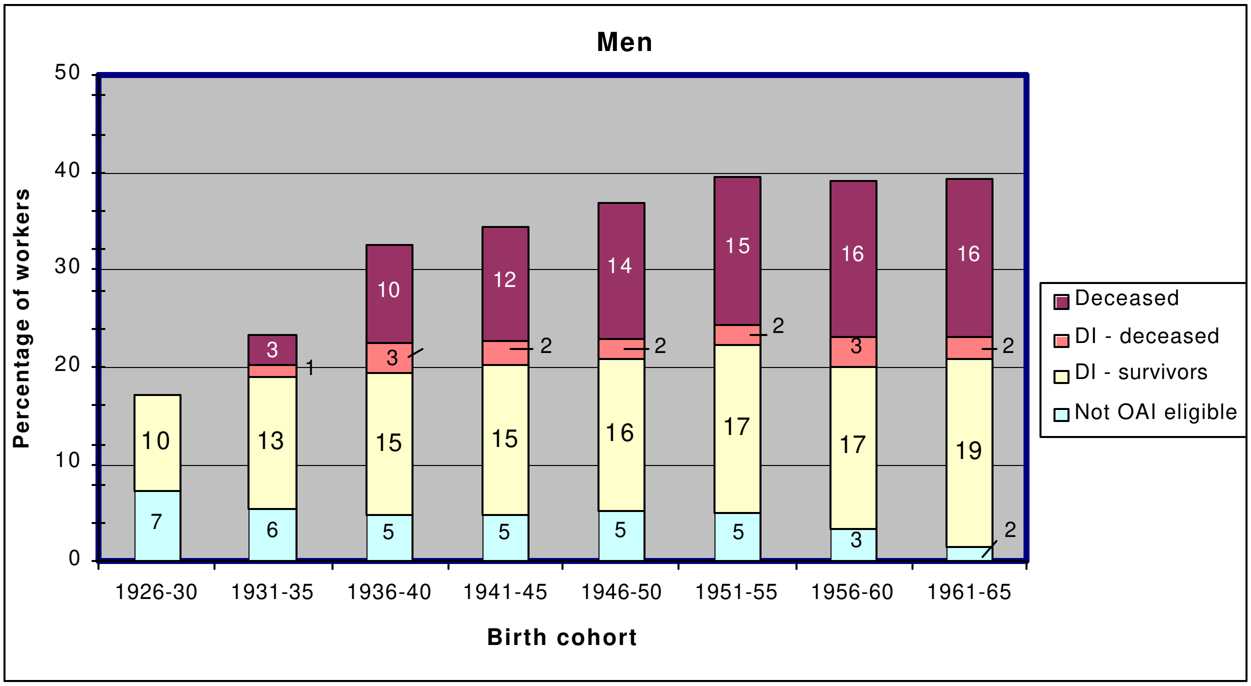
Source: Author's tabulations of MINT 2.1_C data set.

Comparison with the MINT 1.0 stylized earnings profiles. Because of changes in methodology, the new stylized profiles are not directly comparable to the original MINT 1.0 profiles. So we have created new profiles based on the MINT 1.0 data set using the process described above. This allows us to focus on differences in the earnings and disability projections.[13] As shown in Figure 2-19, MINT 1.0 earnings would exclude an even larger portion of the male sample from the trend and level analysis. In addition, the distribution across the four incomplete career groups is markedly different. The contrasts between the MINT 2.1 and 1.0 data sets are most clearly seen in the 1961-65 cohorts, because most of their career earnings are projected. For both men and women in these cohorts, MINT 1.0 has a larger share of disabled workers and almost no one is excluded on the basis of OAI ineligibility.

We then use MINT 1.0 earnings to classify workers into level and trend groups. Comparing Figures 2-16 and 2-20, the two projection methods yield similar distributions by earnings level. However, the trend categories are clearly dissimilar. Figure 2-21 shows a dramatic decline in the portion of men and women with a rising trend in MINT 1.0. Among men there is a large rise in the share of declining trends and for women the level trend becomes dominant. By splicing together historical earnings records, we can better preserve the diversity of individual earnings profiles.

[13] The mortality and disability information from MINT 1.0 was used to identify the career worker sample. New one-third and two-third quantile cutoffs were then calculated from the 1931-40 cohorts. Even in these cohorts, there are marked differences between the MINT 1.0 and 2.1 earnings.

Figure 2-19
Percent of Sample Without a Full or Regular Career - MINT 1.0



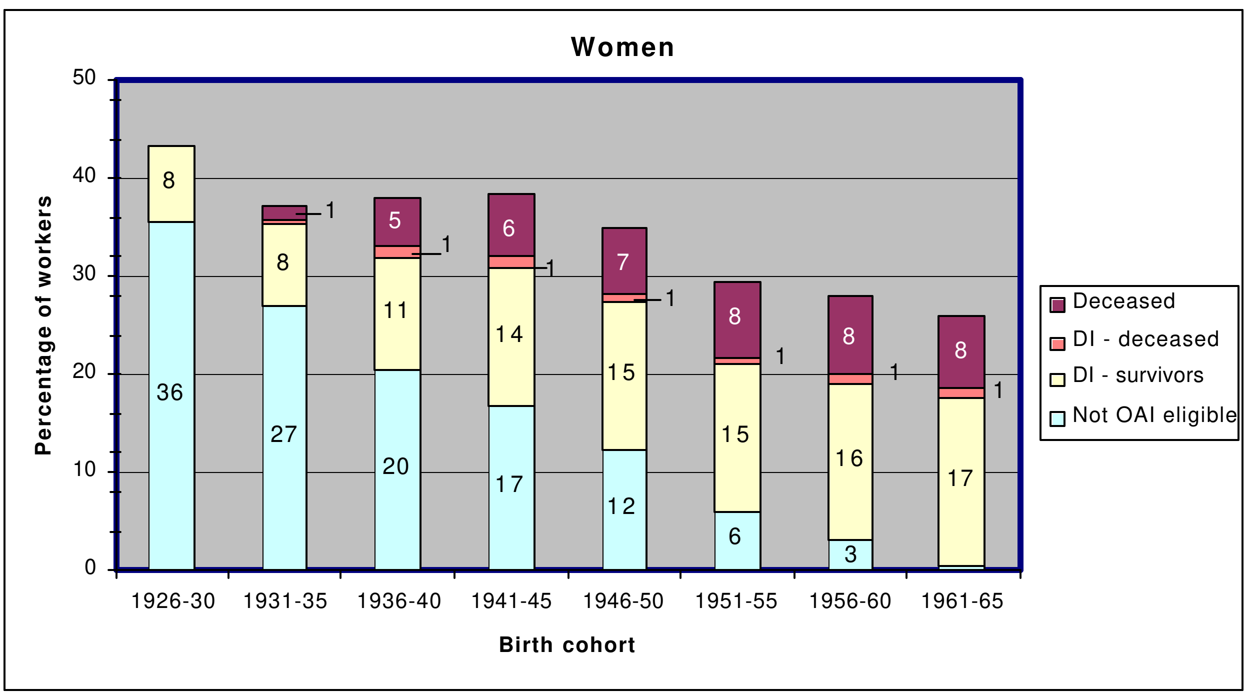
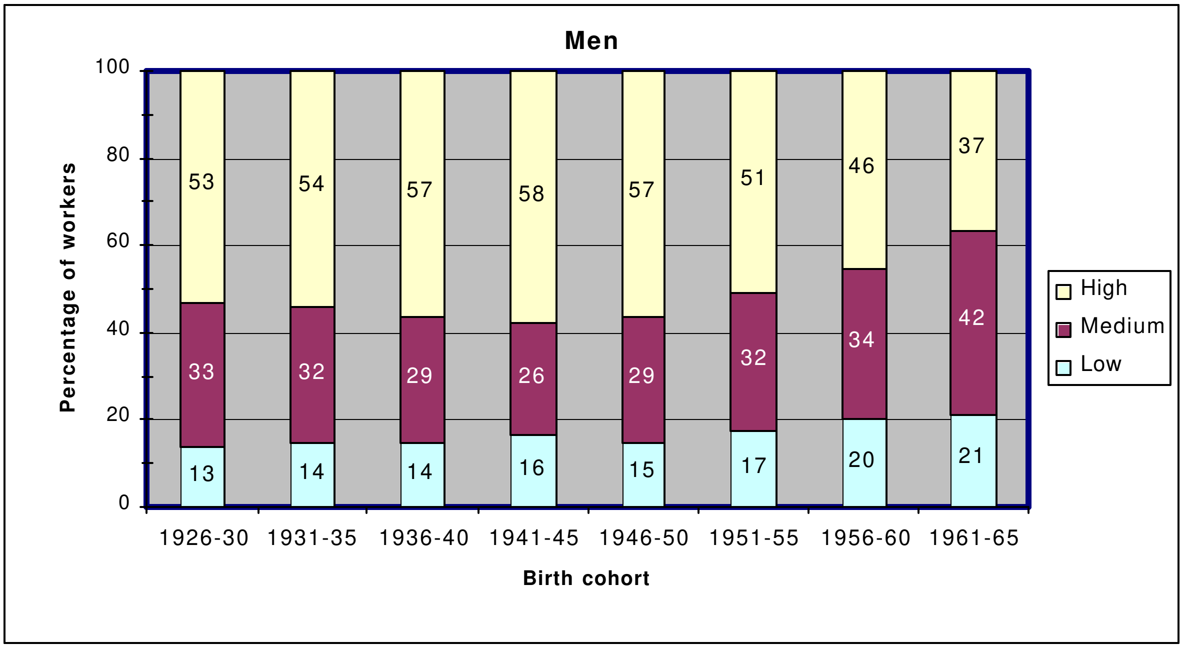


Figure 2-20
Distribution of Average Career Earnings By Level - MINT 1.0



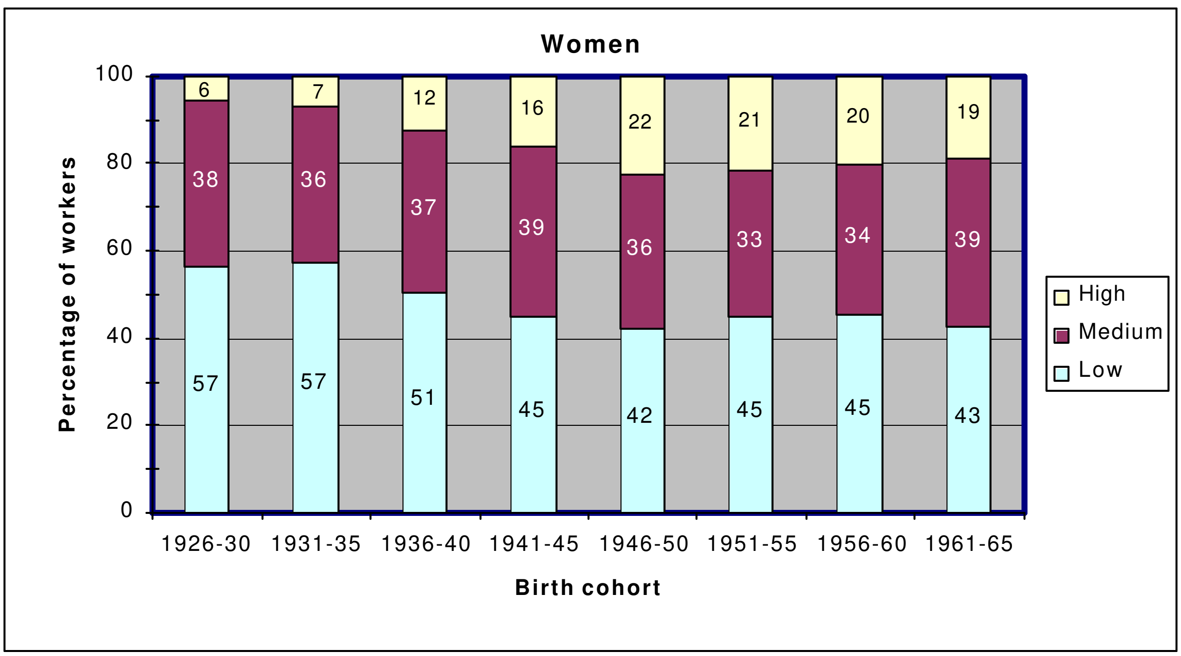
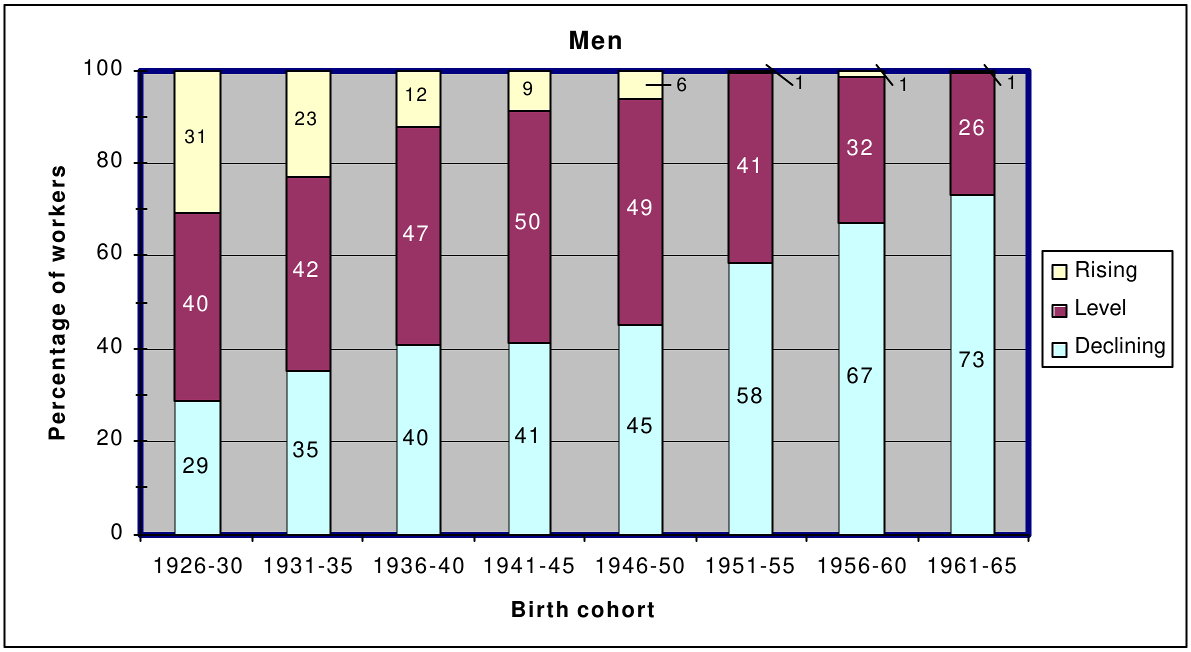
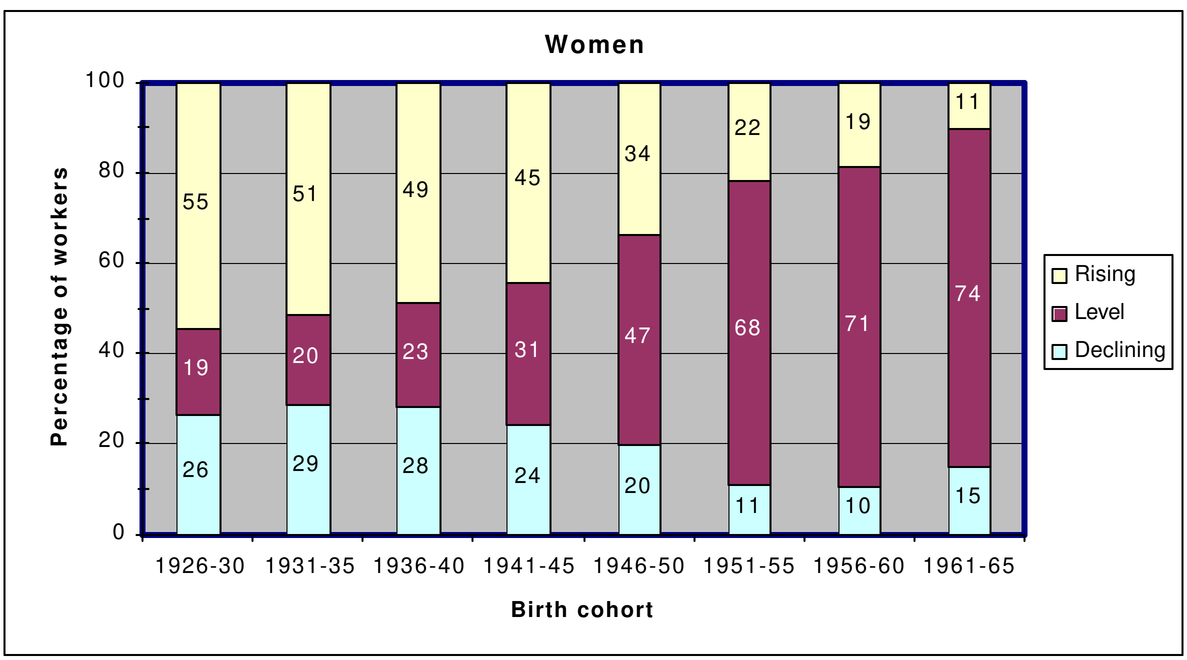


Figure 2-21
Distribution of Average Career Earnings By Trend - MINT 1.0





3. Distribution of Average Indexed Earnings across Successive Cohorts

Tables 2-8 and 2-9 show the trend in the distribution of Average Indexed Monthly Earnings (AIME) across successive birth cohorts. The results in Table 2-8 pertain to men, while those in Table 2-9 refer to women. We have tabulated the AIME distribution for two different samples of workers and using two different measures of annual Social-Security-covered earnings. All of our calculations exclude workers who die by the time they attain age 62. If we did not make this sample exclusion, it would be difficult to compare earnings across cohorts, because the older cohorts obviously exclude many workers who die before attaining the early entitlement age, whereas such workers are included in the younger cohorts who were interviewed in the SIPP.

Our more inclusive sample of workers includes all persons who had positive earnings during at least one year between ages 22 and 61 (see the first and third panels in Tables 2-8 and 2-9). Our more restrictive sample only includes workers if they accumulated enough earnings credits to become entitled to Old-Age Insurance (OAI) benefits by the time they attained age 62 (see the second and fourth panels in Tables 2-8 and 2-9). The taxable maximum level of earnings increased significantly during most of the period between 1951-1991. For this reason, workers in older birth cohorts earned much of their career earnings when the taxable maximum level of earnings was low, limiting the annual level of earnings reported during much of their careers. This is particularly important in the case of men, who often earn enough wages during their peak earnings years to attain the taxable maximum. To make the comparison of earnings more even-handed for younger and older cohorts, we have also calculated the AIME using "less-censored" earnings, our attempt to measure annual earnings under a uniform taxable maximum amount of 2.43 times the economy-wide average wage. The top two panels in Tables 2-8 and 2-9 measure the AIME using the actual taxable maximum; the bottom two panels use less-censored earnings to calculate each worker's AIME.

Using annual earnings amounts that are subject to the actual taxable earnings limit, we find that the AIME generally rises for successive birth cohorts of men up through the 1946-1950 cohort and then declines moderately. However, when the AIME is calculated using less-censored annual earnings amounts, the rise in the average AIME between the oldest cohort and the cohort born between 1946-1950 is much more modest. Moreover, the decline in the average AIME for men born after 1950 appears more pronounced. When less-censored earnings are used, men in the youngest cohort are predicted to have the lowest indexed lifetime earnings of any of the cohorts we consider.

Our calculations also suggest that the inequality of male lifetime indexed earnings is rising over time, with males in the youngest cohorts predicted to have the greatest inequality under the most detailed measure of inequality. The tables use three definitions of inequality: the ratio of earnings at the 90th percentile to earnings at the 10th percentile; the ratio of earnings at the 80th percentile to earnings at the 20th percentile; and the Gini coefficient of inequality. As expected, the upward trend in lifetime earnings inequality is less pronounced using a measure of AIME based on a consistent definition of the taxable maximum level of earnings. Part of the apparent increase in inequality in the AIME over time is due to the fact that the taxable maximum level of earnings has risen over time, which increases the measured earnings gap between top earners and

Table 2-8
Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts: Men

Birth cohort	Mean AIME	90/10 ratio	80/20 ratio	Gini coefficient	% not eligible
A. *Based on earnings up to actual taxable maximum*					
1. Non-deceased at beginning of year attain 62					
1926 - 1930	0.92	6.44	2.73	0.272	5.9%
1931 - 1935	1.00	6.24	2.70	0.276	5.0%
1936 - 1940	1.03	5.95	2.72	0.282	4.6%
1941 - 1945	1.09	6.31	3.06	0.297	4.5%
1946 - 1950	1.10	7.45	3.12	0.309	5.3%
1951 - 1955	1.06	7.14	3.08	0.317	4.9%
1956 - 1960	1.03	6.68	3.13	0.323	4.3%
1961 - 1965	1.00	7.33	3.21	0.331	3.8%
2. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.97	3.92	2.21	0.232	-
1931 - 1935	1.04	4.13	2.35	0.243	-
1936 - 1940	1.07	4.22	2.38	0.253	-
1941 - 1945	1.14	4.65	2.65	0.269	-
1946 - 1950	1.15	4.81	2.63	0.276	-
1951 - 1955	1.12	5.01	2.72	0.287	-
1956 - 1960	1.07	5.18	2.84	0.298	-
1961 - 1965	1.04	5.69	2.92	0.309	-
B. *Based on "less censored" earnings*					
3. Non-deceased at beginning of year attain 62					
1926 - 1930	1.08	7.82	3.20	0.310	5.9%
1931 - 1935	1.12	7.33	3.01	0.303	5.0%
1936 - 1940	1.11	6.53	2.95	0.300	4.6%
1941 - 1945	1.14	6.62	3.22	0.306	4.5%
1946 - 1950	1.12	7.64	3.17	0.313	5.3%
1951 - 1955	1.07	7.18	3.09	0.319	4.9%
1956 - 1960	1.03	6.69	3.13	0.324	4.3%
1961 - 1965	1.00	7.34	3.21	0.331	3.8%
4. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	1.14	4.82	2.61	0.271	-
1931 - 1935	1.18	4.80	2.64	0.272	-
1936 - 1940	1.16	4.64	2.58	0.272	-
1941 - 1945	1.19	4.85	2.76	0.279	-
1946 - 1950	1.17	4.88	2.67	0.281	-
1951 - 1955	1.12	5.02	2.73	0.289	-
1956 - 1960	1.08	5.19	2.84	0.298	-
1961 - 1965	1.04	5.69	2.92	0.309	-

Note: AIME is measured as ratio of the economy-wide average wage.
Source: Authors' tabulations of MINT 2.1_c data file.

Table 2-9
Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts: Women

Birth cohort	Mean AIME	90/10 ratio	80/20 ratio	Gini coefficient	% not eligible
A. *Based on earnings up to actual taxable maximum*					
1. Non-deceased at beginning of year attain 62					
1926 - 1930	0.31	45.99	11.73	0.526	29%
1931 - 1935	0.38	22.19	7.30	0.480	22%
1936 - 1940	0.43	19.00	6.93	0.468	19%
1941 - 1945	0.50	17.16	6.27	0.458	15%
1946 - 1950	0.59	16.19	5.54	0.436	12%
1951 - 1955	0.62	13.20	4.88	0.426	10%
1956 - 1960	0.64	12.23	4.48	0.414	9%
1961 - 1965	0.64	9.74	4.06	0.401	7%
2. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.42	7.48	3.95	0.386	-
1931 - 1935	0.47	7.34	3.73	0.380	-
1936 - 1940	0.52	7.11	3.87	0.381	-
1941 - 1945	0.57	7.81	3.99	0.386	-
1946 - 1950	0.66	7.24	3.71	0.375	-
1951 - 1955	0.69	7.03	3.66	0.373	-
1956 - 1960	0.70	6.88	3.51	0.368	-
1961 - 1965	0.69	6.50	3.47	0.367	-
B. *Based on "less censored" earnings*					
3. Non-deceased at beginning of year attain 62					
1926 - 1930	0.32	46.37	11.87	0.537	29%
1931 - 1935	0.39	22.34	7.32	0.489	22%
1936 - 1940	0.43	19.14	6.94	0.471	19%
1941 - 1945	0.50	17.23	6.26	0.461	15%
1946 - 1950	0.59	16.19	5.52	0.437	12%
1951 - 1955	0.62	13.21	4.88	0.426	10%
1956 - 1960	0.64	12.24	4.48	0.414	9%
1961 - 1965	0.64	9.74	4.06	0.401	7%
4. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.43	7.69	3.98	0.401	-
1931 - 1935	0.48	7.40	3.75	0.389	-
1936 - 1940	0.52	7.14	3.86	0.385	-
1941 - 1945	0.58	7.85	4.00	0.389	-
1946 - 1950	0.66	7.24	3.71	0.376	-
1951 - 1955	0.69	7.03	3.66	0.373	-
1956 - 1960	0.70	6.88	3.51	0.368	-
1961 - 1965	0.69	6.50	3.47	0.367	-

Note: AIME is measured as ratio of the economy-wide average wage.
Source: Authors' tabulations of MINT 2.1_c data file.

workers who earn the median level of earnings. The right-hand column in the table shows the percentage of non-disabled survivors at age 62 who are not eligible for an OAI pension because they have not accumulated enough earnings credits. There is a modest decline in OAI noncoverage among men in younger cohorts.

The trend in the AIME for women shows a pronounced rise in average earnings over time. However, the inequality of lifetime female earnings has fallen significantly in the younger birth cohorts compared with the older ones. The most important reason for the decline in inequality is that many fewer women in the younger cohorts are predicted to have lengthy periods without any covered earnings at all. The historical and predicted increases in female labor force participation have meant that a much larger percentage of women will work steadily during their careers, leaving a much smaller proportion of women with extremely low lifetime earnings. One by-product of this trend is lower lifetime earnings inequality among women. The trend toward higher and more continuous labor force participation is also reflected in the right-hand column in Table 2-9, which shows the percentage of non-disabled women in successive cohorts who do not become eligible for an OAI pension by the time they attain age 62. In the oldest cohort, almost 30% of women attaining age 62 do not accumulate enough earnings credits to become entitled to an OAI pension. In the youngest cohort, we predict that only 7% will reach age 62 without becoming eligible for an OAI pension.

4. Comparison of MINT Earnings Distribution with CPS Distribution

On the whole, the pattern of earnings reflected in the historical MINT data set corresponds well with the pattern observed in the Census Bureau's March Current Population Survey (CPS). We have divided annual earnings reports in both the MINT historical file and the March CPS files into four broad categories: (1) No reported earnings in a year; (2) Positive earnings less than 0.5 times the average economy-wide wage as calculated by the Social Security Administration; (3) Positive earnings between 0.5 and 1.0 times the economy-wide average wage; and (4) Positive earnings greater than 1.0 times the economy-wide average wage.

Figure 2-22 shows the percentages of men and women in the historical MINT file and the March CPS files who have earnings that fall in these four categories. In order to ensure that the calculations cover a similar population, we have restricted the MINT and March CPS samples to the same age and birth-cohort groups. To be included in the sample for a given calendar year, a person must be between 22 and 61 years old and born between 1926 and 1965. (These sample restrictions mean that the distribution of ages in the sample varies over time. The average age of the sample gradually rises as the oldest sample members approach age 61.)

There are two notable differences between the annual earnings distribution reflected in the MINT historical data and in the March CPS. Annual employment rates are higher in the CPS than in the MINT file, and the distribution of earnings among workers who have positive earnings is somewhat different in the MINT file than in the CPS. The top left panel in Figures 2-22 shows a higher incidence of zero earnings among the MINT sample members relative to the CPS respondents. This difference reflects the problem of incomplete Social Security coverage in the SER, for the difference declines slowly in the 1960s and 1970s and at an accelerated rate after 1983, when coverage rates increased. As shown in the second and third panels of Figure 2-22, the MINT data suggest that a somewhat larger percentage of workers who have positive earnings have wages in the bottom part of the earnings distribution (that is, they have earnings below 0.5 of the economy-wide average wage). This discrepancy between the MINT and CPS earnings distributions is especially pronounced in the case of men (see the top right panel of Figure 2-22). In contrast, the MINT and CPS data match closely in terms of the proportion of workers who have earnings between 0.5 and 1.0 of the average wage. The percentage of male workers with earnings above the average wage is less in the MINT than in the CPS file in the early years, although this difference narrows significantly by the 1980s (lower right-hand panel in Figure 2-22).

The low percentage of MINT workers in the top part of the earnings distribution is also reflected in the MINT estimates of the proportion of workers who have earnings that exceed the (actual) taxable ceiling. A smaller percentage of workers in the MINT compared with the CPS have annual earnings above the taxable ceiling in years before 1980. This problem is particularly noticeable for men, who were far more likely than women to earn above-average wages in the 1960s and 1970s. However, this difference between the CPS and MINT files narrows significantly after 1972, and it is never very important for women.[14]

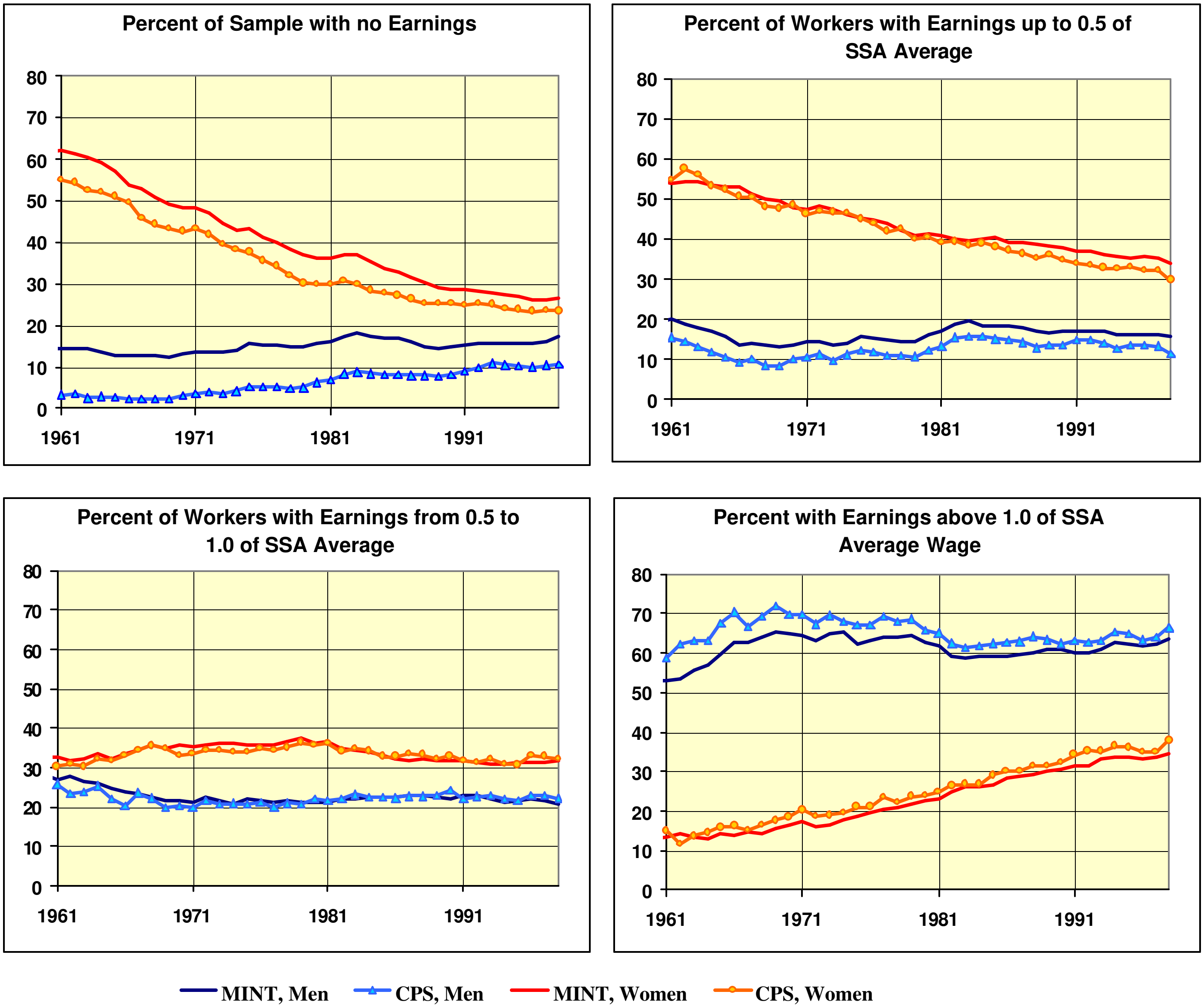
5. Comparison of MINT and OCACT Employment-Population Ratios

Our estimates of the employment-population ratio can be compared with those produced by the OCACT to evaluate the potential value of the historical and predicted employment rates in MINT 2.1. In order to perform this comparison, we have obtained estimates from the OCACT of the historical and projected ratio of OASDI-covered employment to the Social-Security-area population. The projections we use are based on the intermediate-cost assumptions embedded in the 2001 *OASDI Trustees' Report.* The OCACT provides estimates of this ratio by sex and 5-year age groups for each calendar year after 1990 and through the end of the 75-year projection period. We are primarily interested in seeing whether the historical and projected MINT data have a level and trend in the employment-population rate that match the level and trend projected by the OCACT.

We performed our calculation of the MINT employment-population ratio in a straightforward way. We calculated the surviving MINT population within 5-year age groups on January 1 of each calendar year and then computed the percentage of this population that earned at least 2.7% of the average economy-wide wage during the calendar year. Although this employment-population ratio does not correspond exactly with the OCACT rate, the level and trend in this ratio over successive 5-year periods should approximately match the level and trend of employment rates calculated by the OCACT. As a check on our calculations, we also calculated the percentage of surviving members in each age group who had positive earnings on the SER in 1990 and 1995, years in which the MINT 2.1 data set includes Social-Security-covered earnings amounts even if they are less than 2.7% of the economy-wide wage (see below).

[14] For a detailed comparison of the historical MINT earnings data with comparable data from the March CPS files, see Bosworth, Burtless, and Sahm, "The Trend in Lifetime Earnings Inequality and Its Impact on the Distribution of Retirement Income" (July 2001).

Figure 2-22
Comparison of the Annual Earnings Distributions in the March CPS and Historical MINT Files, 1961-1998



Source: Authors' tabulations of MINT 2.0 and March Current Population Survey files.

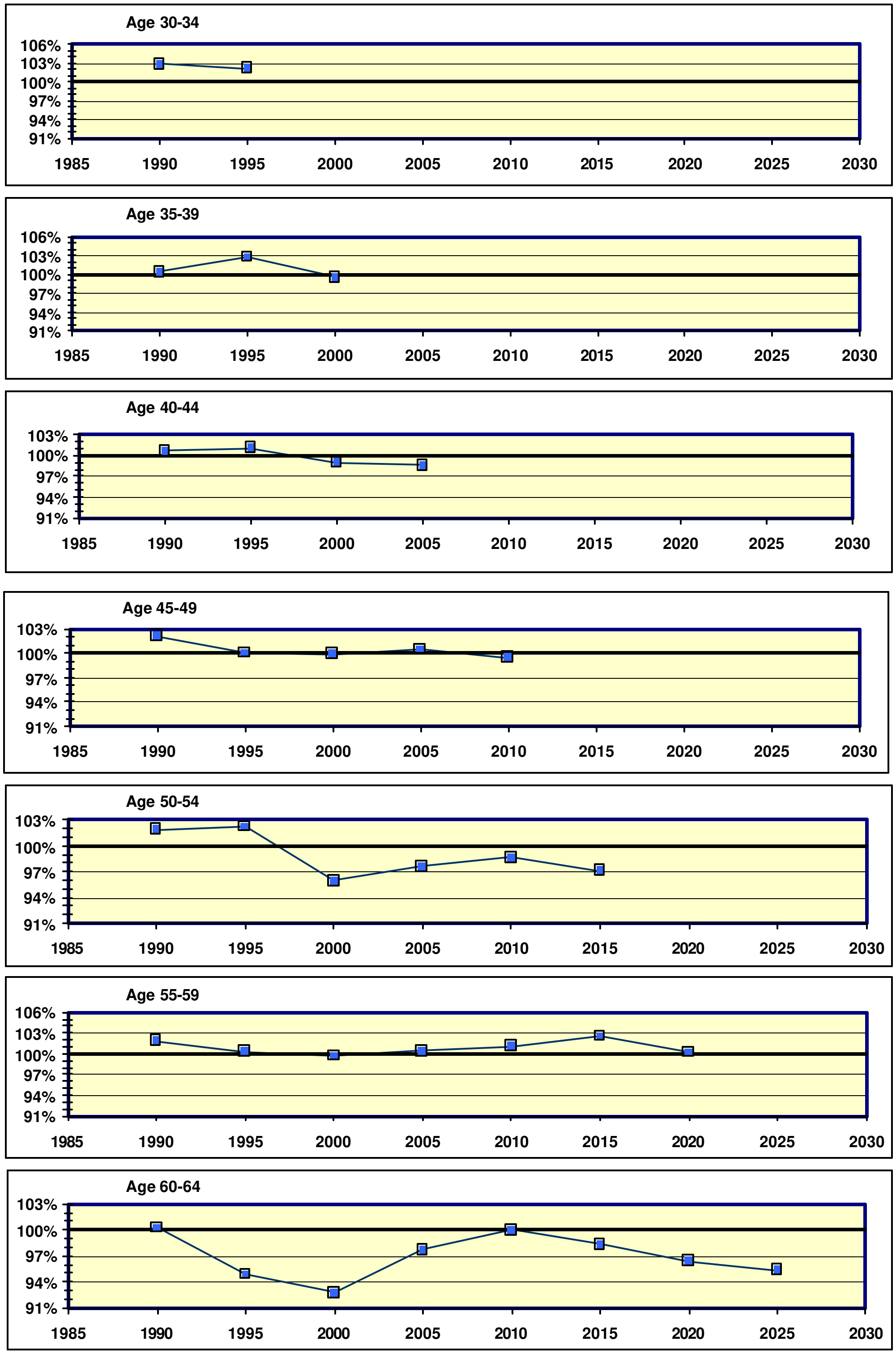
The results of our comparison are displayed in Figures 2-23 (for men) and 2-24 (for women). We have calculated the employment-population rate in the MINT 2.1 data set as a percentage of the employment-population rate estimated or projected by the OCACT for seven age groups. In the top panel of Figure 2-23, for example, we show the MINT 2.1 employment-population rate of 30-34 year-old males as a percent of the OCACT employment-population rate of the same group. We have only calculated this ratio for 1990 and 1995, because the MINT 2.1 sample lacks a full complement of observations to estimate the employment-population rate for this age group in later years. The top panel in Figure 2-23 shows that the estimated employment-population rate in MINT 2.1 matches almost exactly the rate estimated by the OCACT. The correspondence between the MINT 2.1 and OCACT estimates is not so close in older age groups, especially in the case of 50-54 year-old and 60-64 year-old men. Strangely, the MINT projection has greatest difficulty in matching the OCACT estimate in the year 2000, which is the first year of the MINT forecast. On the whole, however, the MINT projections of employment rates are quite close to those of the OCACT for men below the age of 60.

The comparison for women is shown in Figure 2-24. There are two notable discrepancies between the MINT and OCACT estimates. First, the MINT sample uniformly understates the employment-population rate of women in 1990 and 1995. The discrepancy between the two estimates is particularly large in 1990. We believe this difference is explained in part by the difference between the OCACT and MINT definition of "zero earnings." The OCACT defines any positive level of earnings as evidence of OASDI-covered employment. In the MINT data set, we have uniformly re-coded very low levels of earnings (earnings below 2.7% of the economy-wide wage) as zero. Apparently, this recoding has a larger impact on women than on men.

The second important difference between the OCACT and MINT 2.1 estimates is the trend in employment-population ratio. Especially at older ages, the MINT 2.1 forecast implies a stronger increase in participation among women, especially among women at older ages. By 2025, the MINT-projected employment rate of 60-64 year-old women is one-eighth above the rate projected by OCACT. In the MINT 2.1 forecast, the employment-population rate of 60-64 year-old women will climb from 45% in 2000 to 50% in 2025. In contrast, the intermediate-cost projections of the OCACT imply that 60-64 year-old women will see their employment-population rate *fall* from 46% to 45%. In light of the rise in the historical labor force participation rates of women younger than the NRA, the OCACT projection may be surprising. However, it may be the result of almost steady employment rates at each year of age from 60 to 64 combined with a shift in the age composition of 60-64 year-old women. In any event, the projection method embodied in the MINT 2.1 forecasts implies a stronger rise in female employment at older ages than assumed under the OCACT's intermediate-cost forecast.

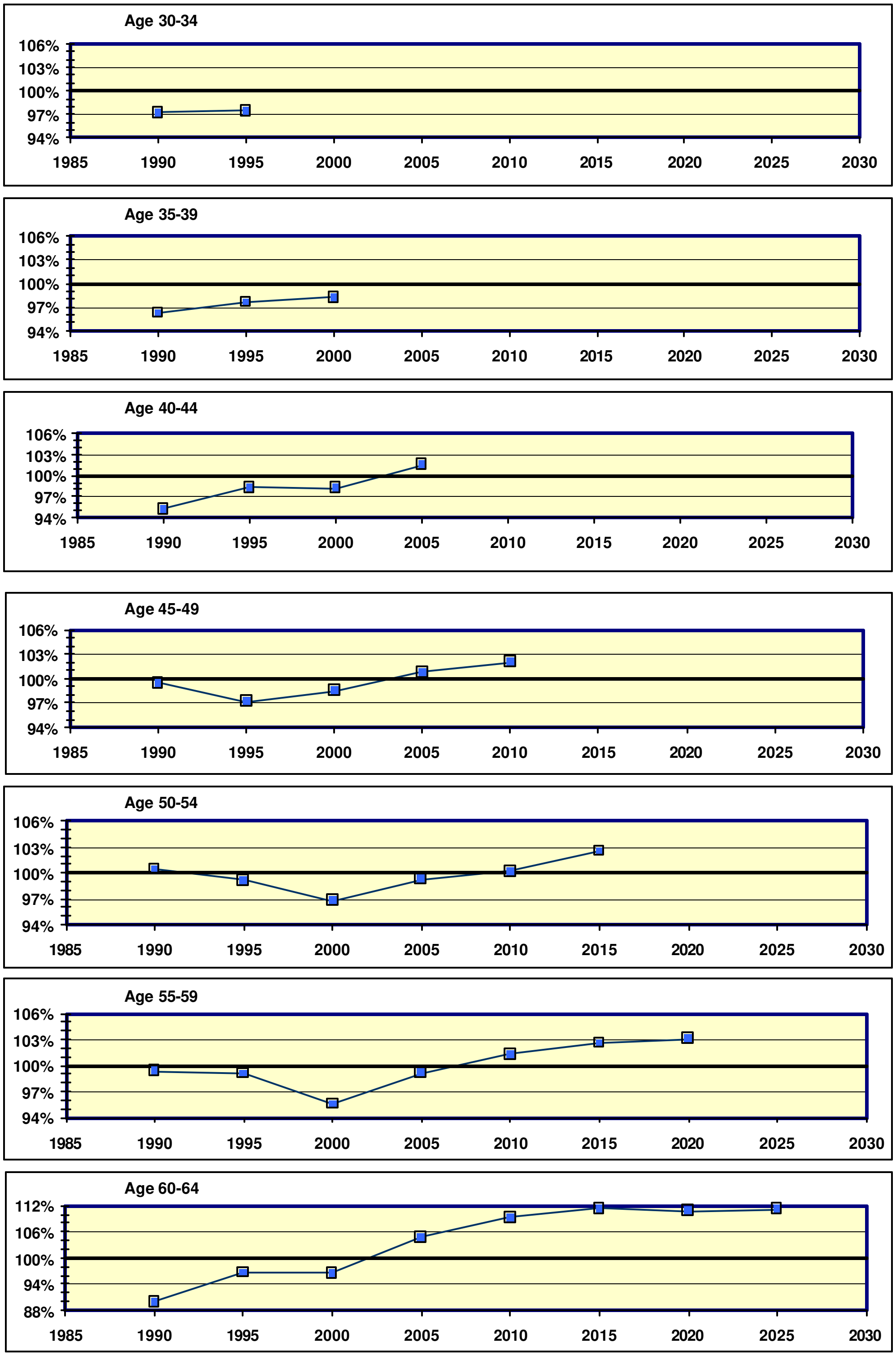
To see whether our procedure for zeroing out earnings amounts below 2.7% of the economy-wide average wage can account for the difference between the OCACT and MINT estimates of the employment-population ratio, we calculated the 1990 and 1995 employment-population rates with the MINT data using earnings amounts that have not been zeroed out. The results of this comparison for 1995 are displayed in Figure 2-25. For each gender and age group

Figure 2-23
Comparison of Estimated Employment-Population Ratio in OCACT Intermediate-Cost Forecast and MINT 2.1, 1990-2025: Males



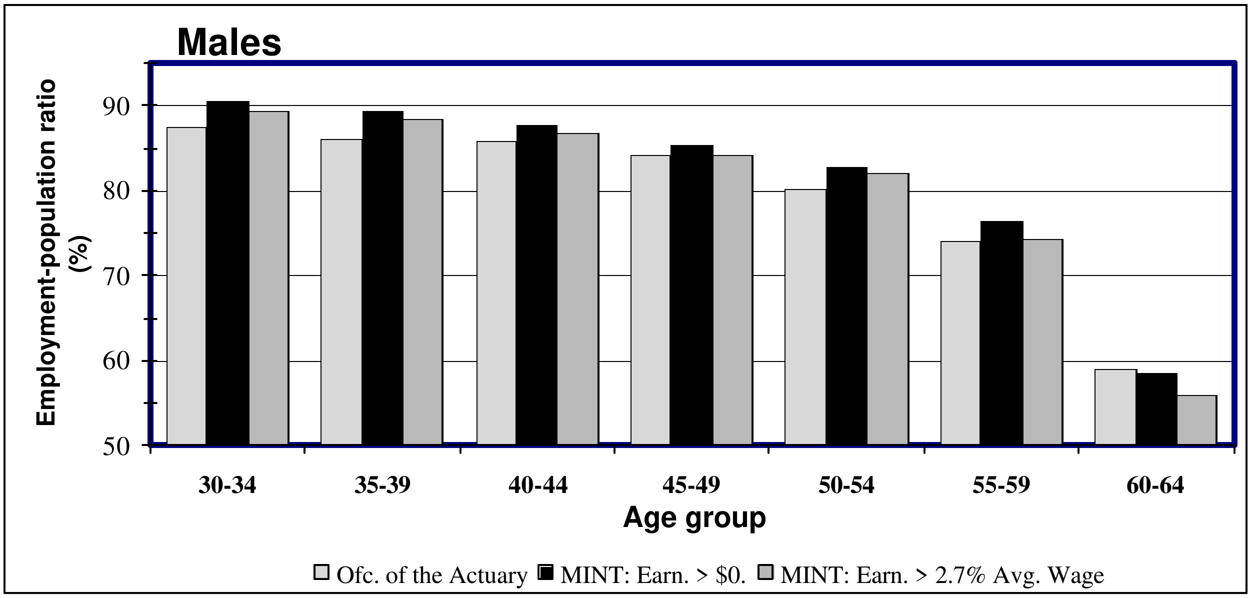
Note: The employment-population ratio in the MINT 2.1 sample is measured as a percent of the predicted ratio of Social-Security-covered employment to Social-Security-covered population as estimated or predicted by the OCACT.

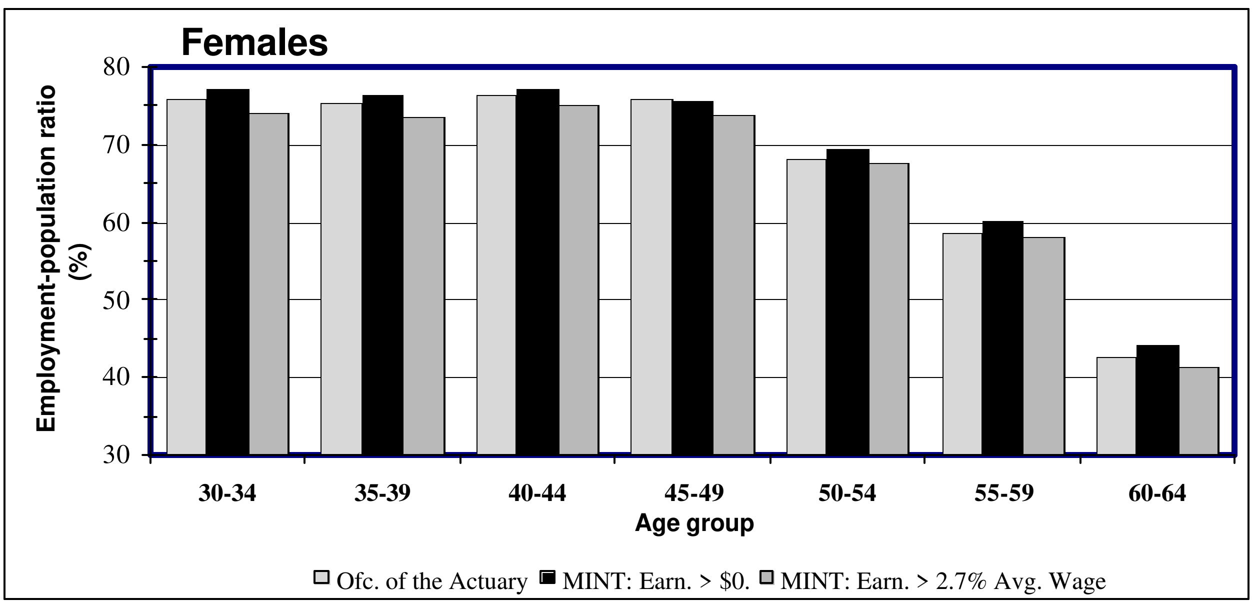
Figure 2-24
Comparison of Estimated Employment-Population Ratio in OCACT Intermediate-Cost Forecast and MINT 2.1, 1990-2025: Females



Note: The employment-population ratio in the MINT 2.1 sample is measured as a percent of the predicted ratio of Social-Security-covered employment to Social-Security-covered population as estimated or predicted by the OCACT.

Figure 2-25
Employment-Population Ratio by Age and Sex under Alternative Measures, 1995





Source: Authors' tabulations of OCACT data and employment rates in the MINT 2.1_C data set.

the chart shows three estimates: (1) the OCACT estimate of the covered employment-population ratio; (2) the MINT estimate when even small positive values are counted as a year of employment (call this estimate "MINT[1]"); and (3) the MINT estimate when covered earnings amounts below 2.7% of the economy-wide wage are converted to zero (call this estimate "MINT[2]"). Except in the oldest age group, the MINT[1] estimate consistently indicates a higher employment-population ratio than the OCACT. The difference averages 1.9 percentage points, and it is particularly large for the youngest groups of men. The difference is about half this large in the case of women. Although we regard these differences as troubling, it is not clear what the source of the difference may be. People surveyed in the SIPP do not represent a random sample of the Social-Security-covered population, which includes some people who reside abroad, on military bases, and in group quarters. Most such people are excluded from the SIPP. On the whole, however, the age pattern of employment shown in the OCACT statistics is faithfully mirrored in the 1995 MINT data.

6. Comparison of MINT and OCACT Projections of Disability Near the NRA

Table 2-4 in Section IV (Subsection 3) above shows the correspondence between our estimates of disability prevalence in the MINT 2.1 sample and the intermediate-cost projections of the Social Security Actuary. The two sets of prevalence estimates are reasonably close in most of the projection years, especially for years after 2020 and for the groups nearest the NRA. It would be desirable to supplement these comparisons with calculations of the percentage of workers reaching the NRA who have ever been DI entitled as primary workers. While this calculation can be performed with the MINT 2.1 data set, the OCACT does not make projections of future disability prevalence in a way that allows the same calculation with the SSA forecast.

VI. ANALYSIS OF PROJECTIONS: SENSITIVITY TESTS

In this section, we have tested the sensitivity of our earnings projections to varying mortality and disability benchmarks and to varying specifications of our earnings matching algorithm. We tested two alternatives to the Social Security Actuary's intermediate cost estimates of the mortality rate and two alternatives to the Actuary's intermediate cost estimates of disability prevalence. We also examined the sensitivity of the earnings projections to the inclusion of controls for marital status, immigration, uncovered employment, self-employment, and earnings above the taxable maximum.

For both mortality and disability, we tested the effects of using the Actuary's high-cost (pessimistic) and low-cost (optimistic) assumptions. Recall that a "high-cost" assumption is one that tends to increase OASDI outlays or reduce OASDI revenues, worsening the long-term outlook of the program. Thus, a "high-cost" mortality assumption is one which reduces the mortality rate compared with the intermediate-cost projection and increases the projected disability rate compared with the intermediate-cost projection.

In all of our sensitivity analyses we duplicated the benchmarking procedures described above that were used to align our forecast of future mortality and disability prevalence with the intermediate-cost projections of the OCACT. However, we varied the benchmark mortality or disability rates that we attempted to duplicate in our forecast. Note that our sensitivity tests vary only one aspect of the long-term forecast at a time..

1. Results of Varying Mortality Assumption

Table 2-10 shows benchmark mortality rates under the OASDI Trustees' low-cost assumptions for each birth cohort in successive periods through 2034. The low-cost (or optimistic) assumptions imply that mortality will be higher than in the main MINT 2.1 data set. Male morality rates are displayed in the first column; female rates are shown in the fourth column. For example, the bottom entry in the first column shows the 2030-2034 mortality rate for males born between 1961 and 1965. We derived this estimate from the OCACT's low-cost predictions of annual mortality in the Social-Security-area population, by year of age, during the period from 2030-2034. Notice that the benchmark rate in this projection is roughly one-sixth higher than the rate implied in the Trustee's intermediate-cost projection (2.2% per year versus 1.9% per year; see Table 2-1 above). In the second and fifth columns we show the initial prediction of mortality for the same birth cohorts in the same years using the splicing methodology described in Section III above. The third and sixth columns contain our final predictions of mortality for men and women, respectively, in each birth cohort and each five-year period. In each case the final predicted mortality rate is very close to the corresponding benchmark rate, indicating that our benchmarking procedure was able to duplicate the OCACT's low-cost mortality projection without any difficulty.

Table 2-11 shows benchmark mortality rates under the OASDI Trustees' high-cost assumptions in successive periods through 2034. The high-cost (or pessimistic) assumptions imply that mortality will be lower than in the main MINT 2.1 data set. For example, the bottom entry in the first column shows that the mortality rate for males born between 1961 and 1965 will be 1.53% in 2030-2034. The benchmark rate in this projection is almost one-fifth lower than the rate implied in the Trustee's intermediate-cost projection (1.53% per year versus 1.9% per year) and more than three-tenths below the low-cost mortality projection (1.53% per year versus 2.2% per year). The third and sixth columns in Table 2-15 contain our final predictions of mortality for men and women, respectively, in each birth cohort and each five-year period. In each case the final predicted mortality rate is very close to the corresponding benchmark rate, indicating that we were able to duplicate the OCACT's high-cost mortality projection with very little difficulty.[15]

[15] Although we do not show the benchmark results here, we did not have any difficulty duplicating the OCACT's intermediate-cost *disability* forecast when we matched the OCACT's low-cost and high-cost *mortality* projections.

Table 2-10
Mortality Rate by Sex and Birth Cohort in Successive Five-Year Periods, Benchmark Rates and Rates in MINT 2.1 Data Set: High Mortality Rate

	Men			Women		
Cohort	Benchmark Rate	Initial MINT Rate	Final MINT Rate	Benchmark Rate	Initial MINT Rate	Final MINT Rate
Years 2000-04						
1931-35	2.45%	2.51%	2.43%	1.51%	1.75%	1.51%
1936-40	1.90%	1.86%	1.88%	1.20%	1.01%	1.19%
1941-45	1.17%	0.99%	1.17%	0.74%	0.74%	0.74%
1946-50	0.74%	0.64%	0.74%	0.46%	0.37%	0.46%
1951-55	0.48%	0.43%	0.49%	0.28%	0.23%	0.28%
1956-60	0.33%	0.25%	0.33%	0.18%	0.14%	0.18%
1961-65	0.23%	0.19%	0.23%	0.12%	0.15%	0.12%
Years 2005-09						
1936-40	2.39%	2.35%	2.38%	1.55%	1.59%	1.55%
1941-45	1.84%	1.71%	1.84%	1.21%	1.04%	1.22%
1946-50	1.12%	0.98%	1.13%	0.73%	0.58%	0.73%
1951-55	0.70%	0.61%	0.70%	0.44%	0.39%	0.44%
1956-60	0.46%	0.43%	0.46%	0.27%	0.22%	0.27%
1961-65	0.32%	0.27%	0.31%	0.17%	0.14%	0.17%
Years 2010-14						
1941-45	2.35%	2.71%	2.34%	1.59%	1.55%	1.60%
1946-50	1.79%	1.49%	1.80%	1.22%	1.02%	1.22%
1951-55	1.08%	1.20%	1.07%	0.72%	0.60%	0.71%
1956-60	0.68%	0.72%	0.68%	0.43%	0.38%	0.43%
1961-65	0.44%	0.51%	0.44%	0.26%	0.28%	0.26%
Years 2015-19						
1946-50	2.30%	2.74%	2.30%	1.60%	1.52%	1.60%
1951-55	1.74%	1.50%	1.75%	1.21%	1.07%	1.21%
1956-60	1.05%	1.26%	1.04%	0.71%	0.67%	0.71%
1961-65	0.66%	0.65%	0.66%	0.42%	0.31%	0.42%
Years 2020-24						
1951-55	2.27%	2.64%	2.25%	1.59%	1.18%	1.60%
1956-60	1.71%	1.61%	1.70%	1.20%	1.06%	1.19%
1961-65	1.02%	1.20%	1.01%	0.70%	0.67%	0.70%
Years 2025-29						
1956-60	2.23%	2.38%	2.24%	1.57%	1.61%	1.57%
1961-65	1.69%	1.80%	1.69%	1.19%	1.24%	1.18%
Years 2030-34						
1961-65	2.20%	2.48%	2.21%	1.55%	1.40%	1.55%

Note: Calculations are based on the OCACT low-cost assumptions regarding mortality and intermediate-cost assumptions regarding disability. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_ma1.

Table 2-11
Mortality Rate by Sex and Birth Cohort in Successive Five-Year Periods, Benchmark Rates and Rates in MINT 2.1 Data Set: Low Mortality Rate

	Men			Women		
Cohort	Benchmark Rate	Initial MINT Rate	Final MINT Rate	Benchmark Rate	Initial MINT Rate	Final MINT Rate
Years 2000-04						
1931-35	2.43%	2.51%	2.40%	1.50%	1.75%	1.49%
1936-40	1.85%	1.86%	1.86%	1.17%	1.01%	1.16%
1941-45	1.14%	0.99%	1.14%	0.73%	0.74%	0.72%
1946-50	0.72%	0.64%	0.71%	0.45%	0.37%	0.45%
1951-55	0.47%	0.43%	0.47%	0.27%	0.23%	0.27%
1956-60	0.33%	0.25%	0.33%	0.18%	0.14%	0.17%
1961-65	0.23%	0.19%	0.23%	0.12%	0.15%	0.12%
Years 2005-09						
1936-40	2.23%	2.62%	2.23%	1.45%	1.16%	1.44%
1941-45	1.69%	1.63%	1.70%	1.12%	1.13%	1.13%
1946-50	1.01%	1.02%	1.01%	0.68%	0.62%	0.68%
1951-55	0.63%	0.56%	0.63%	0.41%	0.40%	0.41%
1956-60	0.41%	0.46%	0.41%	0.24%	0.21%	0.24%
1961-65	0.29%	0.31%	0.29%	0.15%	0.15%	0.15%
Years 2010-14						
1941-45	2.08%	2.75%	2.09%	1.41%	1.12%	1.41%
1946-50	1.55%	1.37%	1.55%	1.08%	0.98%	1.08%
1951-55	0.91%	1.11%	0.91%	0.64%	0.66%	0.64%
1956-60	0.56%	0.59%	0.56%	0.38%	0.45%	0.38%
1961-65	0.37%	0.45%	0.37%	0.22%	0.26%	0.22%
Years 2015-19						
1946-50	1.93%	2.68%	1.93%	1.34%	1.38%	1.35%
1951-55	1.43%	1.57%	1.44%	1.02%	1.03%	1.02%
1956-60	0.84%	1.25%	0.83%	0.61%	0.65%	0.61%
1961-65	0.51%	0.69%	0.51%	0.36%	0.38%	0.35%
Years 2020-24						
1951-55	1.78%	2.71%	1.79%	1.25%	1.27%	1.24%
1956-60	1.32%	1.56%	1.33%	0.95%	1.18%	0.95%
1961-65	0.78%	1.20%	0.77%	0.57%	0.59%	0.58%
Years 2025-29						
1956-60	1.65%	2.66%	1.66%	1.17%	1.64%	1.17%
1961-65	1.24%	1.64%	1.23%	0.89%	1.10%	0.89%
Years 2030-34						
1961-65	1.53%	2.49%	1.52%	1.09%	1.45%	1.08%

Note: Calculations are based on the OCACT high-cost assumptions regarding mortality and intermediate-cost assumptions regarding disability. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_ma3.

Impact of Alternative Mortality Assumptions on AIME Distribution

Tables 2-12 and 2-13 show the effects of a higher assumed mortality rate on the distribution of lifetime earnings among men and women, respectively. Tables 2-14 and 2-15 show the effects of using a lower assumed rate of mortality. In each case we examine the distribution of the AIME among workers who have at least one quarter of earnings credit between age 32 and 61 and who survive to the calendar year in which they attain age 62. As in Tables 2-8 and 2-9, we estimate the AIME distribution using two annual earnings measures, one that reflects earnings up to the actual taxable wage ceiling and the other that reflects earnings up to a consistent maximum value of 2.43 times the economy-wide wage. We also estimate the AIME distribution among the subsample of workers who accumulate enough earnings credits to become eligible for an OAI pension.

Not surprisingly, the alternative mortality assumptions have absolutely no impact on the measured distribution of earnings in the oldest cohorts. These cohorts are either unaffected or very little affected by differences in the mortality rate, because most or all members of the cohorts have already attained age 62 by the time the alternative mortality assumptions begin to affect the survival chances of cohort members. Perhaps more surprisingly, the alternative mortality assumptions also have very little impact on the distribution of lifetime earnings in the younger cohorts. The mean lifetime earnings of the youngest cohorts is predicted to be essentially identical, regardless of the assumed mortality rate. Although the inequality of earnings seems to be more affected by changes in the mortality rate, the apparent effect is mainly the result of random error rather than a systematic effect of higher or lower mortality.[16] As the male mortality rate is reduced from the high rate assumed under the low-cost alternative (Table 2-12) to the intermediate-cost alternative (Table 2-8) to the high-cost alternative (Table 2-14), inequality does not appear to change in a consistent way. Thus, we conclude that the distribution of lifetime earnings in the MINT 2.1 sample will not be materially affected by differences in mortality within the range of rates considered in the 2001 *OASDI Trustees' Report***.**

2. Results of Varying Disability Assumption

Table 2-16 shows benchmark disability rates under the OASDI Trustees' low-cost assumptions for each birth cohort in successive periods through 2029. The low-cost (or optimistic) assumptions imply that disability will be lower than in the main MINT 2.1 data set. Male disability rates are displayed in the first column; female rates are shown in the fourth column. For example, the bottom entry in the first column shows the 2025-2029 disability rate for males born between 1961 and 1965. We derived this estimate from the OCACT's low-cost predictions of annual disability in the Social-Security-area population, by year of age, during the period from 2025-2029. Notice that the benchmark rate in this projection is more than one-sixth below the rate implied in the Trustee's intermediate-cost projection (13.4% per year versus 16.3% per year; see Table 2-3 above). In the second and fifth columns we show the initial prediction of disability for the same birth cohorts in the same years using the splicing

[16] Recall that first-round and back-up donors are selected at random from the donor pool for purposes of imputing part of an earnings record to the end of an incomplete target-worker record. Thus, even if we did not change the benchmark mortality assumption at all, the distribution of earned income would change slightly from one implementation of our splicing procedure to the next, because target workers would be matched to different donors.

Table 2-12
Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts with High Mortality Rate: Men

Birth cohort	Mean AIME	90/10 ratio	80/20 ratio	Gini coefficient	% not eligible
A. ***Based on earnings up to actual taxable maximum***					
1. Non-deceased at beginning of year attain 62					
1926 - 1930	0.92	6.44	2.73	0.272	5.9%
1931 - 1935	1.00	6.24	2.70	0.276	5.0%
1936 - 1940	1.03	5.95	2.72	0.282	4.5%
1941 - 1945	1.09	6.31	3.08	0.297	4.6%
1946 - 1950	1.10	7.20	3.07	0.307	5.1%
1951 - 1955	1.06	7.11	3.11	0.317	4.6%
1956 - 1960	1.04	6.63	3.19	0.323	4.3%
1961 - 1965	1.01	6.46	3.15	0.325	4.0%
2. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.97	3.92	2.21	0.232	-
1931 - 1935	1.04	4.13	2.35	0.243	-
1936 - 1940	1.07	4.23	2.38	0.253	-
1941 - 1945	1.14	4.62	2.66	0.269	-
1946 - 1950	1.15	4.77	2.63	0.275	-
1951 - 1955	1.11	5.14	2.75	0.289	-
1956 - 1960	1.08	5.07	2.86	0.298	-
1961 - 1965	1.05	5.20	2.86	0.302	-
B. ***Based on "less censored" earnings***					
3. Non-deceased at beginning of year attain 62					
1926 - 1930	1.08	7.82	3.20	0.310	5.9%
1931 - 1935	1.12	7.33	3.01	0.303	5.0%
1936 - 1940	1.11	6.53	2.95	0.300	4.5%
1941 - 1945	1.14	6.63	3.23	0.306	4.6%
1946 - 1950	1.12	7.32	3.12	0.311	5.1%
1951 - 1955	1.07	7.14	3.11	0.319	4.6%
1956 - 1960	1.04	6.64	3.18	0.324	4.3%
1961 - 1965	1.01	6.46	3.14	0.325	4.0%
4. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	1.14	4.82	2.61	0.271	-
1931 - 1935	1.18	4.80	2.64	0.272	-
1936 - 1940	1.16	4.65	2.58	0.272	-
1941 - 1945	1.19	4.84	2.77	0.279	-
1946 - 1950	1.17	4.85	2.67	0.280	-
1951 - 1955	1.12	5.17	2.76	0.291	-
1956 - 1960	1.08	5.08	2.87	0.299	-
1961 - 1965	1.05	5.20	2.87	0.302	-

Note: AIME is measured as ratio of the economy-wide average wage.

Note: Calculations are based on the OCACT low-cost assumptions regarding mortality and intermediate-cost assumptions regarding disability. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_ma1.

Table 2-13
Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts with High Mortality Rate: Women

Birth cohort	Mean AIME	90/10 ratio	80/20 ratio	Gini coefficient	% not eligible
A. *Based on earnings up to actual taxable maximum*					
1. Non-deceased at beginning of year attain 62					
1926 - 1930	0.31	45.99	11.73	0.526	29%
1931 - 1935	0.38	22.19	7.30	0.480	22%
1936 - 1940	0.43	19.00	6.93	0.468	19%
1941 - 1945	0.50	17.09	6.27	0.459	15%
1946 - 1950	0.59	16.32	5.48	0.436	12%
1951 - 1955	0.63	12.79	4.81	0.424	10%
1956 - 1960	0.64	12.05	4.45	0.412	9%
1961 - 1965	0.64	10.38	4.04	0.402	8%
2. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.42	7.48	3.95	0.386	-
1931 - 1935	0.47	7.34	3.73	0.380	-
1936 - 1940	0.52	7.13	3.90	0.381	-
1941 - 1945	0.57	7.83	3.98	0.387	-
1946 - 1950	0.66	7.41	3.71	0.375	-
1951 - 1955	0.69	6.99	3.67	0.371	-
1956 - 1960	0.69	6.80	3.44	0.365	-
1961 - 1965	0.69	6.48	3.28	0.361	-
B. *Based on "less censored" earnings*					
3. Non-deceased at beginning of year attain 62					
1926 - 1930	0.32	46.37	11.87	0.537	29%
1931 - 1935	0.39	22.34	7.32	0.489	22%
1936 - 1940	0.43	19.14	6.94	0.471	19%
1941 - 1945	0.50	17.18	6.24	0.461	15%
1946 - 1950	0.59	16.33	5.48	0.437	12%
1951 - 1955	0.63	12.79	4.82	0.424	10%
1956 - 1960	0.64	12.05	4.45	0.412	9%
1961 - 1965	0.65	10.39	4.04	0.402	8%
4. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.43	7.69	3.98	0.401	-
1931 - 1935	0.48	7.40	3.75	0.389	-
1936 - 1940	0.52	7.16	3.86	0.385	-
1941 - 1945	0.58	7.87	4.00	0.390	-
1946 - 1950	0.66	7.43	3.71	0.376	-
1951 - 1955	0.69	7.01	3.67	0.372	-
1956 - 1960	0.69	6.80	3.44	0.365	-
1961 - 1965	0.69	6.48	3.28	0.361	-

Note: AIME is measured as ratio of the economy-wide average wage.

Note: Calculations are based on the OCACT low-cost assumptions regarding mortality and intermediate-cost assumptions regarding disability. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_ma1.

Table 2-14
Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts with Low Mortality Rate: Men

Birth cohort	Mean AIME	90/10 ratio	80/20 ratio	Gini coefficient	% not eligible
A. ***Based on earnings up to actual taxable maximum***					
1. Non-deceased at beginning of year attain 62					
1926 - 1930	0.92	6.44	2.73	0.272	5.9%
1931 - 1935	1.00	6.24	2.70	0.276	5.0%
1936 - 1940	1.03	5.95	2.72	0.282	4.6%
1941 - 1945	1.09	6.31	3.06	0.297	4.6%
1946 - 1950	1.10	7.47	3.09	0.308	5.3%
1951 - 1955	1.06	7.45	3.10	0.318	5.1%
1956 - 1960	1.03	6.82	3.22	0.325	4.2%
1961 - 1965	1.01	6.92	3.21	0.329	4.2%
2. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.97	3.92	2.21	0.232	-
1931 - 1935	1.04	4.13	2.35	0.243	-
1936 - 1940	1.07	4.22	2.38	0.253	-
1941 - 1945	1.14	4.65	2.65	0.269	-
1946 - 1950	1.15	4.78	2.64	0.275	-
1951 - 1955	1.11	4.90	2.74	0.287	-
1956 - 1960	1.07	5.08	2.87	0.300	-
1961 - 1965	1.05	5.28	2.94	0.304	-
B. ***Based on "less censored" earnings***					
3. Non-deceased at beginning of year attain 62					
1926 - 1930	1.08	7.82	3.20	0.310	5.9%
1931 - 1935	1.12	7.33	3.01	0.303	5.0%
1936 - 1940	1.11	6.53	2.95	0.300	4.6%
1941 - 1945	1.14	6.62	3.22	0.306	4.6%
1946 - 1950	1.12	7.63	3.14	0.313	5.3%
1951 - 1955	1.07	7.49	3.12	0.320	5.1%
1956 - 1960	1.03	6.84	3.22	0.325	4.2%
1961 - 1965	1.01	6.93	3.21	0.329	4.2%
4. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	1.14	4.82	2.61	0.271	-
1931 - 1935	1.18	4.80	2.64	0.272	-
1936 - 1940	1.16	4.64	2.58	0.272	-
1941 - 1945	1.19	4.87	2.76	0.279	-
1946 - 1950	1.18	4.88	2.68	0.280	-
1951 - 1955	1.12	4.92	2.76	0.289	-
1956 - 1960	1.07	5.09	2.87	0.300	-
1961 - 1965	1.05	5.29	2.94	0.304	-

Note: AIME is measured as ratio of the economy-wide average wage.

Note: Calculations are based on the OCACT high-cost assumptions regarding mortality and intermediate-cost assumptions regarding disability. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_ma3.

Table 2-15
Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts with Low Mortality Rate: Women

Birth cohort	Mean AIME	90/10 ratio	80/20 ratio	Gini coefficient	% not eligible
A. *Based on earnings up to actual taxable maximum*					
1. Non-deceased at beginning of year attain 62					
1926 - 1930	0.31	45.99	11.73	0.526	29%
1931 - 1935	0.38	22.19	7.30	0.480	22%
1936 - 1940	0.43	19.00	6.93	0.468	19%
1941 - 1945	0.49	17.20	6.27	0.459	15%
1946 - 1950	0.59	15.80	5.51	0.437	12%
1951 - 1955	0.63	13.32	4.95	0.427	10%
1956 - 1960	0.64	11.91	4.50	0.412	9%
1961 - 1965	0.65	10.86	4.07	0.403	7%
2. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.42	7.48	3.95	0.386	-
1931 - 1935	0.47	7.34	3.73	0.380	-
1936 - 1940	0.52	7.13	3.88	0.381	-
1941 - 1945	0.57	7.79	3.99	0.387	-
1946 - 1950	0.66	7.38	3.74	0.376	-
1951 - 1955	0.69	7.12	3.72	0.374	-
1956 - 1960	0.69	6.94	3.51	0.366	-
1961 - 1965	0.69	6.67	3.40	0.365	-
B. *Based on "less censored" earnings*					
3. Non-deceased at beginning of year attain 62					
1926 - 1930	0.32	46.37	11.87	0.537	29%
1931 - 1935	0.39	22.34	7.32	0.489	22%
1936 - 1940	0.43	19.14	6.94	0.471	19%
1941 - 1945	0.50	17.29	6.25	0.461	15%
1946 - 1950	0.59	15.83	5.51	0.438	12%
1951 - 1955	0.63	13.34	4.95	0.427	10%
1956 - 1960	0.64	11.91	4.50	0.413	9%
1961 - 1965	0.65	10.86	4.07	0.403	7%
4. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.43	7.69	3.98	0.401	-
1931 - 1935	0.48	7.40	3.75	0.389	-
1936 - 1940	0.52	7.16	3.86	0.385	-
1941 - 1945	0.58	7.81	4.00	0.390	-
1946 - 1950	0.66	7.37	3.75	0.377	-
1951 - 1955	0.69	7.13	3.72	0.375	-
1956 - 1960	0.69	6.94	3.51	0.366	-
1961 - 1965	0.69	6.67	3.40	0.365	-

Note: AIME is measured as ratio of the economy-wide average wage.

Note: Calculations are based on the OCACT high-cost assumptions regarding mortality and intermediate-cost assumptions regarding disability. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_ma3.

Table 2-16
Disability Rate by Sex and Birth Cohort in Successive Five-Year Periods, Benchmark Rates and Rates in MINT 2.1 Data Set: Low Disability Rate

	Men			Women		
Cohort	Benchmark Rate	Initial MINT Rate	Final MINT Rate	Benchmark Rate	Initial MINT Rate	Final MINT Rate
Years 2000-04						
1936-40	12.80%	14.41%	12.85%	8.71%	8.92%	8.77%
1941-45	10.00%	11.85%	10.08%	7.61%	10.59%	7.74%
1946-50	6.49%	7.98%	6.49%	5.21%	6.96%	5.26%
1951-55	4.43%	4.57%	4.42%	3.64%	4.56%	3.66%
1956-60	3.17%	3.01%	3.19%	2.56%	3.08%	2.57%
1961-65	2.19%	3.33%	2.19%	1.79%	2.24%	1.79%
Years 2005-09						
1941-45	12.61%	11.41%	12.50%	9.48%	8.52%	9.51%
1946-50	9.58%	11.06%	9.53%	7.92%	9.31%	7.90%
1951-55	6.45%	7.31%	6.48%	5.74%	6.46%	5.79%
1956-60	4.40%	5.24%	4.37%	3.89%	4.58%	3.85%
1961-65	3.09%	3.30%	3.06%	2.75%	2.89%	2.78%
Years 2010-14						
1946-50	11.94%	11.60%	12.01%	9.66%	9.36%	9.59%
1951-55	9.40%	10.82%	9.44%	8.36%	9.78%	8.29%
1956-60	6.32%	7.90%	6.37%	5.89%	6.89%	5.84%
1961-65	4.29%	4.66%	4.30%	4.04%	4.97%	4.00%
Years 2015-19						
1951-55	12.00%	11.12%	12.04%	10.08%	9.50%	10.17%
1956-60	9.71%	11.48%	9.62%	8.67%	9.78%	8.64%
1961-65	6.57%	7.81%	6.54%	6.19%	7.09%	6.21%
Years 2020-24						
1956-60	12.43%	11.71%	12.40%	10.37%	9.54%	10.33%
1961-65	10.07%	10.55%	10.13%	8.90%	10.33%	8.93%
Years 2025-29						
1961-65	13.39%	11.75%	13.37%	10.92%	10.24%	10.98%

Note: Calculations are based on the OCACT low-cost assumptions regarding disability and intermediate-cost assumptions regarding mortality. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_da1.

* Final MINT rate differs from benchmark rate by at least 2% of the benchmark rate.

methodology described in Section III above. The third and sixth columns contain our final predictions of disability for men and women, respectively, in each birth cohort and each five-year period. In all cases the final predicted disability rates are close to the corresponding benchmark rate, indicating that our benchmarking procedure was able to duplicate the OCACT's low-cost disability projection with little difficulty

Table 2-17 shows benchmark disability rates under the OASDI Trustees' high-cost assumptions in successive periods through 2034. The high-cost (or pessimistic) assumptions imply that disability will be higher than in the main MINT 2.1 data set. For example, the bottom entry in the first column shows that the disability rate for males born between 1961 and 1965 will be 19.2% in 2025-2029. The benchmark rate in this projection is one-fifth higher than the rate implied in the Trustee's intermediate-cost projection (19.6% per year versus 16.3% per year) and almost half again larger than the low-cost disability projection (19.6% per year versus 13.4% per year). The third and sixth columns in Table 2-17 contain our final predictions of disability for men and women, respectively, in each birth cohort and each five-year period. In most cases the final predicted disability rate is very close to the corresponding benchmark rate, indicating that we were usually able to duplicate the OCACT's high-cost disability projection.[17] In a few cases, however, we could not find enough disabled donors to match the high projections of future disability under the Trustees' high-cost assumptions. We would have to modify our benchmarking procedure to successfully match the OCACT high-cost disability projections.

Impact of Alternative Disability Assumptions on AIME Distribution

Tables 2-18 and 2-19 show the effects of a lower assumed disability rate on the distribution of lifetime earnings among men and women, respectively. Tables 2-20 and 2-21 show the effects of using a higher assumed rate of disability. As in our analysis of the impact of alternative mortality rates, we examine the distribution of the AIME among workers who have at least one quarter of earnings credit between age 32 and 61 and who survive to the calendar year in which they attain age 62. We also estimate the AIME distribution using the two annual earnings measures and two samples of workers in the successive birth cohorts.

The alternative disability assumptions have no impact on the measured distribution of earnings in the oldest cohorts. These cohorts are either unaffected or very little affected by differences in the disability rate, because most or all members of the cohorts have already earned most of their lifetime income by the time the alternative disability assumptions begin to affect the employment and earnings of cohort members. As before, the alternative disability assumptions also have very little impact on the distribution of lifetime earnings in the younger cohorts. The mean lifetime earnings of the youngest cohorts is predicted to be slightly lower when the assumed disability rate is increased, but this impact is almost undetectable in the case of women. The inequality of earnings is also little affected by changes in the disability rate. The measured effect on inequality seems to be primarily the result of random error rather than a systematic effect of higher or lower disability.[18]

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[17] We did not have any difficulty duplicating the OCACT's intermediate-cost *mortality* forecast when we matched the OCACT's low-cost and high-cost *disability* projections.

[18] Recall that first-round and back-up donors are selected at random from the donor pool for purposes of imputing part of an earnings record to the end of an incomplete target-worker record. Thus, even if we did not change the benchmark disability assumption at all, the distribution of imputed earned income would change slightly

Table 2-17
Disability Rate by Sex and Birth Cohort in Successive Five-Year Periods, Benchmark Rates and Rates in MINT 2.1 Data Set: High Disability Rate

	Men				Women			
Cohort	Benchmark Rate	Initial MINT Rate	Final MINT Rate		Benchmark Rate	Initial MINT Rate	Final MINT Rate	
Years 2000-04								
1936-40	12.85%	14.41%	12.89%		8.74%	8.92%	8.77%	
1941-45	10.12%	11.85%	10.13%		7.69%	10.59%	7.74%	
1946-50	6.58%	7.98%	6.56%		5.29%	6.96%	5.34%	
1951-55	4.49%	4.57%	4.45%		3.69%	4.56%	3.70%	
1956-60	3.22%	3.01%	3.20%		2.60%	3.08%	2.60%	
1961-65	2.23%	3.33%	2.24%		1.82%	2.24%	1.81%	
Years 2005-09								
1941-45	13.50%	11.67%	13.55%		10.05%	8.64%	9.91%	
1946-50	10.54%	11.21%	10.59%		8.67%	9.21%	8.67%	
1951-55	7.11%	7.62%	7.04%		6.36%	6.60%	6.38%	
1956-60	4.85%	5.33%	4.84%		4.31%	4.72%	4.31%	
1961-65	3.44%	3.52%	3.41%		3.07%	3.01%	3.10%	
Years 2010-14								
1946-50	14.44%	12.27%	14.23%		11.50%	9.74%	11.27%	
1951-55	11.72%	11.00%	11.79%		10.37%	9.58%	10.27%	
1956-60	7.90%	8.29%	7.95%		7.40%	7.38%	7.38%	
1961-65	5.42%	5.22%	5.44%		5.11%	5.28%	5.12%	
Years 2015-19								
1951-55	**15.98%**	13.13%	**15.48%**	*	**13.30%**	11.34%	**12.69%**	*
1956-60	13.16%	12.73%	13.06%		11.75%	10.94%	11.69%	
1961-65	9.00%	8.77%	9.05%		8.49%	8.13%	8.45%	
Years 2020-24								
1956-60	17.38%	15.09%	17.39%		**14.50%**	12.23%	**13.42%**	*
1961-65	14.27%	13.48%	14.26%		12.63%	11.82%	12.67%	
Years 2025-29								
1961-65	**19.16%**	16.06%	**18.44%**	*	**15.70%**	13.55%	**14.57%**	*

Note: Calculations are based on the OCACT high-cost assumptions regarding disability and intermediate-cost assumptions regarding mortality. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_da3.

from one implementation of our splicing procedure to the next, because target workers would be matched to different donors.

Table 2-18
Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts with Low Disability Rate: Men

Birth cohort	Mean AIME	90/10 ratio	80/20 ratio	Gini coefficient	% not eligible
A. *Based on earnings up to actual taxable maximum*					
1. Non-deceased at beginning of year attain 62					
1926 - 1930	0.92	6.44	2.73	0.272	5.9%
1931 - 1935	1.00	6.24	2.70	0.276	5.0%
1936 - 1940	1.03	5.95	2.72	0.282	4.6%
1941 - 1945	1.09	6.31	3.09	0.297	4.6%
1946 - 1950	1.09	7.44	3.12	0.309	5.6%
1951 - 1955	1.07	7.18	3.12	0.317	5.0%
1956 - 1960	1.03	6.78	3.20	0.324	4.0%
1961 - 1965	1.01	7.07	3.21	0.329	4.3%
2. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.97	3.92	2.21	0.232	-
1931 - 1935	1.04	4.13	2.35	0.243	-
1936 - 1940	1.07	4.22	2.38	0.253	-
1941 - 1945	1.14	4.64	2.66	0.269	-
1946 - 1950	1.15	4.75	2.63	0.275	-
1951 - 1955	1.12	4.92	2.71	0.287	-
1956 - 1960	1.07	5.26	2.92	0.300	-
1961 - 1965	1.05	5.25	2.88	0.303	-
B. *Based on "less censored" earnings*					
3. Non-deceased at beginning of year attain 62					
1926 - 1930	1.08	7.82	3.20	0.310	5.9%
1931 - 1935	1.12	7.33	3.01	0.303	5.0%
1936 - 1940	1.11	6.53	2.95	0.300	4.6%
1941 - 1945	1.14	6.63	3.23	0.307	4.6%
1946 - 1950	1.11	7.58	3.17	0.314	5.6%
1951 - 1955	1.07	7.23	3.13	0.319	5.0%
1956 - 1960	1.04	6.79	3.20	0.324	4.0%
1961 - 1965	1.01	7.07	3.21	0.329	4.3%
4. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	1.14	4.82	2.61	0.271	-
1931 - 1935	1.18	4.80	2.64	0.272	-
1936 - 1940	1.16	4.65	2.58	0.272	-
1941 - 1945	1.19	4.87	2.76	0.279	-
1946 - 1950	1.17	4.84	2.67	0.279	-
1951 - 1955	1.12	4.96	2.73	0.288	-
1956 - 1960	1.08	5.26	2.92	0.301	-
1961 - 1965	1.05	5.26	2.88	0.303	-

Note: AIME is measured as ratio of the economy-wide average wage.

Note: Calculations are based on the OCACT low-cost assumptions regarding disability and intermediate-cost assumptions regarding mortality. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_da1.

Table 2-19
Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts with Low Disability Rate: Women

Birth cohort	Mean AIME	90/10 ratio	80/20 ratio	Gini coefficient	% not eligible
A. *Based on earnings up to actual taxable maximum*					
1. Non-deceased at beginning of year attain 62					
1926 - 1930	0.31	45.99	11.73	0.526	29.1%
1931 - 1935	0.38	22.19	7.30	0.480	22.2%
1936 - 1940	0.43	19.00	6.93	0.468	18.7%
1941 - 1945	0.50	17.19	6.24	0.458	15.2%
1946 - 1950	0.58	16.30	5.53	0.437	12.1%
1951 - 1955	0.62	13.25	4.99	0.426	10.6%
1956 - 1960	0.64	12.22	4.46	0.412	8.8%
1961 - 1965	0.64	10.07	4.02	0.402	7.1%
2. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.42	7.48	3.95	0.386	-
1931 - 1935	0.47	7.34	3.73	0.380	-
1936 - 1940	0.51	7.13	3.90	0.381	-
1941 - 1945	0.57	7.79	3.99	0.386	-
1946 - 1950	0.66	7.40	3.74	0.376	-
1951 - 1955	0.69	7.13	3.70	0.372	-
1956 - 1960	0.70	6.81	3.51	0.366	-
1961 - 1965	0.68	6.67	3.39	0.365	-
B. *Based on "less censored" earnings*					
3. Non-deceased at beginning of year attain 62					
1926 - 1930	0.32	46.37	11.87	0.537	29.1%
1931 - 1935	0.39	22.34	7.32	0.489	22.2%
1936 - 1940	0.43	19.13	6.94	0.471	18.7%
1941 - 1945	0.50	17.25	6.23	0.461	15.2%
1946 - 1950	0.59	16.30	5.53	0.439	12.1%
1951 - 1955	0.62	13.25	5.00	0.426	10.6%
1956 - 1960	0.64	12.22	4.46	0.413	8.8%
1961 - 1965	0.64	10.07	4.02	0.402	7.1%
4. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.43	7.69	3.98	0.401	-
1931 - 1935	0.48	7.40	3.75	0.389	-
1936 - 1940	0.52	7.16	3.88	0.385	-
1941 - 1945	0.58	7.80	4.00	0.390	-
1946 - 1950	0.66	7.43	3.74	0.377	-
1951 - 1955	0.69	7.13	3.70	0.373	-
1956 - 1960	0.70	6.81	3.51	0.366	-
1961 - 1965	0.68	6.67	3.39	0.365	-

Note: AIME is measured as ratio of the economy-wide average wage.

Note: Calculations are based on the OCACT low-cost assumptions regarding disability and intermediate-cost assumptions regarding mortality. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_da1.

Table 2-20
Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts with High Disability Rate: Men

Birth cohort	Mean AIME	90/10 ratio	80/20 ratio	Gini coefficient	% not eligible
A. ***Based on earnings up to actual taxable maximum***					
1. Non-deceased at beginning of year attain 62					
1926 - 1930	0.92	6.44	2.73	0.272	5.9%
1931 - 1935	1.00	6.24	2.70	0.276	5.0%
1936 - 1940	1.03	5.95	2.72	0.282	4.5%
1941 - 1945	1.09	6.30	3.09	0.297	4.6%
1946 - 1950	1.10	7.34	3.13	0.309	5.4%
1951 - 1955	1.07	7.19	3.12	0.317	4.6%
1956 - 1960	1.03	6.60	3.18	0.324	4.1%
1961 - 1965	1.00	6.67	3.16	0.328	3.9%
2. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.97	3.92	2.21	0.232	-
1931 - 1935	1.04	4.13	2.35	0.243	-
1936 - 1940	1.07	4.23	2.38	0.253	-
1941 - 1945	1.14	4.65	2.66	0.269	-
1946 - 1950	1.15	4.76	2.63	0.275	-
1951 - 1955	1.11	5.24	2.74	0.290	-
1956 - 1960	1.07	5.27	2.86	0.301	-
1961 - 1965	1.04	5.26	2.90	0.305	-
B. ***Based on "less censored" earnings***					
3. Non-deceased at beginning of year attain 62					
1926 - 1930	1.08	7.82	3.20	0.310	5.9%
1931 - 1935	1.12	7.33	3.01	0.303	5.0%
1936 - 1940	1.11	6.53	2.95	0.300	4.5%
1941 - 1945	1.14	6.64	3.24	0.307	4.6%
1946 - 1950	1.12	7.47	3.17	0.314	5.4%
1951 - 1955	1.07	7.24	3.14	0.319	4.6%
1956 - 1960	1.03	6.61	3.19	0.324	4.1%
1961 - 1965	1.00	6.67	3.16	0.328	3.9%
4. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	1.14	4.82	2.61	0.271	-
1931 - 1935	1.18	4.80	2.64	0.272	-
1936 - 1940	1.16	4.65	2.58	0.272	-
1941 - 1945	1.19	4.87	2.76	0.279	-
1946 - 1950	1.17	4.85	2.69	0.280	-
1951 - 1955	1.12	5.26	2.76	0.291	-
1956 - 1960	1.07	5.28	2.86	0.301	-
1961 - 1965	1.04	5.26	2.90	0.305	-

Note: AIME is measured as ratio of the economy-wide average wage.

Note: Calculations are based on the OCACT high-cost assumptions regarding disability and intermediate-cost assumptions regarding mortality. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_da3.

Table 2-21
Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts with High Disability Rate: Women

Birth cohort	Mean AIME	90/10 ratio	80/20 ratio	Gini coefficient	% not eligible
A. *Based on earnings up to actual taxable maximum*					
1. Non-deceased at beginning of year attain 62					
1926 - 1930	0.31	45.99	11.73	0.526	29.1%
1931 - 1935	0.38	22.19	7.30	0.480	22.2%
1936 - 1940	0.43	19.00	6.93	0.468	18.7%
1941 - 1945	0.50	17.16	6.27	0.458	15.2%
1946 - 1950	0.58	15.62	5.57	0.437	12.2%
1951 - 1955	0.63	12.64	4.78	0.422	10.1%
1956 - 1960	0.64	12.17	4.40	0.412	8.7%
1961 - 1965	0.64	10.30	4.03	0.400	6.7%
2. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.42	7.48	3.95	0.386	-
1931 - 1935	0.47	7.34	3.73	0.380	-
1936 - 1940	0.52	7.13	3.88	0.381	-
1941 - 1945	0.57	7.79	3.98	0.386	-
1946 - 1950	0.66	7.50	3.80	0.375	-
1951 - 1955	0.69	6.98	3.65	0.371	-
1956 - 1960	0.69	6.81	3.49	0.366	-
1961 - 1965	0.68	6.62	3.41	0.364	-
B. *Based on "less censored" earnings*					
3. Non-deceased at beginning of year attain 62					
1926 - 1930	0.32	46.37	11.87	0.537	29.1%
1931 - 1935	0.39	22.34	7.32	0.489	22.2%
1936 - 1940	0.43	19.13	6.94	0.471	18.7%
1941 - 1945	0.50	17.24	6.25	0.461	15.2%
1946 - 1950	0.59	15.63	5.56	0.438	12.2%
1951 - 1955	0.63	12.65	4.78	0.422	10.1%
1956 - 1960	0.64	12.17	4.40	0.412	8.7%
1961 - 1965	0.64	10.30	4.03	0.400	6.7%
4. OAI Eligible, non-deceased at beginning of year attain 62					
1926 - 1930	0.43	7.69	3.98	0.401	-
1931 - 1935	0.48	7.40	3.75	0.389	-
1936 - 1940	0.52	7.16	3.86	0.385	-
1941 - 1945	0.58	7.84	3.99	0.390	-
1946 - 1950	0.66	7.50	3.80	0.376	-
1951 - 1955	0.69	6.99	3.65	0.371	-
1956 - 1960	0.69	6.81	3.49	0.366	-
1961 - 1965	0.68	6.62	3.41	0.364	-

Note: AIME is measured as ratio of the economy-wide average wage.

Note: Calculations are based on the OCACT high-cost assumptions regarding disability and intermediate-cost assumptions regarding mortality. MINT 2.1 estimates are based on authors' tabulations of MINT 2.1_C_da3.

These findings on the impact of disability on the distribution of lifetime earnings might seem much more surprising than our findings on the impact of alternative mortality assumptions. After all, the different mortality assumptions affect a relative handful of people younger than 62, while alternative assumptions about disability must affect a far larger fraction of the sample. However, our estimate of a worker's AIME is based on the Social Security Administration definition, which measures the AIME differently for disabled workers, on the one hand, and for workers who apply for an OAI pension without a prior period of disability, on the other. A worker who becomes disabled at age 50 does not have her AIME calculated using all earnings through age 61, as is the case when a never-disabled worker applies for an OAI pension. Instead, her AIME is based on earnings through the year before she became entitled. Our analysis shows that this AIME is often high in relation to the average AIME in the MINT sample, because of the stringent eligibility criteria for DI benefits. Workers with very low lifetime earnings or with low earnings in the years leading up to disability onset are only rarely entitled to receive DI benefits, so a higher disability rate will not cause an increased prevalence of very low AIME imputations. When the assumed disability prevalence rate increases, workers will have fewer years in which they have positive earnings, but the distribution of the AIME is not dramatically affected. On the whole, we find that the distribution of lifetime earnings in the MINT 2.1 sample, as measured by the distribution of the AIME, is not materially affected by differences in disability within the range of rates considered in the 2001 *OASDI Trustees' Report.*

3. Marital Status and the Correlation of Husband and Wife Earned Income

The earnings projection in the current MINT model do not take into account the effect(s) of a worker's marital status on his or her earnings pattern or the effects of a spouse's earnings on the worker's earnings.

These two deficiencies are potentially problematic for three reasons. First, historical data indicate that married and single people have different earnings patterns. Married men generally earn more than single men, whereas married women earn less on average than single women. Second, earnings patterns may change after a marital status transition. Empirical research has found a labor supply response to both marriage and divorce (Lillard and Waite 2000, Johnson and Skinner 1986). Also, men and women may respond differently with a marriage transition, so the current earnings projections may overstate the earnings of one group while understating the earnings of the other. And third, not controlling for the level of a spouse's earnings does not allow a wife to react to a change in her husband's labor supply, for example. This may produce earnings of married persons that do not have the appropriate correlation between spouses' lifetime earnings.

Gustman's (2001) review of the MINT earnings projections expressed concern about the lack of interdependence in the patterns of spousal earnings histories. Not capturing appropriate patterns of covariance is particularly problematic for Social Security research since the relationship between spousal earnings histories is critical in determining eligibility for auxiliary benefits. Although the literature suggests that the correlation between spouses' earnings is not very high, it has been growing over time. Using earnings data from the March CPS for 1968-1994, Cancian and Reed (1999) report an increase in the correlation of spouses' earnings beginning in the mid 1970s, with the peak of approximately 0.25 in 1990.

To test the sensitivity of the earnings projections to marital status and spousal earnings, we redid the earnings projections in a two step process. First we controlled for marital status when projecting the earnings of men. Second, when projecting the earnings of women, we controlled for marital status and the earnings of the spouse. These adjustments did increase the labor supply response to divorce and have some affect on age earnings profiles and mean lifetime earnings by marital status, but the change in the aggregate distribution of lifetime earnings is very minor.

Adjusting the Earnings Projections

Incorporating marital status into the projections is not straightforward because we do not have individuals' complete marital profiles—we only have marital status information through the end of the SIPP interviews. Because actual marital status is not available beyond 1993, we use the projected marital histories and future spouses that are generated as another part of MINT.[19]

This part of the MINT data system projects future marital histories and estimates characteristics of future and former spouses. MINT estimates marital transitions using the 1990-1991 SIPP panels and gender-specific continuous time hazard models for marriage and divorce.[20] The control variables in the model are age, education, number of years unmarried, whether widowed, and calendar year after 1980 (Lillard and Panis 1999). MINT also imputes the characteristics of former and future spouses and uses these imputed characteristics to establish a donor from MINT observations. The former or future spouse is statistically assigned from a MINT observation with similar characteristics, or a "nearest neighbor" (Toder et al. 1999).

In these adjusted projections, we control for marital status and spousal earnings. In order to avoid a difficult simultaneous imputation of earnings, we only consider the earnings of the spouse when projecting the earnings of women. We now project earnings in two steps. In the first round we project male earnings based on all the original key variables and a new marital status key variable. In controlling for marital status, we differentiate between the earnings of married individuals and single individuals. We also capture labor supply responses that occur after a marital status transition. To do this, we divide individuals into five separate categories based on their marital status at the beginning and end of the projection period. Two categories are for individuals who remain married or single. Two categories are for individuals who become married or single. The final category is for individuals who are projected to die during the next five years.

In the second round, we impute earnings to women based on the original key variables, the marital status variable, and a key variable that accounts for the earnings level of the husband. For women who are married in the last year of the matching period, we create a key variable for the husband's earnings quintile in that year. We calculate these earnings quintiles by the age of the wife.

[19] Many in MINT are exactly matched to their spouse through the 1990-1993 SIPP survey, because they are married at the SIPP interview and are projected to remain married until retirement age.

[20] The 1990-1991 SIPP data records up to three marriage transitions for individuals.

These matching constraints dramatically increase the number of donor pools. For the men we have increased the potential number of donor pools by a factor of 5. For women, we increased the potential donor pools by a factor of 30. This donor pool expansion has greatly decreased the number of individuals who match on all key variables. Now only 50 percent of women and 65 percent of men match on all key variables (see Table 2-22). A much larger percentage of the population match on all characteristics except education and race, but that matching rate is still substantially lower than in the baseline projections.

Table 2-22
Matching Rates for Non-Disabled Men and Women

	Matching on All Key Variables		Matching on All Earnings Variables	
	Baseline	Adjusted	Baseline	Adjusted
Men				
1931-1935	74.6%	60.0%	94.6%	85.0%
1936-1940	76.5%	64.0%	95.0%	87.4%
1941-1945	77.6%	67.0%	94.9%	88.5%
1946-1950	76.1%	64.7%	93.6%	87.2%
1951-1955	76.1%	65.2%	92.2%	86.5%
1956-1960	76.0%	64.6%	92.0%	86.4%
1961-1965	77.1%	65.6%	92.7%	87.5%
Women				
1931-1935	80.3%	58.4%	95.9%	81.0%
1936-1940	78.6%	50.4%	95.6%	73.8%
1941-1945	78.5%	48.7%	95.5%	73.4%
1946-1950	77.9%	48.5%	95.8%	75.5%
1951-1955	78.7%	50.7%	96.5%	77.6%
1956-1960	78.7%	50.6%	96.8%	78.4%
1961-1965	79.4%	50.5%	97.1%	79.1%

By design, over 99% of individuals match on marital status, but clearly we have to sacrifice some of the detailed earnings categorizations to get this result. Since this sensitivity test is designed to measure the impact of including marital status in the earnings projections, we have given the new key variables high priority in the match. The only key variables that take higher precedence are gender, age, disability, number of years worked and average earnings during the matching period.

Results

To examine the impact of controlling for marital status and spousal earnings, we compare the overall distribution of individual and shared lifetime earnings. We also compare lifetime earnings, annual earnings, and employment rates by marital status at age 62. We find that the adjusted projections do change lifetime earnings by marital status and increase the employment rates of women, but have little impact on the overall distribution of lifetime earnings.

Lifetime Earnings. Controlling for marital status and husbands' earnings does not significantly change the overall distribution of AIME for men or women. Table 2-23 displays the percentage change in mean earnings and earnings inequality after matching on martial status. All of the changes in mean AIME are less than one percent. The changes in the inequality measures vary by sex and cohort and appear to be spurious changes.[21] In terms of Social Security eligibility, men's eligibility does not change, but more women in later birth cohorts become eligible for Social Security.

Since we are interested in the correlation of spousal earnings, we also examine the distribution of shared lifetime earnings. We compute shared earnings by assigning each individual half the total earnings of the individual and his/her spouse in the years when he/she is married and his/her own earnings in years when single. In Table 2-24, we find that controlling for marital status and the level of spousal earnings slightly decreases average shared lifetime earnings (ie, the mean AIME) for later birth cohorts. Shared lifetime earnings fall for men and women, but not by more than one percent.

Although the overall distribution of AIME does not significantly change when we include controls for marital status and husbands' earnings as matching constraints, projections of lifetime earnings by marital status do change. For men, adding marital status controls decreases the AIME of married men in the 1946-1950 birth cohort and increases the AIME of married men in later cohorts (see Figure 2-26). Matching single men to other single men lowers their lifetime earnings. This general pattern reflects empirical research that finds that married men have higher earnings than non-married men.

The new earnings imputations for married women follow a similar pattern as married men. Figure 2-27 displays the mean AIME of women by cohort and marital status at age 62. For married women, the adjustment to the earnings projections decreases mean lifetime earnings for the 1946-1950 cohort and increases lifetime earnings for 1961-1965 birth cohort. Controlling for marital status lowers the projected earnings of single women in 1956-1965 birth cohorts. These two patterns produce new imputations that suggest married women in the 1961-1965 birth cohort will have higher AIMEs than single women. While every birth cohort of married men have higher AIMEs than single men, this is the first time we observe the trend for women. While the mean AIMEs for single and married women were converging prior to the adjustment to the earnings projections, the new results actually project that the mean AIME for married women will exceed the mean AIME for single women.

Annual Earnings and Employment Rates. This section examines how annual earnings and employment rates change when we control for marital status and spouses' earnings in the projections. Recall that we control for spouses' earnings when projecting women's earnings, but not when projecting men's earnings. Figures 2-28 and 2-29 show the percentage change in annual earnings along the age earnings profile for married and single women, respectively. In general, the modified earnings projections increase the earnings of married women during

[21] Recall that first-round and back-up donors are selected at random from the donor pools for purposes of imputing part of an earnings record to the end of an incomplete target-worker record. Thus, even if we did not add new matching constraints, the distribution of earned income would change slightly from one implementation of the splicing procedure to the next, because target workers would be matched to different donors.

Table 2-23
Percentage Change in the Distribution of Individual Average Indexed Monthly Earnings in Successive Birth Cohorts (Martial Status Key Variables Included in the Projections)

Birth Cohort	Mean AIME	90/10 Ratio	80/20 Ratio	Gini coefficient
Based on earnings up to actual taxable maximum				
Non-deceased or disabled at beginning of year attain 62				
Men				
1926-1930	0.0%	0.0%	0.0%	0.0%
1931-1935	0.0%	0.0%	0.0%	0.0%
1936-1940	0.0%	-0.1%	0.1%	-0.2%
1941-1945	0.0%	0.7%	-0.7%	0.1%
1946-1950	-0.4%	-1.5%	-0.6%	0.3%
1951-1955	-0.1%	3.9%	0.5%	1.4%
1956-1960	-0.3%	1.5%	-0.3%	0.6%
1961-1965	-1.0%	1.2%	-1.8%	0.7%
Women				
1926-1930	0.0%	0.0%	0.0%	0.0%
1931-1935	0.0%	0.0%	0.0%	0.0%
1936-1940	0.1%	0.5%	-0.2%	-0.1%
1941-1945	0.1%	-2.8%	-1.0%	-0.3%
1946-1950	-0.1%	1.1%	-2.1%	0.0%
1951-1955	-0.1%	-1.8%	0.3%	0.0%
1956-1960	-0.1%	3.0%	-0.7%	-0.1%
1961-1965	-0.6%	1.8%	1.1%	0.8%

Table 2-24
Percentage Change in the Distribution of Shared Average Indexed Monthly Earnings in Successive Birth Cohorts
(Marital Status Key Variables Included in the Earnings Projections)

Birth Cohort	Mean AIME	90/10 Ratio	80/20 Ratio	Gini coefficient
Based on earnings up to actual taxable maximum				
Non-deceased or disabled at beginning of year attain 62				
Men				
1926-1930	0.0%	0.0%	0.0%	0.0%
1931-1935	0.0%	0.0%	0.0%	0.0%
1936-1940	0.0%	-0.1%	0.1%	-0.2%
1941-1945	0.0%	0.7%	-0.7%	0.1%
1946-1950	-0.4%	-1.5%	-0.6%	0.3%
1951-1955	-0.1%	3.9%	0.5%	1.4%
1956-1960	-0.3%	1.5%	-0.3%	0.6%
1961-1965	-1.0%	1.2%	-1.8%	0.7%
Women				
1926-1930	0.0%	0.0%	0.0%	0.0%
1931-1935	0.0%	0.0%	0.0%	0.0%
1936-1940	0.1%	0.5%	-0.2%	-0.1%
1941-1945	0.1%	-2.8%	-1.0%	-0.3%
1946-1950	-0.1%	1.1%	-2.1%	0.0%
1951-1955	-0.1%	-1.8%	0.3%	0.0%
1956-1960	-0.1%	3.0%	-0.7%	-0.1%
1961-1965	-0.6%	1.8%	1.1%	0.8%

Figure 2-26
AIME of Men by Birth Cohort and Marital Status at 62

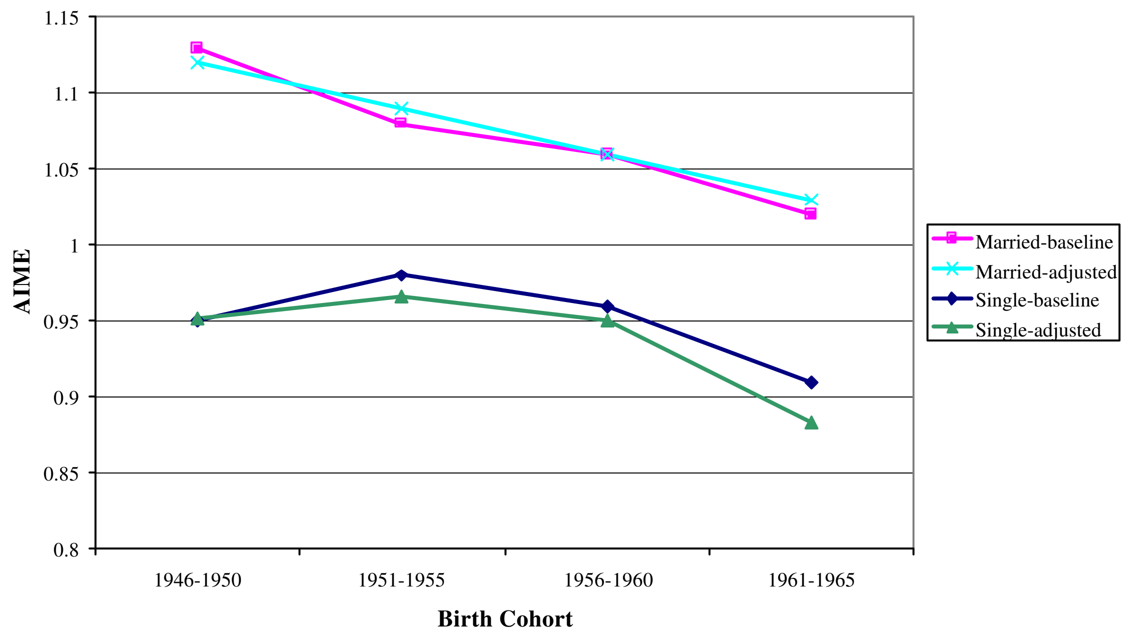
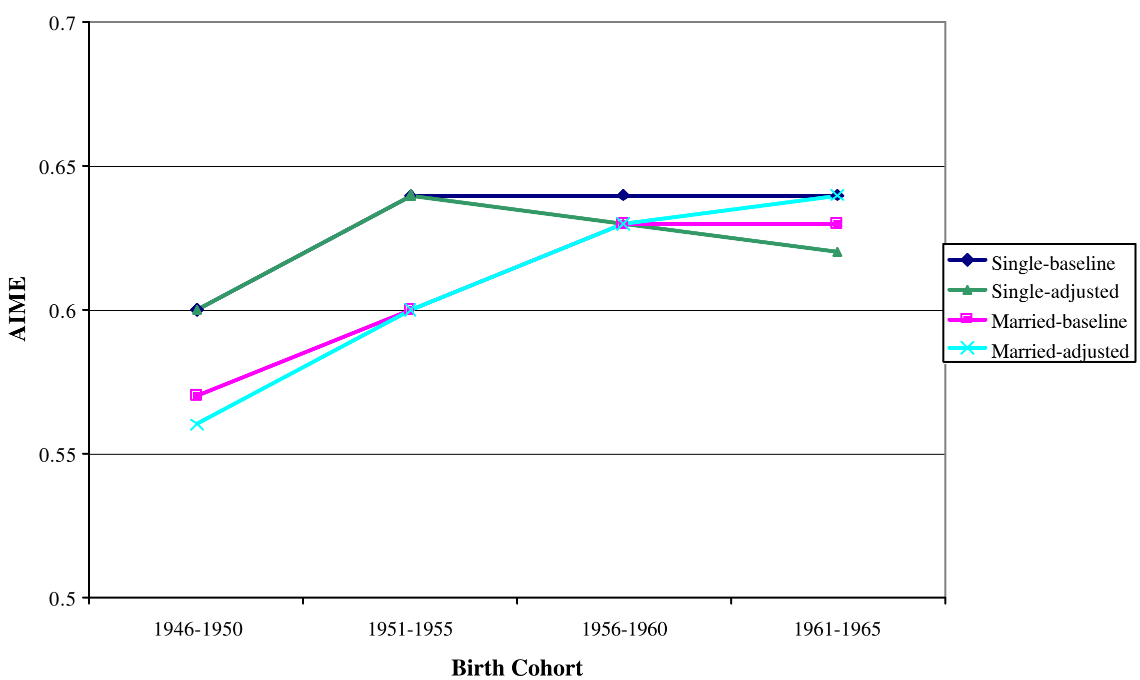


Figure 2-27
AIME of Women by Birth Cohort and Marital Status at 62



middle age (40s and early 50s) and decrease the earnings of married women in their late 50s and early 60s. For single women, controlling for marital status has the opposite effect – it decreases earnings during middle age and increases earnings after age 55.

The periods of increased earnings are the result of rising employment rates. After controlling for marital status and spousal earnings, the female employment rate increases for all women. This result was suggested earlier by the increase in Social Security eligibility among women in later birth cohorts. For women in these cohorts, the new imputation algorithm increases the average number of years with non-zero earnings. Figure 2-30 shows the change in non-zero earnings years by marital status and cohort. The increased employment rate is most evident among the 1961-1965 birth cohort. Since this cohort has the greatest number of imputed earnings years, the effect of a new imputation method is most evident in this group.

Although the new projections show a rise in female employment, the projected earnings of female workers decline at almost every age. For most birth cohorts of women, the average earnings of workers are between 1 and 2 percent lower at each age (see Figure 2-31). The decline is more dramatic for the 1961-1965 birth cohort. Earnings for this cohort of female workers fall by 3 to 6 percent depending on the age.

Earnings around marital status transitions. This section examines how women's employment and earnings change with a change in marital status. We are particularly concerned with the labor supply response to divorce. Women who are divorced at retirement are more likely to be in poverty than married or widowed women. If their marriage lasted less than ten years, divorced women are not eligible for spouse or survivor benefits. The well-being of these women depends on their own earnings history. If women respond to divorce by returning to work or working longer hours, it is important that the MINT earnings imputations capture this response.

We find that including marital status as a key variable does increase the female labor supply response to a divorce. After a divorce, more women enter the labor force and a larger percentage of the women already working increase their labor force participation.[22] Among those women who were not working at the time of their divorce, more women now enter the labor force in the year following their divorce (see Figure 2-32). For women ages 30-39 at the time of their first divorce, the percentage of women starting work increases from 37 percent to 40 percent. For women in their 40s, the modified earnings projections have a larger impact. The percentage of women who start working rises from 21 percent to 33 percent.

[22] We define an increase in labor force participation as an earnings increase greater than 25 percent.

Figure 2-28
Percent Change in the Age Earnings Distribution of Married Women
Baseline vs. Adjusted Projections

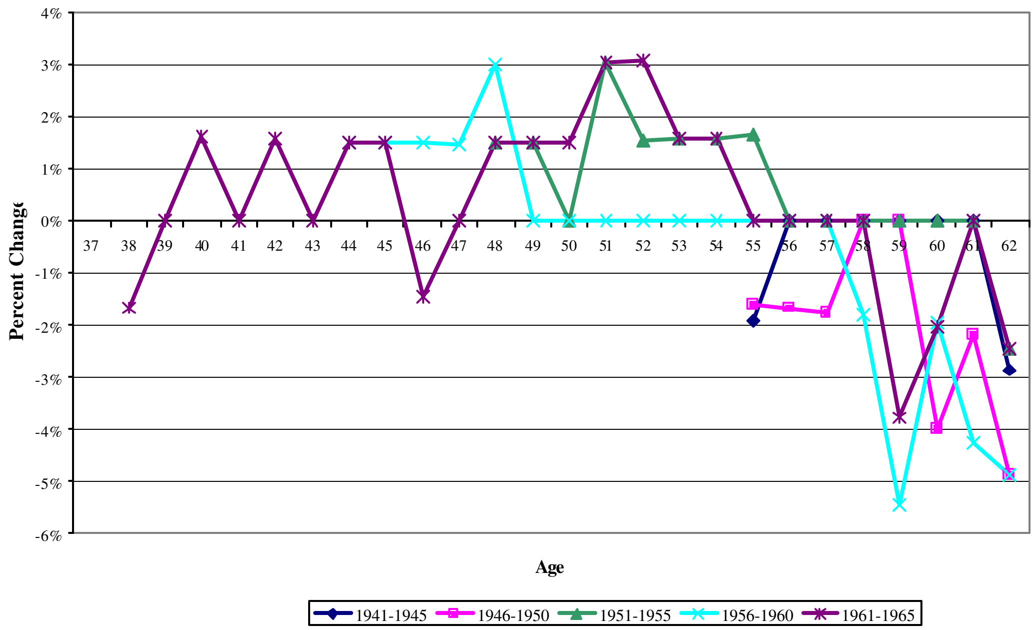


Figure 2-29
Percent Change in the Age Earnings Distribution for Single Women
Baseline vs. Adjusted Projections

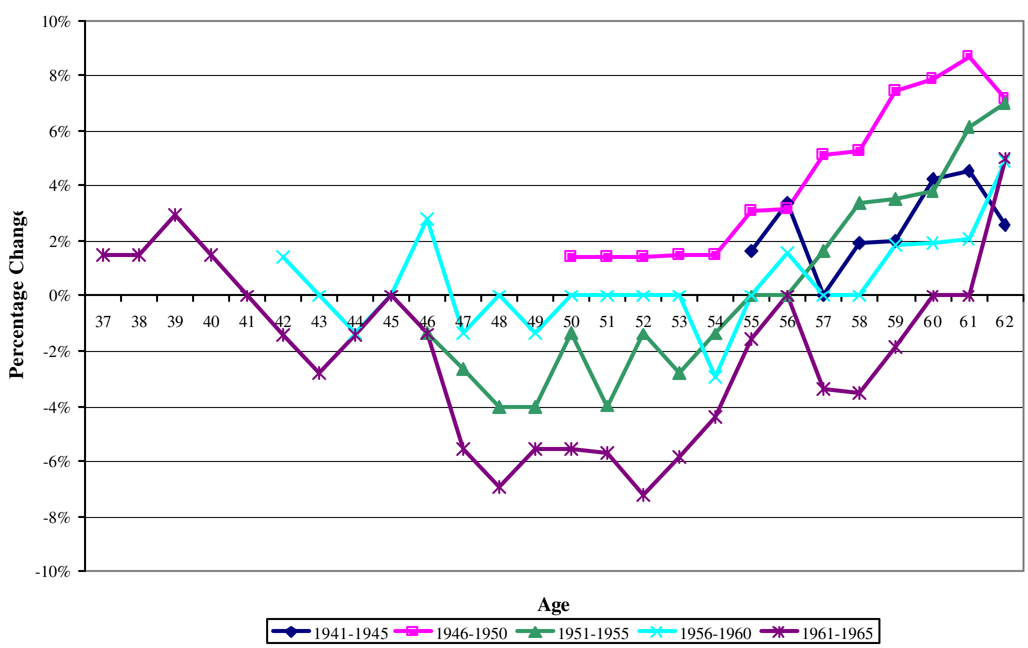
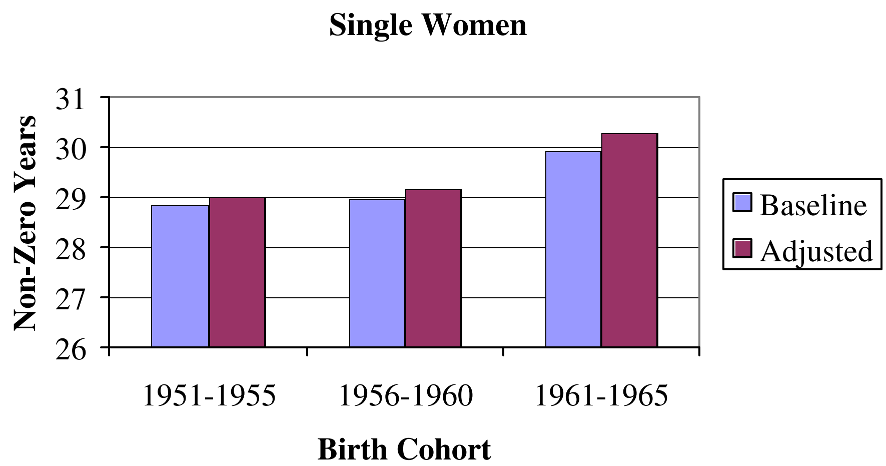


Figure 2-30
Years of Non-Zero Earnings (Ages 22-61) by Birth Cohort and Marital Status at 62



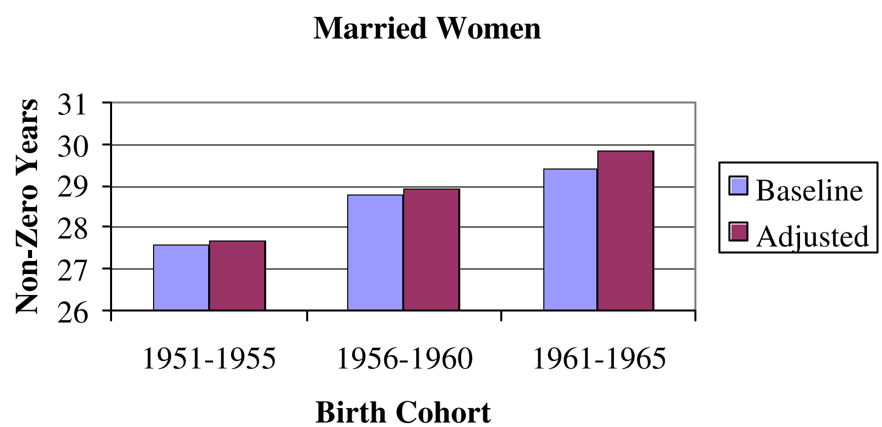


Figure 2-31
Percent Change in the Age Earnings Profiles of Female Labor Force Participants

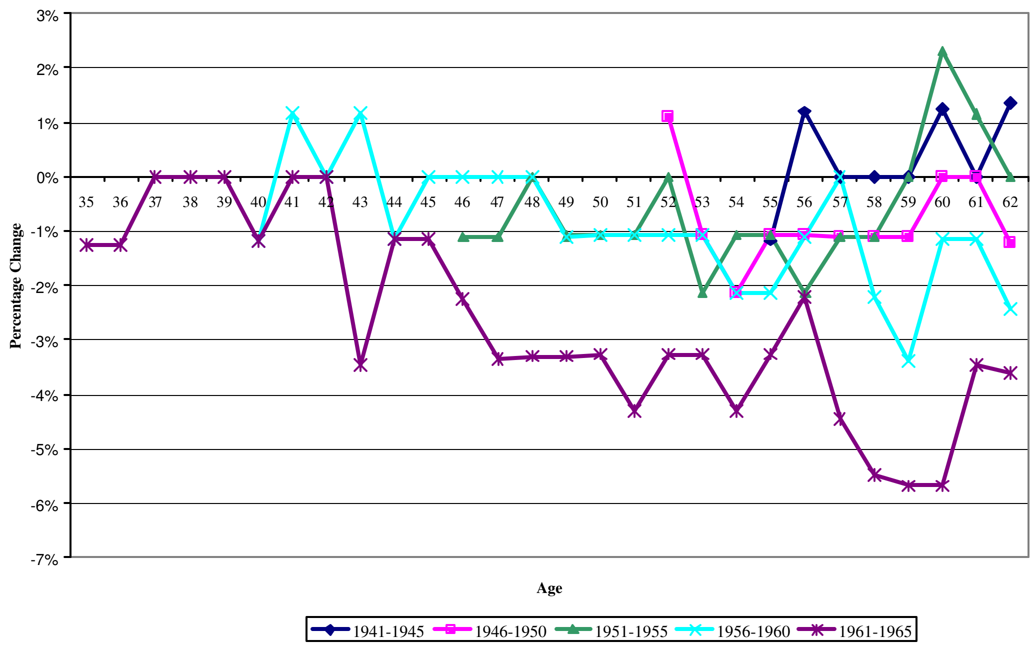
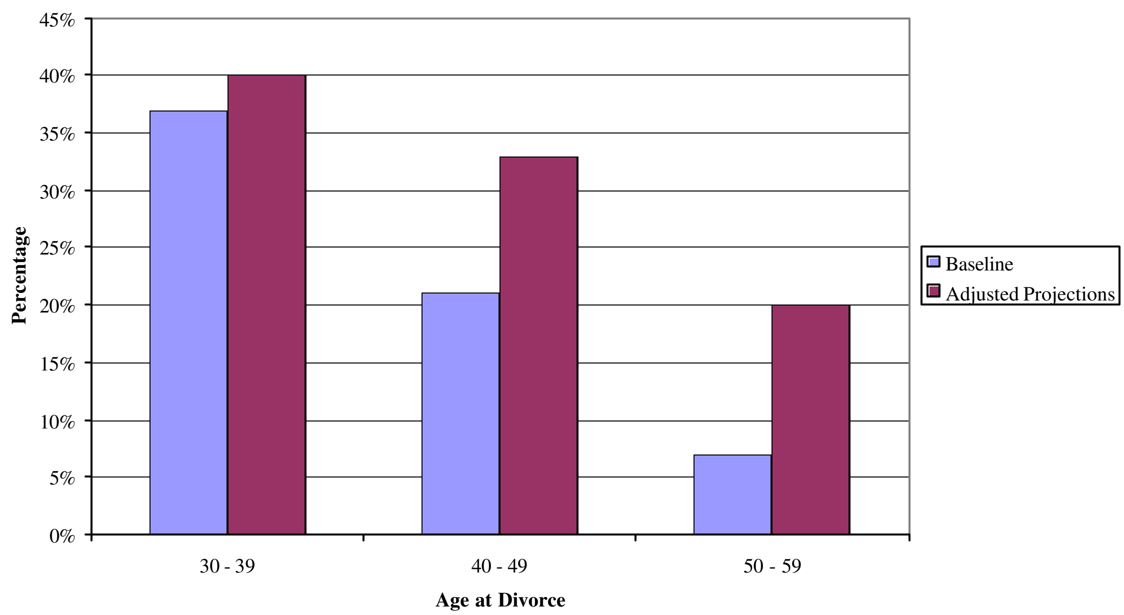


Figure 2-32
Percentage of Women who Start Working After Divorce



While the new projections show an increase in the labor supply of women who divorce, the majority of divorced women do not change their employment behavior. For women who divorce between 2000 and 2009, roughly 60 percent do not change their employment behavior (see Figure 2-33).[23] We expect that fewer divorced women will change their labor supply in the future, since an increasing number of women are working prior to divorce (Iams, Waid, and Morett 2002).

While the labor supply of women who divorce is found to increase when the model controls for marital status, the overall change in women's labor supply is small. This occurs, in part, because only a small fraction of women experience a marital transition during the projection years. Many of the marital dissolutions experienced by individuals in the sample are captured in the baseline MINT model because the dissolutions occurred before the end of the 1999. In these cases, individuals' labor supply responses to the marital dissolution are reflected in the administrative earnings data, and thus the baseline MINT model.

Correlation of spouses' lifetime earnings. In this section we examine how the correlation between spouses' lifetime earnings differs between projections that control for husbands' earnings (and marital status transitions) and projections that do not.[24] Projections based on models that control for husbands' earnings level (i.e., quintile) produce correlations between spouses' lifetime earnings that are either the same or lower than the baseline correlations for the different birth cohorts (see Figure 2-34). While the correlations between spouses' lifetime earnings are lower for some birth cohorts, the differences are small. For example, the correlation for the 1956-60 birth cohorts is lower by 0.01 in the adjusted model as compared to the baseline model (the correlations are 0.13 versus 0.12, respectively).

Controlling for the level of husband's earnings fails to increase the correlation between spouses' lifetime earnings. It may be difficult with the splicing methodology to capture the cohort shift in the correlation of spouses' earnings. With each matching round, we are selecting donors from earlier cohorts. If women with high earning spouses were less likely to work in the past, this pattern may be replicated in the projected data.

Summary

Since this sensitivity test has differential effects by marital status, it may not be surprising that the impact on the overall distribution of earnings is very small. Controlling for marital status and spousal earnings increases the lifetime earnings of married women, while decreasing the lifetime earnings of single women. Employment rates rise for all women in later cohorts, but the earnings of workers fall. While we do find that the baseline projections may understate women's labor supply response to divorce, this bias does not significantly alter the lifetime earnings of divorced women. Finally, controlling for husbands' earnings actually slightly decreases the correlation of spouses' lifetime earnings.

[23] We classify an earnings increase or decrease of less than 25 percent as no change.

[24] Recall that husband's earnings go into the wife's equation, but wife's earnings don't go into the husband's equation.

Figure 2-33
Labor Supply Responses of Divorced Women
2000-2009

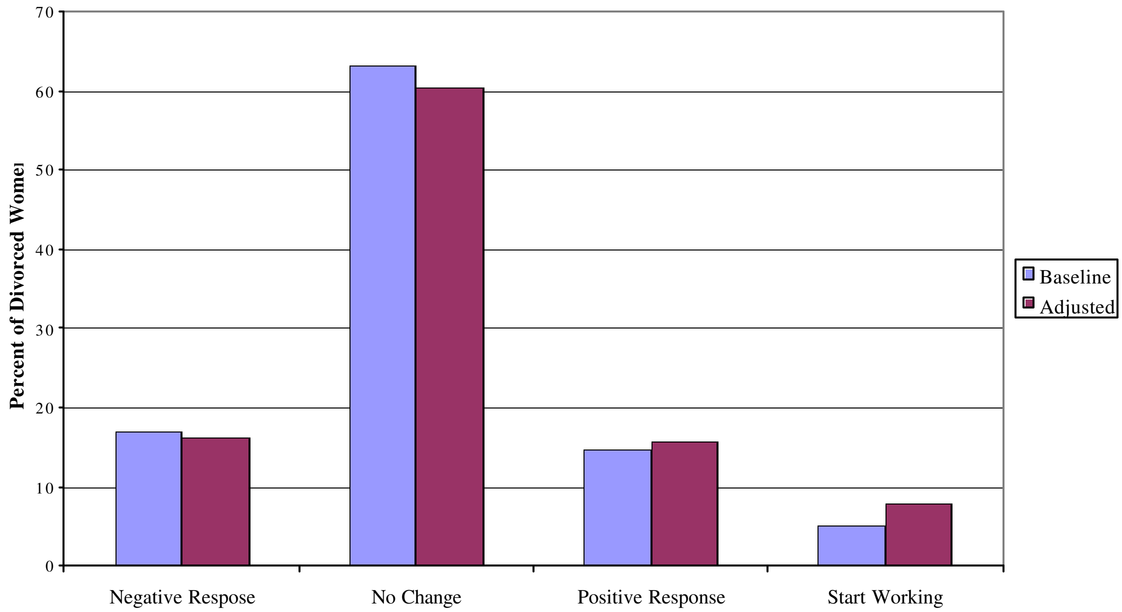
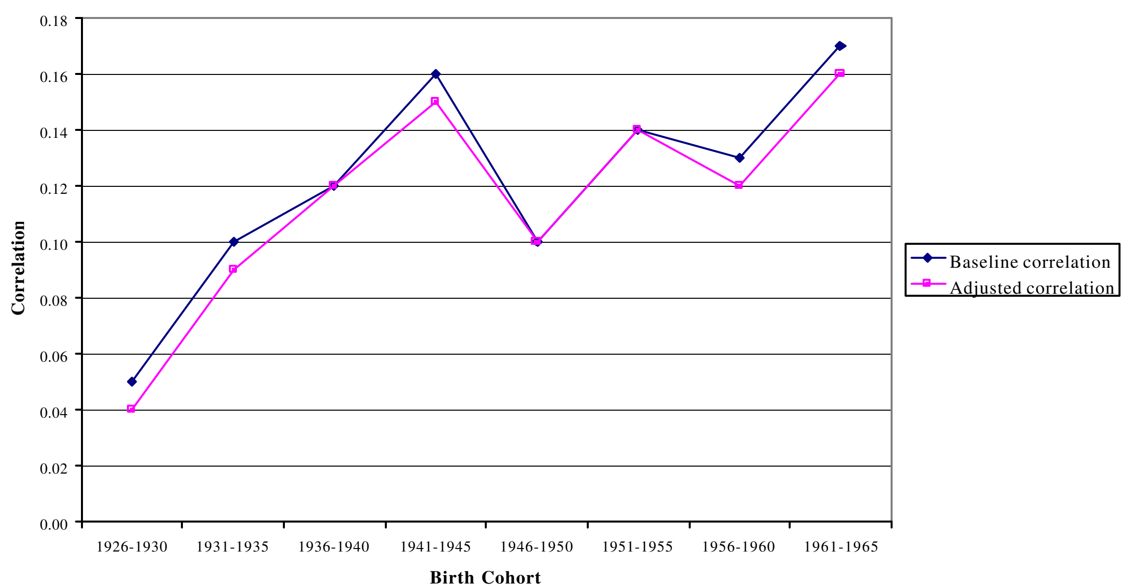


Figure 2-34
Correlation between the Lifetime Earnings of Husband and Wife



4. Immigration

The expert panel's review of the MINT earnings projections raised two concerns about the handling of immigrants. The first concern was the lack of differentiation between immigrants and native born in the earnings projections. The second concern was the absence of immigrants that arrive after the 1993 Survey of Income and Program Participation (SIPP).

The net impact of the lack of differentiation between immigrants and native workers is unclear. The earnings histories of adult immigrants are unique in that they include a string of zeros before the immigrants arrive in the country. This string of zeros is probably not a sign of unemployment, but rather a censored earnings record. The current earnings projections method will likely match recent immigrants to non-workers. The projections may understate the future earnings of immigrants if immigrants' future earnings differ from other non-workers.

Additionally, immigrants may have different earnings trajectories than native workers. When immigrants first arrive in the country, a need for additional human capital, particularly language skills, may limit their initial earnings. After these skills are acquired, their earnings may grow at a faster rate than earnings of native workers (Borjas 1998, Duleep and Regrets 1997). On the other hand, if immigrants' earnings tend not to rise as rapidly as native workers with similar prior gaps in their domestic work activity, then the matching routine may overstate immigrant earnings.

Currently MINT is a closed system. MINT starts with all individuals from the 1990 to 1993 SIPP panels born between 1926 and 1965. Individuals exit the MINT sample through institutionalization or death, but no new members are added. As a result, the MINT population is missing all of the immigrants who arrive after the final SIPP interview. This omission may give a misleading impression of the distribution of earnings and retirement income in the future, as many immigrants have lower Social Security covered earnings and lower entitlement rates than native-born individuals.

In order to test the sensitivity of the MINT results to these concerns, we made three adjustments. First, we adjusted the lifetime earnings measure to account for the censored earnings of immigrants. Second, we included immigrant status as a matching constraint to ensure that immigrants from later cohorts received earnings from immigrants from earlier cohorts. Finally, after modifying the earnings projection, we generated immigrants from the MINT cohorts who arrive in the U.S. between 1993 and 2030. We were then able to examine the impact of these changes on the distribution of earnings.

We found that adjusting the earnings projections to account for immigrant status and the censored lifetime earnings of immigrants does not have a substantial effect on the distribution of earnings. Although the baseline match includes lifetime earnings, it relies primarily on a detailed earnings profile of the last five years. This algorithm appears to be sophisticated enough to distinguish between the immigrant and non-worker who both have a string of zeros in the past. The omission of immigrant status as a matching variable in the original MINT projections does not appear to have biased the results.

Adding new immigrants to the MINT population does lower average indexed monthly earnings (AIME) and increase earnings inequality for men. The new immigrants dramatically increase the percentage of men who are ineligible for Social Security. Unlike men, adding new immigrants does not significantly increase the percentage of women ineligible for Social Security. By not including immigrants in the MINT population, we are likely understating future poverty rates. This is particularly true for Hispanics and Asians who are projected to experience the greatest population growth from new immigrants.

Adjusting the Earnings Projections

Our first task adjusted the baseline earnings projections. We made two modifications to the earnings projections to address the concerns about the treatment of immigrants. First, we included immigrant status (based on information from the SIPP migration history topical module) as a matching variable in the earnings projections. Second, we adjusted the average lifetime earnings key variable so that it included only the years in which the immigrant was a resident in the U.S.

For this sensitivity test we wanted to ensure that all immigrants received earnings from other immigrants. We constrained the match by including immigrant status as the first matching variable after age, sex, and disability. Overall, we were able to match more than 70 percent of individuals on all ten matching variables. In the original MINT projections, over three-quarters of individuals were matched on all variables. The addition of immigrant status as a key variable has not dramatically altered our ability to find donors who match the targets on all key variables. Even when it was not possible to find donors who matched target workers on all ten key variables, we always successfully matched non-disabled workers on age, gender, a measure of average earnings during the match period, and number of years worked during the matching interval.

We examined the impact of this new matching strategy on the lifetime earnings of natives and immigrants. We found that changing the earnings projection method had a negligible impact on mean Social Security AIME. For men, the greatest change in mean AIME is less than one percent (see Table 2-25). For most of the cohorts, the mean AIME is slightly lower under the adjusted projection compared to the baseline projection. There are changes in the 90/10 and 80/20 ratios, but these changes are not in a consistent direction. The gini coefficients are not substantially altered by the new projections. The changes are similar for women. The cohort AIME averages and inequality measures increase or decrease slightly depending on the cohort. No clear trend is evident.

The results of this sensitivity test indicate that the baseline earnings projections are not biased by their omission of immigrant status as a matching variable. With the exception of a lifetime earnings variable, all of the earnings matching characteristics are based on the five-year matching period. None of the individuals in MINT have censored earnings during this period. The matching variables account for both the level and the slope of earnings. Adding immigrant status as a matching variable and adjusting the lifetime earnings measure does not substantively change the results of the earnings projections.

Table 2-25
Percent Change in the Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts (Immigrant Status Included in the Earnings Projections)

Birth Cohort	Mean AIME	90/10 Ratio	80/20 Ratio	Gini coefficient	% not eligible
Based on earnings up to actual taxable maximum					
Non-deceased or disabled at beginning of year attain 62					
Men					
1926-1930	-0.2%	1.3%	0.0%	0.3%	-0.7%
1931-1935	-0.4%	5.6%	0.7%	0.6%	6.1%
1936-1940	-0.6%	0.7%	-0.9%	0.5%	7.2%
1941-1945	0.5%	-1.2%	-0.5%	-0.9%	-5.5%
1946-1950	-0.3%	0.6%	-0.8%	0.0%	0.0%
1951-1955	-0.3%	-0.6%	0.4%	-0.1%	4.5%
1956-1960	-0.5%	-4.2%	-2.4%	-1.5%	-3.2%
1961-1965	0.0%	-8.7%	-4.8%	-2.3%	-6.1%
Women					
1926-1930	-0.2%	-0.3%	2.9%	0.3%	0.9%
1931-1935	0.2%	-2.1%	-0.1%	-0.1%	-0.2%
1936-1940	0.3%	0.1%	1.8%	-0.1%	-0.3%
1941-1945	-1.0%	10.3%	0.7%	1.0%	5.3%
1946-1950	-1.5%	0.7%	3.7%	0.8%	1.3%
1951-1955	-0.5%	-8.9%	-2.0%	-0.8%	-3.5%
1956-1960	0.3%	6.1%	0.1%	0.4%	2.2%
1961-1965	0.5%	-2.9%	-2.1%	-0.7%	-1.4%

Adding New Immigrants

Our strategy for including new immigrants in MINT was to add additional people by replicating the records of immigrants on the SIPP. We added immigrants in the appropriate gender, age-at-migration, and source region categories. For every category of immigrants, we used all the SIPP records of immigrants who arrived in the U.S. in 1980 or later. The donor record provided earnings, educational attainment, race, disability status, and mortality. Earnings, disability date, and death date were all shifted forward. All events continue to occur at the same age, but now they happen in different years. Immigrant earning profiles are maintained relative to the age-at-migration.

We added new immigrants based on Dan Dowhan and Harriet Duleep's projections (2002) of the characteristics of immigrants arriving in the U.S. between 1993 and 2030. The starting point for the Dowhan and Duleep projections was the Immigration and Naturalization Service's record on immigrants that arrived in the country between 1993 and 1998. They added an estimate of net illegal immigration to this INS total. Finally, they have adjusted the projections to account for high rates of emigration among recent immigrants. Their final estimates are a projection of the number of immigrants who enter the country and stay for longer than ten years.

After 1998, Dowhan and Duleep assumed that immigration continues at the rate observed between 1993 and 1998. They argue that since these years postdate the Immigration Reform and Control Act, immigration flows are unlikely to change in the future barring major legislative changes. Although Dowhan and Duleep assume that the composition of the immigrant population by age, gender, and source region will remain constant, the actual age distribution of immigrants added to the MINT population varies because we are only adding the immigrants that are members of the MINT birth cohorts (1926-1965). In 1994, these immigrants will be between 29 and 68 years old. By 2020, new immigrants will be between 55 and 94 years old.

Dowhan and Duleep provide projections for immigrants from eight different source regions and twelve different age ranges. Due to the limitations of the SIPP donor pool, we had to combine some of these categories to have eligible donors. Although we were able to maintain most of the detailed age-at-migration categories, we did aggregate immigrants who migrated at or near retirement (age 60+). Due to cohort limitations, the SIPP sample does not have anyone who immigrated at an age older than 67. We also combined Canada with the other economically developed countries and combined Africa with the Caribbean. Without sacrificing some of the detail in the original projections, we would not be able to satisfy Dowhan and Duleep's primary concern that SIPP immigrant donors be limited to the subsample of SIPP immigrants who entered to the U.S. in 1980 or later.

Adding new immigrants to the MINT system increases the size of the population and changes its composition. The number of individuals alive in 2020 will increase by 4 percent with the inclusion of immigrants. Table 2-26 details the changes in the demographic composition of the MINT cohorts from the addition of immigrants. With the closed MINT system, 10.7 percent of retirees in 2020 are foreign born. If we include new immigrants, the share of individuals born outside the country increases to 14.4 percent.

The new MINT population has more Hispanics and Asians. Currently MINT projects that Hispanics will account for 7.9 percent of the elderly population in 2020. With the inclusion of new immigrants, Hispanics will account for 9.3 percent of the population. A similar trend is evident for Asians. Their share of the population increases from 3.4 percent to 4.5 percent. This is consistent with the immigration projections that predict that 70 percent of future immigrants will be from Asia, Mexico, Central America, or South America.[25]

Our projections also suggest that if the new immigrants have similar characteristics as former immigrants the average educational attainment of retirees will decline with the inclusion of new immigrants. Although the educational attainment of retirees continues to rise, the improvements in educational attainment are slower if new immigrants are included.

[25] This percentage excludes immigrants from Japan who are included with Western Europeans in the projections.

Table 2-26
Changes in Population Demographics and Mean AIME in 2020
With the Addition of Immigrants

	Population Demographics		Mean AIME	
	Original Population	With Immigrants	Original Population	With Immigrants
Nativity				
Native	89.3%	85.6%	0.80	0.80
Foreign Born	10.7%	14.4%	0.63	0.46
Race				
White	79.0%	76.6%	0.83	0.82
Black	9.1%	9.0%	0.63	0.61
Hispanic	7.9%	9.3%	0.58	0.48
Native American	0.6%	0.6%	0.62	0.61
Asian	3.4%	4.5%	0.72	0.54
Education				
HS Dropout	11.0%	12.6%	0.44	0.37
HS Grad	60.5%	59.1%	0.73	0.72
College Grad	28.6%	28.3%	1.03	1.00
Sex				
Female	55.6%	55.9%	0.56	0.53
Male	44.4%	44.1%	1.07	1.03
Age				
60-64	29.2%	29.4%	0.82	0.78
65-69	24.5%	24.5%	0.82	0.79
70-74	19.7%	19.7%	0.81	0.78
75-79	12.8%	12.7%	0.75	0.72
80+	13.9%	13.7%	0.64	0.62
All	100.0%	100.0%	0.78	0.75

In addition to population demographics, Table 2-26 illustrates the effect of new immigrants on average lifetime earnings of the elderly population in 2020. Including immigrants decreases the population mean AIME from 78 percent of the economy-wide average wage to 75 percent of the average wage. While the effect on the population mean is not very large, the impact on the subgroups that experience large population growth from immigrants is much more dramatic. The mean AIME of Hispanics falls by 17 percent, while the mean AIME of Asians decreases by 25 percent.

Adding new immigrants to the MINT population also changes the distribution of earnings. There are two different factors in the change of the earnings distribution. The first is cross-sectional. In any given year, immigrants earn, on average, less than individuals born in the U.S. (Borjas 1998). The second factor concerns longitudinal earnings. For an immigrant who arrives as an adult, his AIME will automatically include a certain number of zero earnings years. The youngest immigrant added to the MINT population arrives in the U.S. at age 29. Most are much older.

Table 2-27 shows the percent change in the distribution of earnings for the MINT population after the addition of immigrants. The mean AIME for men falls with the new immigrants. This difference is more pronounced for the later birth cohorts who have the largest share of new immigrants. While the average AIME has not changed dramatically, there is a more

Table 2-27
Percent Change in the Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts (Includes New Immigrants)

Birth Cohort	Mean AIME	90/10 Ratio	80/20 Ratio	Gini coefficient	% not eligible
Based on earnings up to actual taxable maximum					
Non-deceased or disabled at beginning of year attain 62					
Men					
1926-1930	-0.2%	1.3%	0.0%	0.3%	-0.7%
1931-1935	-0.6%	7.9%	1.0%	1.1%	9.8%
1936-1940	-1.4%	16.4%	2.2%	2.8%	23.5%
1941-1945	-1.1%	16.6%	6.4%	2.7%	25.3%
1946-1950	-2.4%	28.0%	11.2%	4.7%	36.2%
1951-1955	-3.4%	31.3%	12.8%	6.2%	61.0%
1956-1960	-4.6%	33.6%	12.7%	6.2%	61.8%
1961-1965	-5.9%	48.9%	16.8%	8.1%	76.7%
Women					
1926-1930	-0.2%	-0.3%	2.9%	0.3%	0.9%
1931-1935	-0.2%	4.5%	1.1%	0.2%	1.0%
1936-1940	-0.6%	5.4%	4.5%	0.8%	4.0%
1941-1945	-2.3%	16.1%	4.2%	2.1%	12.3%
1946-1950	-3.0%	11.0%	7.8%	2.1%	11.0%
1951-1955	-2.2%	-2.1%	1.2%	0.7%	7.9%
1956-1960	-1.5%	13.5%	3.9%	1.9%	15.8%
1961-1965	-1.3%	4.5%	1.9%	1.1%	16.4%

noticeable increase in earnings inequality for men in the later cohorts. The 90/10 ratio for men born between 1961 and 1965 increases by almost 50 percent with the inclusion of immigrants. The gini coefficient also increases by 8 percent. This change in earnings inequality is less pronounced if the population is limited to OAI eligible individuals. The changes in earnings inequality are driven by a decline in earnings in the bottom of the distribution, and not an increase in earnings at the top of the distribution.

The new immigrants have a different impact on the distribution of women's earnings. The new immigrants have the greatest effect on the earnings distribution of the middle MINT birth cohorts, 1941-1955. The average AIME falls for all women. There is also an increase in inequality. The changes in the distribution of earnings from adding new immigrants are much smaller in percentage terms for women than for men. This may be because more women have spells of zero earnings years even when they are born in this country. In their limited years in the country, immigrant women come closer to matching the earnings of their native counterparts.

Tables noted above apply only for persons with one year of positive earnings between age 22 and 61. Before the addition of new immigrants, this population restriction excluded almost no individuals, especially in the later birth cohorts. But with the addition of immigrants, that is no longer the case. Many of the immigrants that we add to the MINT population arrive after age 61 and by definition cannot be classified as a worker.

The overwhelming majority of immigrants who arrive after age 55 will not qualify for OAI, since few will have the forty covered quarters necessary to receive a benefit. In Figure 2-35, we show the percentage of men and women that survive to age 62, but are ineligible for Social Security on the basis of their own earnings. The graphs in the first column are limited to workers. The second column includes all age 62 survivors.

For women, the population restriction does not make a substantial difference. In both graphs, the percentage ineligible for OAI increases slightly when the new immigrants are added. But immigrants have no affect on the dramatic increase over time in the number of women qualifying for Social Security worker benefits.

Adding immigrants more than doubles the share of ineligible men. In the base MINT projections, we estimate that only 4.3 percent of men born between 1961 and 1965 will be ineligible for Social Security. With the inclusion of new immigrants, the percentage of men born between 1961 and 1965 ineligible for OAI rises to 10.3 percent.

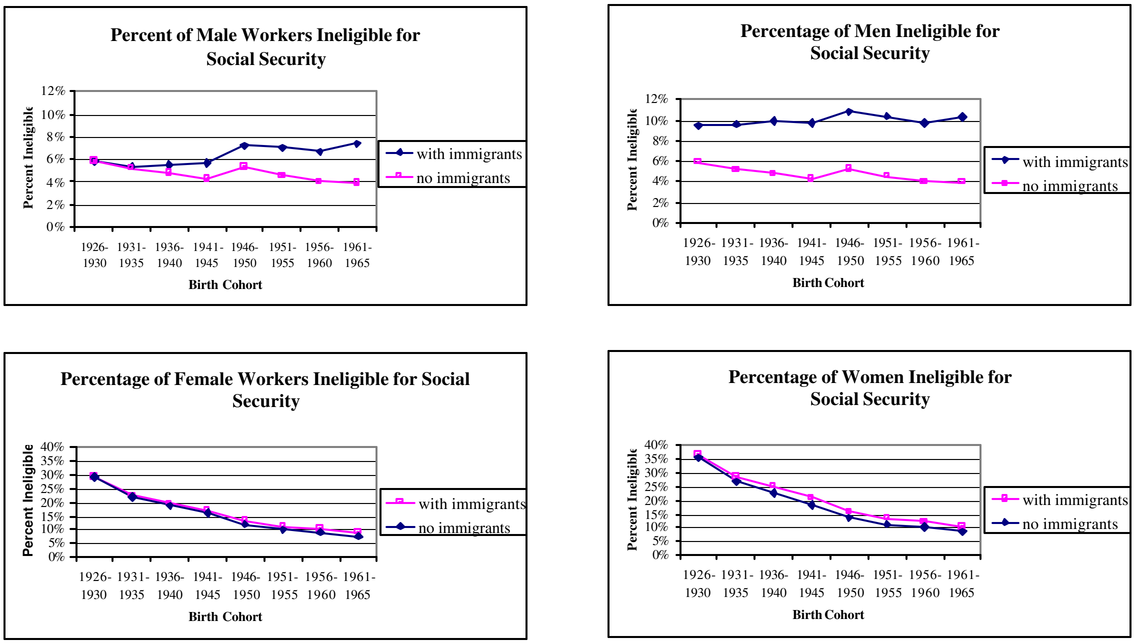
The difference between the population definitions is particularly apparent for men in the early birth cohorts. Since individuals born between 1926 and 1930 are already age 61 when the immigrant projections begin, none of the immigrants added to these birth cohorts will qualify as workers. Additionally, none of the new immigrants are going to qualify for Social Security. When the population is restricted to workers, it seems that adding immigrants to MINT had no effect on the early birth cohorts. But when the graph includes the entire population, it is evident that the arrival of new immigrants will affect the percentage of earlier birth cohorts who are receiving Social Security benefits.

Implications for Poverty

Our sensitivity analysis suggests that not including future immigrants in the MINT population may understate the poverty of the future elderly. Many of the immigrants that are added to the population fail to qualify for Social Security benefits. While these older immigrants may have established family networks that will support them, they are certainly at risk of poverty.

Historically immigrants who arrive in the U.S. at older ages are more likely to be in poverty. Table 2-28 is a tabulation of individuals age 62 and older from the March Supplement of the 2001 Current Population Survey. It shows that poverty rates climb monotonically with age at migration. The CPS also confirms that immigrants who arrive at older ages are being supported by their families. The poverty rate of elderly immigrants declines substantially once the income of co-residents is included. For immigrants who arrive in the U.S. between ages 60 and 64, poverty rates decline from 55.1 percent to 25.3 percent if we include co-resident income. While co-resident income certainly raises the income of late arriving immigrants, the poverty rates for these immigrants are still more than double the poverty rates for individuals born in the U.S.

Figure 2-35
Percent of Individuals Ineligible for Social Security



Note: A worker is an individual with at least one year of positive earnings between age 22 and 61.

Table 2-28
Poverty Rates by Age at Immigration
CPS 2001, Individuals Age 62+

	Poverty Rate Excluding Coresident Income	Poverty Rate Including Coresident Income
Born in U.S.	14.8%	10.9%
Foreign Born	28.2%	16.0%
Age at Immigration		
Less than 20	18.9%	12.1%
20 - 24	19.0%	14.9%
25 - 29	22.2%	13.7%
30 - 34	23.6%	16.0%
35 - 39	25.0%	14.8%
40 - 44	26.8%	17.0%
45 - 49	31.4%	18.3%
50 - 54	36.3%	25.2%
55 - 59	41.3%	19.4%
60 - 64	55.1%	25.3%
65 - 69	53.0%	22.8%
70+	60.5%	24.2%

In addition to understating the poverty of the elderly population at large, the omission of immigrants particularly biases the projections of the well-being of Hispanics and Asians. Over 70 percent of the new immigrants are projected to belong to one of these demographic groups. As a result, the average lifetime earnings of these groups decline most dramatically after immigrants are added to the population.

Summary

Our sensitivity test of the MINT earnings projection method confirms that the baseline method is correctly projecting the different earnings trajectories of immigrants and natives. Our matching modifications to account for immigrant status did not significantly alter the projected earnings distribution.

Adding new immigrants to MINT does change the projections of future population demographic composition and earnings distributions. Immigrants increase the retired population in 2020 by 4 percent. Since the new immigrants are overwhelmingly Hispanic and Asian, the racial makeup of the 2020 population also changes. Many of these immigrants end up in the lower end of the lifetime earnings distribution, both because of lower cross-sectional earnings and fewer years in the country. As a result, adding immigrants decreases mean AIME and increases lifetime earnings inequality.

Many of the immigrants added to the MINT population arrive late enough in their career that they do not have enough covered quarters to qualify for Social Security. In the later birth cohorts, adding new immigrants doubles the percentage of men that reach 62 without having qualified for Social Security. Without a Social Security benefit, these new immigrants are at high risk of poverty.

While the earnings projections do not appear to be biased from the omission of immigrant status as matching variable, the lack of new immigrants in MINT may result in overly optimistic future projections. It is likely that these new immigrants would lower average earnings, increase earnings inequality, and increase the poverty rates of future retirees.

5. Detailed Earnings File Sensitivity Tests

We used the Social Security Administration's Detailed Earnings file matched to the base MINT file to test the sensitivity of the MINT projections to uncovered earnings, self-employment earnings, and earnings above the Social Security taxable maximum. The Detailed Earnings file provides longitudinal uncapped earnings from 1978 to 2000. The data are based on employer wage reports, but because of some reporting changes during the early years of the data, the data quality may be poor. Based on some preliminary analysis, we determined that the Detailed Earnings file matched the Summary Earnings Record (SER) data closely from 1982 on.

Since the baseline earnings projections used the SER, we only had data on covered earnings up to the taxable maximum. The administrative data placed limitations on the baseline earnings projections. We could not distinguish uncovered work from lack of labor force participation. We could only impute a censored earnings distribution. We also lacked projections of future participation in self-employment.

There are two distinct reasons that these limitations may be troubling. The first is that there may be something distinctly different about individuals who have earnings in these categories. Not matching uncovered workers to uncovered workers may be biasing our projections of covered lifetime earnings. The second concern is that our final earnings imputations do not include imputations of uncovered earnings, earnings above the taxable maximum, or a distinct stream of self-employment earnings. As a result, it is impossible to use MINT to answer questions about changes in the way certain earnings are treated by Social Security or the implications of increasing the taxable maximum.

Earnings from Uncovered Employment

The baseline projection method is unable to distinguish between zeros from uncovered employment and zeros from lack of labor force participation. As a result, it is unlikely that the splicing method will capture the appropriate transitions between uncovered and covered employment. If individuals are imputed to return to covered employment, their earnings will likely be too low.

Our inability to control for uncovered work has multiple implications. We may understate the lifetime covered earnings of individuals who are in uncovered employment in the 1990s. This would clearly have implications for their Social Security benefits, but also for their wealth accumulation. We also may be misstating their pension wealth.[26] Finally, we are unable to simulate any change in how Social Security treats certain earnings.

Since the overwhelming share of individuals in the youngest birth cohorts have earnings from covered employment, we did not invest heavily in addressing this problem in the baseline projections. Now that the matched Detailed Earnings file is available, we can control for participation in uncovered employment. This allows us to detect any bias in our projections of lifetime covered earnings and allows us to impute a stream of uncovered earnings that would be useful for wealth and pension projections.

Adjusting the Earnings Projections. To control for uncovered earnings, we create a new matching variable that measures whether an individual had all, some, or none of their earnings in uncovered employment in the last year of the matching period. For the non-disabled, we added this matching constraint after the existing earnings variables, but before education and race. Uncovered employment status is the least important matching variable for the disabled. We matched over 70 percent of individuals on all ten matching variables. More than 90 percent of non-disabled individuals matched to a donor before we relaxed the uncovered employment constraint.

[26] The MINT pension model assumes that anyone who is in uncovered employment at the SIPP interview remains in this job. The individual's earnings from the SIPP interview are updated annually by wage growth.

Results. Changing the matching algorithm does not dramatically alter the projections of lifetime earnings. Mean AIME changes by less than one percent (see Table 2-29). Inequality measures increase and decrease depending on the cohort and inequality measure. There are almost no changes for the first two cohorts. This is to be expected since almost all of their earnings are observed and unlike in the immigration sensitivity test, we have not changed the matching process for those without an SER match. Although mean AIME does not change very much for men in the 1956-1965 birth cohorts, the new matching procedure does seem to increase the number of individuals moving into covered employment. A rise in the bottom of the earnings distribution causes the 90/10 ratio to decline. Additionally, the percentage of men ineligible for Social Security falls.

Adding uncovered employment as a matching constraint allows us to project a reasonable stream of future uncovered earnings. The percentage of economy wide earnings that are uncovered continues to decline at a fairly steady rate (see Figure 2-36). There is no noticeable disruption when the earnings imputations begin in 2000. The new MINT projections also maintain the gender divide in uncovered earnings. A higher share of women's earnings occur in uncovered employment. This is likely because some of the careers traditionally held by women, school teachers and nurses, are frequently not covered by Social Security.

Not surprisingly, if we recalculate AIME including uncovered earnings, mean AIME rises for all cohorts of men and women. The greatest gains are in the 1946-1950 birth cohorts (see Table 2-30). Mean AIME increases by 7.6 percent for men and 7 percent for women. This result is partially an artifact of the data. Uncovered earnings are only available starting in 1982. As a result, early cohorts only have uncovered earnings for the later part of their career. If we had uncovered earnings from 1951 forward, it is likely that the biggest increase in AIME would be for the early birth cohorts who had more people working in uncovered employment. After the 1950 birth cohort, the impact of uncovered earnings begins to decline as more people are in jobs covered by Social Security.

Earnings inequality also declines once uncovered earnings are included. The baseline file overstates earnings inequality because it classifies uncovered workers as zero earners. When we include uncovered earnings in the AIME measure, we raise the bottom of the distribution and reduce inequality.

Self-Employment

Gustman's review of the earnings projection method expressed concern about the implications of not differentiating self-employed individuals. In the baseline MINT projections, an individual who is self-employed at the time of the SIPP might be matched to a wage-and-salary worker during the first splicing period. The earnings patterns of this individual will be continued, but it is no longer possible to determine who is self-employed or to separate out self-employment earnings.

Table 2-29
Percent Change in the Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts (Uncovered Earnings Key Variable Included in the Match)

Birth Cohort	Mean AIME	90/10 Ratio	80/20 Ratio	Gini coefficient	% not eligible
Based on earnings up to actual taxable maximum					
Non-deceased or disabled at beginning of year attain 62					
Men					
1926-1930	0.0%	0.0%	0.0%	0.0%	0.0%
1931-1935	0.0%	0.0%	0.0%	0.0%	0.7%
1936-1940	0.2%	-0.7%	-0.3%	-0.3%	2.3%
1941-1945	-0.1%	2.7%	0.5%	-0.3%	2.2%
1946-1950	0.5%	-8.8%	-2.6%	-1.8%	4.4%
1951-1955	0.3%	2.6%	3.3%	0.5%	6.4%
1956-1960	0.5%	-5.9%	1.3%	-0.4%	-16.7%
1961-1965	0.0%	-4.1%	0.6%	-0.5%	-23.0%
Women					
1926-1930	0.0%	0.0%	0.0%	0.0%	0.0%
1931-1935	0.0%	0.0%	0.0%	0.0%	0.3%
1936-1940	0.0%	0.0%	0.4%	-0.2%	0.6%
1941-1945	-0.5%	-4.2%	-1.5%	-0.1%	-1.0%
1946-1950	0.4%	-6.3%	-3.1%	-0.4%	-4.0%
1951-1955	0.0%	0.6%	0.4%	-0.7%	-1.7%
1956-1960	-0.3%	-0.5%	-0.3%	-0.1%	-6.4%
1961-1965	-0.4%	-1.7%	-0.9%	0.4%	-0.3%

Figure 2-36
Percent of Earnings in Uncovered Employment by Sex and Year

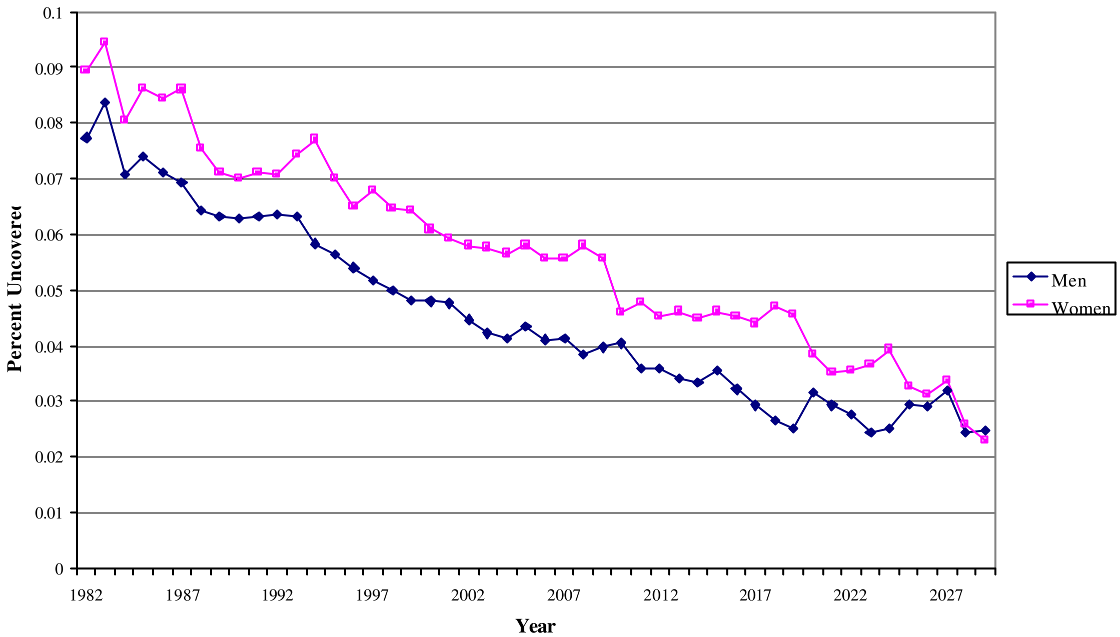


Table 2-30
Percent Change in the Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts (Uncovered Earnings Included in the AIME calculation)

Birth Cohort	Mean AIME	90/10 Ratio	80/20 Ratio	Gini coefficient
Based on earnings up to actual taxable maximum				
Non-deceased or disabled at beginning of year attain 62				
Men				
1926-1930	3.3%	-38.0%	-16.2%	-9.8%
1931-1935	5.4%	-42.0%	-21.3%	-14.5%
1936-1940	5.9%	-40.6%	-22.6%	-14.6%
1941-1945	6.2%	-37.3%	-23.4%	-14.3%
1946-1950	7.6%	-46.2%	-24.3%	-16.1%
1951-1955	6.1%	-30.6%	-15.2%	-10.2%
1956-1960	4.6%	-24.5%	-9.0%	-7.3%
1961-1965	2.8%	-17.7%	-7.7%	-5.2%
Women				
1926-1930	2.3%	-8.2%	-7.6%	-2.1%
1931-1935	4.1%	-7.2%	-7.6%	-2.9%
1936-1940	4.8%	-15.2%	-14.3%	-4.1%
1941-1945	6.1%	-23.1%	-15.8%	-5.7%
1946-1950	7.0%	-21.6%	-16.7%	-6.2%
1951-1955	6.1%	-24.5%	-15.4%	-6.9%
1956-1960	4.7%	-19.4%	-10.0%	-4.9%
1961-1965	3.5%	-20.5%	-13.1%	-4.6%

Although wage-and-salary earnings and self-employment earnings are treated equally in the Social Security benefit calculation, self-employed individuals traditionally have different pension and wealth accrual patterns. Currently the MINT model assumes that anyone is who self-employed at the time of the SIPP interview remains self-employed through retirement. No new individuals are projected to move into self-employment. If MINT projected a separate stream of self-employment earnings, this simplifying assumption would no longer be necessary.

In this sensitivity test, we use self-employment earnings from the Detailed Earnings File. We add a new matching constraint for self-employment. If more than 50 percent of an individual's earnings in the last year of the matching period comes from self-employment, that individual is flagged as self-employed. We added the self-employment flag as the last earnings matching criteria. We matched over 90 percent of individuals on all earnings matching variables including self-employment.

Using self-employment status as a matching criteria does not alter the lifetime earnings distribution. The changes in mean AIME and the AIME inequality measures are very minor (see Table 2-31). Our failure to have controlled for self-employment does not appear to have biased our projections of lifetime covered earnings.

The real advantage of the new method is that it allows us to project a stream of self-employment earnings. We find that a growing percentage of the MINT labor force has at least some percentage of their earnings coming from self-employment (see Figure 2-37). This trend is particularly strong for men. In 1999, 11 percent of men had earnings from self-employment. We project that this percentage will rise to 17 percent by 2030.

The rising percentage of men with self-employment earnings appears to be the result of the changing age distribution of labor force participants. In the administrative records, as men age a larger percentage of them have self-employment earnings. This pattern continues in the projected earnings records (see Figure 2-38). By 2020, the youngest workers in the MINT population are age 55. The rise in the self-employed population in later years is an artifact of the aging of the labor force participants. The later birth cohorts actually have lower rates of self-employment than the cohorts that preceded them. Overall the self-employment patterns produced by with the new earnings projection method appear reasonable. They reproduce the historic age and cohort trends in self-employment.

Although the baseline projection method's failure to differentiate the self-employed does not appear to have biased the earnings projections, using the Detailed Earnings file to impute self-employment earnings does add potentially useful information to the earnings projections. With a stream of self-employment earnings, we can more accurately model the wealth and pension accruals for this unique group of individuals.

6. Earnings Above the Taxable Maximum

While validating the MINT wealth projections, we discovered an anomaly in the MINT earnings matching procedure that artificially reduced the number of records with earnings at or above the taxable maximum. We tested changes in the matching algorithm that appeared to remove this anomaly. These changes involved using the Detailed Earnings file, which includes earnings above the taxable maximum.

Table 2-31
Percent Change in the Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts (Self-Employment Status Included in the Earnings Projections)

Birth Cohort	Mean AIME	90/10 Ratio	80/20 Ratio	Gini coefficient
Based on earnings up to actual taxable maximum				
Non-deceased or disabled at beginning of year attain 62				
Men				
1926-1930	0.0%	0.0%	0.0%	0.0%
1931-1935	0.0%	0.0%	0.0%	0.0%
1936-1940	0.1%	-0.1%	-0.5%	-0.1%
1941-1945	0.7%	-1.3%	-0.3%	-0.9%
1946-1950	0.1%	-2.2%	-1.2%	-0.9%
1951-1955	0.1%	4.4%	2.6%	0.8%
1956-1960	0.0%	-3.1%	0.1%	-0.4%
1961-1965	0.0%	4.3%	-1.6%	0.4%
Women				
1926-1930	0.0%	0.0%	0.0%	0.0%
1931-1935	0.0%	0.0%	0.0%	0.0%
1936-1940	0.2%	-0.8%	0.0%	-0.3%
1941-1945	0.0%	-0.1%	-2.2%	-0.1%
1946-1950	0.7%	-4.2%	0.9%	-0.6%
1951-1955	0.5%	2.1%	0.8%	-0.6%
1956-1960	-0.8%	-2.8%	-2.7%	-0.7%
1961-1965	1.5%	-7.0%	-4.8%	-1.3%

Figure 2-37
Percentage of Male and Female Workers with Self-Employment Earnings by Year

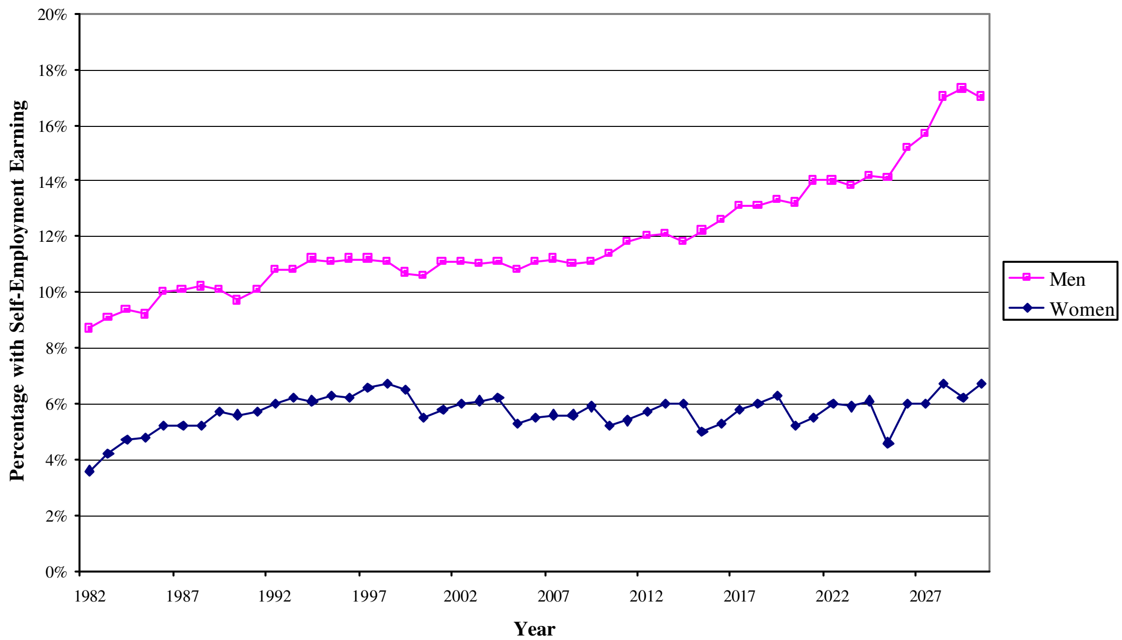
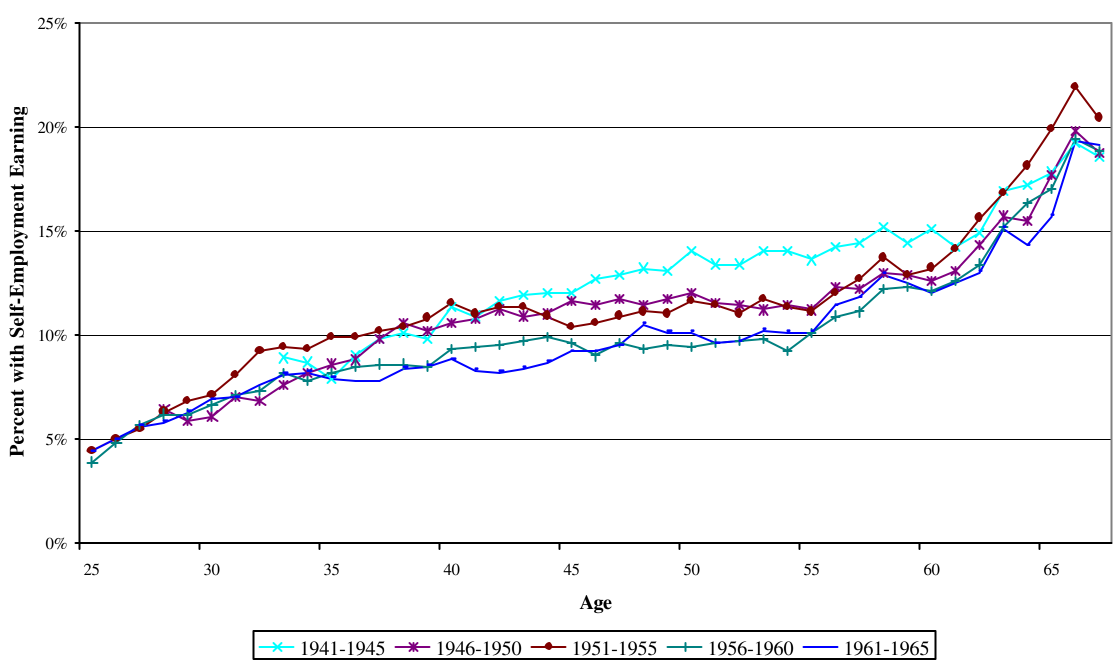


Figure 2-38
Self-Employment Patterns of Men by Age and Birth Cohort



This section discuses the anomaly that we found, describes the alternative procedure that we developed for eliminating it, and reports the results of our sensitivity tests. We have not employed the alternative matching procedure or matches based on the uncensored data file in producing the earnings on the final MINT3 dataset. We believe that a more thorough analysis of the detailed earnings file is needed before it is used to produce the final MINT dataset. Furthermore, projections of earnings above the cap have implications for retirement, pensions, and wealth. Increasing earnings above the cap may increase retirement, increase pension income, and increase wealth for individuals with higher historic and projected earnings. These sections of the model would need to be reestimated if alternative earnings estimates are used.

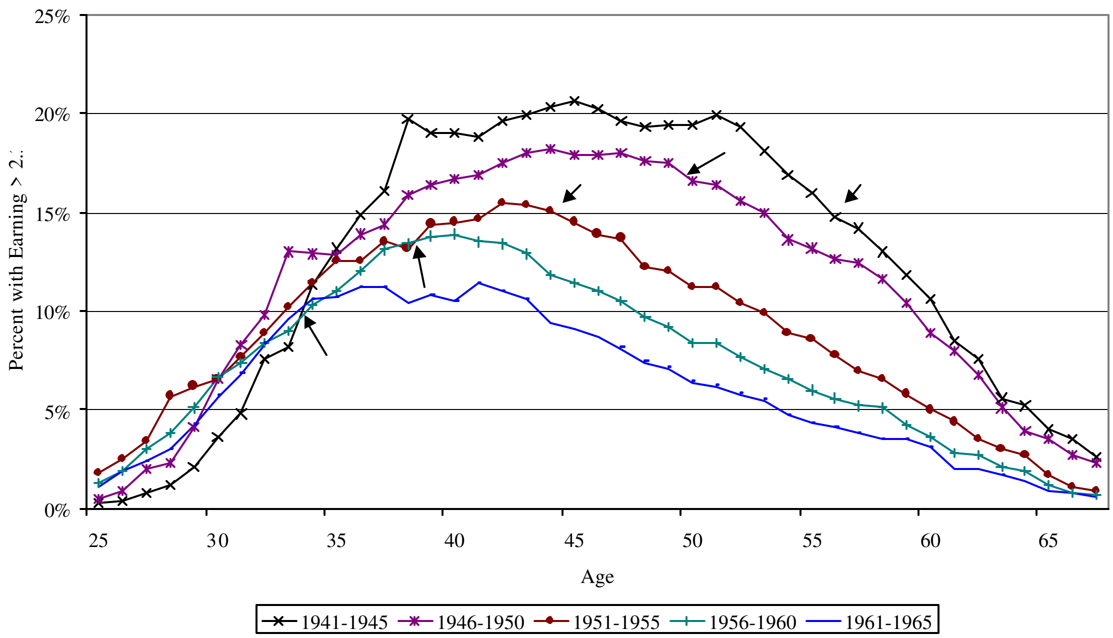
Projections Methodology Anomaly

The impact of the anomaly in the current earnings projection methodology is illustrated in Figure 2-39. That figure shows the percent of men in the current MINT projections that are projected to have earnings above 2.3 times the average wage, arrayed by cohort and age. (The taxable maximum is actually a little higher than 2.3 times the average wage, but it also fluctuates a little from year to year.) For men born between 1941 and 1946, based on actual earnings through about age 55, the percent with earnings above 2.3 times the average wage rises between age 25 and 45 and then declines. For men born in later cohorts, the percentage with earnings above 2.3 times the mean peaks at progressively younger ages and lower levels. In fact, the peaks tend to occur at the point when the MINT projection process comes in (indicated by the arrows in Figure 2-39). For men born between 1961 and 1965, the percent with earnings above 2.3 times the mean peaks at around age 30 instead of at around age 45, as observed in the earlier cohorts. We believe this pattern is the result of a systematic bias that has been introduced by the projection method.

Background. The MINT projection process has two features that appear to interact to produce the result shown in Figure 2-39. One is the impact of the random selection of the donor in combination with the process used to align the donor worker's earnings with the target worker's earnings. The other is the way that quintiles are calculated in the disaggregation process.

Once records are disaggregated and a donor is picked, the donor's earnings are adjusted to align them more closely with the target worker's earnings. This is done by multiplying the donor earnings by W_t/W_d, where W_t is the target worker's average earnings in the 5-year matching period and W_d is the donor worker's average earnings in the 5-year matching period. When the donor's earnings are 10 percent higher that the target's, for example, we would reduce each of the donor's earnings in subsequent years by 10 percent. When donor earnings are 10 percent lower compared to the target, we would increase the donor earnings by 10 percent. We did not apply this adjustment to earnings below 2.7 percent of the average economy-wide wage because it could produce absurdly large or small projected values as the ratio takes on extreme values when W_t or W_d is very small.

Figure 2-39
Percent of Men with Earnings Greater than 2.3 Times the Average Wage
Baseline Projections by Age and Cohort



While we recognized the impact of the adjustment at the low end of the distribution, we did not realize there was an analogous problem at the high end of the distribution. The problem stems from asymmetry in the adjustment process. When the donor record has earnings above the Social Security taxable maximum, the W_t/W_d adjustment does not properly correct for the differences in earnings of the donor and target worker. The problem is exacerbated by a trend shift in earnings patterns across cohorts.

The current projection method splits the donor population into a series of donor pools. Non-disabled workers are divided into groups based on: (1) years of earnings in the 5-year matching period, (2) average earnings quintile in the matching period (plus a zero earnings group), (3) earnings in the fifth year, (4) earnings in the fourth year, (5) average earnings quintile before the 5-year matching period, (6) educational attainment group, and (7) race and ethnicity. The average earnings used to define subgroup 2 is calculated separately for the donor workers and target workers, based on the distribution of their age-, gender-, and cohort-specific values.

Example. The impact of these two elements of the process is most easily understood by looking at an example. In the example, we first describe how the earnings matching process would work if earnings were not capped using a sample of three donors. We then describe how the same matching process works when earnings are capped. The first part of the example is shown in Table 2-32 and the second part is shown in Table 2-33.

Table 2-32
Example Earning Projection with Uncapped Earnings

	Age										Average
	30	31	32	33	34	35	36	37	38	39	Earnings
Target Worker Earnings/AW	1.50	1.60	1.70	1.80	1.90						1.70
Donor Earnings											
Low	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2.00	1.30
Medium	1.50	1.60	1.70	1.80	1.90	2.00	2.10	2.20	2.30	2.40	1.70
High	2.10	2.20	2.30	2.40	2.50	2.60	2.70	2.80	2.90	3.00	2.30
Projected Earnings											Wt/Wd
Low	1.5	1.6	1.7	1.8	1.9	2.09	2.22	2.35	2.48	2.62	1.31
Medium	1.5	1.6	1.7	1.8	1.9	2.00	2.10	2.20	2.30	2.40	1.00
High	1.5	1.6	1.7	1.8	1.9	1.92	2.00	2.07	2.14	2.22	0.74

Table 2-33
Example Earnings Projection with Capped Earnings

	Age										Average
	30	31	32	33	34	35	36	37	38	39	Earnings
Target Worker Earnings/AW	1.50	1.60	1.70	1.80	1.90						1.70
Donor Earnings											
Low	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2.00	1.30
Medium	1.50	1.60	1.70	1.80	1.90	2.00	2.10	2.20	2.30	2.40	1.70
High	2.10	2.20	2.30	2.40	2.46	2.46	2.46	2.46	2.46	2.46	2.29
Projected Earnings											Wt/Wd
Low	1.5	1.6	1.7	1.8	1.9	2.09	2.22	2.35	2.46	2.46	1.31
Medium	1.5	1.6	1.7	1.8	1.9	2.00	2.10	2.20	2.30	2.40	1.00
High	1.5	1.6	1.7	1.8	1.9	1.82	1.82	1.82	1.82	1.82	0.74

The examples assume a high-earner with average earnings in the 5-year overlap period of 1.7 times the average wage. The middle bank of numbers shows the earnings records of three possible donors. The first donor has lower earnings than the target, the second donor has earnings equal to the target, and the third donor has earnings higher than the target. In the matching algorithm, each of the three donors is equally likely to be picked as a donor, with the subsequent years of earnings adjusted to equalize the five-year average. The bottom panel of numbers shows the adjusted imputed earnings associated with each of the three donors. When the model links to the low donor, the adjustment increases imputed earnings by 31 percent. When the model links to the high donor, the adjustment decreases imputed earnings by 26 percent.

Table 2-32 shows how the match process works when earnings are not capped at the taxable maximum. The earnings imputation is balanced with low donors generating higher projected earnings and high donors generating lower projecting earnings. Differences among these three potential matches are illustrated in the left panel of Figure 2-40.

Figure 2-40

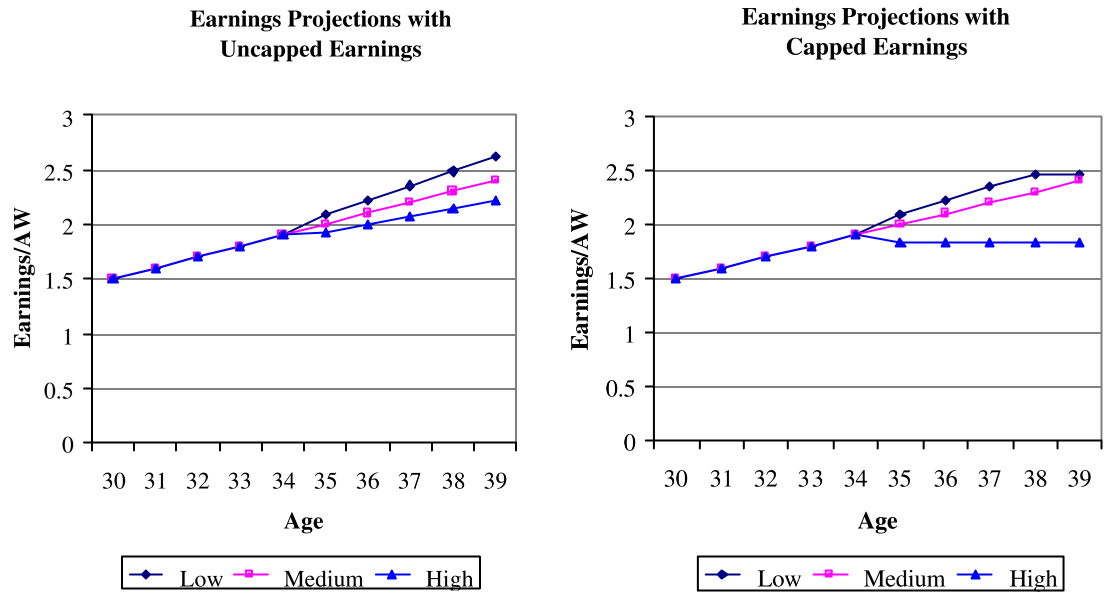


Table 2-33 shows the same projection processes when earnings are capped at the taxable maximum, the situation in the current MINT3 baseline projections. In Table 2-33, when we match to the low donor, the W_t/W_d adjustment increases the donor earnings to values above the cap. When we match to the middle donor, the W_t/W_d adjustment retains the implicit slope of the projections and projects earnings that rise with age. When we match to the high donor, however, the W_t/W_d lowers earnings of the donor and changes the implicit slope. In this case, the projected earnings do not reach the taxable cap, as illustrated in the right panel of Figure 2-40. In short, the imputation with capped earnings produces asymmetric results. Donors with low earnings generate earnings that move towards the cap. Donors with earnings censored at the taxable maximum generate earnings disproportionately below the taxable maximum and with the wrong slope.

The asymmetry of the adjustment process does not fully explain the pattern observed in Figure 2-39. To get the pattern in Figure 2-39, it is also necessary that the probability of being matched to a donor with higher earnings be greater for the later birth cohorts. We believe that this probability does increase because of the interaction of general trends over time in the level of men's earnings and the mechanics of the calculation of the worker's quintile.

The matching process links a donor in an earlier cohort to a target record from a later cohort. Relative to the national average wage, mean earnings of men are lower in later cohorts than in earlier cohorts. Because the boundaries used to define earnings quintiles for matching variable number 2 are cohort specific, the earnings of the target workers tend to be lower than the earnings of the donors. Since the algorithm randomly chooses among all records in the donor pool, it is more likely to match a target worker to a donor with higher earnings than one with lower earnings because the donor pool has higher average earnings levels. As shown in the example in Table 2-33, these high donors systematically project a lower and biased earnings projection.

Solution. We were able to correct this problem by making three separate adjustments:

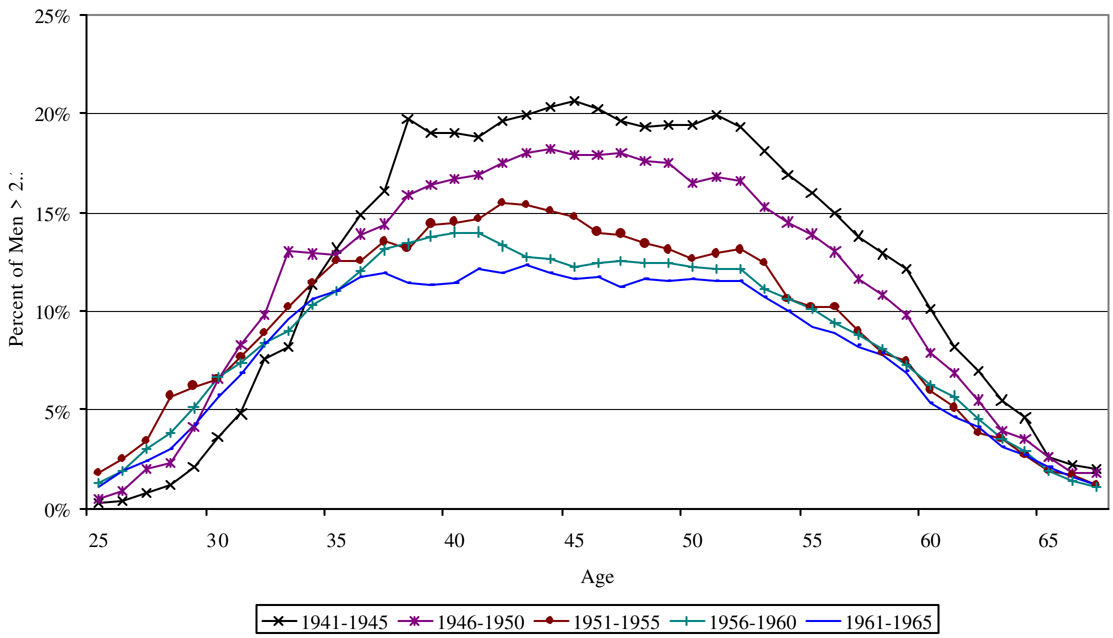
1. We removed the cohort specification in the quintile calculation (key variable 2), grouping workers with similar earnings together, regardless of their cohort. We maintain the age- and gender-specific differences. This effectively shifts workers in later cohorts from the top quintile to the fourth quintile in the selection of donor earnings.

2. Using the Detailed Earnings file, we disaggregated donors by the number of years in the 5-year overlap period that the worker has earnings above the cap as follows: 0 years, 1 to 2 years, 3 or more years. We added this as a new key variable number 6, so that workers with specific number of years above the taxable maximum match donors with similar number of years above the taxable maximum. (We were able to match on this key variable in all but 5 percent of cases, and the cases where no match was made were disproportionately cases with lower earnings and therefore not subject to the cap bias.)

3. We added a search algorithm to select among all valid donors the record with the adjustment (W_t/W_d) closest to one. This minimizes the size of the adjustment factor and effectively chooses the "best" record among all potential donors.

Results. The revised matching algorithm increases the proportion of workers with earnings above 2.3 times the average wage, as is illustrated in Figure 2-41. The revised projections still show a decrease in the share of men with high earnings in later cohorts compared to earlier cohorts. This is consistent with the general trend in average male earnings, and the pattern by age in later cohorts matches the earlier cohorts. We believe this is an improvement over the baseline projection.

Figure 2-41
Percent of Men with Earnings Greater than 2.3 Times the Average Wage With Taxmax Corrections by Age and Cohort



We tested alternative corrections but believe the results in Figure 2-41 are superior to these alternatives. These alternatives include the following:

- Removing the W_d/W_t factor. This alternative produces the same distribution of high earners in later cohorts, but yields a non-continuous distribution at older ages for later cohorts.

- Retaining the W_d/W_t factor on uncapped earnings. This adjustment generates extreme adjustment factors similar to those at the bottom of the earnings distribution. While the adjustment is balanced, it still suffers from the systematic shift in the earnings distribution between cohorts and projects too few workers with high earnings.

- Adding the taxable maximum key variable but maintaining the cohort-specific quintile distribution on earnings. This improves the projections, but still suffers from the bias caused by the systematic shift in the earnings distribution between cohorts.

The revised matching algorithm also increases the share of women with high earnings, as shown in Figure 2-42. The percent of women with high earnings increased for women born from 1941 to 1955, but decreased for women born after 1955. While the revised algorithm increases the projected share of women with high earnings, the percent with high earnings still declines for women born after 1955 compared to women born in 1955.

Figure 2-42
Percent of Women With Earnings Greater than 2.3 Times the Average Wage by Age and Cohort

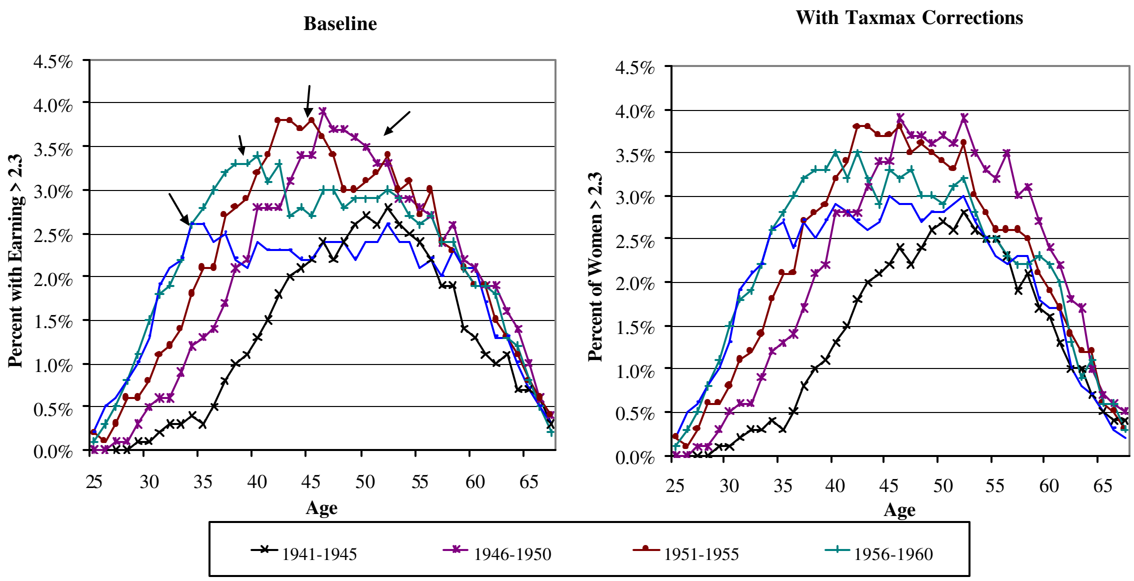


Table 2-34 shows by cohort and sex the change in the mean AIME that the new procedure produced. It also shows how they affect several measures of the distribution of AIMEs. While the adjustments increase the share of workers near the taxable maximum annually, they have surprising little impact on the distribution of Social Security AIMEs for both men and women. The greatest change in men's mean AIME is less than one percent. There is no change in AIME for men born before 1933 where we observe completed work histories from the administrative data. The adjustments lower mean AIME for men born between 1951 and 1960 but increase mean AIME for men born in other cohorts. These changes are small and close inspection of the distribution shows no clear trend by cohort. Rising mean AIMEs do not always coincide with increased inequality. For example, while the mean AIME *increases* for men born between 1946 and 1950, the 90/10 ratio, 80/20 ratio, and gini coefficient *decrease*. In contrast, the mean AIME decreases for men born between 1951 and 1955, and the 90/10 ratio, 80/20 ratio, and gini coefficient also decrease. The adjusted distribution reduces AIME inequality for men born between 1946 and 1950 and increases the AIME inequality for men born between 1961 and 1965.

The revised matching algorithm also has very little impact on women's mean AIME. The change in mean AIME is less than 1.2 percent in all cohorts. There is no change in AIME for women born before 1933 where we observe completed work histories from the administrative data. The adjustments lower mean AIME for women in some cohorts and raise it in others. As with men, no clear trend is evident. The biggest difference for women is in the 90/10 ratio. The ratio is about 17 percent lower after the adjustment for women born between 1961 and 1965, but this is caused by an increase in AIME in the 10th percentile. The 90th percentile remains unchanged. This difference is due to the removal of the cohort in the quintile calculation rather than changes in the share above the cap.

Table 2-34
Percent Change in the Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts

Birth Cohort	Mean AIME	90/10 Ratio	80/20 Ratio	Gini coefficient
Based on earnings up to actual taxable maximum				
Non-deceased or disabled at beginning of year attain 62				
Men				
1926-1930	0.0%	0.0%	0.0%	0.0%
1931-1935	0.0%	0.0%	0.0%	0.0%
1936-1940	0.1%	-0.7%	-0.7%	-0.3%
1941-1945	0.0%	-0.4%	1.7%	-0.1%
1946-1950	0.4%	-11.1%	-4.0%	-2.2%
1951-1955	-0.4%	-1.9%	-1.7%	-0.4%
1956-1960	-0.7%	0.4%	2.7%	0.6%
1961-1965	0.3%	4.5%	3.7%	1.5%
Women				
1926-1930	0.0%	0.0%	0.0%	0.0%
1931-1935	0.0%	0.0%	0.0%	0.0%
1936-1940	0.4%	0.1%	1.4%	-0.3%
1941-1945	-0.1%	2.9%	0.4%	0.2%
1946-1950	0.4%	-4.8%	-2.8%	-0.5%
1951-1955	-0.5%	-3.1%	-1.8%	-0.9%
1956-1960	0.7%	1.2%	-2.8%	-0.7%
1961-1965	1.2%	-16.8%	-6.0%	-2.3%

Impact of earnings above the maximum on the earnings distribution. We generated a measure of indexed total lifetime earnings using the vector of "less censored" earnings from 1951 to 1981 and uncapped earnings from 1982 until age 67. Distributions of Average Indexed Monthly Earnings using these new estimates of total earnings are shown in Table 2-35. As expected, mean average total earnings are higher than the mean AIME computed using the basic MINT earnings file. The change is larger for later cohorts who have more years of earnings in the post-1981 period. For men born between 1926 and 1930 (all administrative data) total AIME increases by about 4 percent compared to covered AIME, and for men born between 1961 and 1965, total AIME increases by over 13 percent. The increase in the mean for later cohorts is due to the increase in the number of years with uncapped earnings and not from an increase in high earnings. The share of workers with earnings above the maximum at any given age actually declines somewhat among the later cohorts.

Measures of lifetime earnings inequality also rise when earnings records include earnings above the maximum. For men born between 1961 and 1965, the gini coefficient increases by about 33 percent (from 0.32 to 0.43). Because we do not have a consistent measure of uncapped lifetime earnings for all of the cohorts, cross-cohort comparisons do not make sense.

Table 2-35
Percent Change in the Distribution of Average Indexed Monthly Earnings in Successive Birth Cohorts (AIME Calculation Includes Earnings Above the Tax Max)

Birth Cohort	Mean AIME	90/10 Ratio	80/20 Ratio	Gini coefficient
Non-deceased or disabled at beginning of year attain 62				
Men				
1926-1930	3.9%	3.2%	1.5%	16.3%
1931-1935	6.2%	5.5%	1.1%	22.5%
1936-1940	9.2%	5.8%	-0.2%	32.9%
1941-1945	12.1%	9.4%	6.2%	42.8%
1946-1950	12.9%	-0.8%	0.4%	32.9%
1951-1955	11.1%	10.1%	2.0%	28.7%
1956-1960	9.7%	11.5%	7.2%	29.1%
1961-1965	13.4%	19.3%	7.7%	32.5%
Women				
1926-1930	0.4%	0.0%	0.1%	0.7%
1931-1935	0.4%	0.0%	0.2%	4.0%
1936-1940	1.3%	1.1%	1.4%	2.9%
1941-1945	1.4%	3.8%	0.8%	8.0%
1946-1950	2.5%	-4.2%	-2.3%	7.5%
1951-1955	2.4%	-1.9%	-1.3%	9.9%
1956-1960	4.8%	2.3%	-3.3%	23.1%
1961-1965	4.9%	-16.3%	-5.5%	15.2%

Our measures of mean total earnings also rise for working women, but not as dramatically. For women, mean AIMEs based on uncapped earnings rise by less than half a percent among those born before 1935 and by only about 5 percent for those born after 1956. Earnings inequality as measured by Gini coefficients also increases among women, but the pattern is less consistent than among men. The pattern of inequality changes among women as it is measured by the 90/10 and 80/20 ratios is not particularly consistent or stable.

Summary

Detailed analysis of the earnings patterns generated by the MINT3 matching process suggest that it is producing too few years of earnings at the taxable maximum. The reason appears to lie in the interaction between the earnings adjustments used to link donor and target workers' earnings, the way earnings quintiles are calculated, and the fact that, once sorted into subgroups, the records are picked at random. An alternative that used a different method for calculating quintile boundaries and for selecting the particular matching record seems to have solved the problem of too few years of earnings at the taxable maximum.

Although the problem appeared serious when we arrayed earnings records by the number of years in which earnings hit a certain level, comparing AIMEs produced under the standard procedure with those produced under the alternative procedure suggests that the impact of the asymmetry was not great. Mean AIMEs and measures of the AIME distribution did not change significantly when the correction was made, and the change was not in a consistent direction.

The revised matching methodology produces a more satisfying earnings pattern, even if the quantifiable difference in AIMEs is slight. At some future date, SSA may wish to change the matching algorithm to incorporate the new approach outlined here. However, such a change may require the recalibration of other elements of the MINT3 model before it can be implemented fully.

7. Recommendations

Finite resources and imperfect data both constrained the baseline earnings imputations. The administrative earnings data on the SER is limited to covered earnings. But, the newly available Detailed Earnings file allows us to test the sensitivity of the MINT earnings projections to uncovered employment, self-employment, and earnings above the taxable maximum. We have also tested the sensitivity of the earnings distribution to controls for marital status and immigration. Although the earnings from these sensitivity tests are not incorporated into the final MINT file, our results suggest that modifying the earnings imputation to include some of these new matching constraints could improve the earnings, pension, and wealth distributions. There is one important caveat to the following recommendations. For each of these sensitivity tests, we added the relevant new matching constraints. We have not tested the repercussions of including all the new key variables at once. It may not be possible to match on all of these new characteristics while continuing to match on the detailed earnings profiles.

Marital Status and the Correlation of Spouses' Earnings

While controlling for marital status did not have a significant effect on the overall earnings distribution, it did change the projections of lifetime earnings by marital status. It also allowed us to capture a labor supply response to a marital status transition. Although the percentage of women who divorce during the projection period is relatively small, a greater share of these women will reenter the labor force or significantly increasing their earnings.

Including the husband's earnings as a matching constraint did not increase the correlation between spouses' lifetime earnings. The correlation actually fell slightly in the adjusted projections. In addition to requiring a two step earnings imputation, our control for spousal earnings increased the number of donor pools by a factor of six. We had to sacrifice matching on some of the earnings characteristics in order to match donors with the same level of spousal earnings. While sacrificing matching accuracy to control for spousal earnings may not be worthwhile, controlling for marital status does affect the distribution of earnings by marital status and may be an improvement to future MINT earnings projections.

Immigration

Although controlling for immigrant status does not change the earnings projections, the MINT results are clearly sensitive to the omission of the immigrant population. The absence of immigrants arriving in the U.S. after the SIPP interview biases our projections of the future well-being of the elderly. Immigrants who arrive late in their careers may not have enough covered quarters to qualify for Social Security. By not including this disadvantaged immigrant population, MINT likely understates future poverty rates.

This sensitivity test was a preliminary analysis of the effect of the omission of immigrants on the earnings distribution. While it seems that MINT would benefit from the addition of immigrants, actually adding this population into MINT would be more complicated than simply projecting their earnings. We would need to project marital histories and spouses for these new immigrants. We would also need to modify the pension and wealth projections to account for the absence of baseline SIPP survey information.

Earnings from Uncovered Employment

While the projections of covered earnings and AIME do not appear to be biased without specifically controlling for uncovered earnings, the failure of MINT to project these earnings make it difficult to assess retirement, pension, and wealth accruals for uncovered workers. While lifetime coverage is increasing over time, the model suffers from an omitted variable bias by not having these earnings. Given their availability from the Detailed Earnings file, it seems worthwhile to include these earnings in the projections.

Earnings from Self-Employment

Although controlling for self-employment does not significantly alter the projections of covered earnings and AIME, self-employed individuals do have different pension, retirement, and wealth accrual patterns. Currently MINT assigns self-employment based on observed SIPP self-employment status. We do not project that any individual will become self-employed or return to wage-and-salary work. This simplifying assumption understates the percentage of individuals in later cohorts that will be self-employed for some period of their life. Using the self-employment earnings from the Detailed Earnings file, we can project transitions into and out of self-employment. This new earnings stream would allow us to more accurately project the pensions, retirement patterns, and wealth accruals of this distinct population of workers.

Earnings above the Taxable Maximum

The current earnings projections method does not do a very good job of projecting very high earners. Part of this stems from an imbalance in the adjustment factor used to align target and donor earnings. Part of this stems from a shift in relative earnings across cohorts. If high-earners are of particular interest to policy makers, improving the earnings projections at the top end of the distribution would be beneficial. This will be particularly helpful for evaluating policy options that raising the Social Security taxable limit. Adding earnings above the cap also has implications for retirement, pensions, and private savings. Given the availability of uncapped earnings from the Detailed Earnings file, it seems worthwhile to include it in the projections. This cannot be done, however, without re-estimating some of the behavioral models in MINT: specifically the retirement, pensions, and wealth models.

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APPENDIX A TO CHAPTER 2
QUALITY OF STATISTICAL MATCHES

The quality of our statistical matches is indicated in Appendix Tables A2-1 through A2-4. The best match is achieved if all key variables of the target worker are matched to all key variables of the donor. In the following tables, this level of match is indicated by a "1." In a level-2 match, all of the key variables except the least important one are matched. In a level-3 match, all key variables except the two least important ones are matched.

In Appendix Tables A2-1 and A2-2 we show the success of our matching algorithm for imputations to nondisabled workers. Appendix Tables A2-3 and A2-4 show our success on imputations to disabled workers. Note that up to seven iterations of the imputation procedure are required for members of the youngest birth-year cohort. In particular, seven iterations are required for the youngest cohort, which was born between 1961 and 1965. We show our success in matching donors to target workers in each required iteration. The tabulations in Tables A2-1 through A2-4 refer to the MINT 2.1_C implementation of our splicing methodology. The results obviously differ slightly for the implementations that seek to match different benchmark rates of mortality or disability prevalence.

Key matching variables for persons who ***have not become disabled*** before the 5-year imputation period:

KeyVar1 **Number of years with positive earnings in 5-year matching period:**
Number of years with earnings during the matching period (workers must have earnings equal to at least 2.7% of the economy-wide average age – or one quarter of Social Security earnings credit – to be credited with positive earnings in any year)

0=Zero;
1=One;
2=Two;
3=Three;
4=Four;
5=Five years and earnings below median for age-gender-years of work group;
6= Five years and earnings above median for age-gender-years of work group.

KeyVar2 **Average earnings in 5-year matching period:**

0=Zero;
1=Bottom one-fifth of earners in cohort-gender-years of work group;
2=Second one-fifth of earners in cohort-gender-years of work group;
3=Middle one-fifth of earners in cohort-gender-years of work group;
4=Fourth one-fifth of earners in cohort-gender-years of work group;
5=Top one-fifth of earners in cohort-gender-years of work group.

KeyVar2b **Earnings level:**

0=No earnings in 5-year matching period;
1=Bottom one-fourth of earnings in the target worker's cohort-gender group;
2=Second one-fourth of earnings in the target worker's cohort-gender group;
3=Third one-fourth of earnings in the target worker's cohort-gender group;
4=Top one-fourth of earnings in the target worker's cohort-gender group.

KeyVar3 **Earnings in fifth year:**
0=No;
1=Yes.

KeyVar4 **Earnings in fourth year:**
0=No;
1=Yes.

KeyVar5 **Average earnings before 5-year matching period:**
1= Bottom one-fifth of cohort-gender group;
2= Second one-fifth of cohort-gender group;
3= Middle one-fifth of cohort-gender group;
4= Fourth one-fifth of cohort-gender group;
5= Top one-fifth of cohort-gender group.

KeyVar6 **Race and ethnicity:**
1=White, non-Hispanic;
2=White, Hispanic;
3=Black;
4=Native American;
5=Asian, Pacific Islander.

KeyVar7 **Educational attainment:**
1=Less than high school diploma;
2=High school diploma;
3=Some college;
4=College graduate and post-graduate.

Definition of matching levels for workers who ***have not become disabled*** before the 5-year imputation period:

Level 1 = sex KeyVar1 KeyVar2 KeyVar3 KeyVar4 KeyVar5 KeyVar6 KeyVar7,
Level 2 = sex KeyVar1 KeyVar2 KeyVar3 KeyVar4 KeyVar5 KeyVar6,
Level 3 = sex KeyVar1 KeyVar2 KeyVar3 KeyVar4 KeyVar5,
Level 4 = sex KeyVar1 KeyVar2 KeyVar3 KeyVar4,
Level 5 = sex KeyVar1 KeyVar2 KeyVar3,
Level 6 = sex KeyVar1 KeyVar2,
Level 7 = sex KeyVar1 KeyVar2b KeyVar3 KeyVar4 KeyVar5 KeyVar6 KeyVar7,
Level 8 = sex KeyVar1 KeyVar2b KeyVar3 KeyVar4 KeyVar5 KeyVar6,
Level 9 = sex KeyVar1 KeyVar2b KeyVar3 KeyVar4 KeyVar5,
Level 10 = sex KeyVar1 KeyVar2b KeyVar3 KeyVar4,
Level 11 = sex KeyVar1 KeyVar2b KeyVar3,
Level 12 = sex KeyVar1 KeyVar2b,
Level 13 = sex KeyVar1,
Level 14 = sex.

Key matching variables for persons who ***became disabled at least once*** before the 5-year imputation period:

KeyVar1 **Mental condition**
1=Disability caused by a mental condition
0=Cause of disability not a mental condition

KeyVar2 **Recovered from disability?**
Did the last DI entitlement (relative to the end of the matching period) end in a recovery?
1=Recovered, not currently entitled
0=Still entitled to DI

KeyVar3 **Current entitlement lasted more than 5 years?**
0=No;
1=Yes.

KeyVar4 **Duration of DI entitlement:**
1=DI entitlement 5 years or less;
2=DI entitlement between 6 and 10 years;
3=DI entitlement greater than 10 years.

KeyVar5 **Average earnings since DI entitlement (for those entitled to DI more than 5 years):**
0=Persons whose KeyVar3=0
1=Zero earnings;
2=Earnings less than the median of the non-zero averages of cohort-gender group;
3=Earnings greater than or equal to the non-zero averages of cohort-gender group.

KeyVar6 **Average earnings prior to DI entitlement (for those entitled to DI 5 years or less):**
0=Persons whose KeyVar3=1;
1=Zero earnings;
2=Earnings less than the median of the non-zero averages of cohort-gender group;
3=Earnings greater than or equal to the non-zero averages of cohort-gender group.

KeyVar7 **Educational attainment:**
1=Less than high school diploma;
2=High school diploma;
3=Some college;
4=College graduate and post-graduate.

Definition of matching levels for workers who ***became disabled at least once*** before the 5-year imputation period:

Level 1 = sex KeyVar1 KeyVar2 KeyVar3 KeyVar4 KeyVar5 KeyVar6 KeyVar7,
Level 2 = sex KeyVar1 KeyVar2 KeyVar3 KeyVar4 KeyVar5 KeyVar6,
Level 3 = sex KeyVar1 KeyVar2 KeyVar3 KeyVar4 KeyVar5,
Level 4 = sex KeyVar1 KeyVar2 KeyVar3 KeyVar4,
Level 5 = sex KeyVar1 KeyVar2 KeyVar3,
Level 6 = sex KeyVar1 KeyVar2,
Level 13 = sex KeyVar1,
Level 14 = sex.

Table A2-1
Matching Levels for Men Who Are Not Disabled and Who Have Full Panel Weights a/

Five-year period / Matching level	Birth cohort 1931-35 No. of Obs.	%	1936-40 No. of Obs.	%	1941-45 No. of Obs.	%	1946-50 No. of Obs.	%	1951-55 No. of Obs.	%	1956-60 No. of Obs.	%	1961-65 No. of Obs.	%
2000-04														
1	1,055	75%	2,221	79%	3,058	84%	4,268	85%	4,899	86%	5,231	86%	4,746	89%
2	196	14%	297	11%	329	9%	407	8%	400	7%	418	7%	364	7%
3	83	6%	145	5%	157	4%	237	5%	172	3%	233	4%	170	3%
4	63	4%	111	4%	104	3%	112	2%	89	2%	84	1%	68	1%
5	11	1%	14	1%	12	0%	4	0%	15	0%	3	0%	0	0%
6	3	0%	6	0%	1	0%	4	0%	0	0%	4	0%	0	0%
7	0	0%	0	0%	0	0%	0	0%	93	2%	104	2%	0	0%
8	0	0%	0	0%	0	0%	0	0%	2	0%	0	0%	0	0%
9	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Total	1,411	100%	2,794	100%	3,661	100%	5,032	100%	5,670	100%	6,077	100%	5,348	100%
2005-09														
1			1,159	74%	2,616	78%	3,589	75%	4,218	77%	4,625	78%	4,391	83%
2			226	14%	365	11%	479	10%	432	8%	457	8%	421	8%
3			95	6%	169	5%	206	4%	231	4%	231	4%	171	3%
4			68	4%	131	4%	165	3%	127	2%	107	2%	95	2%
5			10	1%	17	1%	15	0%	16	0%	12	0%	1	0%
6			3	0%	3	0%	1	0%	2	0%	0	0%	1	0%
7			0	0%	62	2%	320	7%	425	8%	475	8%	192	4%
8			0	0%	1	0%	8	0%	3	0%	6	0%	1	0%
9			0	0%	0	0%	3	0%	2	0%	2	0%	0	0%
Total			1,561	100%	3,364	100%	4,786	100%	5,456	100%	5,915	100%	5,273	100%
2010-14														
1					1,302	71%	3,252	74%	3,837	74%	4,262	74%	4,000	78%
2					306	17%	540	12%	512	10%	541	9%	400	8%
3					119	6%	255	6%	249	5%	275	5%	220	4%
4					90	5%	191	4%	168	3%	136	2%	77	1%
5					12	1%	23	1%	20	0%	10	0%	9	0%
6					3	0%	4	0%	3	0%	3	0%	0	0%
7					0	0%	135	3%	372	7%	487	9%	434	8%
8					0	0%	3	0%	24	0%	6	0%	2	0%
9					0	0%	0	0%	0	0%	2	0%	0	0%
Total					1,832	100%	4,403	100%	5,185	100%	5,722	100%	5,142	100%

Table A2-1 (cont.)

Five-year period / Matching level	Birth cohort 1931-35 No. of Obs.	%	1936-40 No. of Obs.	%	1941-45 No. of Obs.	%	1946-50 No. of Obs.	%	1951-55 No. of Obs.	%	1956-60 No. of Obs.	%	1961-65 No. of Obs.	%
2015-19														
1							1,651	69%	3,474	73%	3,950	73%	3,725	75%
2							426	18%	604	13%	527	10%	444	9%
3							194	8%	281	6%	278	5%	267	5%
4							113	5%	215	5%	198	4%	112	2%
5							23	1%	20	0%	31	1%	11	0%
6							2	0%	3	0%	4	0%	3	0%
7							0	0%	135	3%	404	7%	406	8%
8							0	0%	2	0%	23	0%	7	0%
9							0	0%	0	0%	2	0%	1	0%
Total							2,409	100%	4,734	100%	5,417	100%	4,976	100%
2020-24														
1									1,823	70%	3,550	72%	3,437	73%
2									435	17%	636	13%	476	10%
3									196	8%	372	8%	225	5%
4									116	4%	200	4%	163	3%
5									19	1%	26	1%	15	0%
6									6	0%	10	0%	3	0%
7									0	0%	135	3%	336	7%
8									0	0%	6	0%	23	0%
9									0	0%	0	0%	2	0%
Total									2,595	100%	4,935	100%	4,680	100%
2025-29														
1											1,893	69%	3,106	73%
2											429	16%	527	12%
3											240	9%	296	7%
4											134	5%	185	4%
5											24	1%	20	0%
6											9	0%	5	0%
7											0	0%	112	3%
8											0	0%	5	0%
9											0	0%	1	0%
Total											2,729	100%	4,257	100%
2030-34														
1													1,546	68%
2													376	17%
3													214	9%
4													103	5%
5													16	1%
6													4	0%
7													0	0%
8													0	0%
9													0	0%
Total													2,259	100%

a/ In each successive five-year period, the sample consists of sample members who are not disabled at the beginning of the period.

Table A2-2
Matching Levels for Women Who Are Not Disabled and Who Have Full Panel Weights a/

Five-year period / Matching level	Birth cohort													
	1931-35		1936-40		1941-45		1946-50		1951-55		1956-60		1961-65	
	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%
2000-04														
1	1,055	75%	2,221	79%	3,058	84%	4,268	85%	4,899	86%	5,231	86%	4,746	89%
2	196	14%	297	11%	329	9%	407	8%	400	7%	418	7%	364	7%
3	83	6%	145	5%	157	4%	237	5%	172	3%	233	4%	170	3%
4	63	4%	111	4%	104	3%	112	2%	89	2%	84	1%	68	1%
5	11	1%	14	1%	12	0%	4	0%	15	0%	3	0%	0	0%
6	3	0%	6	0%	1	0%	4	0%	0	0%	4	0%	0	0%
7	0	0%	0	0%	0	0%	0	0%	93	2%	104	2%	0	0%
8	0	0%	0	0%	0	0%	0	0%	2	0%	0	0%	0	0%
9	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Total	1,411	100%	2,794	100%	3,661	100%	5,032	100%	5,670	100%	6,077	100%	5,348	100%
2005-09														
1			1,159	74%	2,616	78%	3,589	75%	4,218	77%	4,625	78%	4,391	83%
2			226	14%	365	11%	479	10%	432	8%	457	8%	421	8%
3			95	6%	169	5%	206	4%	231	4%	231	4%	171	3%
4			68	4%	131	4%	165	3%	127	2%	107	2%	95	2%
5			10	1%	17	1%	15	0%	16	0%	12	0%	1	0%
6			3	0%	3	0%	1	0%	2	0%	0	0%	1	0%
7			0	0%	62	2%	320	7%	425	8%	475	8%	192	4%
8			0	0%	1	0%	8	0%	3	0%	6	0%	1	0%
9			0	0%	0	0%	3	0%	2	0%	2	0%	0	0%
Total			1,561	100%	3,364	100%	4,786	100%	5,456	100%	5,915	100%	5,273	100%
2010-14														
1					1,302	71%	3,252	74%	3,837	74%	4,262	74%	4,000	78%
2					306	17%	540	12%	512	10%	541	9%	400	8%
3					119	6%	255	6%	249	5%	275	5%	220	4%
4					90	5%	191	4%	168	3%	136	2%	77	1%
5					12	1%	23	1%	20	0%	10	0%	9	0%
6					3	0%	4	0%	3	0%	3	0%	0	0%
7					0	0%	135	3%	372	7%	487	9%	434	8%
8					0	0%	3	0%	24	0%	6	0%	2	0%
9					0	0%	0	0%	0	0%	2	0%	0	0%
Total					1,832	100%	4,403	100%	5,185	100%	5,722	100%	5,142	100%

Table A2-2 (cont.)

Five-year period / Matching level	Birth cohort													
	1931-35		1936-40		1941-45		1946-50		1951-55		1956-60		1961-65	
	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%
2015-19														
1							2,038	72%	4,047	74%	4,798	76%	4,830	81%
2							444	16%	754	14%	750	12%	608	10%
3							221	8%	379	7%	455	7%	383	6%
4							127	4%	242	4%	294	5%	112	2%
5							14	0%	20	0%	8	0%	8	0%
6							5	0%	5	0%	0	0%	0	0%
7							0	0%	0	0%	0	0%	0	0%
8							0	0%	0	0%	0	0%	0	0%
9							0	0%	0	0%	0	0%	0	0%
Total							2,849	100%	5,447	100%	6,305	100%	5,941	100%
2020-24														
1									2,211	72%	4,325	73%	4,290	76%
2									443	14%	843	14%	742	13%
3									246	8%	432	7%	386	7%
4									167	5%	272	5%	250	4%
5									14	0%	12	0%	8	0%
6									5	0%	8	0%	0	0%
7									0	0%	0	0%	0	0%
8									0	0%	0	0%	0	0%
9									0	0%	0	0%	0	0%
Total									3,086	100%	5,892	100%	5,676	100%
2025-29														
1											2,376	71%	3,854	73%
2											479	14%	751	14%
3											302	9%	400	8%
4											159	5%	271	5%
5											12	0%	28	1%
6											9	0%	2	0%
7											0	0%	0	0%
8											0	0%	0	0%
9											0	0%	0	0%
Total											3,337	100%	5,306	100%
2030-34														
1													2,009	70%
2													442	15%
3													243	8%
4													163	6%
5													13	0%
6													3	0%
7													0	0%
8													0	0%
9													0	0%
Total													2,873	100%

a/ In each successive five-year period, the sample consists of sample members who are not disabled at the beginning of the period.

Table A2-3
Matching Levels for Men Who Are Disabled in 1999 or Successive Years and Who Have Full Panel Weights a/

Five-year period / Matching level	Birth cohort													
	1931-35		1936-40		1941-45		1946-50		1951-55		1956-60		1961-65	
	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%
2000-04														
1	234	94%	343	87%	249	84%	228	83%	157	79%	112	70%	66	63%
2	12	5%	34	9%	34	12%	32	12%	29	15%	36	22%	22	21%
3	0	0%	5	1%	0	0%	2	1%	4	2%	2	1%	1	1%
4	3	1%	10	3%	6	2%	9	3%	6	3%	5	3%	13	13%
5	0	0%	1	0%	1	0%	0	0%	4	2%	1	1%	1	1%
6	0	0%	3	1%	3	1%	2	1%	0	0%	0	0%	1	1%
13	1	0%	0	0%	2	1%	1	0%	0	0%	5	3%	0	0%
Total	250	100%	396	100%	295	100%	274	100%	200	100%	161	100%	104	100%
2005-09														
1			171	75%	324	86%	276	83%	218	79%	168	77%	91	76%
2			18	8%	34	9%	44	13%	47	17%	30	14%	22	18%
3			1	0%	2	1%	0	0%	1	0%	2	1%	0	0%
4			4	2%	11	3%	8	2%	9	3%	16	7%	4	3%
5			0	0%	0	0%	0	0%	0	0%	1	0%	3	3%
6			0	0%	0	0%	2	1%	1	0%	1	0%	0	0%
13			33	15%	4	1%	2	1%	0	0%	0	0%	0	0%
Total			227	100%	375	100%	332	100%	276	100%	218	100%	120	100%
2010-14														
1					167	59%	400	85%	281	77%	230	80%	140	82%
2					11	4%	46	10%	65	18%	44	15%	22	13%
3					0	0%	9	2%	2	1%	3	1%	3	2%
4					7	2%	11	2%	11	3%	10	3%	4	2%
5					0	0%	0	0%	1	0%	1	0%	0	0%
6					0	0%	0	0%	3	1%	0	0%	1	1%
13					99	35%	2	0%	4	1%	1	0%	0	0%
Total					284	100%	468	100%	367	100%	289	100%	170	100%

Table A2-3 (cont.)

Five-year period / Matching level	Birth cohort 1931-35 No. of Obs.	%	1936-40 No. of Obs.	%	1941-45 No. of Obs.	%	1946-50 No. of Obs.	%	1951-55 No. of Obs.	%	1956-60 No. of Obs.	%	1961-65 No. of Obs.	%
2015-19														
1							218	61%	454	81%	325	77%	190	82%
2							30	8%	91	16%	73	17%	34	15%
3							0	0%	3	1%	0	0%	0	0%
4							3	1%	9	2%	19	5%	8	3%
5							0	0%	0	0%	0	0%	0	0%
6							0	0%	1	0%	3	1%	1	0%
13							107	30%	4	1%	1	0%	0	0%
Total							358	100%	562	100%	421	100%	233	100%
2020-24														
1									248	57%	533	84%	306	78%
2									39	9%	81	13%	69	18%
3									0	0%	4	1%	3	1%
4									1	0%	17	3%	12	3%
5									0	0%	0	0%	0	0%
6									0	0%	1	0%	3	1%
13									144	33%	1	0%	0	0%
Total									432	100%	637	100%	393	100%
2025-29														
1											216	44%	500	83%
2											24	5%	84	14%
3											1	0%	2	0%
4											1	0%	14	2%
5											0	0%	0	0%
6											0	0%	3	0%
13											249	51%	0	0%
Total											491	100%	603	100%
2030-34														
1													145	33%
2													25	6%
3													0	0%
4													1	0%
5													0	0%
6													0	0%
13													263	61%
Total													434	100%

a/ In each successive five-year period, the sample consists of sample members who are disabled at the beginning of the period.

Table A2-4
Matching Levels for Men Who Are Disabled in 1999 or Successive Years and Who Have Full Panel Weights a/

Five-year period / Matching level	Birth cohort 1931-35 No. of Obs.	%	1936-40 No. of Obs.	%	1941-45 No. of Obs.	%	1946-50 No. of Obs.	%	1951-55 No. of Obs.	%	1956-60 No. of Obs.	%	1961-65 No. of Obs.	%
2000-04														
1	140	90%	272	85%	247	83%	179	75%	123	76%	100	72%	54	60%
2	10	6%	29	9%	27	9%	38	16%	26	16%	20	14%	26	29%
3	3	2%	0	0%	0	0%	1	0%	2	1%	0	0%	1	1%
4	1	1%	3	1%	16	5%	9	4%	6	4%	9	7%	8	9%
5	1	1%	11	3%	7	2%	9	4%	2	1%	4	3%	0	0%
6	0	0%	2	1%	1	0%	1	0%	2	1%	0	0%	1	1%
13	1	1%	2	1%	0	0%	1	0%	0	0%	5	4%	0	0%
Total	156	100%	319	100%	298	100%	238	100%	161	100%	138	100%	90	100%
2005-09														
1			136	79%	267	82%	226	76%	157	72%	136	71%	70	59%
2			19	11%	28	9%	41	14%	40	18%	40	21%	30	25%
3			0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
4			2	1%	7	2%	18	6%	11	5%	9	5%	14	12%
5			0	0%	20	6%	10	3%	9	4%	6	3%	2	2%
6			0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
13			16	9%	4	1%	3	1%	0	0%	1	1%	3	3%
8			0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
9			0	0%	0	0%	0	0%	0	0%	0	0%	0	0%
Total			173	100%	326	100%	298	100%	217	100%	192	100%	119	100%
2010-14														
1					140	59%	350	79%	269	76%	184	65%	138	72%
2					29	12%	51	12%	53	15%	69	24%	38	20%
3					1	0%	0	0%	0	0%	0	0%	1	1%
4					2	1%	13	3%	19	5%	8	3%	12	6%
5					0	0%	23	5%	13	4%	12	4%	0	0%
6					0	0%	1	0%	0	0%	1	0%	1	1%
13					64	27%	3	1%	0	0%	11	4%	3	2%
Total					236	100%	441	100%	354	100%	285	100%	193	100%

Table A2-4 (cont.)

Five-year period / Matching level	Birth cohort													
	1931-35		1936-40		1941-45		1946-50		1951-55		1956-60		1961-65	
	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%	No. of Obs.	%
2015-19														
1							193	57%	418	79%	328	74%	201	69%
2							35	10%	73	14%	57	13%	59	20%
3							1	0%	0	0%	0	0%	0	0%
4							1	0%	14	3%	25	6%	10	3%
5							1	0%	27	5%	21	5%	13	4%
6							0	0%	0	0%	1	0%	2	1%
13							105	31%	0	0%	10	2%	6	2%
Total							336	100%	532	100%	442	100%	291	100%
2020-24														
1									213	56%	491	77%	325	74%
2									33	9%	83	13%	56	13%
3									5	1%	0	0%	0	0%
4									1	0%	16	3%	25	6%
5									0	0%	38	6%	23	5%
6									0	0%	0	0%	0	0%
13									131	34%	8	1%	8	2%
Total									383	100%	636	100%	437	100%
2025-29														
1											146	33%	471	76%
2											37	8%	78	13%
3											6	1%	0	0%
4											1	0%	12	2%
5											0	0%	52	8%
6											0	0%	0	0%
13											255	57%	8	1%
Total											445	100%	621	100%
2030-34														
1													105	26%
2													18	4%
3													0	0%
4													1	0%
5													0	0%
6													0	0%
13													279	69%
Total													403	100%

a/ In each successive five-year period, the sample consists of sample members who are disabled at the beginning of the period.

CHAPTER 3

OPTIONS FOR PROJECTING JOB DEMANDS AND HEALTH STATUS

This chapter describes how we incorporate the health and job demands of workers in MINT3 in order to predict retirement behavior. We expected that workers with more physically demanding jobs would retire earlier than workers with less demanding jobs. However, our estimates indicate that job demands have only small and often insignificant effects on retirement behavior, controlling for the health, wealth, pension coverage, and demographic characteristics of the worker. In light of these findings, we and the Social Security Administration (SSA) Task Manager agreed that job demands should not be imputed to workers in MINT3. We did, however, project health status of workers in the MINT3 sample. In Section I of this chapter, we describe our methods and findings on the relationship between job demands and retirement behavior. In Section II, we describe our methods and results for projecting health status and summarize the results of the projections.

I. PROJECTING JOB DEMANDS

1. Measuring Job Demands

The analysis of job demands was based on data from the Health and Retirement Study (HRS), a nationally representative longitudinal survey of noninstitutionalized Americans born between 1931 and 1941. Baseline interviews were conducted in 1992, when respondents were ages 51-61. Respondents have now been interviewed every other year through 1998, so that each respondent has been observed up to four times. Interviews were completed for 9,825 respondents in 1992, 8,843 respondents in 1994, 8,471 respondents in 1996, and 8,232 in 1998. At each wave, respondents were questioned about their hours of work, health, pension coverage, marital status, and other characteristics.

At the baseline interview, employed respondents were asked a series of questions about their job requirements. They indicated how often their jobs required different activities, such as substantial physical effort, intense concentration, maintaining the pace set by others, and learning new things. The full set of questions and the percentage distribution of responses are reported in Table 3-1. About 22 percent of employed respondents reported that their jobs required substantial physical effort all or almost all of the time, while another 18 percent reported that their jobs required substantial physical effort most of the time. About 31 percent reported that their jobs never or almost never required much physical effort. One half of workers reported that their jobs required intense concentration or attention all or almost all of the time. Only 2 percent of workers claimed that their jobs never (or almost never) required intense concentration. One in five workers strongly agreed with the statement that their job involved a considerable amount of stress; only 4 percent strongly disagreed.

Table 3-1
Percentage Distribution of Job Demands for Full-Time Workers Ages 51-61

Job Requirements	None or almost none of the time	Some of the time	Most of the time	All or almost all of the time
	Frequency			
Lots of physical effort	30.5	30.0	17.7	21.8
Lifting heavy loads	55.2	28.9	7.5	8.5
Stooping, kneeling, or crouching	35.8	38.4	13.1	12.8
Good eyesight	2.9	7.7	36.1	53.3
Intense concentration or attention	2.1	11.6	37.6	48.7
Skill in dealing with other people	2.8	10.1	24.4	62.7
Work with computers	48.6	20.1	10.6	20.7
Analysis of data or information	32.2	22.9	19.8	25.2
Maintaining pace set by others	27.4	18.2	24.5	29.9
Doing the same things over and over	11.0	28.1	26.7	34.2
Learning new things	9.2	37.9	26.1	26.8
	Strongly Disagree	**Disagree**	**Agree**	**Strongly Agree**
Job requires very good memory	0.9	6.6	62.2	30.2
Job involves a lot of stress	3.6	31.0	44.6	20.8

Note: The sample is restricted to 4,970 full-time workers ages 51 – 61 in 1992 in the first wave of the Health and Retirement Study (HRS). Estimates are weighted to reflect the sampling design of the HRS.

Source: Urban Institute tabulations from the 1992 wave of the HRS.

Because responses to many of the questions about job requirements are correlated with each other, multicollinearity problems can arise if all of the responses are included in a single retirement model. To reduce the number of different measures in our analysis, we used factor analysis to create aggregate measures of jobs demands. Factor analysis assumes that the observed responses are linear combinations of some underlying, unobservable factors. It uncovers a small number of common factors that linearly reconstruct the larger number of original variables.

We used factor analysis to create an aggregate measure of physical job demands and an aggregate measure of cognitive job demands. The index of physical demands was constructed as a combination of responses to questions about how often jobs required exerting much physical effort, lifting heavy loads, and stooping, kneeling, or crouching. Each response contributed about equally to the aggregate index. The index of cognitive demands was constructed as a combination of responses to questions about how often jobs required intense concentration or attention, work with computers, analysis of data or information, and learning new things, and whether the job required a very good memory. The contributions of each response to the aggregate index were similar, with the question about the analysis of data or information contributing the most to the index. Both indexes were constructed so that higher scores indicated greater job demands.

Table 3-2 presents measures of job demands by gender, education, and race. The first data column reports the percentage of full-time workers who responded that their jobs required much physical effort all or almost all of the time. The second column reports the percentage who responded that their jobs required much physical effort none or almost none of the time. The third column reports the mean score for the physical demands index and the last column reports the mean score for the cognitive demands index. Higher scores indicate greater job demands. As expected, full-time workers with higher levels of education reported lower physical job demands and higher cognitive demands than full-time workers with less schooling. For example, the percentage of men working full-time who reported that their jobs almost always required much physical effort fell from 38 percent among high school dropouts to 5 percent among college graduates. At the same time, the mean score for the cognitive demands index was –0.473 among male high school dropouts working full time, compared with 0.353 among college graduates. Within educational groups, physical job demands were similar for men and women, except that women who completed four or more years of college reported higher physical demands than men who completed college. Women also reported greater cognitive job demands than men, except among high school dropouts. For both men and women, whites reported lower physical job demands and higher cognitive job demands than blacks and Hispanics.

2. Modeling the Retirement Decision

To examine the impact of job demands on the decision to withdraw from the labor force, we estimated multivariate models of retirement behavior. We assumed that every worker has an underlying propensity to leave the labor force, which we modeled as a function of demographics, health, wealth, pension coverage, and job demands:

$$D_{it}^* = \alpha + X_{it}\beta + \varepsilon_{it} \qquad \textbf{(3-1)}$$

where D_{it}^* is the propensity of worker i to retire at the end of period t, X_{it} is a vector of variables thought to influence the retirement decision, and ε_{it} is a random disturbance term. D_{it}^* is not observed; instead we observe a dummy variable D_{it} which equals one if D_{it}^* exceeds some threshold (normalized to zero) and zero otherwise. Thus, the probability that we observe a departure from the career job is equal to $1 - F(-\alpha - X_{it}B)$, where F is the cumulative distribution function for ε.

Table 3-2: Measures of Job Demands by Gender, Education, and Race
(Standard deviations are in parentheses)

	Pct. with jobs requiring much physical effort all or almost all of the time	Pct. with jobs requiring much physical effort none or almost none of the time	Mean Physical Demands Index	Mean Cognitive Demands Index
ALL	21.8	30.5	0.012	–0.013
	(41.3)	(46.0)	(.881)	(.815)
MEN				
All	22.1	29.0	0.076	–0.064
	(41.5)	(45.4)	(.913)	(.785)
Not high school grad	37.9	12.3	0.527	–0.473
	(48.5)	(32.8)	(.900)	(.723)
High school grad	26.7	17.1	0.322	–0.194
	(44.3)	(37.7)	(.890)	(.723)
Some college	15.1	36.3	–0.117	0.148
	(35.9)	(48.1)	(.819)	(.782)
3 College graduate	5.3	56.2	–0.562	0.353
	(22.4)	(49.7)	(.572)	(.665)
White	18.9	31.8	0.003	–0.001
	(39.1)	(46.6)	(.889)	(.770)
Black	34.2	18.6	0.278	–0.261
	(47.5)	(39.0)	(.935)	(.775)
Hispanic	34.0	18.1	0.460	–0.359
	(47.5)	(38.6)	(.964)	(.829)
WOMEN				
All	21.4	32.6	–0.074	0.056
	(41.0)	(46.9)	(.828)	(.850)
Not high school grad	40.9	12.4	0.379	–0.546
	(49.2)	(33.0)	(.872)	(.697)
High school grad	17.0	37.4	–0.163	0.069
	(37.6)	(48.4)	(.799)	(.856)
Some college	15.9	41.6	–0.226	0.326
	(36.6)	(49.4)	(.785)	(.794)
College graduate	12.9	37.1	–0.269	0.436
	(33.6)	(48.4)	(.674)	(.658)
White	18.4	36.1	–0.127	0.154
	(38.8)	(48.1)	(.820)	(.826)
Black	28.6	23.4	0.064	–0.183
	(45.3)	(42.4)	(.823)	(.873)
Hispanic	31.2	22.3	0.079	–0.279
	(46.5)	(41.8)	(.872)	(.808)

Note: The sample is restricted to full-time workers ages 51 – 61 in 1992 in the first wave of the Health and Retirement Study (HRS). There are 2,108 men and 2,862 women. Estimates are weighted to reflect the sampling design of the HRS.
Source: Urban Institute tabulations from the 1992 wave of the HRS.

For each respondent in the sample, we created a separate record for each year he or she remains in the labor force. Each time respondents were observed at work, we observed whether or not they left employment in the next period. Once workers retired, they were dropped from the panel. Under the assumption that ε follows a normal distribution, we can estimate the parameters of Equation 3-1 as a probit model. Thus, we estimated a probit model of retirement on a sample of person-year observations, restricted to those who were working for pay at the beginning of the period. We defined retirement as reporting zero hours of work at the time of the survey interview. We estimated the model separately for men and women. The sample was restricted to persons who were working full time for pay at the time of the baseline interview.

We modeled the retirement decision as a function of a number of characteristics of workers. We included in the equation measures of education, marital status, race, age, self-reported health status, the number of physical impairments, defined benefit pension coverage on the current job, defined contribution pension coverage on the current job, the level of financial assets held by the household at the time of the baseline interview, and baseline job demands. (Unless otherwise indicated, all variables were measured at the time of the interview.) We considered five alternative ways of specifying the impact of job demands. The model was first estimated with an indicator for whether the job required physical effort all (or almost all) of the time, and then with an indicator for whether the job required physical effort none (or almost none) of the time. In an alternative specification, we included the physical demands index score in the model instead of the indicator variables. We then replaced the physical demands score with the cognitive demands index score. Finally, we included both the physical and cognitive demand scores in the model.

3. Results

Table 3-3 reports marginal effects of job demands and personal characteristics on retirement decisions for men, as estimated by our model. Standard errors are reported in parentheses. Asterisks denote effects that differ significantly from zero. We found that job demands did not have significant effects on labor force withdrawals for men, controlling for education, health, pension coverage, age, and other personal characteristics. Men who reported that their jobs never (or almost never) required much physical effort were less likely to retire than other men, as expected, but the effects were not significant. Men who reported that their jobs required physical effort all of the time were also somewhat less likely to retire than other men, contrary to our expectations, but again the results were insignificant. Men were somewhat more likely to retire as the physical and cognitive demands they faced on the job increased, according to the index score, but the effects were small and insignificant.

The estimated effects of other characteristics on retirement decisions for men were generally consistent with other findings. Retirement was positively and significantly related to age, poor health, number of physical impairments, and participation in defined benefit pension plans. Widowed and divorced men were significantly more likely to retire than other men, whereas those who attended college were less likely to retire. Black and Hispanic men in our sample were also more likely to retire than white men, but the differences were only marginally significant.

Table 3-4 reports marginal effects of job demands on retirement decisions for women. Unlike men, women in our sample who reported high physical demands on the job were significantly more likely to retire than those who reported fewer physical demands, controlling for other personal characteristics. However, the effects were not large. Women who reported that their jobs never required much physical effort were 2.9 percent less likely to retire than those who reported that much

Table 3-3
Marginal Effects of Job Demands and Personal Characteristics on Men's Retirement Decisions

	(1)	(2)	(3)	(4)	(5)
Job requires physical effort all the time	–0.002 (.012)	…	…	…	…
Job requires physical effort none of the time	…	–0.015 (.011)	…	…	…
Physical demands index	…	…	0.002 (.006)	…	0.003 (.006)
Cognitive demands index	…	…	…	0.003 (.007)	0.003 (.007)
Age	0.020** (.001)	0.020** (.001)	0.020** (.001)	0.021** (.001)	0.021** (.001)
Education					
Not high school graduate	0.014 (.014)	0.013 (.013)	0.013 (.014)	0.014 (.014)	0.014 (.014)
High school graduate	…	…	…	…	…
Some college	–0.030* (.013)	–0.027* (.013)	–0.029* (.013)	–0.029* (.013)	–0.028** (.013)
College graduate	–0.037** (.013)	–0.032* (.013)	–0.035* (.013)	–0.037** (.013)	–0.035** (.014)
Race					
Black	0.028± (.016)	0.027± (.016)	0.027± (.016)	0.029± (.016)	0.029± (.016)
Hispanic	0.035± (.019)	0.035± (.019)	0.033± (.019)	0.038* (.020)	0.036± (.020)
White or other	…	…	…	…	…
Marital Status					
Currently married	…	…	…	…	…
Widowed	0.141** (.049)	0.140** (.048)	0.140** (.049)	0.139** (.048)	0.138** (.048)
Divorced	0.045* (.018)	0.044* (.018)	0.045* (.018)	0.049** (.019)	0.048** (.019)
Never married	0.041 (.032)	0.042 (.032)	0.041 (.032)	0.040 (.032)	0.040 (.032)

(Continued)

Table 3-3 (continued)

	(1)	(2)	(3)	(4)	(5)
Health Status					
Excellent	…	…	…	…	…
Very Good	–0.002 (.013)	–0.003 (.013)	–0.002 (.013)	–0.003 (.013)	–0.003 (.013)
Good	0.012 (.014)	0.011 (.014)	0.012 (.014)	0.012 (.014)	0.012 (.014)
Fair	0.059** (.021)	0.058** (.021)	0.059** (.021)	0.057** (.021)	0.057** (.021)
Poor	0.208** (.048)	0.208** (.048)	0.209** (.048)	0.210** (.048)	0.211** (.048)
Physical impairments	0.008** (.002)	0.008** (.003)	0.008** (.003)	0.008** (.003)	0.008** (.003)
Financial wealth	0.0003 (.002)	0.0005 (.002)	0.0004 (.003)	0.0001 (.003)	0.0001 (.003)
Defined benefit plan	0.064** (.010)	0.065** (.010)	0.064** (.010)	0.064** (.010)	0.064** (.010)
Defined contribution	–0.019± (.010)	–0.018± (.010)	–0.020± (.010)	–0.020± (.010)	–0.020± (.010)
Log-likelihood	–3399.5	–3398.7	–3395.0	–3369.8	–3365.2
Pseudo r-squared	0.053	0.053	0.053	0.053	0.053

Note: Standard errors are in parentheses. The sample is restricted to 2,108 men ages 51-61 working full time at the time of the baseline survey of the Health and Retirement Study (HRS).

** = p < .01; * = p < .05; ± = p < .10

Source: Urban Institute computations from the 1992-1998 waves of the HRS.

Table 3-4
Marginal Effects of Job Demands and Personal Characteristics on Women's Retirement Decisions

	(1)	(2)	(3)	(4)	(5)
Job requires physical effort all the time	0.004 (.015)	…	…	…	…
Job requires physical effort none of the time	…	–0.029* (.012)	…	…	…
Physical demands index	…	…	0.013± (.007)	…	0.015* (.007)
Cognitive demands index	…	…	…	0.007 (.008)	0.009 (.008)
Age	0.019** (.002)	0.020** (.002)	0.020** (.002)	0.020** (.002)	0.020** (.002)
Education					
Not high school graduate	0.027 (.017)	0.022 (.017)	0.021 (.017)	0.030 (.018)	0.023 (.018)
High school graduate	…	…	…	…	…
Some college	–0.018 (.015)	–0.017 (.016)	–0.017 (.016)	–0.020 (.016)	–0.020 (.016)
College graduate	0.002 (.017)	0.001 (.017)	0.003 (.017)	–0.001 (.017)	–0.001 (.017)
Race					
Black	0.023 (.016)	0.021 (.016)	0.022 (.016)	0.025 (.016)	0.025 (.016)
Hispanic	0.024 (.024)	0.023 (.024)	0.025 (.025)	0.027 (.025)	0.027 (.025)
White or other	…	…	…	…	…
Marital Status					
Currently married	…	…	…	…	…
Widowed	–0.045* (.017)	–0.047** (.017)	–0.047** (.017)	–0.041* (.017)	–0.043* (.017)
Divorced	–0.034* (.014)	–0.035* (.014)	–0.034* (.014)	–0.034* (.014)	–0.034* (.014)
Never married	–0.032 (.026)	–0.032 (.026)	–0.032 (.026)	–0.029 (.027)	–0.030 (.027)

(Continued)

Table 3-4 (continued)

	(1)	(2)	(3)	(4)	(5)
Health Status					
Excellent	…	…	…	…	…
Very Good	–0.011 (.016)	–0.012 (.016)	–0.011 (.016)	–0.011 (.016)	–0.010 (.016)
Good	0.002 (.017)	–0.001 (.017)	0.001 (.017)	0.003 (.017)	0.003 (.017)
Fair	0.067** (.026)	0.065** (.026)	0.064** (.026)	0.068** (.026)	0.065** (.026)
Poor	0.155** (.060)	0.153** (.060)	0.155** (.060)	0.157** (.061)	0.157** (.061)
Physical impairments	0.010** (.003)	0.010** (.003)	0.010** (.003)	0.009** (.003)	0.009** (.003)
Financial wealth ($10,000)	–0.0002 (.005)	–0.0002 (.005)	0.00001 (.005)	–0.0004 (.005)	–0.0001 (.005)
Defined benefit pension plan	0.017 (.012)	0.018 (.012)	0.018 (.012)	0.013 (.013)	0.014 (.013)
Defined contribution pension plan	–0.033* (.012)	–0.031* (.012)	–0.032* (.012)	–0.036** (.013)	–0.035** (.013)
Log-likelihood	–2592.0	–2589.5	–2585.9	–2567.4	–2560.9
Pseudo r-squared	0.042	0.043	0.042	0.041	0.041

Note: Standard errors are in parentheses. The sample is restricted to 2,862 women ages 51-61 working full time at the time of the baseline survey of the Health and Retirement Study (HRS).

** = $p < .01$; * = $p < .05$; ± = $p < .10$

Source: Urban Institute computations from the 1992-1998 waves of the HRS.

physical effort was required at least some of the time.[1] (See column 2). By comparison, women who reported poor health were 15 percent more likely to retire than those who reported excellent health. Retirement probabilities also increased significantly with the physical demands score on the current job. We found no evidence that cognitive job demands affected retirement probabilities for women.

Other variables in our model affected women's retirement behavior in predictable ways. Age, self-reported poor health, and physical impairments significantly increased retirement rates. Unmarried women were less likely to retire than married women, although the differences were significant only for widowed and divorced women, not for never married women. There were no significant differences in women's retirement rates by education, race, or participation in defined benefit pension plans.

II. PROJECTING HEALTH STATUS

1. Data and Estimation

Two sets of health variables have been created for the MINT sample. The first is a 3 category measure of work limitation. The variables L3_51-L3_67 represent work limitation status at each age from 51 to 67. They are coded 0 for persons who do not report an impairment or health problem that limits the kind or amount of paid work they can do; 1 for persons who report such a limitation, but do not report that the limitation prevents them from working at all; and 2 for persons who report a limitation and report that it prevents them from working.

The second set of variables are binary indicators of whether the MINT sample person will report themselves to be in fair or poor health. The variables H2_51-H2_67 are coded 0 if the individual classifies their health as "excellent," "very good," or "good" and 1 if the individual's health rating is "fair," or "poor."

Estimating Health Status at Age 51

These variables were created in two steps. First, health status at age 51 (L3_51 and H2_51) was projected for each person in the MINT database based on parameter estimates derived from the Health and Retirement Study. The models we employ include basic demographic variables (age, race, sex) as well as variables indicating level of schooling, earnings history and whether the respondent will die by age 53 or 55. In general, we find that whites and Asians report better health than other racial/ethnic groups, males report better health than females, and health declines with age. We also find that persons with more education report better health than those with less education, persons with higher average earnings from ages 26-50 report better health than those with low earnings, and those with more positive age-earnings profiles (larger average earnings at ages 46-50 than between 26 and 50) are in better health than those with flatter or negative profiles. These estimates are shown in tables 3-5 and 3-6. For each individual we calculate a predicted probability of each health state:

[1] However, as reported in column 1, women who reported that their jobs required much physical effort all the time were no more likely to retire than women who reported that their jobs required less frequent physical effort.

Table 3-5
Multinomial Logit Model of Work Limitation/Disability Status

	Coefficient	*Std. Error*	z
Limited			
Age	0.019	0.013	1.49
Average Earnings, 26-50	-0.096	0.082	-1.16
Added Earnings, 46-50	-0.774	0.124	-6.22
Male	-0.064	0.086	-0.75
Dropout	-0.080	0.104	-0.77
College	-0.377	0.115	-3.28
Black	-0.331	0.130	-2.55
Other	0.588	0.357	1.65
Asian	0.066	0.406	0.16
Hispanic	-0.360	0.173	-2.09
Two-year survival	-1.057	0.439	-2.41
Four-year survival	-0.120	0.327	-0.37
Constant	-1.719	0.801	-2.15
Unable			
Age	0.054	0.012	4.36
Average Earnings, 26-50	-0.894	0.095	-9.42
Added Earnings, 46-50	-1.847	0.138	-13.37
Male	-0.473	0.087	-5.44
Dropout	0.760	0.084	9.01
College	-1.231	0.176	-6.98
Black	0.496	0.096	5.16
Other	0.464	0.362	1.28
Asian	-0.653	0.629	-1.04
Hispanic	0.136	0.127	1.07
Two-year survival	-0.846	0.313	-2.70
Four-year survival	-1.370	0.214	-6.42
Constant	-2.371	0.751	-3.16
Ln(L)		-4384	
$\chi^2(24)$		1026	
N		7343	

Table 3-6
Logit Model of Fair/Poor Health Status

	Coefficient	***Std. Error***	**z**
Age	0.032	0.010	3.34
Average Earnings, 26-50	-0.397	0.066	-6.04
Added Earnings, 46-50	-0.832	0.100	-8.34
Male	-0.332	0.066	-5.03
Dropout	0.888	0.067	13.29
College	-0.943	0.114	-8.30
Black	0.683	0.077	8.83
Other	0.847	0.276	3.06
Asian	0.020	0.364	0.05
Hispanic	0.497	0.100	4.97
Two-year survival	-0.779	0.287	-2.71
Four-year survival	-1.271	0.190	-6.70
Constant	-1.017	0.596	-1.71
Ln(L)		-3370	
$\chi^2(12)$		1081	
N		7346	

$p0\_51_i = \Pr(L3\_51_i = 0)$, $p1\_51_i = \Pr(L3\_51_i = 1)$, $p2\_51_i = \Pr(L3\_51_i = 2)$.[2] Individuals are then assigned a random number, $u51_i$, drawn from a uniform distribution on the interval [0,1]. Categorical health states are then assigned according to the rule

$$L3\_51_i = \begin{cases} 0, \text{if } u51_i \le p0\_51_i \\ 1, \text{if } p0\_51_i < u51_i \le p0\_51_i + p1\_51_i \\ 2, \text{otherwise.} \end{cases}$$

Fair/Poor health status variables are defined analogously.

Estimating Health Transitions Through Age 67

The second step uses the longitudinal feature of the HRS to estimate transitions from one health state to another. Because the HRS is conducted every two years, we estimate probabilities of a transition over a two year period. Thus, health at age 53 is conditioned on health at age 51; health at 55 is conditioned on health at 53 and so on. The model allows for improvements in health as well as declines in health as an individual ages. Specifically, we estimate multinomial logit models of the form,

$$\Pr(L3\_53_i = j \mid L3\_51_i = g) = \frac{e^{\beta'_{gj} x_i}}{\sum_{k=1}^{3} e^{\beta'_{gk} x_i}}, \text{ for } g, j = 1,2,3.$$ [3]

Analogous logit models are estimated for the health status variable. In these models, the independent variables (x) include age, sex, education, and race/ethnicity.

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[2] In the multinomial logit, predicted probabilities are calculated as follows:

$$\begin{aligned} P(L3_i = 0) &= \frac{1}{1 + \exp(X_i'\beta_1) + \exp(X_i'\beta_2)} \\ P(L3_i = 1) &= \frac{\exp(X_i'\beta_1)}{1 + \exp(X_i'\beta_1) + \exp(X_i'\beta_2)} \\ P(L3_i = 2) &= \frac{\exp(X_i'\beta_2)}{1 + \exp(X_i'\beta_1) + \exp(X_i'\beta_2)} \end{aligned}.$$

In the binomial logit model, probabilities are calculated as

$$\begin{aligned} P(H2_i = 0) &= \frac{1}{1 + \exp(X_i'\beta)} \\ P(H2_i = 1) &= \frac{\exp(X_i'\beta)}{1 + \exp(X_i'\beta)} \end{aligned}.$$

[3] As is the case for estimates of disability status at age 51, the multinomial logit is just one choice that is available for estimating a categorical outcome. Other possibilities include nested logit or probit models, where one equation is used to estimate a model of any limitation, while a second is used to estimate inability to work among those who have a limitation.

Results from the two transition models are presented in tables 3-7 and 3-8. Categorical health states are assigned sequentially by a procedure identical to that described above, but a new random variable is generated for each age. To assign a health state to the even numbered ages, we assume that persons whose health is not predicted to change over a two year period do not experience a change in either single year interval between. Thus, a person predicted to be limited at 53 and 55 is assumed to be limited at age 54 as well. Persons for whom we do predict a health change are assumed to experience that change uniformly between the two ages. Thus half of persons who change health state between 53 and 55 will do so before their 54th birthday, and half will do so after. The transition age for any individual is based on random variables (v51, v53,…, v65) drawn independently from uniform distributions.

Finally, both health variables are set to missing at ages after a sample person is projected to have died.

2. Results of Projections

Figures 3-1 and 3-2 present results on the predicted health states for persons, by age on January 1, 2020. As expected, the pattern of health status is one of declining health with age.

Table 3-9 presents estimates of the prevalence of health problems in the MINT sample as of 2020 as well as prevalence from the MINT sample in 1993. We restrict the sample here to ages 54-66, the range of ages common to the sample in the two years. We also calculate means of several independent variables in the projection models to aid us in understanding the reason for the observed changes.

Overall, there appears to be an improvement in health and disability status between the 1993 and 2020 samples. The fraction who are unable to work declines from 15.2% to 12.5%. The fraction with any degree of limitation declines from 29.0% to 24.5%. The fraction in fair or poor health also fell from 25.4% to 22.1%.

The most important contributor to this decline in predicted health status is a dramatic increase in educational attainment between the two cohorts. While 26.4% of the age group in 1993 had not completed high school, only 11.4% will not have done so by 2020. In addition, the fraction of the population with college education is projected to increase from 18.1% to 26.3% between 1993 and 2020. Estimates based on the HRS that are shown here (and consistently demonstrated in other literature) suggest that persons with more education are significantly less likely to experience health problems later in life. Until the causal nature of this relationship is fully understood, however, we cannot be fully confident that we are correct in assuming that the relationship will persist in future cohorts. Our projections assume that improved educational attainment will lead to better health in the population. This is plausible, but another possibility is that the positive sign on education in the regression reflects the effects of higher relative economic status on health, not an independent effect of more education. Under that interpretation, rising levels of education would not improve average health levels, although the better educated in any cohort will continue to be relatively more healthy than the less-educated.

Table 3-7
Multinomial Logit Models of Work Limitation/Disability Transitions

	No limit at *t*			Limited at *t*			Unable at *t*		
	Coefficient	***Std. Error***	**z**	**Coefficient**	***Std. Error***	**z**	**Coefficient**	***Std. Error***	**z**
Limited at *t+2*									
Age	0.013	*0.008*	1.64	-0.028	*0.012*	-2.23	-0.121	*0.023*	-5.25
Male	-0.088	*0.058*	-1.52	-0.089	*0.092*	-0.96	-0.276	*0.170*	-1.62
Dropout	0.278	*0.069*	4.03	0.199	*0.111*	1.79	-0.570	*0.170*	-3.36
College	-0.390	*0.075*	-5.21	0.078	*0.119*	0.66	0.135	*0.367*	0.37
Black	-0.208	*0.083*	-2.50	0.040	*0.138*	0.29	-0.466	*0.196*	-2.38
Other	0.287	*0.286*	1.00	0.667	*0.437*	1.53	1.019	*1.070*	0.95
Asian	-0.952	*0.416*	-2.29	-1.162	*0.819*	-1.42	-1.527	*0.925*	-1.65
Hispanic	-0.182	*0.109*	-1.67	-0.348	*0.178*	-1.96	-0.833	*0.220*	-3.79
Constant	-3.071	*0.447*	-6.87	1.612	*0.724*	2.23	8.493	*1.365*	6.22
Unable at *t+2*									
Age	0.042	*0.012*	3.47	0.017	*0.014*	1.20	-0.086	*0.020*	-4.25
Male	-0.216	*0.092*	-2.36	-0.132	*0.108*	-1.22	-0.435	*0.148*	-2.95
Dropout	0.819	*0.095*	8.59	0.841	*0.117*	7.16	-0.170	*0.149*	-1.14
College	-0.882	*0.157*	-5.62	-0.326	*0.161*	-2.03	0.117	*0.337*	0.35
Black	0.517	*0.107*	4.83	0.645	*0.143*	4.52	-0.037	*0.168*	-0.22
Other	0.551	*0.426*	1.29	0.962	*0.460*	2.09	1.409	*1.018*	1.38
Asian	-0.275	*0.587*	-0.47	0.078	*0.722*	0.11	-0.743	*0.640*	-1.16
Hispanic	0.528	*0.131*	4.04	0.027	*0.185*	0.15	-0.797	*0.182*	-4.37
Constant	-5.982	*0.703*	-8.51	-1.759	*0.850*	-2.07	7.605	*1.204*	6.32
Ln(L)	-7464			-2914			-2141		
χ^2	330			147			106		
N	18,703			2,774			2,982		

Table 3-8
Logit Models of Fair/Poor Health Transitions

	Excellent/V.Good/Good at *t*			**Fair/Poor at *t***		
	Coefficient	***Std. Error***	**z**	**Coefficient**	***Std. Error***	**z**
Fair/Poor at *t+2*						
Age at *t*	0.025	*0.007*	3.75	0.012	*0.009*	1.39
Male	-0.191	*0.051*	-3.77	-0.252	*0.067*	-3.74
Dropout	0.825	*0.054*	15.22	0.348	*0.068*	5.11
College	-0.671	*0.074*	-9.01	-0.304	*0.116*	-2.62
Black	0.479	*0.062*	7.71	0.131	*0.078*	1.69
Other	0.373	*0.253*	1.47	0.614	*0.296*	2.07
Asian	0.033	*0.274*	0.12	0.594	*0.395*	1.50
Hispanic	0.708	*0.079*	8.97	0.162	*0.095*	1.71
Constant	-3.713	*0.387*	-9.59	0.213	*0.522*	0.41
Ln(L)	-6219			-3063		
χ^2	726			81		
N	19,113			5,447		

Figure 3-1
Percent With Work Limitations, 2020

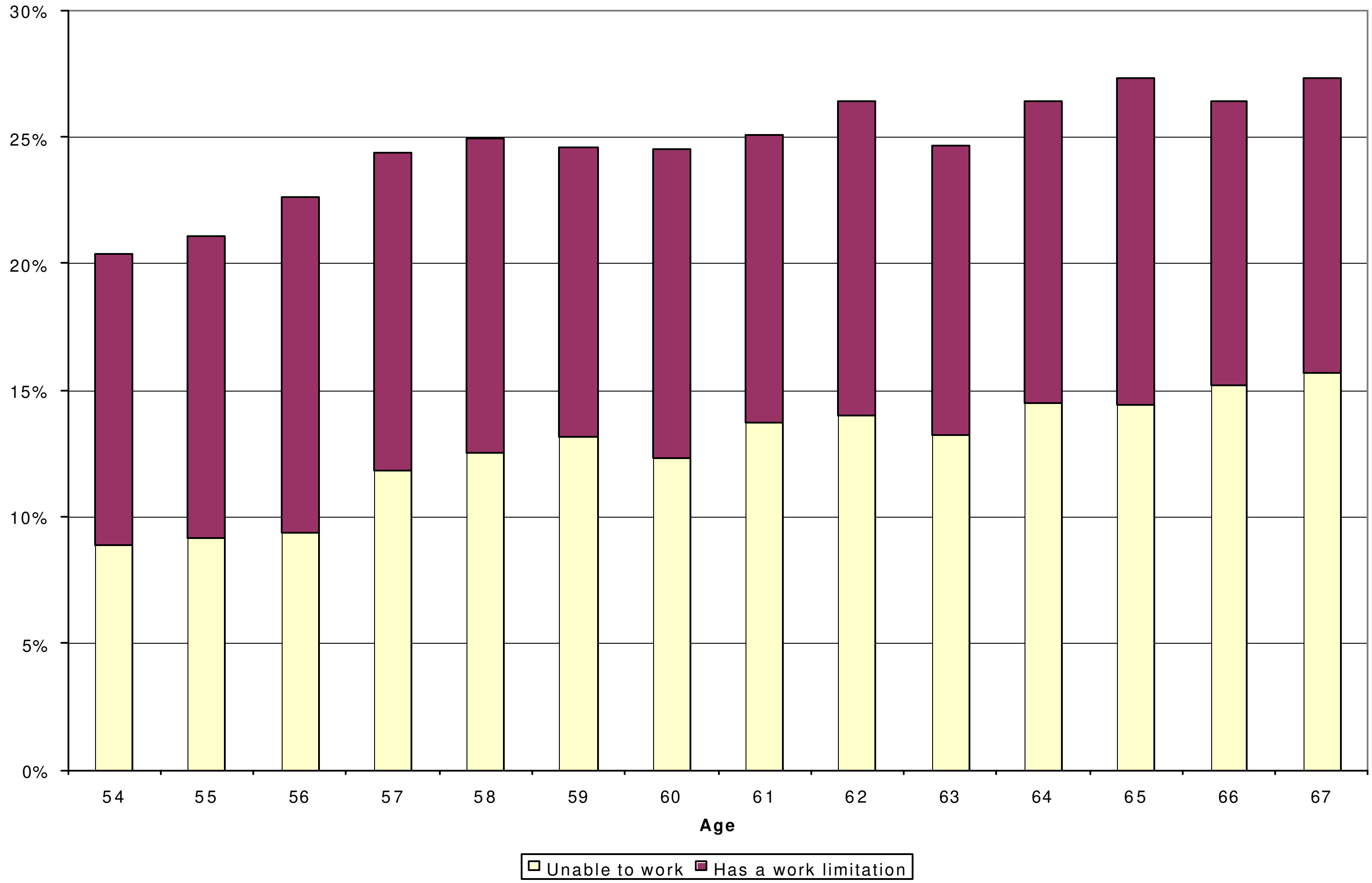

Figure 3-2
Percent In Fair/Poor Health, 2020

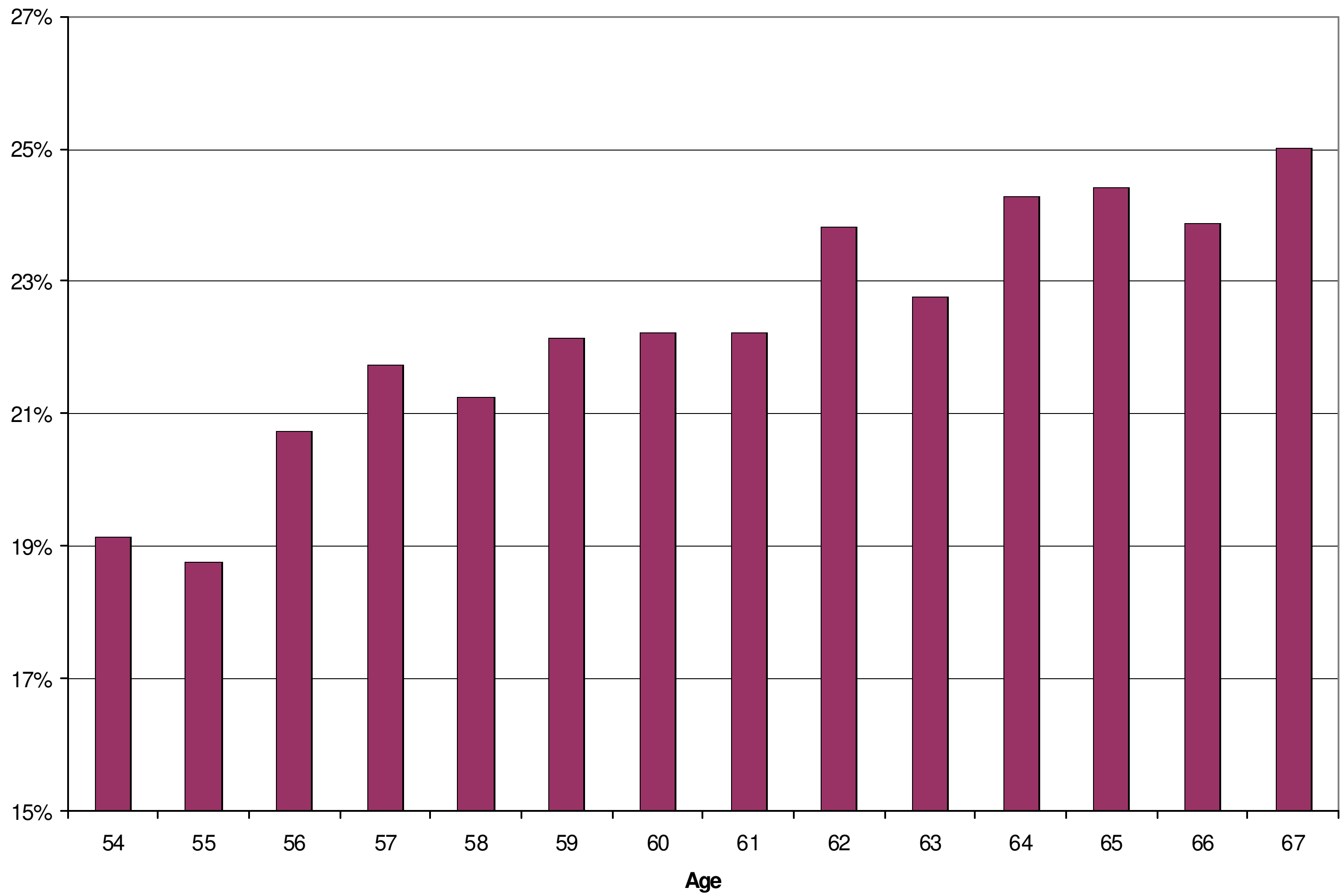

Table 3-9
Distribution Of Health and Demographic Variables for 54-66 Year Olds in 1993 And 2020

	1993	2020
Limited in ability to work (incl. unable) (predicted)	.290	0.245
Unable to work (predicted)	.152	0.125
Fair/Poor Health (predicted)	.264	0.221
Age	59.88	60.02
Male	.474	0.494
Dropout	.264	0.114
College	.181	0.263
Black	.086	0.111
Other	.006	0.007
Asian	.026	0.035
Hispanic	.060	0.100

The other projected demographic change that contributes to our finding of improved health status is a small increase in the fraction male. On the other hand, the projected increase in the fraction of the population who is Black or Hispanic offsets projected improvements in health to some degree because persons in those groups are more likely to report health problems than those in other race/ethnic groups.

3. Sensitivity Tests:

At the urging of the expert panel, we have explored the sensitivity of the parameter estimates to the specification of race/ethnicity. In particular, it was suggested that country of origin/ancestry matters in important ways for health status and self-reports thereof. The HRS contains an oversample of Hispanics, though by its construction, it is largely an oversample of Mexican-Americans in particular (Heeringa and Connor, 1995). To test the sensitivity of the ethnicity specification, we estimated models that distinguished Mexican-Americans from other Hispanics.. We performed tests of the null hypothesis that the health status of Mexican-Americans and other Hispanics are equal. The results of these tests are presented in table 3-10. In the binary health status measure (fair/poor) we could not reject the hypothesis that Mexican-Americans have the same health status as other Hispanics. For the 3-level measure of work

Table 3-10
Tests of Alternate Specifications for Health Status Equations

	Tests of Equality of Mexican and Other Hispanic coefficients	
Dependent Variable	**Chi-2**	**p-value**
Fair/Poor Health	2.33	0.0291
Limited in Ability to Work	4.76	0.4163
Unable to Work	0.66	0.1272

limitation, Mexican-Americans are significantly less likely than other Hispanics (and not significantly different from non-Hispanic whites) in the relative odds of being limited, but they do not differ significantly from other Hispanics in the relative odds of being unable to work. Taken together, this does not seem to support distinguishing Mexican-Americans from other groups of Hispanics in the model of health status.

4. Validity of Findings:

Comparisons with previous research

There are several comparisons that can be made to help evaluate the internal and external validity of the health status projections. The first of these is to compare the trends implied by the projected health status variables to those estimated in the literature. Crimmins, Reynolds and Saito (1999) estimated trends in the fraction of older adults (ages 50-69) unable to work and limited in their ability to work using National Health Interview Survey (NHIS) data from 1982-1993. They found statistically significant declines in these fractions for persons 62 and older. The magnitudes of these declines were generally between 0.4 and 0.7 percentage points per year, with most of the decline concentrated in the "unable to work" category. Waidmann, Bound and Schoenbaum (1995) also used the NHIS to present trends in these measures as well as in the fraction of the population reporting fair or poor health. For both men and women, the fraction of persons 45-64 years old reporting fair or poor health fell by approximately 5 percentage points between 1982 and 1991, or about .5 percentage points per year.

In contrast, the trends implied by the projections in MINT show much smaller annual changes between 1993 and 2020. The population aged 54-67 is projected to experience a 2.7 percent decline in the fraction unable to work, or about 0.1 percentage points per year. The fraction with any limit is projected to decline from 29 to 24.5 percent, or about 0.2 percentage points per year, implying that the fraction limited (but not unable) will decline about 0.1 percentage points per year. The MINT projection of the fraction in fair or poor health declines from 26.4% to 22.1 percent., or about 0.16 percentage points per year.

Two explanations seem possible for these differences. First, while improvements in educational attainment in successive cohorts of older persons account for some of the declines in health problems, Crimmins and colleages (1999) still find significant declines over time even after controlling for the demographic factors we use in projecting future health. Because the MINT projections do not attempt to incorporate time-trends, it should be expected that the implied trends are weaker than those estimated in other literature. Second, as Waidmann et al. (1995) suggest, the trends in self-reported health measures, especially in self-reported work disability are sensitive to changes in the economic and social environment. In particular, some of the large decline in self-reported work disability in the 1980s may be attributable to declines in the availability of disability benefits. On the other hand, the consistent findings that disability (in activities of daily living) among older populations was declining in the 1980s and continued to do so in the 1990s (see Schoeni, Freedman and Wallace, 2001 for a review) suggests that some of the apparent improvement in health may not be related to DI program changes.

Internal Consistency

Two types of consistency checks were conducted. First, a check was made on the correlations between the two health measures in the SIPP data and in the projected data. Second, the projected health status variables were checked against the self-reported values in the SIPP. Self-reports of health status in the SIPP was not used in the projections because we have no longitudinal data on intertemporal correlations in health status over twenty years that would give us a way to use this information. However, these comparisons do demonstrate the extent to which the projection methodology mimics the determinants of health status in actual data.

As for inter-measure correlation, we might expect the correlation between the two projected measures to be less than the correlation in the SIPP data because of common determinants that either unobserved or are not available in the MINT system. However, it is also possible that the random (and distinct) elements that determine these two measures have sufficiently large variance that the correlation between the SIPP measures could be lower than the correlation between the MINT measures.

As for the correlations between actual and projected values, HRS estimates for persons in their 50s show that there is substantial intertemporal correlation in health status. We suspect that the same is true in earlier ages as well, so that persons in poor health in their 30s are more likely than persons in good health at those ages to be in poor health in their 50s. To the extent that the factors used in the projection are sufficient predictors of health status, the correlation between MINT projections and SIPP observations will be high. Conversely, to the extent that unobserved (or unusable) factors determine self-reports of health, the correlation will be low.

Table 3-11 presents results of cross-tabulations of the two health measures with each other both in the MINT projections and in the 1990-93 SIPP data. In particular, we report the fraction of the population aged 54-67 reporting fair or poor health in each sample stratified by work limitation status. Among SIPP respondents reporting no work limitation, 14.63% rate their health as fair or poor, while 72.72% of those who are unable to work rate their health as fair or poor. This correlation is even stronger in the projected status measures in MINT. Only 5.02% of those projected to be free from work limitations are projected to be in fair or poor health while 89.32% of those who are unable to work are projected to be in fair or poor health.

Tables 3-12 and 3-13 present cross-tabulations of each measure across samples. First, for SIPP panel members who would be 51-67 in 1993, we can calculate a projection of health status in 1993 using the methods outlined above. These tables indicate that in aggregate, projected status in 1993 is similar to aggregate levels seen in actual reports, but when tabulations are stratified by self-reported status in SIPP, the matches are less than overwhelming. For example, 21.36% of those who rated their health as excellent, very good or good in SIPP were projected to have health rated as fair or poor, while 32.40% of those in fair or poor health had their health projected that way. Using the measure of work limitation, 24.51% of those reporting no limitation were projected to have some level of limitation with 12.37% projected to be unable to work. Among those unable to work in SIPP, 36.06% were projected to have some limitation with 21.84% projected to be unable to work. The same exercise is performed for SIPP respondents who would be 51-67 in 2020. We find that the relationship between actual status in

Table 3-11
Correspondence Between Health Measures Within Survey

	Percent reporting Fair or Poor Health, age 54-67	
	1990-93 SIPP	2020 MINT
Not limited in ability to work	14.63	5.02
Limited in ability to work, not unable	46.99	59.64
Unable to work	72.72	89.32

Table 3-12
Correspondence Between Actual and Predicted Responses to Health Rating

SIPP Health Status	Percent Projected in Fair or Poor Health	
	1993	2020
Excellent / Very Good / Good	21.36	21.60
Fair / Poor	32.40	30.98

Table 3-13
Correspondence Between Actual and Predicted Responses to Work Limitation Rating

SIPP Work Limitation Status	Percent with some Limit	Percent Unable to Work	Percent with some Limit	Percent Unable to Work
	1993	1993	2020	2020
No limitation	24.51	12.37	24.78	12.32
Limited but not unable to work	26.29	15.44	29.53	13.90
Unable to work	36.06	21.84	34.45	23.97

1990-93 and projected status in 2020 is similar to the relationship between actual responses and projected status in 1993. Thus, there is certainly a correlation between actual and projected health and limitation status, and that correlation is in the expected direction. However, the strength of this correlation is smaller than would be expected if the explanatory variables included in the projection model accounted for a larger share of the variance in the outcome variables.

Thus, the projections appear plausible when considered as aggregate measures. However, the low degree of within-person correlation between actual responses in SIPP and projected responses in MINT suggests that using health projections in conjunction with other types of outcomes is risky.

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CHAPTER 4

ESTIMATES OF RETIREMENT, SOCIAL SECURITY BENEFIT TAKE-UP, AND EARNINGS AFTER AGE 50

I. INTRODUCTION

This chapter describes the models that MINT uses to simulate earnings from age 50 to death, retirement (defined as first exit after age 50 from work of at least twenty hours/week), and Social Security take-up. To generate these outcomes, MINT models five separate processes:

- The path of earnings of individuals ages 50 and over who are not retired;
- The retirement decision (defined as the decision to reduce hours of work below twenty);
- The work behavior of retirees and their earnings prior to Social Security take-up;
- The timing of Social Security take-up; and, finally,
- The labor force participation and earnings of Social Security beneficiaries.

Table 4-1 presents a detailed overview of the models estimated in this chapter. We describe the data sources that we used to estimate model parameters and then describe the models used to estimate each of these five processes. Next, we discuss the results from the projections, highlighting comparisons to data from recent periods and other models. Finally, we test the sensitivity of our results to certain assumptions imbedded in the models.

II. DATA SET AND SAMPLE

The models in this chapter use the Health and Retirement Study (HRS) and the 1990-93 panels of the Survey of Income and Program Participation (SIPP) as data sources. We use the HRS data to estimate the retirement decision and the work behavior and earnings of retirees prior to Social Security take-up, and we use the SIPP data to estimate the remaining functions.

The HRS is the premier data set available to study retirement decisions. It provides six years of data on a large sample of individuals near retirement age and, like the SIPP, can be linked with the SER and the MBR. The HRS sampled 9,824 individuals between the ages of 51 and 61 in 1992 and re-interviewed them every two years. With these data, which are now available through 1998, we can observe labor market behavior for individuals between ages 51 and 67 (and earnings for individuals ages 50 to 66).[1] The HRS provides information on

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[1] Since we estimated the retirement models, an additional wave of HRS data has been released. This means that one could re-estimate the retirement model using eight years of data, through the year 2000 (and thus through age 69).

individuals' demographic characteristics (e.g., age, gender, race/ethnicity, educational attainment, marital status), pension coverage and wealth, Social Security wealth, other assets, and health measures. These variables are included in the estimating equations, as defined below.

Table 4-1
Summary Description of MINT Models of Labor Force Withdrawal

Steps	***Ages***	***Data Set***
1. Estimate earnings trajectories of "non-retired" workers by gender and educational attainment	50 and beyond	SIPP
2. Model "retirement" as defined by reducing work hours below 20 hours per week	51 and beyond	HRS
3. Model labor force participation of "retirees" (as defined in step 2) prior to Social Security eligibility	51 to 61	HRS
4. Model earnings of working "retirees" prior to Social Security eligibility	51 to 61	HRS
5. Model individuals' decisions to take up Social Security benefits (deterministically at ages 60 and 61)	60 to 61 62 to 69	None SIPP
6. Model labor force participation of Social Security beneficiaries	60 to 69 70 and beyond	SIPP SIPP
7. Model earnings of working Social Security beneficiaries	60 to 64 65 to 69 70 and beyond	SIPP SIPP SIPP

The 1990-93 panels of the SIPP were merged with earnings data from the Summary Earnings Records (SER) and the Master Beneficiary Record (MBR). Data from the MBR provide information about the year individuals first receive Social Security benefits and whether an individual received disability benefits. Like the HRS, the SIPP contains detailed information on individuals' demographic characteristics, pension coverage, other financial assets, and health.[2] The 1990 and 1991 SIPP panels provide two full calendar years of information (1990-91, and 1991-92, respectively), while the 1992 and 1993 SIPP panels provide up to three full calendar years of information (1992-94 and 1993-95, respectively).

III. PRE-RETIREMENT EARNINGS

Building on the approach taken in MINT 1.0, we project pre-retirement earnings after age 50 by estimating a fixed-effects model of earnings received by SIPP respondents before they retire. The model takes the form,

$$y_{it} = \mu_i + f(Age) + \varepsilon_{it} \qquad \textbf{(4-1)}$$

where y_{it} is the earnings of individual i in year t, μ_i is an individual-specific error term that is fixed for all time periods, ε_{it} is a random disturbance term for individual i in year t, and f(Age) is a series of five-year age dummies and their associated coefficients. The earnings measure we use is the ratio of earnings to the economy-wide average covered wage, multiplied by 100 to convert it into percentage terms. (The economy-wide average coverage wage is the value estimated by SSA actuaries for the Trustees' Report.) Utilizing this relative earnings measure instead of an absolute measure makes our projections of relative earnings independent of the future trend of economy-wide average earnings.

We estimate Equation 4-1 separately for men and women by educational attainment (less than four years of high school, four years of high school, one to three years of college, and four or more years of college). In the estimates for college graduates, we interact the age dummies with an indicator for any post-graduate education, to capture possible differences in age-earnings profiles between those who completed exactly four years of college and those who received additional schooling. Earnings are derived from the Social Security Summary Earnings Records (again, SER), matched to SIPP respondents. These records are available from 1951 to 1999, but we only used data from 1987 to 1999 in our estimation. The labor market experienced dramatic changes in the 1970s and through the mid 1980s, as pay differentials between low-, middle-, and high-wage workers increased substantially and pay differentials between men and women narrowed sharply. These trends have slowed or leveled off since the late 1980s. If we had included data from this turbulent period in our estimation, we would in effect have been projecting the unusual trends observed in the late 1970s and early 1980s into the indefinite future. Omitting these years is also beneficial because more workers have earnings that are

[2] We draw some of these data (for example, the health status measure) from SIPP topical modules. These data reflect individuals' circumstances at a single point in time, as opposed to every month.

censored at the taxable maximum during the earlier period than in the later period (for example, 14.7 percent of workers had earnings that exceeded the taxable maximum in 1977, compared with 6.1 percent in 1987).

The model is estimated on a sample of individuals who were never entitled to Social Security Disability Insurance, who had not yet retired, and who reported earning at least 0.0436 times the average wage.[3] We define retirement as working fewer than 20 hours per week at age 50 or later. By assumption, no respondents younger than age 50 could be classified as retired. Retirement status is defined using data from the SIPP interviews. However, interview data are not available beyond 1996 and in some cases are only available through 1992 (depending on the panel in which the respondent was surveyed). After the last SIPP observation and before 1999, we define retirement by changes in earnings. We classify workers as retired if actual earnings fall below 50 percent of the earnings they received the last time they were observed in the SIPP panel working at least 20 hours per week.

Coefficient estimates, their standard errors, and 95-percent confidence intervals are reported in Tables 4-2 and 4-3, separately for men and women.[4] The coefficient on a given age variable shows the average change in earnings (relative to the average wage) between that age and those at ages 35 to 39, the omitted reference group, for individuals in the given gender and education group.

We use these coefficient estimates to project earnings after age 50 for those who did not retire by 1999. Figures 4-1 and 4-2 report pre-retirement earnings trajectories for men and women by education. For men, pre-retirement earnings begin to decline slowly once workers reach their forties. The erosion in earnings is similar across educational groups. For women, pre-retirement earnings continue to rise with age through the early sixties. Increases in earnings at all ages, including older ages, are somewhat more pronounced for those with at least some college education than for those who did not continue their education beyond high school.

Figures 4-3 and 4-4 compare earnings trajectories by retirement status for men and women. The curves denoted by diamonds signify pre-retirement earnings. The curves denoted by squares signify earnings as computed using the hot-decking procedure described in Chapter 2, which does not distinguish workers by retirement status. These figures highlight the importance of distinguishing retirement status when projecting earnings at older ages. When earnings for all men are considered, including those who dropped out of the labor force, relative earnings slowly begin to decline for men in their forties and drop sharply by the time they reach their mid fifties. When only non-retired men are considered, the earnings decline after age 50 is much less pronounced. At ages 60 to 64, mean earnings relative to the average wage is 0.948 for non-retired men, compared with 0.563 for all men.

Differences by retirement status are even more pronounced for women. When earnings for all women are considered, earnings begin to drop substantially in the late fifties. However,

[3] This is equivalent to $1000 in earnings at the HRS baseline (1992).

[4] Table A4-1 presents an alternative specification.

Table 4-2
Male Age-Earnings Profiles Before Retirement, By Educational Attainment

Education = less than four years of high school

Fixed-effects (within) regression — Number of obs = 36926; Number of groups = 4411

R-sq: within = 0.0118; between = .0015; overall = 0.0009

Obs per group: min = 1; avg = 8.4; max = 13

F(13,32502) = 29.90

corr(u_i, Xb) = -0.0648 — Prob >F = 0.0000

yratio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age2024	-20.047	1.717	-11.680	0.000	-23.412	-16.682
age2529	-7.878	0.638	-12.340	0.000	-9.129	-6.627
age3034	-2.660	0.503	-5.290	0.000	-3.647	-1.674
age4044	2.406	0.559	4.300	0.000	1.310	3.502
age4549	0.684	0.736	0.930	0.352	-0.758	2.127
age5054	-2.343	1.425	-1.640	0.100	-5.136	0.451
age5557	-6.288	1.863	-3.380	0.001	-9.939	-2.637
age5859	-8.772	2.149	-4.080	0.000	-12.984	-4.561
age6061	-12.569	2.333	-5.390	0.000	-17.141	-7.996
age62	-18.736	2.766	-6.770	0.000	-24.157	-13.314
age6364	-21.991	2.837	-7.750	0.000	-27.551	-16.430
age65	-29.565	4.246	-6.960	0.000	-37.888	-21.243
age66	-40.485	5.071	-7.980	0.000	-50.424	-30.547
_cons	91.600	0.472	194.150	0.000	90.675	92.524

sigma_u 55.139
sigma_e 27.428
rho 0.802 (fraction of variance due to u_i)

Education = four years of high school

Fixed-effects (within) regression — Number of obs = 136636; Number of groups = 13921

R-sq: within = 0.0157; between = .0003; overall = 0.0037

Obs per group: min = 1; avg = 9.8; max = 13

F(13,122702) = 150.56

corr(u_i, Xb) = -0.0320 — Prob >F = 0.0000

yratio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age2024	-25.731	0.870	-29.580	0.000	-27.436	-24.026
age2529	-10.359	0.341	-30.400	0.000	-11.027	-9.691
age3034	-1.561	0.264	-5.910	0.000	-2.079	-1.043
age4044	0.870	0.297	2.930	0.003	0.288	1.453
age4549	-2.871	0.404	-7.110	0.000	-3.662	-2.080
age5054	-6.385	0.898	-7.110	0.000	-8.145	-4.624
age5557	-12.347	1.277	-9.670	0.000	-14.849	-9.844
age5859	-16.782	1.582	-10.600	0.000	-19.883	-13.680
age6061	-19.999	1.778	-11.250	0.000	-23.485	-16.514
age62	-26.831	2.293	-11.700	0.000	-31.325	-22.337
age6364	-30.786	2.375	-12.960	0.000	-35.441	-26.131
age65	-42.814	3.736	-11.460	0.000	-50.136	-35.492
age66	-46.270	5.219	-8.870	0.000	-56.499	-36.041
_cons	115.859	0.211	548.380	0.000	115.445	116.273

sigma_u 60.397
sigma_e 30.490
rho 0.797 (fraction of variance due to u_i)

Table 4-2
(Continued)

Education = one to three years of college

Fixed-effects (within) regression — Number of obs = 78432; Number of groups = 7747

R-sq: within = 0.0298; between = .0077; overall = 0.0209 — Obs per group: min = 1; avg = 10.1; max = 13

F(13,70672) = 166.84

corr(u_i, Xb) = 0.0381 — Prob >F = 0.0000

yratio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age2024	-43.602	1.304	-33.430	0.000	-46.158	-41.045
age2529	-17.862	0.527	-33.900	0.000	-18.894	-16.829
age3034	-3.806	0.404	-9.420	0.000	-4.599	-3.014
age4044	1.416	0.423	3.350	0.001	0.587	2.246
age4549	-3.279	0.550	-5.960	0.000	-4.357	-2.200
age5054	-6.424	1.350	-4.760	0.000	-9.071	-3.777
age5557	-12.207	2.059	-5.930	0.000	-16.243	-8.170
age5859	-14.640	2.593	-5.650	0.000	-19.723	-9.558
age6061	-18.358	2.916	-6.300	0.000	-24.074	-12.642
age62	-24.536	3.769	-6.510	0.000	-31.923	-17.149
age6364	-33.186	3.919	-8.470	0.000	-40.867	-25.505
age65	-50.064	6.358	-7.870	0.000	-62.525	-37.603
age66	-61.158	7.646	-8.000	0.000	-76.145	-46.172
_cons	133.749	0.298	448.310	0.000	133.165	134.334
sigma_u	64.139					
sigma_e	34.294					
rho	0.778	(fraction of variance due to u_i)				

Education = four or more years of college

Fixed-effects (within) regression — Number of obs = 118662; Number of groups = 12542

R-sq: within = 0.0695; between = .0285; overall = 0.0397 — Obs per group: min = 1; avg = 9.9; max = 13

F(26,106691) = 454.14

corr(u_i, Xb) = 0.0517 — Prob >F = 0.0000

yratio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age2024	-94.678	1.585	-59.740	0.000	-97.784	-91.572
age2529	-31.903	0.627	-50.840	0.000	-33.133	-30.673
age3034	-3.963	0.493	-8.040	0.000	-4.929	-2.997
age4044	3.089	0.527	5.860	0.000	2.056	4.122
age4549	0.273	0.677	0.400	0.687	-1.054	1.600
age5054	-3.140	1.735	-1.810	0.070	-6.541	0.260
age5557	-7.984	2.556	-3.120	0.002	-12.994	-2.975
age5859	-12.518	3.168	-3.950	0.000	-18.728	-6.308
age6061	-19.334	3.590	-5.390	0.000	-26.370	-12.297
age62	-28.627	4.612	-6.210	0.000	-37.666	-19.588
age6364	-29.678	4.692	-6.330	0.000	-38.873	-20.482
age65	-45.202	6.957	-6.500	0.000	-58.839	-31.566
age66	-31.785	7.975	-3.990	0.000	-47.416	-16.154
age24g	-17.291	2.719	-6.360	0.000	-22.619	-11.962
age2529g	-18.158	1.008	-18.010	0.000	-20.135	-16.182
age3034g	-6.401	0.759	-8.430	0.000	-7.889	-4.912
age4044g	2.250	0.766	2.940	0.003	0.748	3.752
age4549g	4.538	0.961	4.720	0.000	2.655	6.421
age5054g	8.884	2.296	3.870	0.000	4.384	13.385
age5557g	10.320	3.394	3.040	0.002	3.667	16.973
age5859g	11.576	4.206	2.750	0.006	3.332	19.820
age6061g	12.124	4.784	2.530	0.011	2.747	21.501
age62g	20.414	6.081	3.360	0.001	8.497	32.332
age6364g	20.095	6.183	3.250	0.001	7.976	32.215
age65g	34.618	9.270	3.730	0.000	16.449	52.787
age66g	11.697	10.569	1.110	0.268	-9.018	32.413
_cons	170.883	0.283	603.380	0.000	170.328	171.438
sigma_u	69.229					

Source: 1990-93 SIPP matched to 1987-1999 SSER. Individuals in sample have not yet have retired, have never been entitled to DI benefits, and have earnings of at least .0436 times the average wage ($1000 in 1992).

Table 4-3
Female Age-Earnings Profile Before Retirement, By Educational Attainment

Education = less than four years of high school

Fixed-effects (within) regression
Number of obs = 26263
Number of groups = 3806

R-sq: within = 0.0175
between = .0587
overall = 0.0328

Obs per group: min = 1
avg = 6.9
max = 13

F(13,22444) = 30.82
corr(u_i, Xb) = 0.0561
Prob >F = 0.0000

yratio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age2024	-14.956	1.519	-9.850	0.000	-17.932	-11.979
age2529	-7.692	0.558	-13.770	0.000	-8.786	-6.597
age3034	-4.187	0.406	-10.300	0.000	-4.984	-3.391
age4044	3.349	0.424	7.890	0.000	2.518	4.181
age4549	4.358	0.552	7.890	0.000	3.276	5.441
age5054	5.627	1.191	4.730	0.000	3.293	7.962
age5557	8.844	1.616	5.470	0.000	5.676	12.012
age5859	9.622	1.872	5.140	0.000	5.952	13.291
age6061	10.565	2.075	5.090	0.000	6.498	14.633
age62	11.118	2.497	4.450	0.000	6.224	16.013
age6364	9.601	2.568	3.740	0.000	4.567	14.635
age65	4.053	3.932	1.030	0.303	-3.655	11.760
age66	9.398	5.148	1.830	0.068	-0.693	19.489
_cons	48.944	0.347	141.040	0.000	48.264	49.625

sigma_u 31.683
sigma_e 18.156
rho 0.753 (fraction of variance due to u_i)

Education = four years of high school

Fixed-effects (within) regression
Number of obs = 133595
Number of groups = 15432

R-sq: within = 0.0217
between = 0.027
overall = 0.0190

Obs per group: min = 1
avg = 8.7
max = 13

F(13,118150) = 201.35
corr(u_i, Xb) = -0.0106
Prob >F = 0.0000

yratio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age2024	-16.858	0.690	-24.420	0.000	-18.211	-15.505
age2529	-9.272	0.276	-33.570	0.000	-9.814	-8.731
age3034	-4.675	0.210	-22.230	0.000	-5.087	-4.263
age4044	4.601	0.220	20.940	0.000	4.170	5.031
age4549	7.657	0.283	27.030	0.000	7.102	8.213
age5054	11.908	0.652	18.260	0.000	10.630	13.186
age5557	14.992	0.936	16.010	0.000	13.156	16.827
age5859	16.677	1.152	14.480	0.000	14.419	18.935
age6061	17.351	1.313	13.220	0.000	14.778	19.924
age62	15.548	1.695	9.170	0.000	12.227	18.870
age6364	13.764	1.761	7.810	0.000	10.312	17.217
age65	10.480	2.756	3.800	0.000	5.078	15.883
age66	5.898	3.401	1.730	0.083	-0.769	12.564
_cons	68.223	0.162	421.450	0.000	67.906	68.540

sigma_u 41.617
sigma_e 22.268
rho 0.777 (fraction of variance due to u_i)

Table 4-3
(Continued)

Education = one to three years of college

Fixed-effects (within) regression — Number of obs = 78963; Number of groups = 8561

R-sq: within = 0.0254; between = .0204; overall = 0.0184

Obs per group: min = 1; avg = 9.2; max = 13

F(13,70389) = 140.90

corr(u_i, Xb) = -0.0333 — Prob >F = 0.0000

yratio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age2024	-22.723	1.011	-22.470	0.000	-24.705	-20.741
age2529	-8.759	0.425	-20.600	0.000	-9.592	-7.926
age3034	-3.406	0.328	-10.380	0.000	-4.050	-2.763
age4044	7.833	0.343	22.840	0.000	7.161	8.505
age4549	12.601	0.447	28.220	0.000	11.726	13.477
age5054	18.341	1.150	15.940	0.000	16.086	20.596
age5557	22.208	1.727	12.860	0.000	18.824	25.593
age5859	24.657	2.187	11.270	0.000	20.371	28.944
age6061	28.950	2.511	11.530	0.000	24.028	33.872
age62	29.441	3.291	8.950	0.000	22.991	35.891
age6364	27.969	3.382	8.270	0.000	21.340	34.597
age65	26.774	6.055	4.420	0.000	14.907	38.642
age66	22.120	8.212	2.690	0.007	6.025	38.215
_cons	80.780	0.238	339.130	0.000	80.313	81.247

sigma_u 47.909
sigma_e 27.518
rho 0.752 (fraction of variance due to u_i)

Education = four or more years of college

Fixed-effects (within) regression — Number of obs = 90641; Number of groups = 9706

R-sq: within = 0.0484; between = 0.0154; overall = 0.0219

Obs per group: min = 1; avg = 9.3; max = 13

F(26,80909) = 158.28

corr(u_i, Xb) = -0.0635 — Prob >F = 0.0000

yratio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age2024	-55.559	1.489	-37.310	0.000	-58.478	-52.641
age2529	-10.407	0.627	-16.600	0.000	-11.636	-9.178
age3034	-2.128	0.505	-4.210	0.000	-3.117	-1.138
age4044	7.022	0.568	12.370	0.000	5.909	8.135
age4549	13.780	0.759	18.160	0.000	12.293	15.267
age5054	25.225	1.991	12.670	0.000	21.323	29.126
age5557	35.891	3.234	11.100	0.000	29.551	42.230
age5859	40.829	4.223	9.670	0.000	32.552	49.106
age6061	44.916	4.879	9.210	0.000	35.353	54.479
age62	40.260	6.302	6.390	0.000	27.908	52.613
age6364	39.728	6.611	6.010	0.000	26.770	52.687
age65	35.133	9.734	3.610	0.000	16.055	54.211
age66	43.729	11.643	3.760	0.000	20.908	66.550
age24g	-11.542	2.600	-4.440	0.000	-16.639	-6.445
age2529g	-10.141	1.033	-9.820	0.000	-12.166	-8.116
age3034g	-3.044	0.803	-3.790	0.000	-4.619	-1.470
age4044g	3.011	0.838	3.590	0.000	1.369	4.653
age4549g	4.747	1.082	4.390	0.000	2.626	6.868
age5054g	5.865	2.740	2.140	0.032	0.494	11.236
age5557g	5.909	4.356	1.360	0.175	-2.628	14.446
age5859g	3.636	5.697	0.640	0.523	-7.530	14.802
age6061g	6.240	6.535	0.950	0.340	-6.567	19.048
age62g	8.091	8.459	0.960	0.339	-8.488	24.670
age6364g	18.822	8.822	2.130	0.033	1.531	36.114
age65g	28.870	14.087	2.050	0.040	1.259	56.481
age66g	11.950	18.753	0.640	0.524	-24.806	48.707
_cons	113.701	0.284	400.620	0.000	113.145	114.258

sigma_u 63.851
sigma_e 35.417
rho 0.765 (fraction of variance due to u_i)

Source: 1990-93 SIPP matched to 1987-1999 SSER. Individuals in sample have not yet have retired, have never been entitled to DI benefits, and have earnings of at least .0436 times the average wage ($1000 in 1992).

Figure 4-1
Pre-Retirement Earnings Trajectories for Men, by Educational Attainment

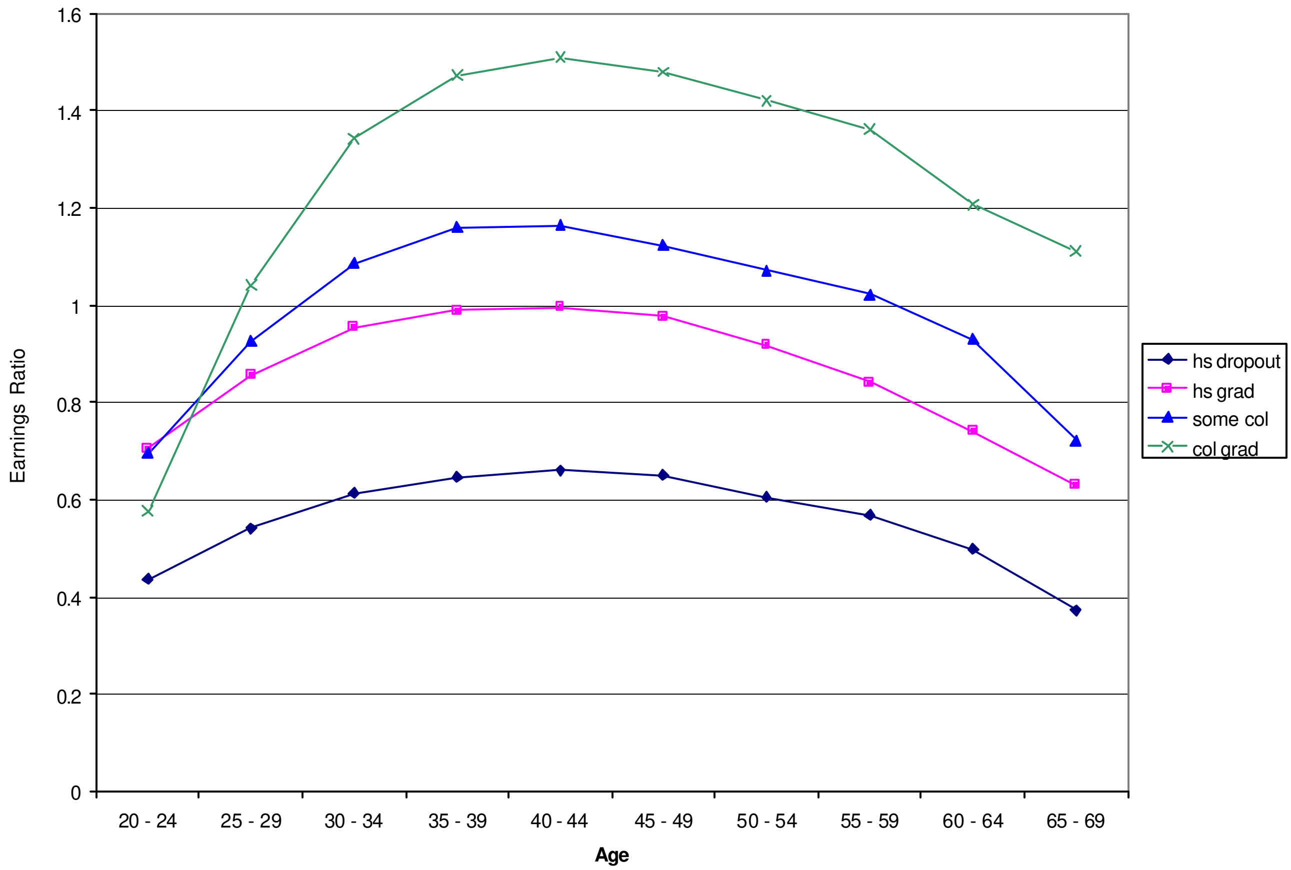


Figure 4-2
Pre-Retirement Earnings Trajectories for Women, by Educational Attainment

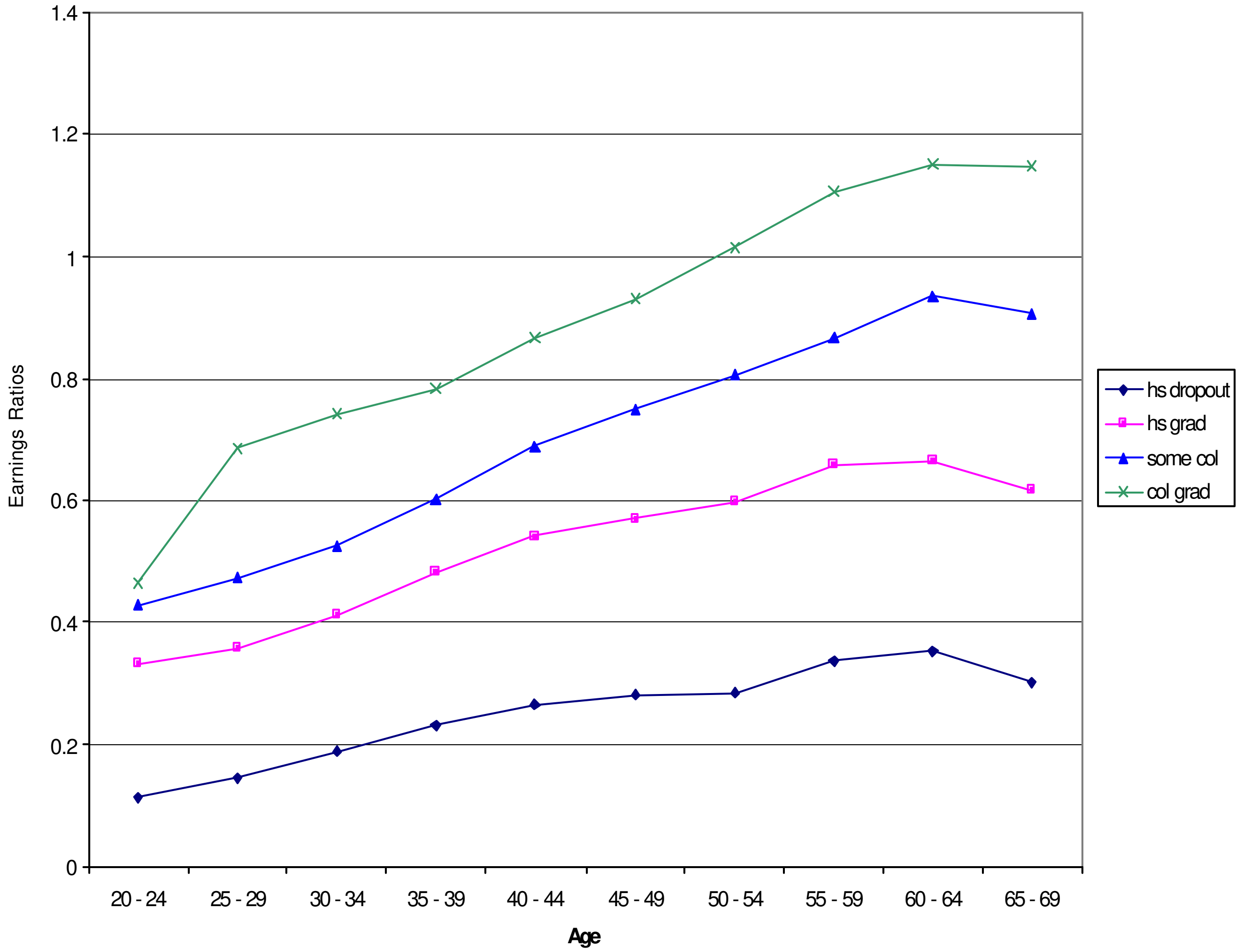


Figure 4-3
Earnings Trajectories by Retirement Status, Men

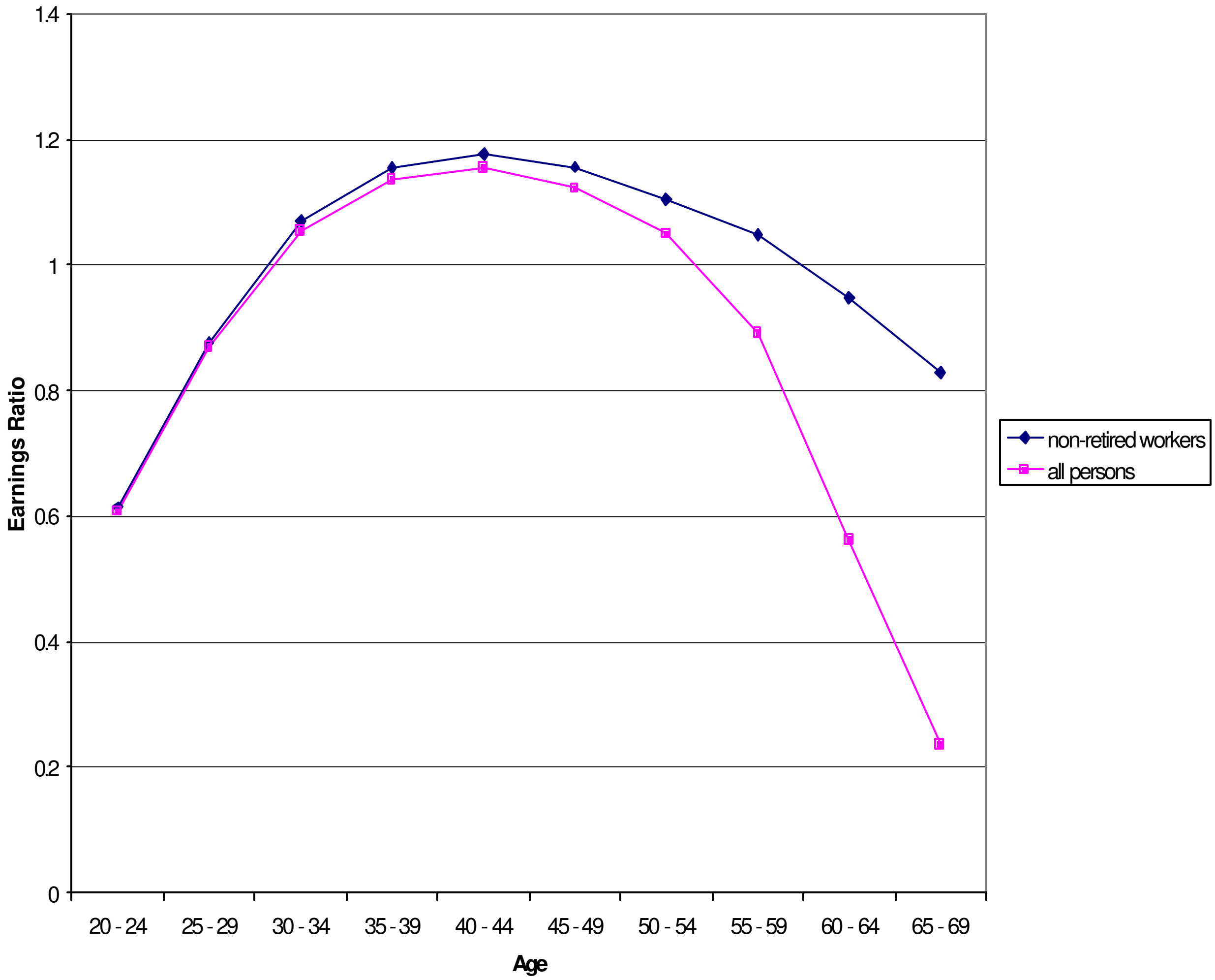
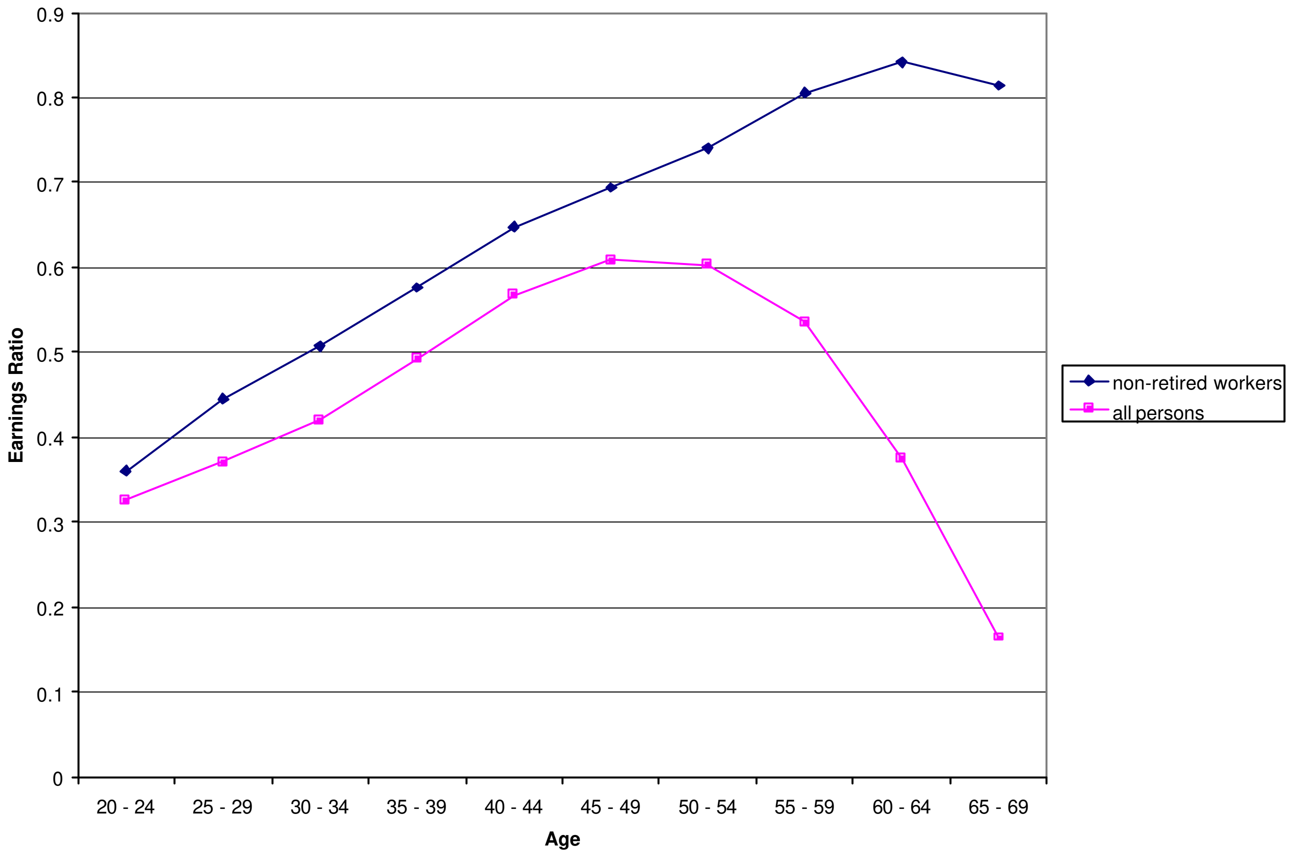


Figure 4-4
Earnings Trajectories by Retirement Status, Women



when we consider only non-retired women, average earnings continue to increase through the early sixties, and decline only slightly after age 65. At ages 60 to 64, mean relative earnings for non-retired women is 0.842, compared with 0.374 for all women. Moreover, because labor force participation rates among those without disabilities are lower for women than men, earnings are substantially higher throughout the life course for non-retired women than all women considered together.

IV. RETIREMENT MODEL

1. Background

Retirement, or the decision to leave work that totals at least twenty hours per week, is a core transition in MINT. Once a person has been slated to retire, we project his or her earnings using alternative functions (not the trajectory method described above). He or she also becomes eligible to take up any employer-sponsored pension benefits to which he or she is eligible. (One's actual date of pension take-up will depend on the eligibility ages incorporated into one's particular plan.) Whether one has retired also has large effects on family Social Security take-up decisions, which in turn will greatly influence well-being in old age.

Because the retirement decision is such an important part of MINT, our model of this transition is fairly elaborate. It is a probit model that contains detailed information about pension and Social Security wealth, accruals, and incentives. The form of the probit model is:

$$D_{it}^* = \alpha + X_{it}\beta + \varepsilon_{it} \qquad \textbf{(4-2)}$$

where D_{it}^* is the propensity of worker i to leave work of twenty hours per week or more at time t, X_{it} is a vector of variables thought to influence the retirement decision, and ε_{it} is a random disturbance term. D_{it}^* is not observed; instead we observe a dummy variable D_{it} which equals one if D_{it}^* exceeds some threshold (normalized to zero) and zero otherwise. Thus, the probability that we observe a departure from work of twenty hours per week or more is equal to $1 - F(-\alpha - X_{it}B)$, where F is the cumulative distribution function for ε.

We model retirement as a function of economic, demographic and health characteristics. Our models also capture the effects of incentives created by Social Security and employer-sponsored pension plans on labor supply. In Social Security and most defined benefit (DB) pension plans, retirement wealth does not accrue evenly over time. Instead, the wealth profiles exhibit spikes and often begin to decline after certain ages. For example, wealth in employer-sponsored plans generally increases sharply at the early and normal retirement ages, when participants can begin receiving benefits. Vested workers who separate before the retirement age can eventually receive benefits, but their deferred benefits are eroded by inflation. Spikes are especially pronounced at early retirement ages for plans that do not allow former employees to collect benefits before the normal retirement age. In addition, pension wealth often drops after the normal retirement age, because the increase in monthly benefits associated with additional work is often insufficient to compensate for the decline in the number of periods in which those who delay retirement collect benefits. Workers appear to respond to these incentives by delaying retirement if continued work would substantially increase their pension and Social Security wealth, and by accelerating retirement once their wealth begins to decline (Coile and Gruber 2000; Gustman and Steinmeier 2000; Samwick 1998; Stock and Wise 1990).

We capture the effects of the future labor supply incentives created by employer-sponsored pension plans and Social Security by following the "premium value" approach developed by Gustman and Steinmeier (2000). The premium value measures the maximum increase in pension wealth associated with continued work, in excess of the current rate of wealth accruals. To compute the premium value, we first calculate the present value of future pension benefits at all future retirement ages. We then recompute pension wealth at every retirement age under the assumption that the annual increase in pension wealth associated with an additional year of work equaled the current accrual. (In reality, annual accruals typically change over time.) The premium value is the maximum difference between these two measures of pension wealth. For example, if pension wealth equaled \$100,000 if the worker retired at time t, \$105,000 if he retired at time $t+1$, \$150,000 at time $t+2$, and \$152,000 at all future dates, then the premium value would equal \$40,000 (\$150,000 minus \$110,000, the value of pension wealth if the current accrual rate of \$5,000 were to continue).

We use the HRS to model the retirement decision. Because Social Security and pension wealth and retirement wealth accruals are such important aspects of our model, we need to drop all observations from the HRS in which individuals were not matched to a Social Security earnings record. We also drop individuals who report DB pension coverage but for whom a link to an employer record was not obtained. Similarly, for married people, we also drop individuals whose spouses lack earnings or DB pension records, as this prevents us from accurately estimating their family retirement wealth, including entitlement to Social Security spouse and survivor benefits.[5] The appendix provides additional detail on the estimation of Social Security and retirement wealth.

The retirement model is comprised of separate probit equations for married persons and unmarried persons. We stratified the sample for married persons on the basis of gender, but the user has the option of using a combined model.[6] In both the equation for unmarried person and the pooled equation for married persons, we interacted gender with several of the important explanatory variables to account for the possibility that certain variables (for example, the premium value of spouse's retirement incentives) may have gender-specific effects.

These models predict retirement transitions across two-year intervals. Because the accounting period in MINT is one year, we transform these probabilities slightly in the simulation (see "Implementation Issues" below), and assume that the independent variables affect annual probabilities in the same way that they affect biannual probabilities.

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[5] We attempted to impute both earnings and pension records to members of HRS sample who did not have them and to their spouses (see Appendix one for details on the imputation). We found, however, that results from analyses in which we used these imputed values were less plausible than results from analyses in which we used only the actual data.

[6] This is implemented by setting the SAS macro variable &separatebysex (located in the SAS macro calcretirement, which is called in retcore.inc) to zero and rerunning giantprogramloop.sas and subsequent programs. It is currently set to one (for production of the file MINT0626.sas7bdat).

2. Estimates

Table 4-4 reports the probit results for married people (both the pooled model and separate by sex), and Table 4-5 reports the results for unmarried people. Standard errors for the coefficients are included in both tables, and asterisks denote statistically significant effects.

For married people (combined men and women), we find that recent earnings (defined as the natural logarithm of average earnings over the past five years) and family wealth (including defined benefit and defined contribution pension wealth from current and past jobs, Social Security wealth, and other financial wealth, like stocks, bonds, and checking accounts) have important effects on the decision to reduce hours of work to less than twenty per week. The higher one's family wealth, the more likely one is to retire, and the higher one's recent earnings, the less likely one is to retire. We also find that individual retirement incentives (defined by premium values) have modest effects on the decision to reduce hours of work to less than twenty per week. That is, the higher the bonus one would receive from one's Social Security and defined benefit pension for postponing retirement, the less likely one is to retire this year. The pension coverage indicators that we include in the models have significant coefficients, indicating that pension coverage has important effects on retirement net of pension incentives. Defined benefit pension coverage increases retirement probabilities, while defined contribution pension coverage decreases them. Education appears to have some important effects, with those with less than a high school education more likely to retire than those with more education. Age and health/disability status have strong effects on retirement in the expected directions.

While one's spouse's age and race have important effects on the retirement behavior of married persons, we see virtually no other effects of spouse characteristics on the retirement decision. We find married men to be slightly more responsive to their spouse's retirement incentives (as expressed through the premium value of combined pensions and Social Security) than married women, but neither effect is statistically significant. (We discuss this finding further, below.)

For unmarried people, our findings differ somewhat (Table 4-5). The effects on the retirement decision of incentives, as measured through accruals to and premium values of retirement wealth, are larger than they were for the married people. Effects of wealth and lifetime income, however, do not differ from zero for the unmarried people. However, an indicator for lagged earnings at the taxable maximum has a positive, significant effect on retirement. We find that the effects of age and health on retirement are similar to those for married people. As with the married people, we find that defined contribution pension coverage decelerates retirement timing, though there is no significant effect of defined benefit pension coverage. An indicator for whether one is a widowed male suggests that these men retire faster than divorced females (the omitted category and most prevalent group of unmarried persons in our estimation sample), but we find no other important gender/marital status interactions.[7]

[7] We have included partnered as a marital category in the HRS estimation, though this is not a category that MINT produces. We therefore do not include it in the simulation.

Table 4-4
Retirement Model: Probit Results for Married People

	Combined Model		Men		Women	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Intercept	-0.8545 **	0.4265	-0.905 *	0.5306	-1.4503	0.9876
Own characteristics						
Lifetime earnings, wealth						
Ln of weighted average earnings, past 5 years	-0.1192 ***	0.0297	-0.0705 *	0.0416	-0.1764 ***	0.0451
Per capita family wealth / average wage	0.0046 ***	0.0014	0.0024	0.0015	0.0143 ***	0.0036
Incentives (all divided by weighted average of recent earnings)						
Year 1 retirement wealth accrual	0.0214	0.0211	0.0166	0.0273	0.0276	0.0343
Year 2 retirement wealth accrual	0.0159	0.0253	0.0371	0.0316	-0.0223	0.0513
Premium value of retirement wealth	-0.0132 *	0.0075	-0.0151	0.0101	-0.0056	0.013
Demographics						
Male	0.0938 *	0.0567	—		—	
Age difference from spouse	-0.0475 **	0.0217	-0.0304	0.0254	-0.0966 **	0.0453
Black	-0.3505	0.2366	-0.6542 *	0.3898	-0.1896	0.3195
Hispanic	0.1636	0.1389	0.0782	0.1809	0.2871	0.2233
Not a high school graduate (Ref=High school graduate)	0.0978 *	0.0566	0.0823	0.0734	0.1298	0.0921
Some college	-0.0817	0.0566	-0.0558	0.0739	-0.0997	0.0906
College graduate	-0.0362	0.0564	-0.0901	0.0719	0.0855	0.0964
Age 52 (Ref=51)	0.1866	0.1465	-0.0246	0.1996	0.393 *	0.2222
Age 53	0.1831	0.1364	0.0386	0.18	0.273	0.2171
Age 54	0.1989	0.144	0.0199	0.1915	0.2601	0.2345
Age 55	0.0052	0.153	-0.0173	0.1969	-0.192	0.2647
Age 56	0.0282	0.1687	-0.0205	0.2142	-0.2173	0.3028
Age 57	0.0396	0.1818	-0.0236	0.2289	-0.1758	0.3326
Age 58	0.0801	0.1991	-0.0189	0.2494	-0.1534	0.3712
Age 59	0.0952	0.2164	0.1118	0.2664	-0.2104	0.4143
Age 60	0.3932 *	0.2328	0.4302	0.2845	0.0133	0.4512
Age 61	0.5676 **	0.2533	0.6629 **	0.3084	0.1517	0.4953
Age 62	0.4299	0.28	0.6322 *	0.3408	-0.2149	0.5414
Age 63	0.5658 *	0.304	0.67 *	0.3654	0.2084	0.6038
Age 64	0.3368	0.3469	0.4662	0.4155	-0.1304	0.6915
Age 65	0.1518	0.4048	0.4265	0.4689	-0.7766	1.0225
Last cohort*female	-0.0267	0.1614	—		-0.1275	0.1794
Pension coverage indicators						
Have a DB	0.1043 **	0.045	0.2065 ***	0.0572	-0.1069	0.0773
Have a DC	-0.1027 **	0.0457	-0.1415 **	0.059	-0.0535	0.0747
Health and disability indicators						
Health fair or poor	0.3241 ***	0.065	0.3559 ***	0.0831	0.2973 ***	0.1084
Disability indicator	0.3186 ***	0.0665	0.3056 ***	0.0859	0.3406 ***	0.1077

Table 4-4
(Continued)

	Combined Model		Men		Women	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Spouse's characteristics						
Spouse's lifetime earnings						
Ln of average earnings, past 5 years	-0.0045	0.0063	-0.0063	0.0078	-0.0035	0.0116
Spouse's incentives						
Retirement wealth accrual, year 1	0.0005	0.0017	-0.0004	0.0019	0.0039	0.0052
Retirement wealth accrual, year 2	0.0013	0.0019	0.0017	0.002	0.001	0.0058
Premium value of retirement wealth if spouse is female	-0.0004	0.0003	-0.0004	0.0003	—	
Premium value of retirement wealth if spouse is male	0	0.0012	—		-0.0004	0.0015
Spouse demographics						
Spouse black	0.4632 **	0.2356	0.8175 **	0.3921	0.2727	0.3143
Spouse Hispanic	-0.2023	0.1413	-0.0424	0.1813	-0.3935 *	0.2319
Spouse age 45-46 (ref= <45)	0.195	0.2086	0.1139	0.2269	0.8627	0.8362
Spouse age 47-48	0.3895 *	0.2233	0.2416	0.248	1.5567 *	0.8476
Spouse age 49-50	0.2277	0.2501	0.072	0.2821	1.1708	0.8787
Spouse age 51-52	0.6292 **	0.2802	0.4237	0.3197	1.8484 **	0.9073
Spouse age 53-54	0.6942 **	0.3181	0.5297	0.3663	1.6934 *	0.9612
Spouse age 55-56	0.7603 **	0.3572	0.5701	0.4132	1.9522 *	1.0251
Spouse age 57-58	0.8955 **	0.3984	0.5152	0.4637	2.4175 **	1.093
Spouse age 59-60	1.007 **	0.4397	0.5651	0.5127	2.6287 **	1.1661
Spouse age 61-62	1.0292 **	0.4813	0.5456	0.5619	2.7234 **	1.2408
Spouse age 63-64	1.0614 **	0.5249	0.5771	0.6203	2.8011 **	1.3171
Spouse age 65-66	1.2395 **	0.5712	0.6714	0.6956	3.1212 **	1.3982
Spouse age 67 or higher	1.3434 **	0.6312	0.8775	0.7867	3.3588 **	1.5087
Spouse pension coverage indicators						
Spouse has a DB	0.073	0.051	0.0675	0.0678	0.1186	0.0809
Spouse has a DC	-0.0513	0.0525	-0.0556	0.0699	-0.0558	0.0827
N	5425		3352		2073	
-2 log-likelihood	5260.991		3118.281		2080.344	

* indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01

Data source: 1992 to 1996 waves of HRS matched to earnings and pension records. Sample is limited to individuals who have never been entitled to DI, who were not retired at t-1, and who earned at least .0436 times the average wage at t-1.

Table 4-5
Retirement Model: Probit Results for Unmarried People

	Coefficient		Standard error
INTERCEPT	-0.1909		0.5045
Lifetime earnings, wealth			
Ln of average earnings, past 5 years	-0.0863	*	0.0507
Wealth / Average wage	-0.0002		0.0048
Incentives (all divided by weighted average of recent earnings)			
Year 1 accrual of retirement wealth	0.0937	*	0.0506
Year 2 accrual of retirement wealth	0.0171		0.0532
Premium value of retirement wealth	-0.0375	**	0.0164
Sex-marital status group (Ref=Divorced female)			
Widow	-0.0513		0.0932
Widower	0.3351	*	0.18
Never married male	0.1106		0.1451
Never married female	-0.0625		0.1353
Divorced male	0.008		0.0904
Other demographics			
Black	0.1404	*	0.0739
Some college (Ref=High school graduate or less)	0.0651		0.0884
College graduate	-0.1428		0.0935
Age 52 (Ref=<51)	0.1135		0.2017
Age 53	0.3234	*	0.1818
Age 54	0.0657		0.1837
Age 55	-0.2352		0.1894
Age 56	-0.0396		0.1817
Age 57	0.1333		0.1813
Age 58	0.2189		0.181
Age 59	0.2154		0.1894
Age 60	0.4881	***	0.1823
Age 61	0.5276	***	0.1912
Age 62	0.4312	*	0.2227
Age 63	0.7503	***	0.2363
Age 64	0.4792		0.3127
Age 65	0.958	**	0.3776
Last cohort*female	-0.217		0.2228
Pension coverage indicators			
Have a DB	0.0144		0.0755
Have a DC	-0.1297	*	0.0753
Data censoring control			
At taxable maximum	0.252	*	0.1475
Health and disability indicators			
Health fair or poor	0.3582	***	0.089
Disability indicator	0.3171	***	0.1082
N	2029		
-2 log-likelihood	-2057.414		

* indicates $p < 0.10$, ** indicates $p < 0.05$, *** indicates $p < 0.01$

Data source: 1992 to 1996 waves of HRS matched to earnings and pension records. Sample is limited to individuals who have never been entitled to DI, who were not retired at t-1, and who earned at least .0436 times the average wage at t-1.

3. Comparisons to Prior Research

Our retirement model estimates qualitatively resemble those of Gustman and Steinmeier (2000), though there are some important differences in the magnitudes of estimated effects. We would expect this to be the case, as we operationalized variables somewhat differently than did Gustman and Steinmeier (for example, by using an "objective" measure of retirement as the dependent variable rather than a hybrid objective-subjective measure), and we needed to exclude those variables that were not projected in MINT.

Our estimates differ more significantly from those of Coile (2000), who finds a strong relationship between spouse's retirement incentives and married men's retirement behavior. There are several reasons for the differences between our respective estimates. First, Coile uses a very different sample. It is a much more restrictive sample, in that she excludes couples in which either spouse has left the labor force, while we include couples in which one spouse has left the labor force. Second, Coile has used retrospective information from the HRS to construct her person-year observations, while we have used only contemporaneous information. Coile's approach has the advantage of greatly increasing sample size (i.e., the number of person-years at risk of retirement). It has the disadvantage of inconsistently treating mortality risks. For example, in this approach, a member of the birth cohort that turned 57 in the HRS baseline year who had died at age 55 would be excluded from the pooled person-years for several years for which he or she was actually alive (ages 51 through 54). This is a problem if the people who die early differ systematically from those who do not, and is a more serious problem for men than for women, who face very low mortality risk at these ages.

V. WORK BEHAVIOR AND EARNINGS OF RETIREES PRIOR TO SOCIAL SECURITY TAKE-UP

1. Work Behavior of Retirees Prior to Social Security Take-Up

The models of work behavior of retirees, like the retirement models, rely on data from the HRS. We use discrete-time hazard models (essentially, logistic regressions that use pooled person-years at risk) to predict whether individuals who are not yet collecting Social Security and who worked fewer than twenty hours at least once since age fifty will work in a given year, conditioned on their status last year (t-1). The form of the discrete-time event history model is as follows:

Continued work model: $\text{prob}\ \{y_{it} = 1 \mid y_{it-1} = 1\} = 1 / (1+e^{-ßXit-1})$ **(4-3a)**

Re-entry model: $\text{prob}\ \{y_{it} = 1 \mid y_{it-1} = 0\} = 1 / (1+e^{-ßXit-1})$ **(4-3b)**

where y_{it} is the observed outcome at time t, and $ßX_{it-1}$ represents a vector of exogenous variables and their coefficients.

In order to promote intertemporal consistency in individuals' work histories, we estimate separate equations for those who were working in the last period (equation 4-3a), and those who were not working at t-1 (equation 4-3b). We further divide the group of people who were working at t-1 into "new retirees," people who were working twenty or more hours per week last year, and "partial retirees," people whose hours of work had dropped below twenty in a prior period after age 50. Table 4-6 presents the coefficient estimates and standard errors for these three equations. Recall that these are logit models, so the coefficients reflect the effects of a one-unit change in a variable on the *log-odds* of working.

For the "new retirees" (those who were working last year and had not yet experienced a drop in earnings below twenty hours per week), there are few predictors of whether one will work (column 1 in Table 4-6). This is probably due in part to the relatively small sample that we have used to estimate this equation. Health appears to be one of the most important determinants of the probability of work, with those in fair or poor health less likely to work than those in better health. Age, wealth, and, for women, cohort also have significant effects on the likelihood of work. Specifically, the probability of continuing work is higher at age 58 than at other ages, and women in later cohorts are more likely to continue working than are women in earlier cohorts). In interpreting this spike at age 58, we should recall that the HRS interviews are spaced two years apart. Thus age 58 represents the time of interview, while age 60 is the time when one actually decides whether or not to work (i.e., it is the year of the outcome). The higher one's family wealth, the more likely that one is to continue working in retirement. This result is on the surface counterintuitive, given that our retirement models suggested that wealth accelerated retirement. The finding suggests that *among retirees*, those with higher levels of wealth are more likely to work.

For the "partial retirees" (again, those whose average hours worked per week had dropped below twenty at least once since age fifty), we see slightly more variables with predictive capacity, but still relatively few good indicators of future work decisions (Equation 2 in Table 4-6). As in the prior equation, this is probably in part due to a relatively small sample size. Once more, one's physical condition appears to be an important determinant of work. An indicator for whether one has a condition that limits the amount or type of work that one can do has a negative effect on the log-odds of remaining employed. Age also appears to have important effects, with the likelihood of continuing to work generally declining with age, though in a non-linear fashion (on the log-odds). Those with less than a high school education are more likely to continue working than those with a high school diploma, and blacks are less likely to continue working than people of other races.

The sample sizes of those retirees who are at risk of re-entering employment (i.e., those who were not working in the prior period) are much larger, and the results are more closely in line with expectations (equation 3 in Table 4-6). Time out of the labor force is a key explanatory variable in this model. If one has been out of the labor force for more than a year, the chance of re-entering employment declines, with each year out implying an even greater decline in the log-odds of retiring. (The reference category is having been out of the labor force for one year.) Those with higher earnings the last time we saw them work (the variable labeled "last observed earnings") are more likely to re-enter employment, while those with higher lifetime earnings, as measured by AIME, are less likely to return to work. Similarly, those from better off families, as measured by per capita family wealth, are less likely to work than those from less well-off

Table 4-6
Labor Force Participation Among Retirees Not Receiving Social Security: Logistic Estimates

	Equation 1: New Retirees (Earnings > 0 at t-1, not retired at t-1)		*Equation 2: Partial Retirees (Earnings > 0 at t-1, retired at t-1)*		*Equation 3: Re-entrants (Earnings = 0 at t-1)*	
	Coefficient	**Standard error**	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**
Intercept	0.0282	0.578	1.1623 ***	0.3286	-0.0063	0.1746
Demographics						
Age 54	0.5046	0.6252	-0.4854	0.4588	——	——
Age 55	0.5196	0.5248	-0.4231	0.4126	——	——
Age 56	0.4968	0.509	-0.517	0.4018	-0.241	0.1564
Age 57	0.5376	0.498	-0.6063	0.4075	-0.2092	0.159
Age 58	0.9042 *	0.5349	-0.6947 *	0.3934	-0.3179 *	0.1627
Age 59	0.0435	0.5308	-0.3659	0.3989	-1.0206 ***	0.1956
Age 60	0.0254	0.546	-0.7749 **	0.3764	-0.4908 ***	0.1594
Age 61	-0.3882	0.5421	-0.9249 **	0.3951	-0.6803 ***	0.1615
Female	0.3326	0.2968	——	——	-0.1505	0.1238
College graduate	0.3872	0.368	0.1557	0.2543	-0.0221	0.1428
Not a high school grad	-0.2312	0.2355	0.7135 ***	0.2419	-0.2123 *	0.1157
Black	——	——	-0.4717 *	0.2456	-0.199	0.1338
Hispanic	——	——	——	——	0.2065	0.1632
Last cohort*female	1.0145 *	0.5696	——	——	0.5628 **	0.2605
Time Since Last Worked						
2 years	——	——	——	——	-0.7142 ***	0.1503
3 years	——	——	——	——	-1.1304 ***	0.1649
4 years	——	——	——	——	-1.3062 ***	0.2305
5 or more years	——	——	——	——	-2.0124 ***	0.125
Earnings History/Wealth						
Lagged earnings	-0.00053	0.00254	——	——	——	——
Last observed earnings			——	——	0.00324 ***	0.000914
AIME * 12 / averge wage	38.5615	34.982	28.311	21.5613	-25.8501 *	14.5705
Per capita family wealth / average wage	0.0458 **	0.02	——	——	-0.025 ***	0.00548
Health and Disability						
Health fair or poor	-0.6475 **	0.2734	——	——	-0.6463 ***	0.1296
Disabled	——	——	-1.0629 ***	0.235	-0.6605 ***	0.1155
N	537		553		5744	
-2 log-likelihood	575.314		671.293		3264.161	

* indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01

Data source: 1992 to 1996 waves of HRS matched to earnings and pension records. Workers must have dropped below 20 hours per week in the previous wave or earlier.

families. In this equation, those with less than a high school education are less likely to work than their more educated peers. Consistent with the prior two equations, both health and disability are negatively associated with returning to work. Age and cohort (for women) also have significant effects.

2. Earnings of Retirees Prior to Social Security Take-Up

To project the earnings of those retirees who choose to work (E_{it}), we use linear regression. Because, once more, promoting within-person consistency in earnings over time is a key objective, we include the lagged endogenous variable in the model, as follows:

$$E_{it} = E_{it-1}K + Z_{it}\Lambda + \varepsilon_{it} \quad \textbf{(4-4)}$$

where E_{it-1} is the value of one's earnings at t-1, Z_{it} is a vector of values for one's additional characteristics, K and Λ are unknown regression parameters to be estimated, and ε_{it} is a normally distributed error term with mean of zero. In our earnings analyses, we only project earnings up to the taxable maximum for Social Security.

We present the regression coefficient estimates in Table 4-7. In this particular model, we interact lagged earnings with one's recent work history (whether one is moving from work to partial retirement, whether one is continuing in partial retirement, or whether one is re-entering work after some time way). In the latter case, we interact work status with the most recent observed earnings rather than lagged earnings, which are by definition zero. We find that the effect of lagged earnings is much greater for those who are moving from work to partial retirement or continuing work in partial retirement. Both those who are continuing in partial retirement and those who are re-entering work after time off have lower intercepts as well. We further find age, education, and gender effects, with earnings declining significantly at ages fifty-seven, sixty, and sixty-one, college graduates expecting higher earnings than high school graduates (the reference category), and women expecting significantly lower earnings than men. Finally lifetime earnings (as measured by AIME) and family wealth are associated with current year earnings. Among those who work, the higher the lifetime earnings, the higher one's earnings at time t, and the higher one's family wealth, the lower one's wealth at t.

As in the equations about the work decisions of retirees who are continuing to work, the predictive value of this equation is modest. The estimated R-squared is 0.4962.

VI. SOCIAL SECURITY TAKE-UP

1. Design

Beginning at age 62, individuals become eligible for taking-up Social Security retirement benefits.[8] We estimate discrete time hazard models for benefit take-up. In the models, if a

[8] As in the earlier version of MINT, we still allow widow(er)s to take up Social Security benefits at ages 60 and 61. The probability that widow(er) will take-up benefit is deterministically assigned to one if (s)he is earning

Table 4-7
Earnings Among Retirees Not Receiving Social Security: OLS and Random Effects Estimates

	Standard OLS model			With random effects		
	Coefficient		Standard error	Coefficient		Standard error
Intercept	39.96904	***	5.55377	42.01864	***	6.15890
Education/Work Group Interactions						
Lagged earnings * entering partial retirement from work	0.68782	***	0.04053	0.37972	***	0.04638
Lagged earnings * continuing in partial retirement	0.56551	***	0.04596	0.36366	***	0.03986
Lagged earnings * reentering work after time off	0.29517	***	0.02968	0.21592	***	0.02929
Indicators of Work Group						
Entering partial retirement from work	-11.95257	***	4.3813	1.854146		4.13266
Continuing in partial retirement	-7.38407	*	3.86089	-0.3473951		3.887755
Demographics						
Age 54	-3.63295		5.45445	-2.44260		5.03385
Age 55	-3.95626		4.78911	-3.67604		4.37138
Age 56	-3.03842		4.98252	-2.60147		4.82255
Age 57	-9.36993	*	4.9304	-7.20263		4.81101
Age 58	-7.25385		5.03225	-8.95233	*	5.10679
Age 59	-6.27604		5.48596	-6.26509		5.57100
Age 60	-14.11138	***	5.18947	-14.44748	***	5.43739
Age 61	-26.28249	***	5.41747	-27.00939	***	5.71717
Female	-10.47531	***	3.35735	-13.05808	***	4.09969
College graduate	7.32289	**	3.49605	12.26677	**	4.37816
Not a high school graduate	-4.26014		3.07711	-6.06367		3.89957
Hispanic	5.64945		4.36995	7.46128		5.37015
Cohort effect: women (born 1936+)	6.54826		6.40462	8.35731		6.28927
Lifetime Earnings/Wealth						
AIME/ average wage	1182.50676	***	365.27942	1951.957	***	437.1592
Per capita family wealth/ average wage	-0.11857	*	0.07172	-0.1313892		0.0822087
Health status						
Health fair or poor	-4.98404		3.41789	-4.74856		3.67652
Variance of transitory error (eit)	1710			26.9168		
Variance of permanent error (ui)	—			28.4463		
Rho (fraction of variance due to ui)	—			0.5276		
N (person years)	1196					
R-Squared	0.4962					

* indicates $p < 0.10$, ** indicates $p < 0.05$, *** indicates $p < 0.01$

Data source: 1992 to 1996 waves of HRS matched to earnings and pension records. Workers must have dropped below 20 hours per week in the previous wave or earlier.

below the exempt amount from the Retirement Earnings Test and zero otherwise. Employing this assumption in previous simulations, we found that patterns of take-up at ages 60 and 61 mirrored historical outcomes.

person does not take up his or her benefits at age 62, then he/she faces the hazard again at age 63. Similarly, if a person does not claim his or her benefits at age 63, then he/she faces the hazard again at age 64, and so forth until finally applying for benefits. At age 70 (the point at which one no longer receives credits for delaying retirement), MINT assumes everyone who is eligible takes up benefits.

We have estimated three discrete-time event history models that predict age of first receipt of Social Security benefits for spouse-only recipients, low earners, and high earners. These models are similar to the take-up models in MINT1.0. They use the same estimation source (the 1990 to 1993 SIPPs), the same unit of analysis (birth years at risk of first Social Security take-up), and many of the same explanatory variables. These variables include dummies for age, race/ethnicity, and education, measures of recent and lifetime earnings, indicators of pension coverage, measures of housing and non-housing wealth, and, where relevant, one's spouse's characteristics.

The new models differ from the prior models in several ways. They now include as predictors health and retirement status (which were not available in MINT 1.0), they use additional years of administrative data on earnings and benefit receipt status (through 1999 instead of 1996), they include additional, more policy relevant variables (for example, an indicator of whether one is a dual entitlee), and they do not assume universal take-up until age 70 (rather than age 67, as in MINT 1.0). Further, we have changed the separate groups for which equations are defined. We now estimate separate equations by Social Security eligibility status (for example as a spouse only or as a worker) and for groups with different ratios of one's recent earnings to the Social Security exempt amount. In contrast, MINT 1.0 estimated separate equations for Social Security benefit take-up for married men, married women, and unmarried people.[9] We made this change because we believe that the process of deciding to take Social Security benefits differs more fundamentally based on one's eligibility and incentives than on one's sex and marital status per se. For example, we would expect that a married woman with high recent and lifetime earnings and a defined benefit pension would behave more similarly (with respect to Social Security take-up) to a man with similar work characteristics than to a married woman who had never been in the labor force and was not eligible for Social Security in her own right. Where appropriate, we incorporated interaction terms into the equations to test for any marital status- or gender-specific effects of the independent variables.

MINT 3.0's overall sequencing played an important role in the take-up model's design. As the Social Security claiming decision follows the retirement decision (that is, the decision to leave work of at least 20 hours per week for the first time) but precedes the earnings decision, we can use retirement status at time t but only earnings at time t-1 as predictors in the take-up model. This makes it challenging to interpret some of our coefficient estimates, as they reflect the effects of variables on Social Security take-up given a prior choice of whether to reduce labor

[9] While we believe that this new take-up model is a significant improvement over that incorporated into MINT 2.0, a few miscellaneous concerns remain. For example, we are unable to identify the eligibility status of those who do not qualify as workers and have unobserved former spouses (i.e., spouses who died or whom they divorced before the SIPP panel). We exclude such cases from our estimation sample, and this could be problematic.

force effort substantially (as indicated by a fifty percent drop in earnings or a drop below twenty hours per week).

In cases where one's entitlement to Social Security is only as a spouse, we process the spouse who is entitled to worker benefits before the spouse who is only entitled to an auxiliary benefit. This means that the spouse's Social Security take-up at time t can be included as an explanatory variable for the latter group. (We did not take this into consideration in MINT 1.0, and this limited the model.)

2. Results

Table 4-8 presents coefficients from our Social Security take-up models for potential spouse only recipients (column 1), for individuals who earned less than the exempt amount at time t-1 (column 2, labeled "Low-Earners"), and for individuals whose earnings exceeded the exempt amount at time t-1 (column 3, labeled "High-Earners"). Once again, because these models rely on logistic regression, the coefficient estimates reflect the effects on a one-unit change in a variable on the *log-odds* of taking up benefits.

Not surprisingly, we find that retirement status and age are key predictors of Social Security take-up among members of all three groups. If one is retired, one is far more likely to claim benefits, all else equal, in each group. The age effects, in contrast, vary across the three groups (age 62 is the reference group). While all groups experience declines immediately after the age 62 spike (reflected in the negative, significant coefficients for age 63), subsequent age patterns differ.

For the spouse only recipients (Table 4-8, column 1), spouse characteristics appear to have great influence on take-up. The important spouse characteristics include his or her take-up behavior, defined contribution pension coverage, and lagged earnings. A spouse's take-up in the past increases the likelihood that a husband or wife will take-up in the present, while higher spousal lagged earnings decrease this likelihood. Defined contribution pension coverage has variable effects for oneself and one's spouse. While having one's own DC pension reduces take-up probability (though not significantly), one's spouse's DC pension coverage increases it.

For those who earned the exempt amount or less last year, a different set of predictors is important (Table 4-8, column 2). One's own PIA, one's lagged earnings, one's marital status-sex group, one's education, and race/ethnicity all influence take-up (in addition to the age and retirement status effects). The higher one's lagged earnings (coded categorically) and PIA, the more likely one is to take up benefits net of retirement status. Not surprisingly, an indicator of dual entitlement has a large, positive coefficient. We would expect to find this relationship because many dual entitlees receive no return on their Social Security contributions: while their benefits increase if they wait to take up benefits because of a lesser actuarial reduction, the primary insurance amount upon which their benefit is based does not change. Dual entitlees therefore should claim benefits more quickly than beneficiaries who have more to gain by waiting (i.e., an increment in the Primary Insurance Amount and a lesser actuarial reduction). Among married persons, spouse take-up remains an important determinant of one's own take-up.

Table 4-8
Social Security Take-Up: Logistic Estimates

	Spouse Only Recipients		Low-Earners		High-Earners	
	Coefficient	**Standard error**	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**
Intercept	-2.6291 **	1.2182	1.0178	0.6724	0.1251	0.2462
Demographics						
Age 63	-1.6105 ***	0.2971	-2.447 ***	0.1771	-0.5105 ***	0.1406
Age 64	-0.61 *	0.3195	-0.4874 ***	0.1795	0.985 ***	0.1334
Age 65	-0.7893 **	0.3824	-0.8079 ***	0.2417	1.4775 ***	0.1883
Age 66	-1.848 ***	0.4702	-2.1402 ***	0.3511	0.8534 ***	0.2375
Age 67	-1.997 ***	0.4698	-1.6892 ***	0.3671	0.4533	0.2876
Age 68	-1.696 ***	0.5377	-2.4754 ***	0.5038	-0.3361	0.3524
Age 69	-0.5682	0.7192	0.1386	0.4691	4.217 ***	0.3878
Education gt 12	—	—-	-0.4707 ***	0.1309	-0.3398 ***	0.1071
Hispanic	—	—-	-0.6936 **	0.3515	—-	—
Black or Native American	—	—-	0.0214	0.1889	—-	—
Asian	—	—-	-0.9565 ***	0.3449	—-	—
Widower	—	—-	-2.415 ***	0.7689	—-	—
Widow	—	—-	-0.9849	0.6864	—-	—
Single male	—	—-	-0.7765	0.7811	—-	—
Single female	—	—-	-2.1393 ***	0.7592	—-	—
Divorced male	—	—-	-2.235 ***	0.7099	—-	—
Divorced female	—	—-	-1.4615 **	0.6883	—-	—
Married female	—	—-	0.1572	0.2086	—-	—
Pension coverage indicators						
DB pension	—	—-	0.4535 ***	0.1332	0.2424 **	0.1004
DC pension	-0.4133	0.2706	—-	—-	-0.2098 *	0.1124
Retirement status, lifetime Earnings / wealth						
Retired at t	1.435 ***	0.329	1.3396 ***	0.1347	2.9728 ***	0.1284
PIA / average wage	—	—-	4.5546 ***	0.4373	—-	—
Lag earnings / avg wage	—	—-	—-	—-	-0.559 **	0.2279
0 < lag earng <= .8 * exempt	—	—-	0.6448 ***	0.1436	—-	—
Lag earnings > .8 * exempt	—	—-	0.9724 ***	0.2821	—-	—
Family wealth / avg wage	—	—-	-0.0167 *	0.00892	-0.0106 *	0.00592
Earnings ages 56-61	—	—-	—-	—-	0.6472 *	0.3702
Earnings 56-61 squared	—	—-	—-	—-	-0.1171	0.1392
Social Security parameters						
Fraction taxed	—	—-	—-	—-	-2.1303 ***	0.31
Above taxaway point	—	—-	—-	—-	-0.2898 *	0.1672
Dual entitlee	—	—-	0.8891 ***	0.2923	—-	—
Spouse characteristics						
Sp tookup Social Sec t-1	1.5205 ***	0.2264	1.3377 ***	0.1948	0.6231 ***	0.1406
Sp adjusted PIA	8.8352	6.4407	-0.7929	0.5539	-3.6211 ***	1.2437
Sp adjusted PIA squared	-9.8016	8.466	—-	—-	5.0256 **	2.5115
Sp lag earnings / avg wage	-0.5621 ***	0.1314	—-	—-	—-	—
Sp DB pension indicator	0.1828	0.2106	0.2303	0.1679	0.0815	0.1465
Sp DC pension indicator	0.4592 *	0.2748	-0.1993	0.1602	0.2469 *	0.1336
Spouse age	—	—-	-0.0372 ***	0.0114	-0.00178	0.00226
N (person years)	628		2173		3473	
-2 log-likelihood	593.449		1839.694		2805.381	

* indicates $p < 0.10$, ** indicates $p < 0.05$, *** indicates $p < 0.01$

Data source: 1990 to 1993 SIPP panels matched to SER. Individuals in the three samples have never received disabled worker benefits. Spouse only recipients are defined as persons with zeros PIAs who have living spouses age 62 or older with positive PIAs (i.e., widows are not included). Low-earners are defined as individuals with earnings either at or below the RET exempt amount. High-earners are defined by earnings above the exempt amount.

Path for output: Regs2001.lst

For the last group of individuals at risk of Social Security take-up, those who earned above the exempt amount at t-1, the fraction of one's earnings last year that would be taxed away by the retirement earnings test influences take-up: the greater the fraction taxed away (labeled "fraction taxed" in the table), the less likely one is to take up benefits, all else equal. Once more, lifetime earnings are an important predictor of the probability of claiming benefits. Pension coverage appears to have especially important effects for members of this group, with DB and DC plans having opposite effects analogous to those found in the retirement model (DB plans accelerate take-up, whereas DC plans decelerate it). Spouse characteristics showed importance to the take-up behavior of individuals in this select group, with spouse PIA (and its square), spouse DC pension coverage, and spouse take-up affecting one's own take-up.

VII. LABOR FORCE PARTICIPATION AND EARNINGS OF SOCIAL SECURITY BENEFICIARIES

Our analysis of Social Security beneficiaries' labor force participation and earnings also relies on several equations. We estimate separate participation and earnings equations that are stratified by beneficiaries' ages. In examining beneficiaries' work decisions, we estimate equations for beneficiaries below age 70 and equations for beneficiaries age 70 and above. For beneficiaries' earnings equations, we look at three age groups: less than the NRA (in these data age 65), between the NRA and 69, and age 70 and older. We separately examine the earnings of these three groups because, in the data used for our analysis (the early to mid 1990s), these three groups faced different RET threshold amounts.[10] Below we discuss the work and earnings equations in turn.

1. Labor Force Participation of Social Security Beneficiaries Below Age 70

We estimate three separate equations for beneficiaries' work force participation. The first equation examines the labor force participation of beneficiaries during their first year Social Security receipt. The second equation examines beneficiaries' exits from employment that occur after their first year of Social Security receipt. For beneficiaries who are working at time *t-1* (say, age 62), this equation estimates the probability of not working at time *t* (i.e., exiting employment between time *t-1* and *t*). Finally, the third equation examines beneficiaries' reentries into employment after their first year of Social Security receipt. This design allows a different decision process regarding employment for persons in their first year as a beneficiary versus subsequent years, and also allows beneficiaries who have exited the workforce to reenter employment at some later time.

To examine beneficiaries' decisions to work in the first year of Social Security receipt we estimate a logit model. This model provides information on how different demographic and economic variables affect individuals' decisions to work in the first year of Social Security receipt. In our sample of 3,247 first time beneficiaries, roughly 47 percent worked during their

[10] For example, in 1995, the RET threshold was $ 8160 for beneficiaries under NRA, $ 11280 for beneficiaries between the NRA and age 70, and there was no threshold for persons 70 and older as RET did not apply to persons in this age range.

first year of receipt. To examine individuals' exits from and reentries into employment, we use a discrete-time multivariate hazard model, where the form of the hazard is a logit. These hazard models provide information on how various demographic and economic variables affect beneficiaries' decisions to exit and reenter employment after the first year of Social Security benefit receipt. Our examination of exits from employment includes 5,837 person-years, where 24 percent of these person-years represent an exit from employment. Our examination of reentries into employment includes 15,155 person-years, where 4 percent of the person-years represent a reentry into employment. While a relatively small percentage of beneficiaries reenter employment, we take reentries into account as it can have important implications for individuals' future economic status.

The set of explanatory variables examined in the three models are virtually identical,[11] but the explanatory variables in the final equations differ across the three models. The baseline explanatory variables are listed below and the regression results, which show the specific explanatory variables included in each model, are presented in Tables 4-9 through 4-11.

- Demographic Characteristics
  - Age indicators (own/spouse)
  - Gender
  - Race/ethnicity
  - Marital status
  - Educational attainment
  - Health status
- Social Security Eligibility Status
  - Eligible as spouse or survivor only
  - Dually entitled[12]
- Labor force Attachment and Prior Earnings
  - Number of years since last worked
  - Lagged earnings
  - Lagged earnings interacted with educational attainment
  - Lagged earnings interacted with Social Security eligibility status
- Other Family Economic Variables
  - AIME
  - Family covered by DB pension
  - Family DC wealth
  - Family non-pension wealth (log of)

[11] The one exception is that the employment exit equation does not include a variable indicating the number of years since the individual was last employed, since all individuals, by definition, were employed in the previous period.

[12] An individual is eligible for both a worker and a spousal benefit, but receives a higher benefit as a spouse.

Table 4-9
Beneficiaries' Labor Force Participation in Year of First Social Security Receipt
1990-93 SIPP Panel Members Ages 60-69
Logit Model Results

Explanatory Variable	Coefficient	Standard Error
Demographic Characteristics		
Age 60-61	0.5294 **	0.2507
Age 63-64	0.2210 *	0.1276
Age 65	0.1772	0.1499
Age 66-69	0.4643 **	0.2292
Male	0.1143	0.1272
Education Less than High School	-0.6196 ***	0.1681
Fair or Poor Health Status	-0.3518 ***	0.1300
Social Security Eligibility Status		
Spouse Beneficiary	-1.0842 ***	0.3120
Labor Force Attachment and Prior Earnings		
Number of Years since Last Worked	-0.9628 ***	0.0524
Lagged Earnings	0.6956 ***	0.1023
Lagged Earnings by Less than High School	1.0887 ***	0.2643
Other Family Economic Variables		
AIME / Average Wage	-0.9076 ***	0.1542
Family DC Wealth	-0.0702 **	0.0309
Family Non-Pension Wealth / Average Wage	-0.0161 **	0.0074
Constant	1.1976 ***	0.1268
Pseudo R-Square	0.401	
Log Likelihood	-1,355.9792	
Observations	3,274	

*** indicates p < 0.01; ** indicates p < 0.05, * indicates p < 0.10
Data source: 60-69 year old Social Security beneficiaries who are in their first year of Social Security receipt.

Table 4-10
Beneficiaries' Employment Exists After First Social Security Receipt
1990-93 SIPP Panel Members Ages 60-69
Logit Hazard Model Results

Explanatory Variable	Coefficient		Standard Error
Demographic Characteristics			
Age 64	-0.2325	**	0.0996
Age 67-69	-0.3683	***	0.0704
Spouse 62 or Older	0.1070		0.0902
Education Less than High School	0.0969		0.0886
Education High School	-0.0820		0.0850
Fair or Poor Health Status	0.2706	***	0.0781
Married	-0.2034	**	0.0806
Social Security Eligibility Status			
Spouse or Survivor Beneficiary	1.1957	***	0.2219
Dually Entitled	0.9485	***	0.2154
Labor Force Attachment and Prior Earnings			
Lagged Earnings	-1.5775	***	0.1429
Lagged Earnings by Spouse or Survivor Beneficiary	-4.7379	***	1.3939
Lagged Earnings by Dually Entitled	-7.5280	***	1.3507
Other Family Economic Variables			
AIME / Average Wage	0.5254	***	0.0971
Family DC Wealth	0.0370	*	0.0221
Family Covered by DB Pension	-0.2522	***	0.0672
Constant	-0.7933	***	0.1111
Pseudo R-Square	0.0567		
Log Likelihood	-3,019.7146		
Observations	5,839		

*** indicates $p < 0.01$; ** indicates $p < 0.05$, * indicates $p < 0.10$
Data source: 60-69 year old Social Security beneficiaries who received Social Security and were employed at time t-1.

Table 4-11
Beneficiaries Employment Reentries After First Social Security Receipt
1990-93 SIPP Panel Members Ages 60-69
Logit Hazard Model Results

Explanatory Variable	Coefficient	Standard Error
Demographic Characteristics		
Age 63	-0.7978 **	0.3088
Age 64	-0.7952 ***	0.3001
Age 65	-0.8103 ***	0.2974
Age 66-69	-1.0176 ***	0.2837
Female	-0.4476 ***	0.0899
Black or Native American	-0.0880	0.1545
Poor Health Status	-0.2902 ***	0.1027
Social Security Eligibility Status		
Spouse Beneficiary	-0.9582 ***	0.1954
Widow Beneficiary	-0.4127 *	0.2354
Labor Force Attachment and Prior Earnings		
Number of Years since Last Worked	-0.3776 ***	0.0266
Other Family Economic Variables		
Log of Family Non-Pension Wealth	-0.0079 *	0.0070
Family Covered by DB Pension	-0.3083 ***	0.0858
Constant	-0.2788	0.2994
Pseudo R-Square	0.083	
Log Likelihood	-2,453.31	
Observations	14,780	

*** indicates p < 0.01; ** indicates p < 0.05, * indicates p < 0.10
Data source: 60-69 year old Social Security beneficiaries who received Social Security and were *not* employed at time t-1.

Labor Force Participation of Beneficiaries at First Social Security Take-Up: Below Age 70

The results of the logit model for workforce participation in the first year of Social Security receipt are presented in Table 4-9. Our analysis suggests that individuals who take up Social Security benefits at age 62 are less likely to work than individuals who take up benefits at any other age between 60 and 69. The results suggest that individuals who take up benefits at 60 and 61 are the most likely to work, followed by 66 to 69 year olds, 63 to 64 year olds, and finally by 65 year olds. Our finding that individuals who take up benefits at ages 60 and 61 are the most likely to work is somewhat surprising, as these individuals are predominantly collecting widows benefits. However, it is not surprising that persons who take up benefits at first entitlement (age 62) are less likely to work upon Social Security take-up than persons who take up Social Security benefits after first entitlement. Individuals who take up benefits when they first become entitled may have a lower taste for work, and thus, take-up benefits and exit employment simultaneously. Our logit model results also suggest that individuals are less likely to work if they have less than high school education and report poor health status. Individuals' Social Security eligibility status is also an important indicator of work participation. Individuals who are only eligible to receive a spousal benefit are less likely to work. Once this indicator of eligibility status is controlled for in our model, variables that identify marital status, gender, and interactions, such as whether an individual is a married female, are not statistically significant.

Individuals' labor force attachment and prior earnings are also strong indicators of workforce participation. As the number of years since an individual worked increases, the probability that they work in their first year as a Social Security beneficiary declines. Individuals with higher lagged earnings are more likely to work than persons with lower lagged earnings. This marginal effect of lagged earnings on current employment is larger for individuals with less than a high school education than for individuals with higher educational attainment, which implies a stronger relationship between earnings and work for less educated beneficiaries. While individuals with high lagged earnings are more likely to work than individuals with lower lagged earnings, individuals with high accumulated past earnings, as measured by their AIME, are less likely to work than individuals with lower AIMEs. We also find that individuals with higher wealth are less likely to work.

Beneficiaries' Exits from Employment: Below Age 70

Our next model examines beneficiaries' exits from employment using a logistic hazard model. With this hazard model, we estimate how different demographic and economic factors affect beneficiaries' decisions to exit employment at time *t*, given they are employed at time *t-1*. Many of the same factors that affect beneficiaries' employment decisions in the year of first Social Security receipt also affect their decision to exit employment in subsequent years (see Table 4-10).

The results of our analysis suggest that beneficiaries who work in their late sixties—ages 67 through 69—are less likely to exit employment than younger beneficiaries. This is not surprising, as these older workers have shown a strong attachment to the labor force by remaining employed. We also find that marital status and spouses' ages play a role in beneficiaries' decisions to exit employment. Married beneficiaries are less likely to exit employment than unmarried beneficiaries, but, among married beneficiaries, those who have a spouse age 62 or older are more likely to exit employment. We also find that beneficiaries who report poor health are more likely to exit employment. Social Security eligibility status also affects beneficiaries' employment exit probability. Individuals who receive a Social Security benefit based on their own past earnings are the least likely to exit employment, followed by individuals who are dually entitled and individuals eligible for a spouse or survivor benefit only, respectively. We look separately at individuals who are dually entitled and those who receive a spouse or survivor benefit and because of the stronger labor force attachment of dual entitlees.

As with our model of employment at first Social Security receipt, prior earnings are also strong indicators of work behavior. We find that individuals with high lagged earnings are less likely to exit employment. This marginal effect of past earnings on employment exits is larger for individuals who receive a spouse or survivor benefit and those who are dually entitled than for individuals who receive a benefit based on their own past earnings. Finally, high AIMEs and DC wealth increase the likelihood of exiting employment, while being covered by the DB pension reduces the likelihood of exiting employment.

Beneficiaries' Re-entries into Employment: Below Age 70

Our third model of beneficiaries' work behavior examines re-entries into employment. Like our examination of beneficiaries' exits from employment, we use a logistic hazard model. In general, we find that older beneficiaries are less likely to reenter employment, although the magnitudes of the estimated coefficients do not increase monotonically with age (see Table 4-11). Consistent with the results of the two previous models that examine work behavior beneficiaries, we find that persons who report poor health are less likely to reenter employment. Individuals eligible for a spousal benefit only are also highly unlikely to reenter employment. Women are less likely than men to reenter employment.

As the number of years since a beneficiary last worked increases, the probability of reentering employment falls. In this model we also examined beneficiaries' last observed wage, but this variable was statistically insignificant and was not included in the final specification. Our analysis also suggests that individuals who are covered by a DB pension are less likely to reenter employment than those who are not covered by DB pension.

2. Work Behavior of Social Security Beneficiaries Age 70 and Over

As in the previous models of work behavior for retirees (those who have left work of twenty hours or more and Social Security beneficiaries), we also estimate separate equations for work entry and exit for individuals who are ages 70 and older. Again, we do this to promote consistency in life trajectories. While some people do re-enter work after a hiatus, even at these advanced ages, it is far more common to work if one has worked recently. Table 4-12 reports the coefficient estimates. Once more, the model is a discrete-time hazard, so coefficients reflect the effects of a one-unit change on the log-odds of experiencing the transition.

Table 4-12
Labor Force Participation of Persons Ages 70 and Higher: Logistic Estimates

	Equation 1: Continuing		Equation 2: Re-entry	
	Coefficient	Standard error	Coefficient	Standard error
Intercept	0.6532 ***	0.1036	-2.1589 ***	0.1975
Education/Lagged Earnings Interactions				
Lagged earnings * dropout	1.9972 ***	0.2843	—	—
Lagged earnings * high school grad	2.5728 ***	0.2744	—	—
Lagged earnings * some college	1.3414 ***	0.1528	—	—
Demographics				
Age 71	—	—	-0.4242 **	0.1719
Age 72	—	—	-0.1845	0.1676
Age 73	—	—	-0.3458 *	0.1815
Age 74	—	—	-0.4086 **	0.1891
Age 75	—	—	-0.3012	0.188
Age 76	-0.2943 **	0.141	-0.5529 ***	0.2147
Age 77	—	—	-0.4822 **	0.2181
Age 78	—	—	-0.8983 ***	0.2589
Age 79	-0.5385 ***	0.1795	-0.7883 ***	0.2596
Age 80	—	—	-0.869 ***	0.2783
Age 81	—	—	-1.3369 ***	0.3744
Age 82	—	—	-0.9279 ***	0.3147
Age 83	—	—	-1.1642 ***	0.3754
Age 84	—	—	-1.2926 ***	0.4276
Age 85	—	—	-1.2869 ***	0.4656
Hispanic	-0.3875 *	0.2319	—	—
Black or Native American	—	—	0.3539 **	0.1597
Asian	—	—	-0.5359	0.5156
Married female	—	—	-0.0597	0.1745
Lifetime Earnings and Wealth				
Own adjusted PIA (wage-indexed)	0.3804	0.2407	1.9999 ***	0.3212
Spouse adjusted PIA (wage-indexed)	—	—	-0.3378	0.4187
Family wealth / average wage	-0.0103 **	0.00499	—	—
Homeowner indicator	0.0998	0.0882	0.2772 **	0.1159
Years Since Last Worked				
2 years	—	—	-0.8369 ***	0.1655
3 years	—	—	-1.3309 ***	0.1891
4 years	—	—	-1.5192 ***	0.1986
5 or more years	—	—	-2.537 ***	0.1159
Health				
Health fair or poor	-0.2497 ***	0.087	-0.483 ***	0.1083
N (person years)	4,471		34,731	
-2 log-likelihood	4,519.78		4,616.49	

* indicates $p < 0.10$, ** indicates $p < 0.05$, *** indicates $p < 0.01$

Data source: 1990 to 1993 SIPP panels matched to SER

When trying to project whether an individual aged 70 or over will continue to work given that he or she was working last year, we find a strong, positive relationship with earnings last year (Table 4-12 equation 1). For our lagged earnings measure we interact prior earnings with one's educational attainment. This follows in the spirit of the earnings trajectory model, which contains separate equations by sex and educational attainment. The association between this year's chance of working and last year's earnings is strongest for those with less than a college education. Age has nonlinear effects on the probability of staying on the job, with one's chances of continuing to work decreasing at ages 76 and 79. (These age variables represent the t-1 ages, so work actually declines at ages 77 and 80.)[13] Hispanics are significantly less likely than non-Hispanics to continue working. The higher one's lifetime earnings (as reflected by PIA), the greater are one's chances of working (though the effect is not significant). This is consistent with findings from Haider and Loughran (2001), who find disproportionate representation of those who are most well off among older workers. As in nearly all of the work and earnings equations we estimate, fair or poor health is negatively associated with work in this group.

In the re-entry model for older persons, we once more observe a strong, negative association between time out of the labor force and probability of re-entering employment (Table 4-12, equation 2). The model also reveals strong age effects, with probability of returning to work declining with age, though again in a non-linear fashion. Fair or poor health, as we would expect, is also associated with lower chances of re-entry into work. Lifetime earnings (as reflected by PIA) and homeownership, in contrast, are both positively associated with probability of re-entering the work force.

3. Earnings of Social Security Beneficiaries

Beneficiaries' earnings are separately examined for individuals in three distinct age ranges: between 60 and 64 (i.e., under the NRA in these data), between 65 and 69, and 70 and over. As mentioned above, we separately examine the earnings of these three groups because, in the data used for our analysis (the early to mid 1990s), these groups of individuals face different RET threshold amounts. While there are differences across these earnings equations, there are some important similarities. A strong consistent finding is that prior labor force participation and last observed earnings (i.e., earnings from the year in which the individual most recently worked) are strong predictors of current earnings. In addition, we find that the relationship between last observed earnings and current earnings is stronger for older beneficiaries than for younger beneficiaries. Below, we discuss the earnings of beneficiaries in these three age ranges in turn.

Earnings of Social Security Beneficiaries Between Ages 60 and 64

We estimate two separate earnings equations for beneficiaries between the ages of 60 and 64. The first equation examines beneficiaries' earnings in their first year of Social Security receipt, while the second equation examines their earnings in subsequent years. We use two

[13] The sample sizes for these two coefficients range from 150 to 285 cases. While these are not large samples, they should be sufficient for estimating the age pattern.

equations because we anticipate that the relationship between lagged earnings and current earnings is not the same in one's first year of Social Security receipt as in one's subsequent years of receipt. We estimate earnings using a straightforward linear equation.

Our examination of 60 to the 64 year-old beneficiaries' earnings in their first year of Social Security receipt shows educational attainment is the only demographic characteristic that significantly affects earnings (Table 4-13). We find lower earnings among beneficiaries without a high school degree than beneficiaries who have completed high school, and that beneficiaries who have completed high school only have lower earnings than their counterparts who have additional education.

In terms of labor force attachment and prior earnings, we find that individuals who did not work in the prior year (i.e., at *t-1*) have lower current earnings (i.e., at *t*). We also find that last observed earnings are a relatively strong predictor of current earnings—the coefficient on last observed earnings is 0.277 (with the standard error 0.020). We also allow an interaction between last observed earnings and an indicator of whether the beneficiary is 64 years old. We do this because individuals' ages are defined as of January 1st in each calendar year,[14] so an individual who is defined as a 64 year old is actually 65 for some part of that calendar year (i.e., they will be 65 by December 31st). Because the RET threshold is higher for 65 year-olds than 64 year-olds (in these data), individuals defined as 64 years old actually face a higher RET threshold for part of the calendar year. By including this interaction term, our model recognizes the possibility that earnings may differ for these individuals. Our results do, in fact, suggest a stronger relationship between last observed earnings and current earnings for 64 year-old beneficiaries as compared to younger beneficiaries— the coefficient on this interaction term is 0.103 (standard error, 0.040).

Next we turn to the earnings of 60-64 year-old beneficiaries *after* their first year of Social Security receipt (Table 4-14). In terms of demographic characteristics, there are considerable differences between this model and the previous model. Here, we find that being 64 years old, reporting poor health, and being a married female are all associated with lower earnings, but that educational attainment does not play a significant role. In terms of labor force attachment and prior earnings, however, the results are similar. We find that individuals who did not work in the prior year have lower earnings and that past earnings are positively related to current earnings. As predicted, we find a stronger relationship between past and current earnings for beneficiaries *after* the first year of receipt as compared to their first year of receipt (Table 4-14 versus Table 4-13). The coefficient on last observed earnings is 0.434 (0.022) in this earnings equation, whereas the coefficient on last observed earnings is only 0.281 in the equation for earnings in the first year of Social Security receipt. As with earnings in the first year of Social Security receipt (Table 4-13), the results suggest a stronger relationship between last observed earnings and current earnings for 64 year-old beneficiaries than younger beneficiaries. We also find a weaker relationship between last observed earnings and current earnings for persons who did not work last period than persons who did work last period. This is not surprising, as we expect a stronger relationship between past and current earnings for persons whose last observed earnings measures their earnings last year as compared to some previous time period.

[14] We do this because earnings from the SER are measured in a calendar year, not birth year.

Table 4-13
Earnings of Beneficiaries at First Social Security Receipt
1990-93 SIPP Panel Members Ages 60-64
Regression Model Results

Explanatory Variable	Coefficient	Standard Error
Demographic Characteristics		
Age 60-61	10.6735 ***	3.8574
Age 63	14.9084 ***	2.9974
Age 64	12.6299 ***	4.2778
Education Less than High School	2.0960	2.5440
Education High School	-0.1093	2.2453
Social Security Eligibility Status		
Spouse or Survivor Beneficiary	5.4274	6.2849
Labor Force Attachment and Prior Earnings		
Not Working at *t-1*	-22.4996 ***	4.2824
Last Observed Earnings	67.4591 ***	1.9722
Last Observed Earnings by Age 64	-1.9927	3.5856
Other Family Economic Variables		
AIME	4.1847	2.7457
Log of Family Non-Pension Wealth	0.0511	0.1512
Constant	0.3063	2.7876
Adjusted R-Square	0.646	
Observations	1,544	

*** indicates p < 0.01; ** indicates p < 0.05, * indicates p < 0.10
Data source: 60-64 year old working Social Security beneficiaries who are in their first year of Social Security receipt.

Table 4-14
Earnings of Beneficiaries *After* First Social Security Receipt
1990-93 SIPP Panel Members Ages 60-64
Regression Model Results

Explanatory Variable	Coefficient	Standard Error
Demographic Characteristics		
Age 64	0.6928	1.6225
Poor Health Status	-1.2440	1.5598
Married Female	-5.4132 ***	1.4716
Labor Force Attachment and Prior Earnings		
Not Working at t-1	-8.0564 ***	2.5722
Last Observed Earnings	31.9217 ***	1.6679
Last Observed Earnings by Age 64	0.5243	2.4190
Last Observed Earnings by Not Working at t-1	-19.9802 ***	4.3264
Other Family Economic Variables		
AIME	-5.4266 ***	1.6176
Constant	17.1983 ***	1.5782
Adjusted R-Square	0.3043	
Observations	1,675	

*** indicates p < 0.01; ** indicates p < 0.05, * indicates p < 0.10
Data source: 60-64 year old working Social Security beneficiaries who have received Social Security benefits for more than one year.

Earnings of Social Security Beneficiaries Between Ages 65 and 69

In examining the earnings of 65 through 69 year-old beneficiaries, we again estimate two equations. The first equation examines beneficiaries' earnings in their first year of Social Security receipt and the second examines their earnings in subsequent years. Beneficiaries' earnings in their first year of Social Security receipt are influenced by age and educational attainment (Table 4-15). As compared with 65 year-old beneficiaries, 67 to 69 year-old beneficiaries have the highest earnings, followed by 66 year-old beneficiaries. Consistent with the finding for younger workers in their first year of Social Security receipt, we find that less educated beneficiaries have lower levels of earnings. We again find that labor force attachment and prior earnings are relatively strong predictors of current earnings. Individuals who did not work in the prior year (i.e., at *t-1*) have lower earnings than their counterparts who did work. Also, there is a positive relationship between last observed earnings and current earnings. Interestingly, the relationship between current earnings and last observed earnings is stronger among 65 to 69 year-olds than among 60 to 64 year-olds. The coefficient on the last observed earnings for the younger beneficiaries is 0.281 (Table 4-13), while is it is 0.483 among the older beneficiaries (Table 4-15).

Turning to the earnings of 65-69 year-old beneficiaries *after* their first year of Social Security receipt, we once more find that age and educational attainment are related to earnings (Table 4-16). Older beneficiaries are found to have higher earnings, and less educated beneficiaries to have lower earnings. We also find that married females have lower earnings. Labor force attachment and prior earnings are the strongest predictors of current earnings. In addition, we find that the relationship between current earnings and last observed earnings is stronger among 65 to 69 year-olds than among 60 to 64 year-olds, which is consistent with the finding above for beneficiaries earnings in their first year of Social Security receipt. The coefficient on last observed earnings is 0.434 for the 60 to 64 year-old beneficiaries (Table 4-14) and 0.756 for the 65 to 69 year-old beneficiaries (Table 4-16).

Earnings of Social Security Beneficiaries Age 70 and Over

To project earnings levels for workers ages seventy and older, we once more rely on OLS regressions. Earnings again depend upon lagged earnings (Table 4-17). For those who worked the previous year, we again interact lagged earnings with educational attainment. The relationship of this year's earnings to last year's earnings increases slightly with education. For those who have re-entered employment, whose lagged earnings are therefore zero, we include an additional indicator variable for that status and a measure of most recent observed earnings. The relationship between this year's earnings and the most recent observed earnings is less strong than is the case for someone continuing to work. There are modest age effects on earnings, with significant earnings declines observed at age 71. Both family wealth and lifetime earnings are positively associated with earnings levels. The higher one's past earnings and wealth, the higher one's earnings are this year.

The earnings equation for older workers has far greater predictive value than several of the prior equations, for example, the equation for the earnings of retirees prior to Social Security

Table 4-15
Earnings of Beneficiaries at Age of First Social Security Receipt
1990-93 SIPP Panel Members Ages 65-69
Regression Model Results

Explanatory Variable	Coefficient	Standard Error
Demographic Characteristics		
Age 66	23.1756 ***	5.4435
Age 67-69	12.9808 ***	4.6787
Education Less than High School	-15.2331 ***	4.8125
Education High School	-8.7267 **	4.1724
Labor Force Attachment and Prior Earnings		
Not Working at t-1	15.9088	11.6115
Last Observed Earnings	72.7864 ***	4.3592
Other Family Economic Variables		
AIME	6.3878	6.5161
Constant	14.7247 ***	5.2068
Adjusted R-Square	0.6573	
Observations	540	

*** indicates $p < 0.01$; ** indicates $p < 0.05$, * indicates $p < 0.10$
Data source: 65-69 year old working Social Security beneficiaries who are in their first year of Social Security receipt.

Table 4-16
Earnings of Beneficiaries *After* First Social Security Receipt
1990-93 SIPP Panel Members Ages 65-69
Regression Model Results

Explanatory Variable	Coefficient	Standard Error
Demographic Characteristics		
Age 65	-1.635535	1.247111
Age 67	2.972955 **	1.2336
Age 68	6.213908 ***	1.266511
Age 69	4.3242 ***	1.2942
Education Less than High School	-3.6096 ***	1.0619
Education High School	-0.8532	0.9780
Poor Health Status	-1.3933	1.0799
Married Female	-1.703988 *	0.9796
Labor Force Attachment and Prior Earnings		
Not Working at t-1	-1.8291	1.6292
Last Observed Earnings	51.1016 ***	0.8826377
Last Observed Earnings by Not Working at t-1	-43.2519 ***	2.506573
Constant	11.39524 ***	1.227754
Adjusted R-Square	0.4694	
Observations	4,457	

*** indicates $p < 0.01$; ** indicates $p < 0.05$, * indicates $p < 0.10$
Data source: 65-69 year old working Social Security beneficiaries who have received Social Security benefits for more than one year.

Table 4-17
Earnings of Workers Ages 70 and Older: OLS and Random Effects Estimates

	Standard OLS model		With random effects	
	Coefficient	Standard error	Coefficient	Standard error
Intercept	-1.68315	1.10597	-1.58872	1.254977
Education/Re-Entry Lagged Earnings Interactions				
Lagged earnings * high school dropout	82.2698 ***	1.85016	77.28169 ***	2.10854
Lagged earnings * high school graduate	83.67175 ***	1.35022	79.39858 ***	1.53427
Lagged earnings * some college	86.91607 ***	0.93531	82.84672 ***	1.06936
Re-entrant	4.35492 ***	1.46287	3.75416 **	1.48944
Lagged earnings * re-entrant	15.50985 ***	2.44661	13.58508 ***	2.47784
Demographics				
Age 71	-2.07321 *	1.18957	-2.19209 *	1.15688
Age 75	-1.89941	1.57467	-2.05479	1.55802
Age 76	2.41833	1.76345	2.31585	1.74713
Female	1.92626 **	0.96365	2.23958 **	1.07651
Lifetime Earnings and Wealth				
Family wealth / average wage	0.2556 ***	0.05241	0.35900 ***	0.06335
AIME / average wage	7.94486 ***	1.70977	10.01891 ***	1.91411
Health				
Health fair or poor	-1.16444	1.04137	-1.45121	1.18242
Variance of error (eit)	657.482		23.507596	
Variance of permanent error (ui)	—		11.544372	
Rho (fraction of variance due to ui)	—		0.19430892	
N (person years)	3953			
R-Squared	0.7845			

* indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01

Data source: 1990 to 1993 SIPP panels matched to SER take-up has. The estimated R-squared is 0.784. At this point in the model, we are left with an extremely select group of workers. It is therefore not surprising that their earnings are more predictable than in other age-ranges.

VIII. IMPLEMENTATION ISSUES

1. Retirement Age and Retirement Earnings Prior to Social Security Take-up

As we have just described, the retirement model that we have integrated into MINT3 is quite complex. One's retirement decision depends upon one's own decisions about other events in the current period, as well as upon spousal attributes and decisions. When implementing the estimated coefficients from the model into MINT, we make several simplifying assumptions to ensure that the model remains computationally feasible. When taking into account the spouse's Social Security take-up decision, for example, we estimate the relationship between the spouse's take-up status last year and the worker's take-up decision this year. This allows us to avoid iterating this decision between spouses.[15] Similarly, when computing accrual and premium values for members of the sample, we calculate these from the maximum of baseline or age fifty using the projected earnings and pension values produced assuming that the individual continues to work another year. We do not re-compute these values to take into account changes in marital status, though the retirement model would implicitly take this into account insofar as person would change from the married persons' equation to the single persons' equation, and the latter takes into account sex and marital status.

A second implementation issue concerns the MINT3 aging. MINT3 outcomes are produced for yearly intervals. However, HRS data are collected every two years.[16] As a result, we needed to develop a method for converting two-year probabilities into one-year probabilities. We generally make this conversion by assuming that probabilities are uniform across the interval. With this assumption, one can obtain single-year survival probabilities by taking the square root of the two-year survival probability. This simplification works reasonably well. At ages 51 and 54, we integrated additional smoothing parameters in order to better fit the data.[17] We also integrated a smoothing parameter for the year 2000, as forecasts for this year dipped relative to prior years.[18]

[15] Iterating would raise issues of which spouse should take precedence. An alternative would be to project Social Security take-up as a couple-level outcome (for example, outcomes would include both spouses take up, one takes up, neither takes up).

[16] While data on quite few important outcomes are available for the years between interviews, we found that the quality of these data was sometimes below necessary standards to permit reliable estimation.

[17] We implement these parameters additively. The age 54 adjustment is quite small (a 1.0 percent reduction in retirement probabilities), while the age 51 adjustment is much more significant (a 2.0 percent reduction in retirement probability, with an additional 11.0 percent reduction for women). The large size of this latter parameter is not especially troublesome, as strictly speaking the HRS data cannot be used cleanly to forecast retirement at age 51.

[18] This parameter, a 2.5 percent decline in retirement probabilities, is implemented multiplicatively.

Integrating cohort effects into women's earnings is a third implementation issue that affects both the retirement model and the functions for earnings of retirees prior to Social Security receipt. By way of background, the cohort terms that we incorporate into MINT enter into five equations: two retirement decision equations (married and single), the decision to work for new retirees, the decision to re-enter work for non-working retirees before the Social Security take-up age, and the earnings levels of retirees before the Social Security take-up age. We estimated them by creating an indicator variable that divides the HRS cohort into two groups (those born 1931 to 1935 and those born 1936 to 1941), and then incorporating this variable into the regressions. This allows us to consider how relevant probabilities/levels differ over the age ranges for which we can observe both groups in HRS (for our purposes, ages 59 through 62). So the cohort effect is the average difference between the younger (6-single-year) cohort and the older (5-single-year) cohort.

In probability equations, we generally impose one twentieth of this estimated increment for a single-year birth cohort.[19] So, MINT women born in 1951 get 1.3 times the cohort effect coefficient, women born in 1952 get 1.35 times it, women born in 1953 get 1.4 times it, and so forth, with women born in 1964 getting the maximum increment of 1.95 times the cohort effect.[20] (Because the cohort effects in the data were based on 6 cohorts, using 1/20 rather than 1/6 is a bit unusual. We mention potential concerns about this again below.)

With this change, the future cohort pattern in women's work now more closely resembles the historical one, with continued increases anticipated until the last (1961-65) cohort. (We discuss these results further below, with our sensitivity analyses.) Without the cohort term, the last four cohorts' work rates track one another fairly closely.

One concern with this approach is that the cohort terms in the affected models were not statistically significant (and, in several cases, were not robust to minor specification changes). So MINT places a lot of weight on an effect that may not differ from zero. Similarly, applying the cohort effect at a slower rate than is implied by the estimation group is somewhat unorthodox. Using a closer parallel to the estimation sample, however, generates unrealistic results: women's work rates soon overtake men's. So, we opt for the less conventional method.

Another concern with this approach is how well it fits in with the rest of the earnings projections. The Task 2 (spliced) and Task 5 (retirement model) earnings may no longer be as consistent with one another when we integrate this cohort term (e.g., it is not consistent to explicitly factor in these effects at ages 51 and older, while only letting compositional changes generate work and earnings shifts before 51). Likewise, earnings after Social Security take-up are not affected by the shift. Developers could potentially integrate cohort terms into some of the other earnings equations (e.g., the equations for Social Security beneficiaries and for earners ages 70 and older). However, forecasting less of a shift in work at older ages may be a more realistic assumption. Ultimately, these decisions are judgmental.

[19] For the first few cohorts, we use smaller increments in order to smooth the transition between observed and projected data.

[20] All post baby boomer women receive this same factor.

A final implementation issue concerns classification of retirement behavior among those persons who retire prior to the last SER observations. Some such persons may have only left the labor force temporarily. We therefore make a correction to ensure that the labor force drop is sustained.[21]

2. Social Security Take-up Age

An important aspect of the Social Security take-up model is how we handle the blending of administrative data from the MBR with simulated data that we generate using the models we have just described. In general, we try to use the administrative data (and not simulate) wherever possible. We can use administrative data completely for most people born before 1931. For some people, though, administrative records may be unavailable or may provide ambiguous information (for example, if the person's listed date of entitlement is not consistent with his or her monthly measures of current payment status). In these cases, we conduct special imputations of a take-up age. Four separate types of issues are especially salient, including the following: 1.) whether an individual's record is right censored, 2.) whether an MBR value is missing because of a lack of match (rather than because take-up has not yet occurred), 3.) whether the reports from the MBR are discrepant with other data on the record, and 4.) whether an individual has a complex Social Security take-up trajectory (for example, multiple Social Security spells because of eligibility for different types of benefits). We handle these situations differently, and in quite a few cases resort to hand-coding an age of first take-up for the person.[22]

Right censoring occurs, for example, when an individual is over age 62 at the time the administrative records end, but has not yet taken up benefits or reached age 70. We handle right censoring by assuming that our model can accurately predict take-up subsequent to the final administrative observation. So, in the year after the last MBR observation (1999), we begin to attribute a probability just as we do to someone with a fully simulated record. This method is consistent with the underlying model structure, a discrete-time hazard model, which one can estimate using censored observations.

For persons without a match to the MBR, we first determine whether they do not have a match because they did not provide a Social Security number or because they have not yet taken up benefits. If the person also does not have an SER, we assume that the former is the case, and apply probabilities from the estimated model from age 62 to baseline age. Otherwise, we assume that the lack of match is due to failure to take up benefits.

Discrepant reports are a small but significant issue when assigning SSAGE from the MBR. For example, for some people the Master Beneficiary record reports that the type of benefit is a disabled worker benefit, but the Burtless/Sahm projections do not identify the individual as a DI recipient. If a person meeting this profile has a take-up age after 60, then we assume that it is just a regular case of retired worker take-up. Other common discrepancies arise from the interaction of birth dates and entitlement dates (for example, a person is listed as taking

[21] We implemented this through the unretire macro in retcore.inc.

[22] For details, see w:\urban\mint3\finalMINT\mergenativity.sas, the program in which we handle these codes.

up Social Security benefits at age 59 and 11 months rather than at age 60 and zero months). When the two dates are fairly close, we assumed that person received benefits in the first possible eligibility year. We have done some tabulations to verify that 60 and 61 year olds are widowed according to their MINT status, but have not guaranteed consistency. We assume that the marital trajectories and take-up ages on the MBR are consistent.

Quite a few of the individuals in the MINT sample have had complex experiences with the Social Security program. For example, a person might receive Social Security in childhood as a result of the death of a parent. Or one might receive benefits in one's prime working years, because one is caring for children after the death of spouse. We tried to code such cases as consistently and realistically as possible, using the following set of rules:

- Disabled widow(er)s: As MINT does not predict these types of cases into the projection period, it does not account for them in the historical period. Rather than assigning SSAGE at the actual take-up age, we treat disabled widow(er)s as beginning to receive widow(er) benefits at age 60.[23]

- Spouses caring for minor children: If the person survives until age 62, we assign Social Security take-up age as the date that he or she is eligible for aged husband/wife benefits.

- Individuals whose date of entitlement to secondary benefits precedes a date of entitlement to worker benefits: We use the date that the individual was entitled to the secondary benefit as the take-up age provided that he or she first received the secondary benefit at or after age 60.

- Adults disabled in childhood: As MINT does not predict these types of cases into the projection period, it does not account for them in the historical period. Such persons are assigned SSAGE only if they accrue entitlement to OASDI benefits through covered earnings or marriage to a covered worker.

We discuss our success at blending historical and projected data in the validation section (below).

3. Accounting for the Retirement Earnings Test

The Social Security Retirement Earnings Test (RET) reduces the Social Security benefits of Social Security beneficiaries whose earnings exceed the RET threshold.[24] During the 1990s, the RET existed for beneficiaries under age 70. The Senior Citizens' Freedom to Work Act of 2000 eliminated the Social Security Retirement Earnings Test (RET) for individuals between the

[23] In future MINT analyses, the government may wish to incorporate these benefits. Women's groups have talked about expansion of these benefits (see, for example, Hartmann and Hill 1999), so they are relevant to current policy debates.

[24] Working beneficiaries who lose benefits because of the RET recover these benefits in actuarial terms through higher future annual benefits.

Normal Retirement Age (NRA) and age 69. Prior to this legislation, the RET reduced the benefits of beneficiaries between the NRA and 69 by $1 for every $3 of earnings in excess of the RET threshold, where the threshold was equal to $15,500 in 1999.[25] Analyses of the RET's effect on earnings have found that, in general, the RET reduces the earnings of working beneficiaries (Friedberg 1999, Toder et al. 1999, Burtless and Moffitt 1984). This suggests that this recently enacted legislation eliminating the RET will increase the earnings of beneficiaries between the NRA and age 69.[26]

The estimated coefficients from the MINT earnings equations are based on data from the early to mid-1990s, so they do not capture the effect on earnings of eliminating the RET. This is important for our projections of beneficiaries' earnings, because projected earnings are based on the estimated coefficients from earnings equations that do not incorporate this recent policy change. For this reason, we adjust upward the earnings of some working Social Security beneficiaries and reduce the earnings of others. The sizes of the behavioral responses that we incorporate into the model are taken directly from a Friedberg study (1999) that examined the effect on men's earnings of the 1983 elimination of the RET for those ages 70 and 71. They are:

- Increase by 50 percent the earnings of workers near the RET exempt amount;[27]
- Increase by 18 percent the earnings of workers who have earnings over the RET exempt amount but below the point where their benefits are fully taxed away;[28] and
- Reduce by 4 percent the earnings of workers who have earnings above the point at which a benefit would be fully taxed away.

IX. VALIDATION ANALYSES

1. Overview

When we apply all of these work and earnings models to results from earlier portions of the MINT3 data system, we produce a wealth of data on earnings and Social Security benefit receipt. To ensure their validity, we compare these projections to historical data and to projections from other models, carefully disaggregating the projections along dimensions that are interesting and important for the analysis of retirement income adequacy. These dimensions include birth cohort, educational attainment, gender, race, beneficiary status, and time period. We discuss each of these validation analyses in turn.

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[25] The RET is still in place for beneficiaries between age 62 and the NRA. Beneficiaries in this age range have their benefits reduced by $1 for every $2 of earnings in excess of the RET threshold, where the threshold was $10,680 in 2001.

[26] Tabulations comparing earnings data for persons ages 65 to 69 from the 1999 and 2001 CPS support this view. A spike that had existed at the exempt amount disappears, and more earners are present at higher levels. (See Appendix Figure A4-1.)

[27] We defined earnings as near the exempt amount if they fall between 40 and 45 percent of the average wage.

[28] This upper bound is individual specific.

To validate our projections of employment rates and earnings, we compare them to historical distributions, primarily based on data from the SIPP matched to the SSER for earlier cohorts and, occasionally, the 2001 Current Population Survey (CPS). We consider cohort-sex specific means, and pay special attention to the full cross-sectional earnings distributions. We also compare results to projections from other models, including actuarial models of the Social Security Administration and MINT2, the earnings file constructed for Chapter 2 that relies on a splicing method rather than a complex series of regression equations. Additionally, we consider longitudinal measures of work and earnings, such as the total number of years a person spends in the work force, and his or her average indexed lifetime earnings.

When examining Social Security take-up patterns, we compare our projections to published data (primarily the *Annual Statistical Supplement to the Social Security Bulletin*) and to tabulations of SIPP data linked to the Master Beneficiary Record.[29]

2. Work rates

We begin our discussion with work rates. Before turning to any external sources, we compare outcomes in the three separate files produced for MINT. These files include: the MINT2 earnings produced using the matching method described in Chapter 2, the task 5 projections of earnings given that one has not yet retired, and the final MINT3 projections that take into account chosen date of retirement.[30] Comparing MINT2 outcomes with MINT3 outcomes offers a useful cross-check, as the two models use such different methods for determining earnings. For these specific analyses, we compare employment rates by age and sex (Figures 4-5 and 4-6).[31]

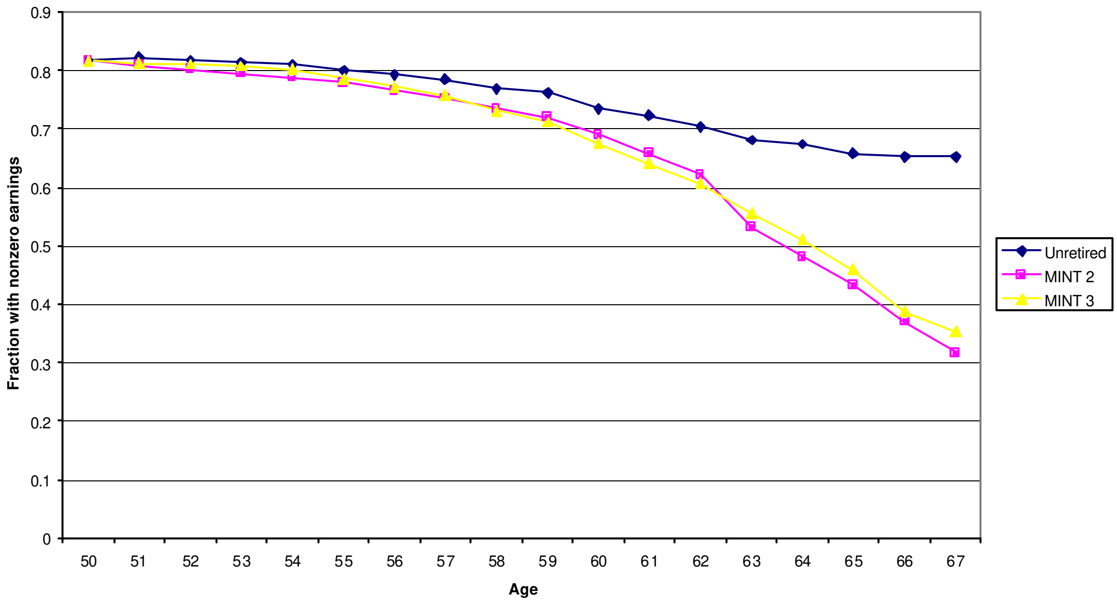
As Figure 4-5 indicates, for men there is a fairly close correspondence between the work patterns that were generated by the statistical match (the series labeled "MINT2") and the patterns that were generated by the retirement model (the series labeled "MINT3"). From ages 55 through 59, the work rates for men in the 1931 to 1960 birth cohorts (the core MINT sample) are essentially the same across specifications. From ages 60 through 62, MINT2 has higher employment rates, while from age 63 onward MINT3 has higher rates. One interesting difference between MINT2 and MINT3 is how each handles the transition between age 62 (the early eligibility age for Social Security benefits) and age 63 (the first age at which the majority of men are receiving Social Security benefits for the full year). The transition from age 62 to age 63 is smoother in MINT3 than in the MINT2 data file, in which actual histories were spliced. To a certain extent, this may be a characteristic of regression analysis, which tries to find linear

[29] In sensitivity analyses, described below, we consider changes to the model specification (e.g., removing error terms, alternative specifications of cohort effects, and alternative specification of Social Security take-up) and hypothesized behavioral changes resulting from changes to Social Security parameters (e.g., the removal of the retirement earnings test at and above the program's normal retirement age), and in separate letter reports we examine abolition of the retirement earnings test at younger ages and changes to spousal and survivor benefits.

[30] File paths on the SAS server at SSA are w:\urban\mint3\data\basemint.sas7bdat, w:\urban\mint3\data\earnpred.sas7bdat, and w:\urban\mint3\data\giantprogramloop.sas7bdat, respectively.

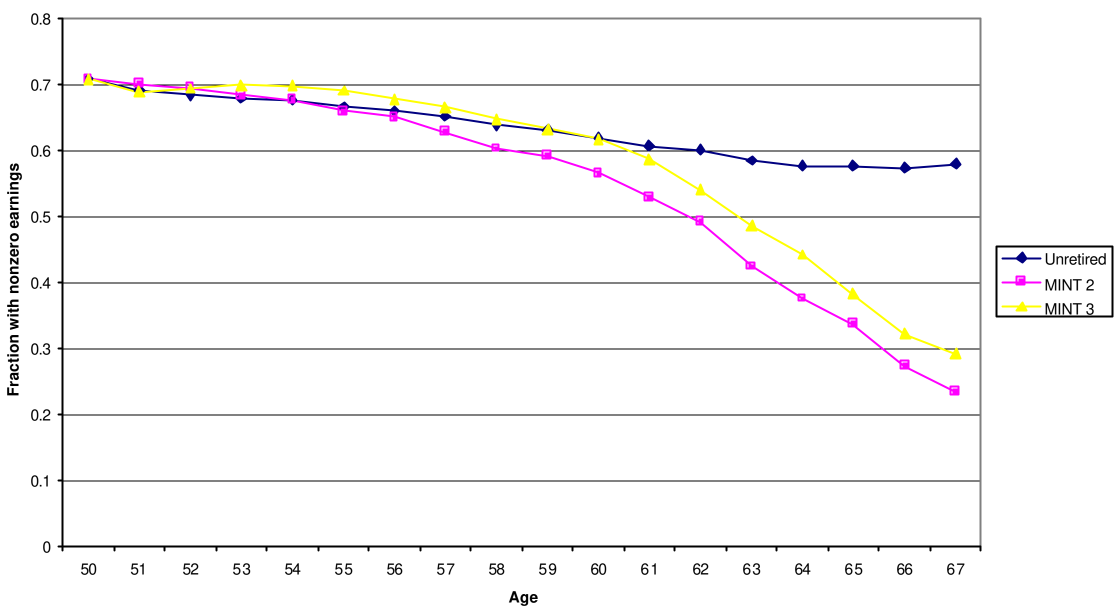
[31] Additional comparisons by educational attainment are included in the referenced figure source file, available on the SAS server at SSA.

Figure 4-5 Comparison of Employment Rates: All Men in the 1921-1960 Cohorts



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\comparerichgarygaint0626.xls, from comparerichgarygiant.lst)

Figure 4-6 Comparison of Employment Rates: All Women in the 1921-1960 Cohorts



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\comparerichgarygaint0626.xls, from comparerichgarygiant.lst) patterns in observed data. In contrast to the relatively close correspondence between the MINT2 and MINT3 work rates, the projections of men's work rates assuming that one continues working at a "career job" (i.e., a job of over 20 hours per week), typically, but not always, exceed the other two forecasts (the series labeled "unretired").[32]

For women in the 1931 to 1960 cohorts, depicted in Figure 4-6, the correspondence in work patterns across the three projection sources is not quite as close as it is for men. At most ages from age 53 onward, we find that the MINT3 work rates exceed the MINT2 rates fairly substantially. This difference is due to the introduction of linear cohort effects into MINT3, discussed earlier. When we do not incorporate these effects, the MINT2 and MINT3 lines more closely track one another. The series in which we forecast work rates assuming continued work on the career job (or "unretired"), unlike with men, does not exceed the other forecasts until age 60.[33]

In Figures 4-7 and 4-8 we examine age-cohort patterns in work status, for men and women, respectively.[34] We find that the men's age patterns in work vary little across the cohorts (Figure 4-7). Men's work rates are typically quite high, at or above 70 percent, up through age 60 for all cohorts that we examine. After age 60, work rates begin to fall fairly dramatically, reaching less than 40 percent by age 66 and less than 30 percent by age 69 again without much difference across cohorts.

For women, in contrast, differentiation in work rates across the cohorts is considerable (Figure 4-8). Namely, we see a fairly marked rise in work rates in successive cohorts (for additional information on cohort patterns in women's labor force participation, see, for example, the discussion by Devine, 1997). Most of this rise occurs prior to the baby boom cohorts. Between the 1926 to 1930 and 1941 to 1945 cohorts, one sees an immense upward shift present at age 50 (and the earlier ages, not shown on the graph) and these increases carry through to later ages. For example, about 54 percent of women in the 1926 to 1930 birth cohort were working at age 50, compared to about 59 percent of the 1931 to 1935 cohort and 65 percent of the 1936 to 1940 cohort. We still see projected work rate increases in successive cohorts during and after the baby boom, though the changes are less dramatic than the changes for these first three groups. Again, this is due to our assumption of linearly increasing women's participation. (Later in the chapter we show what these rates look like without linear cohort effects.)

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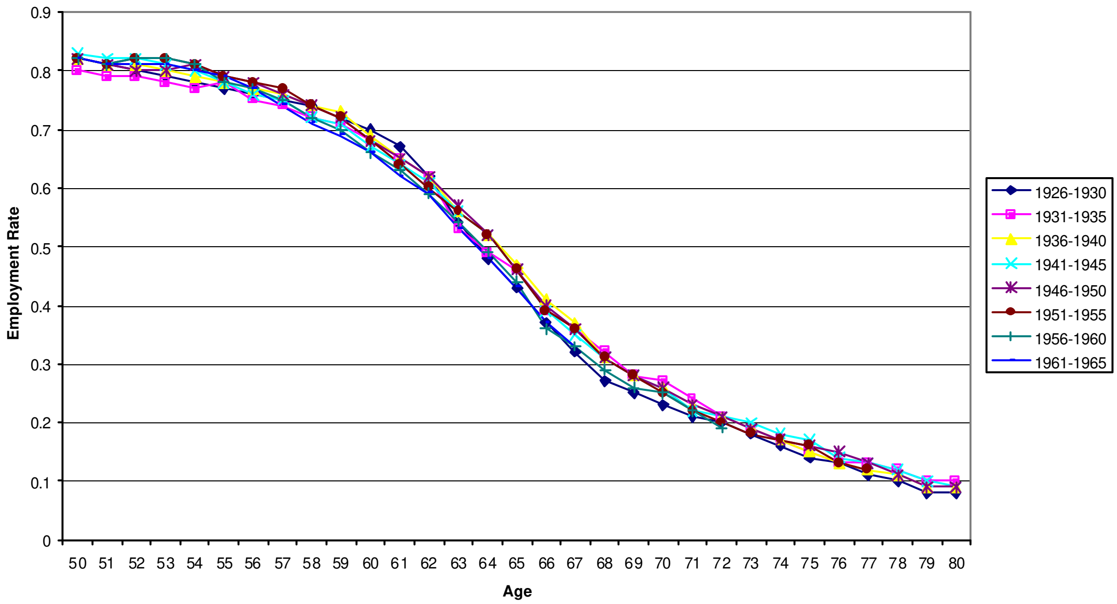
[32] The fact that this rate is not one hundred percent may be confusing, as we are assuming these workers to be non-retired. Recall, however, that the model of earnings for non-retired workers has both a fixed effect component and a transitory error. Because these can be large and negative, earnings can be zero, and thus one can be a non-participant even on this "non-retired" trajectory. In substantive terms, we can consider such workers to have such low earnings potential (perhaps because they have health problems or have been out of the labor force for some time) that they could only garner very low wages.

[33] This suggests that for women, low permanent errors are particularly likely to pull one's earnings to zero.

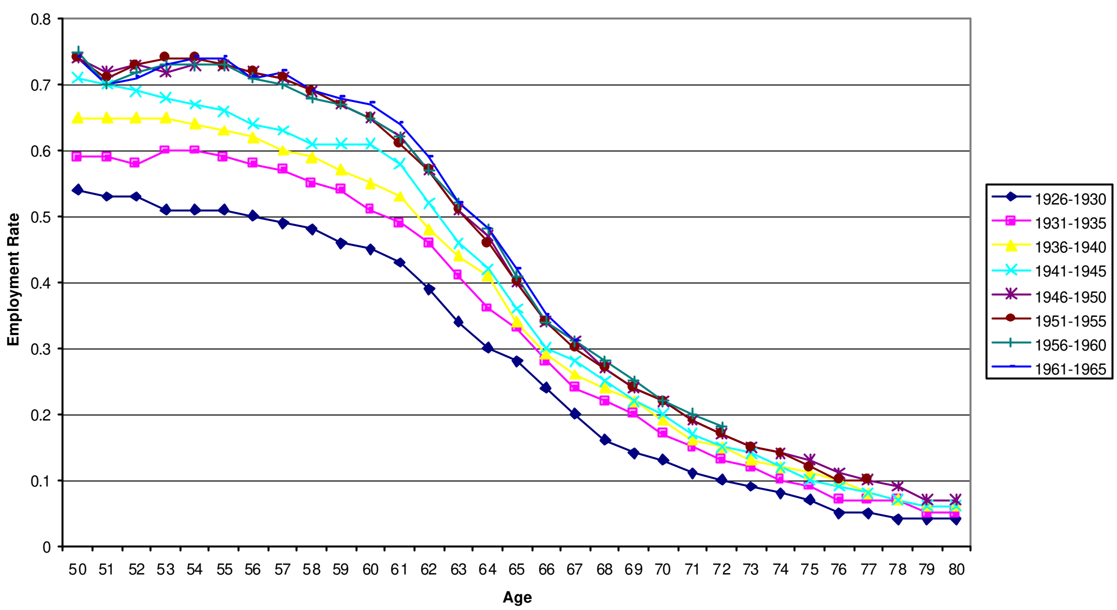
[34] Because MINT relies on SIPP matched to the Summary Earnings Record through 1999, a considerable portion of each of these graphs is based on historical rather than projected data. For example, for the 1926 to 1930 birth cohort, data are completely observed through age 69, are partially observed and partially projected for ages 70 through 73, and are fully projected beginning at age 74. Also, some series do not extend all the way to age 80 (the maximum age represented in the graph). This is because MINT only projects earnings through 2032, so some persons (those born after 1952) have right censored labor force trajectories.

Figure 4-7 Employment Rates of Men by Cohort



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearn2.lst)

Figure 4-8 Employment Rates of Women by Cohort (with Linear Cohort Effect)



Source: Urban Institute Tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls from tabearn2.lst)

Next, we compare MINT3's employment-population ratios to forecasts from the SSA Office of the Actuary (OCACT) used to produce the OASDI Trustees' Report. These are defined as the fraction of persons in a group with any earnings over the course of a year. Figures 4-9 through 4-13 provide age-year-specific comparisons for 5 separate age groups of men (ages 50 to 54, 55 to 59, 60 to 64, 65 to 69, and 70 and older), and Figures 4-14 through 4-18 provide the same information for the corresponding women.[35]

Men's employment rates track OCACT's fairly closely at all age ranges. The Trustees' rates are slightly higher than MINT's at ages 50 through 54 (Figure 4-9), and are essentially identical to MINT's at ages 55 through 59 (Figure 4-10). At ages 60 through 64 (Figure 4-11), the MINT rates are slightly higher than the Trustees', as is the case for ages 65 through 69 (Figure 4-12). At age 70 and older (Figure 4-13), the two models track each other closely, though must interpret rates for this age group cautiously due to censoring.[36] In several of the graphs, there is a small decline in earnings in the first simulation year (2000). (This is consistent with some of the findings in Chapter 2.) This downward shift persists despite the modest correction we imposed (described with implementation issues, above).

The women's rates in MINT3 differ more substantially from the OCACT rates, especially between ages 55 and 64. While MINT and OCACT rates are virtually identical at ages 50 through 54 (Figure 4-14), the MINT values are significantly higher in late fifties and early sixties (Figures 4-15 through 4-17). OCACT rates are not without controversy, so differences between MINT and OCACT, particularly higher projections in MINT, are not necessarily problematic.

Given the considerable difference between MINT and OCACT projections of women's work, especially MINT's dramatically higher projections of women's labor force activity, it's worth directly considering how men and women's work patterns compare. Figure 4-19 depicts the ratio of women's work rates to men's work rates at ages 50 and older, by age and cohort. The figure reveals a rapid narrowing of the gap between men's and women's work rates with successive cohorts. While women worked at only about two-thirds the rate of men from their fifties through their late sixties in the first cohorts (1926-1930), by the last cohort (1961-1965), women's rates are projected to fluctuate between 90 and 100 percent of men's throughout their fifties and early sixties. Women's rates do tend to drop off after age 61, so that the male-female difference is larger at older ages, but an overall pattern of rapidly narrowing gender differences clearly prevails under this specification.

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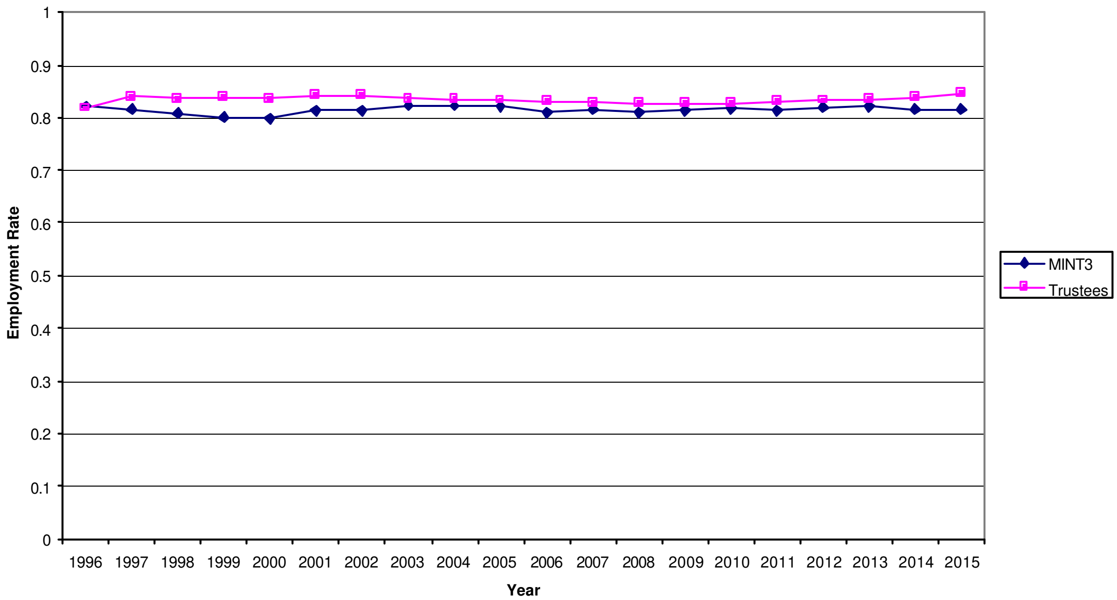
[35] While Figures 4-9 through 4-18 all use the same vertical scale of rates (from 0 to 1.00), they have varying horizontal scales of years. This is because for some age ranges, MINT projections are censored on either the left or the right. Left censoring occurs in those cases where there are no observations (or not a full group of observations) at a given age because no members of the MINT cohort have yet reached that age. For example, the figures for work rates at 70 and older are censored. Right censoring occurs when all age ranges are not represented because the last members of the MINT cohorts have aged out of the population. For example, the figures for work rates at ages 50 to 54 are right censored at 2015, the year when the 1965 birth cohort turns age 50. Readers should keep in mind this censoring issue, especially at ages 70 and older. For this age range, we never have full population, though after many years of simulation we have a more representative group (for example, by 2016 members of the first MINT cohorts have reached age 90).

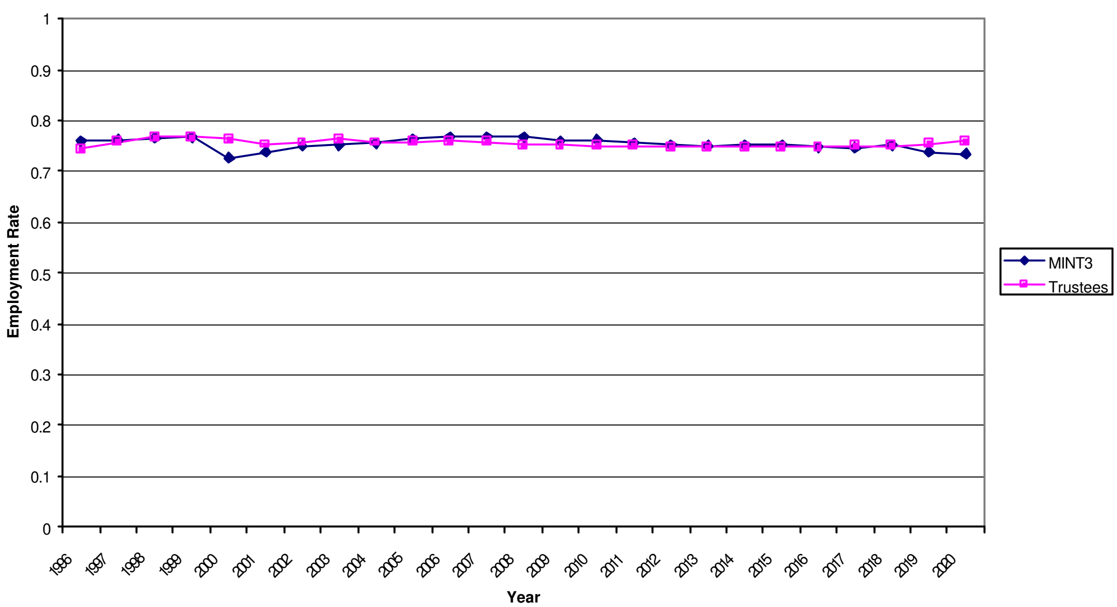
[36] This represents a particularly substantial improvement over MINT1, which projected virtually no work after one left one's late sixties.

Figure 4-9 Employment Rates of Men: Ages 50-54



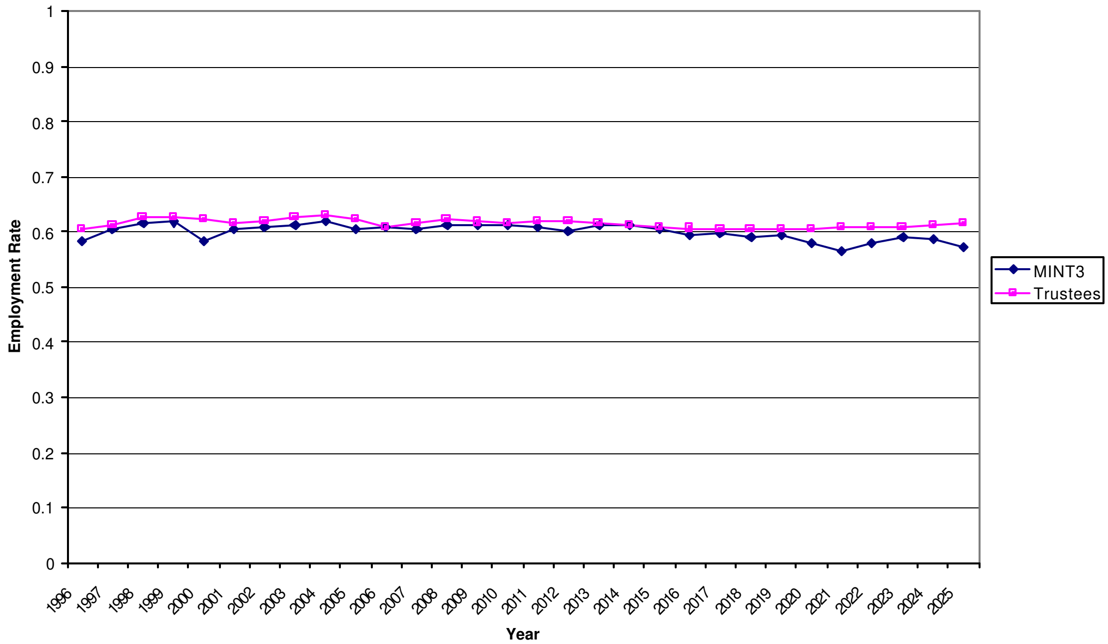
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearnmf.lst), unpublished SSA data

Figure 4-10 Employment Rates of Men: Ages 55-59



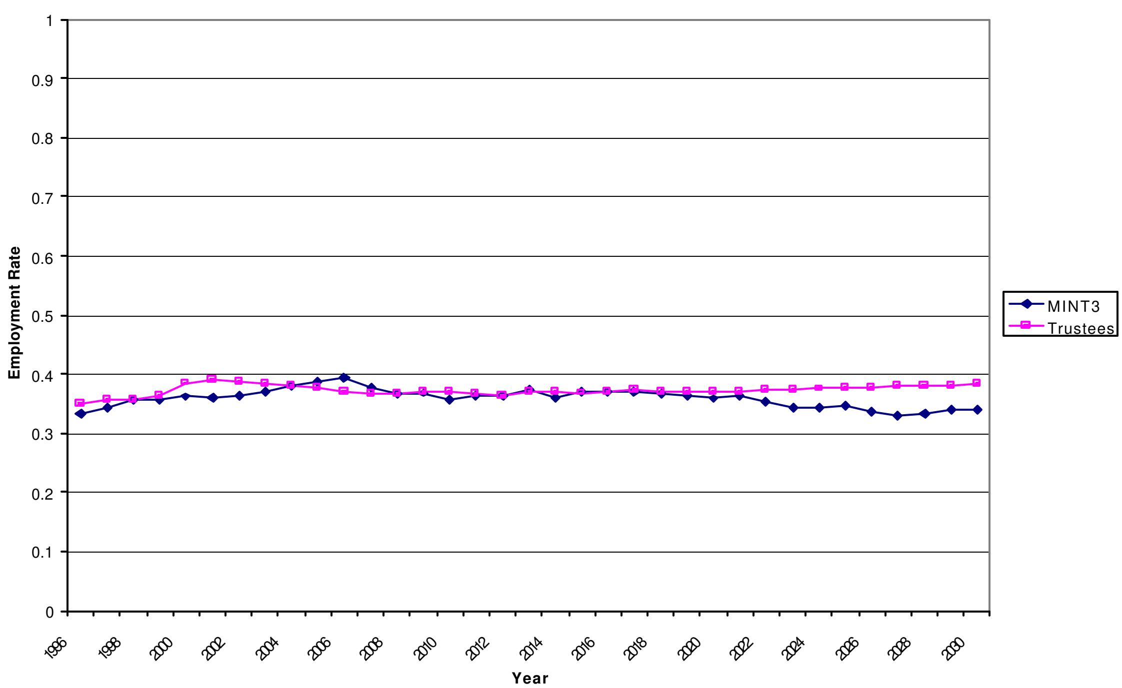
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearnmf.lst), unpublished SSA data

Figure 4-11 Employment Rates of Men: Ages 60-64



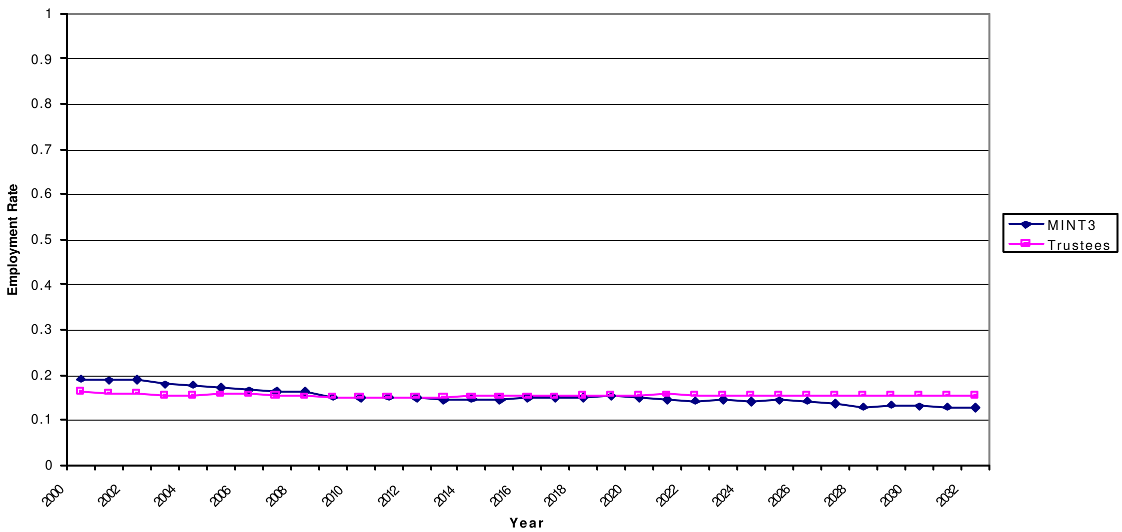
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearnmf.lst), unpublished SSA data

Figure 4-12 Employment Rates of Men: Ages 65-69



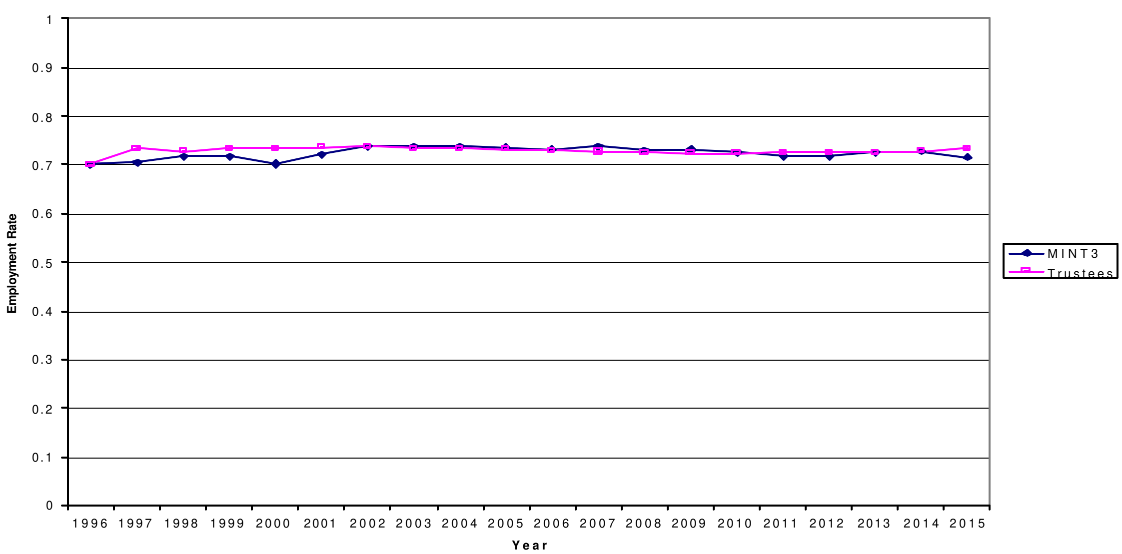
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearnmf.lst) , unpublished SSA data

Figure 4-13 Employment Rates of Men: Ages 70 and Higher (Censored)



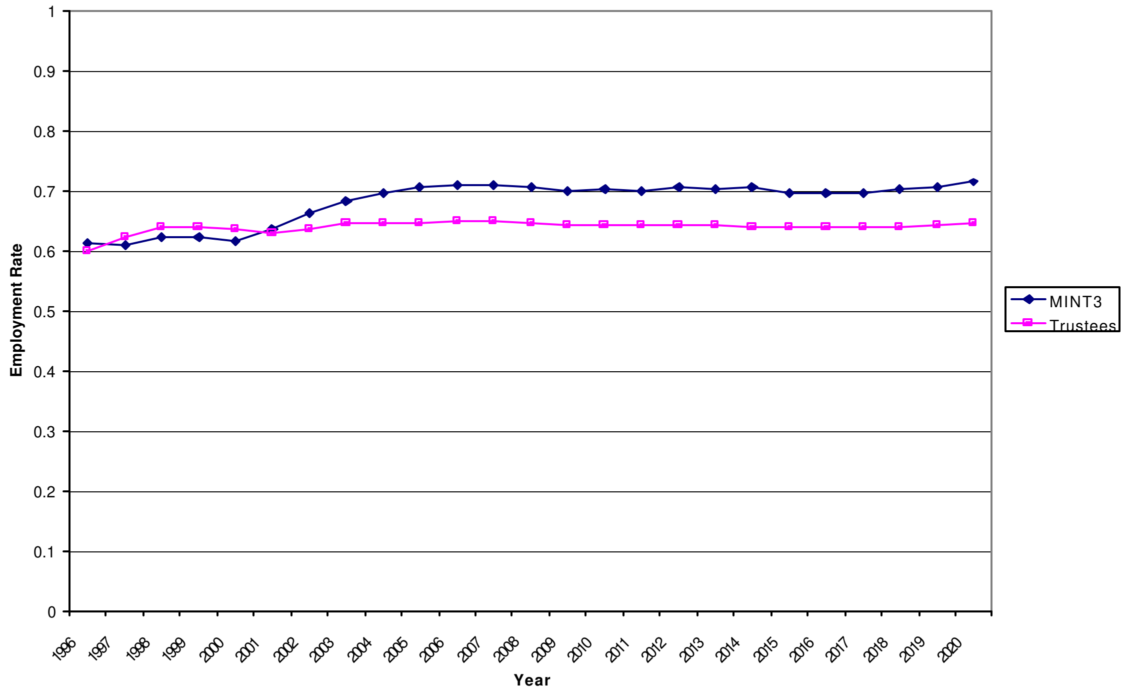
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearnmf.lst) , unpublished SSA data

Figure 4-14 Employment Rates of Women: Ages 50-54 (With Linear Cohort Effect)



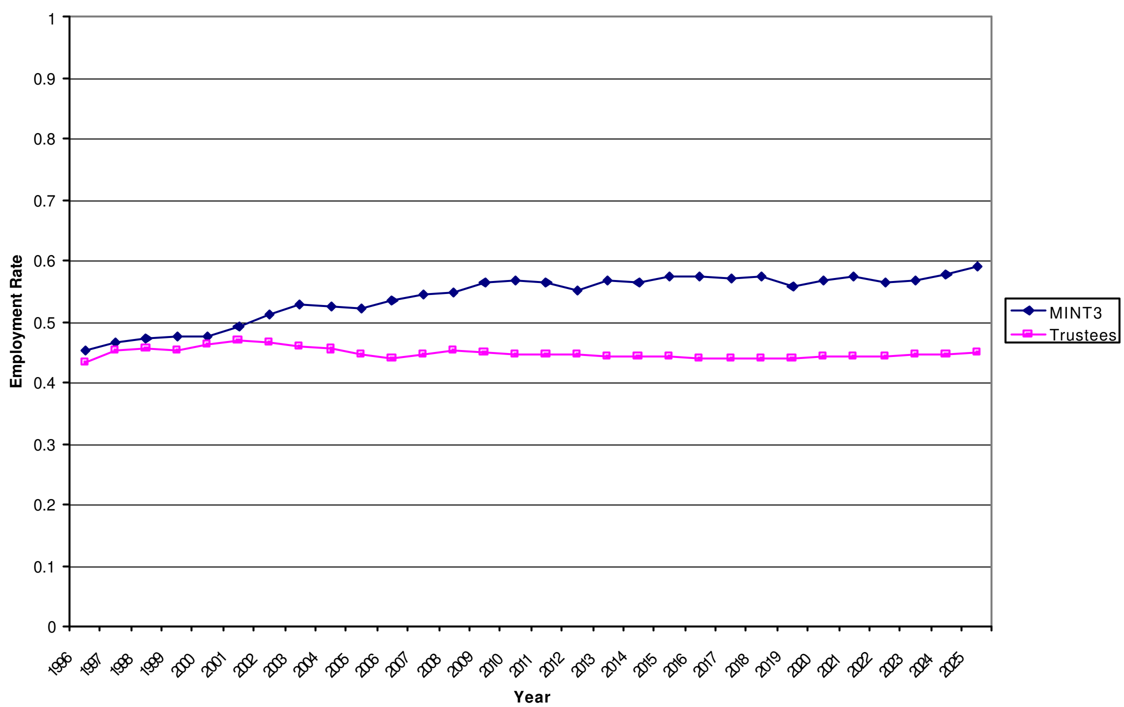
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearnmf.lst), unpublished SSA data

Figure 4-15 Employment Rates of Women: Ages 55-59 (With Linear Cohort Effect)



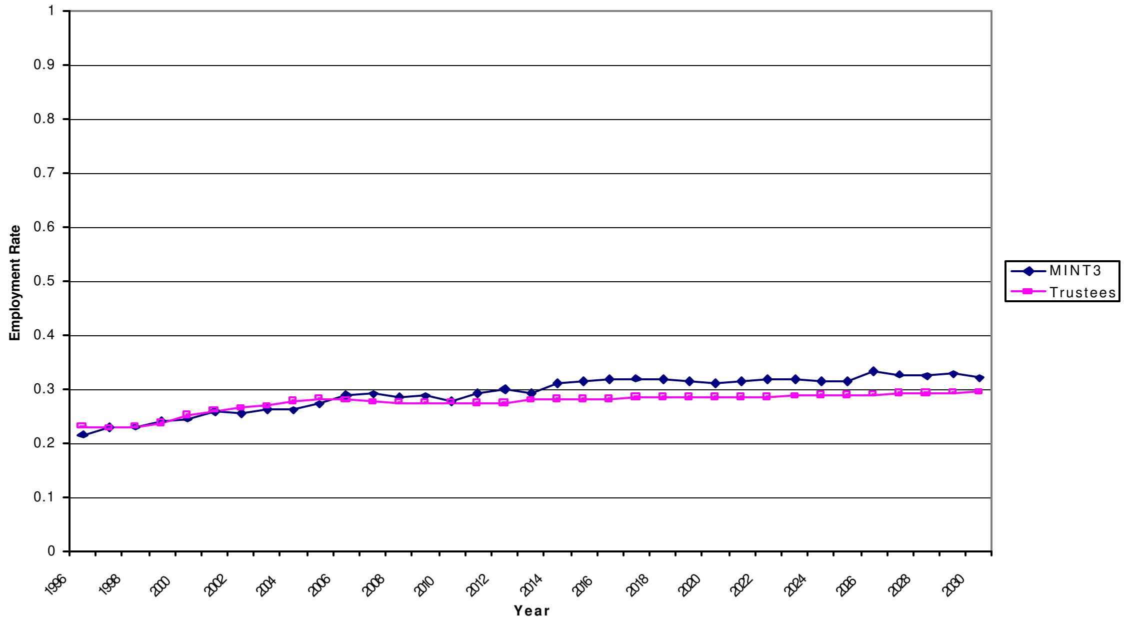
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearnmf.lst), unpublished SSA data

Figure 4-16 Employment Rates of Women: Ages 60-64 (With Linear Cohort Effect)



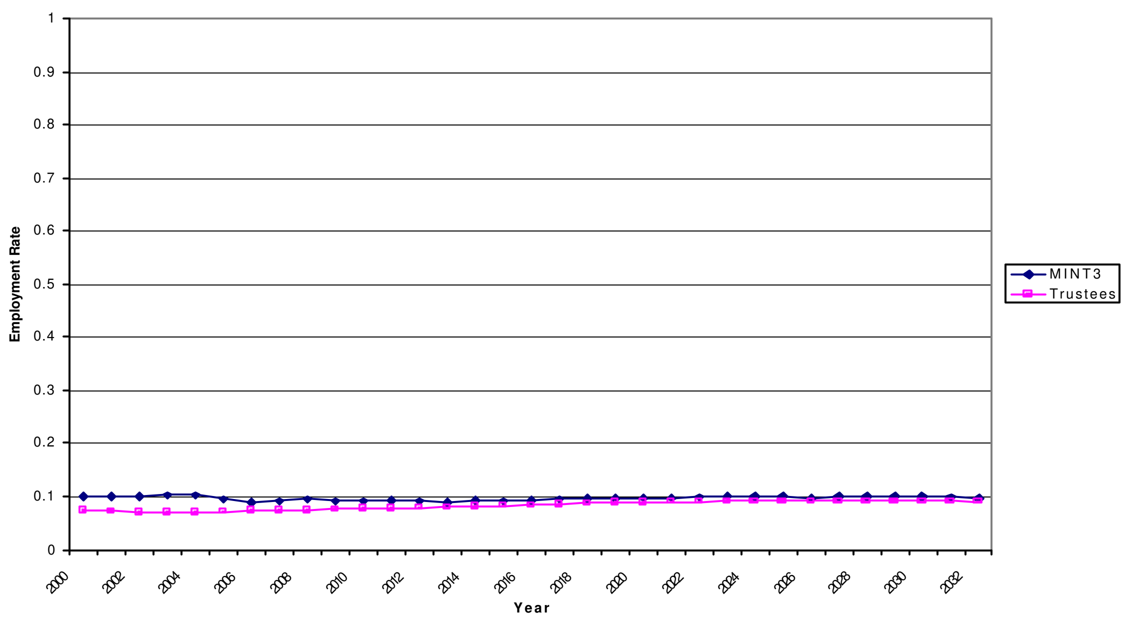
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearnmf.lst), unpublished SSA data

Figure 4-17 Employment Rates of Women: Ages 65-69 (With Linear Cohort Effect)



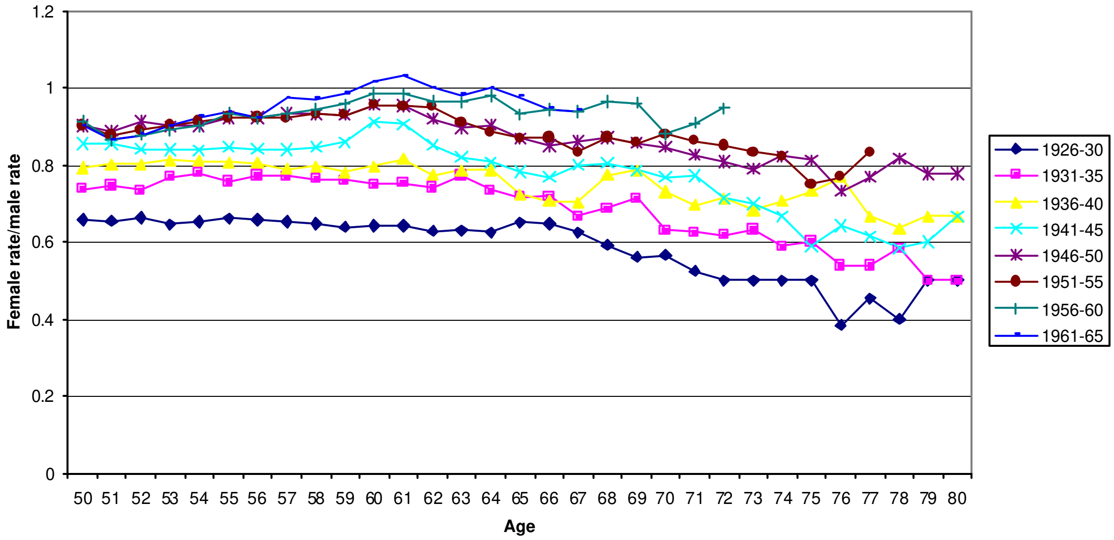
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls), unpublished SSA data

Figure 4-18 Employment Rates of Women: Ages 70 and Older (With Linear Cohort Effect, Censored)



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls), unpublished SSA data

Figure 4-19 Ratio of Female to Male Work Rates by Age and Birth Cohort (With Linear Cohort Effect for Women)



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearn2.lst)

3. Earnings means and distributions

To validate earnings levels, we first consider measures of central tendency in earnings, focusing on means. As with the employment ratios, we begin by comparing the three MINT files themselves (one with statistically matched earnings, one with earnings assuming no retirement, and one with earnings generated by the full retirement model, all labeled as previously). Figures 4-20 and 4-21 present the mean earnings of those individuals with earnings greater than zero for men and women in the 1931 through 1960 birth cohorts. In the figures, we express earnings as a percentage of the average wage in order to remove trends in age growth.

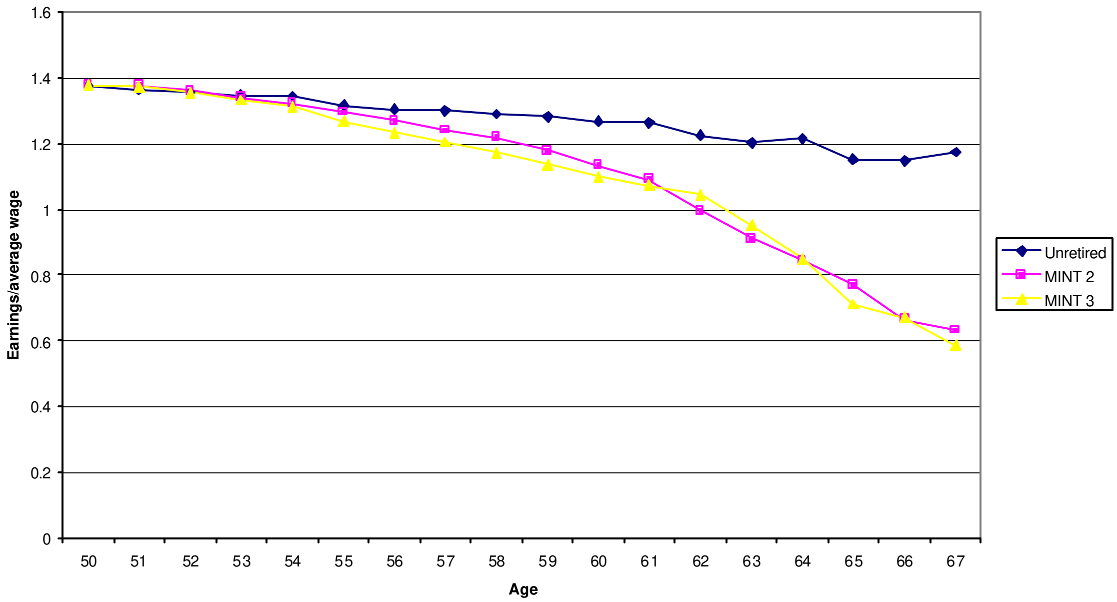
Among the men, we find fairly close correspondence between MINT2 and MINT3 projections of workers' mean earnings (Figure 4-20). Up through age 53, there are no real differences between the models. From ages 55 through 60, MINT2 average earnings are slightly higher than MINT3 averages. There are also some important differences between the models' earnings forecasts at ages 62 and 63, where MINT3 means are higher. At ages 64 and 66, the two forecasts are once more very close. At age 67, the MINT3 earnings drop below MINT2 earnings again. Recall that MINT3 has a correction at ages after the normal retirement age. This correction (an upward adjustment for low earners and a downward adjustment for high earners) could be a factor in the difference with MINT2 at age 67. For all ages from 55 onward, the non-retired earnings are, as we would expect, higher than the results from either MINT2 or MINT3.

For women, the age patterns in mean earnings of workers are quite similar to the patterns for men (Figure 4-21). After closely tracking one another at ages 52 and 53, the forecasts diverge, with MINT3 earnings dipping relative to MINT2 earnings, especially at ages 56 to 60. The MINT3 earnings are higher at ages 62 and 65. Some of these percentage differences are non-trivial. For example, MINT2 average earnings are over 6 percent higher than MINT3 earnings at 59, the age when differences between the two forecasts are greatest. This leads one to the questions of why the MINT3 earnings are lower in the earlier years. An explanation likely lies in the higher incidence of "partial retirement" in the 50s in MINT3. As Chapter 9 explores, we project retirement increases across cohorts (though we cannot use a consistent definition for all of the MINT cohorts), but considerable work effort among retirees who earn less than their nonretired counterparts.

When we consider earnings of the whole population (not just earners, as in the previous figures) by cohort, men's and women's earnings show different patterns (Figures 4-22 and 4-23).[37] For men, we see a dramatic decline in earnings as a fraction of the average wage in each cohort (Figure 4-22). This decline is actually the consequence of increased earnings and participation of women: as women's earnings increase as a percentage of the average wage, men's necessarily decrease. In Figure 4-22, we see some age-to-age transitions in earnings that are not smooth. For example, between ages 50 and 51 in the 1961 to 1965 birth cohorts, mean earnings drop from 1.03 times the average wage to 0.94 times the average wage. This is due in part to the fact that HRS generates two-year transition probabilities, which we apply uniformly (see the discussion of implementation issues above). Probably more importantly in this case, it also results from failure to map errors consistently across the two models.

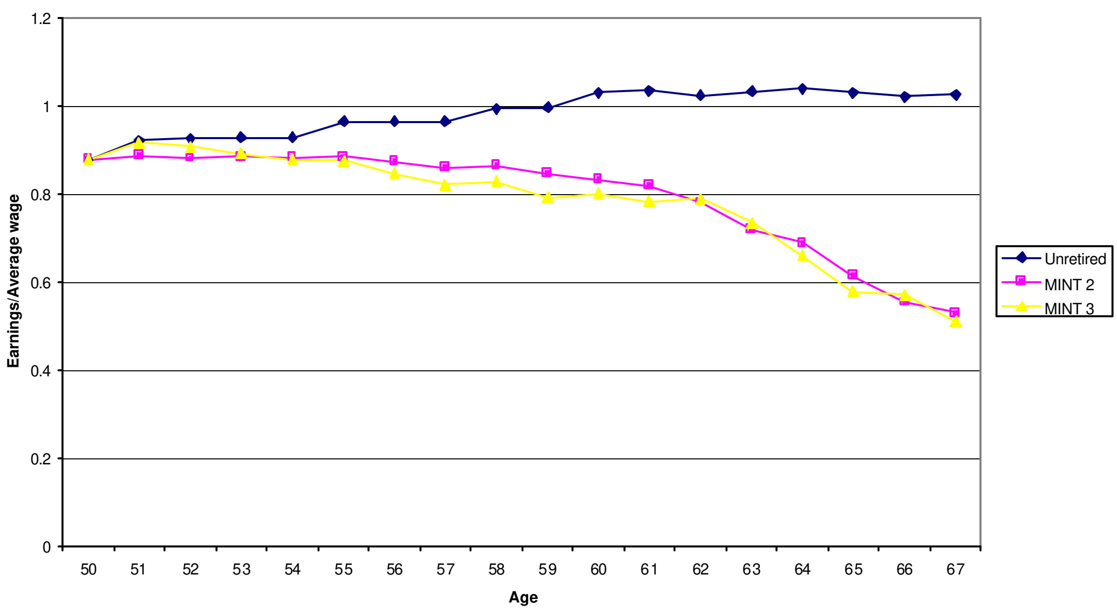
[37] Just as in Figures 4-7 and 4-8, for these figures we combine historical and projected data (see footnote 31 for details).

Figure 4-20 Comparison of Earnings (among Nonzero Earners): Men in the 1931-1960 Cohorts



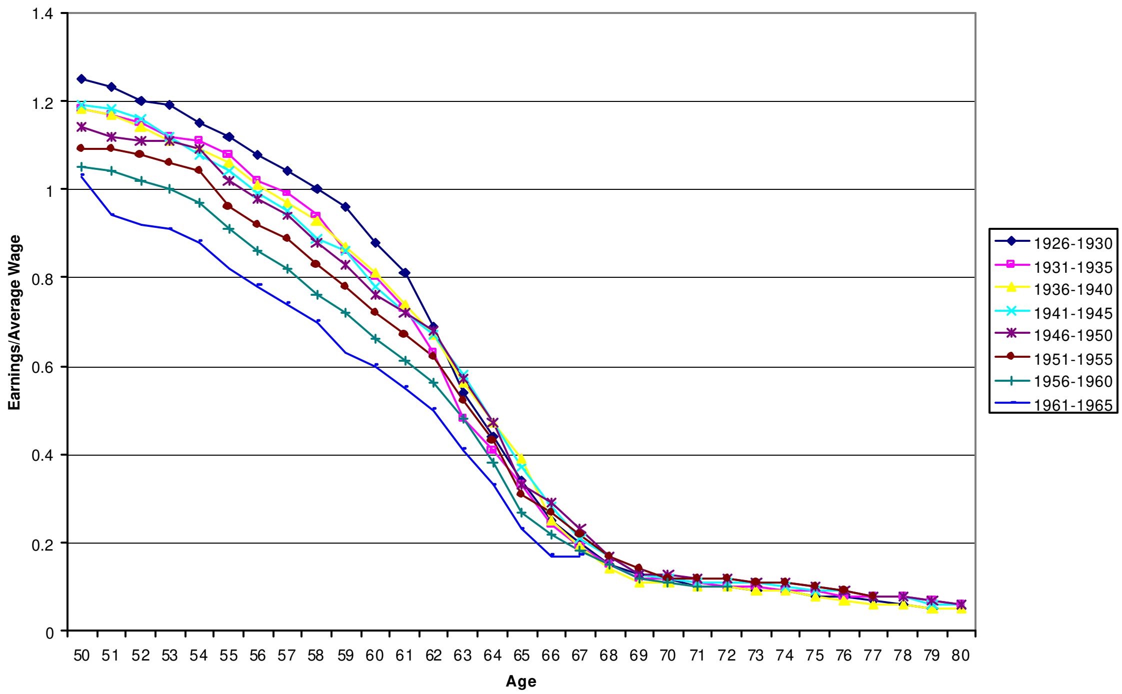
Source: Urban Institute tabulation from MINT2 and MINT3 (w:\urban\mint3\final\comparerichgarygaint0626.xls, from comparerichgarygiant.lst)

Figure 4-21 Comparison of Earnings (among Nonzero Earners): Women in the 1931-1960 Cohorts



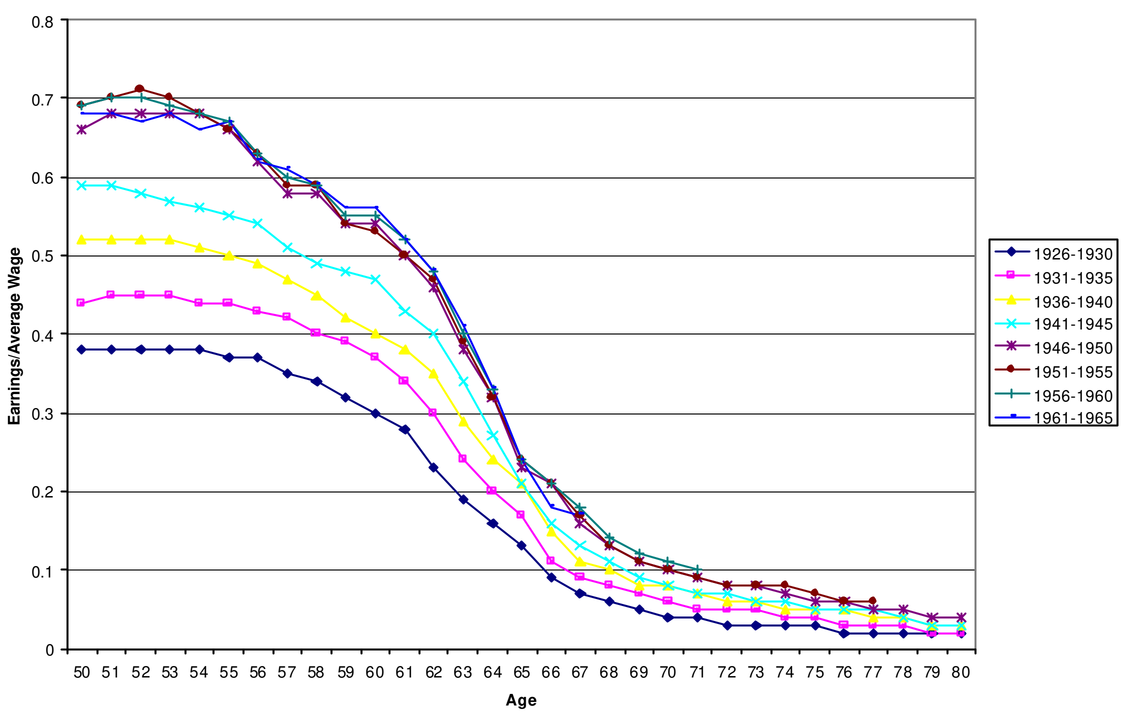
Source: Urban Institute tabulation from MINT2 and MINT3 (w:\urban\mint3\final\comparerichgarygaint0626.xls, from comparerichgarygiant.lst)

Figure 4-22 Mean Earnings of Men by Cohort



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearn2.lst)

Figure 4-23 Mean Earnings of Women by Cohort (with Linear Cohort Effect)



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearn2.lst)

The reverse pattern from Figure 4-22 appears in Figure 4-23. Women become better paid, so their average earnings increase relative to the average wage. Among women, roughness in age-to-age transitions is even more prominent than it is with men. Indeed, there are some ages, for example ages 59 to 60, where declines in earnings actually resemble steps rather than a smooth downward curve (Figure 4-23). Again, this is due in part to the use of two-year probabilities through HRS. At age 51, especially, this may also be due to imperfect correspondence between errors in the trajectory forecasts and in the retirement model forecasts.

When we consider age-sex specific earnings distributions of earners (where age groups are defined as in the comparisons to OCACT data, with separate groupings for ages 50 through 54, 55 through 59, 60 through 64, 65 through 69, and 70 and over), we find that the projected MINT distributions appear reasonable relative to historical data (Figures 4-24 through 4-28 for men and 4-29 through 4-33 for women).[38] For historical benchmarks, we use the SSER matched to the SIPP[39] and the CPS.[40] In these figures, we once more express earnings as a percentage of the average wage. Doing so essentially eliminates the effects of wage inflation over time in these analyses.

Starting with the distributions of men's earnings (Figures 4-24 through 4-28), we find that MINT replicates a full distribution of outcomes. At the younger ages (in the fifties), there are low-earners, a hump near the average wage, and a mode at the high end of the distribution (over 2.2 time the average wage). MINT does capture this high-end mode at several age ranges. However, we do observe that the MINT projections do not reproduce the high end of the distribution with sufficient density. While this could be a function of cohort shifts (e.g., the slower earnings start of the later boomers), we believe that it is principally an artifact of our methodology.[41] (This is an area for further development, as we discuss in our recommendations section in Chapter 11.) At the older ages (65 and above), there is also a mode at very low earnings levels, again a pattern that MINT does capture.

Throughout the various age ranges, it is interesting to note that there is some heaping in the CPS data (i.e., people report earnings in round increments, like tens of thousands), while the SSER and MINT data are smoother. This reveals an important difference between self-report and administrative data, which presumably are more accurate.

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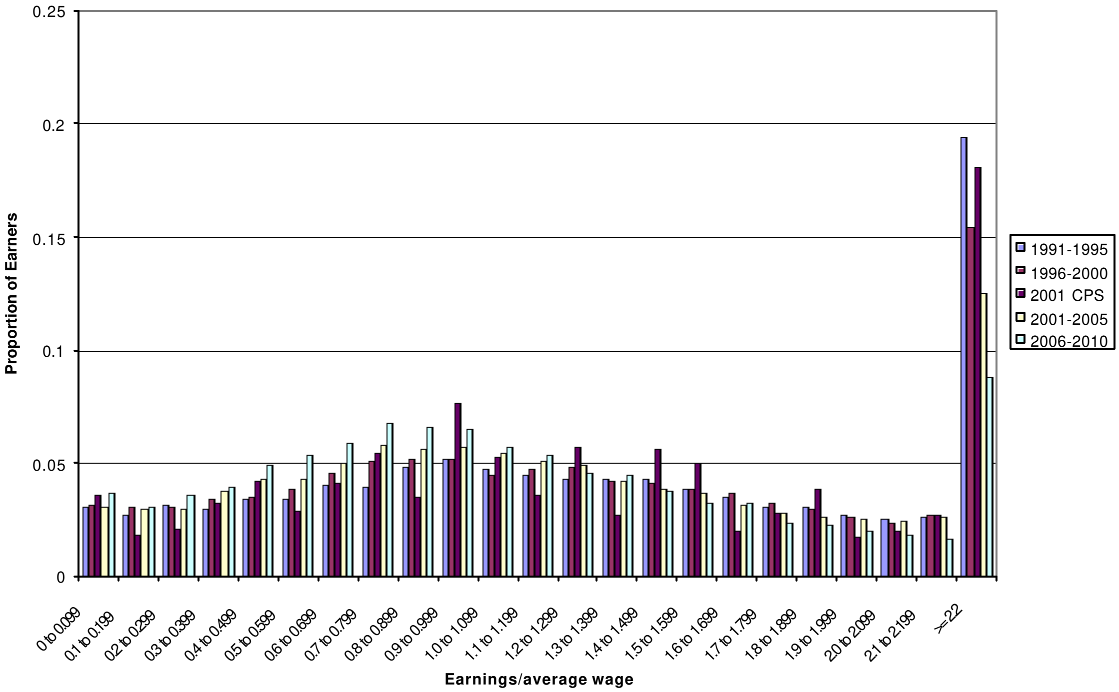
[38] We chose the earnings breaks in the figures (increments of 0.1 times the average wage between minimum earnings and 2.2 times the average wage and older) in such a way as to compare men and women on the same scale. With a much higher high end, too few women are represented at the high end. (Note that in 2000, the taxable maximum was approximately 2.37 times the average wage, or just above the upper threshold in these figures.)

[39] The 1991 through 1995 series in each of these graphs is based completely on SSER data. The 1996 through 2000 series is based on historical (administrative) data for 4 of the 5 years (1996 through 1999).

[40] Additionally, we have tabulated these distributions by four-category educational attainment (less than high school, high school graduate, some college, college graduate or more). They are available in w:\urban\mint3\final\tabearnmf.lst.

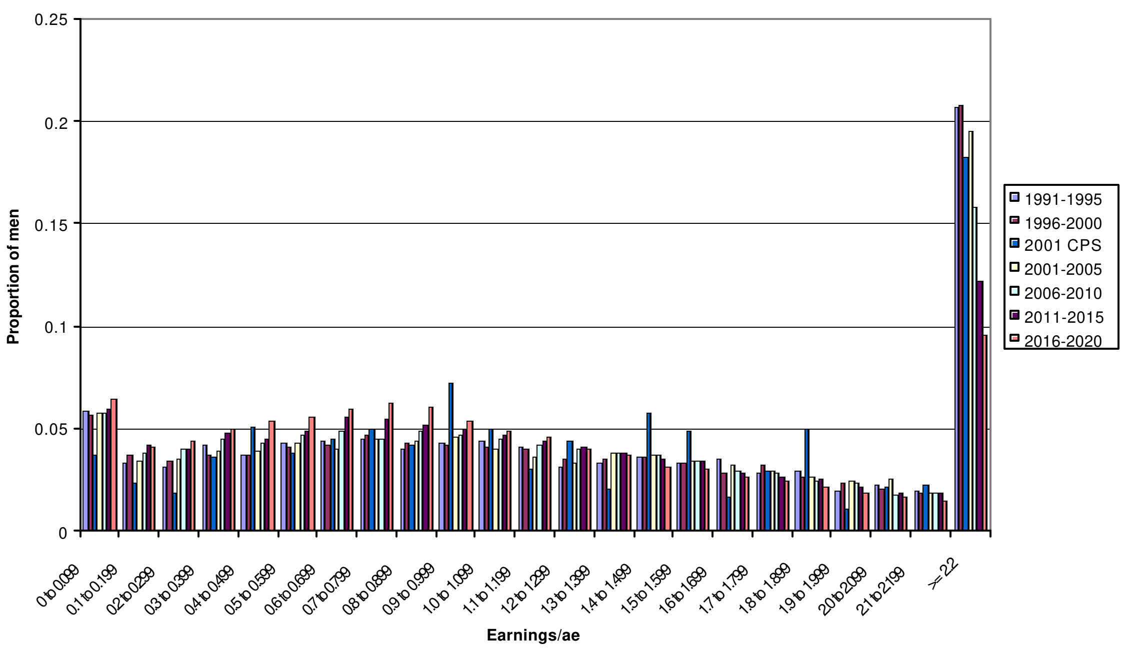
[41] Validation analyses have revealed that the statistical matching algorithm has a bias toward lower values. The trajectory method could potentially be improved to include, for example, a dummy variable indicating recent earnings (or number of years of earnings) at the taxable maximum. This limitation appears to be especially important at ages 60 and older. Until the statistically matched earnings up to age 50 are improved, however, changing the method for projecting trajectories from age 51 onward could be counterproductive.

Figure 4-24 Distribution of Earnings as a Percent of the Average Wage: Men Ages 50-54



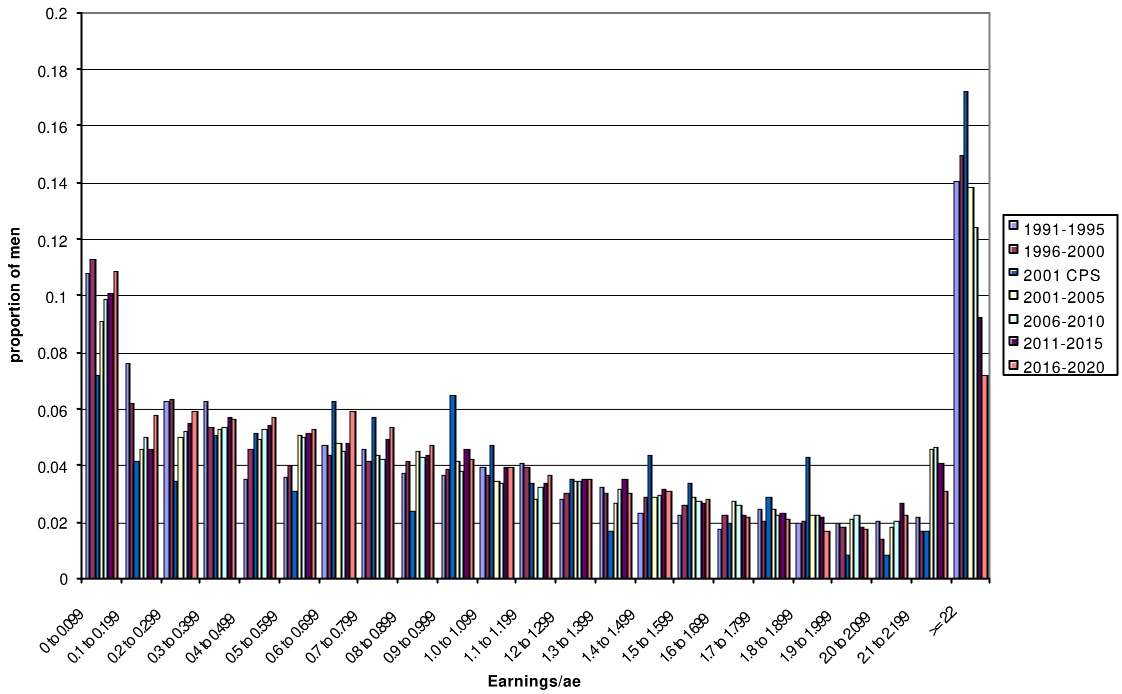
Source: Urban Institute tabulation from MINT3 (path: w:\urban\mint3\final\checkearndist.xls, from tabearnmf.lst)

Figure 4-25 Distribution of Earnings as a Percent of the Average Wage: Men Ages 55-59



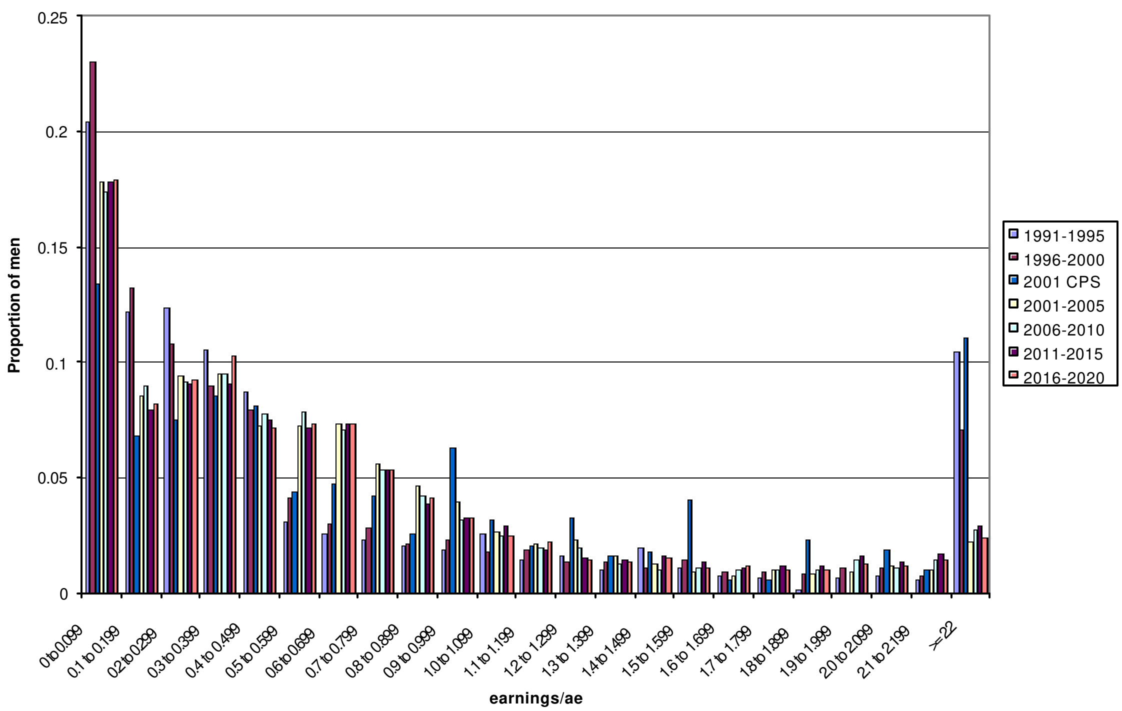
Source: Urban Institute tabulation from MINT3 (path: w:\urban\mint3\final\checkearndist.xls, from tabearnmf.lst)

Figure 4-26 Distribution of Earnings as a Percent of the Average Wage: Men Ages 60-64



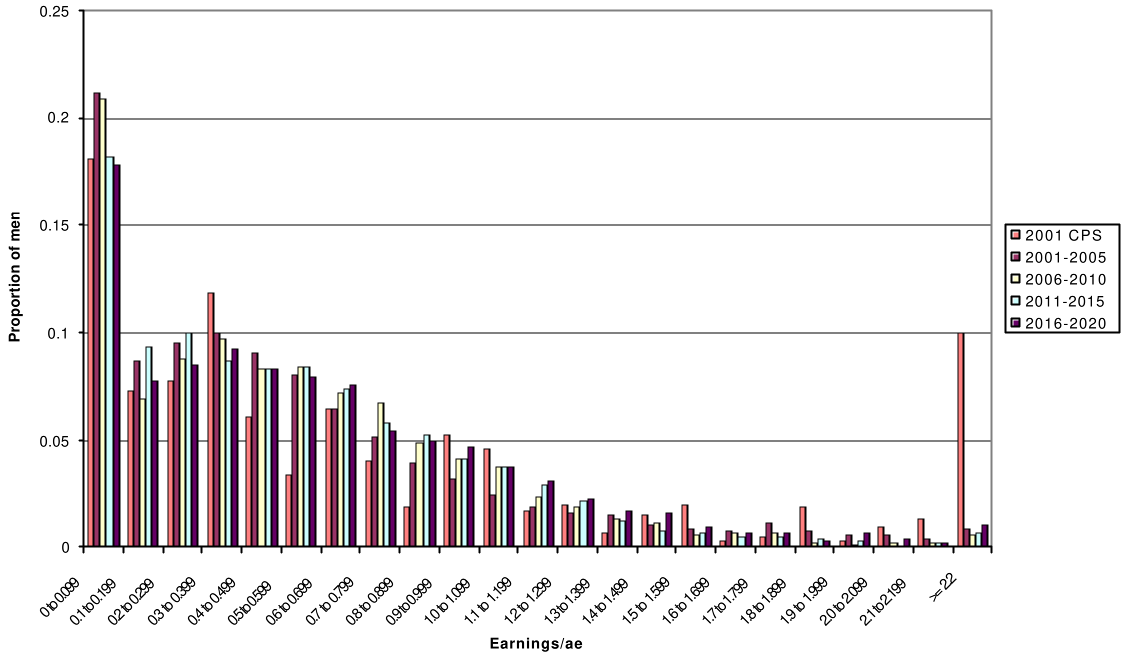
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\checkearndist.xls, from tabearnmf.lst)

Figure 4-27 Distribution of Earnings as a Percent of the Average Wage: Men Ages 65-69



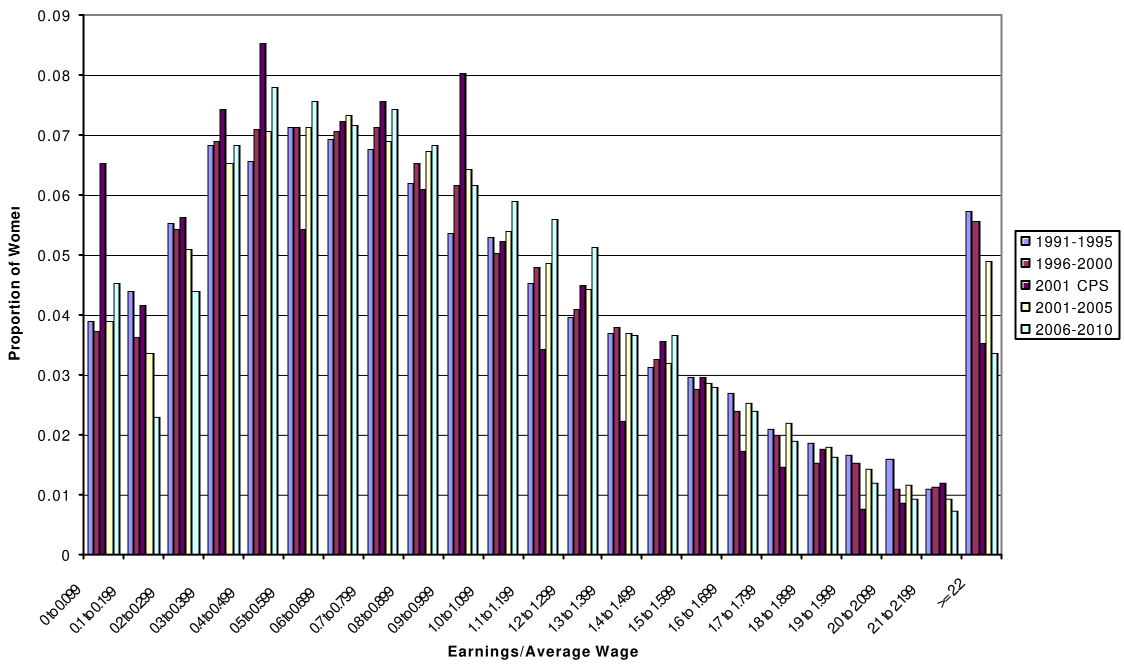
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\checkearndist.xls, from tabearnmf.lst)

Figure 4-28 Distribution of Earnings as a Percent of the Average Wage: Men Ages 70 and Higher



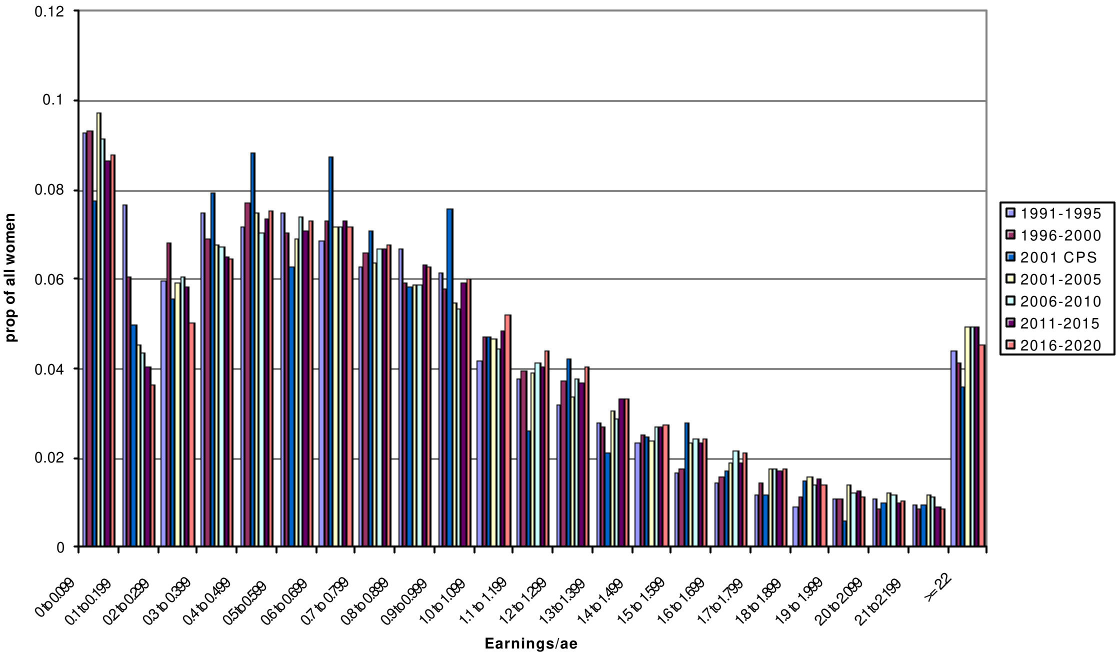
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\checkearndist.xls, from tabearnmf.lst)

Figure 4-29 Distribution of Earnings as a Percent of the Average Wage: Women Ages 50-54



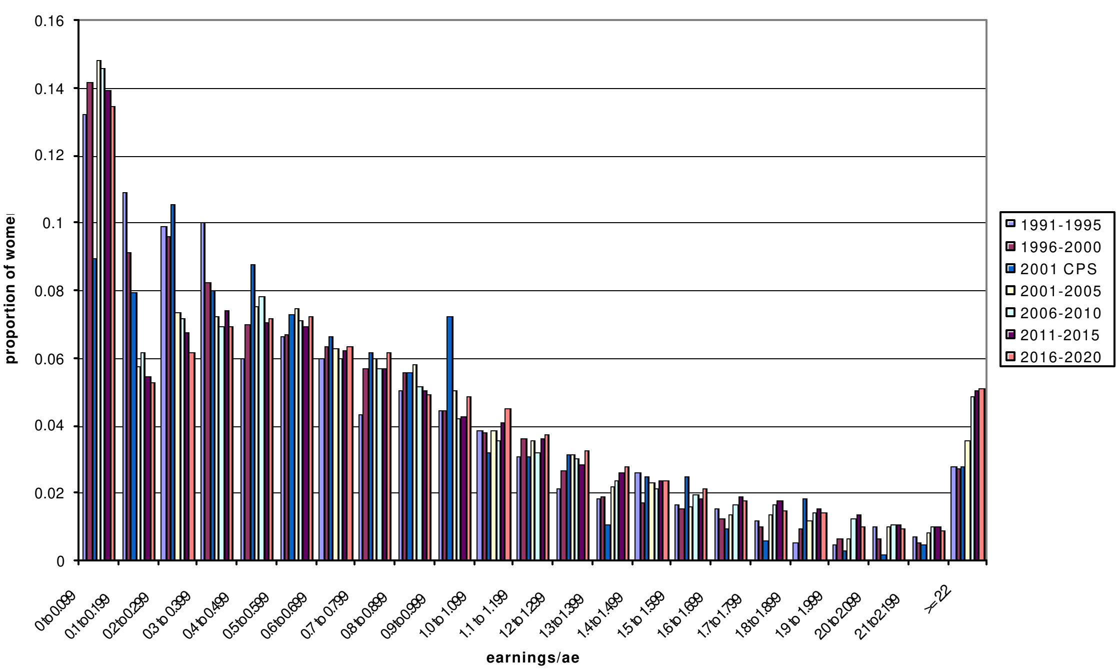
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\checkearndist.xls, from tabearnmf.lst)

Figure 4-30 Distribution of Earnings as a Percent of the Average Wage: Women Ages 55-59



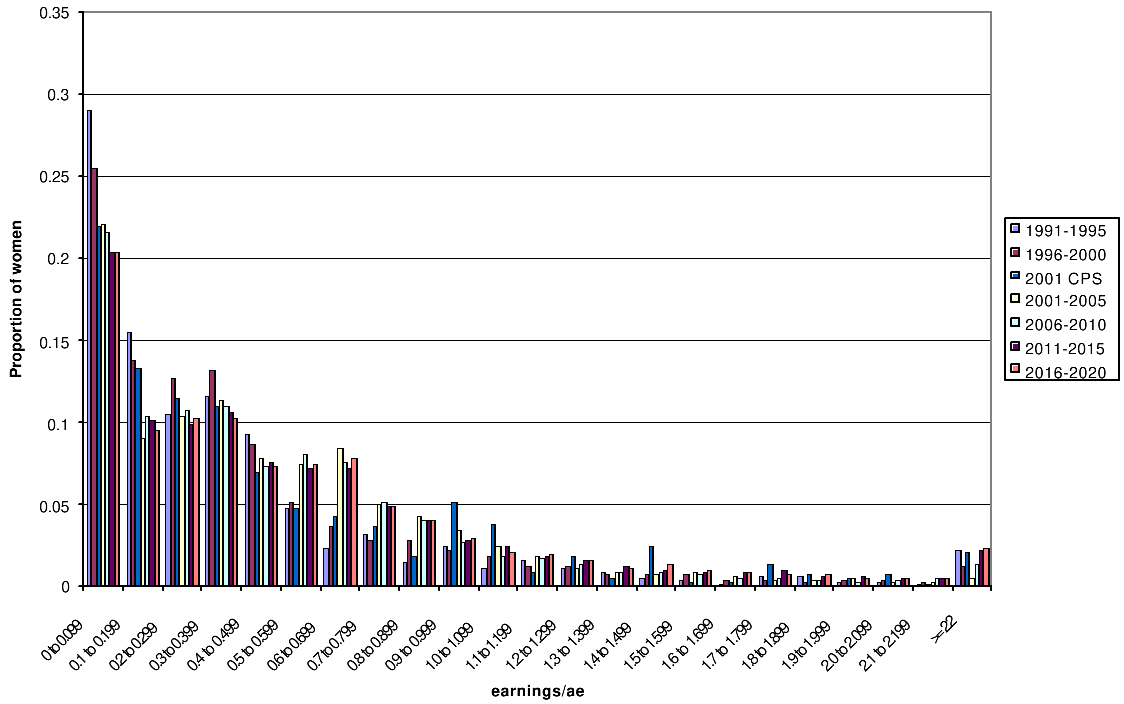
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\checkearndist.xls, from tabearnmf.lst)

Figure 4-31 Distribution of Earnings as a Percent of the Average Wage: Women Ages 60-64



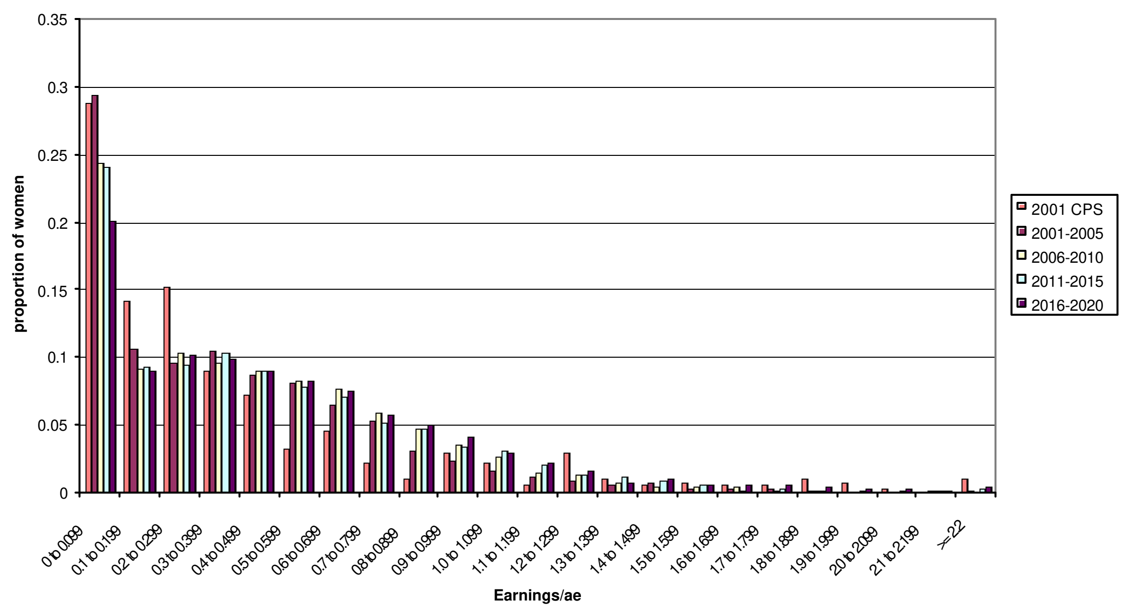
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\checkearndist.xls, from tabearnmf.lst)

Figure 4-32 Distribution of Earnings as a Percent of the Average Wage: Women Ages 65-69



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\checkearndist.xls, from tabearnmf.lst)

Figure 4-33 Distribution of Earnings as a Percent of the Average Wage: Women Ages 70 and Higher



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\checkearndist.xls, from tabearnmf.lst)

The CPS may also represent a somewhat different pool of earnings than is in the SSER or MINT. (Recall that the SSER reflects only Social Security covered earnings, while CPS reflects the economy more broadly, including non-covered work and, potentially, informal sources of income.)

Specifically, at ages 50 through 54, we find that men's earnings in the later, fully simulated years track the earlier years quite closely, except for the failure to reproduce the very high earners (Figure 4-24). At ages 55 to 59, the situation is similar (Figure 4-25). For ages 60 to 64, the model does well at the low-end mode, but again less well at the mode at the high end of the distribution (Figure 4-26). At ages 65 to 69, the projected men do have an appropriate low-end mode, but again appear to be underrepresented at the high end (Figure 4-27). Finally, at ages 70 and older, MINT reproduces the concentration in earnings at the low end of the distribution (Figure 4-28). Once more, though, the high earners are not present in sufficient quantity.

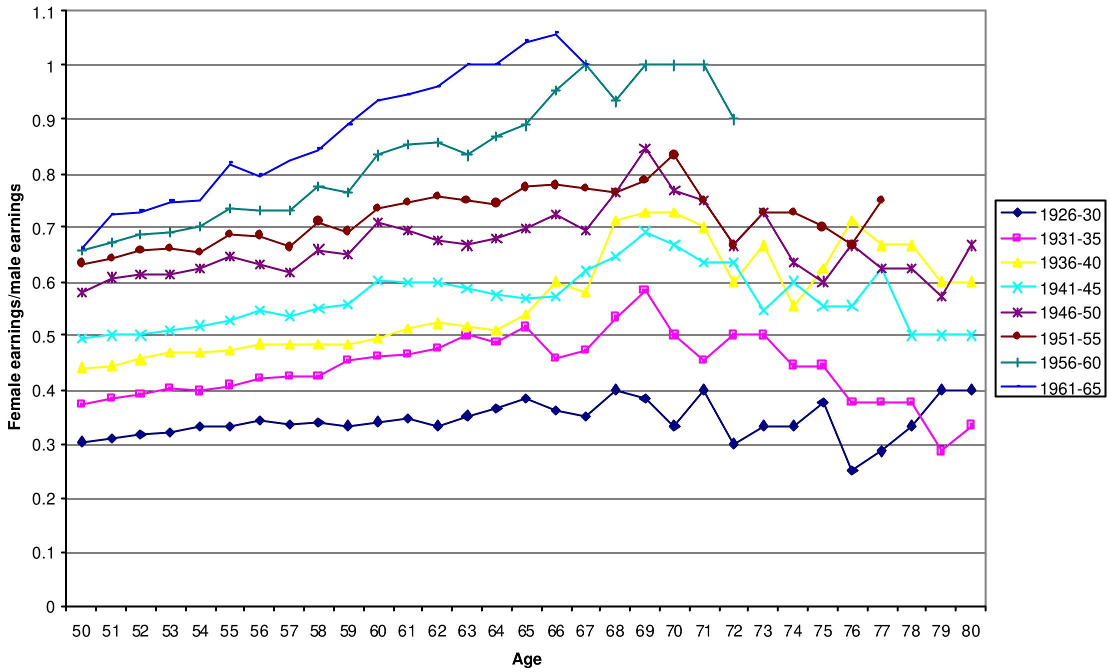
As we would expect, women's earnings tend to shift modestly to the right (i.e., to higher levels) across periods (Figures 4-29 through 4-33). Once more, however, we do observe that the MINT projections do not track the high end of the distribution well and that there is heaping in CPS data. In the age 50 to 55 range, the distributions of women's earnings for later periods are fairly convincing (Figure 4-29). The main difference we see is a greater concentration of women in the later years at between half and 1.499 times the average wage relative to the earlier years. At ages 55 to 59, MINT3 appears to do fairly well forecasting women's earnings, even at the high end. The distribution is fairly similar over time, just with demonstrated earnings growth. The figures for the 60 to 64 and 65 to 69 age ranges (Figures 4-31 and 4-32) provide additional detail. At ages 60 and 64, MINT actually forecasts a modest increase in high-end women relative to what has been observed in the past. This is the only age-sex group for which this occurs. Lastly, the projected MINT3 women seventy and older fairly reasonably replicate past patterns, with very high concentrations of earners in very low-earnings ranges (Figure 4-33).

In the earnings distribution, forecasts of fractions above the taxable maximum have special policy relevance. Given the difficulties that MINT3 has at the upper end of the earnings distribution, when we tabulate fractions of the population at the taxable maximum, we find that MINT projections fall significantly below historical levels.[42] We discuss this problem, and potential solutions, further in our recommendations section.

Just as with employment rates, we find women's earnings actually approaching, and even surpassing, men's at certain ages between 50 and 80 in the latest MINT cohorts. We examine the ratio of women's to men's earnings in Figure 4-34. While the women's earnings fairly consistently remain below 80 percent of men's (on average) at almost all ages for cohorts through 1955, for the 1956 through 1965 cohorts ratios of women's to men's earnings exceed 80 percent starting in the early sixties (for the 1956 through 1960 cohorts) and mid fifties (for the 1961 through 1965 cohorts). An interesting aspect of Figure 4-34 is the increasing slope of the ratio of women's to men's earnings with age from age 50 to ages in the late sixties. It could be that as age goes up those women who continue to work are increasingly select (relative to men).

[42] See, for example, w:\urban\mint3\final\tabearnmf.lst.

Figure 4-34 Ratio of Female to Male Earnings by Age and Birth Cohort (With Linear Cohort Effect for Women)



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmf0626.xls, from tabearn2.lst)

It could also be a function of the specification of cohort effects in the model. They are integrated, as discussed above, in a linear fashion, and only at ages 51 and older.

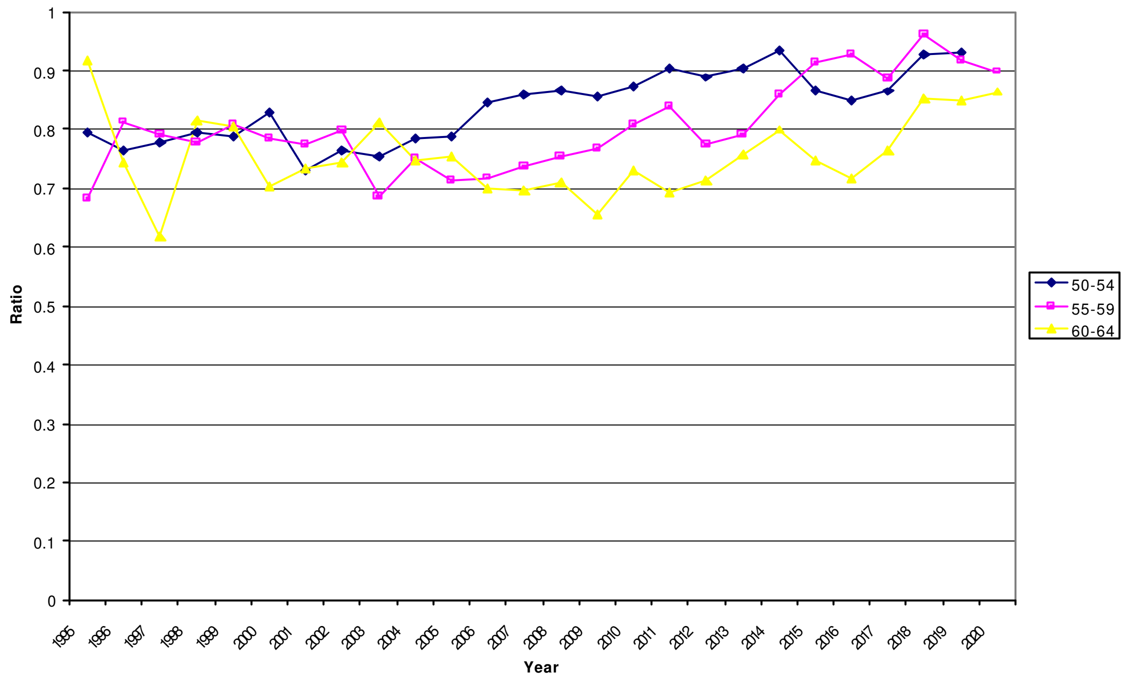
While this discussion has focused on, age, sex, and cohort patterns in earnings, there are several other interesting dimensions along which we validated the MINT3 projections. Given the fact that users' main objectives for using MINT are typically to conduct distributional analyses, it is important to disaggregate and validate the projection along several additional dimensions. Figures 4-35 through 4-40 present joint distributions of earnings (among individuals with nonzero earnings) by age, sex, period and three important other characteristics: marital history (specifically, the ever married versus the never married), race (namely, blacks versus whites), and Social Security beneficiary status (recipients versus non recipients). For these figures, we present the ratio of one group's earnings to the other group's.

The figures that present earnings ratios by marital history reveal important distributional differences between those who do and do not marry (Figures 4-35 and 4-36). For men, those who never marry consistently have lower earnings than those who marry (Figure 4-35), reflected by ratios of less than one. This is true regardless of age (here broken into those ages 50 to 54, 55 to 59, and 60 to 64). For women, the opposite is the case. The ratios are always well over one, indicating that the never married women have higher earnings than the married women. Both these patterns are consistent with historical data. We can gain some insight into how MINT never married to ever married earnings ratios compare to historical data by comparing data from 1995 to 1999, which are observed from Summary Earnings Records, with data from 2000 onward, which are projected. When we do so, we see quite a bit of noise in specific years at specific ages, even in the historical data. As a consequence, it is difficult to verify validity. One clear difference is that in MINT, ratios tend to decline with age (i.e., never married people become less like married people), especially after about 2005, while in the historical data there appears to be less differentiation by age.

When we examine earnings patterns by race, we once more find important differences across the groups between men and women (Figures 4-37 and 4-38). While black men consistently have lower earnings than white men, demonstrated by the ratios of black to white earnings of less than one, black women's earnings are closer to white women's. Again, these relationships hold at virtually every age (here broken into those ages 50 to 54, 55 to 59, 60 to 64, and 65 to 69). Once more, earnings projections in the historical period exhibit a lot of noise at any given age, making it challenging to verify validity.

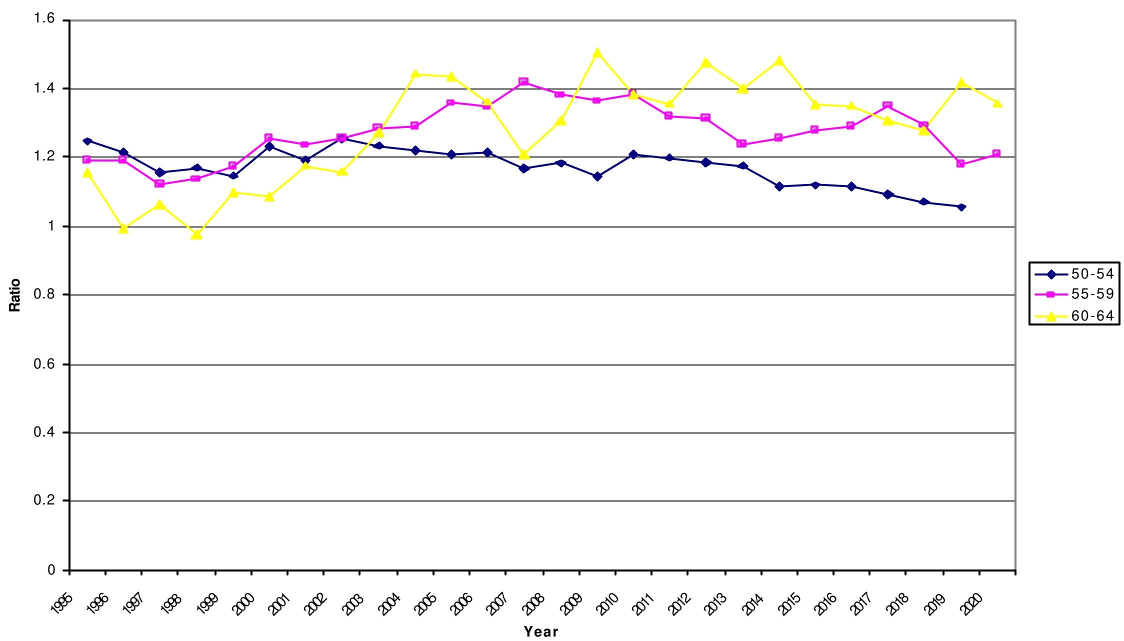
When we consider earnings by Social Security beneficiary status, the differences across groups (beneficiaries versus non-beneficiaries) are most striking of the 3 comparisons (Figures 4-39 and 4-40). For both men and women, earnings are much lower among the beneficiaries: always less than half of beneficiaries' earnings, and often less than a quarter of them. Here, we examine age by single years before the normal retirement age, so ages 62 to 64. Differences in ratios by age between the historical and projected data appear particularly prominent for women. In MINT projections from 2000 onward, the ratios of women beneficiaries are lower than observed historically.

Figure 4-35 Ratio of Mean Earnings (of Earners) of Never Married to Married Persons: Men Ages 50 to 64



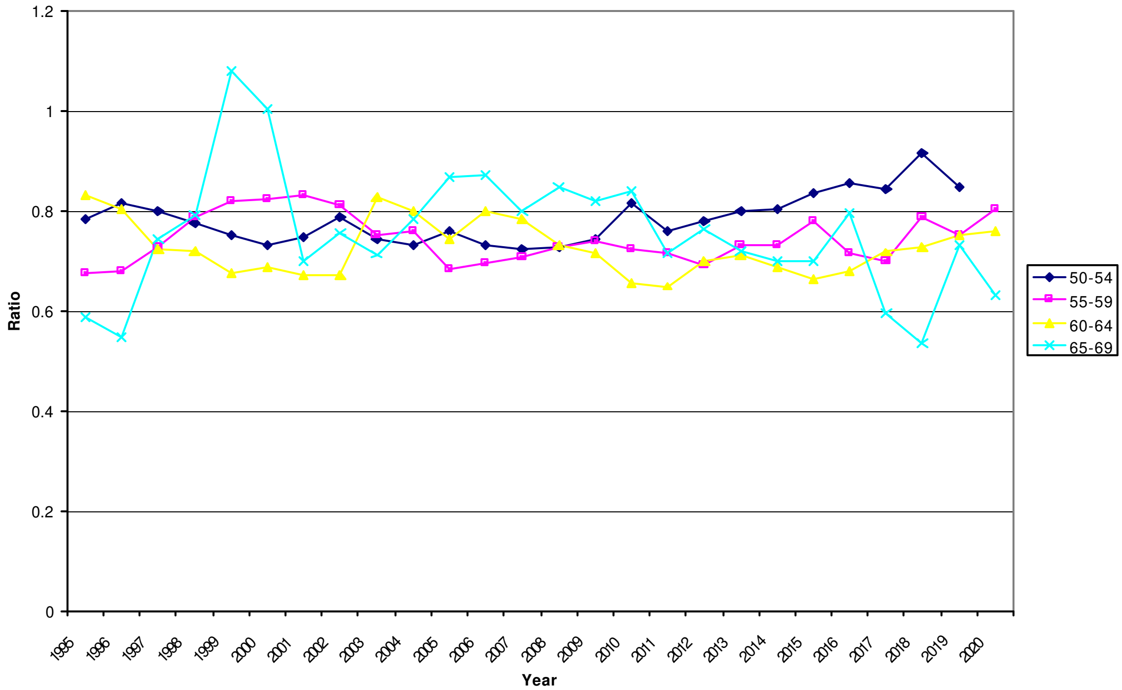
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\comparegroups.xls, from tabearnmf.lst)

Figure 4-36 Ratio of Mean Earnings (of Earners) of Never Married to Married Persons: Women Ages 50 to 64



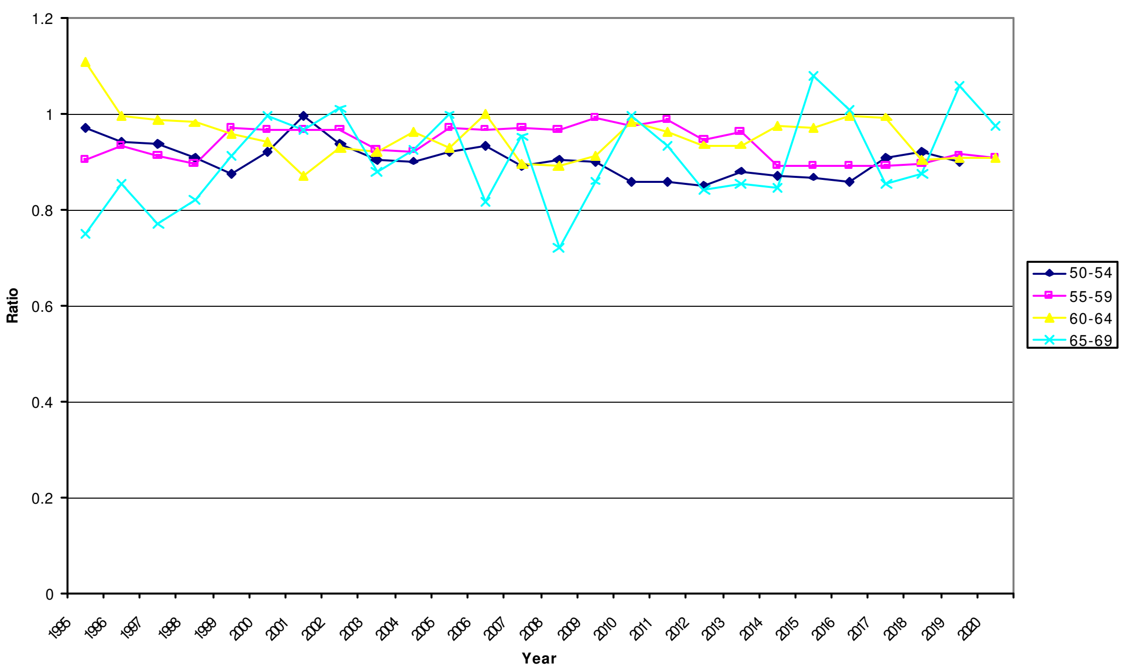
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\comparegroups.xls, from tabearnmf.lst)

Figure 4-37 Ratio of Black to White Mean Earnings (of Earners): Men Ages 50 to 69



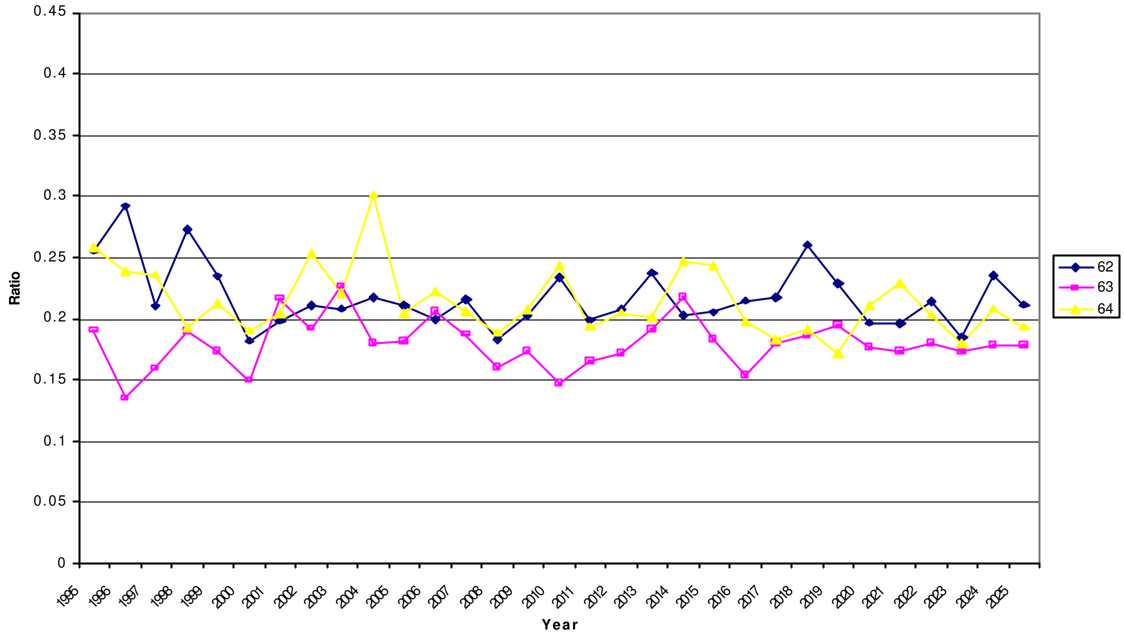
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\comparegroups.xls, from tabearnmf.lst)

Figure 4-38 Ratio of Black to White Mean Earnings (of Earners): Women Ages 50 to 69



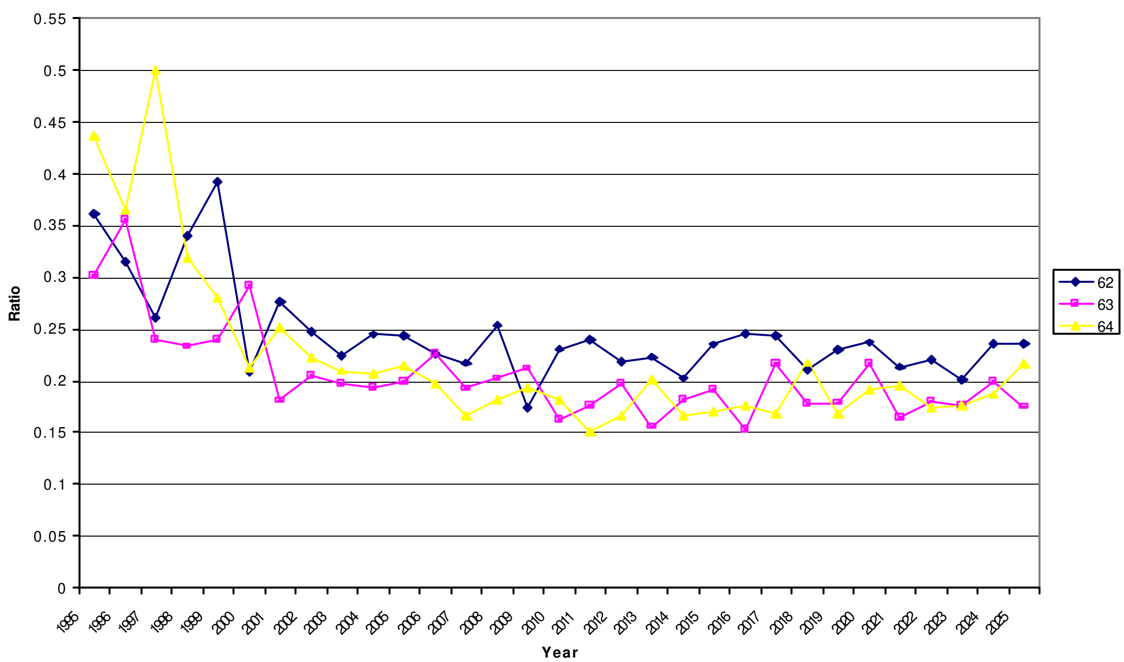
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\comparegroups.xls, from tabearnmf.lst)

Figure 4-39 Ratio of Earnings of Social Security Beneficiaries to Earnings of Non-Beneficiaries, by Age: Men Ages 62 to 64



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\comparegroups.xls, from tabearnmf.lst)

Figure 4-40 Ratio of Earnings of Social Security Beneficiaries to Earnings of Non-Beneficiaries, by Age: Women Ages 62 to 64



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\comparegroups.xls, from tabearnmf.lst)

Chapter 9 further discusses MINT forecasts of earnings at ages 62 and 67, as well as in 2020, by a variety of characteristics, including race, education, earnings, and beneficiary status.

4. Social Security take-up

Individuals' choices about when to begin taking up their Social Security benefits can have profound implications for their well-being later in life. The MINT projections reveal patterns that do not differ dramatically from historical patterns in administrative data (Table 4-18).[43] Just as in historical data, the spike in collection of retirement benefits at age 62 is the most prominent feature of the distribution of take-up ages. As one would expect given the larger MINT model's forecasts of increasing longevity, we see a modest decline in the proportion of person's receiving widow and widower benefits at ages 60 and 61 in the MINT3 cohorts (and across them, see Chapter 9 for details). In the projection period, the model projects somewhat higher rates of take-up at age 64 and somewhat lower rates at age 65 than have been observed historically.[44] Further, the model projects more take-up at ages 66 and older with the increase in the normal retirement age.[45] But generally the model results appear reasonable and consistent with past patterns.

Table 4-18
Comparison of MINT Social Security Take-up Age Distribution with Historical Data

	Green Book (2000)	Author's calculation from SSA (1997)	MINT3 (1926-60 cohorts)	MINT3, historical (1926-28)	MINT3, partially observed (1929-1937)	MINT3, fully projected (1938-1962)
60-61	-	5.9	5.0	6.3	6.1	4.6
62	58.6	56.5	51.9	51.7	51.1	52.3
63	18.8 (63-64 combined)	7.1	8.7	8.2	7.2	9.2
64		9.9	13.8	12.8	13.7	13.9
65	15.6	14.2	10.1	12.7	12.8	9.2
66 plus	7.0	6.3	10.3	8.3	9.2	10.8

Sources: Committee on Ways and Means (2000: 53); author's tabulation from Social Security Administration; author's tabulations from MINT3 (addtab.lst, sagetabnew_nosp.lst)

[43] For historical data, we use two sources: a tabulation from the Green Book (Committee on Ways and Means, 2000) and our own tabulations from the Social Security Administration's 1997 Annual Statistical Supplement to the *Social Security Bulletin* (see Toder et al., 1999, for discussion of how we assigned ages using these data).

[44] This could be due to claiming of retroactive lump sum benefits among age 65 claimants, who thus appear as age 64 recipients, in our estimation sample.

[45] One might question this finding given the elimination of the retirement earnings test above the retirement age. MINT3 allows workers to elect benefits after the NRA. We have conducted a sensitivity analysis to this assumption. (See below.)

Table 4-18 also compares the distribution of ages at first Social Security take-up of those persons in MINT for whom we observe take-up in the administrative records with those for whom we project an application age (in both cases excluding workers receiving benefits on the basis of a disability). The table includes separate columns for those in cohorts where take-up ages are fully completed during the historical period (i.e., those who turn age 70 by 1999), for those whose take-up dates are partially simulated (i.e., those at least age 62 but not yet 70 in 1999), and for those whose take-up dates are fully projected (i.e., those not yet age 62 in 1999). All three groups have relatively consistent take-up patterns. The major differences are at ages 65 (where the later, fully projected cohorts have lower forecasts) and 66 and older (where the later, fully projected cohorts have higher forecasts).

Another important aspect of the MINT assignment of the OASI take-up age is the assignment of missing data codes to individuals who do not receive a value on the variable for some reason. These reasons include the following: becoming entitled to DI worker benefits before collecting OASI, dying before reaching age 62 or electing to take up benefits (or becoming entitled to DI benefits), being ineligible for OASI, being eligible only for OASI benefits as a spouse but one's spouse has not yet reached the early eligibility age, and finally having a censored record (because one has not yet reached the mandatory take-up age of 70 in the last simulation year). Table 4-19 shows patterns in the missing data codes we assigned across MINT cohorts. (As we do not include the last cohort in this table, the censored code does not appear in the table.) Note that in some cases a person may fall into two categories: for example, a person may have died before age 65, and also not have been eligible for Social Security at age 65. In these circumstances, we assign precedence to death. (Generally, disability status has highest priority, followed by death, followed by lack of eligibility, followed by institutionalization, followed by censoring of the record.)

Table 4-19
Percentages Assigned and not Assigned OASI Take-up Age in MINT by Birth Cohort

	Birth Cohort						
	1926-1930	**1931-1935**	**1936-1940**	**1941-1945**	**1946-1950**	**1951-1955**	**1956-1960**
Receive an age	85.0	82.1	77.6	77.6	75.9	75.0	73.9
Disabled	10.4	12.8	14.7	13.3	13.6	13.5	13.9
Died	1.3	3.3	5.7	7.7	9.1	10.4	10.8
Ineligible	3.2	1.7	1.9	1.4	1.2	1.0	1.3
Institutionalized	0.1	< 0.1	0.1	< 0.1	< 0.1	< 0.1	< 0.1
Censored spouse	0.1	0.1	0.2	0.1	0.1	< 0.1	< 0.1

Source: Author's tabulation from MINT3 (addtab.lst)

The cohort pattern in non-assigned OASI take-up ages in Table 4-19 is generally sensible. There is an increase in DI incidence from the 1926 to 1930 through the 1936 to 1940 cohorts that then levels off at a rate of just over 13 percent of a cohort. There is also a decline in fractions that are not eligible for OASI benefits after the first cohort. This reduction coincides with increased OASDI coverage rates in the work force. The increased fractions that die before receiving an OASI take-up age that the table reveals might at first appear problematic because of declining mortality over time. However, as those in later cohorts experience more years at risk of dying than those in earlier cohorts, the pattern is actually sensible. (Recall that all persons in MINT were alive as of the SIPP interview date in the early 1990s. Therefore those in the 1926 to 1930 cohorts, who were ages 60 to 64 in 1990, overwhelmingly survived to take-up age.)

Distributional differences in take-up patterns in MINT3 are also consistent with patterns that we observe in historical data. In the model, women take up their Social Security benefits at earlier ages than do men.[46] Patterns by education also appear reasonable given historical experience (Table 4-20).[47] For example, MINT replicates the pattern of much higher DI prevalence rates, death rates, and rates of ineligibility for Social Security among those with less education. All education groups take-up their benefits in highest proportions at age 62. If we combine those taking up at or before age 62 with those ineligible for Social Security take-up for some other reason, we see that for those with less than a high school education, across cohorts between three-quarters (75.0 percent) and almost nine-tenths (87.7 percent) do not wait until after age 62. For those with a high school education, this figure is lower, ranging from around two-thirds (65.5 percent) to just over seven-tenths (70.6 percent), depending on cohort. Among persons with any college, the corresponding range is lower still, varying from just under half (45.3 percent) to just under three-fifths (57.2 percent) across the cohorts. Accordingly, MINT also projects higher take-up rates at ages 64 and 65 among those with more education, just as we see in the historical data.

Chapter 9 provides additional discussion of distributional differences in Social Security take-up patterns, including tabulations by cohort, gender, and lifetime AIME quintiles.

5. Longitudinal validity of earnings

We also consider several measures of the longitudinal validity of MINT3 earnings. Most importantly, we want to ensure that the model's measures of average indexed monthly earnings (AIME) are reasonable. Figures 4-41 and 4-42 present the AIME distributions that MINT produces for men and women, respectively, by cohort.[48] The AIMEs for each cohort are calculated based on the highest 35 years of earnings through the projected Social Security take-up age and are presented in constant (1998) dollars. This allows us to see the cumulative effects of wage growth and thus to gain some insight into the absolute standard of living that members of the MINT cohorts will be able to afford based on their earnings and Social Security benefits. For the 1926-30 cohorts (and a substantial fraction of the 1931 to 1935 cohorts), these data are almost entirely observed in administrative records, making them a useful benchmark for the projections.

[46] For historical data on this pattern, see Table 5-A-4 in Toder et al. (1999: 150).

[47] Once more, the 1926 to 1930 birth cohort serves as a useful benchmark in this table, given that its experience is almost fully observed from historical data.

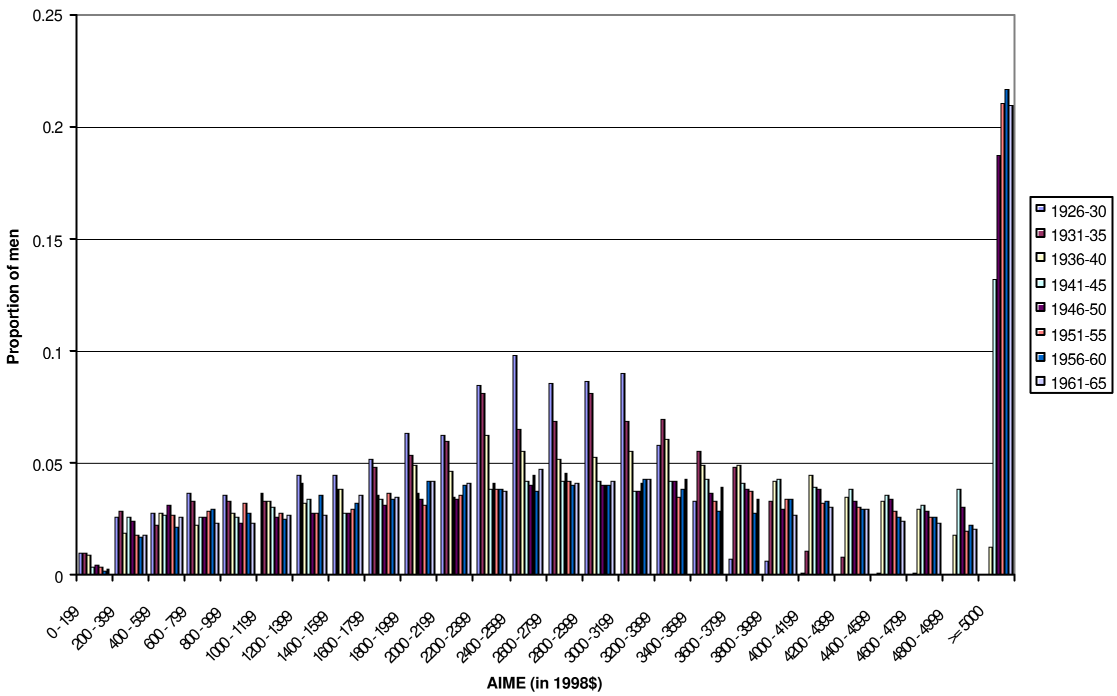
[48] AIME is calculated as of OASI take-up age, and reflects the highest 35 years of earnings. Those with fewer than 40 quarters of coverage have AIME of zero under this definition.

Table 4-20
Distribution of OASI Take-up Age in MINT by Birth Cohort and Educational Attainment

	1926-1930	1931-1935	1936-1940	1941-1945	1946-1950	1951-1955	1956-1960
high school dropouts							
spouse not yet taken-up	0.1	0.2	0.2	0.2	0.3	0.1	0.1
ineligible	4.9	2.7	2.7	2.5	3.3	3.0	4.2
deceased	2.2	4.5	8.3	10.4	13.8	15.7	14.9
disabled	15.5	21.9	25.7	24.4	23.9	20.8	21.6
60-61	6.9	6.3	5.0	6.7	5.5	4.7	4.0
62	41.8	36.4	33.6	35.9	37.6	35.7	35.6
63	5.8	4.7	5.4	5.3	4.1	5.0	5.9
64	9.0	6.8	10.0	6.9	5.7	7.3	6.7
65	6.4	8.2	4.8	4.2	2.6	3.7	2.8
66	0.8	1.6	0.8	0.8	0.6	0.9	1.4
67	0.5	1.1	0.4	0.4	0.7	1.0	0.6
68+	6.0	5.4	2.8	2.2	1.9	2.0	2.1
All	100.0	100.0	100.0	100.0	100.0	100.0	100.0
high school graduates							
spouse not yet taken-up	0.1	0.1	0.1	0.1	0.1	0.0	0.0
ineligible	2.3	1.1	1.4	0.9	0.9	0.6	0.9
deceased	0.9	2.8	5.2	7.6	9.3	10.7	11.3
disabled	9.0	11.2	13.4	13.2	14.9	14.8	14.9
60-61	5.9	4.7	4.5	4.5	3.8	3.5	3.2
62	47.4	47.2	41.9	44.3	40.6	39.6	40.0
63	6.6	5.9	7.1	7.3	6.7	7.0	7.0
64	11.3	10.5	11.9	9.7	10.3	10.0	10.3
65	9.3	10.0	10.2	6.9	5.1	6.2	5.8
66	1.1	1.4	1.1	2.0	3.3	3.0	2.5
67	0.7	1.1	0.9	1.3	1.9	1.8	1.8
68+	5.4	4.2	2.3	2.2	3.0	2.6	2.3
All	100.0	100.0	100.0	100.0	100.0	100.0	100.0
any college							
spouse not yet taken-up	0.0	0.1	0.5	0.0	0.0	0.0	0.0
ineligible	3.1	1.8	2.2	1.6	1.1	1.1	1.0
deceased	0.7	3.0	4.3	6.3	7.1	7.8	8.0
disabled	5.4	5.1	7.2	6.4	7.4	8.2	8.0
60-61	2.4	2.6	2.4	2.7	2.6	1.9	2.4
62	33.7	38.9	33.6	37.8	38.0	37.5	37.8
63	7.9	6.6	7.9	8.2	7.2	7.2	6.9
64	16.1	12.7	14.7	12.8	13.1	12.1	13.6
65	20.6	18.2	18.8	11.4	9.3	8.8	8.8
66	2.2	2.8	2.3	5.2	5.9	5.6	4.4
67	1.8	2.4	2.0	2.9	3.4	4.3	4.0
68+	6.0	5.6	4.1	4.8	4.8	5.4	5.1
All	100.0	100.0	100.0	100.0	100.0	100.0	100.0

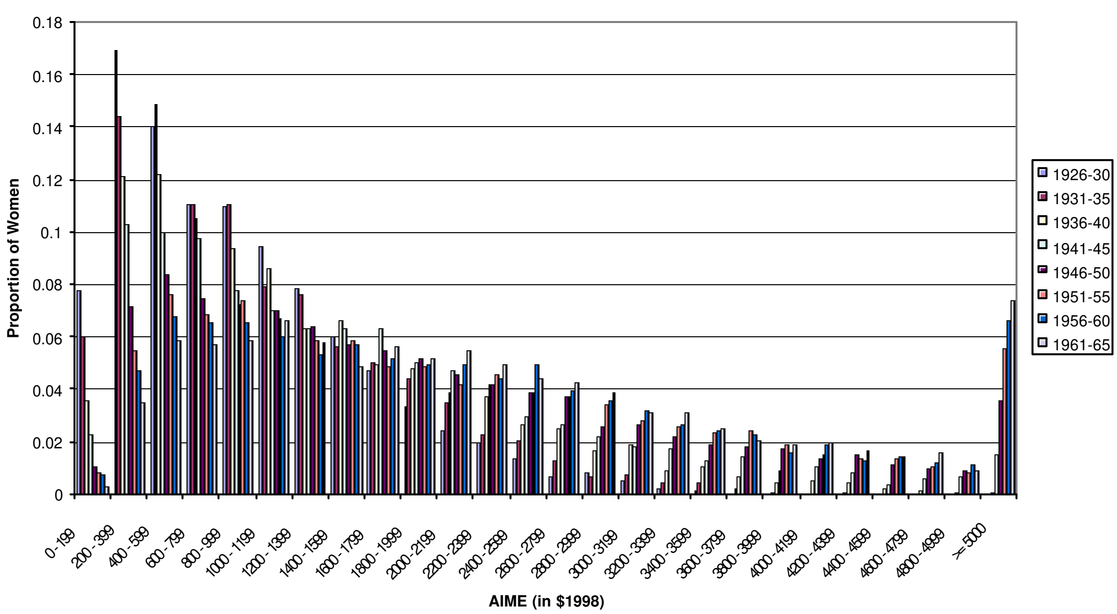
Source: Author's tabulation from MINT3 (addtab.lst)
Note: Ineligible row includes persons institutionalized before Social Security take-up

Figure 4-41 AIME Distribution (in 1998$) by Cohort: Men



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\checkaimedist.xls, from tabearn2.lst)

Figure 4-42 AIME Distribution (in 1998$) by Coho rt: Women



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\checkaimedist.xls, from tabearn2.lst)

For both men and women, the AIME distribution shifts rightward (toward higher values) across cohorts. The growth in lifetime earnings is due primarily to the projected wage growth (OCACT projects a real wage differential of 1.1 percent for years after 2012). For men, a prominent change is the decline in the bulge in the center of the distribution (representing AIMEs of $2000 to $3199 in 1998 dollars) across the MINT cohorts (Figure 4-41). Among women, the rightward shift is particularly marked (Figure 4-42). Their increased participation and earnings, described earlier, explain the even greater shift (relative to men) to higher AIMEs. By the last cohort, almost no women occupy the lowest lifetime earnings range (under $200 in 1998 terms), compared to almost 8 percent of the oldest MINT women and just over 6 percent of women in the 1931 to 1935 birth cohorts. The figure also shows very rapid declines in other lifetime earnings categories below $1200 (1998).

Figures 4-43 and 4-44 further consider these longitudinal issues by contrasting projections of total years in the labor force (i.e., years in which covered earnings are greater than zero) as of age 62 between MINT2 and MINT3. Again, this sort of comparison allows us to see the robustness of the retirement model relative to the splicing method. For men, once more, the two forecasts are nearly identical. In both cases, the distribution has a long thin tail and peaks at 44 and 45 years, representing a full career from high-school age through Social Security take-up. For women, there are more substantial differences between MINT2 and MINT3, reflected in the rightward shift in the distribution in the latter model. The women's distribution has a similar shape to the men's, also peaking at a full work career, but with a much thicker tail at lower levels of work effort in both models, and especially in MINT2.

6. Retirement

Validating retirement dates is particularly challenging, given varying definitions of retirement and inconsistent availability of data (for example, on hours of work) from the historical period.[49] We discuss retirement age distributions in Chapter 9 rather than in this chapter.

X. SENSITIVITY ANALYSES

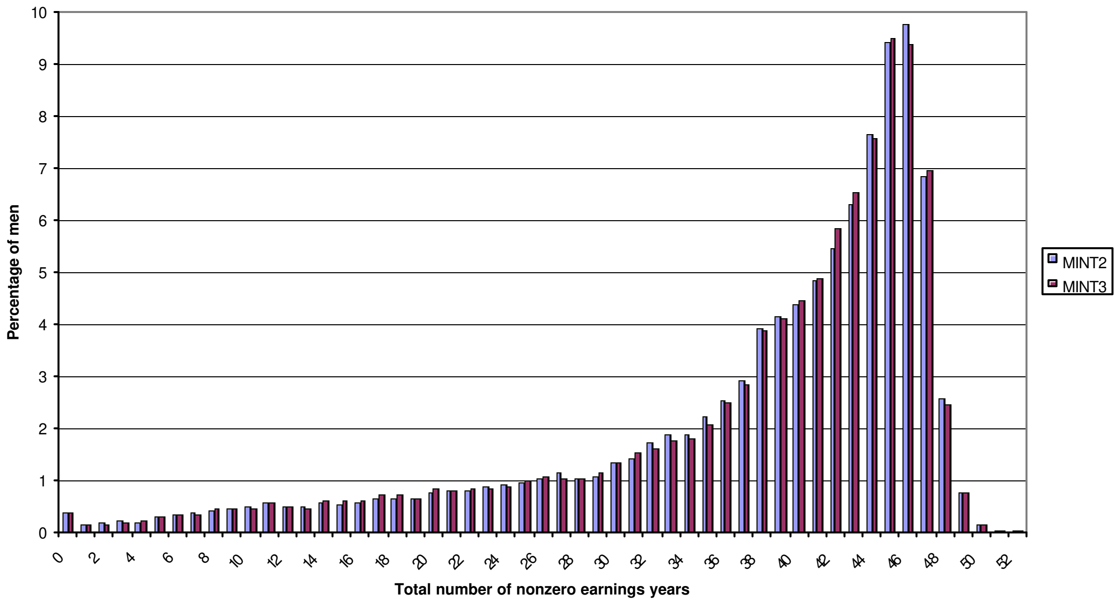
1. Overview

As noted above, we conduct five main sensitivity analyses. In these analyses, we: 1.) re-specify MINT's cohort effects for women; 2.) re-specify error terms for retirement earnings after age 50; 3.) re-specify the Social Security take-up equations so that most covariates are interacted with an indicator for whether one is age 62; 4.) combine the Task 2 earnings with a single Social Security take-up equation (i.e., we "turn off" the retirement model, and let Task 2 determine all earnings through age 67); and 5.) impose full OASI take-up at the Normal Retirement Age.[50]

[49] While earnings data are available from 1951 through 1999, data on hours are only available over the course of the SIPP panels. This means we can observe hours for an interval ranging from 32 months (for members of the 1990 and 1991 panels) to 40 months (for some members of the 1992 panel).

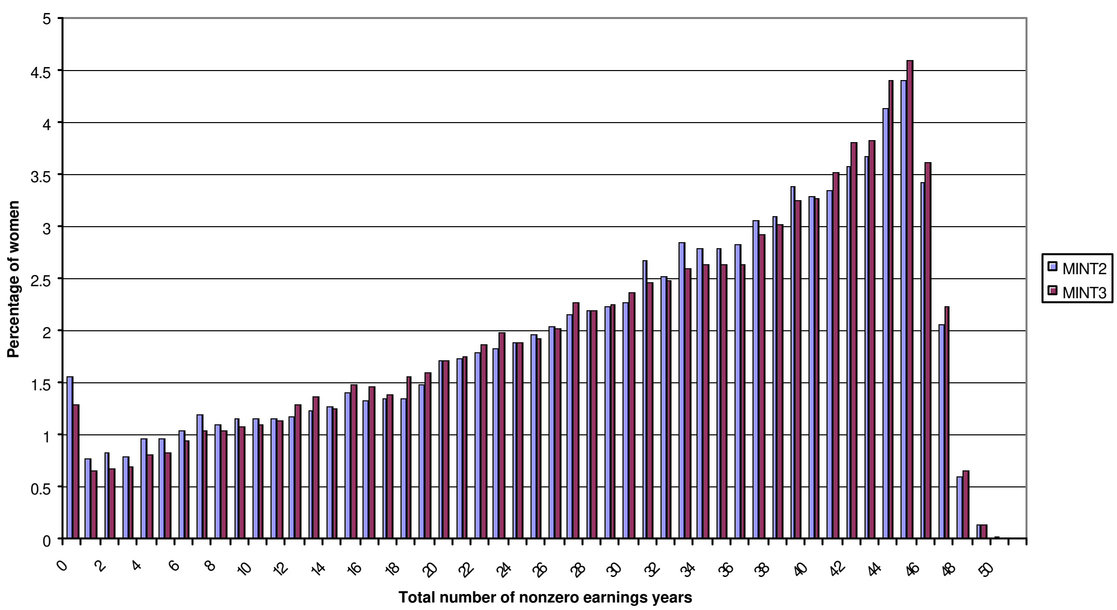
[50] For details, including additional tabulations of projections (beyond those reported in this chapter) under these assumptions, contact Melissa Favreault.

Figure 4-43 Distribution of Work Years through Age 62 for Men: Comparison of MINT2 and MINT3



Source: Urban Institute tabulation from MINT2 and MINT3 (w:\urban\mint3\final\comparerichgarygiant0626.xls, from comparerichgarygiant.lst)

Figure 4-44 Distribution of Work Years through Age 62 for Women: Comparison of MINT2 and MINT3



Source: Urban Institute tabulation from MINT2 and MINT3 (w:\urban\mint3\final\comparerichgarygiant0626.xls, from comparerichgarygiant.lst)

Each of these analyses addresses core substantive, modeling, and policy issues. The first and fifth sensitivity tests suggest solutions to problems posed by a lack of relevant historical data (because a change to Social Security has occurred fairly recently). The second sensitivity analysis tests solutions to a puzzle that has troubled retirement income modelers for decades. The third sensitivity test explores an interesting aspect. The fourth sensitivity test changes the model most dramatically, overwriting much of what happens in task 5.

2. Cohort Patterns in Women's Labor Force Participation

We conducted a sensitivity analysis in which we considered the cohort term in the retirement and retiree work and earnings equations for women to be a single intercept shift for all subsequent cohorts, rather than a linear term (applicable in single-year increments, as described above in "implementation issues"). Figure 4-45 depicts women's work rates by cohort under this assumption, and Figure 4-46 shows the ratio of the women's to the men's work rates. As one would expect, there is much less differentiation among baby boom and post-baby boom women when they all receive the same cohort effect (Figure 4-45). Indeed, the latest cohort (1961-1965) actually participates less than several of its predecessors at many ages after 50 when the cohort effect is uniform. The 1951 to 1955 cohorts (and sometimes 1946 to 1950 cohorts) often work at the highest rates in this simulation, likely reflecting the wage advantages that earlier baby boomers experienced earlier in their lives that render work more lucrative. The female-to-male employment ratios do narrow across cohorts through 1940, but then remain stable. The ratios never exceed one, as they did with the linearly incorporated cohort effects.

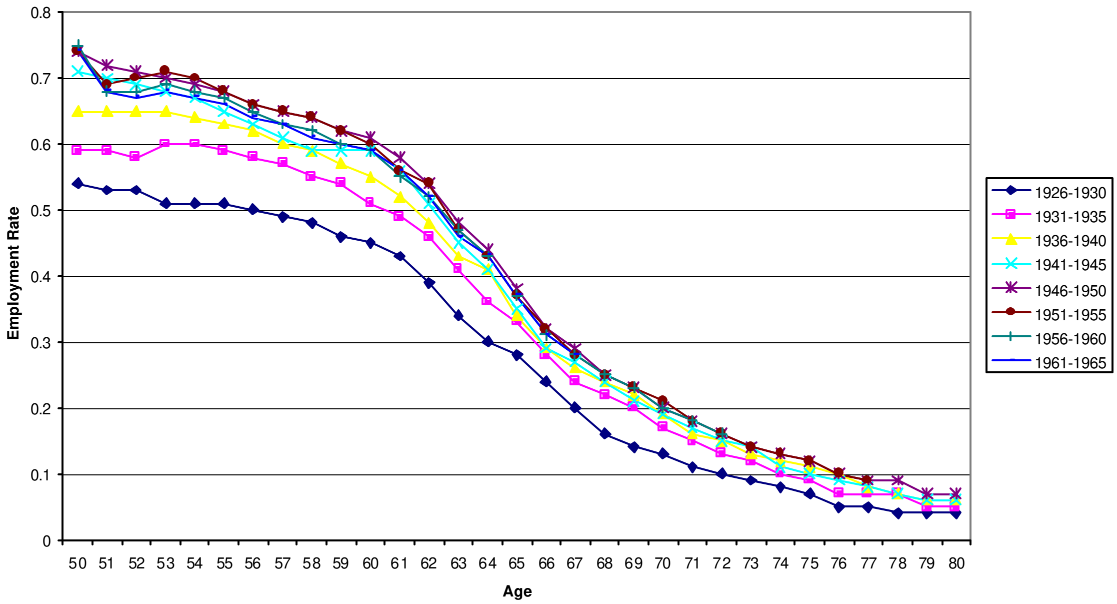
When the cohort effect is applied uniformly, differences in patterns of women's earnings are similar. Figures 4-47 and 4-48 depict the means and female to male ratios for earnings under this simulation. Without the linear cohort effects, the women's earnings (relative to the average wage) increase through the 1946-1950 birth cohorts, but then converge to fairly stable age-specific means (Figure 4-47). The ratios of women's to men's earnings do continue to increase over time even with this lesser effect (Figure 4-48).

3. Suppression of Error Terms

One important aspect of the specification of the model of retirement earnings is the way in which we treat permanent and transitory error components in our functions that predict earnings. A good deal of econometric research supports using both types of errors when modeling earnings (see, for example, Lillard and Willis, 1978), under the assumption that earnings are subject to both systematic and pure random shocks. Our sensitivity analyses revealed that our MINT3 earnings forecasts were quite sensitive to our assumptions about how error terms were structured in the equations for earnings after retirement.

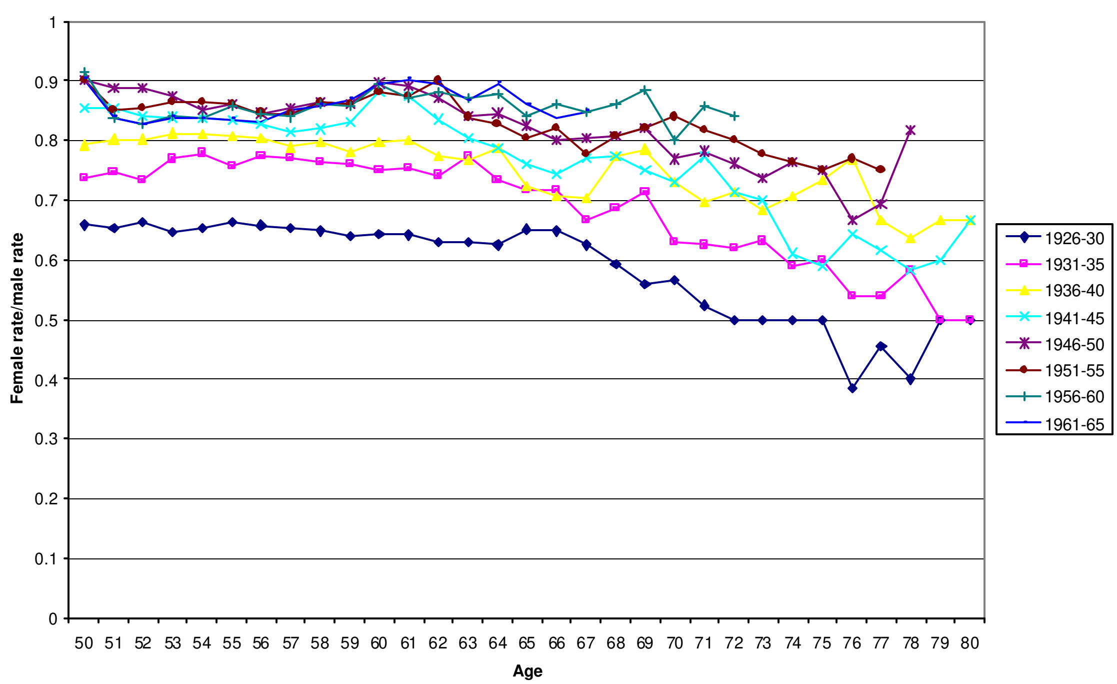
In initial simulations, we did not include the error terms in our equations that predicted earnings after retirement and first Social Security take-up. Our reluctance to include the errors was due in part to the fact that adding these errors caused the earnings of significant numbers of the individuals who we had predicted to work to fall below zero. As a consequence, however, MINT3 was generating too little dispersion in earnings.

Figure 4-45 Employment Rates of Women by Cohort (without Linear Cohort Effects)



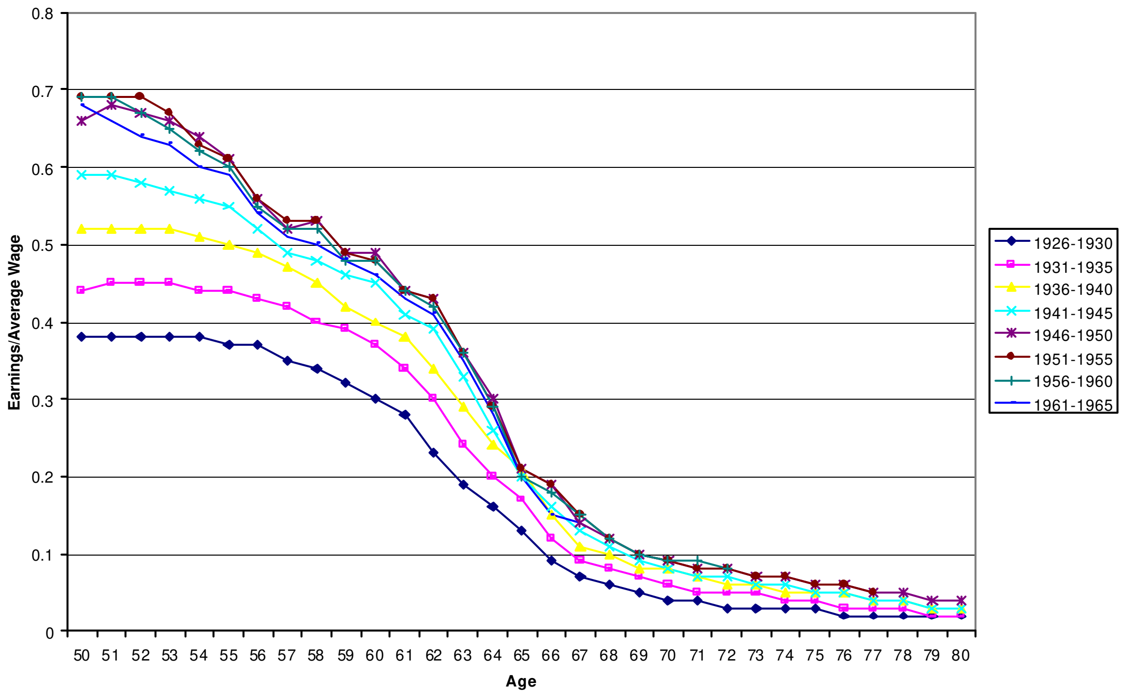
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmfnocohort0626.xls, from tabearn2.lst)

Figure 4-46 Ratio of Female to Male Work Rates by Age and Birth Cohort without Linear Cohort Effects for Women



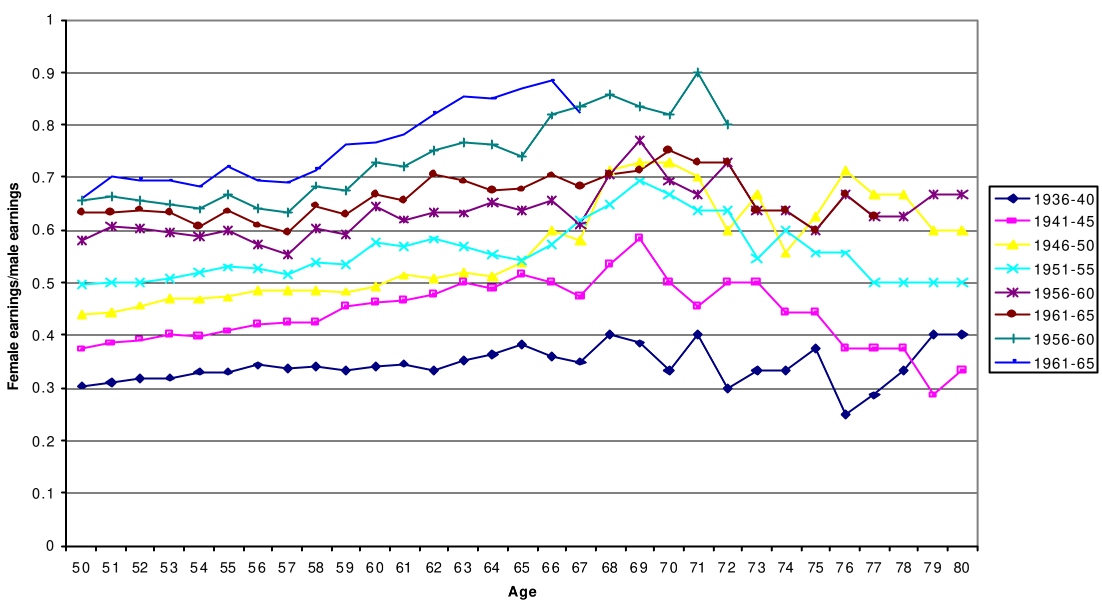
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmfnocohort0626.xls, from tabearn2.lst)

Figure 4-47 Mean Earnings of Women by Cohort (without Linear Cohort Effects)



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmfnocohort0626.xls, from tabearn2.lst)

Figure 4-48 Ratio of Female to Male Earnings by Age and Birth Cohort (without Linear Cohort Effects for Women)



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\retearnmmfnocohort0626.xls, from tabearn2.lst)

Figures 4-49 and 4-50, for example, show earnings as a percent of the average wage for men and women at ages 55 through 59 when error terms are suppressed. In these two figures, we observe much more clumping around the mode in the projection period than in the corresponding figures in which we incorporated error terms (Figures 4-25 and 4-30). Results for other ages were similar (and are available in the spreadsheet referenced as source data for figures 4-49 and 4-50). Once we integrated these terms, we began to do a much better job of tracking the distribution, as discussed earlier.

Additionally, we tried to integrate structured error terms. Specifically, we re-estimated the equations that predict earnings so that they included errors with both permanent and transient components (see Tables 4-7 and 4-17, for example, for coefficient estimates from random effects models).[51] When we integrated random effects into MINT3, we did not replicate earnings distributions as well as we currently do. Our analyses thus revealed that there are tradeoffs between cross-sectional and longitudinal validity.

4. Addition of Age 62 Interactions in Social Security Take-Up Equations

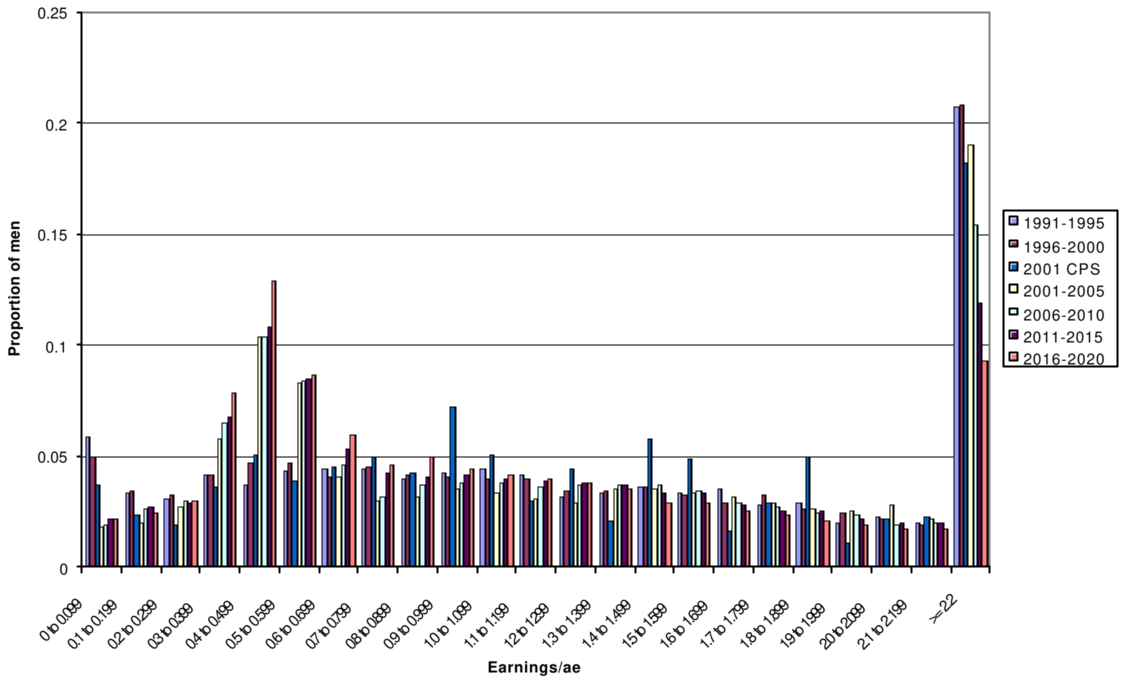
Given that American workers take up their Social Security benefits at the early eligibility age (62) in overwhelming proportions, one might speculate that the process of Social Security take-up differs between age 62 and subsequent ages. To test whether this is the case, we re-estimated our Social Security take-up models using interactions between being age 62 and most important explanatory variables. (Table A4-2 in the appendix presents the Social Security take-up coefficients estimated from the SIPP/SER data.) We then used the coefficients to simulate Social Security take-up (and other, subsequent MINT processes) given the assumed change in the take-up process.

The re-estimation revealed that the effects of some key explanatory variables indeed may differ between age 62 and subsequent ages. For example, in the low-earner equation we find that the coefficient for being a married female is negative and significant. At age 62, though, the effect of being a married female is larger, positive, and significant. This suggests that a married woman is, all else equal, more likely to take up benefits at age 62 than is a married man (the reference category), but less likely to take them up at ages 63 and older. Another example of an important age 62 interaction in this same equation concerns spouse's Social Security take-up. At all ages, the fact that one's spouse was receiving benefits at time t-1 increases take-up, but this is especially true at age 62, when the size of the effect nearly doubles. While the presence of these apparently important interactions might suggest that this model is superior to the one discussed earlier, one must keep in mind that one is adding many additional degrees of freedom to the model, and some cell sizes are quite small in this specification.

When we integrate these coefficients into a simulation, we find that Social Security claiming behavior changes fairly markedly. Most notably, we see a significant decline in claiming at age 62 in the model with the interaction terms. For example, while in the baseline MINT projection 53.3 percent of those in the full sample (1926 to 1965) with non-missing Social Security take-up ages collect their benefits at age 62, only 46.3 percent do under the simulation.

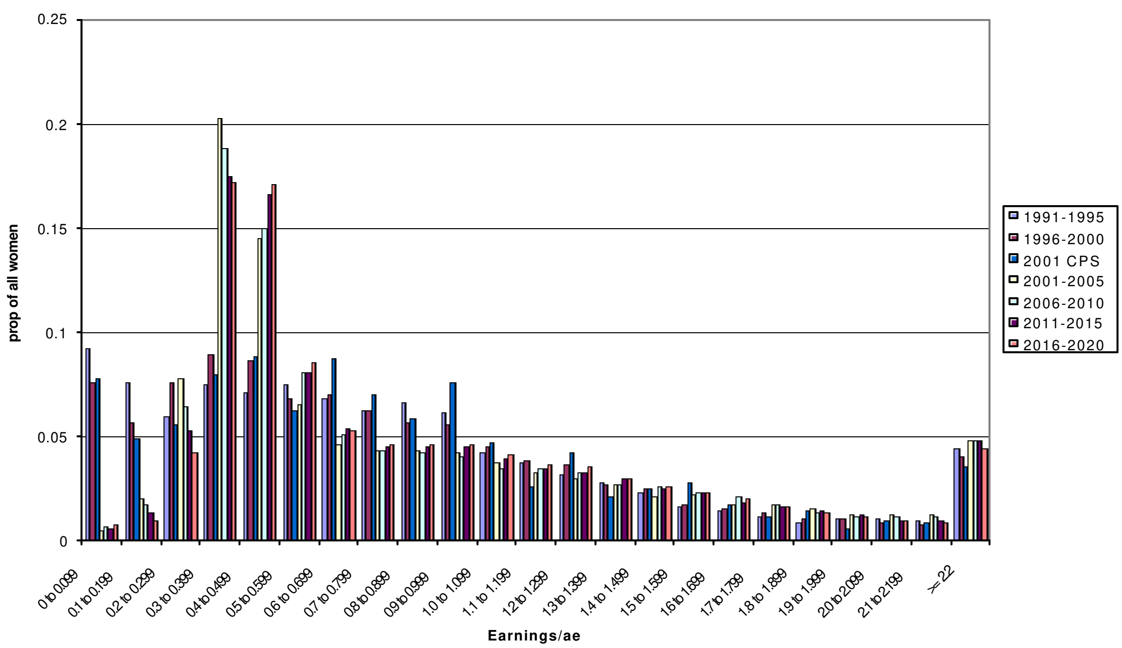
[51] A structure exists so that a user can integrate these coefficients into the model if he or she desires.

Figure 4-49 Distribution of Earnings as a Percent of the Average Wage when Error Terms are Suppressed: Women Ages 55-59



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\task11\noerror\checkearndist.xls, from tabearnmf.lst)

Figure 4-50 Distribution of Earnings as a Percent of the Average Wage when Error Terms are Suppressed: Women Ages 55-59



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\task11\no error\checkearndist.xls, from tabearnmf.lst)

The decline in Social Security take-up at age 62 is particularly marked among men. Because of the dramatic break with historical data, we elect to maintain the current specification of Social Security take-up and leave the question of how to integrate age 62 interaction terms into the model for future investigation.

5. Integrating Task 2 Earnings with an Alternative Social Security Take-up Specification

As we have already noted, the presence of an alternative set of MINT earnings projections provides a useful validity check for the projections of Task 5. In addition to a validation source, these projections could be the basis for a whole alternative model. For this sensitivity simulation, we create an alternative MINT file using the earnings projections through age 67 produced for Task 2.[52] Because the core Social Security take-up model includes an indicator of whether one is "retired," we could not simply generate this file within the existing MINT structure (for example, by shutting off all earnings algorithms).[53] So the first step in constructing this file was to re-estimate the Social Security take-up equations without the retirement indicator. In doing this, we pooled the low- and high-earners to estimate a single equation for the non-spouses. (Table A4-3 in the appendix presents the Social Security take-up coefficients estimated from the SIPP/SER data.)

When we integrate the Task 2 projections together with these take-up coefficients into a new simulation, we find that a number of outcomes, including Social Security claiming behavior, change. Social Security claiming behavior at age 62 is slightly lower than under the baseline (50.2 percent of the persons with a non-missing take-up age, compared to 53.3 percent under the baseline), but higher than in the simulation that integrated the age 62 interaction variables into the Social Security take-up model. Despite the later benefit claiming, which should increase Social Security benefits, total incomes tend to be slightly lower with the Task 2 earnings. For example, family income as a percent of poverty for those ages 62 and older in 2020 averages 5.544 in MINT2, compared to 5.685 in MINT3. This is likely due to the higher women's work rates in MINT3 (discussed earlier, with our validation analyses). While these relationships appear plausible, we recommend additional attention to validating this simulation before SSA researchers use this file extensively.

6. Imposing Full OASI Take-up at the Normal Retirement Age

It is necessary to consider what impact Congress' 2000 decision to eliminate the retirement earnings test at and after the normal retirement age will have on distributions of Social Security take-up ages and on earnings at and after the normal retirement age. Although some people could still have an incentive to postpone take-up, for example if they anticipate that they

[52] The preliminary file is called mintgb.sas7bdat. It is located in the w:\urban\mint3\data directory on the SAS server at SSA. It may be replaced before delivery of final MINT materials to SSA.

[53] One could potentially assign a retirement age using an alternative definition based on earnings (for example, a drop of over 50 percent from t-1). However, when we attempted to do this, we found significant discrepancies from historical means and thus decided against pursuing this option.

or their spouse will live a very long time and could thus still benefit from the delayed retirement credit (see Coile and Gruber, 2000, and Coile, Diamond, Gruber, and Jousten, 1999), we nonetheless simulate a fairly extreme response. When simulating the impact of the change to the earnings test, we assume that everyone who has not to date elected to claim benefits now takes up at the age at which they reach the full retirement age.[54]

Table 4-21 displays selected age at benefit receipt for those with an OASI take-up age (excluding the disabled), by cohort under MINT3 and with an assumption of full take-up of OASI at the normal retirement age. The resulting changes to the age distribution are what one would expect. There is much more clustering at the normal retirement age in each particular cohort. Additional changes occur because of changes to the denominator (some people who did not receive a Social Security take-up age now survive to receive one).

Table 4-21
Social Security Take-up Age Before and After Take-up is Mandatory at the Normal Retirement Age, by Cohort

	Birth Cohort									
	1936-1940		**1941-1945**		**1946-1950**		**1951-1955**		**1956-1950**	
	Before	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*
60-61	5.5	5.3	5.6	5.5	5.1	4.9	4.3	4.2	4.4	4.3
62	50.5	48.9	56.1	55.0	52.8	51.6	53.5	52.5	53.4	52.4
63	9.4	9.1	8.7	8.5	8.6	8.4	8.9	8.8	9.4	9.2
64	15.6	15.2	12.4	12.0	13.9	13.5	13.5	13.2	14.2	13.9
65	12.5	21.5	8.8	11.8	8.1	7.9	8.4	8.2	8.0	7.8
66	1.7	0	3.1	7.2	4.6	13.6	4.3	13.2	3.8	10.3
67	4.9	0	5.4	0	6.9	0	7.1	0	6.7	2.1

Source: Author's tabulation from MINT3 (before: w:\urban\mint3\final\tabretmf.lst;
after: w:\urban\mint3\task11\all at NRA\tabretmf.lst)

Table 4-22 illustrates how this change in Social Security take-up patterns in turn affects incomes. Some persons who would have received delayed retirement credits no longer receive them, reducing their Social Security. However, offsetting this reduction is the fact that some people who did not have Social Security incomes in 2020 now have them. These opposing effects lead to a very small increase in Social Security incomes. However, using the model's assumptions about work behavior, collecting Social Security leads individuals to earn less. The size of the earnings reduction is much larger than the size of the benefit increases. This leads to a net reduction in total incomes in this simulation.[55]

[54] In addition to the direct effect at the normal retirement age, for many workers there will also be an indirect effect at other ages. This operates through a change to one's spouse's Social Security take-up (and possibly earnings), which is an important predictor of a married person's claiming behavior.

[55] Alternatively, one could implement this simulation assuming that workers do not change their behavior in response to taking-up Social Security earlier.

Table 4-22
Average Income (as a Percentage of the Average Wage) of Persons Ages 62 to 89 in 2020, by Source, With and Without Assumption of Full OASI Take-Up at the Normal Retirement Age

	Baseline Assumptions	Assuming Full OASI Take-up at the Normal Retirement Age
Earnings	0.172	0.162
Social Security (Retirement and Survivors)	0.240	0.242
Total Income	0.880	0.873

Source: Author's tabulation from MINT3 (before: w:\urban\mint3\mintfinal\chpt8.lst; after: w:\urban\mint3\task11\all at NRA\chpt8.lst)

(For additional information on the income of the aged in 2020 under current law, see Chapter 9.)

XI. IMPLICATIONS OF VALIDATION AND SENSITIVITY ANALYSES FOR POLICY ANALYSIS USING MINT

Our analyses have indicated that the MINT projections of labor force patterns, earnings distributions (both cross-sectional and distributional), and Social Security take-up are generally reasonable. They track historical data and projections from other models (in which assumptions and projection methods differ). However, the analyses also revealed a number of potential weaknesses that users should bear in mind when using the model for policy analysis. Here we summarize a few key aspects:

- The model does a good job producing the distribution of AIME, suggesting that it will be effective at simulating reforms that alter bend points or the bend percentages used in computing PIA.

- The model also appears to produce a reasonable distribution of years in the labor force. It should thus be able to simulate reforms like changes to the number of computation years in the AIME formula.

- The model may be less successful at replicating earnings at the top of the distribution. MINT does not currently impute earnings above the taxable maximum for Social Security. Therefore one cannot use MINT for simulating proposals that would uncap the amount of earnings subject to payroll tax.

- The model produces a reasonable distribution of Social Security take-up ages. It may be overstating age 64 take-up and understating age 65 take-up (as noted above, this may be related to measurement issues). Users should thus use caution when interpreting results from policy simulations that alter increments and reductions to benefits due to benefit take-up timing.

Additionally, our analyses suggest some technical recommendations for future development of MINT. The Social Security benefit calculator used for the retirement model presented in this chapter differs modestly from the calculator developed and validated by SSA for computing total incomes in MINT. It would be preferable to make the calculator used herein consistent with the SSA-developed and -validated calculator. We discuss this issue in more detail in our recommendations section in Chapter 11.

APPENDIX TO CHAPTER 4

Calculation of Social Security and Private Pension Wealth and Premium Values

In Chapter 4, we have produced estimates of Social Security and pension wealth, accruals, and premium values for members of the HRS sample who are at risk of retirement. To compute the premium values, we compare a person's pension and Social Security wealth across a series of successive years. In each case, we assume that the person works an additional year, with the pension and Social Security wealth that the person would receive if his/her accrual from year one (t-1 to t) were to continue until the quit date. The premium value is the maximum of the present value of these differences. We use age 70 as the upper limit for leaving work when computing both Social Security and pension premium values. This appendix describes the procedures and assumptions that we used when making these calculations.

1. Assumptions and procedures used in the Social Security wealth calculations

- ***Vesting:*** We assign Social Security wealth to be zero when the person is not yet "vested" in Social Security (i.e., he/she has not attained 40 covered quarters). Similarly, if a person's spouse has not attained 40 covered quarters, then one's potential spouse retirement benefit is zero (though one's potential survivor benefit may be nonzero at certain ages if the spouse is currently insured). Note that these assumptions imply that a small number of people experience very dramatic increases in Social Security wealth in the year that they (or their spouses) reach their 40th covered quarter. (It is relatively rare that this happens in the simulation period, as most respondents are fully insured at the HRS baseline.)

- ***Early eligibility age:*** We compute the wealth stream that will commence at the person's selected age (from baseline age to age 70). If a person is married and eligible for future survivor benefits, we assume that he or she would wait to take up survivor benefits until the same year that he or she would take up worker benefits. We evaluate all benefit streams starting from the first month of the calendar year (i.e., you get twelve Social Security payments in every year, and you never receive credits for waiting a few extra months).

- ***Stop age:*** We keep computing Social Security wealth from the selected age until the respondent's probability of survival falls below 0.0001 (we code this as a parameter that the user can easily change). For most people, this occurs between age 105 and age 115.

- ***Spouse retirement age:*** We assume spousal retirement (for Social Security purposes) at age 62, unless the spouse is over age 62 and has not yet taken up Social Security. In this case, we assume the spouse's retirement age is the age he/she will attain next year. (The user can easily change this parameter.) For survivor benefits, the spouse likewise takes up at the earliest possible moment—age 60 or the age he/she will attain next year if he/she is past age 60. As when evaluating a respondent's own retirement age, we always evaluate a spouse's benefit stream from the first month of the calendar year (i.e., he/she receives twelve payments in every year, and never receives credits for waiting a few extra months).

- ***Potential earnings:*** We use a modified version of the HRS convention of taking a weighted average of indexed earnings over the past five years (including baseline) to "forward fill" earnings until the prospective retirement age in question. Weights range from one to five: more recent earnings have a greater weight than less recent earnings. We account for projected wage growth in the future by using the Trustees' assumption about mean wage growth.

- ***Mortality/annuitization:*** We follow the HRS convention of using cohort-sex specific mortality assumptions that are consistent with the OASDI Trustees' Report (which we obtained from Felicity Bell of the SSA Office of the Chief Actuary). We use the 2000 assumptions rather than earlier assumptions (HRS, for example, uses the 1995 assumptions). We do not assume that survival probabilities differ by health or socioeconomic status (e.g., education, lifetime earnings, occupation). The fact that our models will include many other variables that are correlated with life expectancy should allow us to capture additional mortality differences across individuals indirectly.

- ***Widowhood assumption:*** We obtain the widow benefit that enters into the wealth equation by computing the widow benefit for each year from the selected age to the age at which one's survival probability falls below 0.0001. We then compute the weighted average survivor benefit over this interval, with the weight for each benefit being the probability that that year will be the widowing year.

- ***Treatment of Social Security wealth of the disabled (DI recipients):*** Although HRS estimates do not include Social Security wealth estimates for the disabled, our algorithms treat this type of wealth as identical to retired worker benefit wealth. Note that this only affects spouses, as disabled workers are not subjected to the retirement decision.

- ***Treatment of those without a Social Security earnings record:*** We drop these records from the final analyses.[56]

[56] In preliminary analyses, we used a statistical match procedure to assign an earnings record and benefit receipt information to these persons. For the statistical match, we examined men and women recipients in two age groups (51-55 and 56-61) all separately, yielding four donor pools and four recipient pools. We then minimized a distance function to obtain, on the basis of a series of variables, the best match from a subset of individuals in the donor pool (typically those within neighboring birth cohorts, though we relax this restriction for the spouses who fall out of the HRS age range). We obtained weights in the distance function by estimating stepwise OLS regressions of AIME on current earnings, age, race/ethnicity, disability status, marital status, wealth, pension coverage, number of children ever born, and unionization status. The weight for each was equal to the proportion of the variance in lifetime earnings that it explains (partial R-squared). For men, pension coverage and the natural log of financial wealth were the most important predictors of AIME, while for women baseline earnings tended to swamp all other predictors. Note that when we computed minimum distances between pairs of observations, we sampled from the donor pools with replacement. This implies that we used some donors more than once, though we used the

- ***Treatment of those with a spouse without a Social Security earnings record:*** We drop these records from the final analyses.[57]

- ***Treatment of those with missing values within Social Security earnings record:*** A small number of values within non-missing Social Security earnings records are set to –1. In such cases, we assume that the earnings for the missing year are the maximum of zero or earnings in the prior year if that is non-missing.

- ***Treatment of those with a spouse with other pieces of missing information:*** Several records were missing data necessary for computing a spouse Social Security benefit (for example, the spouse's age or gender). We impute values in all necessary fields, but only use this information is reliable (for example, we have a spouse birth year but not spouse age).

- ***Treatment of those with an unobserved spouse*** (spouse who respondent divorced before the start of the panel or spouse who died before the start of panel): While it is the HRS convention to assume zero entitlement to Social Security on the basis of such a spouse, we instead impute a value for the PIA of these spouses, but only for women. We use the age-specific mean for new awards for 62-64 year olds in the group (spouse versus survivor) from 1998 and adjust this for wage inflation.

- ***Discount rate:*** For a discount rate, we use the Trustees' assumption of an ultimate interest rate of 6.3 percent (see p.11 of the Trustees' Report). We actually implement this in the program using the real rate (3.0), rather than the nominal rate (6.3). We code this as a parameter that the user can easily change.

- ***Treatment of those who have benefit information:*** A small fraction of HRS respondents and spouses are collecting Social Security benefits in 1991. For such persons, we do not compute Social Security benefits, but rather simply index existing benefits to the year in question. We do allow such persons to adjust their status if retirement or death of a spouse will result in an increased benefit.

- ***Treatment of those who fall under AMW calculation:*** We ignore the fact that for a small fraction of the spouses of HRS respondents (those born before 1917), Social Security wealth should be calculated on the basis of AMW rather than AIME. Most

overwhelming fraction of donors just once. If a person with missing earnings appeared in our person-year file more than one time, he/she always received the same earnings/benefit receipt vector. We drew the donors of earnings records only from the 1992 observations, though.

[57]In preliminary analyses, we imputed missing spouse earnings using a method analogous to that for missing individual earnings. The main difference was that we broke the donor and recipient pools into eight rather than four pools (males and females, ages < 51, 51-55, 56-61, 61+). The resulting regression weights differed, with age playing a more important role in matching spouses to earnings, especially for the <51 and 61+ age group. An additional complication in this imputation was that some of the spouses needing earnings records were from after 1992. We match such persons to 1992 spouses.

of these persons fall in the category above (i.e., they have 1991 Social Security level reported on their benefit records that we can use to estimate current entitlement).

- ***Retirement test and income taxation of Social Security:*** We do not currently consider these, and thus compute *gross* rather than *net* Social Security wealth. We might wish to consider the effects of retirement test in our calculations.

2. Assumptions used in the pension wealth calculations

- ***Treatment of those who report pension coverage on their current job but do not have detailed plan data:*** We drop these cases from the analyses.[58]

- ***Treatment of those whose spouses report pension coverage but do not have detailed plan data:*** We drop these cases from the analyses.[59]

- ***Treatment of other missing data:*** We treat missing data as above (in the earnings assignment).

- ***Treatment of employer pension reports that are inconsistent with the respondent reports:*** As Johnson, Sambamoorthi, and Crystal (2000) point out, a significant fraction of HRS respondents report their only current pension to be a defined benefit plan, while their employers report it to be a defined contribution plan, and vise versa. For these cases, we overwrite the self-report (our basis for imputing pensions to those with missing data) with the employer report.

[58] In preliminary analyses, we used a statistical match procedure to assign plan numbers to these persons. We assigned full *vectors* of plans by type (up to 3 DB plans or 5 DC plans), thus filling in such persons' entire histories with that type, not just their current plan number. (We also maintained the sequence numbers, work hours, voluntary contribution rates, and start dates that are associated with these plans.) To make this imputation, we examined men and women separately by industry, collapsing a few small industry categories in order to produce pools of appropriate size, within each self-reported plan type (DB or DC) and (current or prior). This yielded twenty donor pools and twenty recipient pools per plan type. (Note that we placed those who report combo plans into the DB pool and excluded them from the DC pool in order to avoid double counting.) We then minimized a distance function to obtain, on the basis of a series of variables, the best match from among the individuals in the donor pool. These variables included current earnings, lifetime earnings, age, binary variables for six broad occupational groups, and unionization status. Because we were unable to estimate weights for the variables in the distance function empirically, we assumed that all the weights were equal. Note that once more when computing minimum distances, we sampled from the donor pools with replacement. This implies that we used some donors more than once, though we used the overwhelming fraction of donors just once. If a person appears in our person-year file more than one time, he/she always received the same pension plan number(s). Donors, as with the earnings records, came only from the 1992 observations, though recipients came from later years as well if they are new spouses. Note that we only imputed pension plan identification number vectors to those who reported pension coverage on the current job, and thus did not assign pensions for prior jobs unless a person has a current pension.

[59] In preliminary analyses, we used the same imputation procedures as for workers, except that the donor and recipient pools include spouses.

- ***Computation of pension wealth:*** For DB plans, we use the HRS pension calculation software, which has an extremely detailed and complicated representation of both pension plans and annuitization. We use runtype3, the program option that computes benefits using all possible quit dates, for current jobs and runtype1, the program option that computes benefits using an observed quit date, for past jobs. Generally we use the pre-programmed defaults in the software, but in some cases we input our own assumptions. For example, we use the option that takes a full earnings vector (rather than just average earnings). In doing so, we input a maximum earnings history of forty years. The earliest year that can appear in an earnings history is 1951. Other non-default options that we use are as follows:

- ***Discount rate:*** As above, we use a discount rate that is consistent with interest rate projections from the 2000 OASDI Trustees' Report (an ultimate real rate of 3.0 percent).

- ***Mortality:*** We use the option to apply mortality probabilities for the 1936 birth cohort (rather than actual cohort). Note that the HRS software relies on the 1995 Trustees' Report, while our Social Security wealth programs rely on the 2000 Trustees' Report.

  For DC plans, we use self-reported account balances. When a person is still on the job, he or she and his/her employer continue to contribute to the plan at the current rate until various quit dates (to age 70, as with DB plans). We max out subsequent contributions at one-eighth of current earnings to limit implausibly high accruals.

- ***Earnings vectors for government workers:*** Because we use the earnings histories option when computing pension wealth, it is important that the wage history data provide an accurate accounting of average wages throughout a person's lifetime, not just in recent years. The wage histories that we use are from Social Security Administration records and thus reflect earnings in Social Security covered employment. For a small number of people, for example those in long-term government employment not covered by Social Security, the wage history from these records will be misleading.

- ***Premium values for those with multiple current plans:*** A small number of respondents and spouses (less than two percent of those with pensions) report more than one current pension. (The person may be working more than one job, or may have two pensions from a single employer.) In these cases, we calculate accruals and premium values for the *combination* of the plans.

Appendix Table A4-1.
Age-Earnings Profiles for Full-Time Workers in Defined Benefit Pension Plans, by Education and Gender

	High School or Less		College	
	Coefficient	Standard error	Coefficient	Standard error
Men				
Age 20-24	-0.728	0.025	-1.308	0.023
Age 25-29	-0.402	0.010	-0.466	0.008
Age 30-34	-0.149	0.007	-0.157	0.006
Age 35-39	--	--	--	--
Age 40-44	0.180	0.007	0.191	0.006
Age 45-49	0.341	0.009	0.351	0.007
Age 50-54	0.454	0.017	0.476	0.016
Age 55-57	0.542	0.023	0.614	0.023
Age 58-59	0.606	0.029	0.716	0.030
Age 60-61	0.664	0.033	0.739	0.036
Age 62	0.688	0.045	0.813	0.048
Age 63-64	0.738	0.047	0.881	0.050
Age 65	0.657	0.084	0.985	0.088
Age 66	0.764	0.129	1.143	0.123
Constant	10.060	0.006	10.297	0.004
sigma_u	0.700		0.785	
sigma_e	0.360		0.376	
rho	0.791		0.814	
Women				
Age 20-24	-0.761	0.037	-1.040	0.027
Age 25-29	-0.467	0.013	-0.410	0.010
Age 30-34	-0.231	0.009	-0.195	0.008
Age 35-39	--	--	--	--
Age 40-44	0.261	0.009	0.287	0.008
Age 45-49	0.481	0.012	0.541	0.010
Age 50-54	0.672	0.021	0.795	0.021
Age 55-57	0.868	0.029	0.971	0.032
Age 58-59	0.954	0.035	1.143	0.042
Age 60-61	1.073	0.040	1.265	0.049
Age 62	1.127	0.053	1.334	0.064
Age 63-64	1.139	0.057	1.413	0.065
Age 65	1.067	0.103	1.471	0.113
Age 66	1.237	0.123	1.609	0.166
Constant	9.490	0.008	9.865	0.006
sigma_u	0.760		0.881	
sigma_e	0.407		0.440	
rho	0.777		0.800	

Note: Fixed-effect estimates from the 1990-1993 SIPP panels matched to SER.
The dependent variable is the natural log of nomimal earnings.

Appendix Table A4-2
Sensitivity Test of Social Security Take-Up: Logistic Estimates With Age 62 Interactions

	Spouse Only Recipients		Low-Earners		High-Earners	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Intercept	-4.9764 **	2.1154	0.6009	0.9873	0.2077	0.4559
Demographics						
Age 63	2.5181	2.6041	-1.9891	1.3638	-0.5176	0.5504
Age 64	3.4657	2.6139	-0.1114	1.3666	0.908 *	0.5519
Age 65	3.2152	2.6198	-0.4383	1.3749	1.5796 ***	0.5742
Age 66	2.2717	2.6305	-1.6238	1.4056	0.9491	0.5909
Age 67	2.1236	2.6177	-1.1938	1.4103	0.5693	0.6092
Age 68	2.5968	2.6546	-1.9282	1.4542	-0.1357	0.646
Age 69	3.6329	2.7251	0.3765	1.4627	4.2298 ***	0.6813
Education gt 12	—	—	-0.243	0.1897	-0.4066 ***	0.1282
Hispanic	—	—	-2.8071 ***	1.0719	—	—
Black or Native American	—	—	0.1756	0.2783	—	—
Asian	—	—	-1.328 **	0.5774	—	—
Widower	—	—	-0.6038	1.1457	—	—
Widow	—	—	-0.4913	0.954	—	—
Single male	—	—	-0.3298	1.0901	—	—
Single female	—	—	-1.5922	1.1448	—	—
Divorced male	—	—	-1.1987	0.9952	—	—
Divorced female	—	—	-0.8739	0.9528	—	—
Married female	—	—	-0.8744 ***	0.3315	—	—
Pension coverage indicators						
DB pension	—	—	0.202	0.1927	0.0826	0.1199
DC pension	-0.3492	0.3158	—	—	-0.0853	0.1298
Retirement status, lifetime						
Earnings / wealth						
Retired at t	1.0405 **	0.4336	1.1596 ***	0.1962	2.7121 ***	0.1582
PIA / average wage	—	—	2.4977 ***	0.6428	—	—
Lag earnings / avg wage	-0.2288	1.3649	—	—	-0.8342 ***	0.2816
0 < lag earng <= .8 * exempt	—	—	0.5269 **	0.2084	—	—
Lag earnings > .8 * exempt	—	—	1.2225 ***	0.4111	—	—
Family wealth / avg wage	—	—	-0.00742	0.0135	-0.00387	0.00651
Earnings ages 56-61	—	—	—	—	0.2127	0.4361
Earnings 56-61 squared	—	—	—	—	0.0179	0.1618
Social Security parameters						
Fraction taxed	—	—	—	—	-1.1439 ***	0.3982
Above taxaway point	—	—	—	—	-0.4282 **	0.1928
Dual entitlee	—	—	0.4905	0.4877	—	—
Spouse characteristics						
Sp tookup Social Sec t-1	1.0164 ***	0.2775	0.9058 ***	0.2896	0.5657 ***	0.1645
Sp adjusted PIA	2.1998	7.9801	-0.303	0.8921	-4.2567 ***	1.4322
Sp adjusted PIA squared	-1.7003	10.3085	—	—	6.5026 **	2.9345
Sp lag earnings / avg wage	-0.3829 **	0.1612	—	—	—	—
Sp DB pension indicator	0.00118	0.2626	0.4119	0.2662	0.1328	0.149
Sp DC pension indicator	0.5213	0.3273	-0.1077	0.2385	0.2787 **	0.1351
Spouse age	—	—	-0.0235	0.0157	-0.00056	0.00266

Appendix Table A4-2. (Continued)

Age 62 interaction variables						
Demographics						
Age 62 * Education gt 12	—-	—-	-0.427	0.2666	0.1622	0.2415
Age 62 * Hispanic	-0.2623	1.1493	2.6836 **	1.1746	0.8272 *	0.4828
Age 62 * Black or Native Americ	-0.8597	0.8235	-0.1715	0.3847	-0.0308	0.3535
Age 62 * Asian	-0.6472	1.753	0.3683	0.7419	-0.9188	0.926
Age 62 * Widower	—-	—-	-2.5427	1.5738	—-	—-
Age 62 * Widow	—-	—-	-0.5498	1.3851	—-	—-
Age 62 * Single male	—-	—-	-0.5546	1.5781	—-	—-
Age 62 * Single female	—-	—-	-0.6551	1.5707	—-	—-
Age 62 * Divorced male	—-	—-	-1.6292	1.433	—-	—-
Age 62 * Divorced female	—-	—-	-0.778	1.3871	—-	—-
Age 62 * Married female	—-	—-	1.7242 ***	0.4425	—-	—-
Pension coverage indicators						
Age 62 * DB pension	—-	—-	0.4195	0.273	0.556 **	0.2281
Age 62 * DC pension	0.0786	0.6232	—-	—-	-0.4535 *	0.2321
Retirement status, lifetime						
Earnings / wealth						
Age 62 * Retired at t	1.3017 *	0.7381	0.4255	0.2754	0.838 ***	0.2805
Age 62 * PIA / average wage	—-	—-	3.8079 ***	0.9011	—-	—-
Age 62 * PIA / avg wage squared	—-	—-	—-	—-	—-	—-
Age 62 * Lag earnings / avg wage	3.7634	3.4846	—-	—-	—-	—-
Age 62 * 0 < lag earng <= .8 * ex	—-	—-	0.2111	0.2929	—-	—-
Age 62 * Lag earnings > .8 * exe	—-	—-	-0.2597	0.579	0.5973	0.5171
Age 62 * Family wealth / avg wag	—-	—-	-0.02	0.0179	-0.0325 **	0.0154
Age 62 * Earnings ages 56-61	—-	—-	—-	—-	1.6425 *	0.8639
Age 62 * Earnings 56-61 squared	—-	—-	—-	—-	-0.4795	0.3292
Social Security parameters						
Age 62 * Fraction taxed	—-	—-	—-	—-	-2.8201 ***	0.6933
Age 62 * Above taxaway point	—-	—-	—-	—-	0.5016	0.4071
Age 62 * Dual entitlee	—-	—-	0.6974	0.6563	—-	—-
Spouse characteristics						
Age 62 * Sp tookup Social Sec t-1	1.1772 **	0.4946	0.8605 **	0.4111	0.2481	0.3262
Age 62 * Sp adjusted PIA	13.5464	13.4781	-0.7538	1.1807	2.0271	2.9954
Age 62 * Sp adjusted PIA squared	-16.6205	17.9016	—-	—-	-4.9995	5.9364
Age 62 * Sp lag earnings / avg wa	-0.4426	0.306	—-	—-	—-	—-
Age 62 * Sp DB pension indicato	0.5461	0.468	-0.3445	0.3565	—-	—-
Age 62 * Sp DC pension indicato	-0.3795	0.615	-0.0973	0.3326	—-	—-
Age 62 * Spouse age	—-	—-	-0.0208	0.023	-0.00566	0.00481
N (person years)	628		2173		3473	
-2 log-likelihood	593.449		1775.238		2755.664	

* indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01

Data source: 1990 to 1993 SIPP panels matched to SER. Individuals in the two samples have never received disabled worker benefits. Spouse only recipients are defined as persons with zeros PIAs who have living spouses age 62 or older with positive PIAs (i.e., widows are not included). Low-earners are defined as individuals with earnings either at or below the RET exempt amount. High-earners are defined by earnings above the exempt amount.
Path for output: Regs2001.lst

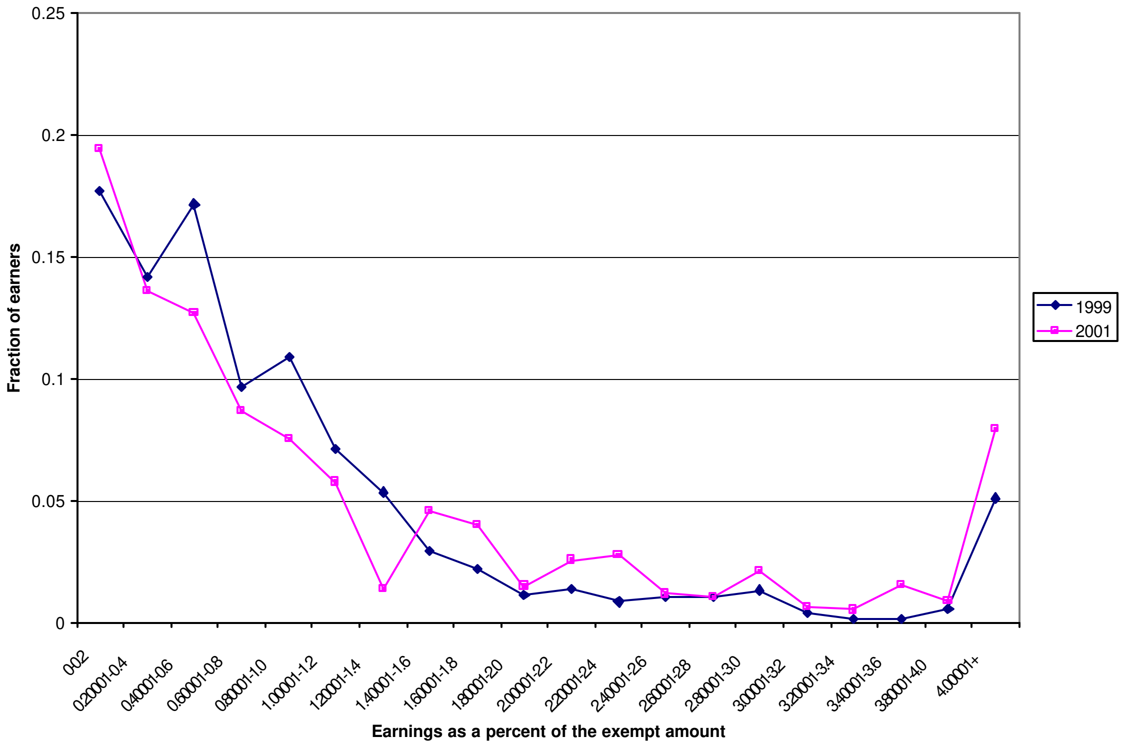
Appendix Table A4-3
Sensitivity Test of Social Security Take-Up: Logistic Estimates Without Retirement Indicator

	Spouse Only Recipients			Covered Workers		
	Coefficient		Standard error	Coefficient		Standard error
Intercept	-1.3001		1.1104	0.1347		0.3073
Demographics						
Age 63	-1.6213	***	0.2919	-1.338	***	0.094
Age 64	-0.6737	**	0.3113	0.0682		0.089
Age 65	-0.8302	**	0.3774	0.7445	***	0.1136
Age 66	-1.7711	***	0.4609	-0.4445	***	0.1595
Age 67	-1.9604	***	0.4606	-0.6516	***	0.1891
Age 68	-1.6263	***	0.5408	-1.2365	***	0.2386
Age 69	-0.4007		0.7184	1.9489	***	0.2646
Education less than 12	---		---	0.1832	**	0.0842
Education greater than 12	---		---	-0.4947	***	0.0753
Hispanic	---		---	-0.1714		0.1945
Black or Native American	---		---	-0.0566		0.1145
Asian	---		---	-0.7062	***	0.2318
Widower	---		---	-0.3576		0.3533
Widow	---		---	0.1347		0.3055
Single male	---		---	0.4364		0.3611
Single female	---		---	-0.3968		0.3592
Divorced male	---		---	-0.5072		0.3206
Divorced female	---		---	-0.1783		0.3114
Married female	---		---	0.1436		0.1216
Pension coverage indicators						
DB pension	---		---	0.4088	***	0.0662
DC pension	-0.4451	*	0.2675	-0.2836	***	0.0778
Retirement status, lifetime earnings / wealth						
PIA / average wage	---		---	6.8041	***	0.686
PIA / avg wage squared	---		---	-7.1144	***	1.0978
Lag earnings / avg wage	-1.1419		1.083	---		---
0 < lag earnings <= .8 * exempt amt	---		---	0.3533	***	0.1211
.8 * exempt < lag earnings <= 1.2 * exempt	---		---	0.4173	**	0.1833
Lag earnings > 1.2 exempt amt	---		---	-1.7436	***	0.0943
Family wealth / avg wage	---		---	-0.00732	*	0.00428
Social Security parameters						
Dual entitlee	---		---	0.6135	***	0.1863
Spouse characteristics						
Spouse took up Social Security by t-1	1.5027	***	0.2214	0.838	***	0.097
Spouse's adjusted PIA	8.3765		6.1984	-1.5366	*	0.8539
Spouse's adjusted PIA squared	-9.2269		8.2013	1.9582		1.7665
Spouse's lag earnings / avg wage	-0.5701	***	0.1304	---		---
Spousal DB pension indicator	0.2859		0.207	0.2048	**	0.0913
Spousal DC pension indicator	0.5043	*	0.2694	0.2289	***	0.0886
Spouse's age	---		---	-0.0111	**	0.00497
N (person years)	628			5646		
-2 log-likelihood	839.119			6180.053		

* indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01

Data source: 1990 to 1993 SIPP panels matched to SER. Individuals in the two samples have never received disabled worker benefits. Spouse only recipients are defined as persons with zeros PIAs who have living spouses age 62 or older with positive PIAs (i.e., widows are not included).
Path for output: Regs2001.lst

Appendix Figure A4-1. Comparison of 1999 and 2001 Current Population Survey Earnings Estimates: Distribution of Earnings (of Non-Zero Earners) as a Percent of the (Historical) Retirement Earnings Test Exempt Amount, Ages 65 to 69



Source: Urban Institute tabulation from the Current Population Survey.

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CHAPTER 5

PROJECTING RETIREMENT INCOME FROM PENSIONS

I. OVERVIEW

The MINT 3.0 pension projection module estimates pension benefits and wealth from defined benefit (DB) plans, defined contribution (DC) plans, Keoghs, and IRAs for future retirees. Two sets of output are produced. The first provides pension wealth estimates under several retirement age scenarios. These estimates are then used in the module that determines each worker's retirement age. The second set of output variables provides estimates of annual DB pension benefits and DC account balances, given that retirement age.

Pension benefits are projected using several data sources. Initial pension coverage information is based on self-reports from the SIPP Retirement Expectations and Pension Plan Coverage topical module. This module includes information regarding the type of pension and years of pension plan participation to date, employee contributions toward pension plans, and 401(k) balances. In addition, the SIPP Annual Income and Retirement Accounts topical module provides information on annual contributions to 401(k), IRA, and Keogh accounts. The SIPP Assets and Liabilities topical module provides additional information about IRA and Keogh account balances.

Data from other sources supplement the SIPP data. Job changes and pension coverage on future jobs are simulated by linking data from the Policy Simulation Group's PENSIM model to the MINT population. Data from the Pension Benefit Guaranty Corporation's (PBGC) Pension Insurance Modeling System (PIMS) are used to determine DB benefits for DB participants. We also incorporate information from the EBRI/ICI database to develop assumptions regarding DC contribution and asset allocation behavior.

In brief, we obtain information regarding pension coverage on current and past jobs from the self-reported information on the SIPP. Next, we use data from the PENSIM model to impute future job changes and pension coverage on future jobs. We then project pension benefits from past, current, and future jobs. DB plan benefits are projected using PIMS DB plan formulas. DC account balances are projected using self-reported information on the SIPP regarding account balances and contribution rates, along with assumptions regarding asset allocations and future contribution rates.

In the sections that follow, this chapter provides more detail on the MINT 3.0 pension module. It begins with a description of how MINT simulates work histories prior to age 50, and in particular how the pension module accounts for job changes. The chapter next goes on to detail how DB benefits are calculated. Then, three sections detail the DC, Keogh, and IRA account balances projections. The chapter's final sections describe the model's results, the improvements over the previous model, a review of the validation exercises conducted, and potential future improvements to the model.

II. DEVELOPING WORK HISTORIES AND PENSION COVERAGE

Accounting for job changes is an important component of accurately estimating pension benefits, especially DB benefits. Self-reported information on the SIPP provides all of the job-related information needed to project pension benefits from prior jobs. It also provides most of the information needed to project pension benefits from current jobs. What is not known, however, is when individuals will leave their current job. Also unknown, are the timing and job characteristics (including pension coverage) of future jobs. To impute this information, the MINT 3.0 pension module explicitly models job changes up to age 50. And after age 50, the retirement module simulates retirement decisions.

For job changes prior to age 50, MINT incorporates data on synthetic work histories from the Policy Simulation Group's PENSIM model, developed for the Department of Labor, Pension and Welfare Benefits Administration (PWBA).[1] PENSIM simulates job histories using job tenure models estimated from the SIPP and applied to a synthetic dataset. PENSIM also simulates pension coverage using Form 5500 data augmented by CPS data for public-sector workers.[2] For each worker in the PENSIM dataset, information is available on the start and stop age for each job, characteristics of each job (industry and firm size), and individual characteristics (gender and education). Pension coverage information is also available for each job. For each job, individuals have either no pension plan, DB coverage only, DC coverage only, or both DB and DC coverage.

MINT assigns job history information, including pension coverage and pension type, from PENSIM to the MINT population. These job histories cover the time from the SIPP interview to age 50. Job histories are assigned (with replacement) based on the following characteristics at the time of the SIPP interview: age, gender, education, industry, tenure, pension coverage, and pension type. Because job and pension histories are assigned to all workers, regardless of pension coverage status, future pension coverage of current non-participants is handled automatically.

One problem with matching PENSIM job histories to the MINT population is that inconsistencies can arise between job histories and MINT's earnings projections. For instance, an individual might be working at a particular age according to the linked job history, but have zero earnings according to the earnings projections. These types of mismatches were minimized by making the number of years until a zero earnings year in the earnings projections part of the matching criteria for the job histories.

[1] Using data from PENSIM to develop work histories in MINT 3.0, while an improvement over prior MINT models, is intended to be a interim method of simulating job changes. It is anticipated that future versions of MINT will incorporate a more sophisticated job history model to simulate job changes for ages prior to age 50.

[2] See Holmer, Janney, and Cohen (2001) for more detail on the PENSIM model.

Matching on the above criteria resulted in successful matches for approximately 90 percent of the MINT population.[3] For the remainder of the sample, we assume that zero earnings years in the earnings projections determine the duration of job spells. We then randomly assign job characteristics such as industry, firm size, and pension coverage and type to each job spell by age and gender at the start of each job spell, based on distributions in the PENSIM data.

Table 5-1 presents the distribution of the number of jobs that result from the PENSIM match. Older birth cohorts have fewer jobs because there are fewer years between the date of the SIPP survey and the date they reach age 50. In contrast, younger cohorts are more likely to have more than one job between the date of the SIPP interview and date they reach age 50.

Table 5-1
Distribution of the Number of Jobs Between Age at SIPP Interview and Age 50, by Birth Cohort

	Number of Jobs				
Birth Cohort	No jobs	1 job	2 jobs	3+ jobs	Total
1941 – 1945	27.2	71.6	1.3	--	100%
1946 – 1950	18.3	74.5	7.0	0.2	100%
1951 – 1955	11.8	66.3	19.5	2.5	100%
1956 – 1960	7.8	56.3	28.8	7.1	100%
1961 – 1965	4.8	41.8	37.1	16.4	100%
Total	11.9	60.1	21.8	6.3	100%

Note: Self-employed workers are excluded from this table. We assume that respondents who are self-employed at the time of the SIPP interview remain self-employed through age 50.

Once the job and pension histories for the MINT population are determined, the appropriate pension benefits from each job can be computed.

III. DEFINED BENEFIT (DB) PLAN ESTIMATES

DB benefits are calculated for DB jobs held at the time of the SIPP as well as for any DB plans held on future jobs as assigned through the PENSIM match. Benefits are also calculated for DB plans on jobs held prior to the time of the SIPP.[4] The benefits from each job are summed to determine the aggregate benefits for each worker.

[3] We define a successful match as one in which there are no more than two mismatched years in a row. A mismatch occurs when someone with positive projected earnings is not working according to the job history data, or vice versa.

[4] Only about 5 percent of individuals age 55 to 64 in the MINT population expect to receive pension benefits from a prior job and were on that job for 5 years or longer. The potential benefits from these prior plans, however, can be substantial as the average tenure under these plans was about 20 years. We assume that all of those expecting benefits from a prior job have a DB plan. Pension benefits are calculated accordingly, using self-reported information on the sector of employment and years of service.

The method of projecting income from a defined benefit (DB) plan varies depending on the sector of employment. For private sector workers, benefits are projected by assigning pension plan formulas from the PBGC's Pension Insurance Modeling System (PIMS). DB benefits for federal workers and military personnel are calculated according to the actual benefit formulas. Benefits for state and local government workers are calculated using replacement rates that vary by years of service and Social Security coverage status.

1. Private Sector Workers

DB benefits for private sector workers are determined by assigning pension plan formulas from the PBGC's Pension Insurance Modeling System (PIMS). The PIMS dataset includes detailed DB plan information and benefit formulas coded, in a generalized form, from Form 5500 Schedule B attachment data for about 600 single-employer plans. Plans are classified into three general types — flat dollar, salary, and hybrid plans, with specific parameters varying by plan. In addition, there are five types of salary based plans, which vary by the Social Security offset method. Other detailed information needed to calculate plan benefits, including service breakpoints, the final salary averaging period, early retirement benefit reduction rates, and benefit supplement rates is also included. Using the PIMS plan formulas means that pension benefits in MINT 3.0 incorporate much more heterogeneity both in terms of differences in plans as well as differences among workers in similar plans, than previous versions of MINT.

PIMS plans are assigned to DB participants based on broad industry (manufacturing or non-manufacturing) and firm size (<1,000, 1,000-4,999, 5,000-9,999, and 10,000+) categories.[5] PIMS plans are assigned to each DB pension job, based on the characteristics of each job. In other words, a worker with three different jobs with DB pensions will be assigned three PIMS plans, one for each job. The pension benefits for each job are calculated based on the job's start and stop dates as well as the worker's earnings on the job.[6] Then, the benefits from each job are summed to determine the aggregate benefits for each worker.

2. Federal Government Workers and Military Personnel

Similar to the MINT 1.0 pension model, DB benefits for federal government workers and military personnel are calculated using the actual benefit formulas for these groups. For federal government workers, the formula varies by whether the worker is covered by Social Security. For non-covered federal employees we use the CSRS formula and for covered federal employees we use the FERS formula.[7] For military personnel, the formula varies by service entry date.

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[5] Because the goal of PIMS is to quantify the financial uncertainty facing PBGC, PIMS oversamples large plans and underfunded plans. According to PBGC, the plans modeled in PIMS are somewhat more generous than the average DB pension plan. This is likely due to the oversampling of large plans. Although the magnitude of the overstatement is unclear, assigning PIMS plans to the MINT population based on firm size should remove some of the bias. This will be examined in the validation section of the chapter.

[6] See chapter 2 for a discussion of how earnings were projected for ages prior to age 50; see chapter 4 for a discussion of how earnings were projected for ages 50 and higher.

[7] We define non-covered status based on class of worker status and earnings. Federal, state, and local workers with less than one-eighth of the national Social Security average wage for three consecutive years are defined as being a non-covered government employee.

Although federal workers are assigned job histories using data from PENSIM, we assume that any simulated job changes are changes within the federal government. In other words, we assume that federal government workers remain in the federal government sector, even if they change jobs. Accordingly, we assume that their DB pensions are based on their cumulative service.

3. State and Local Government Workers

Similar to the MINT 1.0 pension model, DB benefits for state and local government workers are calculated based on BLS tables of replacement rates. These replacement rates vary by years of service and Social Security coverage status.

We had hoped to use more detailed information for state and local plans. The Government Finance Officers Association (GFOA) published information on detailed characteristics of over 350 pension plans for state and local workers.[8] Unlike the PIMS dataset of pension plan characteristics of private plans, this information was not in a format that could be readily used to calculate benefits for state and local workers. Therefore, we decided to continue using the replacement rate arrays that were used in MINT 1.0. Matching plan information from the GFOA is a possible enhancement for future versions of the model.

Similar to our assumptions regarding job changes for federal workers, we assume that any job changes in the state and local government sector take place within that sector. In other words, we assume that state/local government workers remain in the state/local government sector, even if they change jobs. Accordingly, we assume that their DB pensions are based on their cumulative service.

4. Vesting

The model assumes that workers with fewer than 5 years of service are not vested in their DB plan, and will get no DB benefits. Although some workers might have more generous vesting schedules, the present value of benefits for these workers are likely to be quite low, and therefore are more likely to be taken as a lump sum distribution. As a result, our vesting assumption will not affect the results significantly.

5. Benefits Currently Being Collected

About 4 percent of individuals in the MINT sample are currently collecting pension income at the time of the SIPP interview, with their annual pension benefit averaging about $13,000. We assume that everyone in this group is collecting income from a DB plan and use self-reported information to determine whether they chose a joint and survivor option. Benefits are projected forward using assumptions about whether benefits receive COLA adjustments. These assumptions are described in detail below.

[8] See 2000 Survey of State and Local Government Employee Retirement Systems, by the Government Finance Officers Association (GFOA) Research Group.

6. Joint and Survivor Pensions

MINT assumes that the selection of a joint and survivor annuity upon receipt of a pension is a static individual characteristic. We determine each individual's preference for selecting a joint and survivor pension, and apply this preference to each marriage/pension that the individual claims while married.

The SIPP asks respondents who are currently collecting a pension whether they have taken a joint and survivor payment option. We assume that those who opted for a joint and survivor annuity will also choose that option for any future pensions they receive while married. Likewise, we assume that those who chose to forgo a joint and survivor annuity would forgo joint and survivor annuities on any future pensions.

For those not collecting a pension at the time of the SIPP interview, we assign their preference for joint and survivor annuities based on gender and education. The probabilities are derived from 1992 SIPP respondents aged 60-67 who are married and collecting a pension. Table 5-2 presents the likelihood taking a joint and survivor pension.

Table 5-2
Probability of Selecting a Joint and Survivor Option, by Gender and Education
1992 SIPP

Education	Men	Women
Less than high school graduate	0.35	0.11
High school graduate	0.46	0.14
Some college or college graduate	0.56	0.37

7. Cost of Living Adjustments (COLA)

MINT 3.0 uses the same assumptions regarding COLAs as in previous MINT versions. Pension benefits already being collected at the time of the SIPP as well as benefits that are projected to begin in the future are adjusted by COLAs, if applicable.

MINT 3.0 randomly assigns which pensions will receive COLAs, based on assumptions that vary by sector. Based on published data, MINT 3.0 assumes only 10 percent of private sector pensions receive annual cost of living adjustments. This includes not only pensions with automatic adjustments, but also those with ad hoc adjustments. Also according to published data, about 60 percent of state DB pensions receive annual COLAs. All federal and military pensions receive annual COLAs. Table 5-3 summarizes the assumptions regarding the proportion of pension benefits receiving COLAs as well as the amount of the COLAs.[9]

[9] More detail regarding the development of the COLA assumptions can be found in chapter 3 of the MINT 1.0 report, "Modeling Income in the Near Term-Projections of Retirement Income Through 2020 for the 1931-60 Birth Cohorts," Eric Toder et al, September 1999.

Table 5-3
Summary of COLA Assumptions

Sector	Proportion With COLA	COLA Calculation
Private	10%	50% of CPI Increase
State and Local	60%	CPI increase up to 3%
Federal-FERS	100%	Annual adjustments payable only to retirees age 62 or older (unless they are disability or survivor annuities). Adjustments, unless limited by law, are equal to: (1) the increase in the CPI, if the CPI increases 2% or less (2) 2% if the CPI increases between 2 and 3% (3) the CPI increase minus 1%, if the CPI increases 3% or more
Federal-CSRS	100%	Annual adjustments fully indexed to the CPI for all annuitants
Military—Entered on or before 7/31/86	100%	CPI
Military—Entered after 7/31/86	100%	CPI minus 1%

8. Disability Pension Benefits

DB pension participants who become disabled may be eligible to receive disability pension benefits. MINT 3.0 estimates eligibility for these benefits, and benefit payments for those eligible, among workers that MINT simulates to become disabled.[10] Eligibility and benefit payment criteria are determined separately for private and public sector workers.

For private sector workers, eligibility for disability pensions is based on information from the Bureau of Labor Statistics (BLS 1999, tables 139 and 140). According to BLS data, about 60 percent of private sector DB participants can receive disability pensions if they become disabled and meet the minimum age and service requirements. MINT randomly assigns age and service requirements according to the BLS distributions. The age and service requirement categories are: no minimum requirements, 10 years of service, 15 years of service, or age 50 and 10 years of service. If deemed eligible, one of four benefit payment methods is assigned based on the

[10] See chapter 2 for a discussion of how MINT simulates disability.

BLS distributions: immediate, unreduced benefits; immediate, reduced benefits; deferred benefits, based on tenure to disability; or deferred benefits based on tenure to normal retirement age.[11]

Disability benefits are similarly assigned to state and local government workers, using information from the BLS (BLS 2000, tables 120 and 121). However all state and local workers are assumed to have access to disability pensions if they meet the minimum age and service requirements. For federal employees, actual FERS and CSRS eligibility requirements and benefit reduction formulas are used.

9. Output Created for Retirement Module

The pension module creates a set of DB pension benefit and wealth variables that the retirement module (see chapter 4) incorporates into the retirement decision. In particular, the pension model creates variables for DB pension coverage on the current job, DB pension wealth from the current job, DB pension wealth from prior jobs, and DB pension benefits from prior jobs. Output for the latter three variables actually consists of output streams, reflecting values as of each potential retirement age from age 50 to age 70. This permits the retirement module to incorporate all of this information when determining retirement age in a premium value framework.

10. Final Output Created

After the retirement module simulates the worker's retirement age, the pension module produces a stream of DB income from the retirement age onward. The stream of DB benefits is adjusted for joint and survivor reductions and includes COLA adjustments, if appropriate. The income stream continues beyond death so that it may be accessed for surviving spouses.

IV. DEFINED CONTRIBUTION (DC) PLAN ESTIMATES

The MINT 3.0 pension model projects account balances for defined contribution (DC) plans based on self-reports of account balances and worker contribution rates, imputed information on employer match rates and asset allocations, and rates of return that are set stochastically.

Account balances at the time of the SIPP interview are accumulated to the retirement date, along with any new monthly (employee and/or employer) contributions and interest earnings. DC account balances are projected for jobs held at the time of the SIPP as well as for any future jobs as assigned through the PENSIM match. The account balances for each job are calculated based on the job's start and stop dates. Upon a job change, the account balance from the prior job continues to grow with interest until the retirement date. Balances from each job are summed to determine the aggregate balances for the worker.

[11] Assignment varies by broad industry classification — goods producing industries (construction, mining, and manufacturing) and non-goods producing industries.

The MINT 3.0 pension model does not differentiate between 401(k) and non-401(k) DC plans. Instead, account balances and contributions of any 401(k) and non-401(k) plans are combined and reported together.

1. Account Balances as of the SIPP Interview

The SIPP contains account balance information for 401(k) plans, but not non-401(k) DC plans. To estimate account balances at the time of the SIPP interview for non-401(k) plans, monthly contributions are accumulated from the start date of the plan up to the SIPP interview date. Any 401(k) and non-401(k) balances are combined and accumulated forward together, using the information and assumptions regarding employee contributions, employer matches, asset allocation, and rates of return described below.

2. Employee Contributions

Self-reported employee contribution rates are available for workers with a DC plan at the time of the SIPP. For individuals who are simulated to obtain DC coverage through a future job, employee contribution rates are set equal to the average contribution rate, by age and earnings. Table 5-4 contains the contribution rate assumptions, derived from the EBRI/ICI 401(k) database.[12]

Table 5-4
Average Participant Pre-Tax Contribution Rates, by Age and Salary, 1999

Age	Salary Range				
	20,000-$40,000	>$40,000-$60,000	>$60,000-$80,000	>80,000-$100,000	>$100,000
20s	5.3%	6.8%	7.4%	6.8%	4.8%
30s	6.2	6.8	7.2	6.9	5.1
40s	6.7	7.1	7.3	6.8	5.0
50s	7.6	8.3	8.2	7.3	5.1
60s	8.5	9.3	9.0	7.9	5.1

Source: Holden and VanDerhei, 2001.

Because contribution rates can change over time (e.g., increase with age), the MINT 3.0 pension model is structured to vary employee contribution rates according to the trends in the average contribution rates by age and earnings. As workers move across age and earnings categories, the difference in average contribution rates between the subsequent age/earnings cell and the initial age/earnings cell is added to the initial contribution rate. This way, we are able to retain information regarding whether an individual contributes more or less than the average contribution rate.[13] Note that for those whose initial contribution rates are set as the average

[12] Salary range categories for years other than 1999 will be changed to reflect wage growth.

[13] For workers with DC plans at the time of the SIPP, who then go on to have DC plans on a future jobs, we assume that the initial contribution rates on a future job equals the average contribution rate at the age/earnings level of the new job plus the difference between the initial contribution rate reported at the SIPP and the average contribution rate for the given age/earnings level at the time of the SIPP. For example, if a respondent is

contribution rates for their age and earnings categories, the new contribution rates will simply be the average contribution rates for their subsequent age and earnings categories.

3. Employer Contributions

In MINT 1.0, we varied employer match rates by the worker contribution. We randomly assigned employer match rates based on distributions found in the Survey of Consumer Finance (SCF). Currently in MINT 3.0, DC participants are randomly assigned a match level and a match rate. The match level is the percentage up to which an employer will match employee contributions and the match rate is the rate at which employers will match these contributions. The assignment of match levels and rates are based on the distribution reported in the EBRI/ICI database (Table 5-5).[14]

Table 5-5
Distribution of Participants by Plan Match Level and Plan Match Rate, 1999
(Percentage of Participants)

Match Level	Match Rate							
	$0.25	$0.33	$0.50	$0.67	$0.75	$1.00	Other	Total
2%	0	0	2	0	0	3	2	8
3%	4	1	1	0	0	5	1	12
4%	1	0	4	0	1	2	2	9
5%	1	0	1	0	2	5	5	13
6%	2	4	27	5	3	4	5	49
7%	0	0	4	0	0	0	0	5
8%	0	0	1	0	0	0	0	2
9%+	0	0	1	0	0	0	1	2
Total	8	5	41	5	6	20	15	100

Source: Holden and VanDerhei, 2001
Note: Match level is the percentage of salary up to which employee contributions will be matched by the employer.

For instance, we will assume that 27 percent of 401(k) participants will have their contributions up to 6 percent of salary matched at 50 percent. As employee contribution rates change over time, as discussed above, the employer matching contribution will change automatically according to the assigned match rules.

contributing 3 percentage points more than the average for their given age/earnings cell at the time of the SIPP, when they move to a new job, they will continue to contribute 3 percentage points more than the average contribution rate.

[14] When incorporating data from the EBRI/ICI table into MINT, we distributed the percentages from the 'other' match rate column proportionately across the other match rate categories.

Employee and total (employee plus employer) contributions are capped according to the legal limits. Dollar contribution limits vary by year and are set up as arrays to allow for policy simulations which alter maximum contribution amounts.

4. Asset Allocations

MINT 1.0 assumed that any initial DC account balances were allocated 50 percent to stocks and 50 percent to bonds. Similarly, new contributions were allocated 50 percent to stocks and 50 percent to bonds. Separate rates of return were applied to the stock and bond balances and new contributions. No portfolio balancing was simulated.

MINT 3.0 assumes that 401(k) balance and contribution allocations vary by age, according to EBRI/ICI data on 401(k) asset allocations (Table 5-6).

Table 5-6
Percentage of 401(k) Assets Allocated to Equities

Age	Equity Funds	Company Stock	Balanced Funds	Total Equity
20s	55.1	16.7	8.3	76.0
30s	51.2	19.6	8.1	74.9
40s	46.2	21.1	8.0	71.3
50s	42.5	19.5	7.8	65.9
60s	33.9	15.0	7.2	52.5
Total	44.0	19.1	7.8	67.0

Source: Urban Institute calculations based on VanDerhei et al (1999)
Note: Total Equity = Equity Funds + Company Stock + .5*Balanced Funds

The proportion of initial contributions and balances allocated to equities varies by age category. Then, every five years, the model re-balances the portfolios according to the allocation strategy for the individual's attained age category. Subsequent contributions are allocated to match the allocation strategy of the attained age, if different.

5. Rates of Return

Based on input from the Social Security Administration's Office of Research, Evaluation, and Statistics (ORES), we assume a CPI growth rate of 3.50 percent, a real rate of return for stocks of 6.98 percent, and a real rate of return for bonds of 3.00 percent. We subtract one percent from each of the stock and bond real rates of return to reflect administrative costs. These are the same administrative fee assumptions used in the 1994-1996 Advisory Council report for the intermediate return PSA-401(k) plan (1994-1996 Advisory Council). We vary the investment experience by individual and by year by setting the rates stochastically (i.e., drawing them from a normal distribution). Based on prior recommendations from RAND, we assume a standard deviation of 17.28 percent for stocks and 2.13 percent for bonds.

6. Lump Sum Distributions

MINT 1.0 implicitly assumed that upon job termination, all DC balances were either left on account with the employer or rolled over. MINT 3.0, however, uses a more realistic assumption that upon job termination, many DC participants will cash out and spend their DC balances. Two steps are used to determine who cashes out their DC balances. First, it is determined which participants take a lump sum distribution upon job termination, as opposed to leaving the balance on account with the employer. Second, for those who are simulated to have taken a lump sum distribution, it is then determined which cash out their balances, rather than save it through an IRA rollover or other investment.

Information regarding the proportion of workers who take lump sum distributions is very limited. Hurd, Lillard, and Panis (1998) examine lump sum distributions using the HRS. They find that among DC plan holders who leave their jobs between the first and second waves or the second and third waves of the HRS, 43 percent left the account with their former employer for further accumulation or periodic withdrawals. Based on this information, we assume that 57% of those with DC plans who change jobs take a lump sum distribution.

Although the probability of taking a lump sum distribution likely varies by age and/or amount of the DC account balance, these findings apply only to the cohort born 1931 to 1941, who were age 51 to 61 in 1992, the first wave of the HRS. It is likely that younger workers are more likely to take a lump sum distribution, especially if they have low account balances. If and when further data become available, the model has the flexibility to vary the probability that benefits are taken as a lump sum by age at job departure and the size of the DC account balance.

To determine who, among those who take lump sums, actually cash out (i.e., do not save), we use information on the probability of saving a lump sum distribution based on the SIPP and reported in Moore and Muller (2001). This matrix varies by age and amount of the account balance.[15]

Table 5-7
Probability of Saving a Lump Sum Distribution,
by Age and Size of Distribution

Age	<= $1,500	$1,501 - $5,000	$5,001 – $15,000	$15,001 +
< 30 years	39%	46%	57%	65%
30 – 39	37	52	64	76
40 – 49	45	54	69	82
50 – 59	49	55	74	90
60 +	72	72	77	86

Source: Moore and Muller, 2001.
Note: Observations are weighted. The sample consists of 8,348 individuals, ages 24 and over, who had a lump sum distribution from a previous job. The amount of the distribution is in 2000 dollars.

[15] The dollar amounts that define the size of distribution categories are adjusted each year to account for wage growth.

7. Output for Retirement Module

The pension module creates a set of DC pension benefit and wealth variables that the retirement module incorporates into the retirement decision. In particular, variables for DC account balances from the current job and DC account balances from prior jobs are created. Similar to the DB benefit output, the output for these variables consists of output streams, reflecting account balances (including any additional contributions) as of each potential retirement age from age 50 to age 70. (Included in the DC account balances are any Keogh balances, detailed below). This way, the retirement module can use a premium value approach to determine retirement ages (see chapter 4).

8. Final Output

After the retirement model simulates the worker's retirement age, the pension module produces variables reflecting the DC account balance at the retirement age. (Included in the DC account balances are Keogh balances, detailed below.)

V. KEOGH ESTIMATES

The SIPP obtains information regarding Keogh account balances and contributions. Similar to DC plans, Keogh account balances are accumulated to the retirement date, along with any new contributions and interest earnings. Keogh contribution rates are allowed to vary over time by age and earnings, using the same method used for DC plans. Keogh contributions are capped according to the legal limits. Dollar contribution limits vary by year and are set up as arrays to allow for policy simulations which alter maximum contribution amounts.

Keogh assets are allocated the same way as DC assets and rates of return are set stochastically using the same method as that used for DC plans. Only those with Keogh coverage at the time of the SIPP interview have Keoghs. No new Keogh participation is simulated in the MINT 3.0 pension module.

VI. IRA ESTIMATES

The SIPP obtains information regarding IRA account balances and contributions. Similar to DC plans, IRA account balances are accumulated to the retirement date, along with any new contributions and interest earnings. IRA contribution rates are allowed to vary over time by age and earnings, using the same method used for DC plans. IRA contributions are capped according to the legal limits. Dollar contribution limits vary by year and are set up as arrays to allow for policy simulations which alter maximum contribution amounts.

IRA assets are allocated the same way as DC assets and rates of return are set stochastically using the same method as that used for DC plans. Only those with IRA coverage at the time of the SIPP interview have IRAs. No new IRA participation is simulated in the MINT 3.0 pension module.

VII. RESULTS

Tables 5-8 and 5-9 summarize the final output produced by the MINT 3.0 pension module, and Figure 5-1 summarizes the output that is produced for the retirement module. Table 5-8 presents pension coverage rates and Table 5-9 presents pension income and wealth measures, for those with coverage. Each table presents the pension results by demographic characteristics and are presented as of retirement age. As such, there is no fixed age at which the pension coverage, benefit, and wealth figures are presented. We include retirement age as one of the characteristics by which results are presented to illustrate how differences in retirement ages may affect coverage rates and the magnitude of pension wealth.

1. Pension Coverage Rates

Table 5-8 presents pension coverage rates at the age of retirement for the MINT 3.0 sample. Coverage rates by various types of pension coverage – DB, DC, IRAs – are presented by AIME quintiles, gender, educational attainment, marital status, race and ethnicity, and retirement age. Overall, 59 percent of the MINT 3.0 sample have pension coverage at the time of their retirement from either a DB plan, a DC plan, or from savings in an IRA. (Participants can be covered by multiple pension types.) Forty-nine percent have coverage from an employer-sponsored DB and/or DC plan; 33 percent have coverage from a DB and 28 percent have DC coverage. Twelve percent of the MINT population (or about one fifth of those with employer-sponsored pension coverage), have coverage from both a DB and a DC plan. Twenty-three percent of retirees have coverage from IRAs. Thirteen percent of the MINT population (or over half of IRA participants and about one-quarter of those with employer-sponsored plans) have coverage from both an IRA and an employer-sponsored plan.

AIME quintile: Pension coverage is presented by a measure of life-time earnings – AIME quintiles. We calculate cohort-specific AIME quintiles based on historic and projected Social Security earnings from ages 22 through 62.[16] Coverage rates across AIME quintiles increase monotonically for all types of pension coverage. Between the lowest and highest quintile, overall coverage and IRA coverage more than triples, and employer based coverage increases over four-fold.

Gender: In every type of pension coverage, men have higher coverage rates than women, likely due to higher labor force participation rates, longer tenures, and employment in jobs more likely to come with pension coverage. Overall, 64 percent of men have pension coverage at retirement compared to only 53 percent of women. The gender-gap in coverage rates is smallest among IRA plans, with 25 percent of men and 22 percent of women having IRA coverage.

Education: Pension coverage rates increase dramatically with educational attainment. Only 34 percent of individuals without a high school degree have pension coverage either through their employer or an IRA plan, compared with 55 percent of high school graduates and

[16] Note that AIME is used as a measure of life-time earnings only for those with covered Social Security employment. Individuals with non-covered employment will have an AIME of zero and fall in the lowest AIME quintile.

Table 5-8
MINT3 Projected Pension Coverage Rates at Age of Retirement

	Any		Employment-Based		
	Coverage	IRA	DB or DC	DB	DC
Total	59	23	49	33	28
AIME Quintile					
Quintile 1	29	14	18	11	10
Quintile 2	44	16	34	23	18
Quintile 3	63	21	54	36	28
Quintile 4	77	27	68	47	36
Quintile 5	88	43	78	53	51
Gender					
Male	64	25	56	39	31
Female	53	22	42	27	24
Education					
Less than HS	34	6	31	21	14
High School Grad	55	18	46	32	24
College	69	33	56	37	34
Marital Status					
Never Married	49	18	43	28	25
Married	60	25	49	33	28
Divorced	59	20	52	36	25
Widowed	57	18	50	32	29
Race/Ethnicity					
White	62	27	50	34	29
Black	49	6	47	34	22
Hispanic	42	8	39	26	21
Other	52	20	43	27	27
Retirement Age					
By age 55	44	18	33	23	18
By age 60	63	24	53	38	28
By age 62	68	27	59	41	33
By age 65	71	28	61	41	35
By age 67	72	28	62	41	37
By age 70	73	29	64	37	43

69 percent of those with at least some college. Those with higher levels of education are also more likely to have both IRAs and employer-sponsored coverage.

Marital Status: IRA and pension coverage rates are fairly similar by marital status. However, those who are never married have slightly lower coverage rates.

Race/Ethnicity: Whites have the highest overall coverage rates (62 percent), blacks have significantly lower coverage rates (49 percent), and Hispanics have the lowest overall coverage (42 percent). These differences arise primarily from the very low IRA coverage rates of blacks and Hispanics compared with whites – although approximately 27 percent of whites have coverage from an IRA at age 62, only 6 percent of blacks and 8 percent of Hispanics have such coverage.[17]

Retirement Age: DB coverage rates increase between those who retire prior to age 55 (23 percent) and those who retire at ages 55 to 60 (38 percent). Thereafter, coverage rates remain relative stable. The lower coverage rates for the earliest retirees likely reflects their more tenuous attachment to the labor force. In contrast, DC coverage rates continue to increase with increases in retirement age, reflecting the lack of retirement incentives that are inherent in DB plans.

2. Pension Wealth and Benefits

Table 5-9 presents the mean annual benefit from DB pensions, the discounted present value of DB pension benefits (hereafter referred to as DB wealth), and DC and IRA account balances at age 62 for the MINT 3.0 sample. Note that these are means for only those with coverage from each type of pension plan, not means for the entire sample of retirees. Among retirees with DB pension coverage, the average benefit received is 0.42 times the national average wage and average DB wealth is 4.48 times the national average wage. The wealth held in DB pension plans is higher than the wealth held in either DC or IRA accounts at retirement. Average DC account balances are 3.43 times the average wage while IRA account balances at retirement nearly equal the average wage.

AIME quintile: With the exception of the lowest AIME quintile, average pension benefits and wealth increase with AIME. Amounts for the first quintile, however, are greater than the second quintile. The anomalous first quintile arises due to the AIME definition. AIME is a measure of lifetime Social Security earnings. Therefore, government employees without Social Security coverage have an AIME equal to zero due to their having no Social Security earnings. Thus government employees, which tend to have generous pension plans – especially if they are not covered by Social Security – fall into the first AIME quintile, thereby skewing values for that quintile. The pattern is apparent in DB and DC pension plans only. There is little difference in the IRA balances between the first and second AIME quintile. Presumably, government workers, who have generous pension plans, make up a disproportionate share of workers in the lowest AIMEs with pensions. In contrast, government workers may make up more proportionate shares of IRA participants in the lowest AIME quintile.

[17] Note again that no new IRA coverage is simulated.

Table 5-9
MINT3 Projected Pension Wealth and Benefits at Age of Retirement, Among Those with Coverage
(as a ratio to the Social Security national average wage)

	DB Benefit[a]	DB Wealth[a]	DC Balance[a]	IRA Balance[a]
Total	0.42	4.48	3.43	0.96
AIME Quintile				
Quintile 1	0.35	1.83	1.20	0.63
Quintile 2	0.22	1.79	1.19	0.65
Quintile 3	0.27	3.13	1.90	0.78
Quintile 4	0.40	4.84	3.22	0.96
Quintile 5	0.63	7.08	6.03	1.33
Gender				
Male	0.48	4.61	4.06	1.11
Female	0.34	4.30	2.66	0.79
Education				
Less than HS	0.30	2.90	1.59	0.72
HS Grad	0.37	0.37	3.69	2.46
College	0.48	5.26	4.22	1.06
Marital Status				
Never Married	0.44	0.44	4.45	3.56
Married	0.43	4.47	3.46	0.95
Divorced	0.36	4.59	3.12	1.01
Widowed	0.41	4.48	3.32	0.96
Race/Ethnicity				
White	0.44	4.65	3.58	0.97
Black	0.37	3.94	2.34	0.66
Hispanic	0.33	3.45	2.57	0.70
Other	0.40	3.98	3.76	0.90
Retirement Age				
By age 55	0.35	2.82	1.91	0.71
By age 60	0.38	4.38	2.92	0.88
By age 62	0.42	4.87	3.54	0.97
By age 65	0.45	5.40	3.80	1.07
By age 67	0.46	5.45	4.37	1.23
By age 70	0.51	6.04	5.50	1.37

Gender: Across each pension type, men have higher benefits and wealth accumulated than women. Men have DB benefits that are 41 percent higher and DC balances that are 53 percent higher than those for women. Interestingly, DB wealth is only 7 percent higher for men than for women, reflecting higher life expectancies for women and different ages of retirement.

Marital Status: Pension benefits and wealth are fairly similar across marital status.

Education: Similar to pension coverage, the amount of benefits and wealth in pensions are positively correlated with education. Individuals with higher education have higher levels of pension wealth and receive higher pension benefits than individuals with lower education. This is due largely to the income differentials between education groups.

Race/Ethnicity: Similar to the pattern in pension coverage, white pension participants fare better than blacks or Hispanics in terms of the size of their pension benefits and wealth. Differences by race/ethnicity, however, are narrower than those by AIME quintile and education.

Retirement Age: As retirement age increases, pension benefits and wealth as of the retirement age increase – additional years in the labor force result in larger benefits. On average, an individual who retires at ages 68-70 has accumulated twice the DB wealth, nearly twice the IRA wealth, and nearly three times as much in their DC account balances than an individual who retires prior to age 55.

The results for DB wealth are somewhat misleading, however, because they reflect the present value of DB benefits as of the retirement age. Workers retiring early have lower wealth, in part, because they may have to wait several years before they can begin collecting benefits. The pure effect of differences in retirement age can be seen more clearly by comparing DB wealth as of age 62, regardless of the age at which the worker actually retired. For those retiring prior to age 55, DB wealth as of age 62 averages 2.1 times the national average wage. For those retiring between 63 and 65, DB wealth as of age 62 is up to 4.2 times the national average wage. It is only 3.1 times the national average wage for those retiring at ages 68-70. This pattern is more in line with the typical pattern of DB wealth accumulation.

3. Benefit Wealth Streams Produced for Task 5

Figure 5-1 shows the cumulative value of pension wealth for the MINT 3.0 sample with pension coverage, assuming various retirement ages between 50 and 70.[18] Two curves are presented. One shows the value of DC account balances (including Keoghs) and the second shows the value of DB wealth. These curves summarize the data used in the retirement module to predict retirement age based on a premium value model. The underlying assumption is that each employee at age 50 remains on their current job, with wage growth, until the retirement module determines their retirement age.

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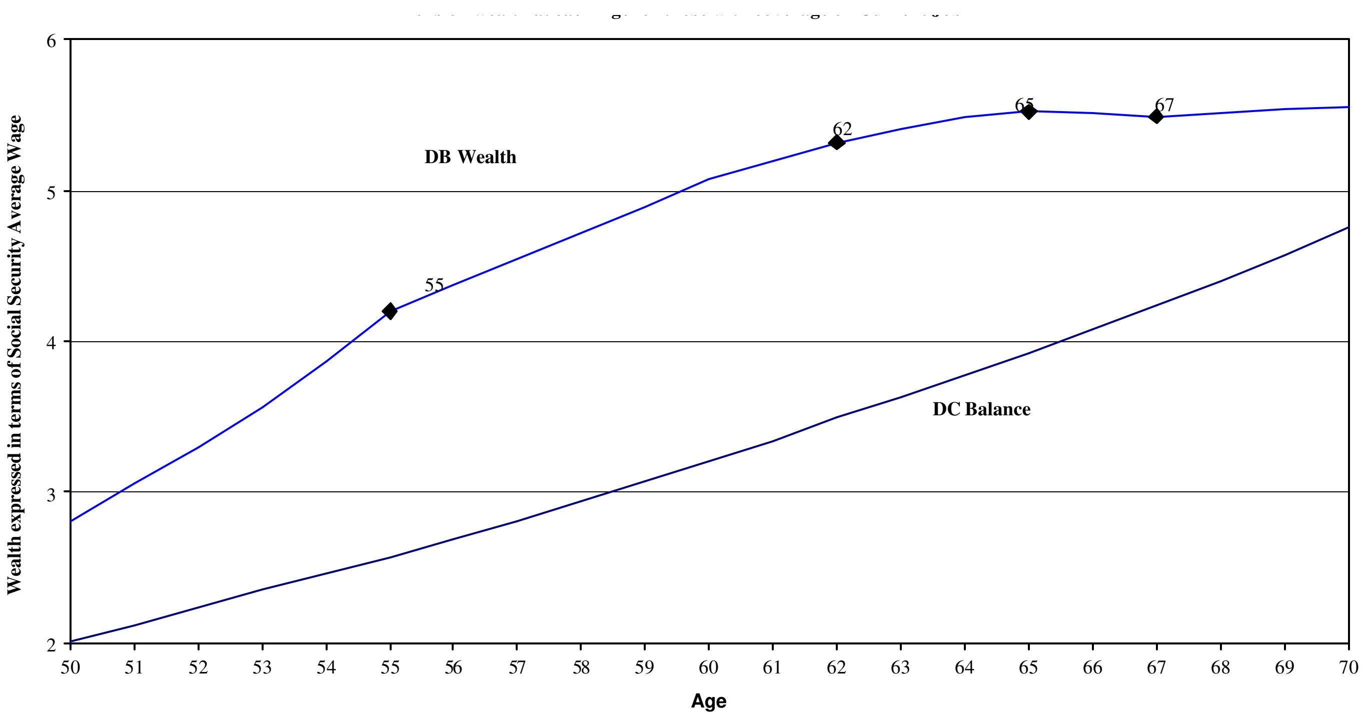
[18] The chart presents only pension accumulation for those on their current job (i.e., jobs which were held at age 50 and from which they will retire).

Figure 5-1
Pension wealth at each Age for those with coverage on Current Job



The figure highlights the accumulation differences between a DB and DC pension plan. At every age, the average pension wealth in DC plans is lower than the average pension wealth held in DB plans. The other striking difference is the shape of the two curves. While DC plans have a constant average growth, the value of DB wealth follows a more complex function. The key ages at which the slope of the function changes are labeled on the chart. Between age 50 and 55, the accumulation of pension wealth in DB plans are accumulating at an increasing rate. Age 55 appears to be an inflection point for the average DB plan, and from 55 through age 65, pension wealth grows at a decreasing rate. At age 62, a significant decrease in the accumulation rate is apparent. The average DB wealth peaks at age 65 and between age 65 and 67, there is a slight decline before flattening out. This pattern appears to follow the typical pattern of wealth accumulation in DB plans. Accruals increase rapidly up to the early retirement age, and then increase more slowly to the normal retirement age. After the normal retirement age, DB accruals can then become negative

VIII. SUMMARY OF IMPROVEMENTS OVER PREVIOUS MODEL

This version of the MINT pension module makes several substantial modifications to the previous model. Many of these improvements aim to produce more realistic heterogeneity in pension benefits and to improve the DB benefit calculations.

1. Incorporating Job Changes

The previous version of the MINT pension model adjusted DB benefits due to job changes in an indirect manner. First, the model randomly assigned a number of job changes to workers. Then, DB benefits were reduced based on the number of jobs held. MINT 3.0 incorporates job changes more directly, by assigning job histories to the MINT population from the Policy Simulation Group's PENSIM model. Then, pension benefits are calculated for each of the jobs separately.

2. Use of PIMS Data to Estimate DB Pensions

The previous MINT pension model used replacement rates published in the BLS Employee Benefits Survey to estimate DB benefits. Using these replacement rates had the effect of assigning everyone with similar years of service, age at retirement, occupation, and final salary the same pension benefit. Variations in benefit generosity across plans were not taken into account. MINT 3.0 incorporates specific DB plan formulas by using data from the PBGC's Pension Insurance Modeling System (PIMS). These plan formulas are randomly assigned (based on industry and firm size) to the MINT population with private DB plans. Federal and military workers continue to have their DB benefits calculated using the actual benefit formulas for those groups. State and local workers continue to have their DB benefits calculated using replacement rates published in the BLS Employee Benefits Survey. Updating the state and local benefit calculations is a potential future improvement, discussed below in section IX.

3. Disability Pensions

Prior versions of MINT ignored pension benefits for workers who become disabled. MINT 3.0 estimates disability pensions for DB participants who become disabled.

4. DC Contribution Rates and Asset Allocations

MINT 3.0 makes several improvements related to DC projections. Rather than assuming that worker contribution rates remain constant over time, MINT 3.0 allows contribution rates to vary by age and earnings. Rather than assuming that assets are allocated 50 percent to stocks and 50 percent to bonds, MINT 3.0 allows for asset allocations to vary by age. In addition, whereas the prior pension model did not adjust for portfolio rebalancing, MINT 3.0 assumes that portfolios are rebalanced every five years.

5. DC Lump Sum Distributions

Prior versions of MINT implicitly assumed that upon job termination, all DC balances were either left on account with the employer or rolled over. MINT 3.0, however, uses the more realistic assumption that upon job termination, many DC participants will cash out and spend their DC balances.

IX. VALIDATION OF RESULTS

Although few sources are available for comparison with our pension projections, we performed the analyses below to evaluate the reasonableness of the pension results.

- Using DB pension participants in the Health and Retirement Study (HRS), we compared the distribution of DB pension wealth calculated according to matched PIMS plans to that calculated using the restricted HRS pension provider data and software.
- We compared pension coverage rates in the HRS with those in the MINT population.
- We examined how the projections of pension coverage and income vary across MINT cohorts.
- We analyzed the differences between the MINT3 results and the MINT1 results.
- We examined the sensitivity of the DC projections to assumptions about equity yields.

Each of these exercises will be discussed in turn.

1. Comparison between PIMS and HRS Pension Information

We used data from the HRS to evaluate the degree to which PIMS plans represent an accurate distribution of pension plans. The HRS is a longitudinal survey that collects detailed information on income, wealth, employment, health, and pension coverage from a nationally representative sample of persons in the 1931-1941 birth cohorts. In addition to the core longitudinal data, the HRS contains supplemental files of Social Security earnings records and detailed pension plan information.

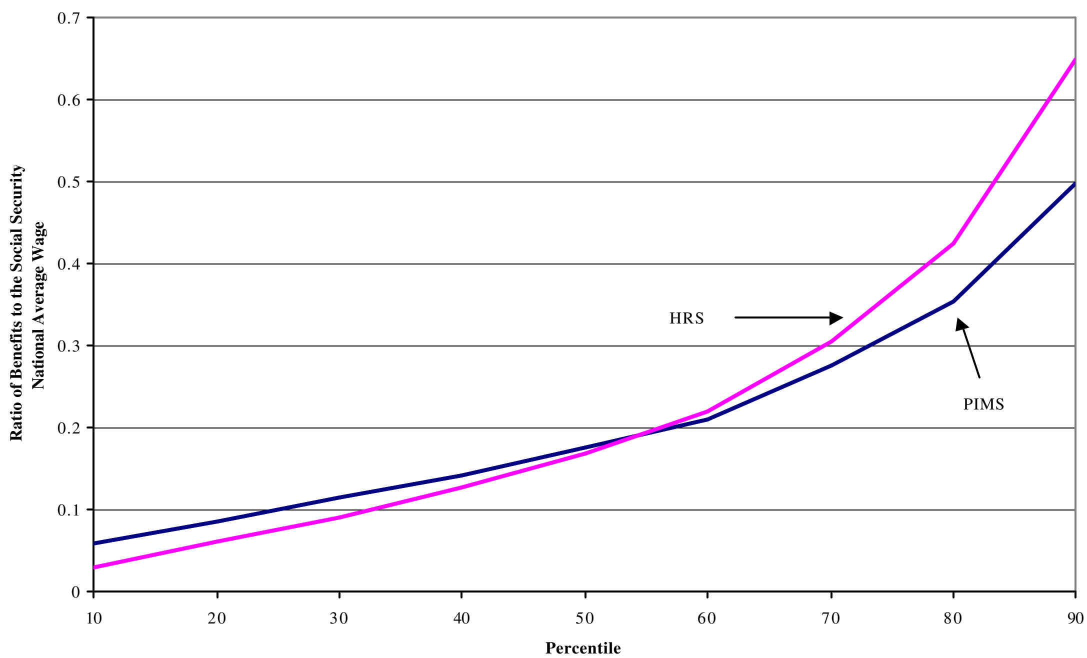
We used the HRS detailed pension plan information along with the Social Security earnings data and core data on employment tenure to produce pension wealth and income estimates for DB participants in the HRS.[19] We assume that all respondents end their current job at the time of the HRS interview and begin collecting benefits at the earliest date possible under the plan. We then match PIMS plans to the HRS DB participants based on the same set of criteria we use to match PIMS plans to MINT respondents (firm size and industry). Using the same assumptions regarding earnings history and tenure used to estimate pension benefits using the HRS pension data, we estimated pension benefits under the PIMS plans.

It is not appropriate to directly compare the benefits calculated according to each pension data source for an individual. Instead, we compared the distribution of benefits calculated using

[19] We restrict the HRS sample to DB participants with linked Social Security earnings records. We further restrict the HRS sample to private sector employees, because the PIMS plans reflect private plans only.

the HRS pension plans to that calculated using the PIMS pension plans. Figure 5-2 shows the distribution of initial pension benefits, expressed as a percentage of the average Social Security wage at the time of first receipt. The distribution of benefits under the PIMS plans is flatter than that for the HRS plans. PIMS plans appear to overstate benefits at the low end of the distribution and understate benefits at the high end of the distribution. Overall, however, the PIMS plans appear to generate a reasonable distribution of benefits.

Figure 5-2
The Distribution of Initial Pension Benefits under HRS and PIMS Plans



Because the sample of PIMS plans is limited to medium-to-large firms and underfunded plans, we had expected PIMS plans to be biased toward more generous pension benefits than what would be found in a more representative distribution of pension plans. However, our comparison suggests that PIMS plans produce a reasonable distribution of pension benefits. That we assigned PIMS plans based on firm size and industry likely helped diminish any potential biases.

2. Comparison of HRS and MINT3 Pension Coverage Rates

To help assess the accuracy of the MINT3 projected employer-sponsored pension coverage rates, we compared them to coverage rates in the HRS. We restricted our comparison to individuals born 1931 to 1940, because the HRS is limited to this cohort.

Table 5-10 shows life-time pension coverage rates for the HRS and MINT3 populations, by type of coverage. The pension coverage rates for the HRS sample reflect life-time coverage at the time of the HRS interview in 1992. Similarly, coverage rates for the MINT3 sample reflect life-time coverage at the time of the SIPP pension coverage topical module. The SIPP-reported information was used to establish initial pension coverage for the MINT3 population.

Table 5-10
Pension Coverage Rates, HRS and MINT3
1931-1940 Birth Cohorts

	Either DB or DC Coverage	DB Coverage	DC Coverage
HRS			
Total	0.47	0.36	0.15
Birth Cohort			
1931-1935	0.46	0.36	0.13
1936-1940	0.49	0.37	0.17
Sex			
Male	0.59	0.47	0.17
Female	0.37	0.27	0.13
MINT3			
Total	0.44	0.35	0.18
Birth Cohort			
1931-1935	0.45	0.38	0.14
1936-1940	0.44	0.32	0.21
Sex			
Male	0.56	0.45	0.23
Female	0.34	0.26	0.14

Overall coverage rates are very similar across the two samples. Furthermore, the patterns of coverage rates by cohort and gender are similar. In both samples, men have higher coverage rates than women for each coverage type, and the younger cohort is more likely to have DC coverage than the older cohort. Differences arise, however, with respect to DB coverage rates by birth cohort. In the HRS, DB coverage rates by cohort are nearly identical. In contrast, the younger MINT3 cohort is somewhat less likely to have DB coverage. Nevertheless, the MINT3 coverage rates appear to compare favorably to the HRS coverage rates.

3. Pension Coverage, Income, and Wealth Across Cohorts

The comparison of coverage rates in MINT3 to those in the HRS suggest that the initial coverage rates for the older MINT3 cohorts are reasonable. However, the comparison cannot assess whether the results for the younger cohorts are reasonable. To help make this evaluation, we examined the trends across cohorts within the MINT3 sample. Table 5-11 shows pension coverage rates, DB benefits at time of receipt, and DC and IRA balances, by birth cohort. Note that the pension coverage rates and benefits presented in the results section above reflect these measures as of the retirement age. In contrast, to increase comparability between cohorts, the pension measures presented here are as of a common age – age 62.

Table 5-11
MINT3 Pension Coverage Rates and Average Benefits and Balances at Age 62

	Coverage (percent)					Average Benefits and Balances (ratio to the SS national average wage)		
	Any		Employment-Based			DB Benefit	DC Balance	IRA Balance
Birth Cohort	Coverage	IRA	DB or DC	DB	DC			
1931-1935	60	34	46	39	14	0.50	2.06	0.94
1936-1940	60	31	47	36	21	0.38	2.14	0.94
1941-1945	59	28	47	34	24	0.29	2.73	1.02
1949-1950	61	25	50	33	29	0.26	3.22	1.03
1951-1955	60	20	51	32	33	0.25	3.27	1.13
1956-1960	59	15	53	32	37	0.24	3.39	1.08
ALL	60	24	50	32	28	0.31	3.06	1.02

Overall pension coverage rates remain fairly steady across birth cohorts at about 60 percent. There are distinct trends by cohort within pension type, however. IRA coverage decreases from 34 percent among the oldest cohort to 15 percent among younger cohorts. This trend was expected because MINT3 does not simulate new IRA participation among those who are not already participating at the time of the SIPP interview. Among IRA participants, however, the average IRA balance is higher for younger cohorts than older cohorts. This likely reflects the longer period of participation among younger cohorts.

Employment-sponsored pension coverage (DB or DC) rates increase slightly by cohort, owing mostly to the large increases in DC coverage among younger cohorts. Although DB coverage decreases somewhat from 39 percent among the oldest cohort to 32 percent in the youngest cohort, DC coverage more than doubles from 14 percent among the oldest cohort to 37 percent among the youngest cohort. The trends by coverage type likely reflect many factors. First, the results reflect the overall shift from DB to DC coverage already in evidence at the time of the SIPP survey. Older workers in the SIPP were more likely to have DB coverage and younger workers were more likely to have DC coverage. The results may also reflect the impact of vesting. To be eligible to receive DB benefits, we assume 5 year cliff vesting. In contrast, we assume there are not vesting requirements for DC benefits. Workers with short tenures on DB jobs would not be eligible to receive benefits, although otherwise similar workers with DC coverage would be. Therefore, any projected tenure decreases by cohort, especially combined with a shift to DC plans, would result in a wider gap between DB and DC coverage rates.[20]

[20] Indeed, MINT3 projected tenure on pension jobs decreased for younger cohorts. Tenure on DB and DC jobs decreased from 17 and 15 years, respectively, among the 1931-1935 cohort, to 13 and 12 years among the 1956-1960 cohort.

Similar trends are evident with respect to DB benefits and DC balances. DB benefits are twice as high for the oldest cohort compared to the youngest cohort. This likely reflects a decrease in tenure on DB jobs and the loss of benefits, in real terms, for participants who leave their DB jobs prior to retirement. DC balances increase for the younger cohorts, likely reflecting an increase in tenure on DC jobs.

4. A Comparison of MINT1 and MINT3 Pension Results

It is also useful to compare the MINT1 and MINT3 pension results. Table 5-12 compares the pension coverage rates and average benefits and balances projected under MINT1 to those projected under MINT3.

Pension Coverage Rates: The overall pension coverage rates in MINT3 are similar to those in MINT1, and generally exhibit the same patterns by birth cohort, gender, and education. Sixty-two percent of the MINT1 population had pension coverage, compared to 60 percent in MINT3. The primary difference between MINT1 and MINT3 is the steeper increase in DC pension coverage among younger birth cohorts. This may result from our methods for projecting job changes and new pension coverage. In MINT1, we assumed that even if someone changed a job, they did not change their pension type. In contrast, in MINT3, we allow for changes in coverage type upon job change. This means that some workers who had DB coverage could obtain DC coverage on future jobs. Indeed, in MINT3, 27 percent of pension participants in the 1956-1960 birth cohort have both DB and DC coverage, compared to only 13 percent in MINT1. The MINT3 results appear more reasonable than the MINT1 results, in light of the continued growth of DC coverage.

Pension Benefits: The DB benefit projections are fairly comparable between MINT1 and MINT3, and exhibit the same patterns by birth cohort, gender, and education. The DC and IRA balance projections, however, are lower in MINT3, especially for the younger cohorts. This was expected for several reasons. First, MINT1 assumed that DC and IRA participants continued working and contributing to their plans until age 62. In contrast, however, many workers retire prior to age 62 in MINT3. Second, MINT1 assumed no portfolio rebalancing; the compounding of large gains to equity allocations resulted in large DC and IRA balances. In contrast, MINT3 rebalances DC and IRA portfolios every 5 years, and also varies portfolio allocations by age—with older workers reducing the share of their balances allocated to equities. Finally, as discussed above, MINT3 does not assume that pension participants who change jobs have the same type of pension coverage on their next job. This means that average tenure on DC jobs will be lower in MINT3 than MINT1, thereby reducing DC balances.

Table 5-12
Pension Coverage Rates and Average Benefits and Balances, Under MINT1 and MINT3
As of Age 62

	Coverage (percent)					Average Benefits and Balances (ratio to the SS national average wage)		
	Any Coverage	IRA	Employment-Based: DB or DC	DB	DC	DB Benefit	DC Balance	IRA Balance
MINT1								
ALL[a]	62	20	47	35	21	0.28	5.67	1.41
Birth Cohort								
1931-1935	63	33	47	39	16	0.42	2.30	0.12
1936-1940	62	28	45	35	21	0.36	3.26	0.52
1941-1945	63	25	47	35	23	0.29	4.45	1.01
1949-1950	65	22	49	36	24	0.27	5.60	1.62
1951-1955	63	18	48	34	24	0.23	6.18	2.34
1956-1960	61	14	48	33	23	0.20	7.54	3.11
Gender[a]								
Male	57	20	33	33	19	0.22	4.98	1.47
Female	67	21	36	36	23	0.34	6.28	1.36
Education[a]								
HS dropout	37	6	28	23	8	0.19	2.60	0.51
HS grad	60	18	46	34	20	0.25	4.71	1.31
College	79	35	61	43	31	0.38	7.62	1.63
MINT3								
ALL	60	24	50	32	28	0.31	3.06	1.02
Birth Cohort								
1931-1935	60	34	46	39	14	0.50	2.06	0.94
1936-1940	60	31	47	36	21	0.38	2.14	0.94
1941-1945	59	28	47	34	24	0.29	2.73	1.02
1949-1950	61	25	50	33	29	0.26	3.22	1.03
1951-1955	60	20	51	32	33	0.25	3.27	1.13
1956-1960	59	15	53	32	37	0.24	3.39	1.08
Gender								
Male	66	26	57	40	33	0.36	3.64	1.18
Female	54	22	43	28	24	0.22	2.35	0.86
Education								
HS dropout	35	6	32	22	14	0.21	1.46	0.76
HS grad	56	18	47	32	25	0.27	2.2	0.81
College	70	34	57	38	35	0.35	3.75	1.13

a. Includes individuals in the MINT population outside the 1931-1960 birth cohorts. These individuals are spouses of the primary MINT population.

5. Alternative Assumptions About Future Equity Returns

To address concerns about the level of future equity returns for DC and IRA plans, we ran an alternative simulation of pension income and wealth with a slightly lower rate of return. In the baseline simulation, we assume an average annual rate of return on stocks and bonds equal to 6.98 percent and 3.00 percent, respectively. In addition to these average returns, we assume a level of variation equal to 17.28 percent for stocks and 2.13 percent for bonds.[21] With these assumptions and a uniformly distributed random number generator we produce a synthetic array of market returns specific to each individual in our sample. We also deduct a 1 percent transaction cost from all annual returns.

Based on papers by John Campbell, Peter Diamond, and John Shoven for the Social Security Board, we run a simulation of pension wealth and benefits with a lowered expected return on equities. Rather than assuming a 6.98 percent average return, we execute our pension module based on 5.00 percent average equities return assumption and compare the outcomes between the two projections. Table 5-13 presents the DC and IRA projected balances for each of the equity return scenarios. Note that the alternative scenario also incorporates changes due to any changes in retirement behavior resulting from different account balance accumulations.

Overall, DC balances under the alternative equity return scenario are 13 percent lower than those under the baseline scenario. The impact is greater among younger cohorts than older cohorts, because they are accumulating balances over a longer period of time; DC balances are only 5 percent lower among the oldest cohort and 15 percent lower among the youngest cohort. The impact is somewhat greater among the younger cohorts, because they are accumulating balances over a longer period of time.

Overall, IRA balances under the alternative equity return scenario are 13 percent lower than those under the baseline scenario. The impact by birth cohort is even greater for IRA participants. Although IRA balances among the oldest cohort are only 1 percent lower under the alternative scenario, balances are lower by 22 percent for the youngest cohort. The differential impact by birth cohort between DC and IRA balances is likely due to the model not simulating new IRA participation among non-participants. As a result, IRA participants in the youngest cohort were participating from the time of the SIPP interview forward. In contrast, DC participants in the youngest cohort might not have had coverage at the time of the SIPP, but were subsequently assigned DC coverage. As a result, IRA participants have coverage for longer than DC participants, and therefore are impacted more by a change in equity return assumptions.

[21] These average returns and variance assumptions are the same that were used in MINT1. The averages were provided from the Social Security Administration and the variances were provided from RAND.

Table 5-13
DC and IRA Balances at Age 62, Under Baseline and Alternative Equity Return Scenarios
(as a ratio to the Social Security national average wage)

	Baseline Scenario Equity Return: 6.98% Bond Return: 3.00%		Alternative Scenario Equity Return: 5.00% Bond Return: 3.00%	
	DC Balance	IRA Balance	DC Balance	IRA Balance
ALL	3.06	1.03	2.66	0.90
Birth Cohort				
1931-1935	2.06	0.94	1.95	0.93
1936-1940	2.14	0.94	1.92	0.89
1941-1945	2.73	1.02	2.42	0.92
1949-1950	3.22	1.03	2.84	0.88
1951-1955	3.28	1.14	2.83	0.93
1956-1960	3.39	1.08	2.87	0.84
AIME Quintile				
Quintile 1	1.24	0.78	1.06	0.69
Quintile 2	1.24	0.75	1.09	0.67
Quintile 3	1.77	0.83	1.56	0.73
Quintile 4	2.92	0.99	2.55	0.87
Quintile 5	5.19	1.38	4.49	1.19
Sex				
Male	3.64	1.18	3.15	1.03
Female	2.35	0.86	2.06	0.76
Education				
HS Dropout	1.46	0.76	1.28	0.72
HS Grad	2.20	0.81	1.92	0.73
College	3.75	1.13	3.26	0.98

X. POTENTIAL FUTURE IMPROVEMENTS TO THE MODEL

1. Incorporate a More Integrated Job History Model

Although the MINT 3.0 pension model uses an improved method to account for job changes relative to the prior MINT model, future versions of MINT might benefit by incorporating a more sophisticated job history model that is tied more closely to the earnings projections.

2. Incorporate PIMS-Type Plans for State and Local Workers

MINT 3.0 continues to use replacement rates published by BLS to estimate DB pension benefits for state and local government workers. In future versions of MINT, it may be desirable to incorporate state and local pension data from the Government Finance Officers Association (GFOA).

3. More Sophisticated IRA Projections

MINT 3.0 assumes that current IRA participants continue to participate in the future and that current non-participants do not participate in the future. In future versions of MINT, it may be desirable to simulate future IRA participation among current non-participants.

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CHAPTER 6

ASSET ACCUMULATION AND SPEND DOWN

I. INTRODUCTION

Under task 7 of MINT3, we significantly revised the models of wealth accumulation that were in MINT1. The new models account for indicators of retirement behavior, disability, and health status, which are newly included in the MINT3 data set. They also incorporate new and revised measures of lifetime earnings, self-employment, and pension eligibility and more detailed representation of the age variable, in response to suggestions of reviewers. Finally, we added results from additional data sources and modified our methods for imputing individual-specific effects in making projections to the SIPP sample based on equations estimated from other data sources.

MINT3 requires estimating wealth as of age 50 and annual changes in wealth thereafter. The initial SIPP wealth values occur at different ages depending both on the specific SIPP panel and the birth cohort. For example, someone born in 1930 was age 61 when the wealth topical module was asked in wave 4 of the 1990 SIPP panel and age 65 when the wealth topical module was asked in wave 7 of the 1993 SIPP panel. The youngest members of the MINT sample are the 31-year-olds from the 1960 cohort who were interviewed in the 1990 SIPP panel. Depending on the starting age, we project wealth for different number of years over different projection equations.

We estimate asset accumulation over two separate and overlapping age ranges from two data sources. We use the Panel Study of Income Dynamics (PSID) to estimate wealth from ages 30 to 50, and the first two waves of the Health and Retirement Study (HRS) to estimate wealth from ages 51 to 63. We estimate wealth from housing and non-pension financial assets separately. For families that do not own a home, we project net home purchases (defined as purchases of a primary residence) based on an annual hazard model estimated from the PSID. Similarly, for all families that do own a home, we project net home sales (defined as the sale of the primary residence with no re-purchase, or shift to rental status) based on an annual hazard model estimated from the PSID. For families projected to own a home, we project the value of the home using a random-effects model. For all families, we project non-pension financial wealth based on a random-effects model. For both home value and non-pension wealth, we estimate separate models for married couples and single individuals. Equity in second homes is included in financial assets.

We use the estimated equations from the PSID and HRS to project wealth at all ages between 50 and 63. We use the PSID equations (estimated for ages 30 to 60) to project home ownership, housing wealth and non-pension financial wealth at age 50 for all cohorts born between 1931 and 1960 in the base 1990-93 SIPP panels. We also use the PSID equations to project home ownership transitions through age 65. We use the HRS equations to project housing wealth (for homeowners) and non-pension financial wealth from ages 50 to 63. Because of large differences in individuals' saving behavior, we believe longitudinal data is vital for estimating wealth changes over time. We believe the PSID provides the best source of longitudinal wealth data for younger ages and the HRS provides the best source of longitudinal wealth data for families near retirement.

In MINT3, we continue to use the wealth spend down model that we estimated in MINT1, using the 1990 to 1993 SIPP panels matched with Social Security Administration Summary Earnings Records and Master Beneficiary Records, to project wealth transitions after age 63. These projections maintain the individual heterogeneity of wealth throughout retirement and closely match the historic wealth distribution by age.

This chapter describes the data and models we use to estimate and project wealth in MINT3. In Section II, we present the methods used to project wealth at age 50. We briefly describe the PSID data and the lifetime earnings measure we used in our estimation and then discuss the equations for home purchase and sale, housing wealth, and financial asset wealth, and how we used the estimates from the equations to project wealth on the SIPP. In section III, we present the methods used to project wealth transitions between ages 50 and 65. We briefly describe the HRS data and then present the HRS-based models for housing wealth and non-pension financial assets. In section IV, we recapitulate the SIPP-based model for asset spend down and describe some modeling issues related to the asset spend down.

In Section V, we present the results of the projections from the base SIPP data to age 50. We start by comparing the observed and predicted home equity and non-pension assets at the base SIPP interview. We compare the base SIPP and PSID samples to understand the differences in the starting projections and error terms. We then examine the trends in the independent variables as MINT ages the SIPP population to understand how their changes will alter the future wealth distribution. In Section VI, we present the results of the projections after age 50. Here we look at the projections of home equity and non-pension assets by age, cohort, and marital status. We examine the distribution of these assets and compare the MINT projections to the 1990 to 1993 SIPP and 1998 Survey of Consumer Finance values. In Section VII, we project wealth using different assumptions, and show how sensitive the projections are to certain assumptions. Finally, in Section VIII, we present concluding comments.

II. PROJECTING WEALTH TO AGE 50

1. Data Used

We used the PSID to project wealth to age 50 and homeownership status to age 65. The PSID is a longitudinal household survey beginning in 1968. All members of the original household are interviewed annually. As children leave the household, they are followed and interviewed as they form their own households. The survey is ongoing with the most recent available interview being done in 1994.

The PSID included special wealth modules in 1984, 1989, and 1994. The wealth modules ask respondents about the following assets:

- IRAs, checking accounts, savings accounts, bonds, and money market balances;
- home equity;

- vehicle equity;
- other real estate equity;
- business equity;
- stocks and mutual fund values; and
- unsecured debt.

Many of the wealth variables on the PSID compare quite well with the SIPP. However, the PSID combines IRA wealth with passbook savings and checking accounts, while the SIPP shows IRA wealth as a separate variable. The PSID combines life insurance value with other financial assets, the SIPP includes it as a separate variable. The PSID does not ask about total pension wealth, and it has very limited information about pension coverage. In addition to the wealth topical modules, the PSID also asks about home ownership in every year and home equity in all but five years (1968, 1973-1975, and 1982).

Limitations of the PSID

We do not have full lifetime earnings for all individuals on the PSID. Earnings are available only after 1968 (the first year of the panel), so that we do not have a measure of full lifetime earnings for older workers in the panel. The PSID collects no earnings information for household members other than the head and spouse. This includes college age children, nonprimary adults in multi-family households, and other nonhead adults. These omissions limit the ability to calculate lifetime earnings for individuals from the PSID because it systematically excludes earnings of young adults and subfamilies. In addition, no income is available for years an individual was not in a sample household, such as for spouses in a marriage formed during the panel. But the PSID, unlike other data sets (HRS, AHEAD, SIPP/SER), does allow us to observe earnings of former spouses of divorced and widowed respondents over the period they were married.

For example, if an 18-year-old in a sample family in 1968 first began a new household in 1975, we would have no earnings for him until he reached age 25 in 1975. If he then married a 30-year-old woman in 1980 who had not previously been in the sample, we would have earnings information for his wife beginning in 1980 (that is, only from age 30.) If they subsequently divorced in 1985, however, we could still observe the earnings of the former spouse between 1980 and 1984, but not after 1984.

Measures of lifetime earnings

One important variable in explaining an individual's wealth is his or her present value of lifetime earnings. The present value of lifetime earnings is a measure of an individual's ability to accumulate wealth, for any given rate of saving and return on assets.

We constructed measures of lifetime earnings for individuals as well as the earnings of their spouses in any year they were married. We calculated the present value of earnings using an historic average real rate of return of 2.7 percent for earnings beginning at age 30 for individuals born in or after 1930.[1] (Even starting at age 30, we have some years of early earnings

[1] The real interest rate of 2.7 percent is the historic average real interest rate on 10-year Treasury Bonds between 1952 and 2001.

missing for all cohorts born before 1938.) We then divide the present value of earnings for each individual at each age by the average present value of earnings for their respective cohort and age. At any age, an individual with low lifetime earnings (up to that age) relative to his or her cohort has a value less than one, and an individual with high relative lifetime earnings has a value greater than one. This measure of earnings captures both individual's lifetime earnings and cohort differences. It allows us to separate out age-wealth profiles and cohort trends.

The earnings collected on the PSID are not censored at the Social Security taxable maximum. However, earnings on the MINT file are censored at 2.46 times the average wage in all years.[2] To be consistent with this definition of earnings, we calculate the present value of earnings using a similarly capped value. We control for this censoring by including the number of years an individual earns more than 2.46 times the average wage as an explanatory variable in the equations.

For married couples, we divide the sum of the present values of earnings of the husband and wife by the husband's age and cohort-specific average. (For the remainder of this chapter, we call this measure the "family present value of earnings"). We restrict the sample to heads with no more than one year of missing earnings from age 30 on. For example, if an individual formed a household in 1975 at age 25, his own present value of earnings would accumulate from 1980 (the year he turns 30) onwards. His wife's present value of earnings would contribute to his wealth accumulation only in the years they are married.

We also calculated an alternative measure for couples that we call the present value of per capita earnings. For this measure, we allocate half of the couple's earnings to both husband and wife and calculate the present value of this shared earnings amount. We then divide this value by the age and cohort-specific average for the household head. In all the models we estimated, we experimented with alternate specifications of the earnings variables (per capita, family, husband only, husband and wife separately). We selected the best performing variable from among this group.

For divorced or widowed individuals, we include in the family present value of earnings the earnings of the former spouse while they were married. Divorced or widowed individuals with longer former marriages have higher family earnings compared to individuals with the same lifetime earnings who have shorter marriages or were never married.

2. Random Effects Models for Projecting Wealth

After considering alternate models, we chose to model wealth using a random-effects model for estimating wealth. The random-effects model is of the form

$$W_{it} = \alpha + X_{it}\beta + v_i + \varepsilon_{it}, \qquad (6.1)$$

[2] Beginning in 1994, the taxable maximum was set at the 1994 level (2.46 times the average wage) updated by wage growth. Historic and projected earnings in MINT are capped at a consistent 2.46 times the average wage level for internal consistency. This level is sufficient for calculating Social Security benefits in the future barring any policy change. See Chapter 2 for more details.

where W is the dependent variable, α is an intercept, X is a vector of independent variables, β is a vector of parameters to be estimated, v_i is an individual-specific error term, ε_{it} is a random error term, T is a time or period, and i is an individual-specific identifier. This model has some nice features. It allows the individual-specific error term to capture an individual-specific "taste for saving" that cannot be explained by the individual's observable characteristics. It also allows us to estimate the variance of both the individual-specific error and the random error.

We use the equations described in this section to project components of wealth at age 50 for individuals in the 1990-93 SIPP files. For these individuals, we have an observation on their starting wealth somewhere between ages 30 and 60. For the older individuals in SIPP, we already have their wealth at 50, but for the younger individuals we need to project how their wealth will change over time.

Our dependent variable is the natural logarithm of wealth divided by the average wage plus an offset. Because the wealth distribution is nonlinear and highly concentrated at the top end of the distribution, and because we are interested in the percent change in wealth over time, we use the natural logarithm of wealth as our dependent variable. Because wealth can be negative and the natural logarithm is undefined at and below zero, we add an offset to the base wealth value to allow the model to predict negative wealth.[3] All MINT projections are done as a percent of the average wage. This allows the projections to be independent of the wage growth assumption and adjusts historic values for period effects.

Independent Variables in the Models and How They Affect Projections

In all models we estimate, we include four types of explanatory variables: 1) age variables, 2) unchanging shift variables, 3) changing shift variables, and 4) age-interaction variables.

- The age variables measure how wealth changes for the individual or couple as the age of the household head increases, holding all other variables fixed. Note that the coefficients on the age variables do not by themselves describe an age-wealth curve, because there are other variables in the equations that change with age.

- Unchanging shift variables are those that remain the same for any individual in the sample as the individual ages. These include variables such as level of education (observed once in the base year SIPP) and race.

- Changing shift variables are those such as relative present value of earnings (compared with the individual's age and cohort group) and marital status that do not necessarily have an age-related trend, but do change over time for individuals.

[3] We tried higher and lower offsets, but 20 percent of the average wage fit the data closely. Offsets closer to zero project wealth that is too high at the bottom of the distribution. Offsets greater than 20 percent of the average wage project an age slope that is too steep as families with large negative wealth have undo influence on the parameter estimates. Between age 50 and 65 we add a wealth offset of 0.02 times the average wage. This reduction is smaller compared to the adjustment at younger ages reflecting the smaller share of wealth that is below zero at older ages.

- Age-interaction terms (such as home ownership or race multiplied by age) show how the growth rate of wealth with age differs among groups. Thus, a positive coefficient on the age-home ownership interaction term in the financial wealth equation would indicate that homeowners accumulate wealth at a higher rate than renters.

In the projections, the coefficients on the age variables, changing shift variables, and age-interaction terms are all used to project how the wealth of a particular individual or couple changes between the observed base year and age 50. The coefficients of the shift variables do not directly affect the growth in wealth between the base year and age 50. They do, however, help determine the *individual-specific effect* for each observation, which depends on the difference between projected wealth and actual wealth in the base year. The individual-specific effect measures the portion of an individual's wealth attributable to characteristics (such as household preferences) that the explanatory variables in the equations fail to capture. We discuss the use of individual-specific effects in the projections in Section II.5 of this chapter.

Alternatives to the Random Effects Model

We examined alternate models that used percent change in wealth and absolute change in wealth as dependent variables. We also tried including lagged wealth as an independent variable. In all cases, of the variables we have available in the MINT projections, nothing explained the changes in wealth - not earnings, health status, retirement, disability, pension eligibility, or age. Similarly, when we used wealth as the dependent variable and lagged wealth as an independent variable, lagged wealth was the only significant variable in the equation.

The major problem with trying to model changes in wealth directly is the poor quality of the wealth data. While differences in reported wealth among individuals in a cross-section may provide a broadly accurate, though imprecise, measure of their wealth at a point in time, indicators of *changes in wealth for an individual* in panel data are unreliable. Our findings in this regard are similar to those of McNeil and Lamas (1988) and Haider et al (2000), who also found that wealth data reported by individuals are extremely variable and have large reporting errors.

Some of the problem explaining observed wealth changes simply reflects the fact that wealth stocks do experience large random fluctuations from year to year, so that observations taken at a few discrete points for an individual may not correctly reflect trends in asset accumulation or decline. But there are also major errors in the reported data. Reporting errors in wealth have a number of sources. Some of it is due to the difficulty people have in correctly estimating their own wealth. For example, housing equity requires having up-to-date information on the local housing market, and stock values change with the variability in the stock market. Also, respondents typically report wealth in round numbers, such as thousands or tens of thousands of dollars. As wealth increases or decreases over time, the reported amounts jump intervals while the actual amounts may vary more continuously. Wealth may increase as a family saves for a vacation or education, for example, and then decline dramatically after a large expenditure. Observable characteristics in the data do not pick up these details.

Measures of changes in wealth introduce further anomalies when couples age, become widowed, or lose their cognitive ability. For example, we often observe huge changes in wealth upon the death of a spouse. While the death of a spouse certainly will have an impact on family wealth, some of the measured change is also due to a change in the financial respondent. In some cases, the new financial respondent may not have much understanding of the financial assets the household owns and may undervalue (or overvalue) wealth. In other cases, however, the new financial respondent may have much greater understanding of the financial assets because the death of a spouse (or divorce) has caused assets to be consolidated and professionally valued.

Measurements of changes in wealth also suffer from regression-to-the-mean. Families that overstate their wealth in period one will tend to report lower wealth in period two. Similarly, families that understate their wealth in period one will tend to report higher wealth in period two. The net result of this error is that it can show families in the lower part of the wealth distribution with wealth increases and those in the upper part of the wealth distribution with wealth declines, solely as a result of reporting error. Given the failure of alternate models to measure changes in wealth over time and the severe problems with regression-to-the-mean in panel data sets, we opted for the random-effects model.

3. Estimating Housing Wealth at Age 50

For estimating and projecting housing wealth, we created a family-year file for all years between 1972 and 1993. We limited the sample to families with heads between ages 30 and 60 with fewer than two years of missing earnings from age 30 and over and non-missing home equity. This yielded a file of 57,257 family-years. We estimate separate models for home ownership status and housing wealth. For home ownership status, we estimate two models – a hazard model for buying a home and a hazard model for selling a home. We then estimate a housing wealth model from a sample limited to homeowners.

Housing Hazard Models

The housing hazard models explain net purchases and sales of homes. We do not count as a purchase or sale transactions in which an individual or couple sells one home in order to acquire another.[4]

For the home purchase hazard model, we limit the sample to families "at risk" of buying a home—that is, those who did not own a home in the prior year. This yields a sample of 23,009 family-years. Within this sample, we observe a home purchase in about 9 percent of the family-year cases.

We use a logistic regression model to estimate the probability that a family buys a home at time t given no home at t-1 (see Table 6-1). We include in the model linear and quadratic terms for family present value of earnings. We also include a measure of the number of years the family head has earnings above the 2.46 times the average wage to tease out the impact of the MINT censored data on the home purchase probability. We include current earnings (divided by the economy-wide average wage) for both heads and spouses. (The current spousal earnings variable is zero for unmarried individuals.) We include an indicator for the family head being never married and married (the omitted group includes divorced, separated, and widowed heads).

[4] We are ultimately interested in projecting home equity of homeowners. We are not interested in distinguishing home trading for this projection.

Table 6-1
Hazard of Buying a Home

	Parameter Estimate	Standard Error	Pr > Chi Square	Odds Ratio
Intercept	-3.2444	0.0982	<.0001	
Family present value earnings / cohort average	0.5386	0.1061	<.0001	1.714
Family present value earnings / cohort average squared	-0.0649	0.0261	0.0130	0.937
Years with earnings above 2.46* average wage	0.0301	0.0133	0.0236	1.031
Head earnings at t0 / average wage	0.4606	0.0537	<.0001	1.585
Wife earnings at t0 / average wage	0.2323	0.0700	0.0009	1.261
Never Married	-0.3814	0.0951	<.0001	0.683
Black	-0.3834	0.0542	<.0001	0.682
Number of children under 18	0.0837	0.0181	<.0001	1.087
First child born	0.6470	0.1151	<.0001	1.910
Head self-employed	0.2787	0.0846	0.0010	1.321
Years divorced	-0.0216	0.00636	0.0007	0.979
Married couple	0.1454	0.0756	0.0544	1.156

Source: The Urban Institute estimates from the PSID.

We include an indicator for the birth of the first child and for the number of children under age 18 in the family. We also include an indicator for the family head being black.

The estimated probability of buying a home in any year is:

- Increasing as the family's present value of earnings relative to the head's cohort increases, but at a declining rate, and is higher for families with more years of earnings above 2.46 times the average wage;
- Increasing as both the head's and wife's current earnings increase;
- About 32 percent lower for never married individuals than for widows and divorced heads;
- About 16 percent higher for married couples than for widows and divorced heads;
- About 32 percent lower for blacks compared to non-blacks;
- About 9 percent higher for families with children under age 18 than for other families and about 91 percent higher in the year of birth of a first child compared to other years.

We experimented with age terms, but age indicators were generally not statistically significant due to the high correlation of age and marital status and child bearing, all of which are in the model. We also found that head's education was not statistically significant, probably because of the high correlation between education and earnings.

For the home sale hazard model, we limited the sample to families at risk of selling a home—that is, those who did own a home in the prior year. This yielded a sample of 38,130 family-years. Within this sample, we observe a home sale in about 4.4 percent of the cases. A home sale requires at least one year of non-home ownership. Families that buy and sell a home in the same year are not flagged as selling a home.

We used a logistic regression model to estimate the probability that a family sells a home at time t given no home at t-1 (see Table 6-2). We include in the model linear and quadratic terms for family present value of earnings. We include current earnings (divided by the economy-wide average wage) for both heads and spouses. (The current spousal earnings variable is zero for unmarried individuals.) We include a linear term in age (age-30) and age interaction terms with Hispanicity and self-employed. We include an indicator for the head being married, widowed, or a single female. We also include an indicator for whether the individual was divorced within the last two years and between three to four years (the omitted group is never married men and those divorced more than 4 years). We include an indicator for the birth of the first child and for the number of children under age 18 in the family.

The estimated probability of selling a home in a given year is:

- Lower for families with higher income, but at a decreasing rate, and it increases with a sharp decline in cross-sectional earnings.
- Declines with age, but at a slower rate for Hispanics and a faster rate for self-employed family heads.[5]
- Lower for singles than for couples and lower for single females than for single males.
- Higher for individuals divorced within the past four years than for other individuals and couples. The impact of divorce on home sale is higher directly after the divorce and declines as divorce duration increases.
- Higher the year the first child is born, but lower as the number of young children in the family increases.

[5] Hispanics may be more likely to relocate compared to non-Hispanics. Respondents who emigrate are not in the sample after leaving the country and do not contribute to the positive parameter estimate.

Table 6-2
Hazard of Selling a Home (age 30-60)

	Parameter Estimate	Standard Error	Pr > Chi Square	Odds Ratio
Intercept	-0.5469	0.1274	<.0001	
Family present value earnings / cohort average	-0.6695	0.1154	<.0001	0.512
Family present value earnings / cohort average squared	0.1334	0.0283	<.0001	1.143
Head Earnings/Average Wage at t0	-0.3154	0.0584	<.0001	0.729
Wife Earnings/Average Wage at t0	-0.3424	0.0923	0.0002	0.710
Head age for Hispanics	0.0103	0.00307	0.0008	1.010
Head age for self-employed heads	-0.00849	0.00225	0.0002	0.992
Head age minus 30	-0.0543	0.00353	<.0001	0.947
Married	-1.1636	0.1037	<.0001	0.312
Widowed	-0.3055	0.1263	0.0156	0.737
Never married female	-0.7921	0.0874	<.0001	0.453
Divorced within the last two years	1.9941	0.0901	<.0001	7.346
Divorced between 3 to 4 years	0.7179	0.1297	<.0001	2.050
First child born	0.4692	0.1887	0.0129	1.599
Number of children under 18	-0.0772	0.0249	0.0019	0.926

Source: The Urban Institute estimates from the PSID.

Home Equity of Married Couples

We estimated separate models of housing wealth for married couples and single individuals. We estimated home equity (value – debt) for married couples with a head between ages 30 and 60 using a random-effects model with the natural logarithm of family home equity divided by the average wage as the dependent variable (see Table 6-3). We included only families with positive home equity in the equation. We omitted observations with home equity above the 99th percentile of equity because these extremely high values have excessive influence on the regression means. Families included in the regression had on average 8.2 years per family head in the PSID panel. The maximum number of years a family was in the panel was 20 and the minimum was one.

Age Variables. We included piece-wise linear age splines at five-year intervals from age 30 to 60. These are set so that as age increases the age slope changes at varying rates at each kink.[6] Each coefficient shows the difference between the annual growth rates (with age) of wealth in the age spline and the previous age spline. Predicted home equity rises with age, though the slope increases and decreases slightly through the age progression. (The separate age spline coefficients after age 35 are not statistically significant, but the group of age splines taken together is statistically significant.)

Unchanging Shift Variables. We included an identifier for high school dropout wives. Couples with dropout wives have about 11 percent lower home equity compared to couples with higher-educated wives. We also included a set of cohort identifiers with the 1930 to 1934 cohorts as the omitted group. Home equity, controlling for earnings, declines for cohorts born after 1934.[7] While some of the specific cohort identifiers are not significant by themselves, they are significant as a group.

Changing Shift Variables. We included as explanatory variables a linear term for family present value of earnings. We also included a count of the number of years a worker in the couple had earnings above 2.46 times the average-wage and the average wage-adjusted earnings in the past 6 years for both the husband and wife. Finally, we included marriage duration (projected in MINT), an indicator for whether the family had one to two children and three or more children under age 18 in the household as explanatory variables.

[6] Each age spline is max(0, age-NN) where NN is 30 for the age30 spline, 35 for the age35 spline, and so forth.

[7] Some of the decline in home equity in later cohorts reflects the increased prevalence of 30-year mortgages over time. Another factor could be the rapid increase in housing values in the 1960s and 1970s, which raised the net housing wealth for earlier cohorts. Finally, the cohort effects (with age held fixed) reflect the increasing use of home equity loans over time. To some extent, this reflects a problem in measuring the relative size of net housing wealth and net non-housing wealth. Since the Tax Reform Act of 1986 eliminated deductibility of consumer interest, people have increasingly used home equity loans (still deductible up to $100,000 per year) to finance cars and other household durable goods. This loan re-characterization makes housing wealth look smaller, and non-housing wealth look larger compared to how they would look if people continued to use cars and other consumer durable goods as collateral for their loans.

Table 6-3
Random Effects Model for Home Equity for Couples Age 30-60
Dependent Variable Log (Home Equity /Average Wage)

	Parameter Estimate	Standard Error	P-Value
Family present value earnings / cohort average	0.14840	0.01954	0.000
Husband mean earnings/ Average wage (t-5 to t0)	0.23553	0.01674	0.000
Wife mean earnings/ Average wage (t-5 to t0)	0.05209	0.01898	0.006
Years with earnings above the taxmax	0.01543	0.00242	0.000
Husband age spline (age-30)	0.03791	0.00480	0.000
Husband age spline (age-35)	-0.01713	0.00593	0.004
Husband age spline (age-40)	-0.01006	0.00615	0.102
Husband age spline (age-45)	0.01407	0.01073	0.190
Husband age spline (age-48)	-0.01517	0.01976	0.443
Husband age spline (age-50)	0.00804	0.01796	0.655
Husband age spline (age-55)	-0.00717	0.01271	0.573
Husband born 1935 to 1939	-0.09685	0.07105	0.173
Husband born 1940 to 1944	-0.06231	0.06632	0.347
Husband born 1945 to 1949	-0.04625	0.06019	0.442
Husband born 1950 to 1954	-0.25481	0.05964	0.000
Husband born 1955 to 1959	-0.42164	0.05696	0.000
Head age by black	-0.00878	0.00088	0.000
Head age by college	0.00467	0.00071	0.000
Head age by self-employed	0.00225	0.00039	0.000
Head age by work limitation	0.00089	0.00037	0.017
Number of years married	0.00980	0.00312	0.002
Wife high school dropout	-0.10630	0.02612	0.000
One to two children	0.07516	0.01411	0.000
Three or more children	0.06203	0.01937	0.001
Intercept	-0.52423	0.06730	0.000
Standard error of the individual-specific error term	0.77391		
Standard error of the random error term	0.57114		
Fraction of variance due to individual-specific error	0.64740		
Number of observations	26497		
Number of groups	3230		
Model overall r-squared	0.3138		

Source: The Urban Institute estimates from the PSID.

Home equity increases as the family present value of earnings increases. More years of very high earnings raises home equity; for every year an earner has earnings above 2.46 times the average wage, home equity increases by about 1.5 percent. As recent earnings of husbands and wives increase, where recent earnings is measured as the average indexed earnings over the last 6 years, home equity increases. Finally, home equity increases with the number of years a couple has stayed married, and couples with children have higher home equity compared to couples without children.

Age-Interaction Terms. We included a set of age-interaction terms. These include the products of the husband's age and dummy variables indicating whether the husband is black, is Hispanic, has a college degree, is self-employed, and has a work limitation.

The estimates show that black couples increase home equity as they age at a slightly lower rate than non-black couples. College educated and self-employed couples increase their home equity at higher rates than lower educated and nonself-employed couples. Couples where the husband has a work limitation increase their wealth at a slightly higher rate compared to couples without work limited husbands. If the impact of the limitation is to reduce earnings relative to the cohort, then work limited couples will have lower wealth than the nonlimited couples (through both the present value and recent earnings measures). But housing wealth for them will increase at a faster rate (or decline at a slower rate) than for nonlimited couples with the same earnings.

Overall, the model explains about 31 percent of the variance in home equity among couples, and the individual-specific error term explains about 65 percent of the variance. The standard error of the individual-specific error is 0.77 and the standard error of the random error is 0.57. Given the large proportion of the variance due to the individual-specific effect, it will be important in the projections to assign this factor properly. We discuss how we assign individual-specific effects in Section II.5 below.

Home Equity of Singles

We also estimate home equity for single individuals between ages 30 and 60 using a random-effects model, with the natural logarithm of family home equity divided by the average wage as the dependent variable (see Table 6-4). We limit the model to families with positive home equity. We omit observations with home equity above the 99^{th} percentile of equity. Single heads have on average 4.5 years in the panel. This is about 3.7 years less than the average duration in the panel for couples. Much of this difference in panel duration is attributable to the fact that for many people single status comes in two phases: time before marriage, and time after marital dissolution. As a result, consecutive years of single status may be lower than the total number of years an individual is in the database.

Age Variables. As with couples, home equity for singles increases with age, and compared to couples, the annual percentage increase is on average lower at younger ages and higher at older ages. While the age splines are not individually statistically significant, they are significant as a group at the 95 percent confidence level.

Table 6-4
Random Effects Model for Home Equity for Singles Age 30-60
Dependent Variable Log (Home Equity /Average Wage)

	Parameter Estimate	Standard Error	P-Value
Former spouse present value of earnings/cohort average	0.24802	0.07596	0.001
Family present value earnings / cohort average	0.12982	0.06522	0.047
Head mean earnings /Average wage (t-5 to t0)	0.13682	0.05772	0.018
Number of years with earnings above the taxmax	0.03661	0.00903	0.000
Widowed dummy	0.15211	0.05829	0.009
Head age spline (age-30)	0.02403	0.01107	0.030
Head age spline (age-35)	0.00590	0.01717	0.731
Head age spline (age-40)	-0.00495	0.01592	0.756
Head age spline (age-45)	0.02315	0.02381	0.331
Head age spline (age-48)	-0.01521	0.04018	0.705
Head age spline (age-50)	-0.01270	0.03466	0.714
Head age spline (age-55)	-0.00499	0.02281	0.827
Head age * black	-0.00285	0.00137	0.037
Head age * Hispanic	0.00667	0.00324	0.040
Head age * college graduate	0.00241	0.00159	0.129
Head age * never married	0.00215	0.00177	0.225
Intercept	-0.68828	0.07035	0.000
Standard error of the individual-specific error term	0.89910		
Standard error of the random error term	0.64706		
Fraction of variance due to individual-specific error	0.65879		
Number of observations	6511		
Number of groups	1462		
Model overall r-squared	0.1936		

Source: The Urban Institute estimates from the PSID.

Changing Shift Variables. As with couples, home equity for singles increases as their family present value of earnings divided by the cohort average increases, where family present value of earnings includes earnings (while married) of former spouses. Home equity is especially sensitive to the former spouse's earnings. Former spouse's earnings relative to family earnings rises the more the former spouse worked and the longer the couple was married. While all the independent variables in the model explain only 20 percent of the variance in home equity, the former spouse's earnings variable alone explains about 4 percent of the variance.

Home equity also increases with the growth in earnings of the individual. Home equity is about 4 percent higher for every year the individual's earnings were above 2.46 times the average wage. Widows have about 15 percent higher home equity than never-married and divorced individuals, in part because they probably inherited the home and other wealth at the death of the spouse.

Unchanging Shift Variables. The single model for home equity does not include any unchanging shift variables. Both cohort identifiers and young children in the household were not statistically significant in the regression.

Age-Interaction Terms. As with couples, single home equity for blacks rises with age at a slightly slower rate than for non-blacks. Home equity for Hispanics rises with age at a slightly higher rate than for non-Hispanics. Home equity rises more steeply for college-educated singles than for less-educated singles. Home equity rises with age at a slightly higher rate for never married singles than for divorced and widowed singles.

4. Estimating Wealth in Non-Pension Financial Assets at Age 50

For non-pension financial assets, we estimate separate equations for married couples and single individuals. We include in the estimation sample data from the three years the PSID asked the special wealth topical module (1984, 1989, and 1994). As with home equity, we constructed a family-year file with family heads ages 30 and older born in 1930 or later. This yielded a sample of 11,203 family-years. Financial assets in the model include balances in savings, money market, and checking accounts, certificates of deposit, savings bonds, values of stocks and mutual funds (including IRAs), equity in residential property (other than own residence), vehicle equity, and business equity, less unsecured debt (credit card debt, doctor bills, and other unsecured debt).

Financial Assets of Married Couples

We estimated net non-pension financial assets of married couples with a head between ages 30 and 60 using a random-effects model with the natural logarithm of family non-pension assets divided by the average wage plus 0.2 as the dependent variable (see Table 6-5).[8] We limit the model to families with positive transformed assets below the 99th percentile of financial assets. Of the 3,285 couples in our sample, married couples had on average 2.0 observations (out of a possible 3) per family head in the panel.

[8] Dependent variable = Log((financial assets/average wage) +0.2). We omit 589 families (about 4 percent of cases) with non-pension debt below 20 percent of the average wage.

Table 6-5
Random Effects Model for Non-Pension Assets for Couples Age 30-60
Dependent Variable Log(Non-Pension Assets /Average Wage + 0.2)

	Parameter Estimate	Standard Error	P-value
Bought home in last 5 years	-0.2376	0.0516	0.000
Sold home in last 5 years	0.1638	0.0856	0.056
Per capita present value earnings / cohort average	0.7172	0.0581	0.000
Husband mean earnings (t5 to t0)	0.2298	0.0373	0.000
Years with earnings above the taxmax	0.0441	0.0056	0.000
Head age spline (age-30)	0.0328	0.0107	0.002
Head age spline (age-35)	-0.0075	0.0175	0.670
Head age spline (age-40)	-0.0114	0.0183	0.533
Head age spline (age-45)	0.0018	0.0225	0.935
Head age spline (age-50)	0.0098	0.0268	0.713
Head age spline (age-55)	-0.0207	0.0257	0.420
Wife age by self-employed	0.0048	0.0013	0.000
Wife age by high school dropout	-0.0030	0.0013	0.017
Wife age by college graduate	0.0070	0.0012	0.000
Head age * homeowner	0.0091	0.0011	0.000
Head age * black	-0.0099	0.0011	0.000
Head age * high school dropout	-0.0042	0.0013	0.001
Head age * self-employed	0.0222	0.0010	0.000
Intercept	-1.3672	0.0581	0.000
Standard error of the individual-specific error term	0.7318		
Standard error of the random error term	0.8301		
Fraction of variance due to individual-specific error	0.4373		
Number of observations	6436		
Number of groups	3285		
Model overall r-squared	0.43		

Source: The Urban Institute estimates from the PSID.

The model for financial assets is similar to the model for home equity, but with some differences. We replaced family present value of earnings with the present value of per capita earnings because the latter measure provided a better statistical fit. We also included an indicator for whether the family bought or sold a home over the 5-year duration between interviews. We used the 1979 home ownership variable to construct the lagged home ownership status for 1984.

Age Variables. Predicted financial assets rise with age with relatively little variation over the 30 to 60 age range, although the age slope does decline slightly after age 55. The age splines are significant as a group at the 95 percent confidence level.

Changing Shift Variables. Financial assets are higher for higher values of the per capita present value of earnings (divided by the cohort average), mean head earnings in the current and prior five years, and the number of years with earnings above the taxable maximum.[9] Financial assets are about 16 percent higher for couples who sold a home within the past 5 years and about 24 percent lower for couples who purchased one in the past five years.

Age-Interaction Terms. Financial assets rise faster with age for homeowners compared with renters, self-employed husbands and wives compared with wage and salary employees, and wives with a college degree compared with wives without a college degree. Both husbands and wives who are high school dropouts accumulate less wealth per additional year of age than their counterparts with high school diplomas. Financial assets increase for blacks at a slightly lower rate compared to non-blacks.

Overall, the independent variables in the model explain about 43 percent of the variance in financial assets, and the individual-specific error term explains about 44 percent of the variance. The standard error of the individual-specific error is about 0.73 and the standard error of the random error is 0.83. These standard errors are larger than the standard errors for home equity, reflecting the larger variance in financial assets compared with home equity.

Financial Assets of Singles

As with couples, we estimated non-pension financial assets for single individuals between ages 30 and 60 using a random-effects model with the natural logarithm of financial assets divided by the average wage plus 0.2 as the dependent variable (see Table 6-6). We limited the model to families with positive transformed financial assets below the 99th percentile of financial assets. Of the 3,974 singles in our sample, single heads had on average 1.6 observations in the panel.

[9] Replacing the present value of per capita earnings with the family present value of earnings renders the cohort identifiers insignificant. This is probably due to the increased influence of wives earning for later cohorts that the per capita measure does not capture. Because the cohort is unchanging over time, all cohort differences are picked up in the individual-specific effect if they are omitted in the model.

Table 6-6
Random Effects Model for Non Pension Assets for Singles Age 30-60
Dependent Variable Log (Non-Pension Assets/Average Wage + 0.2)

	Parameter Estimate	Standard Error	P-value
Per Capita present value of earnings / cohort average	0.56530	0.06580	0.000
Head mean earnings (t-5 to t0)	0.22611	0.05910	0.000
Years with earnings above the taxmax	0.06556	0.00978	0.000
Head age spline (age-30)	0.03182	0.01302	0.015
Head age spline (age-35)	0.00092	0.02266	0.967
Head age spline (age-40)	0.00017	0.02520	0.995
Head age spline (age-45)	-0.01417	0.02870	0.621
Head age spline (age-50)	-0.00092	0.03046	0.976
Head age spline (age-55)	0.00449	0.02764	0.871
Husband born 1935 to 1939	0.15589	0.08881	0.079
Husband born 1940 to 1944	0.35591	0.09882	0.000
Husband born 1945 to 1949	0.30050	0.10796	0.005
Husband born 1950 to 1954	0.35308	0.11159	0.002
Husband born 1955 to 1959	0.44188	0.11645	0.000
Husband born 1959 to 1969	0.57806	0.12297	0.000
Head age * home owner	0.00758	0.00089	0.000
Head age * black	-0.01066	0.00098	0.000
Head age * Hispanic	-0.00757	0.00248	0.002
Head age * high school dropout	-0.00251	0.00109	0.021
Head age * college graduate	0.00410	0.00132	0.002
Head age * self-employed	0.01509	0.00159	0.000
Head age * never married	0.00190	0.00114	0.095
Widowed	0.31316	0.06215	0.000
Intercept	-1.98874	0.12686	0.000
Standard error of the individual-specific error term	0.5674		
Standard error of the random error term	0.7963		
Fraction of variance due to individual-specific error	0.3368		
Number of observations	3974		
Number of groups	2450		
Model overall r-squared	0.4027		

Source: The Urban Institute estimates from the PSID.

The financial asset model for singles is similar to that for couples. Indicators for buying and selling a home were not significant for singles, so they are not included in the final equation. We included an age interaction term with never married status and a widowed identifier. Age slopes for divorced versus widowed were not different and are combined in the omitted category. Neither having a work limitation nor poor health was significant and are not included in the model. To the extent these characteristics affect wealth, they are picked up in the measures of earnings.

Age Variables. Financial assets increase with age. Controlling for earnings, financial assets rise faster between age 30 and 45 and then more slowly after age 45. The age splines as a group are statistically significant at the 95 percent confidence level.

Age Interaction Terms. Blacks and Hispanics increase their financial assets at a slower rate with age than white non-Hispanics. Single individuals with less than a high school education increase their wealth at a slower rate than high school graduates, while college educated and self-employed singles increase their financial assets at a steeper rate than non-graduates and wage and salary employees. Never married singles increase their financial assets at a slightly faster rate than widowed and divorced singles.

Unchanging Shift Variables. Individuals born after 1934 have more financial assets than individuals born between 1930 and 1934. The cohort identifiers are significant as a group at the 95 percent confidence level.

Changing Shift Variables. Financial assets for single individuals increase with the per capita present value of earnings, average earnings in the last 6 years, and number of years with earnings above 2.46 times the average wage. Also, widows have about 31 percent more financial assets at each age compared to other divorced and never married individuals reflecting most probably inheritance that other singles do not enjoy.

Overall, the independent variables in the model explain 40 percent of the variance in financial wealth and the individual-specific effect explains 33 percent of the variance.

5. Assignment of the Individual-Specific Error Term

We estimated the models on the PSID, but need to do the projections on the SIPP. This requires making some assignment of the individual-specific effect to the SIPP sample. We observe financial assets in the SIPP, and can calculate predicted values of housing and financial assets for the base year and compare them to the actual values. One possibility is to assume that 100 percent of the observed error (actual wealth - predicted wealth) is the individual-specific effect. This is the procedure we used in the projections in MINT1. The MINT1 procedure was a simplification that was better than ignoring the observed value altogether and simply using the projection equation to generate wealth in a future year. But, in fact, the difference between actual and predicted wealth includes both the individual-specific effect and a random error. In MINT3, we use a statistical match procedure to impute individual-specific effects to the SIPP projection sample from the estimates on the PSID sample.

We statistically matched individual-specific error terms for housing from the PSID sample to the SIPP sample by finding the PSID observation within the same family present value of earnings decile with the most similar values of predicted home equity and observed home equity. We minimized a distance function of the form:

$$D_i = (X_{di} - X_{ri})^2 + (Y_{di} - Y_{ri})^2 \mid P_{di} = P_{ri} \qquad (6.2)$$

where D is the distance, X is the predicted home equity, Y is the actual home equity, P is the family present value of earnings decile, d is the donor (PSID) value, r is the recipient (SIPP) value, and i is an individual identifier. We assign an individual-specific error term to all individuals on the SIPP sample, regardless their homeowner status at the SIPP interview. Non-home owners on the SIPP should match PSID donors who are not homeowners in the particular period, but who become homeowners. We used an identical procedure for assigning the individual-specific error term for financial assets.

6. Projecting Housing and Financial Assets to Age 50

In projecting housing assets to age 50, we age people from their observed SIPP interview age to 50 in one-year increments. Homeowners are subject to the annual home sale hazard, and non-homeowners are subject to the home purchase hazard. If the hazard probability is greater than a uniform random number, the family changes their home status.

We then project the home equity for those individuals projected to own a home. For homeowners, the predicted value is XB + Eu + Ei, where XB is the sum of the Xi times Bi, Eu is the imputed individual-specific error, and Ei is a normal random number with the standard error from the random-effects estimates. In order to ensure consistent projections for intact couples at the SIPP interview, we use a transformation of the husband's random access record count for the seed in the random number generator. Thus, husbands and wives will buy and sell homes in the same year and will have the same predicted home equity and financial assets.

For projecting non-pension financial assets to age 50, we use a similar procedure, except that we do not age wealth year by year. Instead, we project wealth at age 50, based on the equations in Tables 6-5 and 6-6 and the imputed individual-specific errors. The age interaction terms other than age 50 are important only in improving the overall model fit and the selection of the individual-specific error.

For individuals who are over age 50 at the SIPP interview, we do no projections using the equations estimated from the PSID. Their wealth in the first year available is simply the wealth reported on the SIPP. We do, however, assign individual-specific error terms to them. These individual-specific error terms are necessary to generate projections for wealth changes beyond the base year from the equations that project wealth accumulation and spend down for older individuals.

III. PROJECTING WEALTH FROM AGES 51 TO 63

1. The Health and Retirement Study (HRS) Data

The HRS is a national panel study, begun in 1992, of 7,600 households with sample respondents born between 1931 and 1941 (51- to 61-year-olds in 1992) and their spouses. These sample respondents are interviewed at two-year intervals. Currently, there are four waves of the panel available (1992, 1994, 1996, and 1998) with sample respondents being 57- to 67-years old in 1998. The HRS over-samples Hispanics, blacks, and Florida residents. Like the SIPP, the HRS has been linked to the Social Security Administration Summary Earnings Records (SER) and Master Beneficiary Record (MBR). These linked data, however, are restricted to the first two waves of the HRS. Because of the importance of lifetime earnings in our models, we were limited to using the only the first two waves. This limitation means that we really observe families between ages 51 and 63, although including spousal characteristics in the married couple regressions gives us some information about younger and older individuals. We did explore looking at changes in wealth across the four waves without the earnings measure, but the wealth data are too unstable between waves for individuals, as discussed above. None of our models that estimated changes in wealth proved informative.

The HRS asks the most knowledgeable person in the family about the family's financial assets. This includes the following:

- checking, saving, and money market balances;
- certificates of deposit, government bonds, and treasury bills;
- bonds and bond funds;
- IRA and Keogh balances;
- stocks and mutual fund values;
- home equity;
- vehicle equity;
- business equity;
- other real estate equity;
- unsecured debt; and
- defined contribution plan balances.

We constructed a family-year file from the first two waves of the HRS. We obtained 6,946 families from the first wave and 6,389 families from the second wave. For individuals who do not have an SER earnings record, we imputed lifetime earnings using a statistical matching algorithm (see appendix for more details).

We constructed the present value of earnings from age 20 and older on the HRS using the SER earnings. We use a real rate of return of 2.7 percent. Unlike the PSID, we do not observe earnings of former spouses. We do, however, observe the earnings of the current spouse from before the marriage began. We divide each person's present value of earnings by their age and cohort-specific average present value of earnings. For couples, the family's present value of earnings divided by the cohort average is the sum of the husband's present value of earnings divided by the cohort average and the wife's present value of earnings divided by the cohort average.

2. Estimating Assets From Age 51 To 63

We use the PSID-based equations to project assets to age 50. From age 51 to the Social Security early retirement age, we project wealth using the coefficients of random-effects models estimated on the HRS. The HRS models use the same functional form as the PSID models represented by equation (6.1) above.

For these estimates, however, we project wealth changes on a year-by-year basis. To do this, we use the HRS cross-sectional estimates and apply the percent change in wealth implicit in the age slopes and change in earnings variables. The basic random-effects model shown in equation 6.1 can be applied to calculate change in wealth as follows:

$$W_{it} - W_{it-1} = [\alpha + X_{it}\beta + v_i + \varepsilon_{it}] - [\alpha + X_{it-1}\beta + v_i + \varepsilon_{it-1}], \tag{6.3}$$

This solves to the following:

$$W_{it} - W_{it-1} = [X_{it} - X_{it-1}]\beta + [\varepsilon_{it} - \varepsilon_{it-1}], \tag{6.4}$$

Calculating changes in wealth from the base age 50 value is just a matter of determining the change in the X variables and change in the random error term. We obtain a significant amount of heterogeneity in these wealth changes by including a number of time-varying variables in the equations. In the HRS equations, these variables include the following: earnings, disability status, health status, marital status, pension status, and homeowner status.[10]

In each of the models described below, we experimented with three measures of relative present value of earnings, each based on the individual observation's earnings divided by the cohort average. These measures are own present value of lifetime earnings, spouse present value of lifetime earnings, and family (husband plus wife) present value of lifetime earnings. In each equation, we use the earnings measure that contributes the most to predicting wealth.

Because the HRS interviews spouses of age eligible couples, we do observe couples with husbands older than age 63 in the second wave. We have included these couples in an effort to tease out the age-slopes of older individuals. In all cases, however, there is an age eligible respondent in the family. We characterize the HRS models as estimates for the age 51 to 63 population; in fact, they cover a slightly wider age range.

3. Projections of Homeownership and Housing Wealth to Retirement

We project homeownership status to age 65, using the hazard model estimated on the PSID to project net home purchases and sales (see Section II.3). At the projected sale of a home, we shift all of the home equity into financial wealth. At the purchase of a home, we subtract the

[10] We include self-employment in the age interaction terms, but have not implemented a self-employment hazard model in MINT3. Individuals keep their initial SIPP interview self-employment status.

home equity from financial wealth. After age 65, we assume homeownership status remains unchanged.

If a couple divorces, both the husband and wife are subject to the home sale hazard model, with independent random seeds. Each partner keeps half of the assets. If the husband is projected to sell his home, and the wife is not, for example, the husband has his financial assets increased by his share of the home equity. The wife keeps her home equity constant, before accounting for changes in earnings and marital status. Both the husband and wife, however, have half their prior family wealth.

Home Equity of Couples

We used the HRS to estimate home equity for married homeowners from ages 50 to 63 (Table 6-7). As with the PSID, we used a random-effects model with the logarithm of home equity divided by the average wage as the dependent variable.

Age Variables. The HRS-based model for couple home equity includes a linear term for the age of the husband. Other measures of age (except for age-interaction terms) such as age splines or age squared were not statistically significant. Couple housing equity as a percent of the average wage increases by about 3 percent per year with age, holding all other variables constant.

Unchanging Shift Variables. Compared with couples where the wife is a high school graduate, couples have 16 percent less home equity if the wife is a high school dropout, 12 to 13 percent more home equity if the wife is college graduate or has post-graduate training.

Changing Shift Variables. Housing equity is higher for couples where the husband has a high present value of earnings, relative to the cohort average. The husband's present value of earnings was used in the model because it had greater explanatory power than the family present value of earnings.[11]

Age-Interaction Terms. The change in housing equity with age depends significantly on a number of characteristics of the household. Couple home equity increases at a higher rate for husbands with a DC pension or DB pension than those with no pension, college graduate husbands than lower-educated husbands, and self-employed husbands than nonself-employed husbands. Couple home equity increases at a slower rate (or decrease at a faster rate) if the husband is black compared to non-black, a high school dropout compared to high school graduates, and for each child the couple has ever had.

We have not included any specific controls for retirement in the model. Families that retire early typically have higher wealth than those that retire later. Using retirement as an explanatory variable would thus be subject to simultaneous-equations bias. It would show retirement associated with higher wealth, while in fact early retirement is likely to reduce the growth of wealth or make wealth decline.

[11] The earnings above the Social Security cap variable was not significant and is not included in the home equity model.

Table 6-7
Random Effects Model for Couple Housing Wealth Age 50 to 63
Dependent Variable Log(Home Equity /Average Wage)

	Parameter Estimate	Standard Error	P-value
Head present value of earnings/cohort average	0.16005	0.01913	0.000
Husband age	0.02970	0.00261	0.000
Husband age * poor health	-0.00083	0.00041	0.040
Husband age * have DC pension	0.00222	0.00039	0.000
Husband age * have DB pension	0.00091	0.00035	0.009
Husband age * husband self-employment	0.00334	0.00048	0.000
Husband age * black	-0.00532	0.00070	0.000
Husband age * college graduate	0.00365	0.00060	0.000
Husband age * high school dropout	-0.00383	0.00056	0.000
Husband age * number of children ever had	-0.00051	0.00011	0.000
Wife high school dropout	-0.16000	0.03467	0.000
Wife college graduate	0.12634	0.05120	0.014
Wife post college graduate	0.11903	0.05224	0.023
Intercept	-1.05322	0.15704	0.000
Standard error of the individual-specific error term	0.73958		
Standard error of the random error term	0.43147		
Fraction of variance due to individual-specific error	0.74607		
Number of observations	7283		
Number of groups	4152		
Model overall r-squared	0.1602		

Source: The Urban Institute estimates from the HRS.

The present value of earnings variable to some degree captures the effects of the shift in employment status on equity build-up. In general, wealth in the HRS cross-section is higher for people with higher lifetime earnings, relative to their cohort. Retirement will lead to a decline over time in the relative present value of lifetime earnings of the retiree. Thus, retirement in the model *indirectly* affects the projection of wealth through its effect on earnings.

We have some concerns about using the coefficients on DB and DC pension indicators in the projections even though they are significant. As the parameter estimates show, families with a DC pension accumulate housing equity faster than families with a DB pension, who accumulate housing faster equity than families with no pension. This may simply reflect the fact that families with a taste for saving are more likely to have both pension plans and more non-pension wealth. Over time there has been a shift in the types of pensions workers receive—away from DB pensions and towards DC pensions. As this shift continues for later cohorts in the MINT population, it will cause the model to project more home equity and other financial assets than it would otherwise project. While it is reasonable to project that individuals with DC pensions are likely to have more other wealth than individuals without DC pensions, it may not be reasonable to project that expansion of DC pensions will cause total non-pension wealth to increase. We examine the sensitivity of the projections to alternate assumptions on pension slopes in section VII.2 in this chapter.

Home Equity of Singles

The HRS-based model for the logarithm of single home equity divided by the average wage is shown in Table 6-8. The following variables predict home equity of individuals:

Age Variables. Age enters as a simple linear variable. As with couples, other measures of age (except for age-interaction terms) such as age splines or age squared were not statistically significant. Individuals are estimated to have about 1.5 percent more home equity as a percent of the average wage per year as their age increases from 50 to 63.

Changing Shift Variables. Individuals are estimated to have 0.8 percent more housing equity for each year they were previously married. (This is a changing variable because MINT projects divorce or widowhood in different years after age 50.) Individuals' housing equity increases about 2 percent per year the worker has earnings above the taxable maximum (2.46 average earnings). The relative present value of earnings of individuals was not a significant variable in the regression. This presumably reflects the progression of mortgage payments towards home equity that accrues independent from earnings among homeowners for workers below the Social Security cap.

Age-Interaction Terms. Home equity increases with age at a greater rate for individuals with DB or DC pension coverage than for individuals with no pension coverage, for the self-employed than for employees, and for college graduates than for those without a college degree. Home equity increases at a slower rate (or declines at a faster rate) for individuals with more children over their lifetime compared to individuals with fewer children. Home equity also increases at a slower rate for individuals who are in poor health than good health, who dropped out of high school than graduated high school, and are male than female.

Financial Assets of Couples

We estimated net non-pension financial assets for married couples with head between ages 50 and 63 using a random-effects model with the natural logarithm of family non-pension assets divided by the average wage plus 0.02 as the dependent variable (see Table 6-9).[12] We limited the model to families with positive transformed assets below the 99th percentile of financial assets. Of the 8,368 couples in our sample, couples had on overage 1.8 observations (out of a possible two) per family in the panel.

[12] We used a smaller offset for financial assets at older ages to adjust wealth values for debt. This reflects the much smaller share of families with financial debt after age 50 compared to before age 50. We tried different adjustments, but 0.02 fit the data closely. We omit 901 families (about 6 percent of cases) with transformed assets below zero.

Table 6-8
Random Effects Model for Single Housing Wealth Age 50 to 63
Dependent Variable Log (Home Equity /Average Wage)

	Parameter Estimate	Standard Error	P-value
Number of years with earnings above the taxmax	0.01840	0.00505	0.000
Head age	0.01494	0.00682	0.028
Head age * number of children ever born	-0.00087	0.00026	0.001
Head age * poor health	-0.00277	0.00082	0.001
Head age * have DC pension	0.00288	0.00080	0.000
Head age * have DB pension	0.00080	0.00083	0.337
Head age * self-employed	0.00448	0.00129	0.001
Head age * College graduate	0.00351	0.00134	0.009
Head age * high school dropout	-0.00424	0.00119	0.000
Head age * male	-0.00391	0.00127	0.002
Total number of years married	0.00865	0.00244	0.000
Intercept	-0.41236	0.38267	0.281
Standard error of the individual-specific error term	0.92778		
Standard error of the random error term	0.46789		
Fraction of variance due to individual-specific error	0.79724		
Number of observations	2195		
Number of groups	1351		
Model overall r-squared	0.11280		

Source: The Urban Institute estimates from the HRS.

Table 6-9
Random Effects Model for Couple Non-Pension Assets Age 50 to 63
Dependent Variable Log (Non-Pension Assets /Average Wage + 0.02)

	Parameter Estimate	Standard Error	P-value
Husband + wife present value earnings/cohort average	0.09465	0.02758	0.001
Family number of years with earnings above the taxmax	0.02858	0.00250	0.000
Husband age * home ownership	0.02714	0.00403	0.000
Husband age * renters	0.01801	0.00410	0.000
Husband age * poor health	-0.00313	0.00064	0.000
Husband age * family SS DI receipt	-0.00438	0.00087	0.000
Husband age * have DC pension	0.00644	0.00064	0.000
Husband age * have DB pension	0.00107	0.00058	0.066
Husband age * husband self-employment	0.01439	0.00078	0.000
Husband age * black	-0.00930	0.00107	0.000
Husband age * Hispanic	-0.00629	0.00131	0.000
Husband age * college graduate	0.00493	0.00093	0.000
Husband age * high school dropout	-0.00756	0.00086	0.000
Husband age * number of children ever had	-0.00100	0.00016	0.000
Wife age * wife self-employment	0.00655	0.00106	0.000
Wife high school dropout	-0.55288	0.06190	0.000
Wife high school graduate	-0.25759	0.04799	0.000
Intercept	-1.23472	0.24452	0.000
Standard error of the individual-specific error term	1.15513		
Standard error of the random error term	0.80035		
Fraction of variance due to individual-specific error	0.67565		
Number of observations	8368		
Number of groups	4689		
Model overall r-squared	0.3962		

Source: The Urban Institute estimates from the HRS.

Unchanging Shift Variables. Compared with the college graduate wives, couple's financial assets as a percent of the average wage are about 55 percent lower if the wife is a high school dropout and 26 percent lower if the wife is a high school graduate only. Race and ethnicity are included in the model through age-interaction terms as is husband's education. Wife's education, however, fit better as an intercept variable than as a slope variable.

Changing Shift Variables. The family present value of earnings relative to the cohort average has a significant positive effect on wealth, as does the number of years either the husband or wife had earnings above 2.4 times the average wage.

Age-Interaction Terms. Couples who own their home increase financial assets as a percent of the average wage about 2.7 percent per year while renters increase their financial assets by about 1.8 percent per year. Couples with DC or DB pensions increase financial assets at a faster rate than couples without pension coverage. Self-employed husbands and wives increase financial assets faster than wage and salary workers, with the husband's self-employment having a larger contribution. Compared to husbands with a high school degree, financial assets increase at a faster rate for couples with college-educated husbands and at a lower rate if the husband does not have a high school degree.

When the head is in poor health or receiving a Social Security disability benefit, the couple's financial assets increase at a lower rate compared to those in good health. Blacks and Hispanics increase financial assets at a lower rate than non-blacks and non-Hispanics, and families with more children increase financial assets at a lower rate than families with fewer children.

Overall, the independent variables in the model explain 40 percent of the variance in financial wealth and the individual-specific effect explains 68 percent of the variance.

Financial Assets of Singles

The HRS-based model for the logarithm of single non-pension financial assets divided by the average wage plus 0.02 are displayed in Table 6-10. As with couples, we limited the model to single families with positive transformed assets below the 99th percentile of financial assets. Of the 3,923 singles in our sample, they had on overage 1.7 observations (out of a possible two) per individual in the panel.

Changing Shift Variables. The individual's present value of earnings, relative to the cohort average, has a significant effect on wealth, as does the number of years the individual was married.

Age-Interaction Terms. Financial assets increase faster for homeowners than renters, self-employed individuals than wage and salary workers, widowed individuals than those divorced or never married, college graduates than high school graduates, and males than females. Individuals with DC plans accumulate wealth faster than individuals with DB plans who accumulate wealth faster than individuals with no pension coverage.

Table 6-10
Random Effects Model for Single Non-Pension Assets Age 50 to 63
Dependent Variable Log (Non-Pension Assets /Average Wage + 0.02)

	Parameter Estimate	Standard Error	P-value
Present value of earnings/cohort average	0.45477	0.05980	0.000
Head age * home ownership	0.01216	0.00101	0.000
Head age * number of children ever had	-0.00117	0.00028	0.000
Head age * poor health	-0.00633	0.00102	0.000
Head age * have DC pension	0.01463	0.00113	0.000
Head age * have DB pension	0.00419	0.00117	0.000
Head age * self-employed	0.01765	0.00176	0.000
Head age * widowed	0.00401	0.00121	0.001
Head age * black	-0.01153	0.00124	0.000
Head age * college graduate	0.01371	0.00161	0.000
Head age * high school dropout	-0.01236	0.00130	0.000
Head age * male	0.00291	0.00134	0.030
Total years ever married	0.01637	0.00291	0.000
Intercept	-2.00576	0.09519	0.000
Standard error of the individual-specific error term	1.23613		
Standard error of the random error term	0.97193		
Fraction of variance due to individual-specific error	0.61796		
Number of observations	3923		
Number of groups	2310		
Model overall r-squared	0.4805		

Source: The Urban Institute estimates from the HRS.

Financial assets increase with age less rapidly (or decrease faster) the more children an individual has had in his or her lifetime. Financial assets also increase less rapidly (decrease faster) for individuals in poor health than good health, who are black than white, and who dropped out of high school than graduated high school.

Overall, the independent variables in the model explain 48 percent of the variance in financial wealth and the individual-specific effect explains 62 percent of the variance.

IV. ASSET SPEND-DOWN MODEL

For MINT3, we continue to use the MINT1 asset spend-down model. We reiterate these results below (see Toder et al 1999 for more detail). This model was estimated from a synthetic panel constructed from the 1984, 1990 to 1993 SIPP panels linked to the SER and MBR. MINT has a limited number of available characteristics for describing changes in wealth after age 67. These are limited to Social Security income, pension income, marital status, age, and age of death. Variables that others (Haider *et al*, 2000) have found significant in explaining wealth among the very old (medical expenses, ADLs, inheritance or other large wealth transfers, shares of wealth in stocks and bonds) are not projected in MINT. Because of the limited set of explanatory variables available for modeling asset spend-down, it is particularly important to tease out a descriptive age-wealth profile in retirement.

While in the asset accumulation phase, we separately model financial assets and retirement accounts, we combine them in the asset spend-down phase. Our measure of financial assets in retirement is the sum of family IRA, Keogh, and 401(k) balances; vehicle, other real estate, and farm and business equity (value - debt); stock, mutual fund, and bond values; checking, saving, money market, and certificate of deposit account balances, less unsecured debt.

We estimated financial wealth for married couples and single individuals separately. In estimating financial wealth for married couples, we included explanatory variables for both the husbands' and wives' characteristics. We omitted two families with exceptionally high values of financial assets (over 100 times the average wage) from the couple estimation sample. Including these observations might bias the results towards showing a higher average wealth in the year in which these individuals were included relative to the sample years that did not include any very high-wealth individuals.

Single individuals are a diverse group. They include widows from historically high earning families and from low earning families, as well as individuals who are divorced or never married. While we have historical earnings information for individuals in our sample, we do not have data on the historical earnings of former spouses who were absent or deceased at the time of the SIPP panel. Because many women in our estimation cohorts have little or no earnings, their earnings could be a poor predictor of financial assets at retirement, which would depend more on earnings of former spouses. Therefore, for single people, we omit the earnings explanatory variable and depend on family Social Security benefit to control for lifetime earnings. This provides the best, though imperfect, available indicator of the combined lifetime earnings of the individual and any former long-time spouses.

The regression results are displayed in Table 6-11. For married couples, other financial wealth is positively correlated with increased Social Security benefit, home value, pension income, and average indexed earnings between ages 50 and 60. The husband's level of education is positively related to wealth. For the husband, completion of a high school education increases estimated financial wealth by about 44 percent and completion of a college education increases estimated financial wealth by about 66 percent, compared to high school dropouts (the omitted education category in the regressions). The return for women's education is not as large as for men's education, but it is still positive. Compared with high school dropouts, wives'

Table 6-11
OLS Regression Results by Marital Status for Dependent Variable Log Financial Assets Age 62 and Older

Variable	Couples		Singles	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Intercept terms				
Intercept	**-2.523**	0.772	**-1.790**	0.516
Social Security benefit	**1.130**	0.184	**2.524**	0.203
Log of home wealth	**0.405**	0.033	**0.342**	0.032
Head DB pension	**0.726**	0.094	**1.374**	0.117
Wife DB pension	**0.376**	0.228	.	.
Head average earn age 50 to 60	**0.400**	0.073	.	.
Wife average earn age 50 to 60	0.026	0.079	.	.
Male	.	.	0.063	0.062
Divorced	.	.	**-0.366**	0.103
Widow	.	.	**1.924**	0.585
Black	.	.	**-0.904**	0.220
Hispanic	.	.	-0.317	0.189
Head high school	**0.438**	0.064	**0.498**	0.053
Wife high school	**0.426**	0.063	.	.
Head college	**0.658**	0.099	**0.937**	0.096
Wife college	**0.450**	0.119	.	.
Head age initial entitlement	0.011	0.010	**0.016**	0.007
Wife age initial entitlement	**0.019**	0.007	.	.
1906<=head born<=1910	-0.106	0.121	**-0.277**	0.082
1911<=head born<=1916	**-0.290**	0.111	**-0.405**	0.085
1917<=head born+	**-0.437**	0.115	**-0.588**	0.102
Head or wife dies within 27 months	**-0.207**	0.079	**-0.256**	0.085
Slope terms				
Head age by homeowner	**-0.019**	0.003	**-0.016**	0.002
Head age by black	-0.004	0.003	.	.
Head age by white	**0.009**	0.002	**0.007**	0.003
Head age by family get pension	**-0.003**	0.001	.	.
Head age by high earnings			**0.004**	0.001
Head age by widowed			**-0.027**	0.008

Source: The Urban Institute tabulations of the SIPP merged with SER and MBR data.
Notes: Bolded parameter estimates are statistically significant at the 95 percent confidence level.

completion of a high school education increases the couple's estimated financial wealth by about 43 percent and their completion of a college education increases estimated financial wealth by about 45 percent.

Age of initial Social Security entitlement increases the estimated value of other financial wealth. Most families that postpone retirement continue to work and presumably also save. Postponing retirement also increases the Social Security benefit, both due to the effect of the actuarial reduction for early retirement and to the inclusion of a potentially higher level of earnings in the AIME calculation. For a husband, estimated other financial assets increase one percent for every year he waits to collect Social Security. For a wife, estimated other financial assets increase about two percent for every year she waits to collect Social Security.

Financial assets vary among cohorts, but in a complicated way. The first earnings observation we have for any individual is 1951. Therefore, we have fewer earnings observations for each earlier birth cohort. For earlier birth cohorts, the 1951 earnings are for late in the career, and therefore higher on average. These high earnings were subject to a lower taxable maximum, because the taxable maximum was considerably lower in the 1950s than in the 1980s. Social Security beneficiaries first entitled before 1978 (born before 1917) were based on an average monthly wage calculation (AMW). Beginning in 1979, Congress changed the formula for calculating Social Security benefits to be based on the average indexed monthly earnings (AIME). This effectively reduced the Social Security entitlement for those born in 1917 or later. As a political gesture, Congress phased in the effect of the AMW to AIME switch for individuals first entitled to Social Security between 1979 and 1983 (born between 1917 and 1921).

We included cohort identifiers in the model to control for these complex changes. Our results show that husbands born between 1906 and 1910 have about 11 percent lower estimated financial assets compared to husbands born before 1906. Husbands born between 1911 and 1916 have 29 percent lower estimated financial assets compared to husbands born before 1906, and those born after 1917 have 44 percent lower estimated financial assets. These figures indicate the expected wealth in any cohort, controlling for fixed amounts of other independent variables. While not all of the cohort parameter estimates are individually statistically significant at the 95 percent confidence level, the group of cohort parameters estimates is statistically significant. One reason that later cohorts have lower wealth, relative to the other predictors is that they have higher covered earnings than earlier cohorts, reflecting increased Social Security taxes and benefits over time. This occurs because Social Security replaces a larger percent of high earnings (determined by the taxable maximum) for younger than for older cohorts in the estimation sample. Despite the negative parameter estimates for wealth for the later cohorts, *holding other explanatory variables constant*, later cohorts have on average a higher estimated ratio of financial assets to the average wage than do earlier cohorts.

We controlled for the effect of mortality on wealth by including in the model a term for whether a person is in the last 27 months of life. If poorer families systematically die younger, then the average wealth for younger families will be low compared to the average value of just the survivors. Educational attainment, race, and earnings control for much of the wealth variation attributed to mortality. Additionally, Lubitz, Beebe and Baker (1995) found that health care spending in the last year of life is very high. From the MBR, we can observe mortality up until age 73. Our model shows that other financial wealth declines by about 20 percent as either the husband or wife nears death. The dramatic decline in estimated financial wealth may be in part due to the high out-of-pocket spending families incur near death for health and long-term care. But a full explanation of the factors that cause household wealth to decline dramatically in the last year or two of life is beyond the scope of this report.

The key parameter of interest for our projections is the relationship between age and financial wealth. We included four variables in the model for married couples that capture the interaction between age and other characteristics: age of head times a dummy for homeownership status, age of head times a dummy indicating whether the head is black, age of head times a dummy indicating whether the head is white, and age of head times a dummy indicating whether the family receives a pension. Separate terms for age and age-squared did not significantly affect the level of financial wealth, once the age-interaction terms are included in the equation. Also, age interacted with a positive earnings indicator and age interacted with age of death indicators did not have significant effects.

The estimates show that financial assets decline for married homeowners as they age. At the same time, the value of a home has a large positive effect on the predicted level of wealth. The combined effect of these two coefficients is that homeowners begin retirement with substantially higher estimated financial wealth than renters, but experience a larger decline in financial assets as their age increases past retirement. The home provides the family some precautionary saving. Therefore, homeowners can consume more of their financial assets relative to renters and maintain the same level of precautionary saving as renters.

The story is similar for individuals with defined benefit pensions. Other financial wealth declines faster with age for pensioners than for nonpensioners. Pensioners also begin retirement with substantially higher estimated financial wealth than nonpensioners.

The age slope coefficient for blacks is negative, but positive for whites. This indicates that blacks reduce their financial assets more quickly than whites, and in fact whites may increase their financial assets as they age. Given the shorter life expectancy of blacks relative to whites, a steeper slope for blacks is a logical result.

Alternative Data Sources

We explored modeling wealth spend-down on the New Beneficiary Data System (NBDS). The NBDS is a national cross-sectional survey of new Social Security beneficiaries in 1982. The original database has been expanded with information from administrative records and a second round of interviews in 1991. The NBDS does not have a full age range of older individuals. It includes only Social Security beneficiaries, and at only two points in time. Because we were interested in estimating more detailed age-wealth profiles, the very select nature of the survey rendered it of limited use for our purposes.

We also explored modeling wealth spend-down on the Asset and Health Dynamics Among the Oldest Old (AHEAD). The AHEAD is a national panel study, begun in 1994, of over 7,400 individuals ages 70 and older and their spouses. Respondents were interviewed again in 1996 and 1999. We estimated similar spend-down models on the AHEAD as we had on the SIPP data and obtained similar results. Because the AHEAD only covers individuals age 70 and over, we opted to continue to use the SIPP-based model.

Projections After Age 63

After an individual is retired, we combined projected DC plan balances with non-pension financial assets. The equation from Table 6-11 is used to decay combined financial wealth outside of DB pension plans. The age at which we combine DC and other wealth for an individual is based on the following:

- Before age 60, we estimate DC balances and other financial wealth separately.

- Between ages 60 and 65, we combine DC balances and other wealth for individuals who have retired (and are therefore no longer contributing to DC plans even though they may have some earnings), but continue to model DC balances and other wealth separately for the non-retired.

- After age 65, we combine DC balances and other financial wealth for everyone.

- The home ownership hazard model is only projected to age 65. After age 65, home assets are held constant in real terms. This simplification is based on other research that finds that there is very little home turnover among the elderly (Hurd 1990; Venti and Wise 1998).

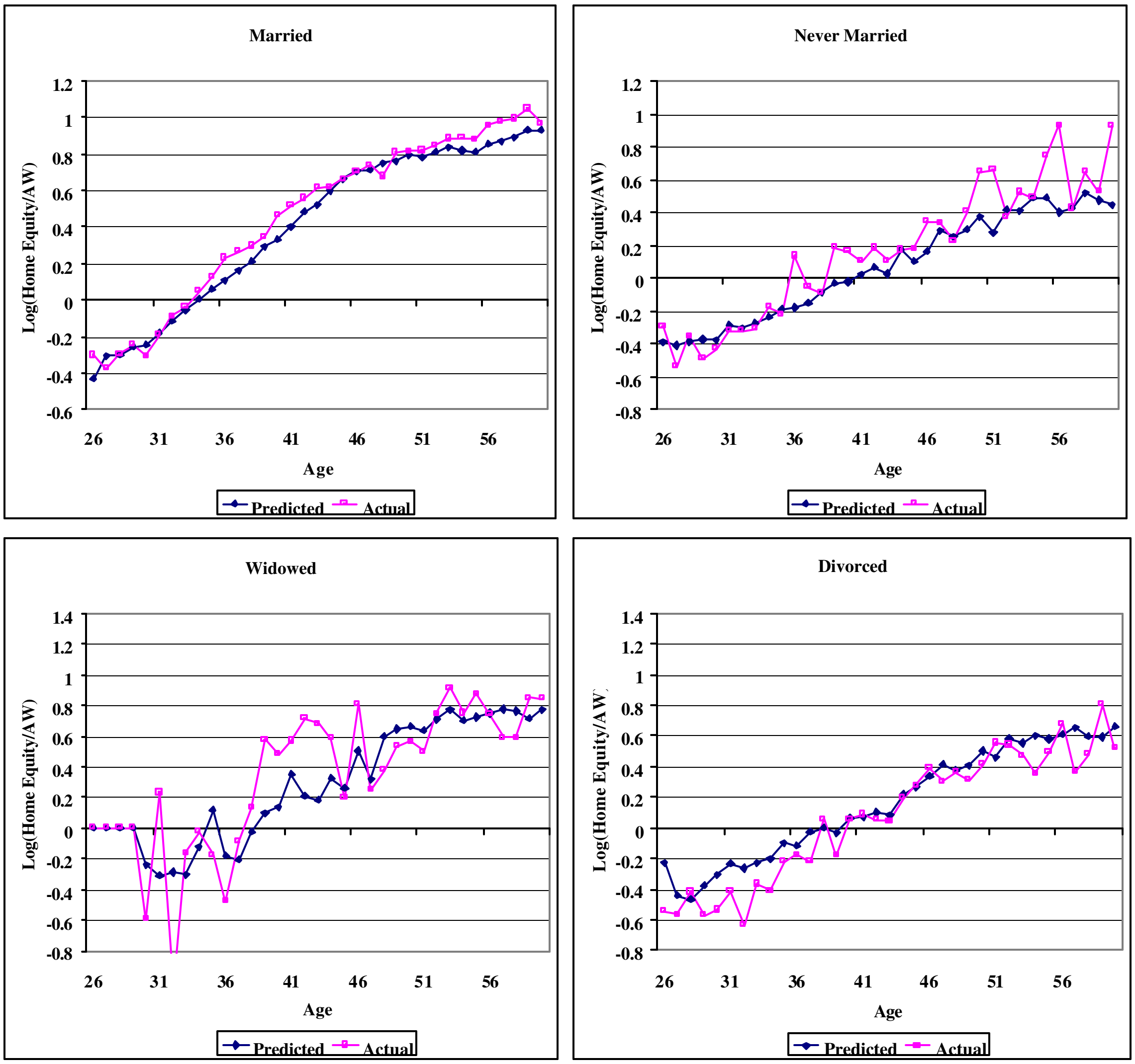
- We project assets of couples and individuals. Upon the death of a spouse, the survivor inherits all assets (DC balances, non-pension assets, and home). At divorce, the couple splits the assets.

V. PROJECTIONS OF WEALTH AT AGE 50

1. Actual Versus Predicted Assets

MINT home equity projections using the PSID-based regression, after an intercept adjustment, match the base SIPP data well by age and marital status. Figure 6-1 shows the predicted and actual logarithm of home equity divided by the economy-wide average wage by age and marital status using the PSID-based home equity model on the base 1990 to 1993 SIPP data with a modest intercept adjustment. We decrease the intercept by 0.125 for married couples and by 0.09 for singles. While we use these regressions to predict home equity from the SIPP interview date to age 50, the model fits the data closely at all ages. Predicted home equity is too low for young widows compared to the observed SIPP equity, but widowhood at young ages is rare and the observed data is noisy.

Figure 6-1
Actual Versus Predicted Logarithm of Home Equity/Average Wage of Home Owners by Martial Status and Age
1990 to 1993 Survey of Income and Program Participation



Source: Urban Institute tabulations from MINT and 1990-1993 SIPP.

MINT non-pension asset projections using the PSID-based regression match the base SIPP data well by age and marital status. Figure 6-2 shows the predicted and actual logarithm of non-pension assets divided by the economy-wide average wage minus 0.2 by age and marital status using the PSID-based financial asset model on the base 1990 to 1993 SIPP data with a fairly large intercept adjustment. We decreased the intercept by 0.614 for married couples and by 0.475 for singles. The error term further calibrates the individual-specific starting values so that they match the observed data less the assigned random error. While we use these regressions to predict non-pension assets from the SIPP interview date to age 50, the model fits the data fairly closely at all ages.

These intercept adjustments calibrate the models for differences in the PSID and SIPP sample home equity and non-pension asset means. The mean values are highly influenced by some large outliers, especially for non-pension assets. The individual-specific error term further calibrates the individual-specific starting values so that they match the observed data less the assigned random error. It is not surprising that the PSID sample means are higher than the SIPP for two reasons. First, the PSID measures the wealth of families including subfamily wealth. We have excluded subfamily wealth on the SIPP. Second, the wealth data on the PSID were asked 17, 22, and 27 years into the panel. Sample attrition is most common among the most economically disadvantaged households. Sample weights adjust for this attrition, but the regressions are unweighted.

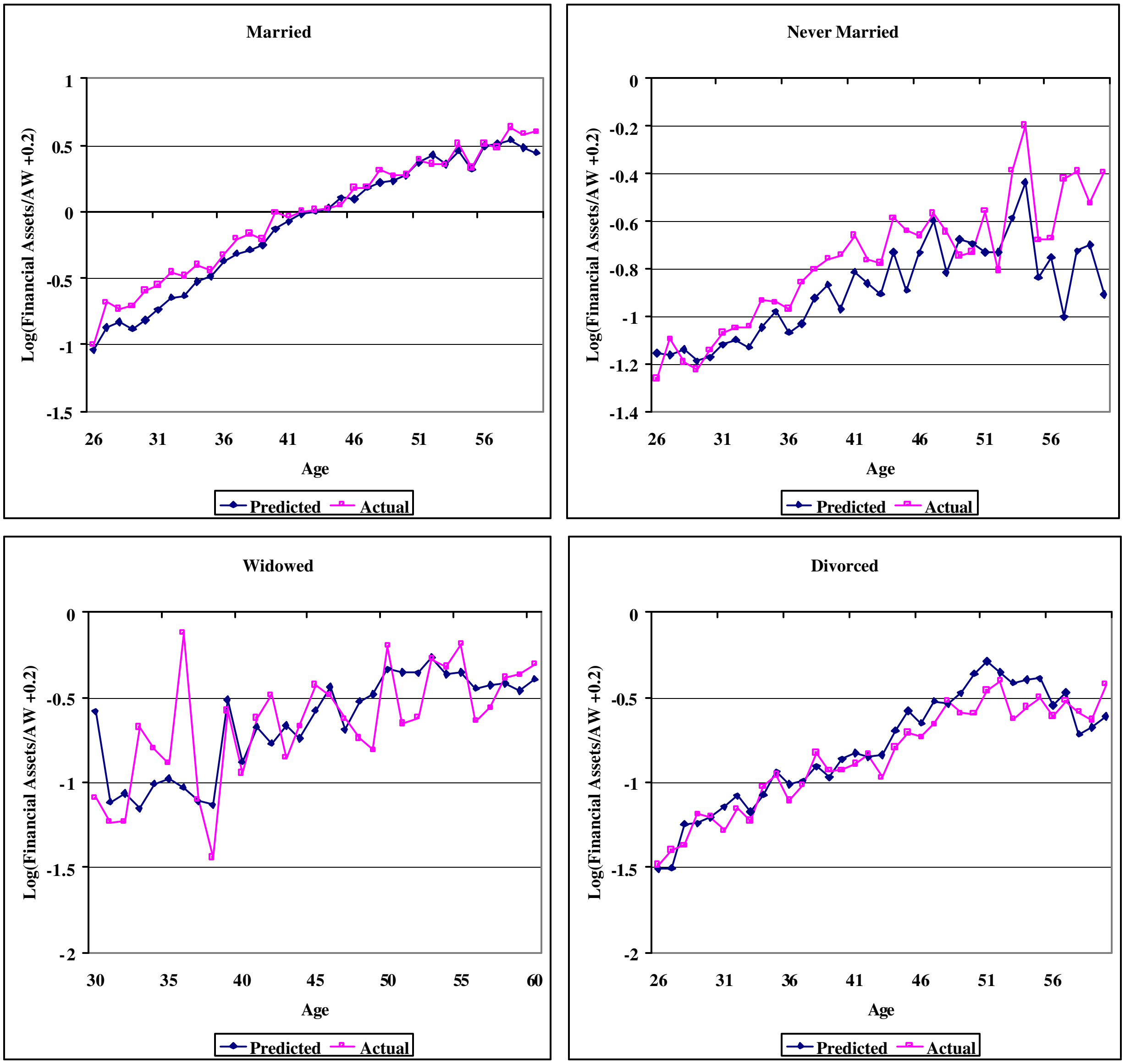
2. Comparison of SIPP and PSID Independent Variables

Most of the independent variables are reasonably comparable between the PSID and SIPP samples by marital status and age (see Table 6-12). While some of the levels differ for couples and singles, the age patterns remain very comparable. Compared to PSID couples, SIPP couples have lower home ownership rates, lower male earnings in both the current and preceding five years and lower female earnings in both the current and preceding five years. SIPP husbands are slightly more likely to be self-employed compared to the PSID, though this is mostly due to a difference in the self-employment determination. Self-employment on the SIPP is based on having self-employment income, while self-employment on the PSID is based on the characteristics of the main job. Compared to the PSID, SIPP couples have shorter marriage durations. SIPP wives are more highly educated than PSID wives for the same age ranges and cohorts, but SIPP husbands have lower educational attainment compared to the PSID, though the differences are small. The SIPP has a higher share of black and Hispanic couples compared to the PSID.[13] SIPP husbands are in poorer health than PSID husbands. SIPP couples have fewer children under age 18 in the household at younger ages compared to PSID couples.

These general patterns hold true for singles as well (see Table 6-13). Compared to PSID singles, SIPP singles have lower home ownership rates, lower earnings in both the current and preceding five years and *lower* former spouse earnings in the preceding five years. Compared to the PSID, SIPP widowed and divorced individuals had shorter marriage durations. SIPP singles are similarly educated compared to PSID singles for the same age ranges and cohorts. Among

[13] The PSID does not pick up the large Hispanic immigration that occurred in the United States since 1968, the first year of the PSID sample. The PSID added a supplemental sample of Hispanics in 1990. The Hispanic sample does not have historic earnings and are not included in our PSID estimation sample.

Figure 6-2
Actual Versus Predicted Logarithm (Financial Assets/Average Wage+0.2)
by Martial Status and Age
1990 to 1993 Survey of Income and Program Participation



Source: Urban Institute tabulations from MINT and 1990-1993 SIPP.

Table 6-12
Mean of the Independent Variables for Married Couples by Age: PSID and SIPP

	PSID			SIPP		
	30	40	50	30	40	50
Own Home	0.67	0.87	0.89	0.53	0.75	0.80
Per capita present value earnings / cohort average	1.00	1.06	1.03	1.05	1.06	1.07
Husband mean earnings (t5 to t0)	1.13	1.57	1.55	0.99	1.25	1.26
Years with earnings above the taxmax	0.08	1.66	3.14	0.40	2.09	4.24
Family present value earnings / cohort average	2.03	1.88	2.07	1.97	1.96	2.05
Head earnings/average wage at t0 (capped at 2.46*aw)	1.28	1.56	1.49	1.07	1.25	1.21
Spouse present value of earnings/cohort average	1.00	0.93	0.89	0.60	0.52	0.45
Head Black	0.05	0.06	0.05	0.09	0.10	0.09
Head Hispanic	0.03	0.04	0.03	0.12	0.09	0.07
Head high school dropout	0.09	0.06	0.18	0.13	0.11	0.18
Head college graduate	0.31	0.41	0.28	0.29	0.34	0.30
Head self-employed	0.18	0.17	0.24	0.17	0.24	0.25
Head disabled	0.01	0.02	0.01	0.01	0.03	0.06
Number of years married	7.96	17.17	27.17	6.13	13.84	22.93
Number of children under 18	1.41	1.82	0.60	1.14	1.77	0.61
First child born	0.04	0.01	0.02	0.11	0.02	0.00
One to two children	0.51	0.66	0.40	0.52	0.59	0.36
Three or more children	0.20	0.19	0.03	0.11	0.23	0.04
Wife earnings/average wage at t0	0.50	0.54	0.48	0.53	0.58	0.57
Wife mean earnings/ average wage (t-5 to t0)	0.74	0.92	0.83	0.45	0.53	0.54
Wife self employed	0.06	0.13	0.11	0.10	0.12	0.12
Wife college graduate	0.21	0.21	0.11	0.27	0.27	0.21
Wife high school dropout	0.08	0.07	0.13	0.10	0.09	0.14

Source: Urban Institute tabulations from MINT.

Table 6-13
Mean of the Independent Variables for Single Individuals by Age: PSID and SIPP

	PSID			SIPP		
	30	**40**	**50**	**30**	**40**	**50**
Own Home	0.18	0.42	0.69	0.11	0.31	0.49
Per capita present value earnings / cohort average	0.99	0.90	0.96	0.89	0.90	0.90
Husband mean earnings (t5 to t0)	0.72	0.99	1.16	0.64	0.80	0.76
Years with earnings above the taxmax	0.03	0.47	1.72	0.14	0.66	1.67
Family present value earnings / cohort average	1.06	1.11	1.51	1.02	1.17	1.35
Head earnings/average wage at t0 (capped at 2.46*aw)	0.90	1.06	1.14	0.72	0.84	0.73
Former spouse present value of earnings/cohort average	0.08	0.25	0.31	0.10	0.27	0.50
Head Black	0.25	0.16	0.20	0.17	0.22	0.14
Head Hispanic	0.03	0.03	0.01	0.12	0.09	0.07
Head high school dropout	0.09	0.08	0.22	0.13	0.17	0.18
Head college graduate	0.22	0.21	0.23	0.24	0.25	0.23
Head self-employed	0.08	0.06	0.05	0.09	0.12	0.17
Head disabled	0.00	0.02	0.12	0.01	0.04	0.07
Head never married	0.62	0.23	0.06	0.79	0.47	0.27
Widowed	0.01	0.08	0.19	0.01	0.03	0.13
Never married female	0.29	0.12	0.06	0.42	0.51	0.60
Divorced within the last two years	0.08	0.03	0.03	0.05	0.05	0.02
Years divorced (divorced only)	2.22	5.74	8.23	0.96	4.15	6.71
Number of years married	2.20	6.85	11.39	0.95	4.35	9.65
Number of children under 18	0.61	0.75	0.27	0.43	0.57	0.23
First child born	0.02	0.02	0.02	0.01	0.00	0.00
One to two children	0.26	0.35	0.17	0.20	0.27	0.17
Three or more children	0.07	0.09	0.01	0.05	0.05	0.01

Source: Urban Institute tabulations from MINT.

singles, SIPP has fewer blacks and more Hispanics compared to the PSID. SIPP singles are in poorer health than PSID singles. As with married couples, SIPP singles have fewer children under age 18 in the household at each age compared to PSID singles, and never married singles have fewer young children than divorced and widowed singles in both samples. Among divorcees, the share divorcing at each age on both samples is very similar.

3. Trends in Dependent and Independent Variables Over Time

The initial MINT values for home equity and non-pension assets are based on the observed SIPP values. The projections over time depend on the changes in the models' independent variables relative to the observed starting values. Table 6-14 shows the mean of the dependent and independent variables at age 50 between 1992 and 2015 for all individuals in MINT. Below is a brief description of these trends.

Dependent Variables

- Mean home ownership rates remain fairly constant at age 50, ranging from 72 to 78 percent with no obvious trend.
- Mean home equity at age 50 generally declines over time from 1.7 times the average wage in 1992 to 1.28 times the average wage in 2015.
- Mean non-pension assets at age 50 fluctuate over time. It falls between 1992 and 1995, but then rises through 2005 before falling through 2015. These means are based on single cohorts and single ages and are variable due to small sample size. Also, means are highly influenced by outliers.
- Between 2 and 4 percent of families became new homeowners at age 50 and there is no obvious time trend. The home purchase hazard decreases at later age as most initial home purchases occur before age 50.
- Between 1 and 3 percent of families sell their homes to become renters at age 50. Again, there is no obvious time trend.

Independent Variables

- Average per capita income divided by the cohort average should be one in every year. In practice, because husbands and wives tend to be in different cohorts, the mean is slightly above one. Couples have higher values in all years compared to single individuals and these differentials do not vary over time but the variance may.
- Mean earnings of the family heads over the last six years (t-5 to t0) at age 50 declines about 25 percent between 1992 and 2015. This will **reduce** both housing and non-pension assets for later cohorts compared to early cohorts.
- Mean family years above the taxable maximum (measured as earnings greater than 2.3 times the average wage) at age 50 declines by about 80 percent between 1992 and 2015. Married couples have both higher initial values and greater reductions compared to single individuals. This will **reduce** both non-pension assets and home equity for later cohorts compared to early cohorts, especially for married couples.

Table 6-14
Mean of the Dependent and Independent Variables at Age 50 by Year

Year	1992	1995	2000	2005	2010	2015
Birth Cohort	**1942**	**1945**	**1950**	**1955**	**1960**	**1965**
Own Home	0.75	0.73	0.77	0.76	0.78	0.72
Per Capita Home Equity/Average Wage	1.70	2.18	1.77	1.52	1.37	1.28
Per Capita Non-Pension Assets/Average Wage	1.95	1.32	1.89	2.03	1.67	1.35
Buy Home	0.04	0.04	0.03	0.03	0.02	0.03
Sold Home	0.01	0.02	0.02	0.03	0.01	0.03
Per capita present value earnings / cohort average	1.04	1.04	1.04	1.02	1.03	1.04
Husband mean earnings (t5 to t0)	1.21	1.14	1.11	1.04	1.02	0.97
Years with earnings above the taxmax	3.89	3.01	3.59	2.86	2.76	2.16
Family present value earnings / cohort average	1.83	1.84	1.79	1.75	1.79	1.69
Head earnings/average wage at t0 (capped at 2.46*aw)	1.14	1.16	1.09	1.03	1.01	0.95
Former spouse present value of earnings/cohort average	0.42	0.45	0.49	0.51	0.56	0.50
Head Black	0.10	0.13	0.12	0.12	0.14	0.12
Head Hispanic	0.06	0.08	0.09	0.09	0.11	0.13
Head high school dropout	0.17	0.15	0.10	0.11	0.12	0.14
Head college graduate	0.31	0.33	0.34	0.28	0.28	0.27
Head self employed	0.23	0.18	0.21	0.19	0.15	0.10
Head disabled	0.04	0.05	0.06	0.05	0.05	0.06
Head never married	0.05	0.07	0.07	0.09	0.10	0.16
Widowed	0.02	0.02	0.02	0.02	0.02	0.03
Never married female	0.14	0.14	0.13	0.14	0.16	0.22
Divorced within the last two years	0.02	0.01	0.01	0.01	0.01	0.01
Years divorced (divorced only)	12.34	12.05	12.22	13.11	12.94	13.41
Number of years married	18.91	17.49	17.72	17.33	16.98	14.75
Number of children under 18	0.61	0.73	0.80	0.62	0.64	0.77
First child born	0.00	0.00	0.01	0.01	0.02	0.01
One to two children	0.34	0.31	0.34	0.28	0.29	0.32
Three or more children	0.05	0.08	0.09	0.07	0.07	0.09
Wife earnings/average wage at t0 (married couples only)	0.57	0.61	0.66	0.68	0.69	0.68
Wife mean earnings/ average wage (t-5 to t0) (married couples only)	0.54	0.57	0.64	0.63	0.67	0.66
Wife self employed (married couples only)	0.10	0.11	0.12	0.12	0.10	0.10
Wife college graduate (married couples only)	0.21	0.23	0.30	0.25	0.26	0.31
Wife high school dropout (married couples only)	0.15	0.14	0.08	0.10	0.12	0.14

Source: Urban Institute tabulations from MINT.

- Mean family present value of earnings divided by the cohort average, which adds husband's and wife's values is centered around 2, while for never married individuals, it is centered around 1. The mean value for widowed and divorced individuals, who get some credit for former spouse earnings, is centered around 1.5. The aggregate mean declines between 1992 to 2015 from about 1.8 to 1.7 as a larger share of the 50-year-old population is unmarried in later years compared to earlier years. Within marital status group, the change will **not alter** the mean projected non-pension assets or home equity.
- Mean present value of spouse's earnings (including former spouses) at age 50 increases from about 0.4 in 1992 to about 0.5 in 2015. The increase comes primarily from increased earnings of married women. However, for widowed and divorced individuals at age 50, the mean value declines between 1992 and 2015. This variable is used to project single home equity, so its decline for this group should **reduce** home equity for singles in later cohorts compared to early cohorts.
- The MINT population is projected to become more ethnically diverse including a greater share in later cohorts that are black and Hispanic compared to earlier cohorts. This will **reduce** aggregate wealth of later cohorts compared to earlier cohorts.
- Educational attainment of 50-year-olds family heads is projected to rise between 1992 and 2000 and then decline between 2000 and 2015. This will cause wealth to rise for individuals born between 1930 and 1950 and then fall for individuals born after 1950. Married individuals tend to be more highly educated compared to unmarried individuals, so the decline in educational attainment will **reduce** the wealth of married couples more than singles.
- Mean self-employment rates for family heads between 1992 to 2015 decline by more than half. Self-employment is based on the employment status of the individual at the SIPP interview. The probability of being self-employed increases with age. Because we project no new self-employment, the proportion projected to be self-employed at age 50 declines over time. This will **reduce** both projected non-pension assets and home equity for later cohorts compared to earlier cohorts. MINT would project higher non-pension assets and home equity if MINT projected new self-employment.
- Between four and six percent of 50-year-olds are projected to be in disabled, with the rate initially rising between 1992 and 2000 and declining between 2000 and 2015. This variable only affects couple home equity, and the rate for married couples does not change over time. This will **not change** the trend in couple home equity.
- The share of the population that is never married at age 50 rises from about 5 percent in 1992 to about 16 percent in 2015 with the largest increase in the last year. Within the unmarried group, never married singles are projected to have higher non-pension assets and home equity compared to widows and divorced singles. As the never married share increases over time, MINT will project **higher** non-pension wealth and home equity in later cohorts compared to earlier cohorts. (The MINT marriage hazard rates appear too low at young ages. While marriage rates have been declining, age at first marriage has also been increasing. The latter trend results in a shift in the age of the peak marriage hazard. MINT does not appear to pick this up. The dramatic rise in the share of population that is never married in 2015 compared to 2000 reflects a persistent four percentage point differential that 1965 cohort has compared to the 1960 cohort.)

- The share of the population that is widowed at age 50 is between two and three percent. Widows have more per-capita non-pension assets and home equity compared to singles, but MINT projects **no change** in the trend in these assets due to widowhood.
- Between one and two percent of the age 50 population is newly divorced and there is no obvious time trend. Most divorce occurs before age 50, but the annual divorce hazard is small at all ages. The divorce hazard influences the home purchase and sale probabilities. While the divorce hazard remains small, the share of the population entering retirement divorced is projected to increase between 1992 and 2020.
- The mean number of years ever married at age 50 declines between 1992 and 2015 by about 28 percent. Most of the decline reflects the increase in divorce rates. It declines slightly among married couples reflecting and increase in the age of first marriage. The decline in the number of years married will **reduce** home equity for couples in later cohorts compared to earlier cohorts, but this change is small.
- The mean number of children under age 18 living in the household is projected to increase by 18 percent between 1992 and 2015, but this trend masks some important fertility differentials between cohorts. Women in later cohorts had fewer children compared to women in earlier cohorts, but had them at older ages. As a consequence of the increase in age at first birth, more of these children remain in the household at older ages among the later cohorts than among the earlier cohorts. Children influence the home purchase hazard and home equity for couples in MINT. The change in the timing of children will alter the age-specific pattern of wealth accumulation. The reduction in the number of children will **reduce** the home equity of couples in later cohorts compared to earlier cohorts.
- Among married couples, average current and recent wife's earnings at age 50 are projected to rise by about 18 percent between 1992 and 2015. The rise in wife's earnings will **increase** home equity and home ownership for couples in later cohorts compared to earlier cohorts.
- Among married couples, average self-employment at age 50 of wives declines by about 4 percent between 1992 and 2015. Because MINT projects no new self-employment, the self-employment rate does not increase with age as it should. Because women are less likely to be self-employed than men, the failure of MINT to project new self-employment affects women less than it affects men. The decline in wives' self-employment rates will **reduce** couple assets in later cohorts compared to earlier cohorts.
- As with family heads, wives' educational attainment rises between 1992 and 2000. While educational attainment declines for family heads between 2000 and 2015, the trend is mixed for wives. Between 2000 and 2005, the share of wives with a college degree is projected to decline. Between 2005 and 2015, both the share of high school dropouts and college graduates rises. This difference is a function of both changing educational attainment and changes in projected marriage rates among different educational groups. The rise in college educated wives will **increase** non-pension assets of couples. The rise in high school dropout wives will **decrease** non-pension assets of couples. Both of these trends occur at the same time with an unclear impact on aggregate couple non-pension assets over time.

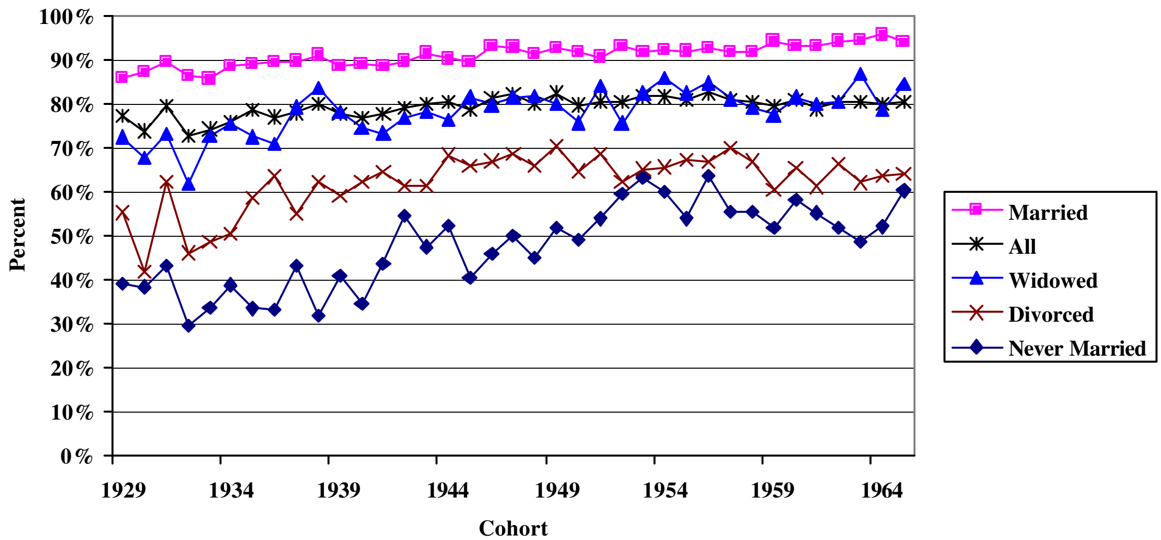
To summarize, some of the trends will increase assets over time and some will decrease assets over time, and many of the trends vary by marital status. Home ownership rates remain fairly constant despite a decline in the proportion of the population that is married. Mean home equity initially rises and then falls. Mean non-pension assets at age 50 fluctuates over time with the later cohorts projected to accumulate fewer non-pension assets compared to earlier cohorts.

VI. PROJECTIONS OF WEALTH AFTER AGE 50

1. Home Ownership Rates and Home Equity

MINT projects that the aggregate home ownership rates at age 62 will increase about six percent over time from about 76 percent for 62-year-olds born between 1931 and 1935 to about 80 percent for 62-year-olds born between 1961 and 1965, but the aggregate rate masks projected differences by marital status (see Figure 6-3). Home ownership rates increase about 50 percent for never married 62-year-olds from about 35 percent for 62-year-olds born between 1930 and 1935 to about 54 percent for 62-year-olds born between 1961 and 1965. MINT projects that homeownership rates of widowed and divorced 62-year-olds will increase over the same time period by smaller amounts. These increases are due primarily to increases in female earnings and single families with children. The latter occurs because of increased divorce rates among women with children and an increase in out-of-wedlock births in later cohorts compared to early cohorts.

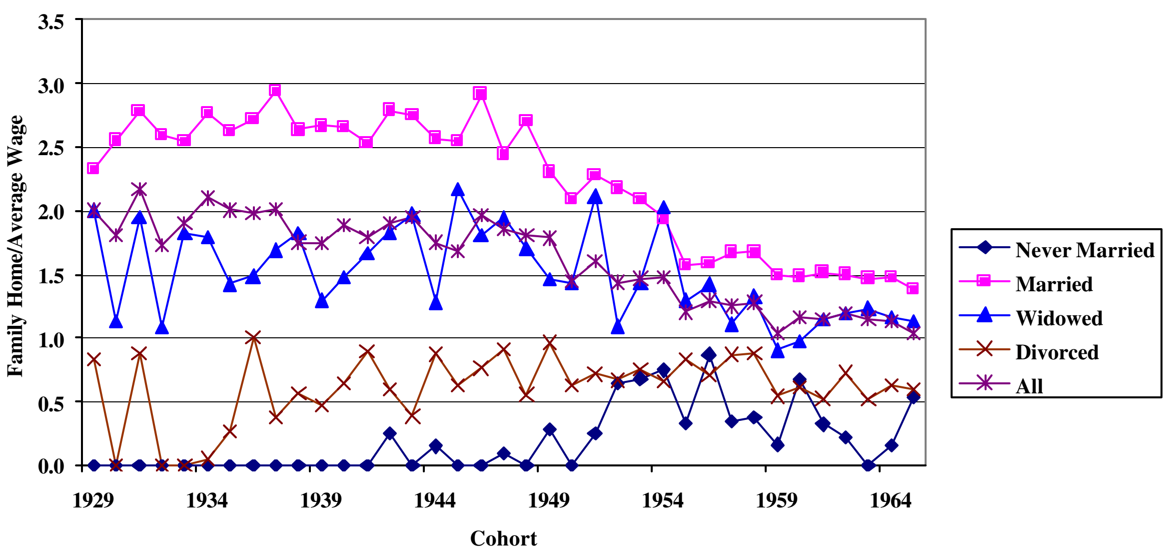
Figure 6-3
Percent of Families Who Own a Home at Age 62 by Marital Status and Cohort



Source: Urban Institute tabulations from MINT.

While MINT projects that homeownership rates at age 62 will increase over time, it also projects that median home equity will decline over time. Here too, the aggregate trend masks important differences by marital status (see Figure 6-4). Median home equity is expected to decline from about 2.5 times the average wage for couples born in the early 1930s to about 1.5 times the average wage for couples born in the early 1960s. As homeownership rates of never married 62-year-olds rises above 50 percent for singles born after the mid-1940s, median home equity rises above zero.

Figure 6-4
Family Median Home Equity at Age 62 by Cohort and Marital Status
(Equity as a Percent of the Economy-Wide Average Wage)



Source: Urban Institute tabulations of MINT.

The decline in median home equity is the result of a number of salient trends including the following:

- Declining earnings of men in later cohorts compared to earlier cohorts.
- Declining family size, as women in later cohorts had fewer children than women in earlier cohorts.
- A rise in the share of families in later cohorts that are black and Hispanic compared to earlier cohorts, and these minority groups typically have lower home equity.
- A rise in the prevalence of 30-year mortgages over time. These longer-term mortgages that are prevalent among later cohorts build home equity more slowly than shorter-term mortgages that were more prevalent for the early cohorts.
- A rapid increase in housing values relative to wage growth in the 1960s and 1970s, which raised the net housing wealth for earlier cohorts but not later cohorts.
- An increasing use of home equity loans over time that effectively exchanges home equity for other consumption. Home equity loans have become more common since

the Tax Reform Act of 1986 eliminated deductibility of consumer interest while home mortgages remain deductible.

MINT projects that home equity at age 62 will become increasingly unevenly distributed between the early 1990s and 2010 (see Table 6-15). Inequality will decline between 2010 and 2020, but will not return to its early 1990 level. The family at the 95th percentile of home equity had three times the average home equity in the early 1990s. This ratio is projected to rise to 3.9 in 2010 before declining to 3.7 in 2020.

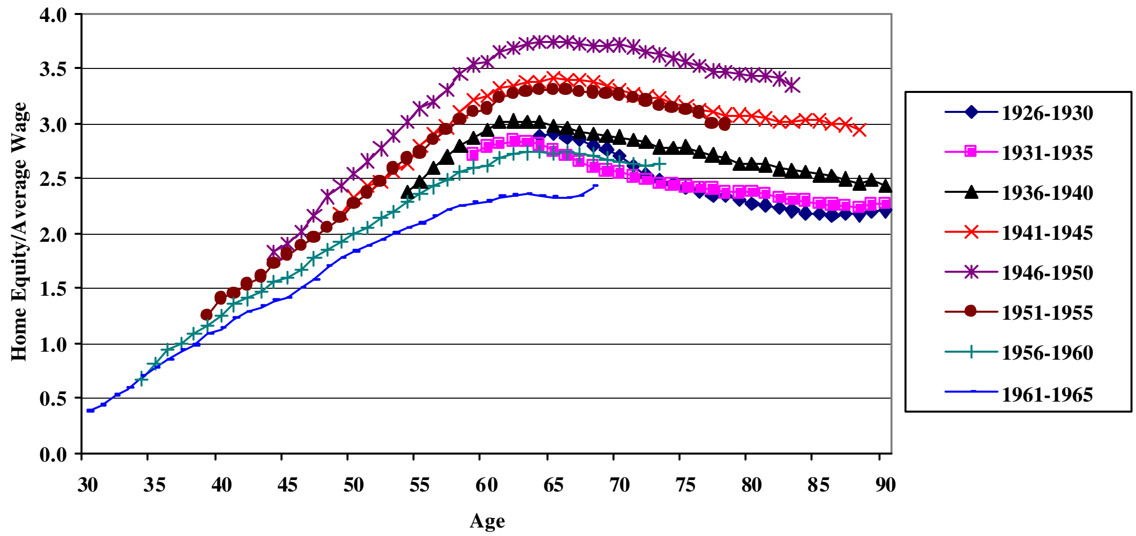
Table 6-15
Home Ownership Rate and Mean Home Equity at Different Points in the Distribution at Age 62 by Year
(Ratio of Equity to the Economy-Wide Average Wage)

Year	Own Home	Mean	20th Percentile	50th Percentile	70th Percentile	80th Percentile	95th Percentile	95th/ Mean
1990-1993	77%	2.88	0.11	2.22	3.67	4.77	8.65	3.00
2000	80%	3.06	0.02	1.75	3.76	5.17	10.08	3.29
2005	80%	3.47	0.00	1.96	3.93	5.68	12.31	3.55
2010	80%	3.70	0.07	1.81	3.48	5.51	14.41	3.90
2015	82%	3.25	0.20	1.47	3.00	4.64	11.38	3.50
2020	80%	2.76	0.09	1.28	2.70	4.08	10.20	3.70

Source: Urban Institute tabulations of MINT.

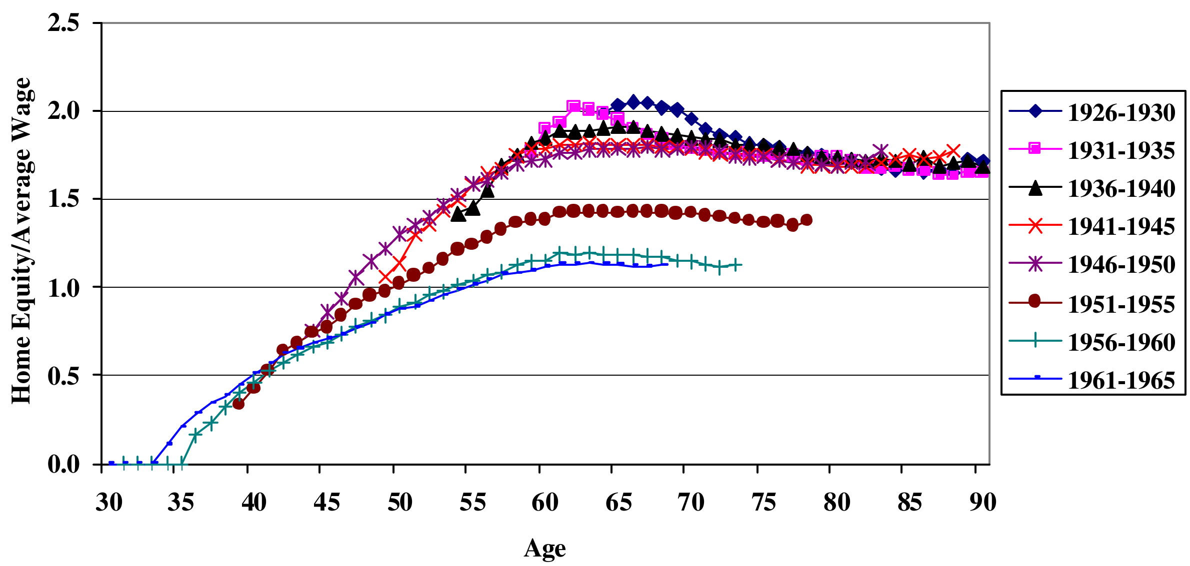
Figure 6-5 shows the projected mean home equity divided by the economy-wide average wage by age and cohort over the age-range projected in MINT. It clearly shows the rise in relative home equity between families born in the early 1930s to families born in 1950 and the subsequent decline in home equity for families born after 1950. The peak cohort is the group reaching age 62 in 2010 and coincides with the peak in inequality. The median of home equity, on the other hand, decreases for each subsequent cohort for the reasons outlined above (see Figure 6-6).

Figure 6-5
Family Mean Home Equity by Age and Cohort
(Equity as a Percent of the Economy-Wide Average Wage)



Source: Urban Institute tabulations of MINT.

Figure 6-6
Family Median Home Equity by Age and Cohort
(Equity as a Percent of the Economy-Wide Average Wage)



Source: Urban Institute tabulations of MINT.

Compare MINT Home Equity with SIPP and SCF

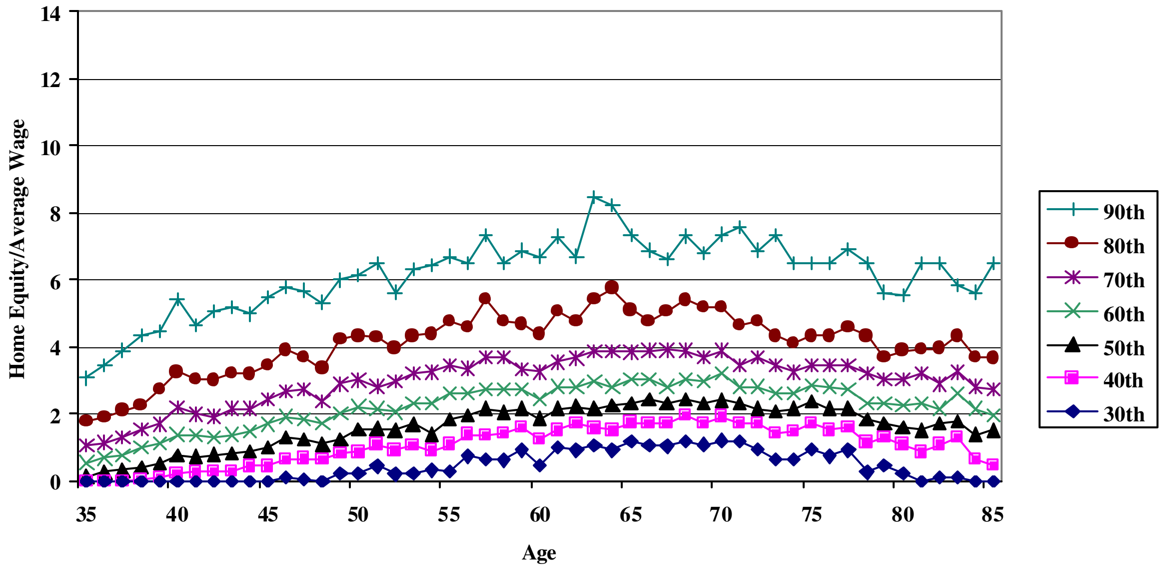
Figure 6-7 shows the distribution of home equity in the early 1990s by age based on the 1990 to 1993 SIPP observed family home equity. This is the starting distribution for MINT. Figure 6-8 shows the same distribution in 1998 based on the Survey of Consumer Finance (SCF). This dataset is regarded by many as having the best wealth data. The SCF over samples the wealthiest households based on tax returns. As a consequence, it captures more wealth at the top end of the wealth distribution. Because the SCF has a smaller sample size (4,305 households) compared to the combined SIPP panels (71,555 observations), the distribution by age on the SCF is much noisier than the SIPP distribution, but the basic patterns are similar. Family home equity rises with age through the late 60s and then declines at older ages. The median home equity at age 62 is about two times the average wage on both datasets. The 90th percentile is about eight times the average wage on both datasets. Figure 6-9 shows the distribution of home equity in 2000 based on the MINT projections. Home equity rises with age through the late 60s and then declines at older ages. The median home equity at age 62 is about two times the average wage, and the 90th percentile is just under eight times the average wage. Figure 6-10 shows MINT projected home equity in 2020. As in earlier years, home equity rises with age through the late 60s and then declines. The median home equity at age 62 is about 1.8 times the average wage, and the 90th percentile declines to about seven times the average wage. Striking, however, is the increase at the top of the distribution of families in their 70s. This reflects a rapid rise in home equity for families born between 1946 to 1950 who are systematically more educated and have higher lifetime earnings than families born both earlier and later.

Figure 6-11 shows the median family home equity by age for the 1990 to 1993 SIPP panels, 1998 SCF, and 2000, 2010, and 2020 MINT projections. The early SIPP data shows a dramatic decline in the median home equity after age 65 that is not evident in the 1998 SCF data or the MINT projections. The MINT projections show a general decline in the median home equity over time as more families near retirement unmarried and men's earnings decline relative to the average wage compared to earlier periods. Figure 6-12 shows the 80th percentile home equity by age for the same periods. Here the cohort shift is more apparent as the peak individuals born in the mid-1940s progress through the late 50s in 2000, late 60s in 2010, and late 70s in 2020. Individuals born both before and after this peak group have lower home equity.

2. Non-Pension Assets

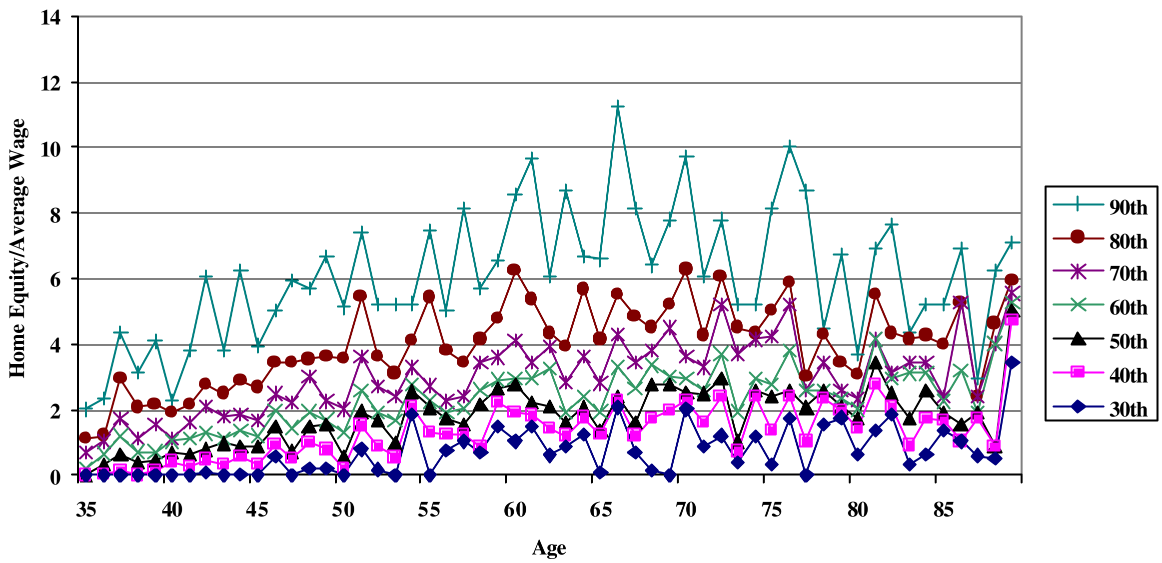
MINT projects that the median of family non-pension assets as a percent of the economy-wide average wage at age 62 will increase for individuals born between 1930 and 1955 and then fall for later cohorts. As with home equity, the aggregate trend masks important differences by marital status (see Figure 6-13). The median of non-pension assets generally rises from about two times the average wage for couples born in the early 1930s to about 2.3 times the average wage for couples born in the late 1940s. While the median of non-pension assets is projected to fall for couples in later cohorts, it is projected to rise for singles in successively later cohorts. As singles become a larger share of families near retirement over time, they have greater influence on the aggregate non-pension asset trend causing it to rise over time.

Figure 6-7
Percentile Distribution of Home Equity by Age, 1990 to 1993 SIPP
(Equity as a Percent of the Economy-Wide Average Wage)



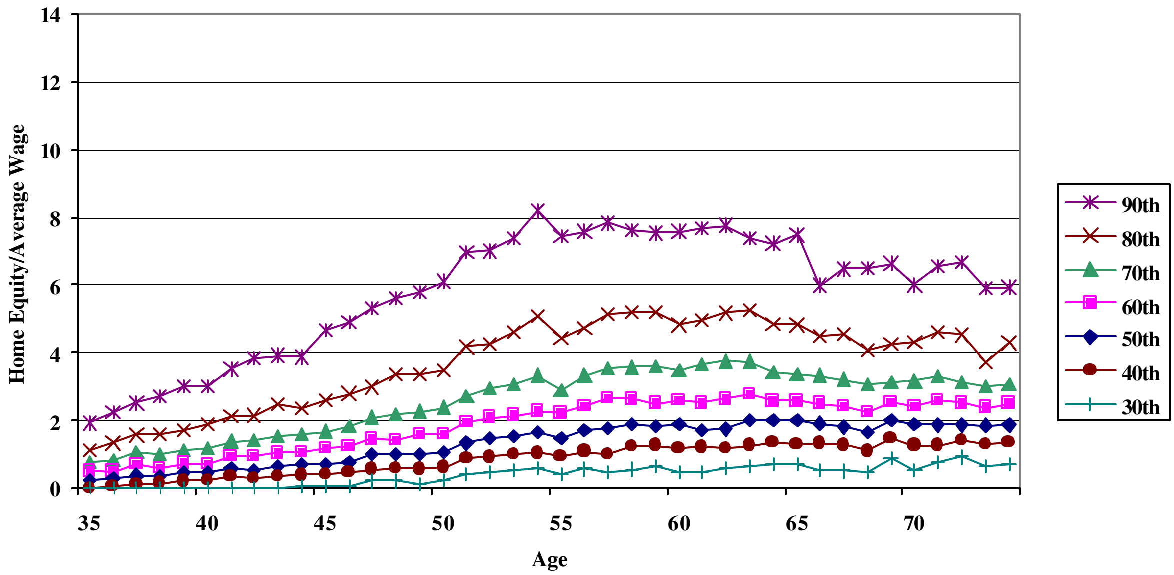
Source: Urban Institute tabulations of 1990 to 1993 SIPP.

Figure 6-8
Percentile Distribution of Home Equity by Age, 1998 Survey of Consumer Finance
(Equity as a Percent of the Economy-Wide Average Wage)



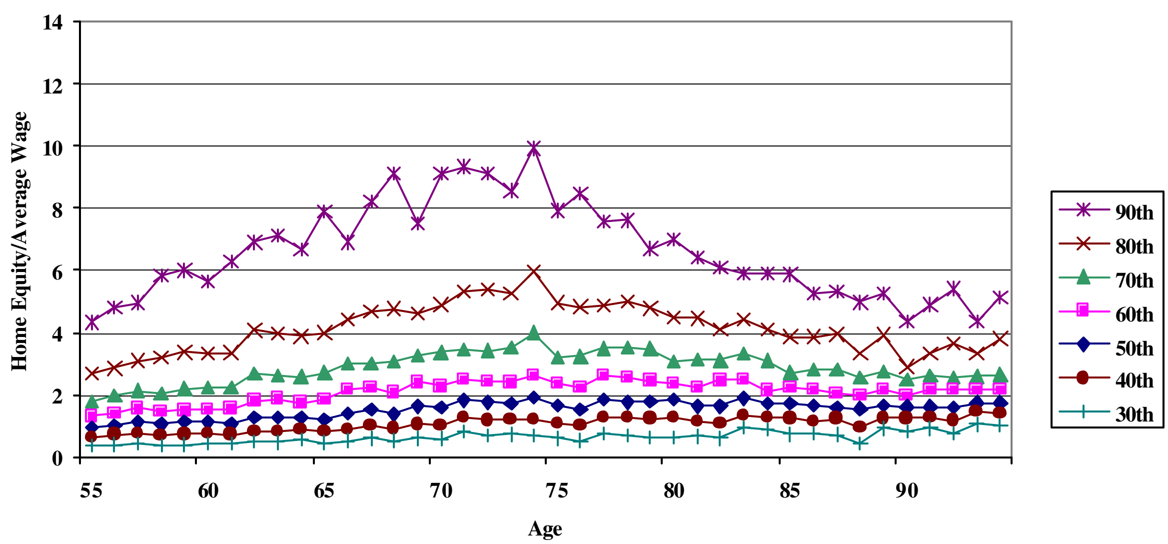
Source: The Urban Institute tabulations of the 1998 SCF.

Figure 6-9
Percentile Distribution of Home Equity by Age, 2000 MINT
(Equity as a Percent of the Economy-Wide Average Wage)



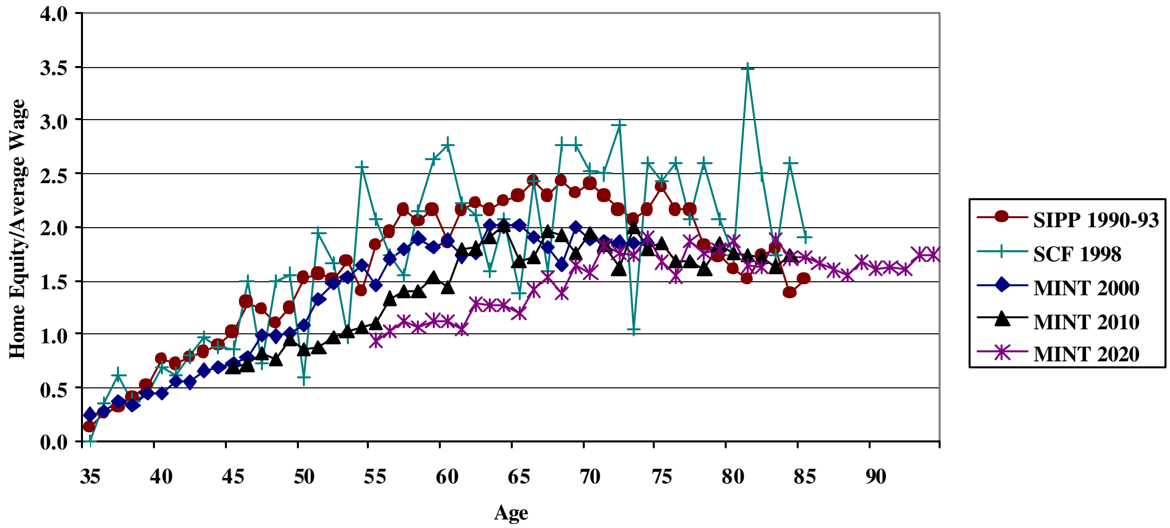
Source: Urban Institute tabulations of MINT.

Figure 6-10
Percentile Distribution of Home Equity by Age, 2020 MINT
(Equity as a Percent of the Economy-Wide Average Wage)



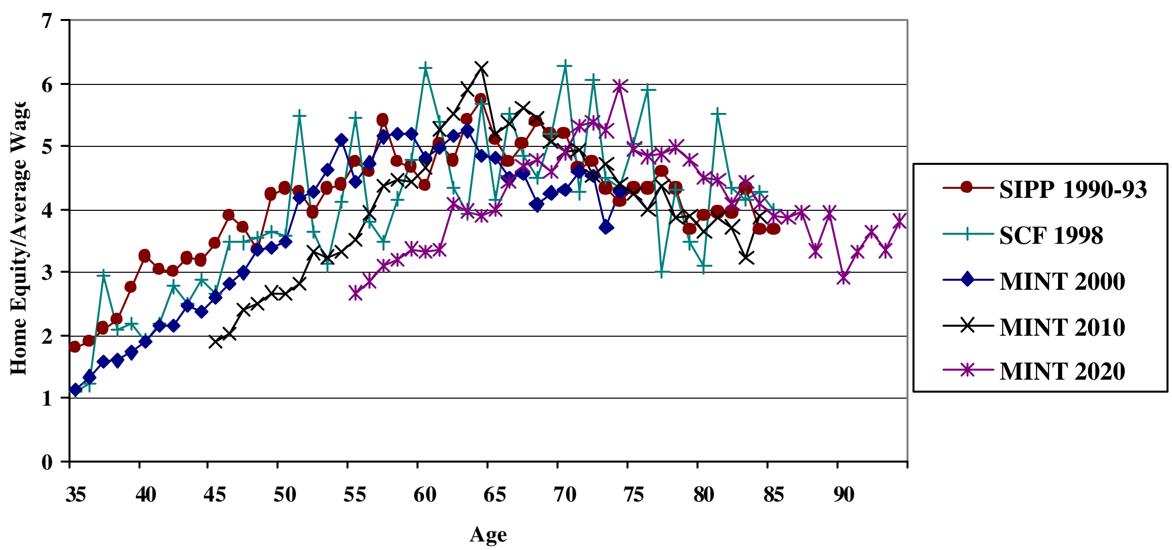
Source: Urban Institute tabulations of MINT.

Figure 6-11
Median Home Equity by Age and Year
(Equity as a Percent of the Economy-Wide Average Wage)



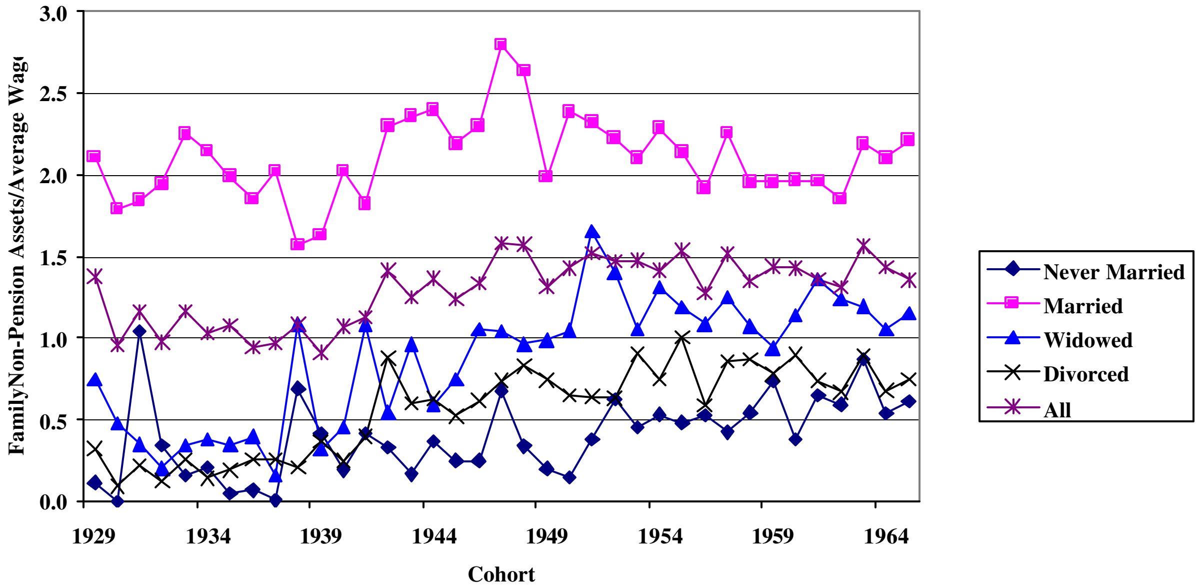
Source: Urban Institute tabulations of MINT, 1998 SCF, and 1990-1993 SIPP.

Figure 6-12
80th Percentile Home Equity by Age and Year
(Equity as a Percent of the Economy-Wide Average Wage)



Source: Urban Institute tabulations of MINT, 1998 SCF, and 1990-1993 SIPP.

Figure 6-13
Family Median Non-Pension Assets at Age 62 by Cohort and Marital Status
(Assets as a Percent of the Economy-Wide Average Wage)



Source: Urban Institute tabulations of MINT.

Non-pension assets are highly concentrated among the wealthiest families (see Table 6-16). The family at the 95th percentile of non-pension assets had over four times the assets of the average family non-pension assets the early 1990s. This ratio is projected to rise to 4.31 in 2005 before declining to 3.9 in 2020. The family at the 95th percentile of non-pension assets had 2.8 times the non-pension assets as the family at the 80th percentile. MINT projects this ratio to rise to over 3.7 in 2020.

Table 6-16
Mean Family Non-Pension Assets at Different Points in the Distribution at Age 62 by Year
(Ratio of Equity to the Economy-Wide Average Wage)

Year	Mean	20th Percentile	50th Percentile	70th Percentile	80th Percentile	95th Percentile	95th/ Mean
1990-1993	3.40	0.10	0.92	2.80	4.85	13.84	4.06
2000	3.90	0.06	1.08	3.00	5.67	16.11	4.13
2005	5.55	0.08	1.25	3.96	6.98	23.89	4.31
2010	5.05	0.21	1.57	3.70	5.94	18.68	3.70
2015	6.66	0.21	1.48	3.52	6.37	25.32	3.80
2020	5.50	0.24	1.35	3.43	5.78	21.48	3.91

Source: Urban Institute tabulations of MINT.

Figure 6-14 shows the projected mean non-pension assets divided by the economy-wide average wage by age and cohort over the age-range projected in MINT. It clearly shows the rise in relative assets between families born in the early 1930s to families born in the early 1950s and the subsequent decline in assets for families born after 1955. The peak cohort is the group reaching age 62 in 2015. The median of non-pension assets are about 70 percent lower than the mean, and the rank order of the cohorts shifts a bit (see Figure 6-15). Based on the mean, individuals born between 1951 and 1955 have the highest assets; based on the median, individuals born between 1946 and 1950 have the highest assets. Individuals born between 1926 and 1930 have the lowest assets with both measures.

Compare MINT Non-Pension Assets with SIPP and SCF

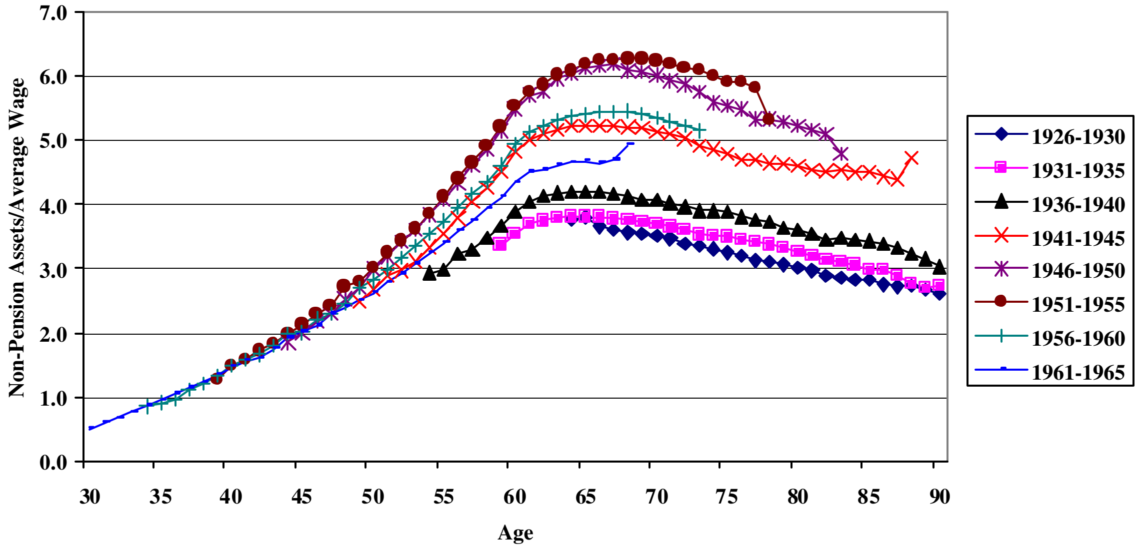
Figure 6-16 shows the distribution of non-pension assets in the early 1990s by age based on the 1990 to 1993 SIPP observed family non-pension assets. This is the starting distribution for MINT. Figure 6-17 shows the same distribution in 1998 based on the Survey of Consumer Finance (SCF). The distribution of family non-pension assets rises with age through the late 60s and then decline at older ages. The median of non-pension assets at age 62 is about 0.9 times the average wage on both datasets. The 90th percentile is about nine times the average wage on the SIPP, but 18 times the average wage on the SCF. The 90th percentile of -pension assets is about 50 percent lower on the SIPP than on the SCF.

Figure 6-18 shows the distribution of non-pension assets in 2000 based on the MINT projections. As with the SIPP and SCF, the distribution of non-pension assets rises with age through the late 60s and then declines at older ages. The median at age 62 is about 1.1 times the average wage, and the 90th percentile is about ten times the average wage. Figure 6-19 shows MINT projected non-pension assets in 2020. As in earlier years, the distribution rises with age through the late 60s and then declines. The median at age 62 rises to about 1.4 times the average wage, and the 90th percentile remains high at 12 times the average wage.

In all cases, the SCF has considerably higher non-pension assets at the top end of the distribution than either the SIPP or MINT. The top of the non-pension asset distribution in MINT 2000 is wider than the early 1990 SIPP distribution, but it still falls short of the 1998 SCF distribution. We calibrate the starting MINT wealth projections to match the SIPP wealth. Without the extreme wealth holders from the base SIPP file, MINT will have difficulty replicating the top end of the distribution. This is further complicated by the fact that MINT projects no new self-employed, who typically have higher assets, and no earnings above 2.46 times the average wage, whose workers would typically be the top wealth holders. While we try to compensate for the censored earnings, our adjustment does not produce enough outliers. To replicate the high end of the distribution, we would need to adjust the base SIPP wealth distribution and project uncensored earnings and self-employment.

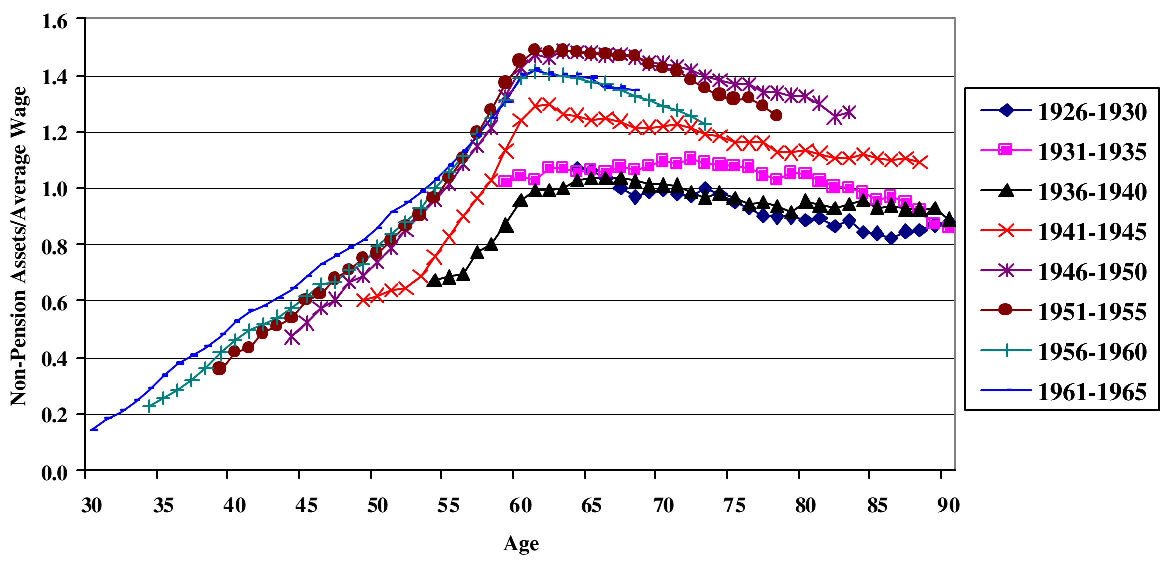
Figure 6-20 shows the 10th percentile of family non-pension assets by age for the 1990 to 1993 SIPP panels, 1998 SCF, and 2000, 2010, and 2020 MINT projections. SIPP, SCF, and MINT all show that the 10th percentile of non-pension assets rises with age, but is less than zero through about age 57. After age 57, the 10th percentile remains very close to zero in all three sources. The MINT projections show a general increase in the 10th percentile of non-pension assets over time, but the 2020 projection for 62-year-olds is only 0.03 times the average wage or

Figure 6-14
Family Mean Non-Pension Assets by Age and Cohort
(Equity as a Percent of the Economy-Wide Average Wage)



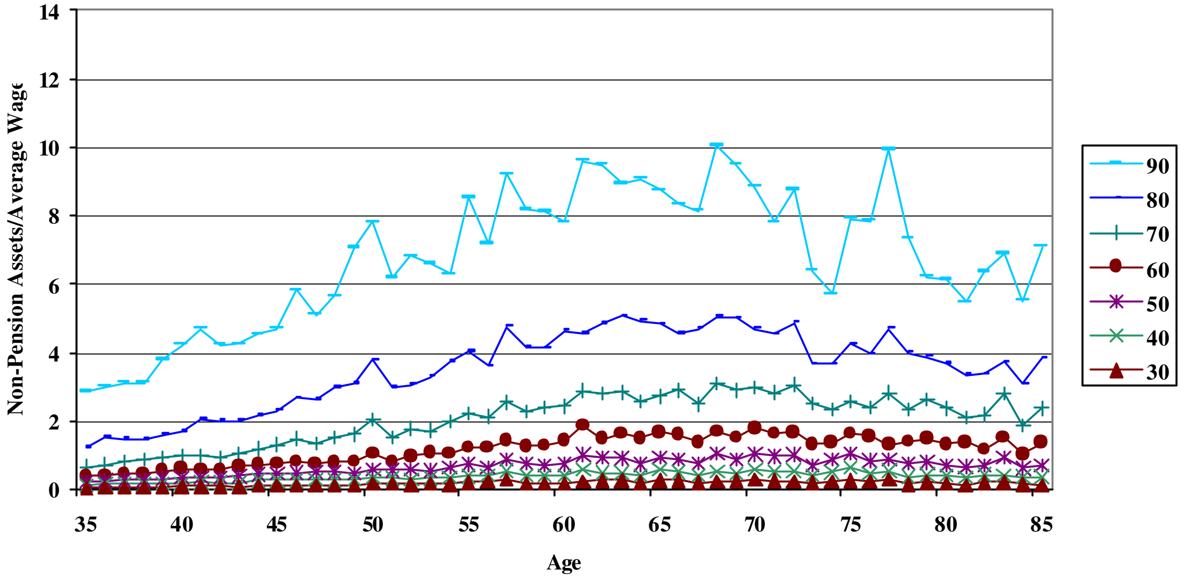
Source: Urban Institute tabulations of MINT.

Figure 6-15
Family Median Non-Pension Assets by Age and Cohort
(Equity as a Percent of the Economy-Wide Average Wage)



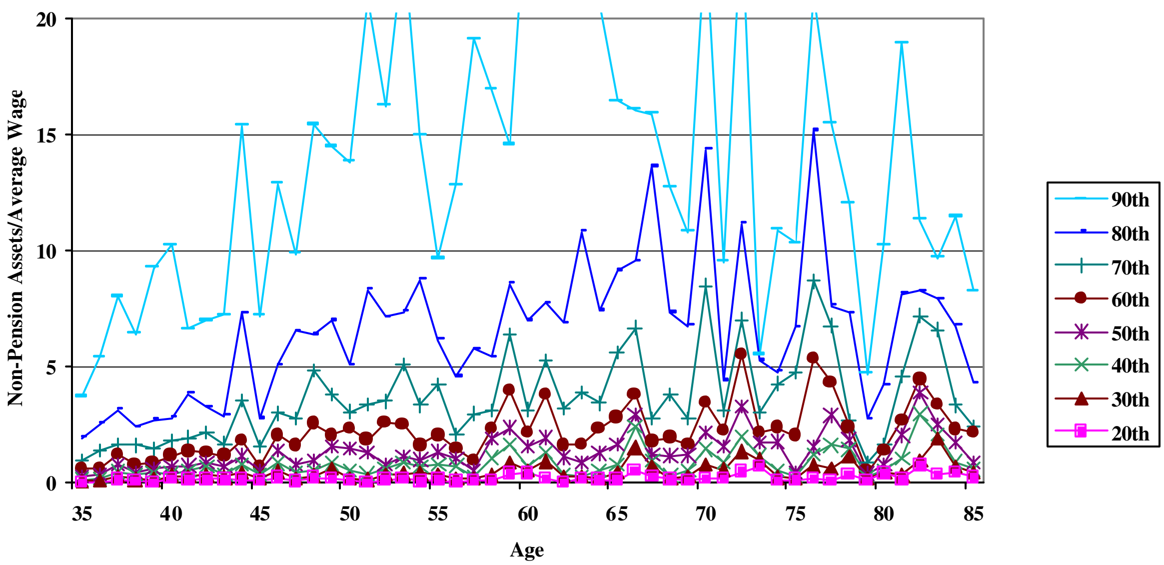
Source: Urban Institute tabulations of MINT.

Figure 6-16
Percentile Distribution of Non-Pension Assets by Age, 1990 to 1993 SIPP
(Assets as a Percent of the Economy-Wide Average Wage)



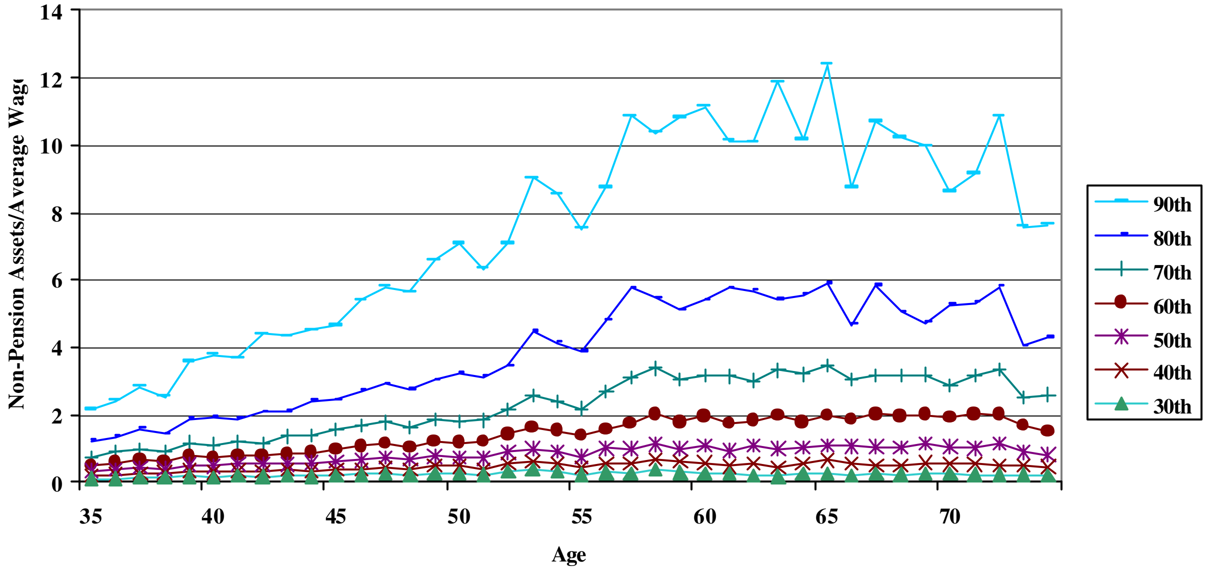
Source: Urban Institute tabulations of 1990-1993 SIPP.

Figure 6-17
Percentile Distribution of Non-Pension Assets by Age, 1998 SCF
(Assets as a Percent of the Economy-Wide Average Wage)



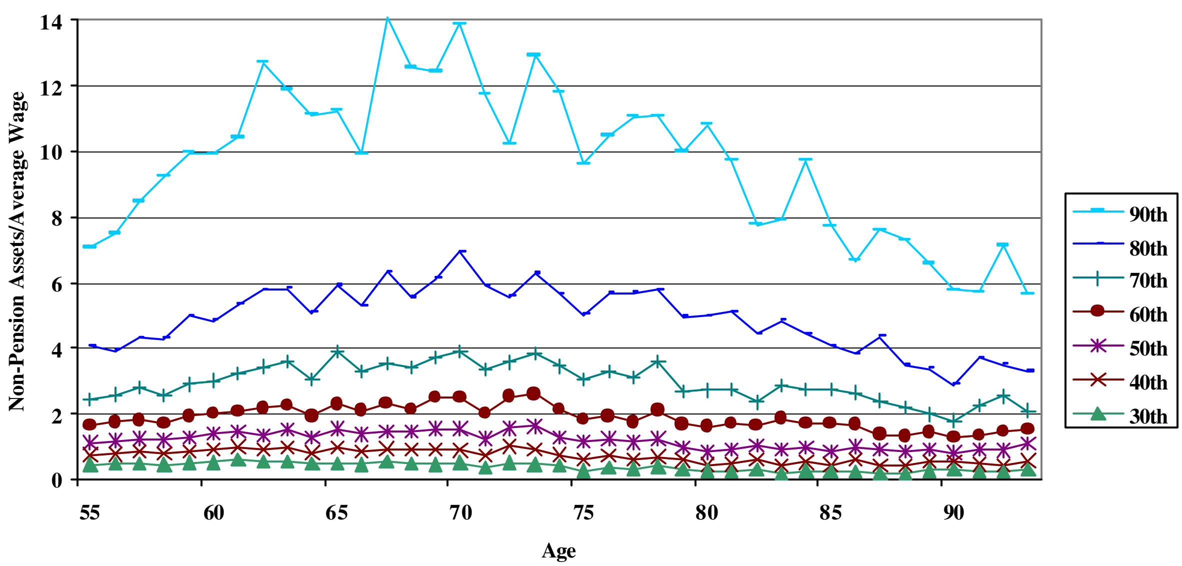
Source: The Urban Institute tabulations of the 1998 SCF.

Figure 6-18
Percentile Distribution of Non-Pension Assets by Age, 2000 MINT
(Assets as a Percent of the Economy-Wide Average Wage)



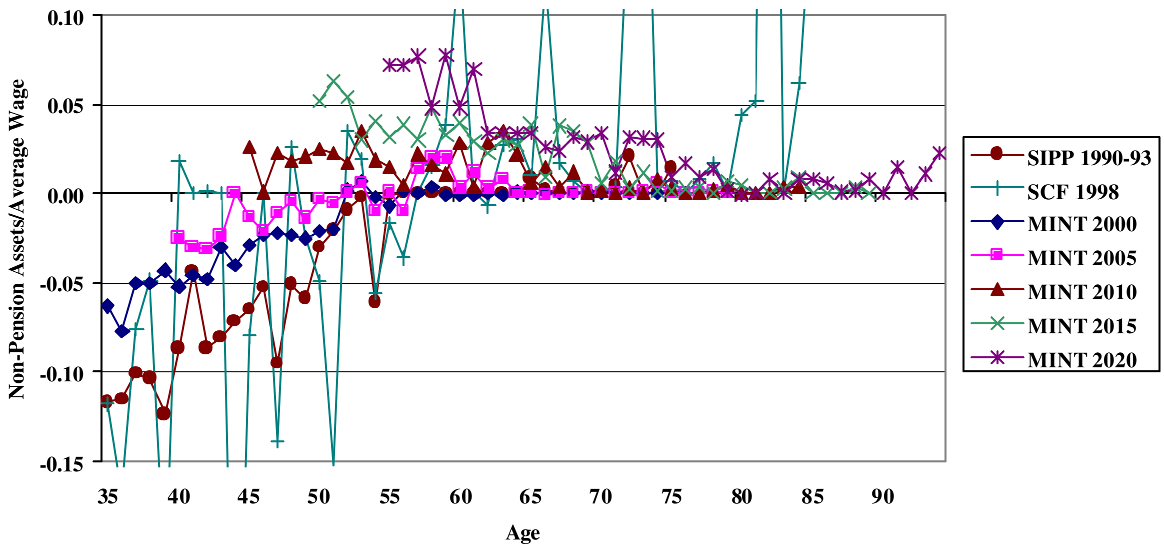
Source: The Urban Institute tabulations of MINT.

Figure 6-19
Percentile Distribution of Non-Pension Assets by Age, 2020 MINT
(Assets as a Percent of the Economy-Wide Average Wage)



Source: Urban Institute tabulations of MINT.

Figure 6-20
10th Percentile Non-Pension Assets by Age and Year
(Equity as a Percent of the Economy-Wide Average Wage)

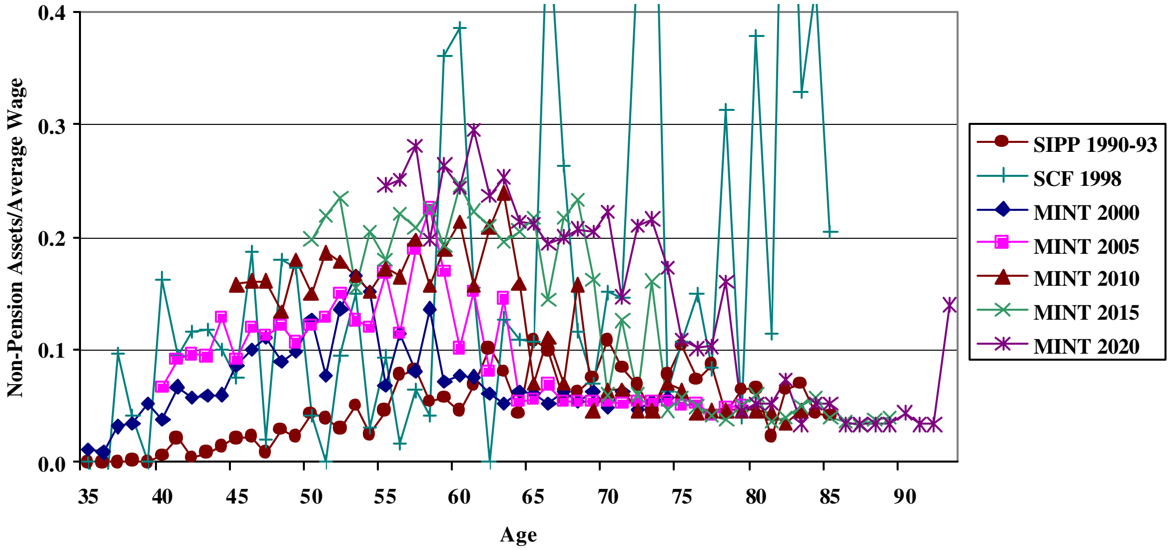


Source: Urban Institute tabulations of MINT, 1998 SCF, and 1990-1993 SIPP.

about $1000 in 2002 wage-adjusted dollars. While the 10th percentile at age 62 is higher in 2020 than in 1990, it is comparable to the 10th percentile on the SCF and by all measures is still inadequate saving for a comfortable retirement. This gradual improvement is mostly due to increases in earnings and labor force participation of women in later cohorts compared to women in earlier cohorts. Figure 6-21 shows the 20th percentile of non-pension assets by age for the same years. MINT projects that the 20th percentile will also rise over time, and the MINT 2000 distribution is quite similar to the SCF distribution between ages 35 and 60. After age 60, the 20th percentile of non-pension assets on the SCF rises, but falls in MINT. The MINT distribution after age 60 more closely matches the early 1990s SIPP distribution. Figure 6-22 shows the median of non-pension assets by age for the same periods. At about the 50th percentile, the SCF values begin to rise above the MINT projections. MINT projects a rise in the median of non-pension assets over time, and the age-pattern matches that found in SIPP and SCF. Finally, Figure 6-23 shows the 80th percentile of non-pension assets by age for the same time periods. The age-patterns are similar including the asset build-up and asset spend-down, but the SCF values are about 50 percent higher than the MINT values. This is true at the 90th percentile as well.

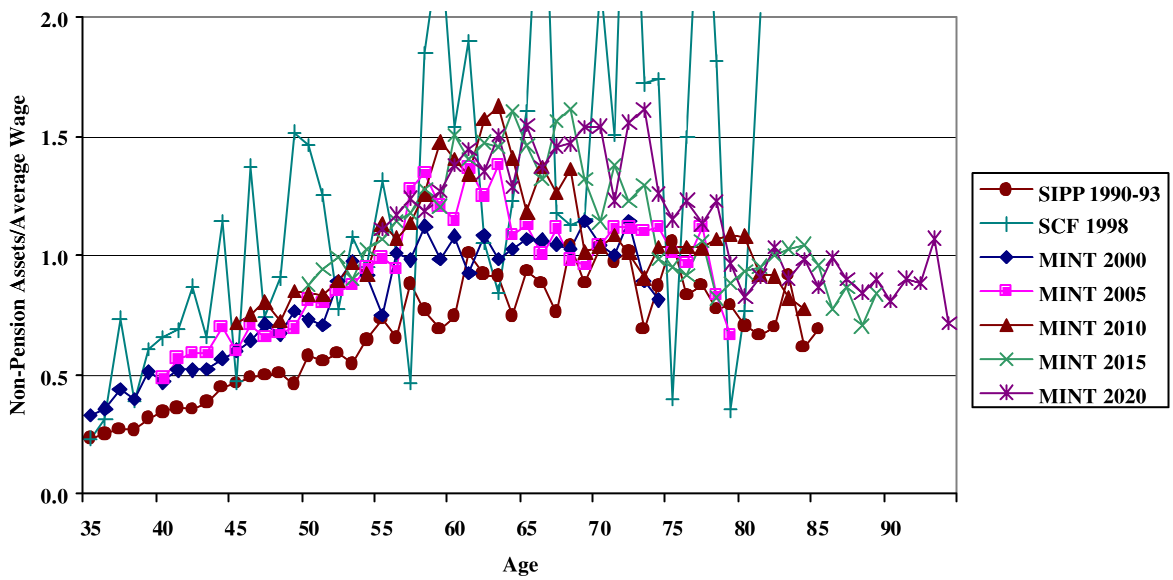
Comparisons of home equity and non-pension assets by education, race, and marital status on the SIPP, SCF, and MINT confirm that assets are higher for families with more educational attainment, higher for married couples than unmarried individuals, and higher for non-Hispanic whites than for blacks and Hispanics. The basic age-wealth patterns of the MINT projections by subgroup and age match those of the SIPP and SCF in all years.

Figure 6-21
20th Percentile Non-Pension Assets by Age and Year
(Equity as a Percent of the Economy-Wide Average Wage)



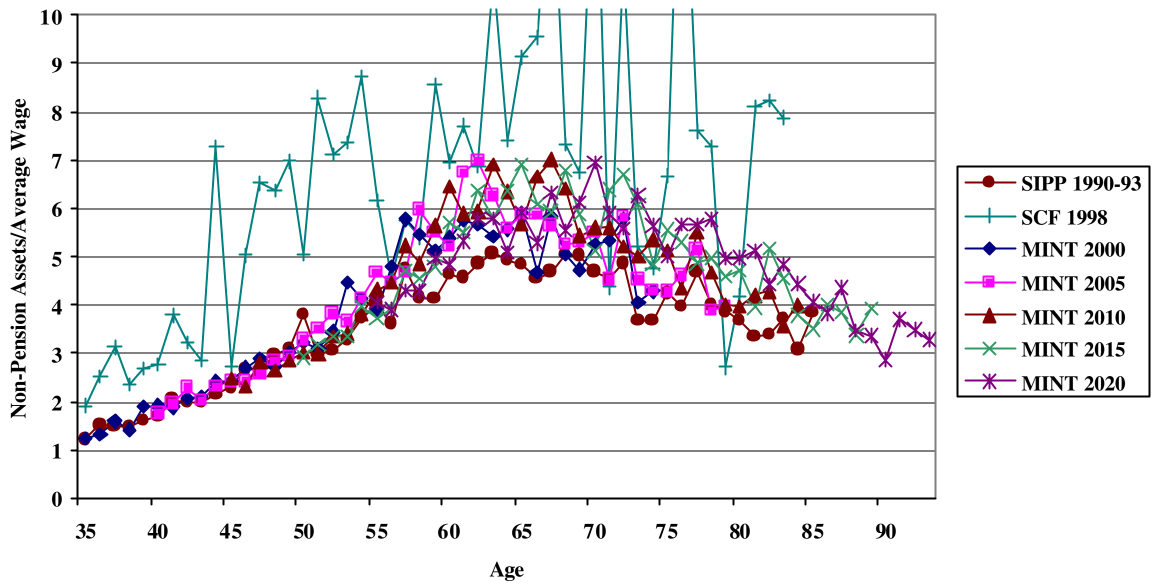
Source: Urban Institute tabulations of MINT, 1998 SCF, and 1990-1993 SIPP.

Figure 6-22
Median Non-Pension Assets by Age and Year
(Equity as a Percent of the Economy-Wide Average Wage)



Source: Urban Institute tabulations of MINT, 1998 SCF, and 1990-1993 SIPP.

Figure 6-23
80th Percentile Non-Pension Assets by Age and Year
(Equity as a Percent of the Economy-Wide Average Wage)



Source: Urban Institute tabulations of MINT, 1998 SCF, and 1990-1993 SIPP.

VII. SENSITIVITY OF WEALTH PROJECTIONS TO ASSUMPTIONS

In this section, we display the results of three wealth sensitivity tests. We display them here, because they are strictly wealth related, but this analysis relies on the results shown in Chapter 5 (pensions), Chapter 9 (income in retirement), and Chapter 10 (poverty) of this volume.

We tested the sensitivity of the wealth projections to the following three alternate assumptions:

- First, in valuing income from assets, we fully annuitize all retirement account balances at projected retirement age based on an actuarially-fair real (price-adjusted) joint and survivor annuity, rather than annuitize 80 percent of these assets. In the baseline, we decay financial assets based on the rates shown in Table 6-11. We calculate income from assets based on an actuarially-fair real joint and survivor annuity the family could purchase each year with 80 percent of its financial assets each year. See Chapter 10 for more discussion of issues related to valuing assets. Under the option, we remove retirement account balance from financial assets, but continue to decay non-pension assets as under the baseline. Under this option, there is no inheritance of unpaid retirement account balances and no risk of outliving one's retirement account assets. This option alters the payment mechanism for retirement accounts, but uses the same annuity rates to convert assets into income. The two differences are the inclusion of all account balance in the annuity, which should increase income compared to annuitizing 80 percent of the account balance, and the lack of inheritance for the survivor of the unlucky annuitant who died young, which will reduce incomes of surviving spouses.

- Second, we adjust the non-pension wealth coefficient for having a defined contribution (DC) pension to match the coefficient for having a defined benefit (DB) pension. The empirical evidence finds that people with pensions save more than people without pensions, and based on our HRS estimates, people with DC pensions save more than people with DB pensions. Some of the difference in saving behavior between DB and DC pension holders may reflect differences in the skill level and job types of workers within each pension type. If this is the case, then as more workers switch from DB pensions to DC pensions, as is projected in MINT, then it may not be reasonable to assume that the historic differential will persist. We expect this option to reduce financial assets compared to the baseline.

- Third, with the relatively recent appearance of tax-deferred saving plans and the increased prevalence of the DC pension plans, some economists argue that these plans simply displace other savings. If we think of DC plans as a substitute for DB plans, then individuals should save at the same rate despite the change in pension type. If, however, people think of their DC plan as a substitute for their private savings, then it is reasonable to expect some reduction in non-pension private savings. With no clear consensus from the economics literature, as a sensitivity test, we chose to reduce non-pension assets by 50 cents for every dollar the individual saves in his or her retirement account. We expect this option to reduce financial savings compared to the baseline.

1. Annuitize All Retirement Account Balances at Retirement

When we fully annuitize retirement account balances at retirement, per capita pension and asset income increase by less than 1 percent, but the impact varies by cohort (see Table 6-17).[14] MINT projects that total per capita pension and asset income will decrease by one percent for individuals in the 1995 retirement group and increase by one percent for individuals in the 2020 retirement group. The annuity rate for both retirement accounts and non-pension assets is identical and the wealth at retirement is unchanged. The option should increase income because we annuitize 100 percent of the retirement account balance under the option and annuitize only 80 percent of the retirement account balance under the baseline. The later retirement groups have higher DC pension balances and have a larger gain under the full annuitization scheme compared to earlier retirement groups with smaller balances. This option should increase calculated income for most families. Individuals can lose under the option in the case of early death. When families annuitize their assets and then have shorter than average lives, they do not inherit the unpaid balance from the annuity. Under the baseline specification, if a spouse dies, the survivor inherits the balance. Because the earlier retirement groups have higher mortality rates compared to later retirement groups, a larger share of the earlier retirement group reach age 67 with a deceased spouse.

[14] We include retirement account balances with financial assets before retirement in calculating income from financial assets. After retirement, we separate the retirement accounts and non-pension assets and fully annuitize the retirement account balance.

In 2020, total per capita income and family income divided by poverty decrease by 0.5 percent under the option compared to the baseline (see Table 6-18). Under the option, both income measures increase for 62- to 69-year-olds, but decrease for older individuals. Overall, families realize more income through full annuitization at younger ages, but less income at older ages. Because survivors forego inheritance in the case of early death through forced annuitization and MINT projects that families spend down their assets more slowly than an actuarially fair annuity would imply, older individuals are worse-off with forced annuitization than self annuitization.

Table 6-17. Per-Capita Income and Percent Change in Pension and Asset Income at Age 67 for the MINT Baseline and the Option, by Cohort

Annuitize 100 Percent of Retirement Account Balance at Retirement

Retirement Group	**1995**	**2000**	**2005**	**2010**	**2015**	**2020**	**All**
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
			BASELINE Per-Capita Income/Average Wage				
Financial Asset Income	0.17	0.19	0.24	0.28	0.31	0.28	0.26
Pension Income	0.15	0.11	0.09	0.08	0.08	0.07	0.09
Total Pension and Asset Income	0.32	0.30	0.33	0.37	0.38	0.35	0.35
			OPTION Per-Capita Income/Average Wage				
Financial Asset Income	0.15	0.16	0.20	0.23	0.25	0.22	0.21
Retirement Account Annuity	0.02	0.03	0.04	0.06	0.06	0.07	0.05
Pension Income	0.15	0.11	0.09	0.08	0.08	0.07	0.09
Total Pension and Asset Income	0.32	0.30	0.33	0.37	0.38	0.35	0.35
Total Annuitized Assets /1	0.17	0.14	0.13	0.14	0.13	0.14	0.14
Total Asset Income /2	0.17	0.19	0.24	0.29	0.31	0.28	0.26
			Percent Change				
Total Pension and Asset Income	-1.2%	0.0%	0.3%	0.5%	0.8%	1.1%	0.3%
Total Annuitized Assets /1	16.1%	31.2%	51.2%	67.5%	78.7%	91.7%	56.7%
Total Asset Income /2	-2.3%	0.0%	0.4%	0.7%	1.0%	1.4%	0.4%

Source: The Urban Institute tabulations of MINT3.

1/ Total annuitized assets is the sum of pension income and annuitized retirement accounts.

2/ Total asset income is the sum of financial asset income and annuitized retirement accounts.

Table 6-18. Per Capita Income and Family Income Divided by Poverty in 2020, by Age
Annuitize 100 Percent of Retirement Account Balance at Retirement

Age in 2020	62 to 64	65 to 69	70 to 74	75 to 79	80 to 84	85 to 89	ALL
			Per Capita Total Income				
Baseline	0.98	0.93	0.89	0.81	0.73	0.72	0.88
Option	0.99	0.93	0.89	0.79	0.71	0.70	0.88
Percent Change	0.5%	0.3%	-0.2%	-1.4%	-2.9%	-4.0%	-0.5%
			Family Income Divided by Poverty				
Baseline	6.50	6.05	5.68	5.11	4.62	4.48	5.69
Option	6.54	6.06	5.66	5.03	4.50	4.29	5.66
Percent Change	0.5%	0.3%	-0.3%	-1.5%	-2.8%	-4.0%	-0.5%

Source: The Urban Institute tabulations of MINT3.

2. DC Pension Holders Save Like DB Pension Holders

Under this option, per capita non-pension assets decline by about 6 percent at age 67 compared to the baseline, and total financial assets (retirement account balance plus non-pension assets) decline by about 5 percent at age 67 (see Table 6-19 and Table A9-6a). The reduction is larger for later retirement groups compared to earlier retirement groups as the later groups accumulate wealth over more years at the lower rate compared to earlier retirement groups. The reduction is also larger at older ages for the same reason.

The percent change in per capita total financial assets (DC pension and non-pension) is greater among individuals in the higher end of the total financial wealth distribution compared to individuals in the lower end of the distribution (see Table 6-20 and Table A9-7). Both retirement accounts and non-pension assets are highly concentrated at the top end of the distribution. Thus the change is more concentrated at the top end of the distribution, but the option reduces assets throughout the distribution.

In 2020, both total per capita income and family income divided by poverty decrease by 1.5 percent under the option compared to the baseline (see Table 6-21). The largest reduction is among 65- to 69-years-olds. The option has little impact on the 85- to 89-year-olds, who had few or no years of exposure to the option. Many of the 62- to 64-year-olds are still working and accumulating assets. They have not had full exposure to the option in 2020. Because few individuals at the bottom of the income distribution have DC assets, this option does not change poverty rates in 2020.

Table 6-19. Mean Projected Financial Wealth, by Age and Cohort (Ratio of Wealth to the Economy-Wide Average Wage) DC Pension Holder Save Like DB Pension Holders

Retirement Group		1995	2000	2005	2010	2015	2020	All
Year of Birth		1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
				Per-Capita Asset/Average Wage				
Non-Pension Financial Wealth at Age								
	50	.	.	1.70	1.88	2.02	1.84	1.89
	55	.	1.90	2.18	2.48	2.68	2.39	2.40
	60	2.14	2.33	2.83	3.18	3.44	3.03	2.97
	62	2.28	2.49	3.03	3.43	3.70	3.20	3.14
	67	2.36	2.56	3.17	3.69	3.97	3.40	3.32
Total Financial Wealth (Excluding Defined Benefit Plans)								
	50	.	.	2.20	2.49	2.70	2.60	2.55
	55	.	2.45	2.89	3.30	3.61	3.40	3.26
	60	2.67	2.99	3.67	4.24	4.60	4.31	3.98
	62	2.86	3.17	3.92	4.56	4.93	4.55	4.20
	67	2.94	3.26	4.09	4.88	5.24	4.79	4.41
Non-Pension Financial Wealth at Age					Percent Change			
	50	.	.	-0.1%	-0.4%	-0.5%	-0.6%	-0.5%
	55	.	-0.7%	-2.0%	-2.6%	-2.9%	-2.8%	-2.5%
	60	-0.5%	-2.1%	-4.0%	-4.7%	-5.0%	-4.9%	-4.3%
	62	-0.8%	-2.7%	-4.6%	-5.3%	-5.7%	-5.6%	-4.8%
	67	-1.2%	-3.3%	-5.7%	-6.3%	-7.0%	-6.6%	-5.8%
Total Financial Wealth (Excluding Defined Benefit Plans)								
	50	.	.	-0.1%	-0.3%	-0.4%	-0.4%	-0.3%
	55	.	-0.5%	-1.5%	-2.0%	-2.2%	-2.0%	-1.9%
	60	-0.4%	-1.8%	-3.2%	-3.6%	-3.9%	-3.6%	-3.3%
	62	-0.7%	-2.3%	-3.7%	-4.2%	-4.5%	-4.1%	-3.8%
	67	-1.0%	-2.8%	-4.7%	-5.0%	-5.6%	-5.0%	-4.6%

Source: The Urban Institute tabulations of MINT3.

Notes: Total financial wealth is the sum of non-pension assets and retirement accounts.

Table 6-20. Distribution of Per Capita Assets at Age 62 by Cohort (Ratio of Wealth to the Economy-Wide Average Wage)
DC Pension Holder Save Like DB Pension Holders

	Mean	20th Percentile	50th Percentile	80th Percentile	90th Percentile	95th Percentile	95th Percentile/Mean	95th Percentile/ 80th Percentile
Year of Birth				**Per Capita Non-Pension Assets**				
1931-1935	2.28	0.07	0.82	3.26	5.98	9.74	4.26	2.99
1936-1940	2.49	0.05	0.73	3.48	6.50	10.93	4.39	3.14
1941-1945	3.03	0.10	0.89	3.72	7.27	12.73	4.20	3.42
1946-1950	3.43	0.16	0.99	4.00	7.95	13.50	3.94	3.38
1951-1955	3.70	0.17	0.99	3.79	7.67	13.76	3.72	3.63
1956-1960	3.20	0.18	0.90	3.44	7.05	12.44	3.89	3.62
				Per Capita Financial Assets (DC pension + non-pension)				
1931-1935	2.86	0.10	1.20	4.47	7.46	11.42	4.00	2.55
1936-1940	3.17	0.09	1.19	4.80	8.31	13.30	4.19	2.77
1941-1945	3.92	0.17	1.44	5.55	9.80	15.49	3.95	2.79
1946-1950	4.56	0.29	1.75	6.18	10.75	16.67	3.65	2.70
1951-1955	4.93	0.34	1.77	6.02	11.06	17.55	3.56	2.92
1956-1960	4.55	0.37	1.72	5.87	10.70	17.15	3.77	2.92
				Percent Change in Financial Assets (DC pension + non-pension)				
1931-1935	-0.7%	0.0%	-0.5%	-0.7%	-1.0%	-0.8%	-0.2%	-0.2%
1936-1940	-2.3%	-1.1%	-0.7%	-1.5%	-2.0%	-1.5%	0.8%	0.0%
1941-1945	-3.7%	-1.2%	-1.6%	-3.6%	-3.8%	-3.1%	0.6%	0.5%
1946-1950	-4.2%	-0.7%	-2.6%	-3.7%	-4.4%	-5.2%	-1.1%	-1.6%
1951-1955	-4.5%	-0.6%	-2.2%	-3.5%	-3.9%	-3.8%	0.7%	-0.3%
1956-1960	-4.1%	-1.1%	-2.4%	-3.3%	-3.9%	-3.4%	0.8%	0.0%

Source: The Urban Institute tabulations of MINT3.

Table 6-21. Per Capita Income and Family Income Divided by Poverty in 2020, by Age
DC Pension Holder Save Like DB Pension Holders

Age in 2020	62 to 64	65 to 69	70 to 74	75 to 79	80 to 84	85 to 89	ALL
			Per Capita Total Income				
Baseline	0.98	0.93	0.89	0.81	0.73	0.72	0.88
Option	0.97	0.91	0.87	0.79	0.72	0.72	0.87
Percent Change	-1.0%	-1.7%	-1.8%	-1.7%	-1.2%	-0.4%	-1.5%
			Family Income Divided by Poverty				
Baseline	6.50	6.05	5.68	5.11	4.62	4.48	5.69
Option	6.44	5.94	5.57	5.01	4.57	4.46	5.60
Percent Change	-1.0%	-1.7%	-1.9%	-1.9%	-1.1%	-0.4%	-1.5%

Source: The Urban Institute tabulations of MINT3.

3. Reduce Non-Pension Assets 50 Cents for Every Dollar Saved in Retirement Accounts

Under this option, per capita non-pension assets decline by about 16 percent at age 67 compared to the baseline, and total financial assets (retirement account balance plus non-pension assets) decline by about 12 percent at age 67 (see Table 6-22 and Table A9-6a). The reduction is larger for later retirement groups compared to earlier retirement groups as the later groups offset savings over more years compared to earlier retirement groups. The reduction is also larger at older ages for the same reason.

The largest percent change generally occurs for individuals with per capita financial assets near the 90th percentile (see Table 6-23 and Table A9-7). The percent change rises between the 20th percentile and the 90th percentile and then falls between the 90th and 95th percentile. Both retirement accounts and non-pension assets are highly concentrated at the top end of the distribution, but retirement accounts represent a larger share of financial savings for the middle of the wealth distribution. While retirement account balances are larger at the top end of the wealth distribution, non-pension assets remain the bulk of assets despite the offset. Few individuals at the bottom of the financial asset distribution have retirement accounts, so the offset affects them less than individuals in the middle of the distribution.

In 2020, total per capita income decreases by about 3.5 percent and family income divided by poverty decreases by 3.6 percent under the option compared to the baseline (see Table 6-24). The largest reduction is among the youngest groups who have larger retirement account balances than older groups. Poverty rates increase from 4.2 percent in the baseline to 4.3 percent under the option and with similar increases in all age groups.

VIII. CONCLUSIONS

MINT projects that homeownership rates will increase slightly over time, but home equity will decline. Projected non-pension assets will rise for individuals born between 1930 and 1955 and then fall for individuals born after 1955. MINT projects that home equity at age 62 will become increasingly unevenly distributed between the early 1990s and 2010. Inequality will decline between 2010 and 2020, but will not return to its early 1990 level. The 2000 MINT home equity projections align closely with 1998 SCF values by age throughout the home equity distribution.

MINT projects that mean non-pension assets will rise for families born in the early 1930s to families born in the early 1950s and then fall for families born after 1955. Non-pension assets are considerably more unevenly distributed than home equity with the family at the 95th asset percentile having about 4 times the mean assets and about 15 times the median assets.

Table 6-22. Mean Projected Financial Wealth, by Age and Cohort (Ratio of Wealth to the Economy-Wide Average Wage) Reduce Non-Pension Assets 50 Cents for Every Dollar Saved in Retirement Accounts

Retirement Group	1995	2000	2005	2010	2015	2020	All
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
			Per-Capita Asset/Average Wage				
Non-Pension Financial Wealth at Age							
50	.	.	1.68	1.82	1.90	1.68	1.78
55	.	1.90	2.17	2.40	2.55	2.20	2.30
60	2.15	2.34	2.84	3.10	3.31	2.82	2.87
62	2.29	2.49	3.00	3.27	3.51	2.91	3.00
67	2.36	2.48	3.00	3.24	3.47	2.77	2.96
Total Financial Wealth (Excluding Defined Benefit Plans)							
50	.	.	2.19	2.43	2.58	2.44	2.45
55	.	2.46	2.88	3.22	3.48	3.22	3.16
60	2.67	3.01	3.69	4.16	4.47	4.10	3.89
62	2.86	3.18	3.90	4.42	4.74	4.27	4.07
67	2.94	3.18	3.94	4.45	4.75	4.16	4.05
Non-Pension Financial Wealth at Age				**Percent Change**			
50	.	.	-1%	-4%	-6%	-9%	-6%
55	.	-1%	-2%	-6%	-8%	-10%	-7%
60	0%	-2%	-4%	-7%	-9%	-12%	-7%
62	-1%	-3%	-5%	-10%	-11%	-14%	-9%
67	-1%	-6%	-11%	-18%	-19%	-24%	-16%
Total Financial Wealth (Excluding Defined Benefit Plans)							
50	.	.	-1%	-3%	-5%	-7%	-4%
55	.	0%	-2%	-4%	-6%	-7%	-5%
60	0%	-1%	-3%	-6%	-7%	-8%	-5%
62	-1%	-2%	-4%	-7%	-8%	-10%	-7%
67	-1%	-5%	-8%	-13%	-14%	-17%	-12%

Source: The Urban Institute tabulations of MINT3.

Table 6-23. Distribution of Per Capita Assets at Age 62 by Cohort (Ratio of Wealth to the Economy-Wide Average Wage) Reduce Non-Pension Asset 50 Cents for Every Dollar Saved in Retirement Accounts

	Mean	20th Percentile	50th Percentile	80th Percentile	90th Percentile	95th Percentile	95th Percentile/ Mean	95th Percentile/ 80th Percentile
Year of Birth				Per Capita Non-Pension Assets				
1931-1935	2.29	0.07	0.80	3.26	5.97	9.75	4.26	3.00
1936-1940	2.49	0.05	0.70	3.36	6.55	11.07	4.44	3.30
1941-1945	3.00	0.05	0.77	3.62	7.23	12.82	4.27	3.54
1946-1950	3.27	0.05	0.76	3.57	7.55	13.22	4.04	3.71
1951-1955	3.51	0.04	0.71	3.28	7.11	13.57	3.87	4.14
1956-1960	2.91	0.03	0.61	2.86	6.19	11.55	3.98	4.04
				Per Capita Financial Assets				
1931-1935	2.86	0.10	1.19	4.47	7.44	11.51	4.02	2.58
1936-1940	3.18	0.09	1.17	4.75	8.33	13.30	4.18	2.80
1941-1945	3.90	0.17	1.39	5.39	9.58	15.27	3.91	2.83
1946-1950	4.42	0.29	1.64	5.77	10.09	16.24	3.68	2.81
1951-1955	4.74	0.33	1.64	5.52	10.10	16.50	3.48	2.99
1956-1960	4.27	0.35	1.57	5.32	9.65	15.66	3.67	2.94
				Percent Change in Financial Assets				
1931-1935	-0.5%	0.0%	-1.3%	-0.7%	-1.3%	0.0%	0.5%	0.7%
1936-1940	-2.1%	1.1%	-2.7%	-2.5%	-1.8%	-1.5%	0.6%	1.0%
1941-1945	-4.2%	0.0%	-5.1%	-6.3%	-5.9%	-4.5%	-0.3%	1.9%
1946-1950	-7.2%	-2.7%	-8.7%	-10.0%	-10.3%	-7.6%	-0.4%	2.7%
1951-1955	-8.1%	-3.2%	-9.4%	-11.5%	-12.2%	-9.6%	-1.5%	2.2%
1956-1960	-10.1%	-6.2%	-11.0%	-12.5%	-13.3%	-11.8%	-1.9%	0.8%

Source: The Urban Institute tabulations of MINT3.

Table 6-24. Per Capita Income and Family Income Divided by Poverty in 2020, by Age Reduce Non-Pension Assets 50 Cents for Every Dollar Saved in Retirement Accounts

Age in 2020	**62 to 64**	**65 to 69**	**70 to 74**	**75 to 79**	**80 to 84**	**85 to 89**	**ALL**
			Per Capita Total Income				
Baseline	0.98	0.93	0.89	0.81	0.73	0.72	0.88
Option	0.95	0.88	0.83	0.77	0.73	0.79	0.85
Percent Change	-2.8%	-4.7%	-6.4%	-4.0%	-0.7%	8.7%	-3.5%
			Family Income Divided by Poverty				
Baseline	6.50	6.05	5.68	5.11	4.62	4.48	5.69
Option	6.32	5.76	5.31	4.91	4.61	4.88	5.48
Percent Change	-2.8%	-4.8%	-6.6%	-3.9%	-0.3%	9.0%	-3.6%
			Poverty Rate				
Baseline	4.6%	4.1%	4.0%	4.0%	3.9%	4.7%	4.2%
Option	4.8%	4.2%	4.1%	4.1%	4.0%	4.8%	4.3%
Percent Change	4.3%	2.4%	2.5%	2.5%	2.6%	2.1%	2.4%

Source: The Urban Institute tabulations of MINT3.

While MINT projects very high wealth holders, the 90th percentile non-pension asset projection in MINT is about 50 lower than the 90th percentile on the 1998 SCF. This shortfall is primarily due to the shortfall in the initial SIPP non-pension asset values. Without the extreme wealth holders from the base SIPP file, MINT will have difficulty replicating the top end of the distribution. The shortfall is further complicated by the fact that MINT projects no new self-employed, who typically have higher assets, and no earnings above 2.46 times the average wage, whose workers would typically be the top wealth holders. While we try to compensate for the censored earnings, our adjustment does not produce enough outliers. To replicate the high end of the distribution, we would need to adjust the base SIPP wealth distribution and project uncensored earnings and self-employment.

Fully annuitizing retirement account balances has little effect on aggregate income in retirement. This option slightly increases retirement incomes of younger retirees and reduces retirement income of older retirees because of differences in inheritance and asset spend-down.

If future DC pension holders save like current DB pension holders, then MINT overstates asset income by about five percent and total income by about 1.5 percent. Because pensions are concentrated among the wealthiest families, most of the reduction in asset income would be among the wealthiest families and aged poverty rates would be unchanged.

If individuals treat DC accounts as a substitute for private savings rather than as a substitute for DB pensions, then MINT overstates asset income by about 16 percent and total income by about 3.5 percent. Again, because pensions are concentrated among the wealthiest families, most of the reduction in asset income would be among the wealthiest families.

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APPENDIX TO CHAPTER 6

We used a statistical match procedure to assign an earnings record and benefit receipt information to individuals without a match to the Summary Earnings Record. For the statistical match, we examined men and women recipients in two age groups (51-55 and 56-61) all separately, yielding four donor pools and four recipient pools. We then minimized a distance function to obtain, on the basis of a series of variables, the best match from a subset of individuals in the donor pool (typically those within neighboring birth cohorts, though we relax this restriction for the spouses who fall out of the HRS age range). We obtained weights in the distance function by estimating stepwise OLS regressions of AIME on current earnings, age, race/ethnicity, disability status, marital status, wealth, pension coverage, number of children ever born, and unionization status. The weight for each was equal to the proportion of the variance in lifetime earnings that it explains (partial R-squared). For men, pension coverage and the natural log of financial wealth were the most important predictors of AIME, while for women baseline earnings tended to swamp all other predictors. Note that when we computed minimum distances between pairs of observations, we sampled from the donor pools with replacement. This implies that we used some donors more than once, though we used the overwhelming fraction of donors just once. If a person with missing earnings appeared in our person-year file more than one time, he/she always received the same earnings/benefit receipt vector. We drew the donors of earnings records only from the 1992 observations, though.

CHAPTER 7

SUPPLEMENTAL SECURITY INCOME AND LIVING ARRANGEMENTS

I. OVERVIEW

In this chapter, we explain how MINT projects Supplemental Security Income (SSI) benefits and eligibility status from age 62 until death. In order to project these outcomes, MINT needs to identify each person's living arrangements at each of these ages. At SSA's request, we specifically differentiate among three types of living arrangements: independent living, co-residence in another person's home, and institutionalization. In making these projections, it was also helpful to have information about an individual's health status. We therefore also model health status for ages 68 and over**.**

MINT annually determines the five events in a sequence: 1) health, 2) institutionalization, 3) living arrangements given that one is not institutionalized, 4) SSI eligibility, and 5) SSI take-up. It accounts for simultaneity between living arrangements and SSI receipt by using individuals' contemporaneous living arrangements to predict their SSI receipt and their lagged SSI receipt to predict their living arrangements.[1] Likewise, health affects other outcomes.

This chapter provides a detailed description of the models and the data sources we use to estimate their parameters. It discusses important specification choices, including whether to model levels or transitions and whether or not to incorporate unmeasured individual heterogeneity. After presenting the models, it discusses the results that they generate. This includes extensive discussion of the validity of coresidence and SSI outcomes. It also includes sensitivity tests to assumptions about SSI program parameters. An appendix discusses a set of cross-cutting implementation issues.

II. THE MODEL – SEQUENTIAL DETERMINATION OF HEALTH, LIVING ARRANGEMENTS, AND SSI ELIGIBILITY AND RECEIPT

The model consists of four separate state spaces, for outcomes: 1) health status, 2) institutionalization, 3) living arrangements given that one is not institutionalized, and 4) SSI receipt, respectively.[2] All four of the state spaces include just two outcomes, defined as follows:

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[1] Because SSI benefits are reduced (by one third) for residence in another person's home, SSI recipients may make different choices about changing their place of residence than do similar persons who do not face an income loss. SSI recipients' eligibility for Medicaid could also affect their decisions about living arrangements. (For additional detail on the rationale for these interactions, see Favreault, Smith, and Wolf, 2001.)

[2] SSI eligibility (set to one if an individual is eligible for benefits and zero otherwise) is also part of the state space of the model. We do not discuss it in detail here because we determine it by applying rules rather than by using an empirically estimated model (see the Appendix).

$Y1_{it}$ = 0 if i is in excellent, very good, or good health at t;
$Y1_{it}$ = 1 if i is in fair or poor health at t;

$Y2_{it}$ = 0 if i is in an institution at t;
$Y2_{it}$ = 1 if i is in the community at t;

$Y3_{it}$ = 0 if i is living independently at t;
$Y3_{it}$ = 1 if i is living with others at t;

$Y4_{it}$ = 0 if i is not receiving SSI at t;
$Y4_{it}$ = 1 if i is receiving SSI at t.

The model processes health, institutionalization, living arrangements of the non-institutionalized, SSI eligibility, and SSI take-up in sequence. As the introduction notes, the model incorporates the contemporaneous value of living arrangements as a determinant of SSI receipt and the lagged value of SSI receipt as a determinant of living arrangements. Health also impacts subsequent processes.

For all four processes (health, institutionalization, living arrangements and SSI receipt), we estimated binary logit models. We assume institutionalization to be an absorbing state (once one enters an institution, one never returns to the community), and therefore we only model entries. For the other three processes, one can transition between states (independent living and shared accommodation, receiving and not receiving SSI, and good health and poor health). In the case of health status we directly model these transitions (both entries and exits). In the case of SSI and living arrangements, we model statuses rather than transitions, but use the lagged endogenous variable as a predictor to promote intertemporal consistency. The models are specified as follows:

Entry models: $\text{prob}\ \{yn_{it} = 1 \mid yn_{it-1} = 0\} = 1 / (1+e^{-ßX_{it-1}})$ (7-1a)
Exit models: $\text{prob}\ \{yn_{it} = 0 \mid yn_{it-1} = 1\} = 1 / (1+e^{-ßX_{it-1}})$ (7-1b)
Status models: $\text{prob}\ \{yn_{it} = 1\} = 1 / (1+e^{-(ßY_{it-1} + ßX_{it-1})})$ (7-1c)

where X_{it-1} is a set of exogenous regressors, Y_{it-1} is the lagged endogenous variable, and the ß terms are a set of parameters to be estimated. Predictors (the elements of X_{it-1}) included standard demographic and economic variables, such as age, sex, race, marital status, whether native-born, education, income sources (Social Security, pensions, and asset income), and wealth (home-ownership status). They also included children ever born, the closest we can come to representing the composition of the kin group, which has been shown by past research to be an important correlate of living arrangements among the elderly. For married persons, predictors include several characteristics of the spouse (his/her age, economic resources, and so forth).

A potentially important determinant of the SSI receipt decisions is the expected SSI benefit. Incorporating the expected SSI benefit as an explanatory variable, however, raises several complications. If one controls for income levels by source (including earnings, pensions, Social Security, and asset income), it is not possible to include the expected Federal SSI benefit among eligible recipients because it is a deterministic (and therefore perfectly collinear) transformation of the included income variables. Further, including earned income in participation models raises concerns about endogeneity, as one may choose SSI participation and earnings jointly.

As a result of these concerns, we do not include earnings and the expected federal SSI benefits in the SSI models. Rather, we compute the expected state supplement to the base SSI benefit among eligible recipients who live in states that opt for the various supplements. In carrying out simulations based on this model, we ignored state-to-state migration as a way of avoiding the possible endogeneity of access to supplemental SSI benefits. In place of earnings, we use measures of labor force experience (for example, total years in the labor force since 1951 or years since last spell of work).

Certain predictors enter some of the equations and not others. For example, the generosity of state SSI benefits affects decisions about taking up SSI benefits, but not choice of living arrangements.

For several reasons it is desirable to include unmeasured heterogeneity terms in the model.[3] We have estimated alternative versions of the SSI and living arrangements models that incorporate normally distributed, individual-specific components using random effects models (for details, see Favreault, Smith, and Wolf, 2001). We did not, however, implement these models into MINT because of concerns about appropriately assigning the random effects both to the initial conditions and to the transition models. (For discussion of this problem in another context, see Blau, 1994.)

III. DATA SOURCES FOR ESTIMATION

To estimate model parameters, we use the Survey of Income and Program Participation (SIPP) matched to Social Security Administration records. The SIPP is an ideal source for this investigation. The data are relatively current, are nationally representative, and cover the entire age range (62 to death) over which we must estimate and project living arrangements and SSI receipt. When we pool data from the 1990 to 1993 panels of SIPP, the resulting sample contains well over 1500 unique SSI recipients. The SIPP also accounts for SSI participation and income as well as or better than other data sources.

[3]First, the pooling of observations introduces dependencies across observations in the pooled data. We would expect, for example, that a given person's living arrangement/SSI outcomes would be correlated over time because our regression equations cannot take into account all of the important dimensions along which he/she differs from others. The introduction of time-invariant individual-level effects is a standard way to correct for these interdependencies. Second, the explicit representation of the time-invariant individual effects will produce superior forecasts, because living arrangements are expected to be more stable than would be implied by a model in which the probability of each outcome is treated as conditionally independent, based on current-period observables. So we can expect both better parameter estimates and more realistic life paths using these terms. A particular advantage of the unmeasured-heterogeneity version of the panel logit model is that SIPP data on living arrangements and SSI participation at each wave's interview can be used in the estimation. But simulations can still be performed on a year-by-year basis, because the underlying model structure is invariant to time aggregation.

We link the SIPP to Social Security's lifetime earnings and SSI receipt records (the Summary Earnings Record, or SER, and Supplemental Security Record, or SSR). This allows us to develop reliable estimates of Social Security eligibility and benefits (which are necessary for determining SSI eligibility and benefits) and SSI participation. We also match the SIPP records to the Numident file, which allows us to determine an individual's year of death if the person died in the historical period (through 1999).

Our only major concern with using the SIPP for our model of SSI and living arrangements is that it may not measure transitions into institutions well. For example, the reported reasons why individuals ages 61 and above left their households between interview one and interview two of the 1990 SIPP include 102 deaths, 45 entries into institutions, 6 emigrations, and 144 "other reasons." Some of these other reasons may in fact be entries into institutions. Calibrating the institutionalization function to data from an external source would be one strategy for contending with this data limitation.[4]

IV. PARAMETER ESTIMATES

1. Health Status Model

The first step in developing projections of living arrangements and SSI benefit receipt is to model health status for those who are ages 68 and over. While the MINT 3.0 contract does not directly require modeling health status for those over 68, an explicit model of health status improves the projections by ensuring that shocks to assets, retirement earnings, and living arrangements and/or SSI are appropriately correlated. In this model, we use the same dichotomous definition of health that MINT 3.0 uses for health projections prior to age 68 (see Chapter 3): a self-report that health is fair or poor compared with all other classifications. Using this definition allows us to pick right up from the age 67 projection, thereby promoting consistency in individual trajectories.

To estimate parameters in the aged health status model, we use data from the 1990 SIPP, including the topical modules on functional limitations and disability and demographic and socioeconomic information from the core survey. We merge these data with Social Security administrative records on earnings (the SSER) and mortality (Numident). The relevant topical modules were spaced exactly a year apart, and this allowed us to estimate yearly health transitions.[5] We chose a transition approach over a levels approach for this section of MINT, as it ensures relative stability in health status. (We cannot incorporate unobserved heterogeneity using random effects into this model, as we have too few observations on individuals.)

[4] Candidates for providing calibration targets include the Medicare Current Beneficiary Survey, or MCBS, and papers that use other appropriate data files, like the National Long-Term Care Survey (see, for example, Dick, Garber, and MaCurdy, 1994). The MCBS includes both the institutionalized and non-institutionalized populations in its starting sample and is specifically geared toward tracking institutionalization.

[5] We could not use the 1991-1993 SIPPs, as they asked the health status question just once.

For our model of entry into poor health, we estimate separate equations for men and women, while for our model of continuation in poor health, we pool observations on men and women. All three models include age, educational attainment, current and lifetime family income (for which Social Security income is proxy variable), race, and a dichotomous variable indicating that death will occur in the next twenty-four months as predictors. While it may appear counter-intuitive to use death to predict health rather than the reverse, we do so because death is predicted prior to health in MINT (i.e., for our purposes, it is completely exogenous). We believe that ensuring consistency between these two processes is essential, even though to capture this correlation we must reverse their sequence and causal relationship.

We report the coefficient estimates and standard errors from these three models in Table 7-1. Asterisks denote statistically significant effects. We find stronger results for the two models that estimate entry into fair or poor health than for the model that estimates continuation of poor health. For entry to poor health, age and education work in the expected directions for both men and women. The indicator for impending mortality also has large and significant effects for both groups. Among women, those who never married are less likely to enter poor health than their married peers. Both wealthier men and women are less likely to enter poor health than individuals who are less well off in terms of assets. African American and Native American women are also more likely to enter poor health than are white women.

For continuation in poor health, we find that fewer predictors have significant effects. The nearing death indicator is the chief one among these, again increasing the probability of remaining in poor health. Individuals with earnings in the previous year are less likely to remain in poor health. Family lifetime earnings and race have additional effects on the probability of remaining in poor health, with those with higher family AIME at 62 less likely to remain in poor health than those with lower AIME, and blacks more likely to stay in poor health than whites.

2. Institutionalization Model

The institutionalization hazard is a small component of MINT 3.0. To model the transition into an institution, we use SIPP data from 1990 to 1993. While our health models used annual observations, this section of MINT used observations from each wave (i.e., observations that were spaced four months apart, the time between SIPP interviews). We assume that by applying the wave-specific probability three times, we can properly produce the annual probability of institutional entry. As SIPP transitions into institutions are exceedingly rare (just over 200 observed in almost 200,000 SIPP person waves), SSA might at some point wish to calibrate the projections to an external estimate of admissions (see footnote 4).

Table 7-2 reports the coefficient estimates from our discrete-time event history model. As with health status transitions, it was important that we correlate institutionalization risk with impending mortality and other important economic and demographic characteristics. The indicator variable that signals that death will occur in the next twenty-four months has a large, positive statistically significant coefficient. Health similarly is strongly correlated with institutionalization, even net of mortality. Those in fair or poor health are more likely to enter an institution than are those in good to excellent health. Age, education, nativity, race, and wealth have additional effects on probability of institutionalization. The chance of entering an

Table 7-1
Health Transitions, Ages 68 and Higher

	Entry into poor health				Remain in poor health	
	Men		Women			
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-5.5120 ***	1.1932	-5.5666 ***	0.9290	0.1529	0.8032
Age	0.0573 ***	0.0157	0.0529 ***	0.0123	0.0130	0.0108
Never married	0.2975	0.3901	-1.0547 ***	0.3905	—	—
Divorced or separated	0.2247	0.3580	0.1766	0.2550	—	—
Widowed	0.2017	0.1960	0.1985	0.1358	—	—
Lagged earnings	-0.2572	0.2805	-0.6166	0.4409	-1.5731 ***	0.4595
Wealth	-0.0284 *	0.0171	-0.0444 **	0.0222	—	—
Family AIME at 62	—	—	—	—	-0.1130 *	0.0626
Not high school graduate	0.2762	0.1825	0.3557 **	0.1405	0.0259	0.1289
Some college education	-0.4914 **	0.2130	-0.3096 *	0.1725	-0.2078	0.1659
Black or Native American	0.2742	0.2509	0.6241 ***	0.2073	—	—
Black	—	—	—	—	0.2815 *	0.1593
Hispanic	0.4177	0.3428	0.4768	0.3410	—	—
Asian	-0.2488	0.5241	-0.5374	0.6351	—	—
Number of children	—	—	0.0431	0.0438	—	—
Homeowner	-0.1364	0.1871	0.1764	0.2035	—	—
Death impending (< 24 mths)	1.1174 ****	0.2519	0.7017 ***	0.2459	0.5818 ***	0.1858
N (person years)	1,156		1,793		1,912	
-2 log-likelihood	1117.841		1755.484		2119.806	

Data source: 1990 SIPP
*** indicates $p < 0.01$; ** indicates $p < 0.05$, * indicates $p < 0.10$

Table 7-2
Institutionalization Hazard, Ages 62 and Older

Variable	Coefficient		Standard Error
Intercept	-18.2536	***	1.1335
Age	0.1013	***	0.0131
Never married indicator	0.4002		0.2753
Divorced or separated indicator	-0.5491		0.3703
Widowed indicator	-0.3810	**	0.1551
Indicator not a high school graduate	4.2471	***	0.5830
Black indicator	-0.6834	**	0.2635
Foreign born indicator	-0.5956	**	0.2715
Home ownership indicator	-0.7613	***	0.1793
Health fair or poor indicator	0.7907	***	0.1653
Impending death (w/in 24 months) indicator	1.3638	***	0.1617
N (person waves)	200,000		
-2 log-likelihood	2495.907		

Data source: 1990-1993 SIPP
*** indicates $p < 0.01$; ** indicates $p < 0.05$, * indicates $p < 0.10$

institution increases with age and if one's completed education totals less than twelve years, while it is lower if one is black, owns a home, or was born outside of the United States.

3. Living Arrangements Model

We define shared living arrangements based on the ages and relationships of the persons with whom one resides. SSI regulations that reduce benefits for sharing a home focus on whether one receives "support and maintenance in kind" from the persons with whom one lives. Only a small fraction of adults who share a home with someone else are living in situations that SSA would classify as dependent in this way. To avoid wrongly classifying older persons as co-residing in a dependent relationship when in fact they are providing support or accommodation to others in their household (for example, to their children who return home after finishing school or getting a divorce), we use a number of rules. For example, the person with whom one resides must be at least thirty years of age in order for the relationship to qualify as one of co-residence. The person or persons with whom one lives must also be relatives (i.e., we assume that roommates live independently in financial terms). Point five in the appendix describes how we then translate this measure of shared living with relatives who are ages 30 and over into a measure appropriate for determining SSI eligibility and benefits.

As most members of the MINT sample are less than age 62 at the start of the simulation, we need to impute starting values for their living arrangements. The first component of the living arrangements model is thus the assignment of co-residence status at baseline (1999 or age 62, whichever comes later) using a logit model. The coefficients from this model demonstrate relationships that are consistent with findings from previous literature (Table 7-3). We find a strong association between kin availability and living arrangements: the higher the number of children one has had, the more likely one is to co-reside with kin. Those born abroad are also more likely to co-reside, suggesting differences in norms across cultures about sharing a home with one's extended family. Asians, African-Americans, and Hispanics are all more likely to co-reside than non-Hispanic whites, while Native Americans are less likely to co-reside than whites. Resources, in terms of both financial and human capital, appear to be an important determinant of co-residence. The higher one's Social Security, pension, or asset income or one's education, the less likely one is to live in with one's relatives. Health concerns, like resource limitations, increase the likelihood that one will co-reside, as evidenced by the positive coefficients for fair or poor health and impending death.

As we noted in the overview section, after baseline, the model of shared living arrangements is comprised of a subsequent coresidence model that includes the value of the lagged endogenous variable. Like the baseline assignment, our findings on subsequent co-residence are consistent with prior literature (Table 7-4). Kin availability remains a strong predictor of maintaining shared living arrangements, as do place of birth, and race. Lower resources are still associated with the likelihood of subsequent co-residence. Asset income decreases the chances one becomes or remains a coresident. Further, SSI eligibility, a good proxy for poverty, increases these chances. As we would expect, net of eligibility, SSI participants are less likely to remain co-residents than are otherwise similar persons.

Table 7-3
Baseline Coresidence Status, Ages 62 and Over

	Coefficient		Standard Error
Intercept	-1.6479	***	0.0879
Male indicator	-0.1222	***	0.0138
Never married indicator	1.0686	***	0.0595
Indicator divorced or separated	0.0984	*	0.0575
Widowed indicator	0.4224	***	0.0563
Age	-0.0028	**	0.0011
Age 62 indicator	-0.0500	*	0.0283
Spouse age	-0.0040	***	0.0008
Family earnings	-0.0436	***	0.0154
Family Social Security benefits	-0.5275	***	0.0437
Family pension benefits	-0.1632	***	0.0267
Family asset income	-0.6430	***	0.0290
Indicator of some college education	-0.1648	***	0.0173
Indicator not a high school graduate	0.0895	***	0.0145
Black indicator	0.3409	***	0.0190
Hispanicity indicator	0.2081	***	0.0327
Asian indicator	0.7921	***	0.0397
Native American indicator	-0.1964	*	0.1027
Foreign born indicator	0.4719	***	0.0206
Number of children ever born	0.1374	***	0.0033
SSI participant at t-1	-0.3201	***	0.0302
Eligible for SSI at time t	0.2754	***	0.0243
Health fair or poor indicator	0.0379	***	0.0130
months)	0.1783	***	0.0272
N (person waves)	213,065		
-2 log-likelihood	181122.030		

Data source: 1990-1993 SIPP
*** indicates p < 0.01; ** indicates p < 0.05, * indicates p < 0.10

Table 7-4
Subsequent Coresidence Status, Ages 63 and Over

	Coefficient		Standard Error
Intercept	-5.3171	***	0.2716
Male indicator	-0.0369		0.0467
Age	0.0060	*	0.0036
Family earnings	0.0609		0.0505
Family Social Security benefits	-0.1106		0.1508
Family asset income	-0.2648	***	0.0804
Spouse age	-0.0054	***	0.0007
Indicator of some college education	-0.0381		0.0591
Indicator not a high school graduate	0.1463	***	0.0515
Black indicator	0.1069		0.0710
Hispanicity indicator	-0.0380		0.1252
Asian indicator	0.4843	***	0.1568
Native American indicator	-1.1186	***	0.3116
Foreign born indicator	0.2510	***	0.0773
Number of children ever born	0.0740	***	0.0111
Eligible for SSI at time t	0.2960	***	0.0934
SSI participant at t-1	-0.3866	***	0.1164
Health fair or poor indicator	0.0335		0.0463
Death impending (< 24 months)	0.0174		0.0948
Shared living arrangements at t-1	7.9798	***	0.0426
N (person waves)	176,458		
-2 log-likelihood	22716.350		

Data source: 1990-1993 SIPP (ssipartreg.lst)
*** indicates $p < 0.01$; ** indicates $p < 0.05$, * indicates $p < 0.10$

4. SSI Participation Model

The SSI participation model uses separate equations for individuals ages 62 through 64, who are eligible only for the disability program, and individuals ages 65 and older, who are eligible for the aged program (but who may have converted from the disability program). Among those ages 65 and older, we model program participation using the lagged endogenous variable. For all SSI participation equations, we restrict the population to individuals whose assets and unearned income place them below SSI thresholds.[6] If an individual has not yet elected to take up Social Security benefits, we compute the Social Security benefit to which he or she would be entitled and include this as part of unearned income when applying the eligibility screen.[7] To simulate eligibility for SSI benefits from ages 62 to 64, we also need to make an assumption about whether one is disabled. We assume that an individual is disabled for SSI purposes if he or she reports a health condition that limits the amount or kind of work that he/she can do.

The SSI take-up equation for the eligible disabled ages 62 and 64 exhibits many of the expected relationships (Table 7-5). SSI participation is more prevalent among those with poorer health. Never married and divorced people are more likely to take up SSI disability benefits than married people. Those with less education are also more likely to participate in the program than their more educated peers, and Asian Americans are more likely to participate than whites. State supplements are associated with an increased likelihood of participation in SSI, as we would expect. Previous literature has also revealed the importance of SSI generosity for take-up decisions. Co-residence, which decreases expected SSI benefits in some circumstances, reduces the likelihood of participation. Work experience decreases participation probability, while longer intervals out of the labor force increase participation.

At ages 65 and older, the models reveal the pivotal importance of lagged SSI status, which is positively associated with receipt (Table 7-6). An age 65 indicator is, not surprisingly, positively and significantly associated with participation given that this is the first point at which one can apply for aged SSI benefits. Those with less education are more likely to participate than those with a high school education. Asians and Hispanics are more likely to participate than whites and non-Hispanics, and those born abroad are more likely to participate than those born in the U.S. The greater one's labor force experience, the less likely one is to participate in SSI after age 65. Homeownership likewise reduces participation. Poor health greatly increases participation probability, as does residence in the South.

Because of the relative rarity of exits from SSI for non-eligibility reasons, we deterministically assign probability of program exit (for reasons other than death or change in eligibility status) to just over zero.

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[6] We ignore provisions for disregarding work-related expenses of the blind and disabled when determining eligibility.

[7] In order to qualify for SSI benefits, a person must first apply for every other form of income/public benefit for which he/she is eligible. This is one reason why SSI is often described as the "program of last resort."

Table 7-5
SSI Participation among Eligible Persons, Ages 62 to 64

	SSI Status: Ages 62 to 64	
Variable	Coefficient	Standard Error
Intercept	-2.9721 ***	0.2752
Never married indicator	1.3857 ***	0.1779
Indicator divorced or separated	1.1696 ***	0.1245
Widowed indicator	0.1855	0.1284
Total years in labor force	-0.0391 ***	0.0062
Years elapsed since last earned	0.0245 ***	0.0048
Family Social Security	1.3844	1.0932
Family pension income	-1.8207	1.6968
Family asset income	3.0241	3.7403
Family Social Security exposure	0.3462	0.2179
Spouse earnings	-1.0336 **	0.4468
Indicator of some college education	-0.6355 ***	0.1940
Indicator not a high school graduate	0.3685 ***	0.1180
Black or Native American indicator	0.1073	0.1072
Asian indicator	0.7615 ***	0.2165
Foreign born	-0.3962 ***	0.1445
Annual state supplement/average wage	3.8172 ***	0.8269
Shared living arrangements	-0.3846 ***	0.1086
Number of children	0.0439 *	0.0226
Home ownership indicator	-0.0558	0.0992
Health is fair or poor	1.9520 ***	0.1122
N (person waves)	3,052	
-2 log-likelihood	3040.779	

Data source: 1990-1993 SIPP (ssipartreg.lst)
*** indicates $p < 0.01$; ** indicates $p < 0.05$, * indicates $p < 0.10$

Table 7-6
SSI Participation among Eligible Persons, Ages 65 and Higher

Variable	Coefficient	Standard Error
Intercept	-0.1706	0.5688
Male indicator	-0.1087	0.0918
Never married indicator	-0.1412	0.1567
Indicator divorced or separated	-0.0352	0.1266
Widowed indicator	-0.1636	0.1038
Age	-0.0396 ***	0.0076
Age 65 dummy	0.9956 ***	0.1204
Total years in labor force	-0.0093 *	0.0054
Years since last employment spell	-0.0046	0.0040
Family Social Security	-0.4099	0.7259
Family Social Security exposure	0.4489 **	0.1741
Individual pension income indicator	-0.4358 *	0.2465
Spousal pension income indicator	0.2481	0.3070
Family pension income	6.0555 ***	1.8511
Family asset income	4.9473 **	2.2999
Indicator of some college education	0.0670	0.1473
Indicator not a high school graduate	0.2439 **	0.0977
Black or Native American indicator	0.1070	0.0889
Hispanic indicator	0.2540 *	0.1350
Asian indicator	0.8083 ***	0.1702
Foreign born indicator	0.7332 ***	0.1153
Annual state supplement/average wage	0.6731	0.6758
Indicator of Southern residence	0.2276 **	0.0905
Indicator of shared living arrangements	-0.0446	0.0833
Number of children	0.0701 ***	0.0181
Home ownership indicator	-0.2178 ***	0.0834
Health is fair or poor	0.2787 ***	0.0767
Previous SSI experience	6.4222 ***	0.0973
N (person waves)	16,144	
-2 log-likelihood	5766.214	

Data source: 1990-1993 SIPP

*** indicates p < 0.01; ** indicates p < 0.05, * indicates p < 0.10

Note: South is defined as Alabama, Arkansas, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Mississippi, Missouri, North Carolina, South Caroline, Tennessee, Texas, Virginia, and West Virginia.

The manner in which we structure the SSI model has important ramifications for policy simulation using MINT. At the request of the Social Security Administration, we have developed methods that enable the user to implement different versions of the SSI component of the model to meet different objectives. For example, we have entered individual account balances into the calculator for use in simulations. They are currently set to zero for all persons. Additionally, we have integrated a parameter that allows one to make take-up of Social Security deterministic (rather than stochastic). For details on these parameters, contact Melissa Favreault.[8]

V. Implementation Issues

As with implementing the function that projects Social Security take-up age, in projecting SSI participation and benefits we need to pay careful attention to the MINT transition between administrative and projection data. We use SSR data through 1997, and project thereafter. We assume that those persons who do not have an SSER record and do not have an SSR record are merely missing the SSR record, and accordingly impute additional participation to such persons.

In order to improve the transition between the observed (historical) and projection periods, we have added alignment parameters (i.e., additive intercept adjustments) to the MINT3 SSI take-up equations. The magnitude of this parameter is 3.4 in the equation for those ages 62 through 64, and 0.70 in the equation for those ages 65 and older.

Automobiles are included in the MINT measure of non-housing, non-pension wealth. It may be preferable to take vehicles out before creating the measure of income from other financial assets that is used in the SSI benefit calculator. However, our parameter that allows individual's assets to slightly exceed SSI thresholds (discussed in the appendix) should in part compensate for this limitation.

We discuss additional implementation issues (for example, treatment of SSI parameters into the future) in the Appendix.

VI. Adjustments To Other Components Of MINT Imposed In The SSI Module

Computing historical SSI benefits is a revealing test of the overall model. As MINT assigns eligibility for SSI benefits deterministically (based on disability status, marital status, state of residence income and asset sources), these projections could be biased upward or downward if any of the previous modules of health, income, or assets contain biases. Given that

[8] SSA has expressed interest in calculators that allow one to compute benefits under an option that changes Social Security benefits, thus changing the size of SSI benefits for many participants, but not changing individuals' take-up behavior. The existing calculator can be adapted fairly readily to meet this objective when coding a policy simulation. (One key mechanism that we use to alter take-up incidence is the coefficient on the expected state supplement.) For details, again contract Favreault.

the income and asset thresholds for SSI are so low, MINT could, for example, underpredict SSI eligibility (and, by extension, SSI participation) if its parameters slightly underestimated the number of people with very low or zero assets.

Early analyses of SSI projections suggested that MINT3 was underpredicting SSI eligibility in early years of the simulation. To compensate for the underpredictions, we made adjustments to the assets, work limitations status, and Social Security benefit projections of certain persons. We tried to make these adjustments in as limited a manner as possible, often restricting them to individuals who were receiving SSI at baseline according to the administrative records (SSR).

If an individual who is receiving SSI at baseline is rendered ineligible for benefits because of wealth after the last SSR observation, we adjust his/her family wealth downward so that it falls just below the threshold in the SSI asset test. We adjusted 1,464 individuals whose wealth values alone put them over the limit, and an additional 327 whose combined head and spouse retirement account balances exceeded the threshold. While the average size of a wealth adjustment was substantial, 75 percent of those with an adjustment received an adjustment of 0.02 percent of the average wage (about $700 in 2000 dollars) or less.

A second wealth adjustment impacts those with assets between one and two times the asset threshold for SSI benefits (and is not restricted to historical SSI recipients). Such persons have their assets reduced to just below the threshold. We adjusted 4,671 individuals using this criterion. Again, most persons experienced a very small reduction in assets in absolute terms as a function of this change.

For widows ages 62 and older at baseline receiving SSI benefits whose spouses were not observed over the historical period, we adjusted Social Security benefits in case they were matched to a spouse whose earnings were significantly higher than their actual spouse's. We adjusted the benefits of 969 individuals. Additionally, in the spouse match program, such persons received negative permanent income values to increase the probability that they would be matched to a low-income spouse.

For persons under age 65 who are receiving SSI benefits in the historical period, we ensure that the indicator of work limitations is positive. We adjusted work limitations predictions at least once for 1,067 persons in MINT. Finally, we correlate health status for these persons, adjusting health status predictions to fair or poor (from excellent, very good, or good) for 974 persons who had work limitations adjustments.

VII. Validation: Living Arrangements

To validate our projections of living arrangements, we compare MINT projections with historical data. Hurd (1990) reports the living arrangements of the elderly and shows that the percentage living alone increased between 1960 and 1988 – from 12 to 16 percent for men and from 24 to 41 percent for women. This finding is due in large part to the increased economic resources of the elderly during this time period. Over time the elderly have been less likely to live with relatives and non-relatives. This is true for the young-old (65-74 years old), as well as the old-old (75 or more years old). Still, overall in 1988 some 9 percent of men and 19 percent of women lived with relatives or non-relatives. The percentages are higher for women than for men, and higher for the 75 and over age group than for the 65 to 74 age group.

Using SIPP data, we estimate that in the early 1990s 16.5 percent of 62- to 89-year-olds resided with relatives other than or in addition to a spouse (Table 7-7). Co-residency rates decreased with higher education. Asian/Native Americans, Hispanics, and blacks were more likely to co-reside than non-Hispanic whites, and females were more likely to co-reside than males. Married retirees had much a lower co-residency rate than unmarried retirees; less than half of the rate for the never married. The rate of co-residency declined with age from 16.4 percent at age 65 to 14.5 percent at age 79 and then increased through age 89 to about 24.8 percent.

The poverty rate of co-residers was significantly higher than the overall poverty rate of the 62- to 89-year-old population (23.0 percent compared with 7.8 percent). These differences were evident for all subgroups of the population, though they were largest for the most vulnerable subgroups – high school dropouts, blacks, Hispanics and Asian/Native Americans, females, the never married, and the oldest age groups. Co-residence improved the economic well-being of these co-residers by 17.4 percentage points overall (compare 23.0 percent before co-residing with 5.6 percent poverty after co-residing). Again, co-residence had the greatest impact on the family poverty rate of the most vulnerable subgroups.

The majority of those co-residing in the early 1990s lived with their adult children (69.7 percent – Table 7-8). Other co-residers lived with other relatives (19.5 percent), siblings (10.5 percent), and parents (4.5 percent). Blacks were more likely to live with their kids, while Asian/Native Americans were more likely to live with other relatives than were other race/ethnicity groups. Those who are married were most likely to live with their children (81.9 percent), while those who are never married were most likely to live with siblings (69.5 percent). Those widowed and divorced were also most likely to live with their children (69.8 and 60.3 percent, respectively); however, the other 29.7 percent of divorced co-residers were equally as likely to live with their siblings, parents, and other relatives. Older age groups were much less likely than younger age groups to co-reside with their parents or siblings – no doubt because their immediate family members were less likely to still be living. Finally, differences in living arrangements were small across educational and gender groups.

A number of factors contribute to the projected changes in co-residence patterns over time, including changing kin availability (an important component of our model). The share of the aged population who co-reside is projected to decline between the early 1990s and 2020 – from 16.5 to 13.1 percent (Table 7-9). Co-residency rates are projected to decline for all subgroups except high school dropouts – their rates will increase only slightly in 2020. The decline will be largest for high school graduates, Hispanics and Asian/Native Americans, females, widowed males and females, and 85- to 89-year-olds.

Table 7-7
Co-residency and Its Impact on Poverty in the Early 1990s

	Percent Co-residing	Poverty Rate: Entire Population	Poverty Rate: Co-resider	Poverty Rate: Family w/ Co-resider	Poverty Rate: Impact
Total	16.5%	7.8%	23.0%	5.6%	-17.4%
Educational Attainment					
High School Dropout	20.4%	13.7%	32.5%	8.4%	-24.1%
High School Graduate	14.4%	4.0%	14.6%	3.3%	-11.3%
College Graduate	11.9%	2.5%	10.7%	1.1%	-9.6%
Race					
White, non-Hispanic	14.4%	5.6%	16.7%	3.6%	-13.1%
Black	26.2%	23.8%	38.2%	13.4%	-24.8%
Hispanic	30.6%	18.8%	44.8%	11.0%	-33.8%
Asian/Native American	34.0%	11.8%	47.7%	7.9%	-39.8%
Gender					
Female	18.1%	10.1%	28.8%	6.3%	-22.5%
Male	14.3%	4.5%	13.1%	4.5%	-8.6%
Marital Status					
Never Married	26.4%	18.5%	40.4%	5.4%	-35.0%
Married	12.7%	2.3%	9.0%	3.8%	-5.2%
Widowed	22.1%	14.2%	33.3%	7.3%	-26.0%
Divorced	18.4%	20.9%	34.5%	7.7%	-26.8%
Marital Status by Gender					
Never Married Male	23.9%	15.9%	35.6%	6.3%	-29.3%
Married Male	12.8%	2.3%	8.5%	3.8%	-4.7%
Widowed Male	20.3%	8.0%	17.4%	5.7%	-11.7%
Divorced Male	14.5%	15.2%	22.2%	6.1%	-16.1%
Never Married Female	28.3%	20.5%	43.7%	4.8%	-38.9%
Married Female	12.5%	2.4%	9.6%	3.7%	-5.9%
Widowed Female	22.4%	15.3%	36.3%	7.7%	-28.6%
Divorced Female	20.8%	24.4%	39.9%	8.5%	-31.4%
Age					
62 to 64	16.2%	6.2%	18.8%	6.1%	-12.7%
65 to 69	16.4%	6.4%	17.9%	5.1%	-12.8%
70 to 74	15.5%	7.1%	19.7%	3.9%	-15.8%
75 to 79	14.5%	8.7%	28.9%	7.8%	-21.1%
80 to 84	19.7%	11.6%	32.0%	6.3%	-25.7%
85 to 89	24.8%	11.2%	31.4%	4.5%	-26.9%

Source: The Urban Institute computations from the 1990-1993 SIPP.

Table 7-8
Living arrangements of the Co-resident Aged Population in the Early 1990s

	Adult Child	Sibling	Parent	Other Relative
Total	69.7%	10.5%	4.5%	19.5%
Educational Attainment				
High School Dropout	70.6%	11.0%	1.9%	20.3%
High School Graduate	70.2%	9.5%	6.4%	19.0%
College Graduate	62.9%	12.7%	9.8%	18.1%
Race				
White, non-Hispanic	69.2%	11.0%	4.9%	19.1%
Black	74.2%	11.6%	3.0%	14.6%
Hispanic	68.8%	8.2%	4.1%	22.7%
Asian/Native American	68.7%	4.7%	2.6%	35.1%
Gender				
Female	69.4%	10.8%	4.1%	20.2%
Male	70.3%	10.1%	5.2%	18.4%
Marital Status				
Never Married	5.1%	69.5%	10.0%	19.3%
Married	81.9%	2.4%	4.2%	16.0%
Widowed	69.8%	8.4%	2.4%	23.8%
Divorced	60.3%	13.3%	11.3%	18.1%
Marital Status by Gender				
Never Married Male	0.0%	72.4%	12.0%	17.6%
Married Male	81.0%	2.5%	4.4%	16.5%
Widowed Male	69.7%	7.6%	1.7%	26.2%
Divorced Male	45.7%	20.1%	15.1%	19.9%
Never Married Female	8.6%	67.6%	8.7%	20.4%
Married Female	83.0%	2.2%	4.1%	15.5%
Widowed Female	69.9%	8.5%	2.5%	23.4%
Divorced Female	66.7%	10.3%	9.7%	17.4%
Age				
62 to 64	69.0%	8.5%	11.5%	16.2%
65 to 69	70.7%	9.0%	6.6%	17.8%
70 to 74	72.9%	11.3%	3.0%	17.4%
75 to 79	70.3%	13.7%	0.7%	20.2%
80 to 84	65.8%	11.6%	0.7%	25.5%
85 to 89	62.7%	5.9%	0.0%	31.4%

Source: The Urban Institute computations from the 1990-1993 SIPP.

Table 7-9
Co-residency and Its Impact on Poverty-Adjusted Family Income in the Early 1990s and 2020

	1990s			2020		
	Percent Co-residing	Family Income/Poverty (Exclude Co-resident Income)	Family Income/Poverty (Include Co-resident Income)	Percent Co-residing	Family Income/Poverty (Exclude Co-resident Income)	Family Income/Poverty (Include Co-resident Income)
Total	16.5%	2.42	3.48	13.1%	4.46	5.47
Educational Attainment						
High School Dropout	20.4%	1.71	2.78	20.9%	2.47	4.11
High School Graduate	14.4%	2.78	3.92	13.0%	4.23	5.33
College Graduate	11.9%	4.56	5.17	10.7%	6.48	6.80
Race						
White, non-Hispanic	14.4%	2.65	3.74	11.2%	4.92	5.87
Black	26.2%	1.78	2.49	18.5%	3.23	4.68
Hispanic	30.6%	1.52	2.50	20.7%	2.96	4.22
Asian/Native American	34.0%	1.86	3.58	24.9%	4.80	5.16
Gender						
Female	18.1%	2.08	3.37	14.1%	4.09	5.42
Male	14.3%	3.00	3.66	11.9%	5.04	5.55
Marital Status by Gender						
Never Married Male	23.9%	2.09	3.07	21.1%	2.98	3.56
Married Male	12.8%	3.40	3.83	11.2%	5.50	5.63
Widowed Male	20.3%	2.16	3.50	13.9%	3.69	5.95
Divorced Male	14.5%	2.09	3.08	11.3%	4.73	6.16
Never Married Female	28.3%	1.92	3.23	27.8%	3.45	4.42
Married Female	12.5%	3.15	3.65	11.8%	5.43	5.84
Widowed Female	22.4%	1.55	3.25	14.5%	2.94	5.44
Divorced Female	20.8%	1.63	3.17	15.8%	3.04	5.08
Age						
62 to 64	16.2%	3.07	3.69	14.2%	5.15	5.79
65 to 69	16.4%	2.84	3.56	12.7%	4.50	5.39
70 to 74	15.5%	2.42	3.46	13.2%	4.42	5.46
75 to 79	14.5%	2.01	3.42	12.0%	4.00	5.28
80 to 84	19.7%	1.67	3.25	13.8%	3.73	5.23
85 to 89	24.8%	1.61	3.46	13.6%	4.29	5.55

Source: The Urban Institute computations from the 1990-1993 SIPP and projections from MINT3.

In both the early 1990s and 2020, co-resident income increases poverty-adjusted family income for all subgroups of the aged population. However, in absolute and relative terms, it had a much larger impact on overall income in the early 1990s than it is projected to have in 2020.

VIII. Validation: SSI Benefits and Eligibility

To validate our projections of SSI benefits, we consider several different characteristics. These include: eligibility rates (the fraction of the total population that is eligible for SSI benefits based on age, income, and disability status), receipt rates (fraction of the total aged population collecting benefits), take-up rates (fraction of the eligible population that files for benefits), and benefit means and distributions. We examine benefits for individuals and couples separately. We also consider important joint distributions, like the joint distribution of OASDI benefits and SSI benefits, and the joint distribution of earnings and SSI benefits. These intersections are important because of the potential for interactions between Social Security and SSI reform.[9]

1. Participation and Take-up Rates

Figure 7-1 reports the percentage of the population that is receiving SSI benefits, separately by age (62 through 64, 65-74, and 75 and older) and sex from 1997 through 2020. As in the historical period, MINT projects that women are more likely then men to receive SSI, and that benefit receipt increases with age.

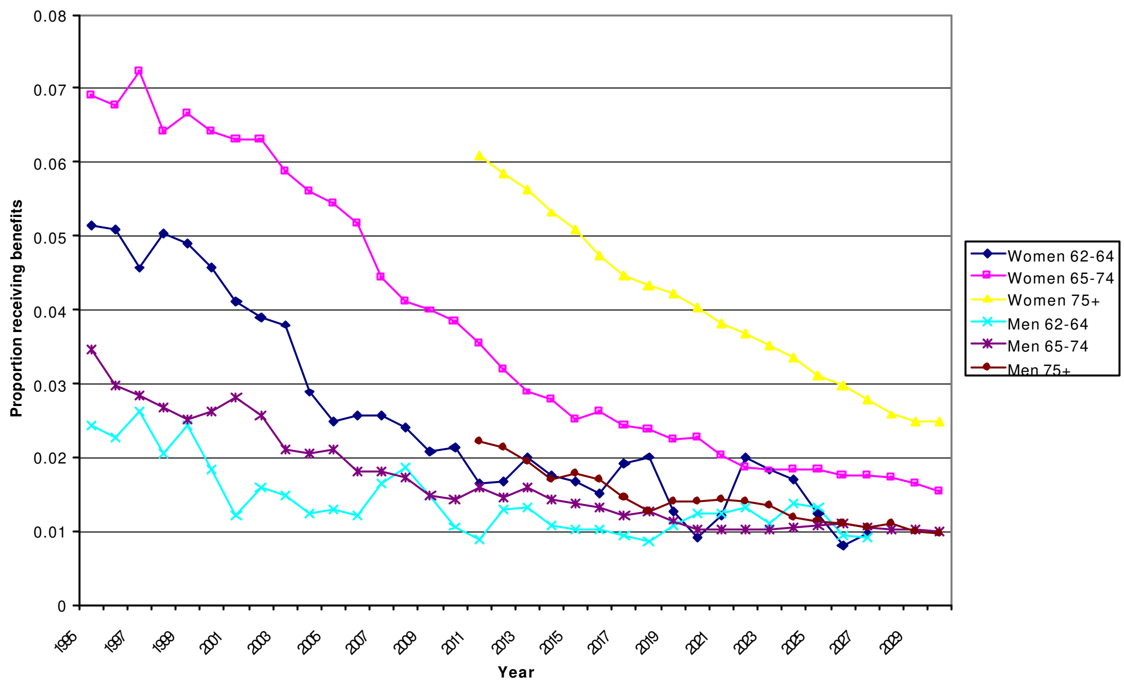
When we compare the MINT and OCACT projections (Figures 7-2 and 7-3), which are disaggregated by age but not by sex, we find a number of important differences. Most striking in these comparisons is that MINT projects far fewer SSI beneficiaries into the future than does OCACT (Social Security Administration, 2002). While both models project that the fraction of the population receiving SSI will decline over time, the slope is much steeper in MINT. This is especially true among the younger aged persons (65 to 74). Wage growth, which affects lifetime earnings and Social Security receipt and also wealth, is likely the driving force in caseload reductions. A partial explanation for the stark difference in the two forecasts is that the MINT does not include immigrants who arrived in the United States after the baseline observation (in the mid-1990s). Immigrants are known to rely on SSI in higher proportions than members of the wider population (Scott and Ponce, 1994). We therefore conducted a sensitivity analysis concerning the effects of immigrants on SSI rolls, and discuss the results below.

Take-up rates for SSI eligible persons in MINT are somewhat higher than previous researchers have estimated in earlier studies (for example, Davies et al., 2000, who find participation rates of about 63 percent[10]). As Table 7-10 indicates, over the 2000 to 2020 period the total take-up rates in MINT range from 67.7 percent to 78.2 percent at ages 65 to 74 and from 82.3 percent to 85.3 percent at ages 75 and older (a censored age range). These rates are much higher than historical levels (which tend to be in the low to mid 60 percents) because of the

[9] For example, any reform that increases or decreases Social Security benefits would have implications for SSI caseloads.

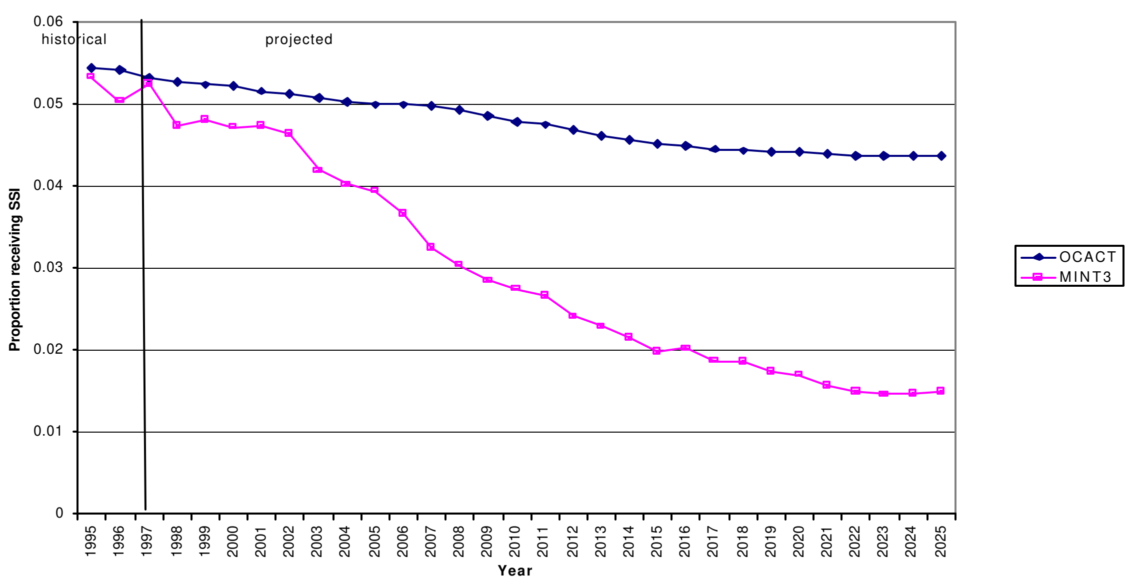
[10] Earlier studies (see, for example, McGarry, 1996, Warlick, 1982, Urban Systems, 1981), which used less reliable data, typically found lower participation rates, ranging between 50 and 60 percent of those eligible.

Figure 7-1
SSI Beneficiary Rates by Age and Sex, 1995 to 2020



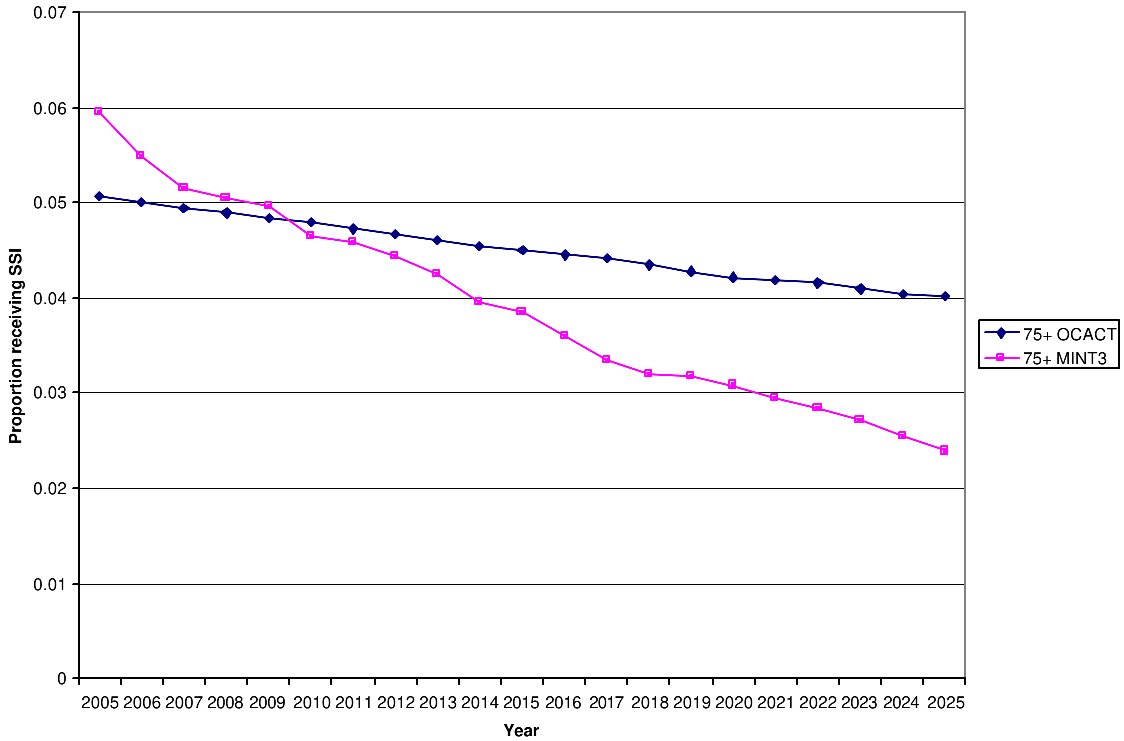
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

Figure 7-2
Comparison of MINT and OCACT SSI Population Forecasts: Ages 65 to 74



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

Figure 7-3
Comparison of MINT and OCACT SSI Populations: Ages 75 and Older



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

Table 7-10.
Fractions of Persons Eligible for SSI Taking Up Benefits in MINT, by Age and Sex, Selected Years

	Men		Women		All	
	65-74	75+	65-74	75+	65-74	75+
2000	0.614	NA	0.701	NA	0.677	NA
2005	0.688	NA	0.817	NA	0.782	NA
2010	0.621	0.714	0.825	0.855	0.765	0.826
2015	0.624	0.736	0.760	0.856	0.710	0.833
2020	0.649	0.699	0.742	0.878	0.715	0.853

Notes: NA indicates that a reliable estimate is not available due to censoring
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

calibration parameters that we added to MINT's SSI module in order to better track historical data (discussed above with implementation issues). In a sensitivity test where we run the model without the calibration parameters, we found take-up rates to be closer to those observed.

2. Time Series of Mean Benefits

MINT's projections of mean SSI benefits are fairly consistent between the historical period and the projections (Table 7-11). The table reports the mean benefits, by age and sex, as a percent of the average wage. As we would expect, average benefits expressed this way trend downward, given that wages are projected to grow faster than prices (and thus SSI benefits, which are indexed to the CPI). Differences in benefit means by age and sex appear minimal.

Table 7-11.
Mean SSI Benefits (as a Percent of the Average Wage) of Beneficiaries in MINT, by Age and Sex, Selected Years

	Men		Women		All	
	65-74	75+	65-74	75+	65-74	75+
1995	0.115	NA	0.115	NA	0.115	NA
2000	0.105	NA	0.119	NA	0.115	NA
2005	0.099	NA	0.104	NA	0.103	NA
2010	0.091	0.088	0.103	0.104	0.100	0.101
2015	0.085	0.083	0.103	0.099	0.097	0.096
2020	0.073	0.089	0.094	0.096	0.088	0.095

Notes: NA indicates that a reliable estimate is not available due to censoring
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

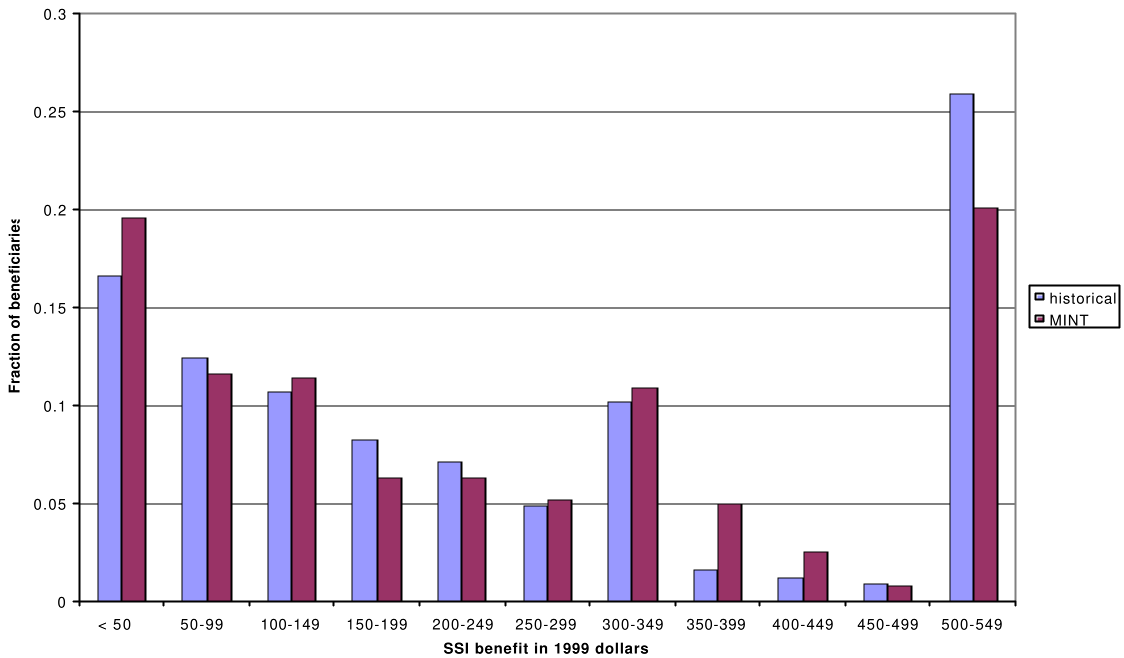
3. Distributions of SSI Benefits

We find fairly strong agreement when we compare MINT's 1999 and 2000 SSI benefit distributions with data from the *Annual Statistical Supplement* (Figures 7-4 and 7-5 for 1999 and Figures 7-6 and 7-7 for 2000).[11] Just like the historical individual distribution, the MINT distribution is skewed, with the two largest groups of beneficiaries falling at the tails (either receiving the full SSI benefit or receiving a very small SSI benefit). For couples, there is a single mode, representing the full (maximum) benefit amount in both the historical data and in our simulated MINT population. This provides especially strong support for model validity, given that SSI benefit levels depend upon joint distributions of earnings, Social Security benefits, wealth, and asset income.

Looking at two later distributions (2010 and 2020), we find that SSI benefits are forecast to remain skewed (Figure 7-8 for individuals and 7-9 for couples). For ease of comparison, we present these forecasts in 2000 dollars. Singles continue to have high concentrations in the tails

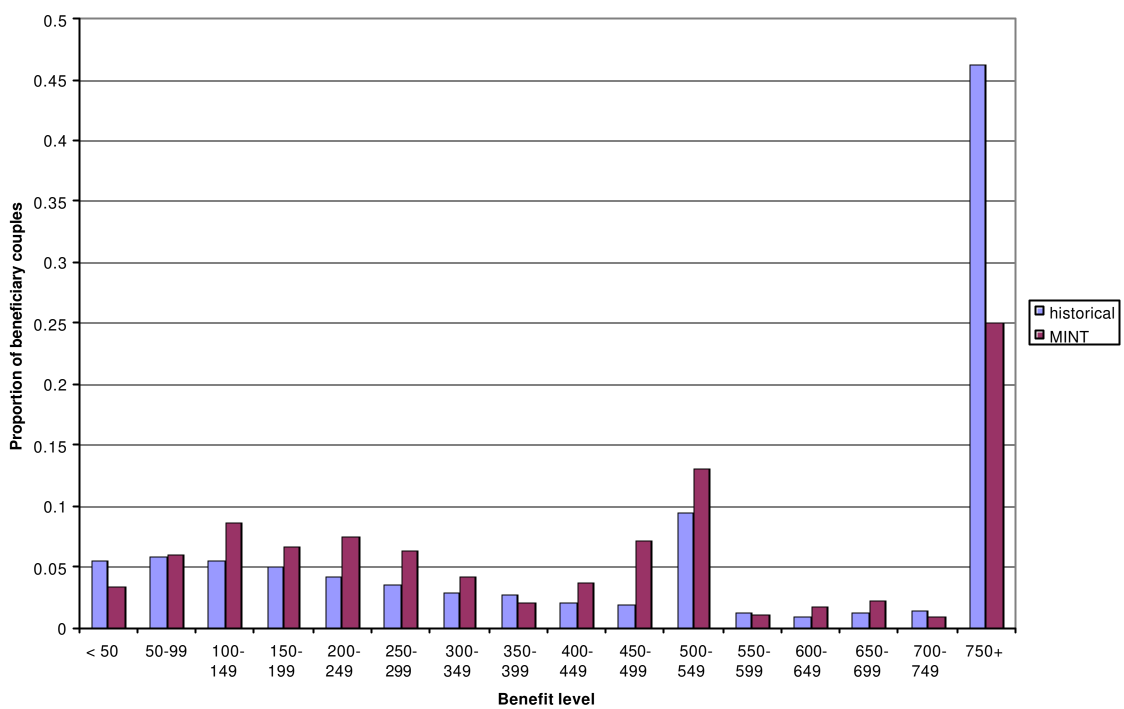
[11] These figures reflect federal SSI benefits only (i.e., state supplements are not included).

Figure 7-4
Distribution of SSI Benefits for Aged Individuals in 1999: MINT Compared to Historical



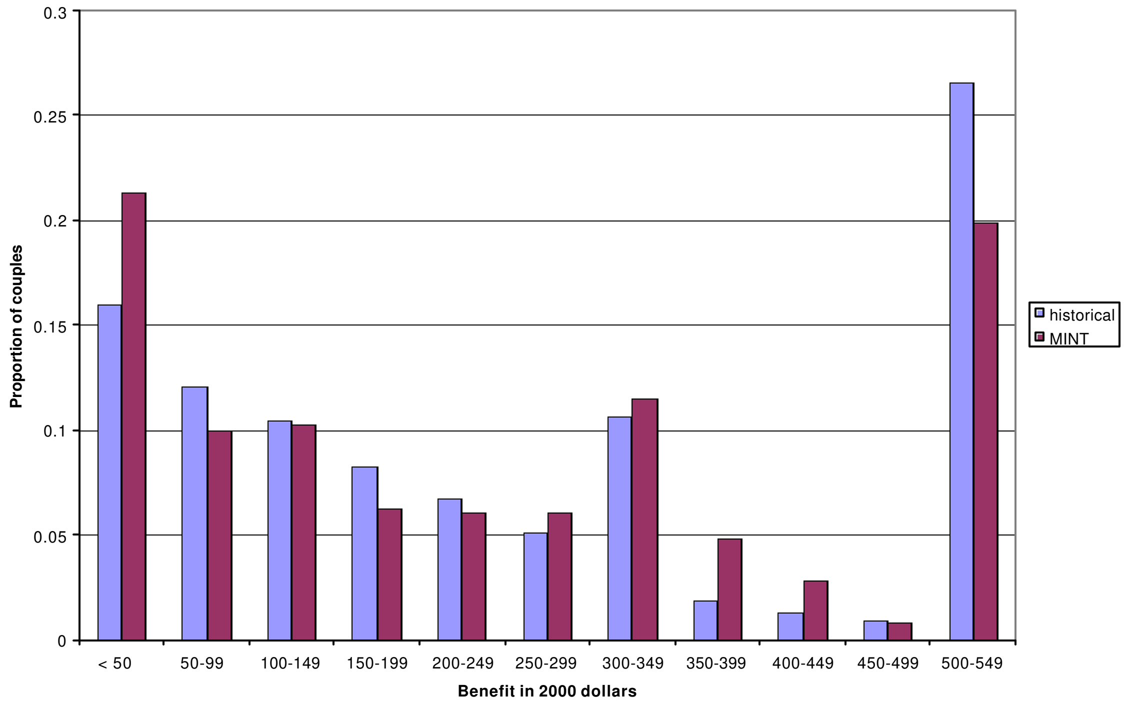
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

Figure 7-5
Distribution of SSI Benefits for Aged Couples in 1999: MINT Compared to Historical



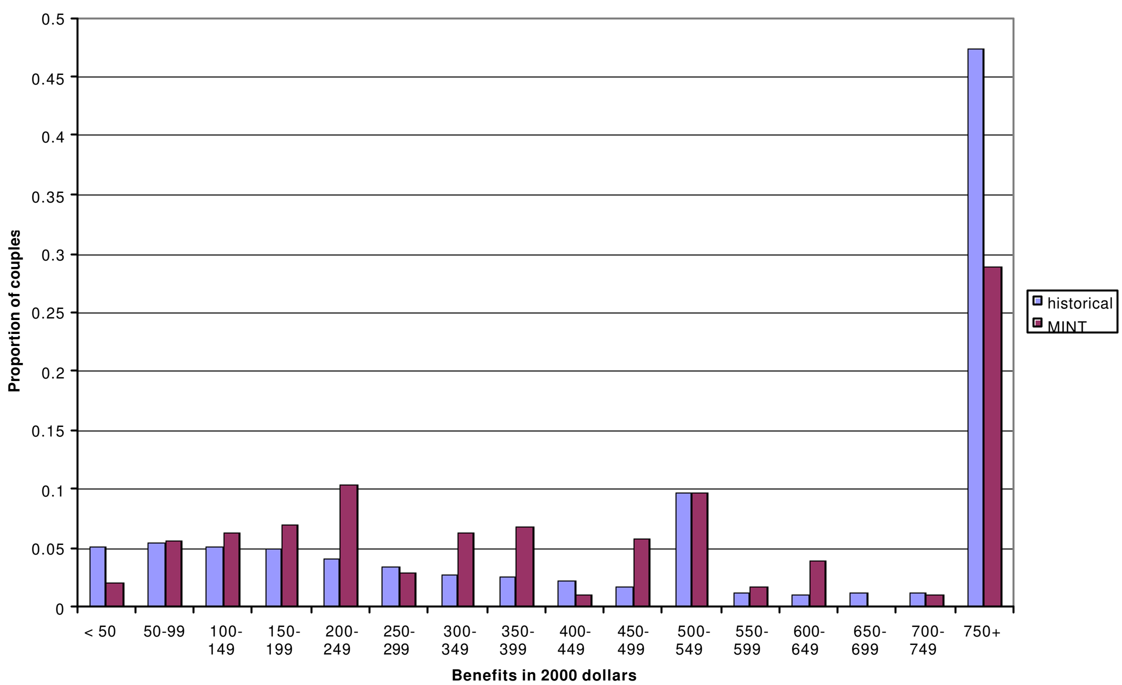
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

Figure 7-6
SSI Benefit Distribution for Aged Individuals in 2000: MINT Compared to Historical



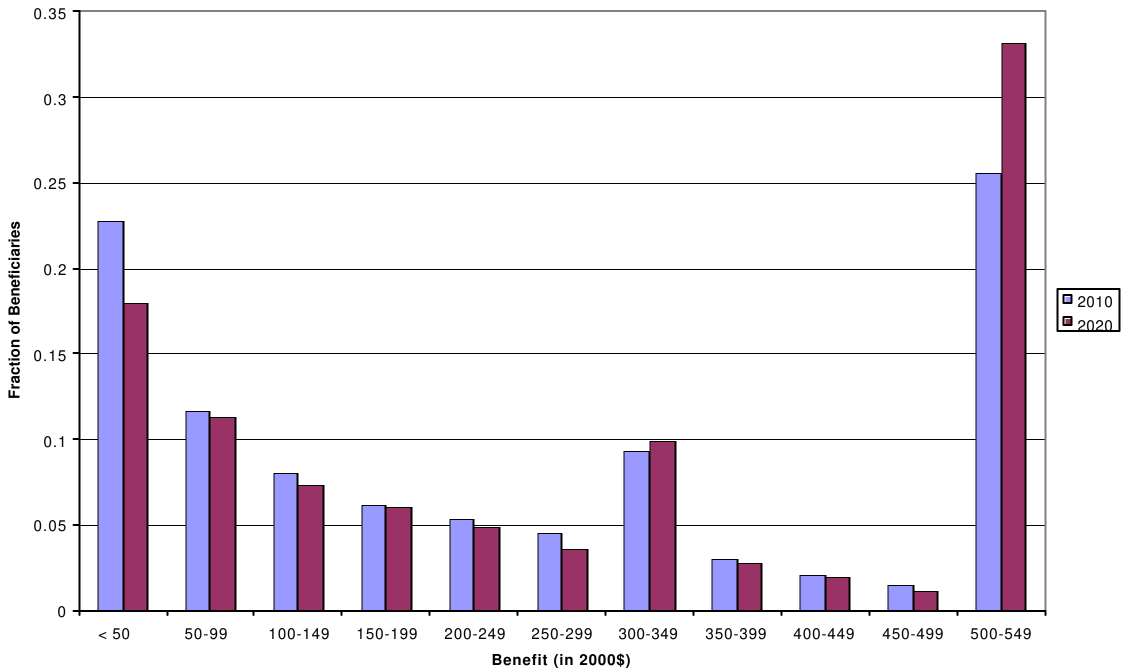
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

Figure 7-7
Distribution of Aged Couples' SSI Benefits in 2000: MINT Compared to Historical



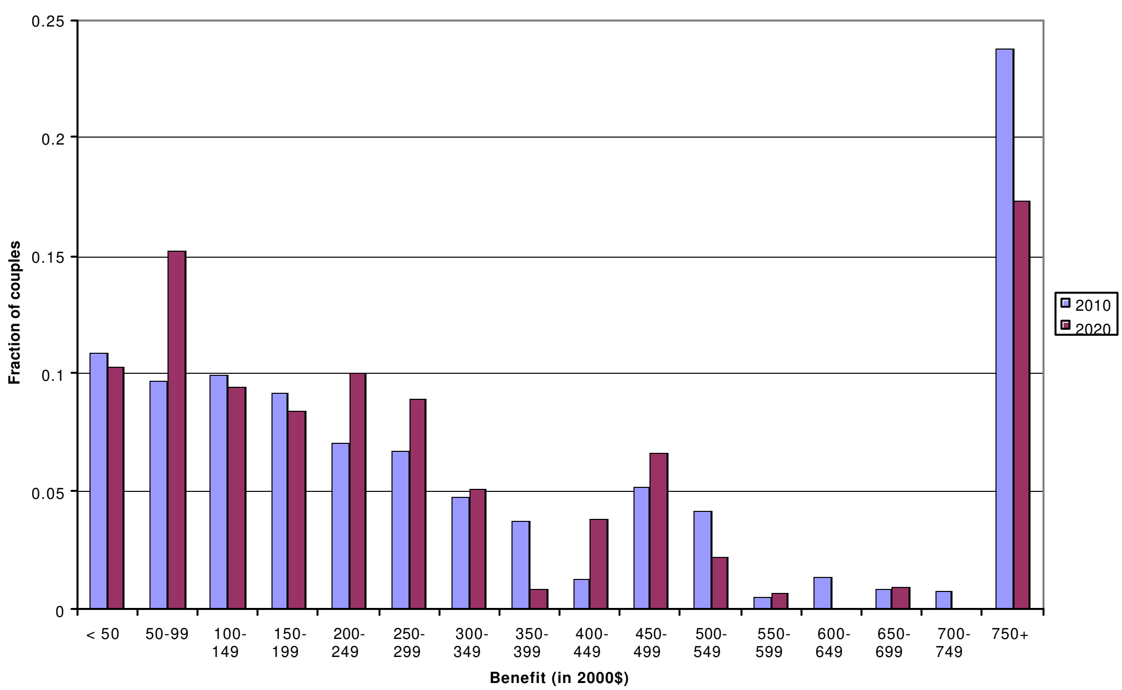
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

Figure 7-8
Projected MINT3 Distribution of SSI Benefits for Aged Individuals, 2010 and 2020



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

Figure 7-9
Projected MINT3 Distribution of SSI Benefits for Aged Couples, 2010 and 2020



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

of the distribution, while couples continue to have the single mode at the maximum benefit amount.

4. Joint Distributions of SSI, Earnings, Social Security, and Asset Income

In recent years, about 60 percent of aged SSI recipients were concurrently receiving OASI benefits (Social Security Administration, 2001, Table 7.D1). In MINT3, fairly similar proportions receive both SSI and Social Security (Table 7-12). At ages 65 to 74, the fraction receiving benefits from both programs ranges from 0.588 to 0.652, clearly reasonable in the context of the historical SSA estimate of around 60 percent. At ages 75 and older, fractions are even more stable, ranging from 0.566 to 0.590. It is not surprising that this fraction would remain stable or even increase modestly over the next two decades, as coverage rates for Social Security have increased, and as MINT does not include new immigrants to the United States. Also not surprising, men who receive SSI are somewhat more likely to be receiving Social Security benefits than are their women counterparts.

Table 7-12.
Fractions of SSI Beneficiaries Receiving OASDI Benefits in MINT, by Age and Sex, Selected Years

	Men		Women		All	
	65-74	75+	65-74	75+	65-74	75+
1995	0.658	NA	0.649	NA	0.652	NA
2000	0.645	NA	0.568	NA	0.588	NA
2005	0.675	NA	0.601	NA	0.618	NA
2010	0.694	0.671	0.570	0.572	0.599	0.590
2015	0.667	0.713	0.550	0.562	0.587	0.588
2020	0.694	0.669	0.578	0.545	0.609	0.566

Notes: NA indicates that a reliable estimate is not available due to censoring
Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

Statistics from the Social Security Administration indicate that only about sixteen percent of SSI beneficiaries ages 65 and older have some other type of unearned income (besides Social Security). In MINT, this fraction is much higher, typically just over half. This is not necessarily a cause for alarm, though, given that these income levels tend to be quite low (just over zero in many cases).

SSI beneficiaries are not likely to work. This is especially true for persons ages 62 and over. In the historical period, only about two percent of SSI recipients ages 65 and older have also had Social Security covered earnings (Table 7.D1). In MINT (Table 7-13), a slightly higher percentage of SSI beneficiaries had some earnings in the historical period. This is likely due to the fact that the MINT cohorts include a disproportionate share of younger persons in early years of the simulation. Historically, men on SSI are more likely than women on SSI to be earners. As the MINT cohorts age, aged SSI recipients are less likely to work. Work rate forecasts are less smooth than Social Security receipt status forecasts, given the very small number of individuals involved. Gender differences remain in most future years.

Table 7-13.
Fractions of SSI Beneficiaries Ages 65 and older with Earnings in MINT, by Sex, Selected Years

	Men	Women	All
1995	0.100	0.037	0.056
2000	0.016	0.007	0.009
2005	0.025	0.012	0.015
2010	0.013	0.004	0.006
2015	0.004	0.003	0.003
2020	0.013	0.009	0.010

Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst)

Chapter 9 provides a great deal of additional detail on SSI benefits, including distributional differences by race, educational attainment, and lifetime earnings quintiles.

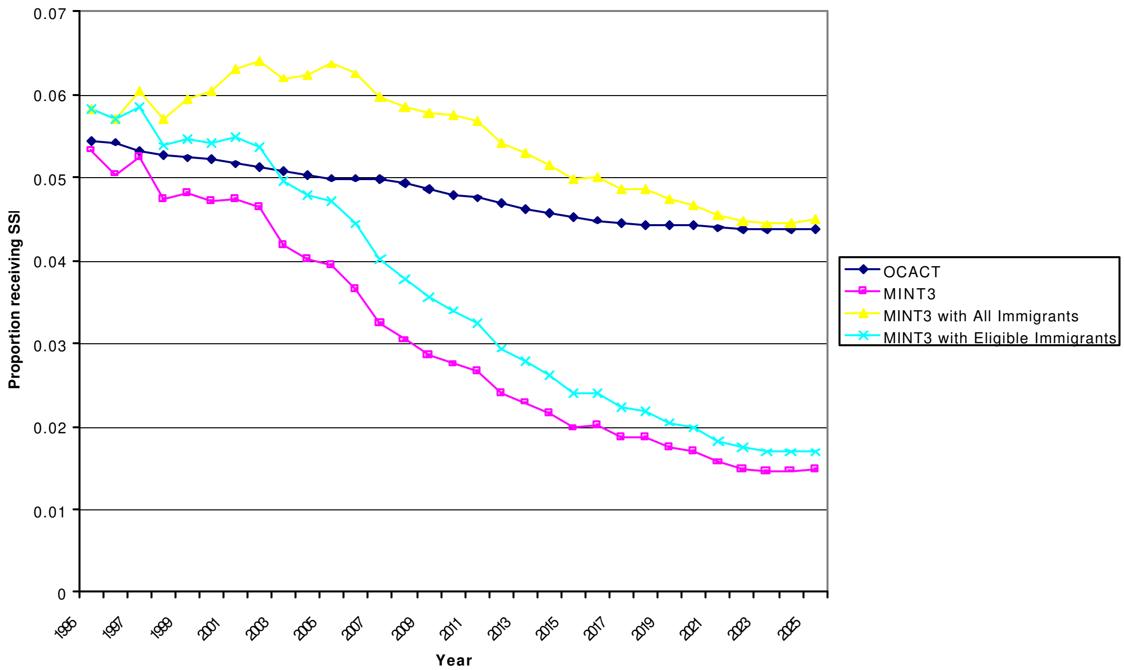
IX. Sensitivity Analyses: SSI Benefits and Eligibility

We test the sensitivity of our SSI benefit projections to several of our most important assumptions. One such assumption is the absence of immigration. Given that newcomers to the U.S. have historically been overrepresented in the SSI roles (Scott and Ponce, 1994), the fact that the MINT population does not include immigrants after the SIPP interview date is surely problematic and leads us to understate future SSI rolls.

In our first sensitivity analysis, we therefore try to estimate how much larger the future SSI population would be with post-SIPP immigrants (as discussed in the immigration sensitivity test in Chapter 2). The lines marked by triangles (and labeled "MINT3 with all Immigrants") in Figures 7-10 and 7-11 represent the maximum SSI population that arises assuming that immigrants have as income only the Social Security benefits to which they are entitled on the basis of their imputed earnings. In these analyses, we further assume that all post-baseline immigrants have no non-housing assets that exceed SSI thresholds, and that they are unmarried (thus having no sources of spousal income). While these assumptions are of course quite extreme, they provide us with a maximum level of immigrant SSI eligibility (and thus participation).

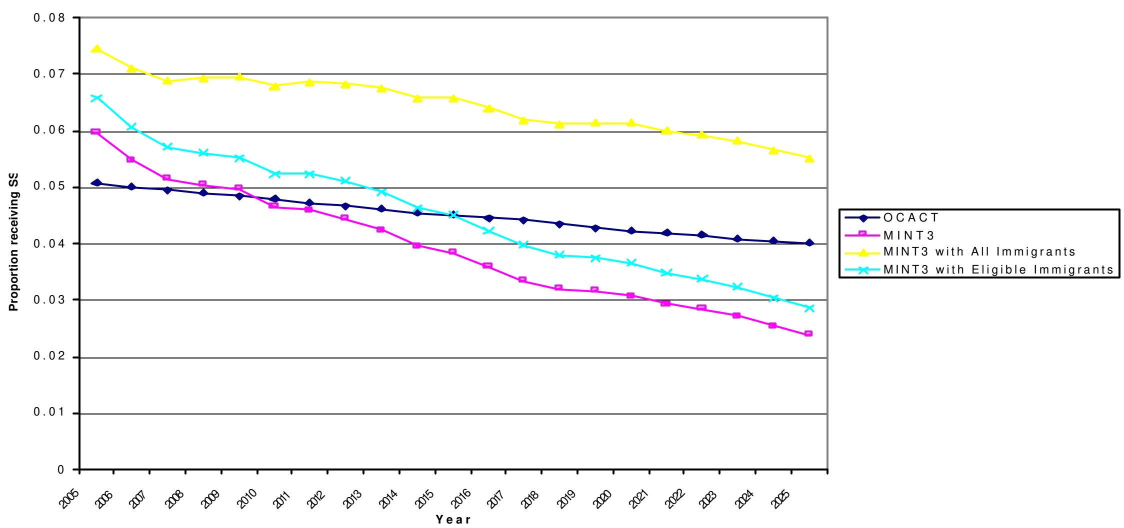
At ages 65 through 74, the addition of all immigrants could lead MINT to meet and even exceed OCACT forecasts (Figure 7-10, the series labeled "MINT3 with all Immigrants"). The adjusted MINT forecasts are higher than the projected OCACT numbers though 2020, and about equal to them from 2021 to 2025. At ages 75 and older (Figure 7-11, again labeled "MINT3 with all Immigrants"), the adjusted MINT forecast exceeds OCACT for all periods.

Figure 7-10
Comparison of MINT and OCACT SSI Population Forecasts: Ages 65 to 74 with Total and Eligible Immigrants (Sensitivity Test)



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst, w:\urban\mint3\final\tabssiwithimmig.lst, and w:\urban\mint3\final\tabssiwithimmiglaw.lst)

Figure 7-11
Comparison of MINT and OCACT SSI Population Forecasts: Ages 75 and older with Total and Eligible Immigrants (Sensitivity Test)



Source: Urban Institute tabulation from MINT3 (w:\urban\mint3\final\tabssimmfnew.lst, w:\urban\mint3\final\tabssiwithimmig.lst, and w:\urban\mint3\final\tabssiwithimmiglaw.lst)

However, not all immigrants are currently eligible for SSI. Under changes enacted with welfare reform, many immigrants are no longer eligible to receive benefits from the program. A series of subsequent changes to the original revocation of benefits essentially grandfathered current SSI recipients. These changes also established certain protected groups (those with military service, or those who have suffered from domestic abuse, to name just a few), but otherwise the law now requires that one have at least 40 covered quarters of employment in order to receive SSI.[12] If we adjust the MINT estimates to include only those on SSI in the historical period or having at least 40 covered quarters, then out forecasts look very different. These results still represent an improvement over the MINT aggregate estimates without immigrants (Figures 7-10 and 7-11, the series labeled "MINT3 with eligible immigrants"). At both ages 65 to 74 and ages 75 and older, MINT's projections are closer to the OCACT forecasts than without the immigrant adjustment. Though certainly the gap between MINT and OCACT forecasts nonetheless remains considerable, especially at young ages.

Even in this simulation, we still make fairly dramatic assumptions about immigrants' other resources (e.g., they have assets below SSI thresholds and no spousal income). In subsequent analyses, it may be desirable to consider the effects of immigration on SSI participation (and benefit levels) under less naïve assumptions.

A second important assumption to which we test the sensitivity of MINT outcomes is the fraction by which we allow an individual's self-reported assets to exceed SSI thresholds (as captured with the parameter &approx, located in SSImint-updated2002.inc). Our baseline assumption is that an individual's or couple's assets may exceed the threshold by 10 percent and he or she can still be considered to be eligible for benefits (the appendix discusses our rationale for this). In our second sensitivity analysis, we raise this percentage to 20 percent. When we do so, we find negligible changes in aggregate SSI benefits and participation. For example, the SSI participation rate in 2020 does not change by more than one hundredth of a percent. The modesty of this change is due in part to our existing wealth adjustments (discussed above, under "Adjustments to Other Components of MINT"). Additional simulation details are available upon request.

A final critical assumption of the model concerns how Congress will treat the SSI program's income exclusions (both the general income exclusion and the earned income exclusion). These exclusions have not changed since the program's start, and have thus eroded tremendously in real value (for discussion, see Social Security Administration, 2000). In the third sensitivity analysis, we see how SSI participation might change if these thresholds were increased by a factor of two, effective in the first simulation year (1998). When we make this change, increases in SSI eligibility and participation are much more significant than they were with the increase in asset limits. For example, the SSI participation rate in 2020 increases from 1.70 percent to 1.71 percent at ages 65 to 74 and from 3.08 percent to 3.15 percent at ages 75 and older. Additional details from the simulation are available upon request.

[12] For details on eligibility of immigrants for SSI, see Committee on Ways and Means (2000) or Social Security Administration (2002).

X. Implications of Validation and Sensitivity Analyses for Policy Analysis Using MINT

Users should exercise caution when using MINT for certain types of policy analyses. A first important caveat is, as we stated earlier, that we have calibrated the intercepts in our take-up equations in order to provide a better fit with recent historical data. This was necessary due in large part to imperfect matching with unobserved former spouses. However, with this adjustment we cannot readily interpret the take-up estimates. Likewise, given this significant calibration we cannot make any inferences about the type of behavioral response that is likely to arise should SSI benefits become more or less generous as a consequence of some sort of policy intervention.

Another important lesson from our sensitivity analyses is that assumptions about immigration have the potential to dramatically alter MINT projections of SSI expenditures. We recommend that SSA devote attention to this problem, and consider integrating immigrants if tracking patterns in aggregate SSI projections is a goal.

XI. CONCLUSIONS AND RECOMMENDATIONS

In an earlier report, we described seven key goals and constraints for the design of MINT's models of living arrangements and SSI receipt. These included: improving income and poverty estimates, drawing from appropriate literature, incorporating interdependencies, allowing feedback relationships with other parts of MINT, incorporating predictors that are themselves predicted and available to the module, balancing cross-section and longitudinal concerns, and facilitating policy analysis.

The approach in this chapter meets many of these objectives. Virtually all of the SSI income that we simulate is directed to the poverty population, though SSI benefits lift few out of poverty.[13] The predictors from the models of SSI and living arrangements are limited, for the most part, to those that are available in MINT.[14] Model parameters reflect relationships found in previous literature. The living arrangements and SSI take-up processes are correlated with one another, and with other relevant parts of the model (for example, health and mortality). To facilitate policy analysis, we estimated SSI and living arrangements separately, and MINT 3.0 users can determine whether to let policy changes influence SSI take-up behavior and/or subsequent living arrangements.

We have tried to balance cross-sectional and longitudinal concerns by using status models that include the lagged endogenous variable when projecting SSI receipt and coresidence. We had initially planned to incorporate random effects into our models as well.

[13] This pattern changes more significantly when we add the income of co-residents to the model (see point 6 in the Appendix).

[14] Two noteworthy exceptions are number of children ever born, which is censored in a fraction of cases, and state of residence, which may change from baseline. The appendix discusses how we handle these variables in the projection period.

We did not complete this portion of the project, as the need to correlate unobserved heterogeneity terms in both initial conditions and transitions complicated the estimation and simulation problems.

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APPENDIX TO CHAPTER 7

IMPLEMENTATION ISSUES

Our report has focused on the most fundamental issues of specification for Task 8. This appendix describes how we handled nine additional issues that arose when estimating and implementing the model.

1. Choosing an Accounting Period

We use an accounting period of one year for Task 8. This is consistent with most other MINT functions. In this framework, we, in essence, model each person's living arrangements for just one day in the year, and do not award part-year SSI benefits.

2. Assigning Eligibility for SSI and Benefit Levels Among Recipients

The contract requires that we determine SSI eligibility for each member of the sample. We assigned SSI eligibility algorithmically using SSI regulations and MINT projections of assets (including housing and other financial wealth) and income (including pensions, Social Security, and earnings). While these algorithms do not account for all possible income and asset sources (e.g., they will not include veterans' benefits or TANF), they provide a reasonable approximation. We contend with measurement error in the eligibility assignment process by allowing individuals' assets to fall within a range of some of the eligibility parameters, for example 1.10 times the asset limit threshold. Individuals this close to the thresholds could likely alter their asset holdings (for example, by holding assets in cash, burial plots, or automobiles, rather than in a checking or savings account) or work behavior to become eligible in a short time. Further, historical data reveal that individuals with SIPP reported assets within this range frequently receive SSI, so the adjustment is not inconsistent with past experience. Estimating a more sophisticated model that accounted for measurement concerns more rigorously (see, for example, McGarry, 1996, or Davies, 2000) was not viable given resource constraints.

Likewise, among those who elect to take-up SSI benefits, we use an algorithmic approach to assign benefit levels. We roughly replicate SSI's benefit calculation rules, first for the federal program and then, where applicable, for the stylized state supplements (see below for details).

3. Treatment of Federal SSI Parameters into the Future

The federal SSI benefit guarantee is subject to annual cost-of-living adjustments (and has thus declined in real wage terms for most of its history.) We index the federal guarantee using the OASDI Board of Trustees' (2002) assumptions about inflation.

The federal SSI eligibility parameters (e.g., limits on non-housing assets), however, are not indexed. They have increased just a few times since the program's 1974 inception, and have not kept up with inflation. We increased these parameters annually at a real rate that matches the average change observed over the historical period rather than by inflation.

Similarly, the SSI program's income disregards are not indexed, and their levels have not changed over the historical period, though definitions of income (for example, treatment of the EITC) have changed slightly. For these parameters, indexation is not appropriate. We assume that they remain constant, but can change this assumption at the government's request. (For illustrative purposes, one sensitivity test altered this assumption. See above for details.)

4. Treatment of State SSI Parameters, Both at Baseline and into the Future

To obtain reliable estimates of poverty, it is helpful to consider state-level variation in SSI. Several states provide supplements of significant size, enough to put some people over the poverty threshold. We therefore conducted a limited, somewhat stylized replication of state supplements, coupled with an assumption of no state-to-state migration. We based this section of MINT on the Urban Institute's Transfer Income Model (TRIM).

TRIM simplifies state supplements to SSI by focusing on state supplements to the non-institutional population (the core group of interest for MINT as well as for TRIM). As our youngest SSI recipients are age 62, we do not model differences between state disability and aged supplements, but rather assume that all recipients receive the aged supplement. We consider each state program at its 2000 TRIM level. If the state's 2000 benefit is higher than the 1999 benefit, then we index the state's guarantee to inflation. If the 2000 benefit is less than or equal to the 1999 benefit, then we hold the benefit constant at the 2000 level. In future simulations, we could use either a state-specific or cross-state average of the rate of real benefit decline for forecasting state programs (see, for example, Committee on Ways and Means, 2000, pp. 236-239).

5. Identifying Relationships Within Shared Households

SSA initially requested that we classify unmarried individuals who are residing in another person's home into two groups: those who are living with relatives and those who are living with unrelated persons. To reduce the number of outcomes and thus simplify the model, we defined co-residence more narrowly. As we discussed briefly in the section on the living arrangements model, we classify individuals primarily using data on ages and relationships of all persons in the household. Once we know whether a person is in shared accommodation, we then make a further determination of whether one is co-residing according to SSI definitions (i.e., a person "receives support and maintenance in kind" from others in the household). We assume that a person who has zero unearned income (Social Security, pension, or asset income) is dependent and that all others are not dependent.

6. Imputing and Updating Characteristics of the Households of Aged Co-Residents

Once we have determined whether members of the MINT sample are residing in another person's household, we need to determine the characteristics of the people with whom they reside. In particular we are interested in the income of other household members and the total family composition. Family composition is important because it determines the family's poverty threshold. We imputed family characteristics by using a statistical matching technique to match MINT coresidents with coresidents on the baseline SIPP. One advantage of the statistical matching technique is that it preserves the correlation between family composition and total family income.

The donor pool is 4,739 SIPP respondents age 62+ who are coresiding with a relative older than 30. We divide the donor pool into 16 groups based on marital status, home ownership, nativity, and kin availability. For each MINT sample member living in shared accommodations in a given year, the match finds the SIPP respondent in the same group whose per-capita income[15] is closet to the MINT individual. The selected SIPP respondent donates the income of other household members and the family's calculated Census poverty threshold.

7. Ensuring Consistency in Spouses' Projections

Because our models use individuals rather than couples as units of analysis, some formulations could produce estimates that do not realistically reflect the living arrangements of married people. For example, the model could generate an unusual number of couples living apart. One approach for contending with this problem includes using couples as the unit of analysis for certain transitions (e.g., living with others or independently), while having other states/transitions (e.g., institutionalization) remain an individual level transition. A complication of this approach is that spouses may have different eligibility status for SSI. Another potential solution uses marital status and spousal attributes as predictors of SSI/living arrangements states or transitions. A third solution would ensure that members of couples received the same random draw in this process. We have chosen a combination of these second and third approaches. We use marital status as a predictor of baseline living arrangements, and make random number draws for this module on the basis of a seed that is a complex function of household ID (so that married persons always receive the same draw).

8. Accounting for Likelihood of Additional Children Among Members of the MINT Sample with Censored Fertility Histories

Many of the women in the MINT sample are still in their childbearing years at baseline (between 1990 and 1993, depending on their SIPP panel). The information contained in their fertility histories is therefore censored.[16] Because we use number of available kin as a predictor of living arrangements, we needed to produce an uncensored estimate of the number of children ever born to each member of the sample.

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[15] Per-capita income includes the individual's earnings, Social Security benefit, income from assets, and pension income. If the individual is married, the spouse's income is included in the calculation and the total value is divided by two.

[16] This problem affects only a fraction of the MINT population. MINT's core sample consists of members of the 1931 to 1960 birth cohorts. We can safely assume that women reaching age 45 at or before the fertility history topical module (i.e., women born before 1945-1948, depending on their SIPP interview dates), report their completed histories. For individuals in the later cohorts, a large fraction of the childbearing years are still observed (about half for even the youngest cohort, and very close to one hundred percent for the oldest). These youngest sample members are also still fairly young at the finish of the simulation: members of the 1960 birth cohort do not reach age 62 (and hence become at risk of the model's co-residence/SSI receipt routines) until 2022.

We made a simple adjustment to the censored fertility histories of members of the sample. Our imputation procedure assigns additional children to those persons born after approximately 1950 using fertility rates based on age, parity, and race/Hispanicity. We used rates from Vital Statistics (Ventura et al, 2001). We then adjusted these rates to take into account the effect of marital status (by age and race/Hispanicity, but not parity). One concern with our approach is that it may not adequately capture joint distributions of fertility histories, marital histories, and earnings trajectories (e.g., earnings are not adjusted on the basis of these assignments).

9. Assignment of Starting Values for Living Arrangements, SSI Participation, and SSI Benefit Levels

SIPP reports of living arrangements could provide starting values for a fraction of individuals in MINT. These include those who were at least age 62 in one of their SIPP interviews, i.e., some people from the 1931-32 cohorts in later SIPP panels. (Note that at its start, MINT does not contain persons in institutions, though SIPP does monitor individuals' transitions into institutions over the panel). Since relatively few people in the base MINT population have valid starting values, we used the model to assign values to all members of the sample regardless of their observed residential status at 62.

Relying on historical data is more important for SSI than for living arrangements, at least for SSI participation. We therefore assign SSI benefits prior to 1998 using reported values from administrative records. (Data for 1998 were incomplete at the time of implementation.) Details are provided above (under implementations issues).

Appendix A7-1
Transitions into and out of Coresidence, Ages 62 and Over

	Entries into Coresidence		Exits from Coresidence	
	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-3.0634 ***	0.3450	-0.8446 ***	0.2791
Male indicator	0.0465	0.0606	0.1317 ***	0.0503
Never married indicator	0.0539	0.1976	-0.3630 ***	0.1205
Indicator divorced or separated	0.0273	0.1118	-0.1242	0.0871
Widowed indicator	0.5028 ***	0.0683	-0.1739 ***	0.0571
Age	-0.0332 ***	0.0049	-0.0240 ***	0.0039
Family earnings	-0.0306	0.0608	-0.0668	0.0618
Family Social Security benefits	-0.4386 **	0.1910	-0.0747	0.1587
Family pension benefits	0.1144	0.1064	0.1909 **	0.0932
Family asset income	-0.8850 ***	0.1451	-0.0191	0.1013
Indicator of some college education	0.0697	0.0786	0.0164	0.0640
Indicator not a high school graduate	0.2543 ***	0.0679	-0.0063	0.0529
Black indicator	0.3101 ***	0.0855	0.0576	0.0653
Hispanicity indicator	0.2591 *	0.1414	-0.4024 ***	0.1301
Asian indicator	0.8719 ***	0.1559	-0.1376	0.1329
Native American indicator	-0.4779	0.5046	0.9042 ***	0.2676
Foreign born indicator	0.3749 ***	0.0938	-0.0846	0.0769
Number of children ever born	0.1620 ***	0.0173	0.0168	0.0138
Number of children missing	-0.0480	0.1138	-0.0552	0.0937
SSI participant at t-1	-0.3551 **	0.1473	0.1840	0.1160
Eligible for SSI at time t	0.1649	0.1156	-0.1506	0.1015
Health fair or poor indicator	0.0712	0.0593	-0.0046	0.0475
Death impending (< 24 mnths)	0.1662	0.1186	0.1624 **	0.0888
N (person waves)	160,536		32,599	
-2 log-likelihood	15333.852		16324.064	

Data source: 1990-1993 SIPP
*** indicates p < 0.01; ** indicates p < 0.05, * indicates p < 0.10

Appendix A7-2
SSI Participation Transitions among Eligible Persons, Ages 65 and Higher

	SSI Entry			SSI Exit		
Variable	Coefficient		Standard Error	Coefficient		Standard Error
Intercept	-4.6819	***	1.2466	-2.8493	***	0.7565
Male indicator	-1.0772	***	0.2059	-0.1269		0.1461
Never married indicator	0.8713	**	0.3694	-0.0131		0.2644
Indicator divorced or separated	0.4050		0.2879	-0.3293		0.2385
Widowed indicator	0.6212	**	0.2814	-0.1562		0.2187
Total years in labor force	0.0099		0.0115	0.0547	***	0.0100
Years since last employment spell	0.0103		0.0092	0.0666	***	0.0074
Family Social Security	-4.7738	***	1.4708	-2.9762	***	0.6985
Family pension income	1.0314		1.3720	1.5910		2.5371
Family asset income	-9.4221		7.7512	7.4047		5.4086
Family Social Security exposure	0.5958		0.4382	—		—
Indicator of some college education	-0.9943	***	0.3757	-0.6890	***	0.2512
Indicator not a high school graduate	-1.1262	***	0.2570	-0.1023		0.1325
Age 65 dummy	0.4209		0.2826	—		—
Age	-0.0325	**	0.0158	0.0034		0.0096
Spouse 65 or older	—		—	-0.5796	**	0.2459
Black or Native American	-0.2538		0.1888	0.3278	**	0.1282
Hispanic indicator	-0.5216	**	0.2654	0.0131		0.1714
Asian	1.3236	***	0.4845	-0.1348		0.1889
Foreign born	1.2925	***	0.2765	-0.4542	***	0.1675
State supplement	0.0010		0.0009	0.0025	***	0.0005
Southern residence	-0.8798	***	0.2040	-0.3529	***	0.1329
Shared living arrangements	-0.0243		0.1934	0.1172		0.1159
Number of children	-0.1221		0.1789	0.0776	**	0.0308
Number of children missing	—		—	0.1403		0.1990
Home ownership indicator	-0.1060		0.1804	-0.1030		0.1435
Health is fair or poor	0.6522	***	0.1627	-0.0689		0.1090
Death impending (< 24 mnths)	0.9013	**	0.3631	0.6152	***	0.1852
Previous SSI experience	8.3560	***	0.4093	—		—
Time since last SSI receipt	-0.9500	***	0.1020	—		—
Duration of current SSI spell	—		—	-0.5435	***	0.0289
N (person waves)	6,865			7,242		
-2 log-likelihood	1128.500			2504.708		

Data source: 1990-1993 SIPP
*** indicates $p < 0.01$; ** indicates $p < 0.05$, * indicates $p < 0.10$

CHAPTER 8

MORTALITY ADJUSTMENTS AND RESULTS BY DEMOGRAPHIC GROUP

I. INTRODUCTION

This chapter explores the impact of several new techniques for projecting mortality that were introduced in MINT3. In MINT1, mortality for the entire population was projected using regression coefficients that predicted mortality as a function of age, education, race, and marital status (Panis and Lillard, 1999). The same set of coefficients was used to make initial mortality projections for the population over age 65 in MINT3, but these projections were then adjusted to assure consistency between marital status and mortality projections and to introduce a differential based on previous receipt of Disability Insurance. For the population under age 65, MINT3 mortality was projected as part of the earnings matching procedure. Earnings records were adjusted to ensure that the total number of deaths by age, sex and DI beneficiary status among the MINT population matched the comparable totals underlying OCACT projections.

The adjustment to ensure consistency between mortality and marital status was necessary because the procedures for determining mortality among those under age 65 in MINT3 did not consider or affect the projections of marital status that had been carried over from MINT1. Without explicit adjustments, the spouse of a deceased worker could still be coded as married and a person coded as a widow could still have a living spouse.

The disability differential was introduced into post-65 mortality in MINT3 to reflect the fact that mortality rates are substantially higher for persons who have ever received DI benefits than for the rest of the population. For instance, Zayatz (1999) finds that men who have ever received Social Security disability benefits are more than 2.2 times as likely to die at age 67 as are 67-year-old men who never received disability.[1] This ratio declines to about 1.4 at age 80, and it falls to just over 1.0 at about age 89. Among women, the comparable ratio is even higher. Those who have previously received DI are 2.9 times as likely to die at age 67. That ratio also declines as women age, falling to just over 1.0 at about age 94.

The procedure used to generate earnings records would produce similar differentials among DI recipients and non-recipients under 65. The disability differential had to be inserted after age 65, however, to maintain this relationship in the MINT3 population as it aged. MINT1 did not have differential mortality rates based on DI beneficiary status.

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[1] These differentials are based on the mortality rates of Social Security disabled beneficiaries from 1991 to 1995 from Zayatz (1999) divided by the total mortality rate from Social Security Administration (1995) by gender and age.

This chapter begins by explaining the procedures used to introduce the disability differential and to assure consistency between marital status and mortality. It then analyzes the resulting structure of mortality by comparing MINT3 to MINT1 and other benchmarks. These comparisons focus first on differential mortality rates among the disabled and then on the patterns of mortality across various demographic subgroups, such as race, education level, and marital status.

While mortality prior to age 65 was adjusted to meet the gender- and age-specific rates assumed in the OCACT projections, mortality after age 65 was not benchmarked against the OCACT assumptions. After examining differences among subgroups, this chapter looks at the difference between the OCACT estimates and the MINT3 estimates based on the Panis and Lillard work. This includes noting how important model results, including average income projections, would have changed had the OCACT mortality rates been used instead.

II. METHODOLOGY

1. The Disability Differential

We used a simulation approach to introduce the disability differential into the original MINT1 mortality projections of those over age 65. The adjustments were designed to preserve the MINT1 gender- and age-specific total mortality rates while adding the historic differential mortality rate among the DI population.

We did not change the date of death of individuals projected to die before age 65. For individuals not projected to die before age 65, we assigned a date of death using a "disability-adjusted" RAND mortality function. The adjustment involved increasing the intercept and decreasing the slope in the mortality hazard for those ever disabled and, to keep total mortality constant, decreasing the intercept and increasing the slope in the mortality hazard for those never disabled.

RAND's mortality function is of the following form:

$$\ln h^m = \gamma' T(t) + \beta' X_t$$

where $\ln h^m$ is the log-hazard of dying at time t; $\gamma T(t)$ captures the piecewise-linear age dependency and a linear calendar time trend; and $\beta' X_t$ represents the effects of the exogenous covariates (race, educational attainment, marital status, and permanent income). Within the parameters of the model, we adjusted the $\beta' X_t$ term to include "ever-disabled" and "never-disabled." We also changed the age spline coefficient, γ, to reflect the decaying affect of disability on mortality over time.

We determined the "ever-disabled" and "never-disabled" values of β by simulation. Specifically, we added a variable amount to the $\beta' X$ term and determined the value that increased the mortality probability at age 65 by the desired amount compared to RAND's unadjusted total mortality rate. We then adjusted the age slope, γ, so that the DI rate converged with the total mortality rate at age 97. This slope adjustment was just the change in Y (change in the intercept β'X) divided by the change in X (the age range over which the slope decays).

Because we increased the mortality rate for DI beneficiaries, we also needed to reduce the mortality rate for individuals who never received DI benefits to retain the total mortality rates estimated by RAND. Again, we calculated this adjustment by simulation. We subtracted a variable amount from the β'X term and determined the value that retained RAND's unadjusted total mortality rate. We then adjusted the age slope accordingly. The specific reduction for the never-disabled depended on the disability prevalence at age 65 for both men and women. The prevalence determined the relative weighting of the never- and ever-disabled for the total mortality rate.

2. The OCACT Mortality Rates

We adjusted MINT mortality projections to match those of OCACT in order to test the sensitivity of our results to our mortality assumptions. This required two modifications. We needed to adjust both the time trend and the intercept in the mortality function. Again, we used a simulation approach to determine these adjustments. First, we added a variable amount to the β'X term to determine the intercept adjustment to match OCACT morality rates at age 65. Then we added a variable amount to the time trend $\gamma T(t)$ to determine the value that increased the mortality probability between ages 65 and 100 by the desired amount for each cohort.

3. Ensuring Consistency with Marital Status

RAND's competing hazards model is already set up to produce consistent marriage and widowhood dates given the updated projected date of death. After adjusting the demographic file, we reran the MINT1 statistical matching program to find former and future spouses on the MINT3 file.[2]

III. PROJECTING THE DISABILITY DIFFERENTIAL

Based on the simulations for ever-disabled men, we increased the intercept term in the MINT1 model by 0.93 and decreased the slope by 0.029. The slope is simply the change in Y divided by the change in X. Here the change in Y is the intercept adjustment (0.93) and the change in X is the change in age over which the disability differential operates (32 years, from 65 to 97). For never-disabled males, we decreased the intercept by 0.05 and increased the slope by 0.0016. For ever-disabled females we increased the intercept by 1.09 and decreased the slope by 0.034, and for never-disabled females, we

[2] See Appendix to Chapter 2 of Toder et al (1999) for more details on the spouse matching algorithm.

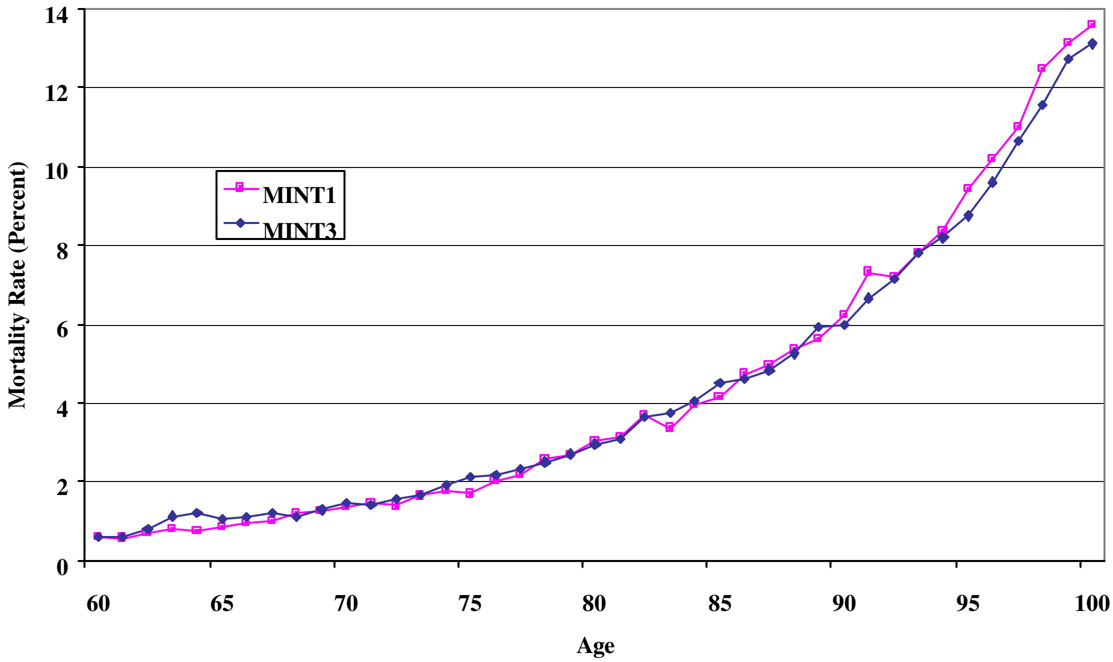
decreased the intercept by 0.05 and increased the slope by 0.0016. We applied these adjustments only to individuals projected to survive to 65 after 1998, the last year of actual mortality data from the Social Security Administration's NUMIDENT file.

The combined adjustments had the desired effects. They preserved the total mortality rate and projected the desired higher mortality rate for individuals who are entitled to DI and lower mortality rate for individuals who are not entitled to DI. RAND's MINT1 female mortality rate rises at an increasing rate from 0.87 percent at age 65 to 13.5 percent at age 100. The adjusted MINT3 rates match these rates closely (see Figure 8-1). RAND's MINT1 male mortality rate also rises at an increasing rate from 2.2 percent at age 65 to 23 percent at age 100. The adjusted MINT3 rates match these rates closely (see Figure 8-2).

The MINT3 projections preserve the desired differential mortality by disability status (see Table 8-1). Ever-disabled males are more than twice as likely to die (2.18) at age 67 compared to all 67-year-old males, and ever-disabled females are 2.35 times more likely to die at age 67 compared to all 67-year-old females. The DI differential decreases to about 1.4 at age 85, and converges to 1 around age 95 for men and women.

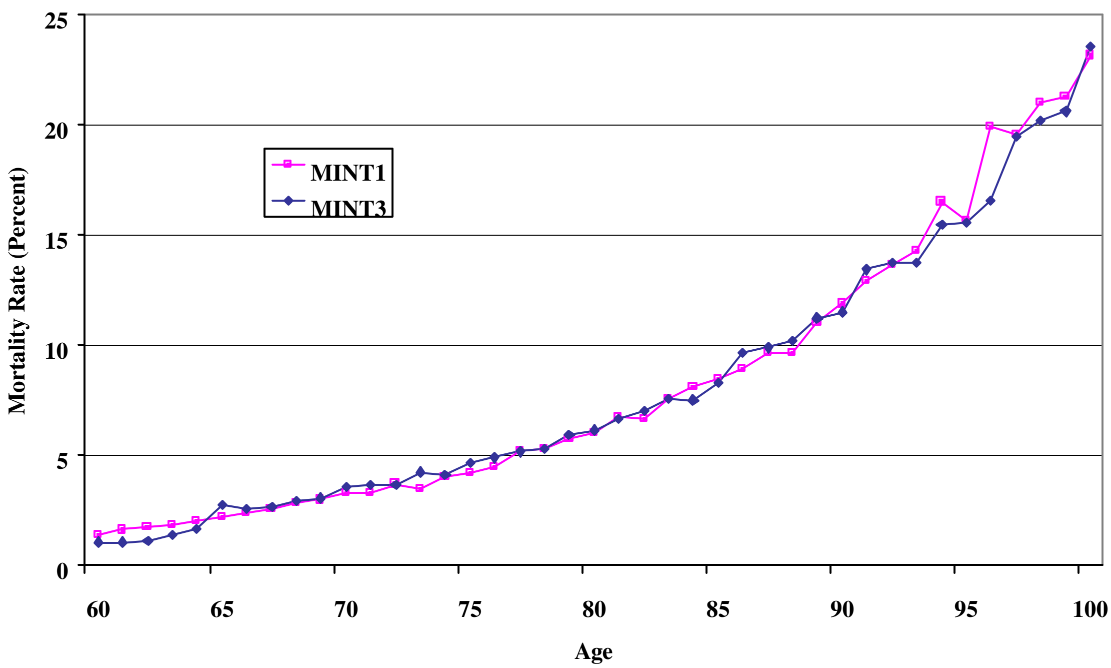
The projected male DI mortality differential does not decline as fast as the historic differentials. This occurs because the framework of the model limits us to an age slope adjustment to decay the DI differential. If we set the differential to decline faster, it would have the undesired effect of predicting lower mortality rates at older ages for ever-disabled individuals compare to never-disabled individuals. We chose instead to decay the differential at a constant rate over a reasonable life span. For both men and women, compared to Zayatz, the MINT3 DI-differentia1 is slightly lower between ages 67 and 70, slightly higher between ages 70 and 90, and essentially equal at higher ages.

Figure 8-1
Female Total Mortality Rates by Age: MINT1 Versus MINT3



Source: The Urban Institute tabulations of MINT1 and MINT3.

Figure 8-2
Male Total Mortality Rates by Age: MINT1 versus MINT3



Source: The Urban Institute tabulations of MINT1 and MINT3.

Table 8-1
Projected Ratio of Ever Disabled Mortality Rate to Total Mortality Rate by Age and Gender

	Zayatz		MINT3	
Age	Male	Female	Male	Female
	Ever DI / Total Mortality Rate			
67	2.25	2.86	2.24	2.46
68	2.18	2.75	2.23	2.65
69	2.14	2.69	2.09	2.82
70	2.09	2.62	2.09	2.79
71	2.04	2.54	1.83	2.13
72	1.98	2.47	2.15	2.22
73	1.86	2.33	2.03	1.87
74	1.75	2.18	2.01	2.10
75	1.69	2.11	1.82	2.12
76	1.63	2.03	1.92	1.61
77	1.57	1.96	1.75	1.95
78	1.51	1.89	1.54	1.89
79	1.46	1.82	1.78	1.64
80	1.40	1.76	1.50	1.57
81	1.35	1.69	1.56	1.87
82	1.30	1.62	1.64	1.71
83	1.25	1.55	1.59	1.66
84	1.21	1.48	1.69	1.50
85	1.17	1.42	1.43	1.49
86	1.13	1.36	1.39	1.49
87	1.09	1.30	1.26	1.41
88	1.06	1.25	1.47	1.41
89	1.03	1.20	1.33	1.26
90	1.04	1.19	1.49	1.33
91	1.04	1.14	1.27	1.33
92	1.05	1.11	1.22	1.14
93	1.05	1.07	1.38	1.14
94	1.06	1.04	0.60	1.13
95	1.06	1.04	1.03	0.93
96	1.06	1.04	1.09	0.98
97	1.07	1.04	1.13	1.12
98	1.07	1.04	1.09	1.02
99	1.07	1.04	0.85	0.85
100	1.07	1.04	1.21	1.05

Source: The Urban Institute calculations based on Zayatz (1999) and Social Security Administration (1995). The Urban Institute projections from MINT.

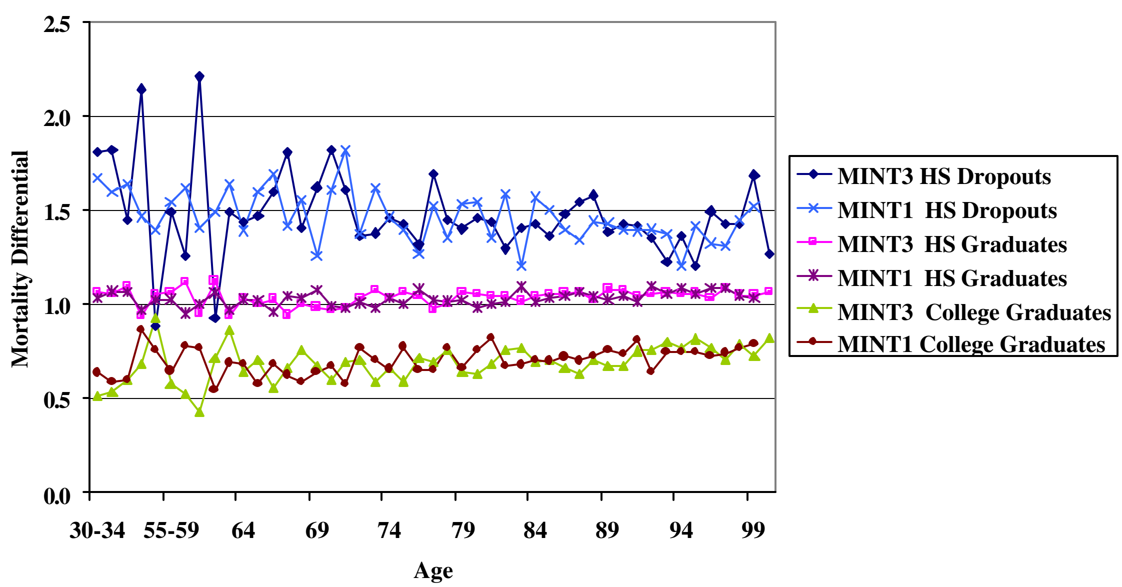
IV. MORTALITY RATES BY SUBGROUPS

To verify that MINT3 mortality projections give the expected patterns, we examined total mortality rates and mortality differentials by education, race, and marital status. We also compared MINT3 projected mortality rates by these subgroups to the mortality rates from MINT1 and the Panel Survey of Income Dynamics (PSID). Deaths on the PSID have systematically come from earlier cohorts than the MINT cohorts, making age-specific comparisons between the two samples particularly difficult given the declining mortality rates over time. We therefore compared mortality rate differentials rather than overall mortality rates.

1. Female Mortality Rates by Education

MINT mortality rates are higher among lower-educated individuals than higher-educated individuals at all ages. Female high school dropouts in MINT3 are about 50 percent more likely to die compared to all women, female high school graduates have about average mortality rates, and female college graduates are about 35 percent less likely to die compared to all women (Figure 8-3). The MINT1 and MINT3 differentials are similar even at younger ages despite their different projection techniques. MINT3 uses a matching algorithm while MINT1 uses a regression-based approach.

Figure 8-3
Female Mortality Differential by Education and Age
Subgroup Mortality Rate/Total Mortality Rate: MINT1 Versus MINT3



Source: The Urban Institute tabulations of MINT1 and MINT3.

As with MINT, PSID mortality rates are higher among lower-educated women than higher-educated women. Despite dramatic changes in educational attainment over the last five decades (U.S. Census Bureau 2000), the mortality differentials by education on the PSID and MINT3 are similar. Female high school dropouts are on average 42 percent more likely to die compared to all women, while high school graduates have about average mortality rates, and female college graduates are on average 45 percent less likely to die compared to all other women in the PSID (see Table 8-2). The mortality differentials in the PSID data fluctuate considerably because of small sample size. Compared to the PSID, MINT3 projects slightly lower mortality differentials for college-educated women and slightly higher mortality differentials for high school dropouts.

Table 8-2
Female Mortality Differential by Education and Age
Subgroup Mortality Rate/Total Mortality Rate: PSID Versus MINT3

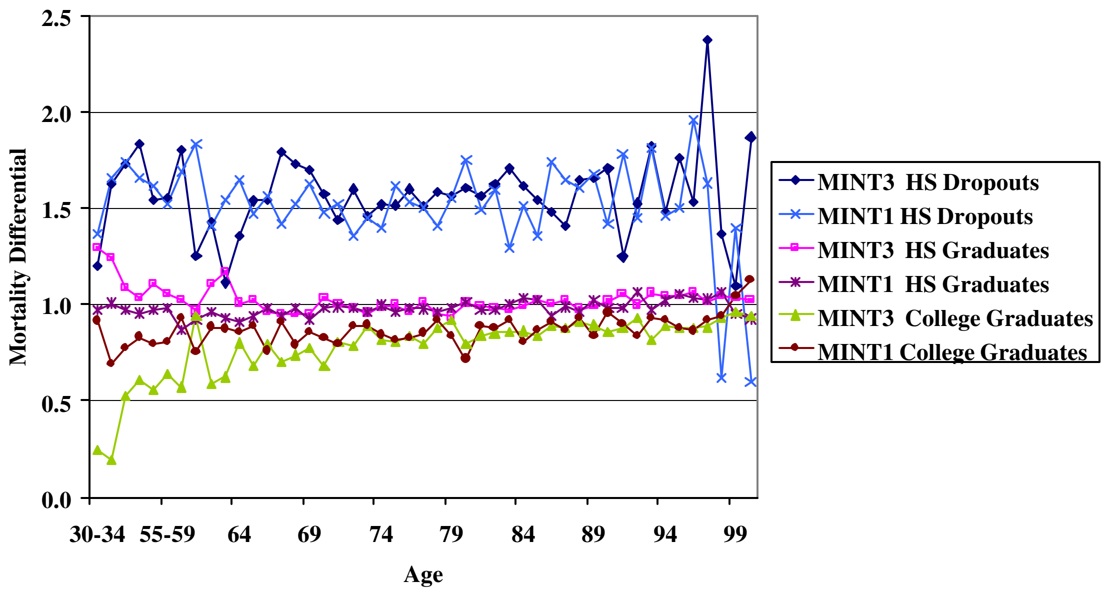
	PSID			MINT3		
Age	**Drop Out**	**High School Graduate**	**College Graduate**	**Drop Out**	**High School Graduate**	**College Graduate**
30-34	2.27	1.00	0.24	1.81	1.06	0.51
35-39	1.45	0.84	0.70	1.82	1.05	0.54
40-44	1.20	0.95	0.97	1.44	1.09	0.60
45-49	1.64	0.99	0.12	2.14	0.93	0.68
50-54	2.23	0.59	0.30	0.88	1.05	0.93
55-59	1.47	0.87	0.42	1.49	1.06	0.58
60-64	0.95	1.15	0.40	1.45	1.03	0.66
65-69	1.24	0.84	0.82	1.58	0.99	0.67
70-74	1.40	0.73	0.43	1.52	1.02	0.65
75-79	1.03	1.04	0.69	1.45	1.03	0.68
80-84	1.09	0.89	0.82	1.40	1.04	0.71
85-89	1.07	0.98	0.64	1.46	1.06	0.68
Average	1.42	0.91	0.55	1.54	1.03	0.66
30-50	1.64	0.95	0.51	1.80	1.04	0.58
50-65	1.55	0.87	0.37	1.27	1.05	0.72

Source: The Urban Institute tabulations of the PSID and MINT3.

2. Male Mortality Rates by Education

As with women, MINT mortality rates are higher among lower-educated men than for higher-educated men. Male high school dropouts in MINT3 are about 55 percent more likely to die compared to all men, male high school graduates have average mortality rates, and male college graduates are about 40 percent less likely to die compared to all men (see Figure 8-4).

Figure 8-4
Male Mortality Differential by Education and Age
Subgroup Mortality Rate/Total Mortality Rate: MINT1 Versus MINT3



Source: The Urban Institute tabulations of MINT1 and MINT3.

MINT3 and MINT1 mortality differentials are similar at older ages but are different at younger ages. At younger ages, MINT3 projects lower mortality rates than in MINT1 for college graduates and higher mortality rates than in MINT1 for high school graduates. While mortality is rare at younger ages, making the sample size small, the matching algorithm in MINT3 clearly kills off younger men at different rates by education group than the regression-based approach used in MINT1.

As with MINT, the PSID mortality rates are higher for lower-educated men than higher-educated men, and the MINT3 differentials more closely match the PSID differentials than the MINT1 differentials (see Table 8-3). Male high school dropouts in PSID are about 42 percent more likely to die compared to all men, male high school graduates are about 12 percent less likely to die compared to all men, and male college graduates are about 30 percent less likely to die compared to all men. Compared to the PSID, MINT3 projects higher relative mortality differentials for high school dropouts at older ages. While mortality rates for high school graduates are higher than for college gradates on both the PSID and MINT, the differential is smaller on the PSID than on MINT. In both datasets, the differential declines with increased age.

Table 8-3
Male Mortality Differential by Education and Age
Subgroup Mortality Rate/Total Mortality Rate: PSID Versus MINT3

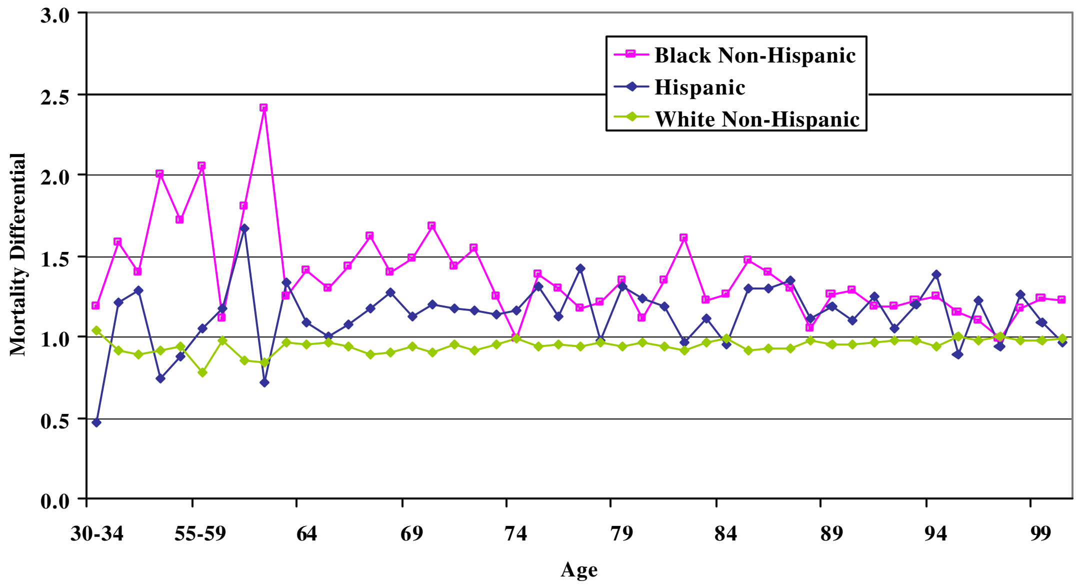
	PSID			MINT3		
Age	**Drop Out**	**High School Graduate**	**College Graduate**	**Drop Out**	**High School Graduate**	**College Graduate**
30-34	1.71	1.25	0.21	1.20	1.29	0.24
35-39	1.88	1.22	0.23	1.63	1.24	0.19
40-44	1.15	0.90	1.07	1.73	1.09	0.52
45-49	1.98	0.73	0.62	1.83	1.03	0.61
50-54	1.63	0.67	0.85	1.54	1.11	0.55
55-59	1.48	0.89	0.45	1.55	1.06	0.64
60-64	1.35	0.85	0.59	1.37	1.06	0.71
65-69	1.24	0.88	0.67	1.66	0.97	0.74
70-74	1.24	0.65	1.21	1.51	0.99	0.80
75-79	1.22	0.84	0.61	1.55	0.97	0.85
80-84	0.98	1.02	0.96	1.61	0.99	0.84
85-89	1.18	0.69	0.94	1.53	1.00	0.88
Average	1.42	0.88	0.70	1.56	1.07	0.63
30-50	1.68	1.03	0.53	1.60	1.16	0.39
50-65	1.49	0.80	0.63	1.49	1.07	0.63

Source: The Urban Institute tabulations of PSID and MINT3.

3. Female Mortality Rates by Race and Ethnicity

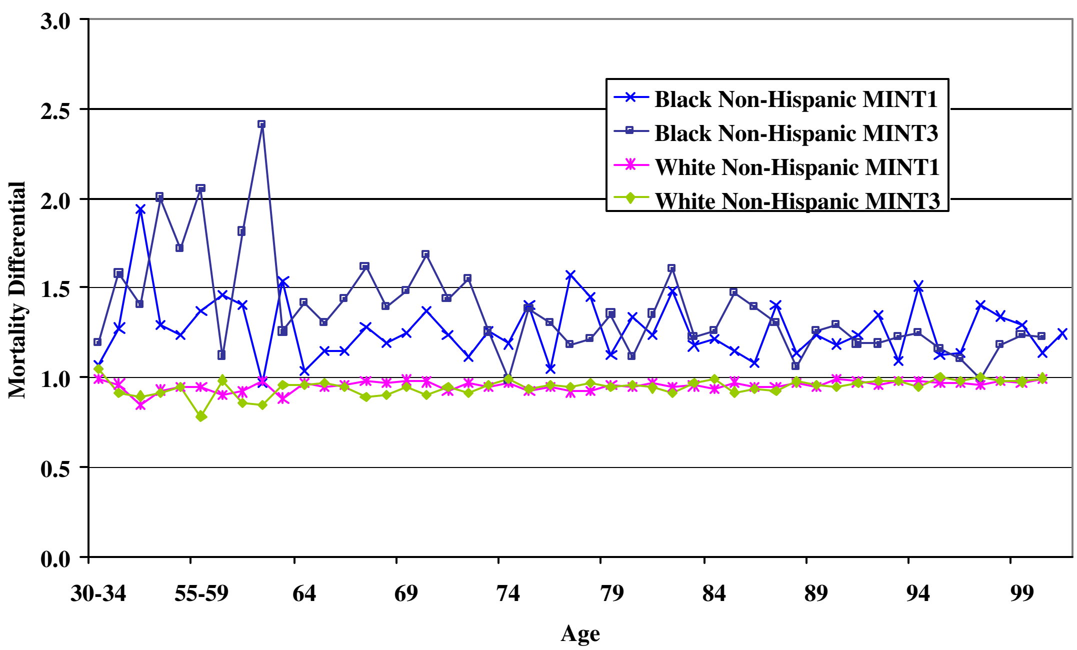
MINT3 mortality rates are higher among black females than among white and Hispanic females. Compared to total female mortality rates, non-Hispanic black women are on average about 50 percent more likely to die, Hispanic women are on average 6 percent more likely to die, and non-Hispanic white women are about 7 percent less likely to die at all ages (Figure 8-5). Hispanics have higher relative mortality rates even though the mortality model does not specifically control for Hispanicity. These higher rates are generated mostly through the education and permanent income measures. Female mortality differentials are similar on MINT1 and MINT3, though MINT3 has slightly greater mortality differentials at younger ages than MINT1 (see Figure 8-6).

Figure 8.5
Female Mortality Differential by Race and Age
Subgroup Mortality Rate/Total Mortality Rate: MINT3



Source: The Urban Institute tabulations of MINT3.

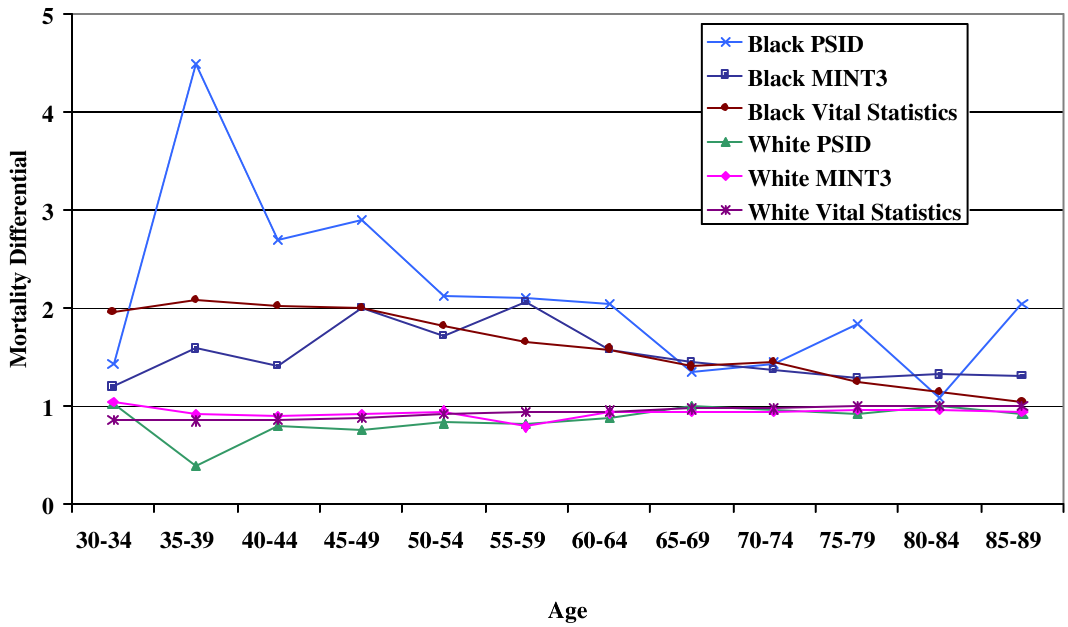
Figure 8-6
Female Mortality Differential by Race and Age
Subgroup Mortality Rate/Total Mortality Rate: MINT1 versus MINT3



Source: The Urban Institute tabulations of MINT1 and MINT3.

As with MINT, Vital Statistics and PSID mortality rates are higher for black women than for white women (see Figure 8-7).[3] The MINT differential is smaller at young ages than both PSID and Vital Statistics. Some of the dramatic difference in PSID mortality differential at younger ages is due to the small sample size for young black women in the PSID. Some of the difference may also be due to misclassification of reason for leaving the sample in the PSID. The mortality differential between white and black women diminishes with increased age on all three data sources. Despite different mortality rates, the rank ordering is preserved across MINT1, MINT3, Vital Statistics and the PSID.

Figure 8-7
Female Mortality Differential by Race and Age
Subgroup Mortality Rate/Total Mortality Rate: MINT3, PSID, and Vital Statistics



Source: The Urban Institute tabulations of MINT3, Vital Statistics, and PSID.

4. Male Mortality Rates by Race and Ethnicity

As with women, MINT3 mortality rates are higher for black men than for Hispanic and white men (see Figure 8-8). Compared to all men, black men in MINT3 are on average 60 percent more likely to die. The differential fluctuates considerably at young ages, but stabilizes beyond age 65. Hispanic men are about 5 percent more likely to die compared to all men on average, but the rate at young ages is less than one and becomes greater than one after age 65. White men are about 7 percent less likely to die compared to all men, but the gap diminishes at older ages. Male mortality differentials are similar on MINT1 and MINT3, though MINT3 projects slightly higher mortality rates for black men at younger ages compared to MINT1 (see Figure 8-9).

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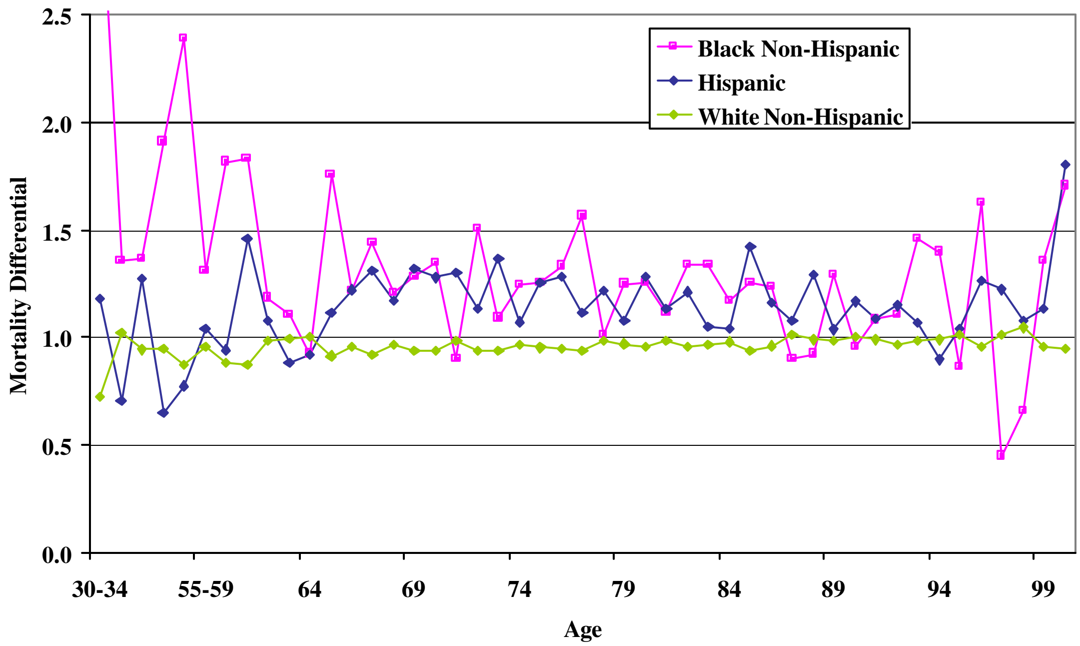
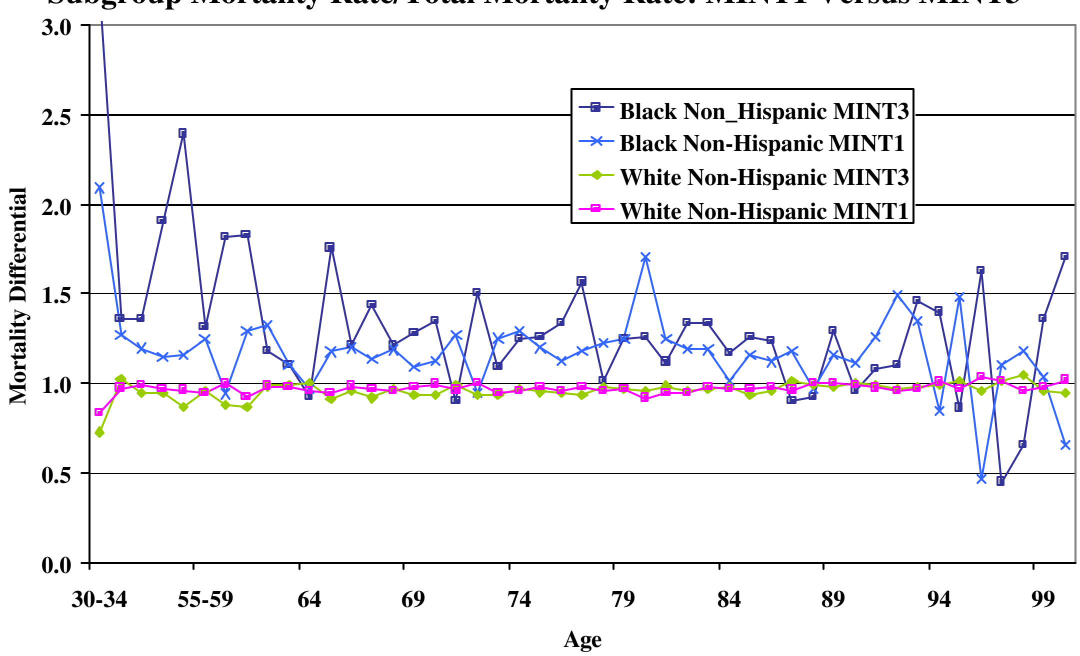
[3] The Vital Statistics race differentials are based on 1997 data (Anderson 1999) and do not separate out Hispanics.

Figure 8-8
Male Mortality Differential by Race and Age
Subgroup Mortality Rate/Total Mortality Rate: MINT3



Source: The Urban Institute tabulations of MINT3.

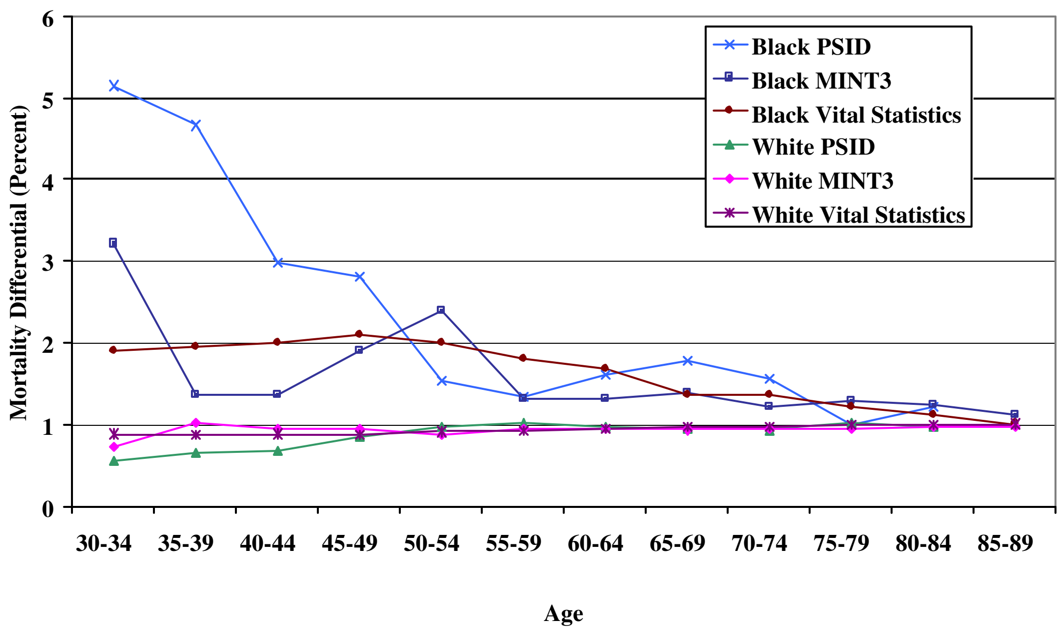
Figure 8-9
Male Mortality Differential by Race and Age
Subgroup Mortality Rate/Total Mortality Rate: MINT1 Versus MINT3



Source: The Urban Institute tabulations of MINT1 and MINT3.

As with MINT, Vital Statistics and PSID mortality rates are higher for black men than for white men (see Figure 8-10). The MINT differential is smaller at younger ages than both the PSID and Vital Statistics. Again, the differentials on the PSID are influenced by some extremely high values at younger ages. The mortality differential between white and black men diminishes with increased age on all three data sources. Despite different mortality rates, the rank ordering is preserved across MINT1, MINT3, Vital Statistics and the PSID.

Figure 8-10
Male Mortality Differential by Race and Age
Subgroup Mortality/Total Mortality Rate: MINT3, PSID, and Vital Statistics

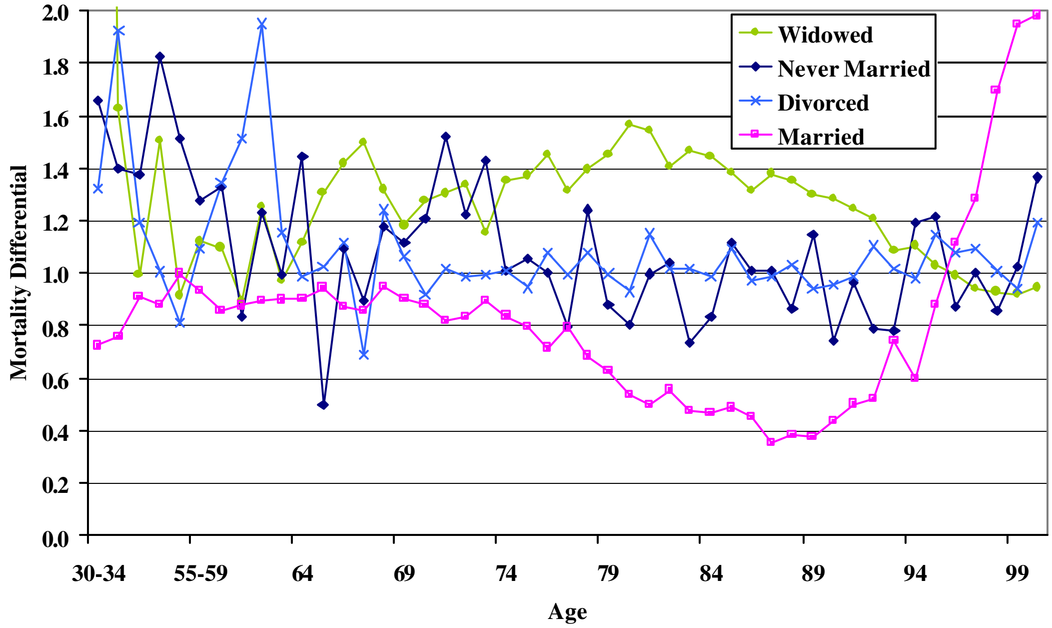


Source: The Urban Institute tabulations of MINT3, Vital Statistics, and PSID.

5. Female Mortality Rates by Marital Status

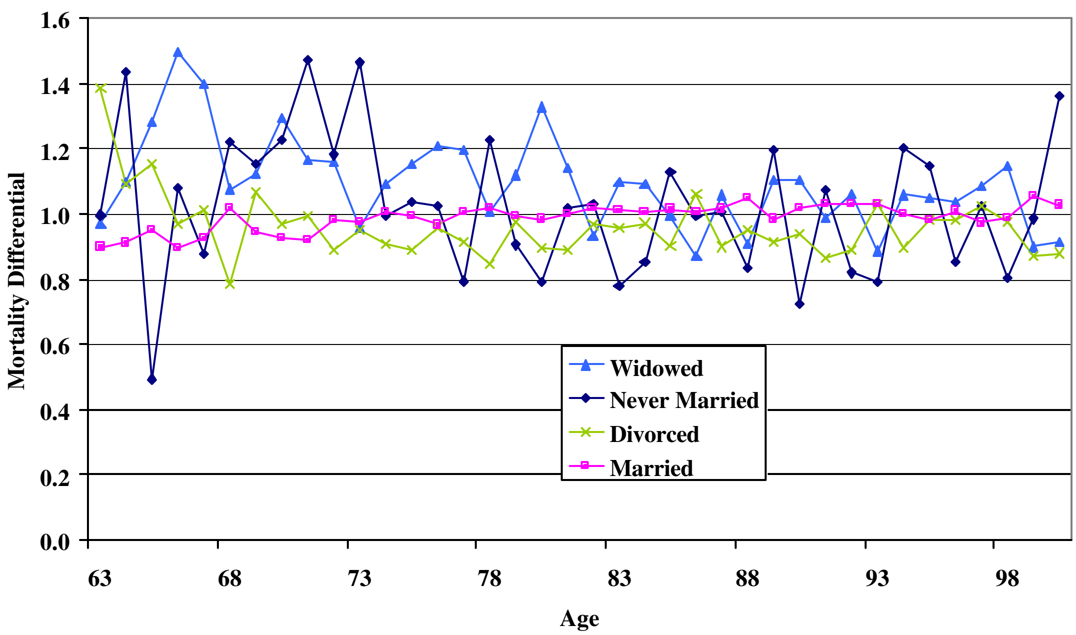
MINT3 mortality rates are higher for single women than for married women at all ages (see Figure 8-11). The differential widens between ages 73 and 96 as MINT3 projects lower mortality rates for married women and higher mortality rates for widowed women. This difference appears to be the result of the remarriage hazard among widowed women rather than a difference in mortality. In fact, the coefficient in the mortality hazard is negative (less likely to die) for widowed women, though other covariates for widowed women contribute to their higher predicted mortality rates. Because marital status changes over time, we also examined the pattern of mortality rates when women are categorized by marital status at age 62 rather than marital status each year. When we do this, the differentials by marital status disappear (see Figure 8-12).

Figure 8-11
Female Mortality Differential by Marital Status and Age
Subgroup Mortality Rate/Total Mortality Rate: MINT3



Source: The Urban Institute tabulations of MINT3.

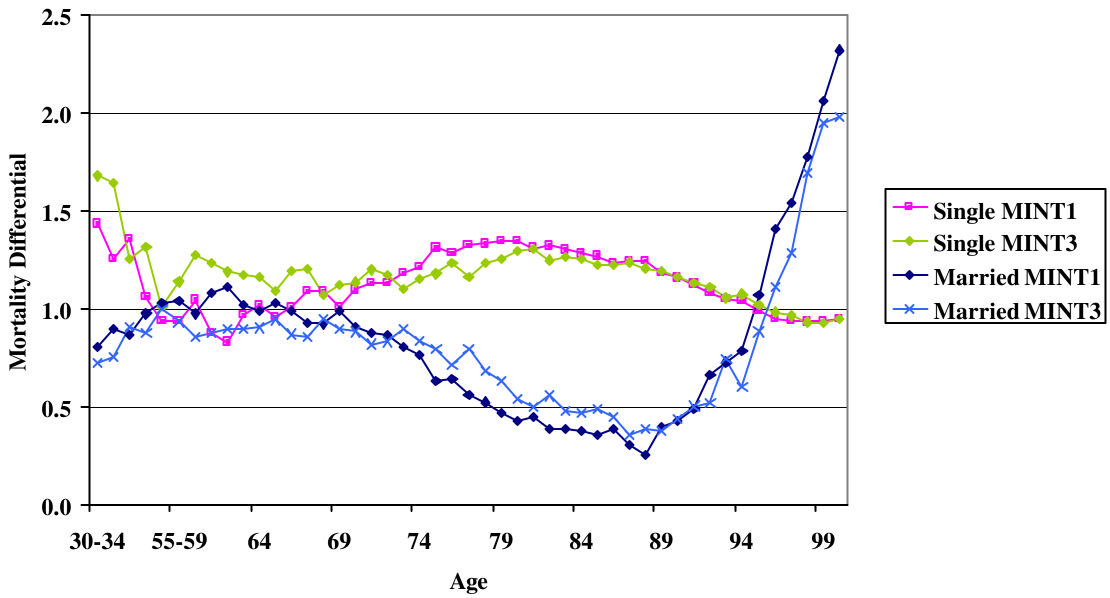
Figure 8-12
Female Mortality Differential by Marital Status at Age 62 by Age
Subgroup Mortality/Total Mortality Rate: MINT3



Source: The Urban Institute tabulations of MINT3.

MINT1 and MINT3 have similar mortality differential patterns, but MINT3 has higher mortality rates for single women until age 72, and lower mortality rates for single women between 82 and 85 compared to MINT1 (see Figure 8-13). After age 85, the differentials in MINT1 and MINT3 are similar. The reverse is true for married women. MINT1 has higher mortality rates for married women until around age 72 after which MINT3 has higher mortality rates compared to MINT1. These differences are solely due to changes in the matching algorithm in MINT3 compared to the regression-based technique used in MINT1.

Figure 8-13
Female Mortality Differential by Marital Status and Age
Subgroup Mortality Rate/Total Mortality Rate: MINT1 Versus MINT3



Source: The Urban Institute tabulations of MINT1 and MINT3.

As with MINT, Vital Statistics and PSID mortality rates are higher for single women than for married women at all ages (see Table 8-4).[4] Unlike MINT, the Vital Statistics and PSID female mortality rates for married and widowed women do not diverge at older ages. Instead, the mortality differential for married women converges to one for both married and widowed women. This result is consistent with the widowed women coefficient in the mortality hazard. Divorced women have higher than average mortality rates at older ages from the Vital Statistics, while they have lower than average mortality rates in MINT. Again, the MINT results may reflect its remarriage model rather than its mortality model for older unmarried women.

[4] Vital Statistics numbers are from Bell (1997).

Table 8-4
Female Mortality Differential by Marital Status and Age
Subgroup Mortality Rate/Total Mortality Rate: MINT3, PSID, and Vital Statistics

	MINT3				PSID				Vital Statistics			
Age	**Married**	**Never Married**	**Widowed**	**Divorced**	**Married**	**Never Married**	**Widowed**	**Divorced**	**Married**	**Never Married**	**Widowed**	**Divorced**
30-34	0.72	1.66	8.64	1.32	0.84	0.96	0.00	2.04	0.75	1.87	2.72	1.50
35-39	0.76	1.40	1.63	1.92	0.75	4.11	0.00	0.79	0.78	1.95	2.09	1.51
40-44	0.91	1.37	0.99	1.19	0.79	1.47	4.95	1.33	0.83	1.82	1.71	1.53
45-49	0.88	1.82	1.51	1.01	0.92	3.74	0.50	1.02	0.84	1.52	1.58	1.45
50-54	1.00	1.51	0.91	0.81	0.82	3.36	1.33	1.24	0.86	1.39	1.45	1.35
55-59	0.93	1.28	1.12	1.09	0.84	2.55	1.58	0.79	0.89	1.41	1.25	1.34
60-64	0.88	1.18	1.11	1.28	0.74	3.53	1.49	0.81	0.91	1.33	1.24	1.29
65-69	0.90	0.96	1.34	0.99	0.96	1.79	1.14	0.38	0.91	1.18	1.12	1.33
70-74	0.85	1.27	1.30	0.92	0.83	3.63	0.92	1.33	0.91	1.16	1.08	1.32
75-79	0.72	0.99	1.41	0.95	1.14	2.47	0.85	0.72	0.90	1.15	1.04	1.37
80-84	0.50	0.88	1.49	0.94	0.86	3.64	0.86	0.73	0.86	1.13	1.04	1.32
85-89	0.41	1.03	1.35	0.94	1.11	3.94	0.77	0.69	0.87	1.18	1.06	1.07
Average	0.79	1.28	1.90	1.11	0.88	2.93	1.20	0.99	0.86	1.42	1.45	1.37
30-50	0.82	1.56	3.19	1.36	0.82	2.57	1.36	1.30	0.80	1.79	2.03	1.50
50-65	0.94	1.32	1.05	1.06	0.80	3.15	1.47	0.94	0.88	1.37	1.31	1.33

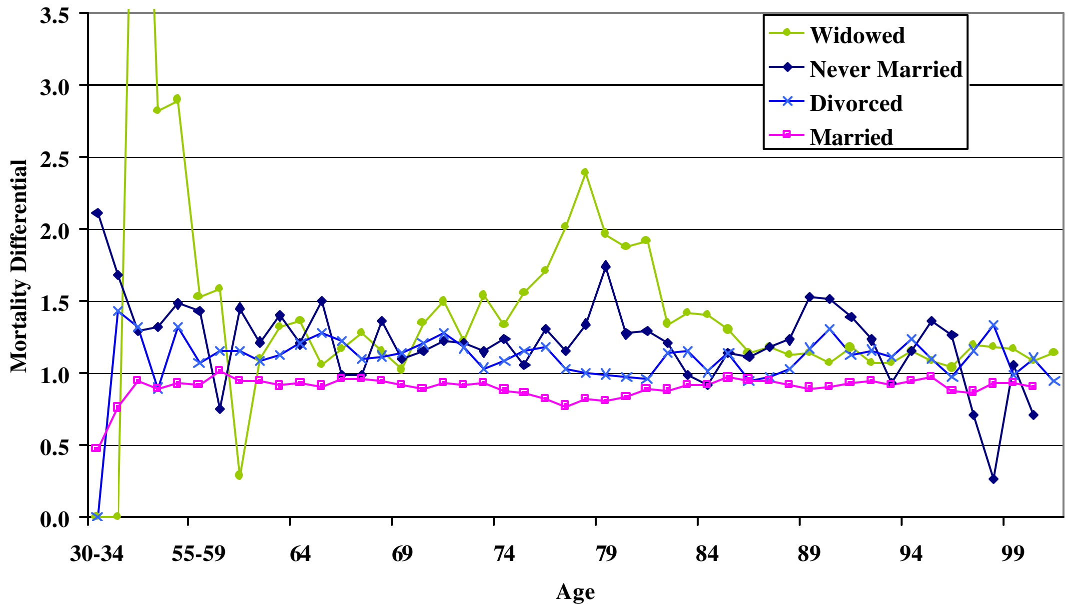
Source: The Urban Institute tabulations of MINT3, PSID, and Bell (1997).

6. Male Mortality Rates by Marital Status

As with women, MINT3 mortality rates are higher for single men than for married men (see Figure 8-14). MINT3 projects higher mortality rates for widowed men between ages 74 and 82 and lower mortality rates for married men in the same age range, though the increase in the differential gap is not as dramatic for men as it is for women. This pattern is mostly due to the MINT marriage hazard rather than the mortality hazard.

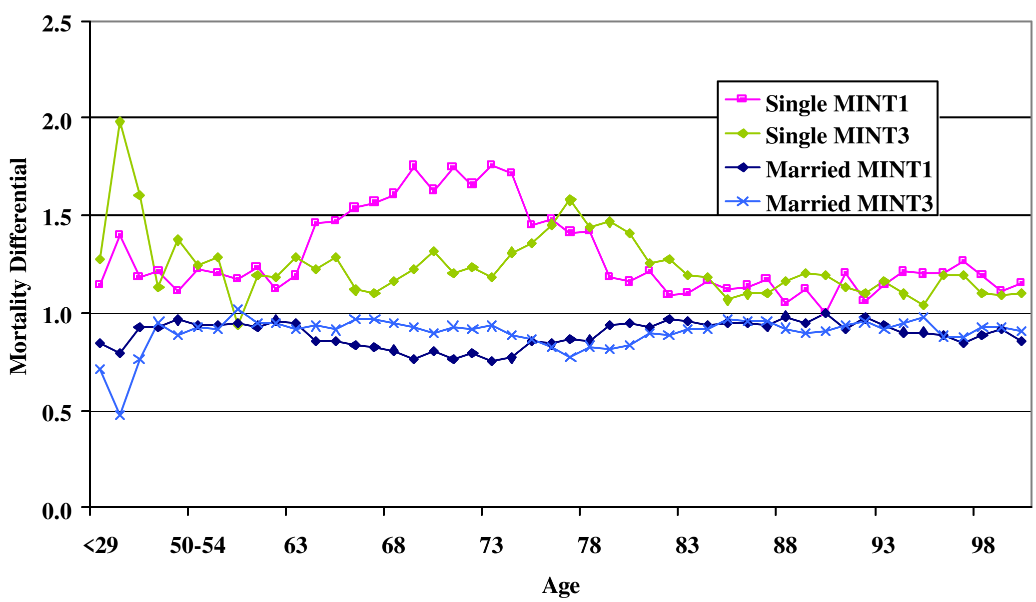
As with women, MINT1 and MINT3 have similar male mortality differential patterns, but MINT3 has lower mortality rates for single men between ages 64 and 76 compared to MINT1 and higher mortality rates for married men compared to MINT1 over the same age range (see Figure 8-15). The mortality differences before age 65 are due to the changed mortality algorithm between MINT1 and MINT3. Reasons for the differences after age 65 are less clear.

Figure 8-14
Male Mortality Rate Differential by Marital Status and Age
Subgroup Mortality/Total Mortality
MINT3



Source: The Urban Institute tabulations of MINT3.

Figure 8-15
Male Mortality Rate Differential by Marital Status and Age
Subgroup Mortality Rate/Total Mortality Rate
MINT1 Versus MINT3



Source: The Urban Institute tabulations of MINT1 and MINT3.

As in MINT, Vital Statistics and PSID mortality rates are higher for single men than for married men (Table 8-5). Unlike MINT, the Vital Statistics and PSID mortality rates for married and widowed men do not diverge at older ages. Instead, the mortality differential converges to one for both married and widowed men. On the PSID at younger ages, never married men have the highest mortality rates while on the SIPP and Vital Statistics widowed men do. Mortality differentials by marital status decline at higher ages on all data sources. The relative ranking between single and married are preserved on all data sources, though they differ slightly in the ranking among unmarried men. The peculiar rise in male mortality rates between ages 63 and 73 from MINT1 is not present on the MINT3, PSID, or Vital Statistics datasets.

Table 8-5
Male Mortality Differential by Marital Status and Age
Subgroup Mortality Rate/Total Mortality Rate: MINT3, PSID, and Vital Statistics

	MINT3				PSID				Vital Statistics			
Age	**Married**	**Never Married**	**Widowed**	**Divorced**	**Married**	**Never Married**	**Widowed**	**Divorced**	**Married**	**Never Married**	**Widowed**	**Divorced**
30-34	0.47	2.12	0.00	1.43	0.42	4.04	0.00	1.29	0.75	1.64	4.72	2.08
35-39	0.76	1.68	6.63	1.33	0.42	7.28	27.3	0.34	0.78	2.09	3.93	2.00
40-44	0.95	1.29	2.83	0.90	0.68	8.02	0.00	0.86	0.83	1.82	2.66	1.87
45-49	0.89	1.32	2.90	1.33	0.66	9.87	5.16	1.86	0.84	1.83	1.87	1.99
50-54	0.93	1.48	1.53	1.07	0.85	6.11	1.29	1.55	0.86	1.87	1.66	1.97
55-59	0.92	1.44	1.59	1.15	0.78	5.90	2.92	2.22	0.89	1.58	1.50	1.81
60-64	0.95	1.21	1.12	1.18	0.87	2.95	2.09	1.99	0.91	1.41	1.44	1.69
65-69	0.94	1.20	1.21	1.16	0.84	3.00	1.06	2.90	0.91	1.32	1.45	1.53
70-74	0.91	1.20	1.44	1.15	0.93	1.87	1.09	1.52	0.91	1.32	1.37	1.44
75-79	0.82	1.32	2.00	1.04	0.90	2.01	1.17	1.11	0.90	1.50	1.27	1.52
80-84	0.89	1.15	1.48	1.08	0.86	2.34	1.05	1.00	0.86	1.61	1.31	1.43
85-89	0.94	1.22	1.15	1.07	0.81	3.06	0.72	2.23	0.87	1.57	1.14	1.18
Average	0.86	1.39	1.99	1.16	0.75	4.70	3.65	1.57	0.86	1.63	2.03	1.71
30-50	0.77	1.60	3.09	1.25	0.60	7.06	6.75	1.18	0.80	1.84	3.30	1.98
50-65	0.93	1.38	1.41	1.14	0.83	4.99	2.10	1.92	0.88	1.62	1.53	1.82

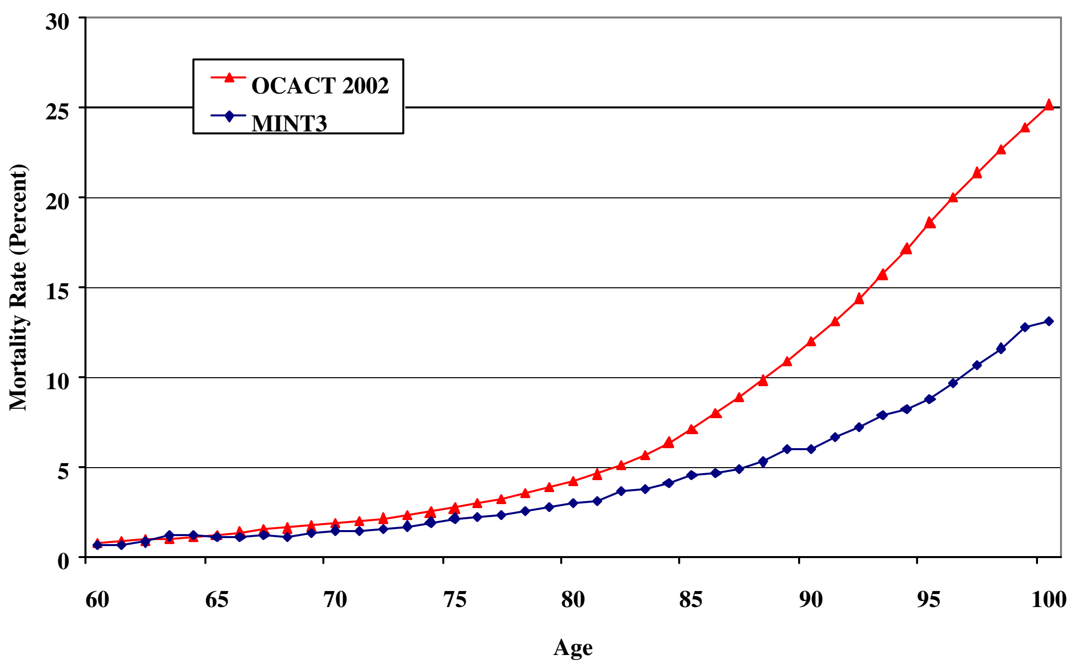
Source: The Urban Institute tabulations of MINT3, PSID, and Bell (1997).

V. SENSITIVITY TEST USING OCACT MORTALITY RATES

1. Comparing MINT and OCACT Mortality Rates

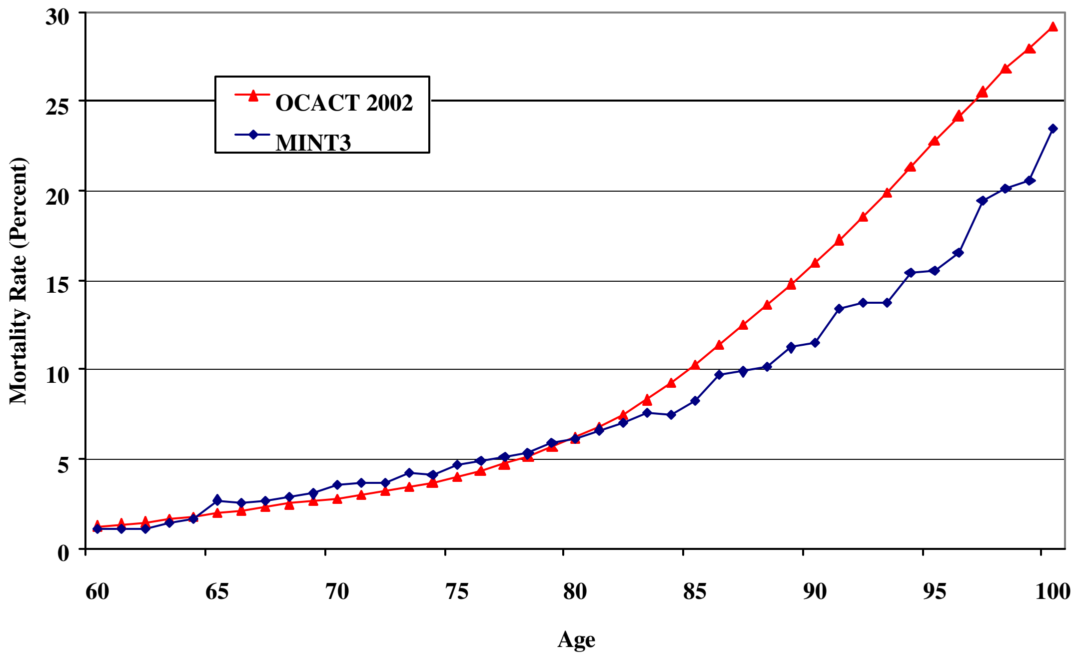
In order to test the sensitivity of the MINT results to the mortality projections, we calibrated the MINT3 mortality projections to match the OCACT 2002 projected mortality rates both before and after age 65. MINT3 mortality rates for females are lower than the OCACT mortality rates for all ages (see Figure 8-16). For men, the pattern is somewhat different. Before age 65, MINT3 baseline projections are calibrated to OCACT projections, and they do match OCACT rates. MINT3 male mortality rates are slightly are higher than OCACT mortality rates between ages 65 and 79 and slightly lower than OCACT rates after age 79 (see Figure 8-17).

Figure 8-16
Female Mortality Rates by Age



Source: The Urban Institute tabulations of MINT3 and OCACT projections.

Figure 8-17
Male Mortality Rates by Age

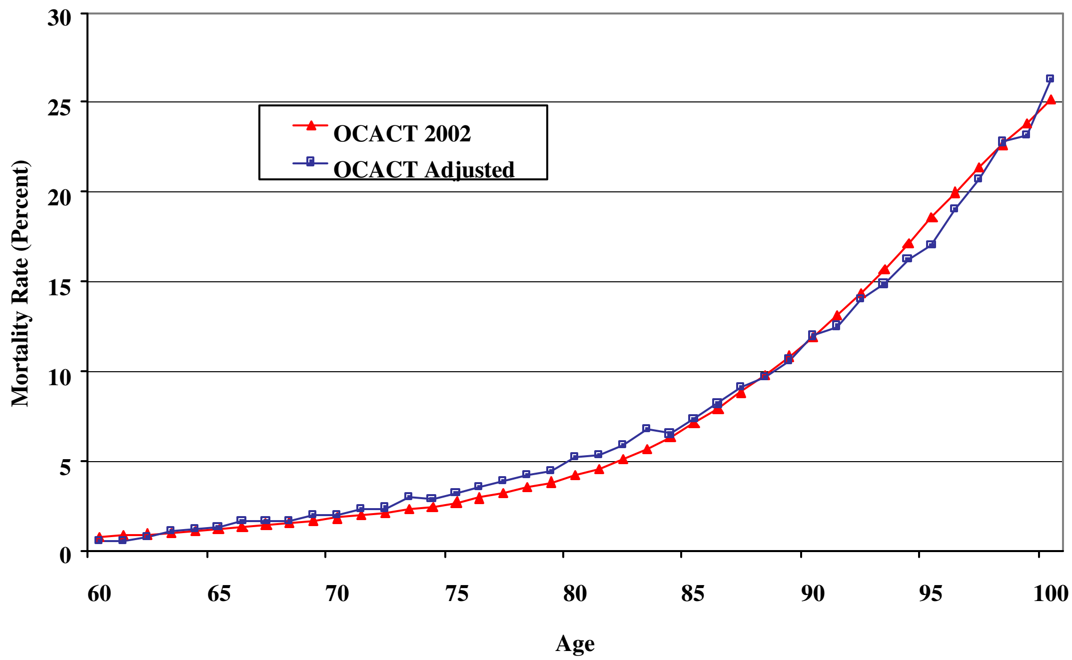


Source: The Urban Institute tabulations of MINT3 and OCACT projections.

We made two adjustments to the MINT3 mortality hazard to calibrate them to OCACT's projections: an intercept adjustment and a time trend adjustment. To adjust for the higher male mortality rates in MINT at age 65, we lowered the intercept term by 0.82. We made no intercept adjustment for females because MINT3 mortality projections at age 65 match those of OCACT. Mortality rates are lower in MINT3 than in OCACT, so we increased the time trend coefficients for both males and females.[5] This adjustment increases the mortality hazard rate and slows the projected mortality rate decline for later MINT cohorts to match the OCACT projected rates. The final adjusted mortality rate (labeled OCACT adjusted), which includes the DI adjustment in addition to the OCACT adjustment, is slightly higher than the OCACT projections until age 80, and slightly lower than OCACT projections for those above age 80 (see Figures 8-18 and 8-19). Still, the adjusted MINT3 projections closely follow the OCACT mortality projections for both males and females.

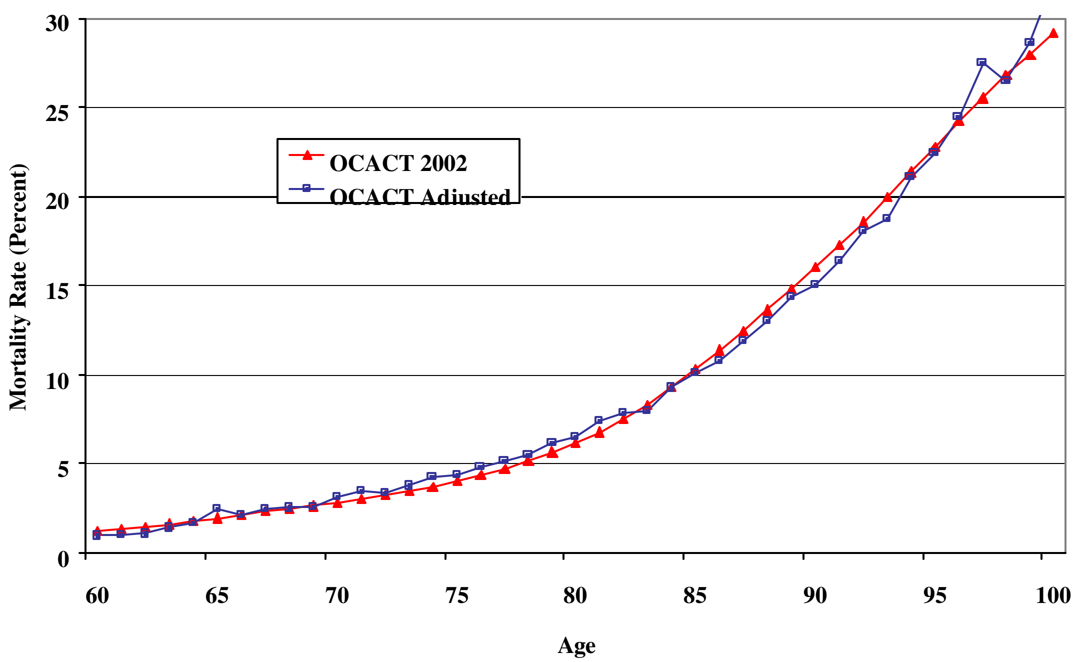
[5] We increased the time trend coefficients by (birth year - 1925) * (-0.00047) + 0.03 for males, and by (birth year - 1925) * (-0.00006) + 0.013 for females.

Figure 8-18
Female Mortality Rates After OCACT Adjustment by Age



Source: The Urban Institute tabulations of MINT3 and OCACT projections.

Figure 8-19
Male Mortality Rates After OCACT Adjustment by Age



Source: The Urban Institute tabulations of MINTSIM and OCACT projections.

Using OCACT mortality rates affects the demographic distribution of the MINT3 population, which affects income and poverty projections in the year 2020. The adjustments made to match MINT3 projections to OCACT projections reduces life expectancy in MINT3 and reduces the size of the retired population compared to the baseline MINT projection.

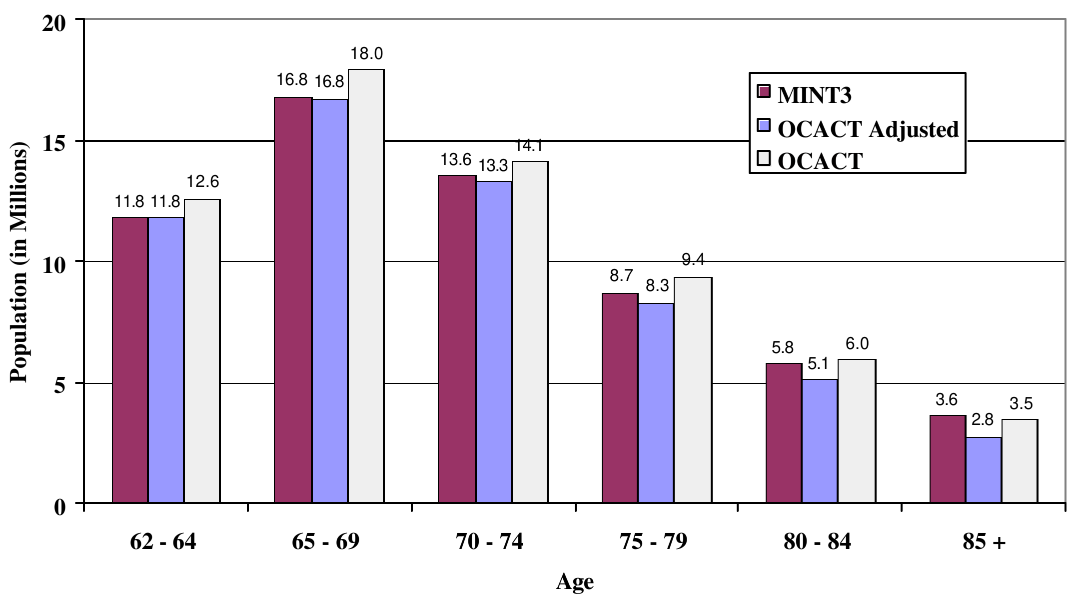
2. Demographic Projections

Figure 8-20 compares the baseline MINT3 2020 population to the population produced by combining MINT3 projections with OCACT mortality rates after age 65 ("OCACT adjusted"). The figure also compares both of these projections to the population projections prepared directly by OCACT.

OCACT projections include the Social Security area population, which is a larger population than in MINT. This includes institutionalized population, individuals living abroad who are eligible to collect Social Security benefits, and future immigrants, all of which are not in the MINT projections. The result is that the basic OCACT population projection between ages 62 to 89 in 2020 is about 5 percent lower than in MINT3 (63.5 million versus 60.4 million).

When the higher OCACT mortality rates are applied to the MINT3 projections, the MINT3 population falls by about 3.6 percent (from 60.4 million to 58.2 million). Most of this decrease is among individuals age 85 and older, where MINT3 had originally projected 3.6 million people and the OCACT adjusted projection is 2.8 million people, a 22 percent reduction.

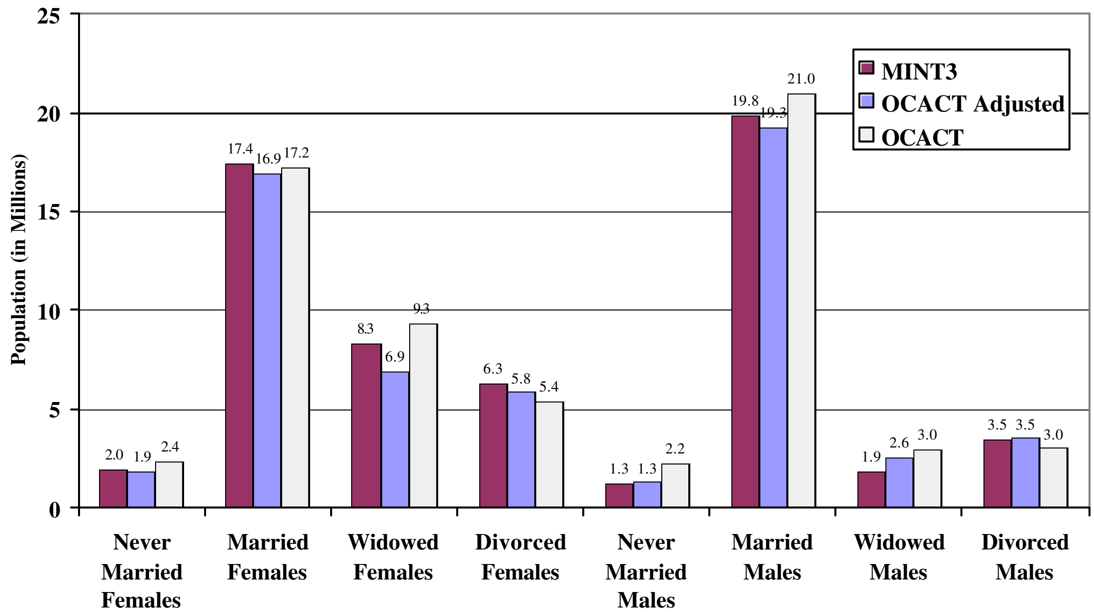
Figure 8-20
Total Population of 62 to 89 Year-Olds by Age in Year 2020 (in Millions)
MINT3 Compared with OCACT Adjusted MINT and OCACT Projections



Source: The Urban Institute tabulations of MINT3, MINTSIM, and OCACT projections.

The adjusted OCACT projection reduces the number of women within all marital status groups compared to the baseline MINT projection, with the largest decrease occurring for widowed women (see Figure 8-21). MINT3 projects 8.3 million widowed women, while the OCACT adjusted projection falls to 6.9 million. Compared to MINT3, the OCACT adjusted projection decreases the number of married men by 2.5 percent (from 19.8 million to 19.3 million), increases the number of widowed men by 37 percent (from 1.9 million to 2.6 million people), and leaves the number of never married and divorced men unchanged.

Figure 8-21
Population Totals of 62 to 89 Year-Olds by Marital Status in Year 2020 (in Millions)
MINT3 Compared with OCACT Adjusted MINT and OCACT Projections



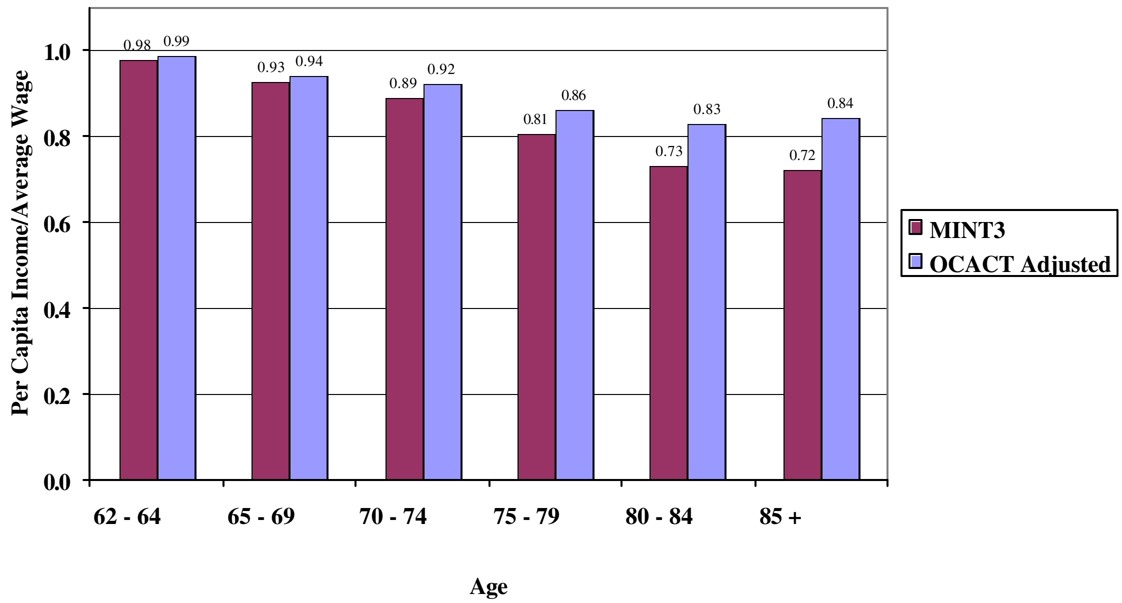
Source: The Urban Institute tabulations of MINT3, MINTSIM, and OCACT projections.

3. Per Capita Income by Marital Status, Age and Type of Retirement Income [6]

Under the OCACT adjusted projection, we annuitize financial assets over fewer years compared to the baseline MINT projection. This increases financial assets relative to the baseline projections and the increase is larger at older ages compared to younger ages (see Figure 8-22). The OCACT adjusted projection increases average per capita income by about one percent for 65- to 69-year-olds and by about 16 percent for 85- to 89-year-olds compared to the baseline MINT projection.

[6] The comparisons cited here are to the MINT3 estimates of total income per capita, which are reported in detail in Chapter 10.

Figure 8-22
Average Per Capita Income of 62- to 89-Year-Olds by Age in Year 2020: MINT3 Versus OCACT Adjusted (Ratio of Income to the Economy-Wide Average Wage)

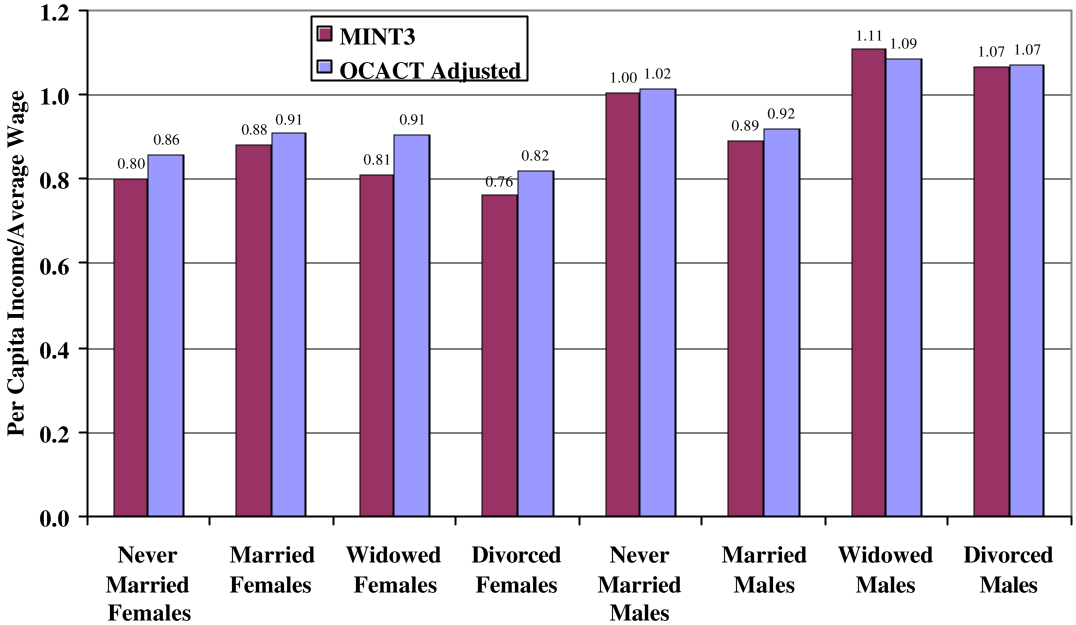


Source: The Urban Institute tabulations of MINT3 and MINTSIM.

Women across all martial status groups, fare better in terms of per capita income under the OCACT adjusted projection compared to the baseline MINT projection (Figure 8-23). The biggest increase is among widowed women (12.3 percent) but never married women's per capita income increases by 7.5 percent (from 0.80 times the average wage to 0.86 times the average wage), married women's income increases by 3.4 percent and divorced women's income increases by 7.9 percent.

Using OCACT mortality rates also increases average per capita income for men compared to the MINT3 baseline, but by a smaller amount than for women. The largest gain is for married men (3.3 percent). Average per capita income also increased by 1.8 percent for divorced men, by 1.1 percent for never married men, and by 1.8 percent for widowed men.

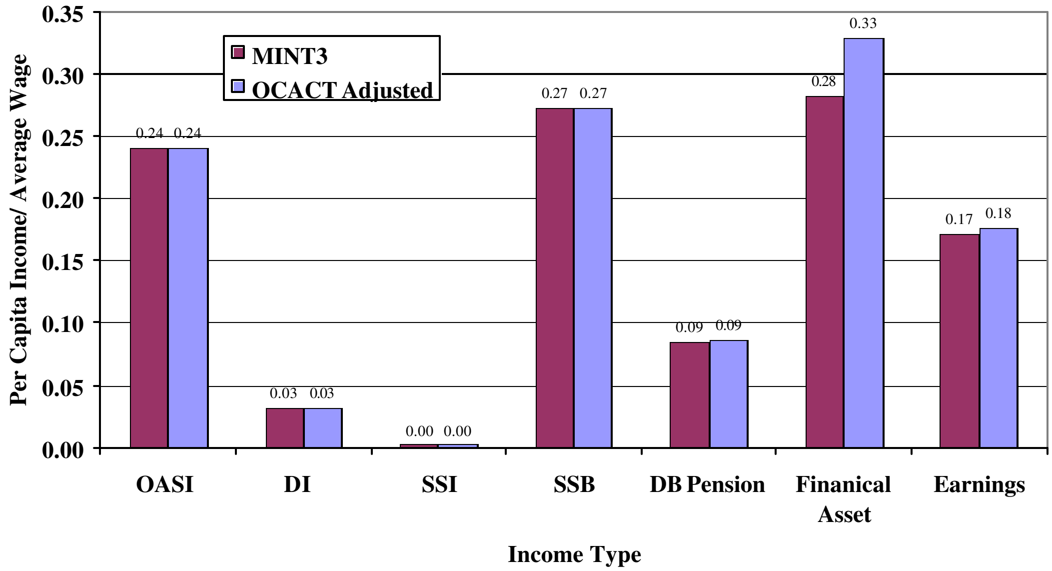
Figure 8-23
Average Per Capita Income of 62- to 89-Year-Olds
by Gender and Marital Status in Year 2020: MINT3 Versus OCACT Adjusted
(Ratio of Income to the Economy-Wide Average Wage)



Source: The Urban Institute tabulations of MINT3 and MINTSIM.

The OCACT adjusted model does not change projected mean per capita income from OASI or SSI, compared to the baseline MINT projection, but it does increase mean per capita income from Social Security DI benefits, DB pension income, financial asset income, and earned income (see Figure 8-24). Most of the increase in total per capita income comes from a significant increase in financial assets as financial assets are annuitized over fewer years under the OCACT mortality rate assumptions. Average DI, DB pensions and earnings also increase under the OCACT adjusted projections because the increased mortality rates reduce the population of low-earners compared to high-earners.

Figure 8-24
Average Per Capita Income of 62- to 89-Year-Olds
by Retirement Income Type in Year 2020: MINT3 Versus OCACT Adjusted
(Ratio of Income to the Economy-Wide Average Wage)

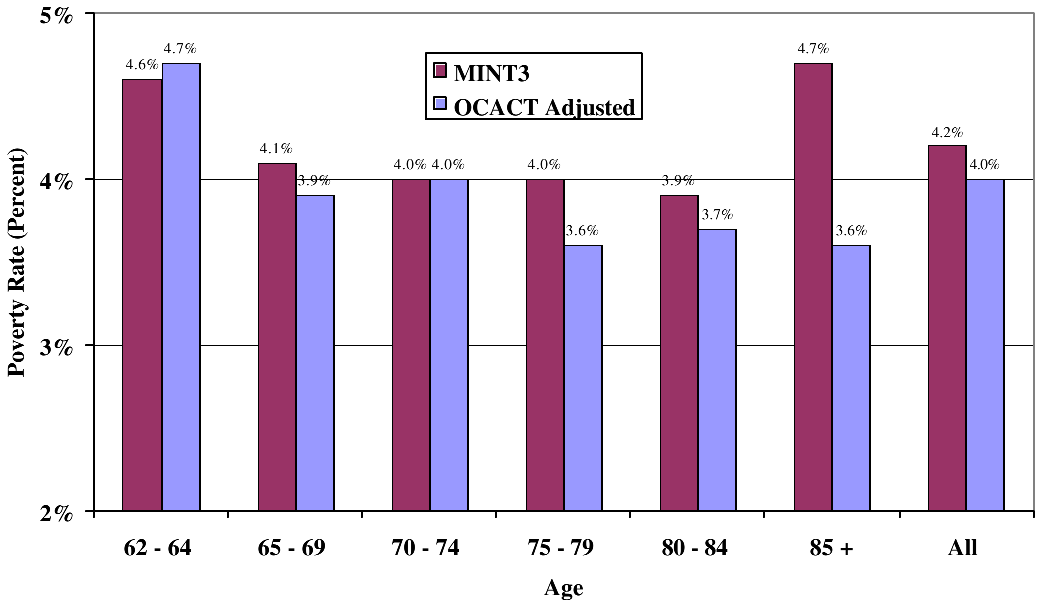


Source: The Urban Institute tabulations of MINT3 and MINTSIM.

4. Poverty Rates

Declining life expectancies result in a reduction of poverty rates. Overall the poverty rate declines in 2020 from 4.2 percent under the MINT3 projection to 4.0 percent under the OCACT adjusted projection (see Figure 8-25). Poverty rates increase for the 62– to 64-year-olds but remain unchanged for 70- to 74-year-olds. The poverty rate decreased for all other age groups with the largest reduction being for the 85- to 89-year-old population (4.7 percent using the projected MINT mortality rates declining to 3.6 percent using the projected OCACT adjusted mortality rates). The reduction in the poverty rate for this group reflects both the decline in the share of the 2020 population that is widowed (who tend to have higher poverty rates compared to other marital groups) and the higher annuity value of asset income with OCACT projected mortality rates compared to the MINT baseline mortality rates.

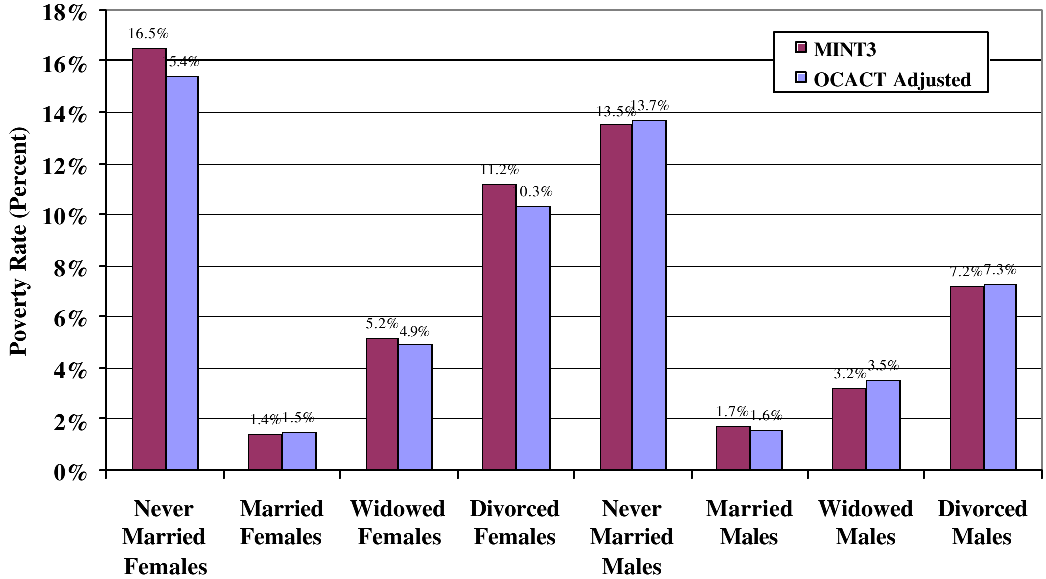
Figure 8-25
Poverty Rate of 62- to 89-Year-Olds
by Age in Year 2020: MINT3 Versus OCACT Adjusted



Source: The Urban Institute tabulations of MINT3 and MINTSIM.

Compared to the MINT3 baseline, OCACT adjusted poverty rates are higher for some marital status groups and lower for others. It is higher for married females, never married males, divorced and widowed males, but lower for never married females, widowed and divorced females and married males (see Figure 8-26). Poverty rates increase for widowed, divorced and never married males because they are projected to live longer under the OCACT adjusted mortality projections and receive lower annuity income. Poverty rates are lower across all the other marital status groups because they are projected to die sooner under the OCACT adjusted mortality projections and receive higher annuity income. Within marital status group, poverty rates also change under the simulation because of changes in imputed spouses as the mortality projections change compared to the MINT3 baseline.

Figure 8-26
Poverty Rate of 62- to 89-Year-Olds
by Gender and Marital Status in Year 2020: MINT3 Versus OCACT Adjusted



Source: The Urban Institute tabulations of MINT3 and MINTSIM.

VI. CONCLUSIONS

The final MINT3 mortality projections retain the OCACT-calibrated mortality rates before age 65 from Tasks 2 and 3 and are consistent with the projected mortality rates in the MINT1 data system by gender and age. The MINT3 mortality projections improve on the MINT1 projections by applying a higher mortality rate for individuals who receive a Social Security disability benefit while preserving the total mortality rate at each age. MINT3 should give a better prediction of the surviving population in 2020 compared to MINT1

Mortality rates are higher for lower-educated individuals compared to higher-educated individuals, higher for blacks compared to whites, and higher for singles compared to married individuals based on the MINT1, MINT3, PSID, and Vital Statistics rates. The mortality rates by marital status appear a bit skewed due primarily to shortfalls in the remarriage hazard rather than the mortality hazard. MINT will likely overstate the share of married individuals and understate the share of widows in 2020.

The MINT3 mortality projections are calibrated to match OCACT mortality rates before age 65; they are not calibrated to match OCACT projections after age 65. Instead, MINT3 projections are calibrated to match MINT1 projections. These MINT1 mortality rates are higher for men at younger ages (between age 65 and 79) and lower for men at higher ages (age 80 and older) compared to the OCACT projections. The MINT1 projections are equal at age 65 for women, but are lower than OCACT at older ages. The MINT3 projections preserve these differentials.

Sensitivity tests using the OCACT adjusted mortality rates result in shorter life expectancies and a reduction in the projected population of the 62- to 89-year-olds in 2020, particularly among widowed and older women. This increases average per capita income primarily from financial assets due to higher annuity rates. It also increases other income by selectively killing off lower-income individuals compared to the baseline. Overall, using the OCACT mortality rates reduces poverty in 2020 from 4.2 percent under the MINT3 projection to 4.0 percent under the OCACT adjusted mortality projection.

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CHAPTER 9

SUMMARY OF MODEL RESULTS

I. OVERVIEW

This chapter brings together the various components of the MINT3 project that have been discussed in the previous sections of the report. It presents the results of our baseline projections and discusses the policy options that the model can be used to address.

As noted in Chapter 1, the projections produced by the MINT3 model begin with a synthetic panel of household records consisting of multiple panels of the Survey of Income and Program Participation data merged with earnings data from the Summary Earnings Records and Social Security entitlement and mortality data from the Master Beneficiary Records. The initial sample consists of those individuals born between 1926 and 1965. Earnings, mortality and disability status prior to age 67 are developed following the procedures described in Chapter 2. Health status is projected using the methods outlined in Chapter 3.

Employment and retirement behavior after age 50 are projected following the procedures described in Chapter 4. This includes first the creation of revised projections of earnings after age 50 and prior to retiring, dying or becoming disabled. For those who do not die or become disabled, it then involves projecting the retirement decision, which is defined as deciding to reduce earnings by at least 50 percent. Additional steps in the process simulate the decision to file for Social Security retirement (or survivor) benefits and the work behavior of the individual after retiring and/or beginning to collect Social Security benefits

Projections of other sources of income are added to the projections of earnings and Social Security benefits to derive each individual's total income. Defined benefit and defined contribution pensions are projected according to the procedures described in Chapter 5, and other assets are projected as described in Chapter 6. The methods outlined in Chapter 7 are used to simulate living arrangements and eligibility for Supplemental Security Income (SSI) benefits and, if eligible, the decision to take these benefits. Marital status is projected using the original demographic projection methodology developed for MINT1 by the RAND Corporation and updated to be consistent with the mortality projections described in Chapter 2. The MINT1 RAND methodology is also used to project mortality after age 67 with an additional adjustment to account for differential mortality of DI recipients.

MINT projects income and wealth as a ratio to the economy-wide average wage each year. The average wage figure used in the development of the model and the projection of future incomes is the average used to construct the Social Security wage index series. Projections reported here are based on the economics underlying the 2002 Trustees' Report.

This chapter will discuss the new projections produced by several of the important modules of MINT3, including the work and benefit claiming behavior of the aged, average wealth and pension coverage. It will then summarize the results of the income projections, beginning with the status of the respective birth cohorts first as they reach age 62 then as they reach age 67. The projections at age 67 will also include the living arrangements of the people living to age 67 and their SSI claiming behavior. This will be followed by an examination of the average incomes among the members of the respective cohorts still living in 2020. An appendix to this chapter contains tables showing the projection results in greater detail.

I. THE MINT3 POPULATION

MINT3 projects that future retirement cohorts will be better educated than those turning 62 in the mid-1990s, contain a higher percentage of African Americans, Hispanic Americans, and other minority groups, and have proportionately more divorced and never married people. These trends reflect the differences among birth cohorts in the initial SIPP population and the impact of the MINT3 projections of mortality and changes in marital status. They are summarized in Table 9-1.

Educational attainment improves among the cohorts reaching age 62 between 1993 and 2012, but begins to deteriorate thereafter. Among the 2015 retirement group (i.e., the cohorts reaching age 62 between 2013 and 2017), only 9 percent will be high school dropouts, which is less than half the proportion found in the 1995 retirement group (cohorts reaching age 62 between 1993 and 1997). The proportion of the last group that dropped out of high school will be slightly higher, however, at 11 percent. Thirty-two percent of the members of cohorts reaching retirement age around 2010 will be college graduates. By comparison, only 19 percent of those in cohorts turning 62 in the mid-1990s were college graduates. The fraction graduating from college declines among cohorts reaching retirement age after 2013, however, falling to 27 percent among the 2020 retirement group, the last cohort in the MINT3 projection.

The white, non-Hispanic proportion of the population declines steadily, from 82 percent of the 1995 retirement group to 75 percent of the 2020 group. This decline is offset by a slight increase in the proportion that is African-American and a substantial increase in the proportion that is Hispanic. African-Americans increase from 9 percent to 11 percent of the retirement cohorts over the projection period, while Hispanic-Americans increase from 6 percent to 10 percent. Asian-Americans and Native-Americans also account for a slightly larger portion of the later retirement cohorts.

Table 9.1
Population Characteristics at Age 62, By Cohort

Retirement Group	**1995**	**2010**	**2015**	**2020**
Year of Birth	1931-35	1946-50	1951-55	1956-60
Year Turned 62	1993-97	2008-12	2013-17	2018-22
Total	100%	100%	100%	100%
Educational Attainment				
High School Dropout	24	10	9	11
High School Graduate	57	58	61	62
College Graduate	19	32	30	27
Race/Ethnicity				
White, Non-Hispanic	82	79	78	75
African-American	9	9	10	11
Hispanic	6	8	9	10
Other	3	4	4	4
Gender				
Female	53	51	52	52
Male	47	49	48	48
Marital Status				
Never Married	4	5	7	7
Married	75	71	70	69
Widowed	10	7	7	7
Divorced	10	17	17	17

Source: The Urban Institute projections from MINT3.

The combination of marriage and mortality trends causes a noticeable shift in the household composition of future retirees. Future cohorts have proportionately fewer married and widowed persons and proportionately more who are never married or divorced. MINT3 projects that the proportion of the retirement cohort that is married will fall from 75 percent of the 1995 group to 69 percent of the 2020 group. Also, improvements in mortality will result in fewer widow(er)s, down from 10 percent of the 1995 group to 7 percent of the 2020 group. These declines are offset by increases in the proportion that is never married (from 4 percent to 7 percent) and the proportion that is divorced (from 10 percent to 17 percent).[1]

II. HEALTH AND DISABILITY

MINT3 projections of health and disability status are summarized in Table 9-2. MINT3 projects significant improvements in health status between the 1995 and 2010 retirement groups both at age 62 and at age 67. The picture is less clear for subsequent retirement groups, with both men and women showing gradual deterioration.

Among women, the percent reporting poor health at age 62 is projected to decline from 31 percent to 26 percent between the 1995 retirement group and the 2010 group. The decline at age 67 is equally large, from 34 percent to 29 percent. On the other hand, health status among women worsens between the 2010 and 2020 retirement groups with the percentage of women in poor health increasing to 31 percent at age 67. Among men, the percent reporting poor health is projected to decline between the 1995 and 2010 retirement groups from 24 percent to 20 percent at age 62 and from 26 percent to 22 percent at age 67. Among the last retirement group, however, the fraction reporting poor health is somewhat higher. The improvements in health between the 1995 and 2010 retirement groups reflect, in part, increases in educational attainment, while the decrease in health between the 2010 and 2020 retirement groups reflect both the decrease in the share of non-Hispanic whites and a slight reduction in educational attainment among the later groups.

In MINT3, trends in the incidence of claiming disability insurance are adjusted to correspond with the projections in the 2002 Trustees' Report. This produces a gradual increase in disability prevalence among the total population at age 62. This rise can be explained by a dramatic increase in disability prevalence among women. By the 2020 retirement group, disability prevalence for women is much closer to disability prevalence for men than it had been for earlier retirement groups. A good part of the narrowing of gender differences is the result of the increased fraction of the female labor force that is insured for disability benefits owing to stronger labor force attachment among later retirement cohorts.

[1] Appendix Table 8A-1a shows detailed breakdown of population characteristics at age 62 by cohort, education, race and ethnicity, gender, and marital status. Appendix Table 8A-1b shows the same results but at age 67.

MINT3 attributes much of the increase in disability insurance prevalence to changes among white, non-Hispanic and African-American workers. The fraction of African-American workers receiving disability benefits at age 62 rises by 5 percentage points, from 17 to 22 percent of the population. White, non-Hispanic workers also experience an increase in disability prevalence, but the increase is smaller in absolute terms. MINT3 projects a decrease in the prevalence of disability among Hispanic workers, though they will continue to experience disability at greater rates than white, non-Hispanic workers through 2020.[2]

Table 9-2
Health and Disability Status

Retirement Group	**1995**	**2010**	**2020**
Year of Birth	1931-35	1946-50	1956-60
Year turned 62	1993-97	2008-12	2018-22
Percent in Poor Health[a]			
At age 62:			
Female	31%	26%	27%
Male	24	20	22
At age 67:			
Female	34	29	31
Male	26	22	23
Percent receiving Disability Insurance Benefits At age 62 (including SSI concurrents):			
Total:	11	11	12
Female	8	10	11
Male	14	12	14
White, Non-Hispanic	10	10	11
African-American	17	18	22
Hispanic	17	15	15

a/ Percent in fair or poor health.
Source: The Urban Institute projections from MINT3.

[2] Appendix Table A9-2a shows the percent of men and women expected to be in fair or poor health by age, gender and cohort. Appendix Table A9-2b shows the percent of individuals expected to receive DI or SSI at age 62 by gender, race, and cohort.

III. RETIREMENT PATTERNS

The projections show an increase in the fraction of persons who have "retired" by age 62 or 65 and a slight decline in the overall fraction that files for Social Security retirement benefits by the time they have reached either age. MINT3 does project some significant shifts in the distribution of those filing for Social Security retirement benefits, however. These projections are summarized in Table 9-3.

In MINT3, workers are considered "retired" when they experience a 50 percent or more decrease in earnings for early cohorts or a drop in hours below 20 hours per week for later cohorts.[3] Under this definition, between the 1995 and 2020 retirement groups the retirement rate increases from 58 percent to 67 percent at age 62 and from 79 percent to 80 percent at age 65. This trend should be treated with caution, however, as much of this rise reflects a definitional change rather than a behavioral change.

Overall, age-specific Social Security benefit take-up rates are projected to remain fairly constant between the 1995 and 2020 retirement groups. The percentage taking-up Social Security benefits declines between the retirement groups – from 58 to 57 percent taking-up by age 62 and from 91 percent to 89 percent taking-up by age 65. This slight decrease in the overall age-specific take-up rate masks larger shifts that occur among higher and lower earners in the respective cohorts. Among workers with AIMEs in the lowest quintile, filing rates are projected to be higher for the later retirement groups than for the earlier retirement groups, both at age 62 and at age 65. On the other hand, among workers with AIMEs in the highest quintile, filing rates at both ages are projected to be lower among the later retirement groups than the earlier groups. In effect, MINT3 projects that future high earners will delay filing for benefits while low earners will file at progressively younger ages. The earlier filing among the low earners occurs despite the gradual increase in actuarial reduction factors associated with the phased increase in the normal retirement age. Much of the decline in Social Security take-up in the higher AIME group is due to a rise in both wife's earnings and in defined contribution pension coverage, while the decline in Social Security take-up age in the lower AIME group is due to increased Social Security coverage among all workers and increased Social Security eligibility among women based on their own earnings. These women no longer need to wait for their husbands to take up Social Security to collect a benefit.[4]

Labor force participation rates show dramatic changes across retirement groups, as shown in Table 9-4. Between the 1995 and 2020 retirement groups at age 62, male

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[3] See table 4.1 in chapter 4 for details.

[4] Appendix Table A9-3a shows more detailed projections of retirement age by gender and cohort. Appendix Table A9-3b shows more detailed projections of Social Security benefit take-up age by gender and cohort. Appendix Table A9-3c shows more detailed projections of Social Security take-up by AIME quintile and cohort.

Table 9-3. Retirement and Benefit Take-Up Rates
Percent of Each Cohort Who Have Filed for Benefits, By Age

	By Age 62		By Age 65	
Retirement Group	**1995**	**2020**	**1995**	**2020**
Year of Birth	1931-35	1956-60	1931-35	1956-60
Year turned 62	1993-97	2018-22	1993-97	2018-22
Retirement Rate[a]				
Total	58%	67%	79%	80%
Female	64	69	81	80
Male	51	65	76	81
Social Security Benefit Take-Up Rate				
Total	58	57	91	89
Male	60	59	88	89
Female	55	55	93	90
Bottom AIME Quintile	52	70	73	92
Second AIME Quintile	69	67	93	94
Third AIME Quintile	59	57	95	91
Fourth AIME Quintile	59	57	97	87
Top AIME Quintile	52	39	94	81

a/ Retirement is defined as working 20 hours or less or a 50% earnings drop; persons not in the labor force at age 50 are considered retired. Disabled individuals are excluded from table.
Source: The Urban Institute projections from MINT3.

Table 9-4
Percentage of Workers with Positive Earnings[a]

	By Age 62		By Age 65	
Retirement Group	**1995**	**2020**	**1995**	**2020**
Year of Birth	1931-35	1956-60	1931-35	1956-60
Year turned 62	1993-97	2018-22	1993-97	2018-22
By Gender				
Total	59%	65%	42%	48%
Male	71	66	50	49
Female	49	64	36	46
Social Security Beneficiaries				
All Beneficiaries	52	51	43	43
Male Beneficiaries	63	50	50	45
Female Beneficiaries	43	53	38	42

a/ Table is limited to non-institutionalized workers (have earnings after age 50) who never get DI benefits.
Source: The Urban Institute projections from MINT3.

labor force participation rates decrease from 71 percent to 66 percent while female rates increase from 49 to 64 percent. At age 65, male rates decrease from 50 percent to 49 percent and female rates increase from 36 percent to 46 percent.

Claiming Social Security retirement benefits doesn't necessarily mean dropping out of the labor force. As shown in Table 9-4, MINT3 projects that a substantial fraction of beneficiaries will continue to work. MINT3 projects that 52 percent of beneficiaries in the 1995 retirement group and 51 percent of beneficiaries in the 2020 retirement group will continue to work at age 62. In both retirement groups, MINT3 projects that 43 percent of beneficiaries will continue to work at age 65. The consistency in the rates at which beneficiaries as a whole work is the result, however, of a significant decline in work among male beneficiaries offset by an increase in work among female beneficiaries.[5]

IV. PENSION COVERAGE

Table 9-5 shows the MINT3 pension coverage projections at age 62 by retirement group and pension type. Overall, MINT3 projects that job based pension (DB or DC) coverage will increase slightly over time and the mix in pension type will shift away from defined benefit pensions to defined contribution pensions. MINT3 does not project any new IRA accounts beyond those observed on the base SIPP data nor does it project IRA roll-overs from DC accounts. As a result, IRA coverage rates decline for later retirement groups and DC coverage rates probably increase more than they otherwise would, with the net effect on coverage rates unclear for later retirement groups.

Employment pension coverage rates for 62-year-olds (excluding the wealthiest five percent of each cohort) increase from 44 percent in the 1995 retirement group to 52 percent in the 2020 retirement group. DB rates decrease from 38 percent for the 1995 retirement group to 31 percent for the 2020 group, while DC coverage increases from 13 to 35 percent across the same period. The rate of dual coverage (have both DB and DC pension plans) increases from 7 percent in the 1995 retirement group to 14 percent in the 2020 retirement group. The rise in dual coverage reflects, in part, the increase in job changes among later retirement groups compared to earlier groups, which increases the probability of having multiple pension types, and the increase in employers that provided dual coverage. The rise in overall coverage rates reflects mostly an increase in female coverage arising from increased female labor force participation. Male coverage rates decrease slightly over time.

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[5] Appendix Tables A9-4a and A94b show more detailed projections of labor force participation. Table A9-4a includes individuals who never work from age 50 and older; Table A9-4b excludes them. Table A9-4c shows the employment status and earnings by benefit type (DI, OASI, none) at age 62. MINT3 appears to project substantial increases in work effort among non-beneficiaries. This is partly due to an increase in Social Security coverage rates and worker eligibility, where a larger share of non-beneficiaries in early cohorts were retired from non-covered employment or not qualified for Social Security under their own work history compared to later cohorts, and partly due to the projection process, which tends to assign a very low number for annual earnings rather than a zero to someone who is essentially out of the labor force.

Table 9-5
Pension Coverage at Age 62[a]

Retirement Group	**1995**	**2005**	**2020**
Year of Birth	1931-35	1941-45	1956-60
Year turned 62	1993-97	2003-07	2018-22
All Individuals at Age 62			
Any coverage (DB, DC, or IRA)	59%	57%	57%
DB or DC coverage	44	45	52
DB coverage	38	32	31
DC coverage	13	22	35
IRA coverage	32	26	13
DB or DC			
Female	33	36	44
Male	57	54	56
Bottom AIME Quintile	17	13	26
Second AIME Quintile	27	26	41
Third AIME Quintile	49	48	53
Fourth AIME Quintile	59	62	67
Top AIME Quintile	72	76	77

a/ Excludes individuals whose asset income places them in the top 5 percent of their respective cohort.
Source: The Urban Institute projections from MINT3.

Employment pension coverage increases as earnings increase in all years, but the rate of coverage among high and low earners changes over time. Between the 1995 and 2005 retirement groups, MINT3 projects that coverage rates among low earners will decline slightly (from 17 percent to 13 percent for the bottom AIME quintile) and then rise dramatically (from 13 percent to 26 percent) for the 2020 retirement group. Coverage in the top earnings group, on the other hand, will increase slightly between 1995 and 2005 and between 2005 and 2020.[6]

V. RETIREMENT WEALTH

Future retirement cohorts are projected to have substantially more financial wealth when they reach retirement age than earlier retirement cohorts have had (Table 9-6). The increase comes from substantial growth both of assets in defined contribution pension plans, including IRAs, and of financial wealth outside of pension plans. The top fifth of the wealth distribution among all retirement groups has a large share of both forms of wealth. Over time, DC account balances comprise a rising fraction of total financial wealth. Home ownership rates increase slightly, mainly among single

[6] Appendix Table A9-5a shows pension coverage by pension type, gender, and cohort. Appendix Table A9-5b shows the same by AIME quintile and cohort.

individuals. Housing equity values rise with successive cohorts until the 2010 retirement cohort and fall thereafter.

The cohorts reaching age 62 in the mid-1990s had, on average, financial assets equal to 290 percent of the average wage. The average rises to 460 percent of the average wage for the 2010 retirement group and to 450 percent for the 2020 retirement group. The wealthiest households own a large fraction of the total assets of each cohort. This is illustrated in the second set of financial wealth numbers in Table 9-6, which repeat the earlier calculations but exclude from each cohort the wealthiest five percent of individuals. When the wealthiest five percent are excluded, average total assets decrease by about 30-35 percent and the growth of DC pension plans becomes relatively more important as a source of growth of financial wealth in general. For the entire sample, DC plans grow from about 21 percent of total financial wealth among the 1995 retirement group to nearly a third of total wealth among the 2020 group.

Home ownership projections present a mixed picture. Among married couples, home ownership rates are projected to be roughly constant across the retirement cohorts in the neighborhood of 82 to 83 percent. Mean housing wealth among married homeowners is projected to rise and then fall, from 1.7 times the average wage for the 1995 retirement group to 2.3 times the average wage for the 2010 group and back to 1.7 times the average wage for the 2020 group. These trends reflect differences in initial housing values and in projected lifetime earnings levels among couples.

MINT3 projects a more optimistic situation for single individuals. It projects that homeownership rates will increase across the successive retirement cohorts from 58 percent among those reaching retirement age in the mid 1990s to 67 percent among those reaching retirement age around 2020. And the mean value of the housing equity as a percent of the average wage among singles who own their own home is projected to rise less and fall less than married couples over the same time period. Specifically, MINT3 projects mean values will rise from 1.9 times the average wage in the 1995 retirement group to 2.4 for the 2010 group and 2.2 times the average wage for the 2020 group.[7]

Table 9-7 focuses more directly on the distribution of wealth. Less than half of the 1995 retirement group had a DC pension plan balance when they reached age 62. DC plan balances appear to be concentrated among the wealthiest individuals. Among the 1995 retirement group, the individual at the 95th percentile held nearly 3 times the amount held by the individual at the 80th percentile and 4.7 times the cohort average. Despite increasing DC coverage rates, the concentration increases slightly over time. Among the 2020 retirement group, the individual at the 95th percentile held 3.1 times the amount held by the individual at the 80th percentile and 4.7 times the cohort average.

[7] Appendix Table A9-6a shows detailed wealth projections by age and cohort including the top 5 percent of asset holders. Table A9-6b shows the same results excluding the top 5 percent of asset holders. Table A9-6c shows home ownership rates by age, marital status, and cohort including the top wealth holders. Table A9-6d shows the same without the top wealth holders.

Table 9-6
Mean Wealth of Retirement Cohorts at age 62
(Ratio of Wealth to the Economy-Wide Average Wage)

Retirement Group	**1995**	**2010**	**2020**
Year of Birth	1931-35	1946-50	1956-60
Year turned 62	1993-97	2008-12	2018-22
Financial Assets (per capita)			
Entire Sample (mean)			
Total	2.9	4.6	4.5
Defined Contribution Plans (including IRAs)	0.6	1.1	1.4
Non-Pension Financial Wealth	2.3	3.4	3.2
Bottom 95% of wealth distribution (mean)			
Total	2.0	3.0	2.9
Defined Contribution Plans (including IRAs)	0.5	1.0	1.1
Non-Pension Financial Wealth	1.6	2.0	1.8
Housing Wealth (per household)			
All Units			
Portion with Positive Housing Wealth	76%	77%	77%
Mean Wealth of Those of Having Wealth	1.7	2.3	1.8
Married Persons			
Portion with Positive Housing Wealth	83%	82%	82%
Mean Wealth of Those of Having Wealth	1.7	2.3	1.7
Single Individuals			
Portion with Positive Housing Wealth	58%	67%	67%
Mean Wealth of Those of Having Wealth	1.9	2.4	2.2

Source: The Urban Institute projections from MINT3.

Table 9-7
Mean Wealth at Age 62 at Different Points in the Wealth Distribution
(Ratio of Wealth to the Economy-Wide Average Wage)
(Percentiles apply to each form of wealth)

	Mean Wealth	20th Percentile	50th Percentile	80th Percentile	95th Percentile
1995 Retirement Group					
DC pension wealth	0.57	0.00	0.00	0.91	2.67
Non pension wealth	2.30	0.07	0.82	3.29	9.74
Total financial wealth	2.87	0.10	1.21	4.49	11.51
Housing wealth	1.74	0.01	1.20	2.82	4.02
2020 Retirement Group					
DC pension wealth	1.28	0.00	0.22	1.96	6.07
Non pension wealth	3.17	0.18	0.92	3.49	12.63
Total financial wealth	4.53	0.37	1.75	5.97	17.12
Housing wealth	1.83	0.15	0.79	2.50	6.87

Source: The Urban Institute projections from MINT3.

Both housing wealth and non-pension financial wealth are distributed somewhat more equally than are DC account balances. Among the 1995 retirement group, the individual in the 95th percentile has non-pension financial wealth equal to about 4.2 times the cohort average and housing wealth equal to 2.3 times the cohort average. Among the 2020 group, non-pension wealth appears less concentrated, but housing wealth appears slightly more concentrated compared to the earlier retirement group. The ratio of the 95th percentile to the mean falls from 4.2 to 4.0 for non-pension financial wealth, but rises from 2.3 to 3.8 for housing wealth.[8]

VI. INCOME AT AGE 62

Per capita incomes at age 62 are projected to rise between the 1995 retirement group and the 2010 retirement group, the initial cohorts of the baby boom generation. The financial situation of subsequent groups deteriorates, leaving the 2020 retirement group worse off than the 1995 group (Table 9-8). From an average of 90 percent of the average wage among the earliest retirement group, per capita incomes are projected to rise to 95 percent for the 2010 group before dropping back to 88 percent for the 2020 group. (In order to insulate the income trends from the effect of changes among a few outliners, these calculations exclude the records of the five percent of the sample in each cohort that had the highest asset income.)

[8] Appendix Table A9-7 shows detailed wealth distributions by cohort and asset type at age 62.

Table 9-8
Per Capita Income at Age 62 by Retirement Cohort
(Ratio of Income to the Economy-Wide Average Wage)[a]

Retirement Group	**1995**	**2010**	**2020**
Year of Birth	1931-35	1946-50	1956-60
Year turned 62	1993-97	2008-12	2018-22
All Individuals	0.90	0.95	0.88
By Source:			
Social Security Benefits	0.17	0.16	0.17
Financial Assets	0.11	0.15	0.15
Defined Benefit Income	0.15	0.07	0.06
Earned Income	0.42	0.51	0.46
Imputed Rental Income	0.05	0.07	0.05
By Gender:			
Females	0.88	0.94	0.88
Males	0.92	0.97	0.88
By Marital Status:			
Never Married	0.72	0.80	0.87
Married	0.89	0.96	0.88
Widowed	0.95	0.88	0.81
Divorced	0.97	0.99	0.92
By Race/Ethnicity:			
White, Non-Hispanics	0.93	1.02	0.95
African-Americans	0.74	0.71	0.61
Hispanics	0.67	0.66	0.65
By Education Level:			
High School Dropouts	0.60	0.52	0.49
High School Graduates	0.92	0.88	0.81
College Graduates	1.25	1.27	1.25
By AIME Quintile:			
Bottom	0.25	0.23	0.22
Second	0.55	0.54	0.49
Third	0.81	0.86	0.78
Fourth	1.18	1.30	1.18
Top	1.88	2.10	1.99

a/ Excludes individuals whose asset income places them in the top 5 percent of their respective cohort.
Source: The Urban Institute projections from MINT3.

Improvements between the 1995 group and the 2010 groups are the result of increases in income from financial assets (including DC pension and IRA balances), earnings, and imputed rental income. These increases are offset partially by a significant reduction in income from defined benefit pensions. MINT3 projects that income from financial assets will rise from an average of 11 percent of the average wage among the 1995 retirement group to 15 percent of the average wage among the 2010 group. It also represents 15 percent of the average wage of the 2020 retirement group. Whereas Social Security was more important than asset income in the earlier cohorts, asset income rises to about equal Social Security income in the later cohorts, even when the wealthiest five percent are excluded form the analysis.

A comparison of the situation of different subsets of these populations shows that the greatest improvement between the 1995 and 2010 retirement groups occurs among white, non-Hispanic persons, married persons, and members of the top two AIME quintiles. These subsets have the greatest holdings of financial and housing assets and benefit disproportionately from the increased importance of these two income sources. Other subsets, including high school dropouts, high school graduates, African-Americans, Hispanics, and widowed persons, experience significant declines between the 1995 and 2010 retirement groups. In all cases, financial and housing assets are far less important sources of income than in the respective retirement groups as a whole. Finally, African-Americans appear to be harmed more by the fall off in defined benefit pension income than are the other ethnic groups.

The deterioration in the economic status of the 2020 retirement group compared to that of the 2010 group is the result of significant declines in imputed rental income and earned income and a slight decline in income from defined benefit pensions. The declines, in absolute terms, are proportionately larger for males than females and for married persons than for widowed and divorced persons. On average, persons who were never married are the only group who do not experience the decline. The rise in the total income of the never married group is driven by small increases in earnings and asset income.[9]

VII. AVERAGE INCOMES AT 67

Average incomes at age 67 for each cohort and for most subgroups within each cohort are lower than those among the same subgroup at age 62, largely because of sharply reduced levels of earnings that are only partially offset by higher average Social Security benefits and slightly higher income from most other sources (Table 9-9). Average per capita income among those first becoming eligible to retire in the mid-1990s is 74 percent of the average wage. It is 80 percent of the average wage for those first becoming eligible around 2010, but falls back to 74 percent for the group becoming eligible around 2020.

[9] Detailed cross tabulations by cohort and income source for each marital status, ethnic group and AIME quintile at age 62 are shown in Appendix Tables A9-8a to A9-8f.

Table 9-9
Per Capita Income at Age 67 by Retirement Cohort
(Ratio of Income to the Economy-Wide Average Wage)[a]

Retirement Group	1995	2010	2020
Year of Birth	1931-35	1946-50	1956-60
Year turned 62	1993-97	2008-12	2018-22
All Individuals	0.74	0.80	0.74
By Source:			
Social Security Benefits	0.25	0.29	0.28
Financial Assets	0.12	0.17	0.17
Defined Benefit Income	0.16	0.09	0.08
Earned Income	0.15	0.18	0.17
Imputed Rental Income	0.05	0.07	0.05
By Gender:			
Females	0.72	0.79	0.74
Males	0.75	0.81	0.75
By Marital Status:			
Never Married	0.61	0.66	0.68
Married	0.72	0.80	0.73
Widowed	0.80	0.80	0.75
Divorced	0.77	0.84	0.80
By Ethnicity:			
White, Non-Hispanics	0.77	0.86	0.81
African-Americans	0.61	0.58	0.52
Hispanics	0.53	0.56	0.54
By Education Level:			
High School Dropouts	0.51	0.44	0.41
High School Graduates	0.75	0.75	0.69
College Graduates	1.02	1.03	1.02
By AIME Quintile:			
Bottom	0.24	0.24	0.23
Second	0.47	0.48	0.43
Third	0.68	0.71	0.64
Fourth	0.94	1.04	0.96
Top	1.53	1.79	1.69

a/ Excludes individuals whose asset income places them in the top 5 percent of their respective cohort.
Source: The Urban Institute projections from MINT3.

Most of the differences among cohorts and subgroups that were observed at age 62 can also be observed at age 67. As is the case at age 62, the improvement between the 1995 retirement group and the 2010 group can be traced primarily to higher incomes from financial assets, partially offset by declines in income from defined benefit pensions. In the case of 67 year-olds, however, there is also an increase in average income from Social Security benefits. Social Security benefits remain the most important source of income for 67 year-olds in all cohorts. As was the case at age 62, the financial condition at age 67 of persons in the last two retirement groups (2015 and 2020) deteriorates relative to that of the 2010 group primarily because of reductions in defined benefit pension incomes, earnings, and imputed rent. Comparing the 2010 retirement group to the 1995 group, the most dramatic improvements in mean income occur among non-Hispanic whites, married persons and those in the top AIME quintiles. These groups also tend to experience large declines between the 2010 and 2020 retirement groups, although significant declines are also experienced by African-Americans and high school graduates.[10]

VIII. LIVING ARRANGEMENTS AND SSI BENEFITS

Living arrangements and SSI beneficiary status as of age 67 are summarized in Table 9-10. About 86 percent of the population lives independently at age 67. Independent living is more common among non-Hispanic whites than among African Americans, Hispanics, or others. It is also associated with education, with those with higher education more likely to live independently, probably because they have greater resources to support a separate household. Men are more likely to live independently than are women, and among both men and women, married couples are the most likely to be independent, while never married persons are the least likely.

The projections indicated that about 3 percent of the population will be eligible for SSI at age 67. This number declines with successive retirement groups, since SSI program parameters are either not indexed or indexed only to changes in prices. Among the group reaching retirement age around 2020 (and age 67 around 2025), only 2 percent are projected to be eligible for SSI. High school dropouts and never married persons are more likely to be eligible for SSI than other groups. Hispanic and African-American individuals are also more likely to be eligible for SSI than are white, non-Hispanic individuals.

SSI take-up rates are projected to average around 69 percent. More highly educated people and men are projected to have lower take-up rates than less educated people and women. Hispanics and African-Americans are projected to have higher take-up rates than white, non-Hispanics.

[10] Detailed cross tabulations by cohort and income source for each marital status, ethnic group and AIME quintile at age 67 are shown in Appendix Tables A9-9a to A9-9f.

Table 9-10
Living Arrangements and SSI Recipiency at Age 67[a]

	% Living Independently (All)	% Eligible for SSI	SSI Take Up Rate	Average SSI Benefit[b]	% Living Independently (SSI Recipients)
All	86%	3.1%	69%	0.10	71%
By Education Attainment					
High School Dropout	78	12.2	76	0.11	69
High School Graduate	87	2.2	64	0.10	75
College Graduate	89	0.8	55	0.11	73
By Race/Ethnicity					
White, Non-Hispanic	88	2.0	63	0.10	78
African American	79	8.2	76	0.10	67
Hispanic	79	7.9	72	0.09	65
Other	73	4.9	79	0.13	59
By Gender/Marital Status					
Female:	85	4.1	72	0.11	73
Never Married	71	16.4	72	0.12	67
Married	87	1.4	59	0.07	77
Widowed	82	5.1	78	0.11	75
Divorced	84	7.6	74	0.11	74
Male:	88	2.1	64	0.09	67
Never Married	76	12.6	73	0.12	55
Married	89	1.1	61	0.08	75
Widowed	84	2.5	62	0.10	74
Divorced	87	3.4	58	0.08	74
By Retirement Group (birth cohort)					
1995 (1931-1935)	84	6.2	68	0.11	69
2000	84	4.8	73	0.11	73
2005	86	3.0	73	0.10	73
2010	87	2.7	64	0.10	72
2015	88	2.3	66	0.09	72
2020	86	1.9	73	0.10	69

a/ Excludes individuals whose asset income places them in the top 5 percent of their respective cohort.
b/ Ratio of mean SSI benefit to average wage.
Source: The Urban Institute projections from MINT3.

Among those drawing benefits, the never married and the members of earlier retirement cohorts appear to have somewhat higher benefits, on average, than other marital status groups and members of the later retirement cohorts.

IX. INCOMES IN 2020

MINT3 tracks the annual income of all people from age 62 for as long as they are projected to live, simulating the spend down of their accumulated assets, their changes in marital status – particularly changes resulting from the death of a spouse, changes in labor force behavior and earnings, and the cost of living adjustments in their private and public pension plans. The result is a snapshot of the population aged 62 through 89 in the year 2020 that is summarized in Table 9-11.[11] Many of the patterns seen in this table were also visible in the analysis of incomes at age 62 or age 67. [12]

Per capita income of the aged population in 2020, not including co-resident income, is projected to average 75 percent of average annual Social Security earnings. Sixty percent of mean income will come from two sources, financial wealth (including defined contribution pension balances) and Social Security benefits. Per capita income from financial assets is projected to average 18 percent of the average wage, and per capita income from Social Security is projected to average 27 percent of the average wage. Of the rest of the income sources, the most important component is earnings, which will average almost 60 percent of the amount received from Social Security benefits. Imputed rental income and defined benefit pension income will be of lesser importance.

The relative importance of the different income sources varies widely, however, and these overall averages are not necessarily representative of the situation for the majority of individuals. This is particularly true for the relative role played by financial asset income in 2020. If the wealthiest five percent were included in this analysis, mean per capita income from financial assets would be higher than Social Security benefit income. A similar picture emerges in the comparison of income sources by income quintile in Table 9-11.[13]

Earned income is concentrated among a relatively few individuals. For example, those in the highest per capita income quintile have average earnings equal to 54 percent of the economy-wide average wage. In contrast, earnings are far less important for the bottom three quintiles. Earnings are also highly concentrated among the youngest age-groups.

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[11] These results exclude the wealthiest five percent.

[12] The characteristics of the non-institutionalized survivors in 2020 are shown in Appendix Table A9-10a.

[13] Appendix Table A9-10b shows detailed results including the wealthiest five percent.

Table 9-11
Per Capita Income in 2020 of Persons Aged 62-89
(Ratio of Income to the Economy-Wide Average Wage) [a]

	Percent of Individuals	Total Income[b]	Social Security Benefits	DB Pensions	Other Financial Wealth	Earnings	Imputed Rental Income
All	100	0.75	0.27	0.08	0.18	0.16	0.06
By Education Attainment							
High School Dropout	11.1	0.43	0.21	0.04	0.07	0.07	0.03
High School Graduate	62.0	0.70	0.27	0.08	0.16	0.14	0.05
College Graduate	26.9	1.01	0.30	0.11	0.28	0.23	0.09
By Race/Ethnicity							
White, Non-Hispanic	78.9	0.80	0.28	0.09	0.20	0.17	0.07
African American	9.2	0.55	0.24	0.08	0.08	0.11	0.03
Hispanic	7.9	0.53	0.22	0.05	0.09	0.13	0.04
Other	4.0	0.74	0.23	0.07	0.18	0.20	0.07
By Gender							
Female	56.5	0.74	0.27	0.09	0.17	0.15	0.06
Male	43.5	0.77	0.27	0.08	0.19	0.18	0.06
By Marital Status							
Never Married	5.4	0.70	0.23	0.07	0.15	0.20	0.04
Married	61.7	0.76	0.26	0.08	0.19	0.17	0.06
Widowed	16.8	0.72	0.30	0.08	0.18	0.07	0.09
Divorced	16.2	0.79	0.27	0.12	0.16	0.19	0.06
By Age							
62 to 64	19.6	0.86	0.20	0.06	0.15	0.39	0.05
65 to 69	27.9	0.78	0.29	0.08	0.17	0.18	0.06
70 to 74	22.5	0.75	0.30	0.09	0.19	0.09	0.07
75 to 79	14.5	0.68	0.29	0.09	0.19	0.05	0.06
80 to 84	9.6	0.64	0.26	0.09	0.20	0.03	0.05
85 to 89	6.0	0.64	0.24	0.11	0.21	0.02	0.05
By SS Benefit Status							
OASI Recipient	80.7	0.76	0.29	0.09	0.19	0.12	0.06
DI Recipient	9.8	0.59	0.30	0.07	0.12	0.06	0.04
SSI Recipient	1.7	0.19	0.06	0.02	0.00	0.00	0.02
Non-beneficiary	7.8	1.03	0.04	0.05	0.18	0.69	0.06
By Per-Capita Income Quintile							
Bottom quintile	21.1	0.24	0.16	0.01	0.03	0.01	0.02
Second quintile	21.0	0.45	0.26	0.04	0.08	0.04	0.04
Third quintile	21.1	0.66	0.29	0.08	0.14	0.10	0.05
Fourth quintile	21.0	0.98	0.31	0.12	0.26	0.21	0.08
Top quintile	15.8	1.67	0.34	0.20	0.47	0.54	0.13

a/ Excludes individuals whose asset income places them in the top 5 percent of their respective cohort.
b/Total income does not include co-resident income.
Source: The Urban Institute projections from MINT3.

The MINT3 estimates show dramatic income differences by education level and race and ethnicity, and somewhat less dramatic differences by age and marital status. Mean income of college graduates is projected to be almost two-and-a-half times that of high school dropouts and one-and-a-half times that of high school graduates. Social Security benefits are the great equalizer, varying only moderately among the different education groups. Financial asset income is the source that is most skewed to the more highly educated. College graduates had four times as much asset income per capita as high school dropouts and almost twice as much as high school graduates. Among the other major income sources, college graduates tend to have three to four times as much income as high school dropouts and twice as much as high school graduates.

The differences among race and ethnic groups are also substantial. MINT3 projects average income among white, non-Hispanic households to be one-and-a-half times as high as that among Hispanics or African-Americans. The gap is due primarily to differences in financial asset income. Lesser differences occur in other income sources, such as imputed rent, earnings, and defined benefit pensions. White, non-Hispanic households have higher Social Security benefits than do any of the other race and ethnicity groups, but the differences in Social Security benefits are smaller than those among other income sources. In these projections, African-American and Hispanic households have similar mean income, although there are some relatively minor differences among some of the particular income sources.[14]

Projected per capita incomes are higher among married households than among those who have become widowed. On a per capita basis, the income of divorced persons is projected to be higher than that of married couples, although married couples are likely afforded a higher standard of living owing to the economies of scale of living together. In the MINT projections, never married persons appear to be the worst off with the lowest per capita income. This difference can be explained by lower Social Security benefits, less income from financial assets, and less income from imputed rent.

When households are arrayed by age, the young-old are clearly better off than the old-old in these projections. Up to age 70, much of the difference in mean per capital income is due to differences in earnings. Above age 70, older cohorts have lower mean income from imputed rent and Social Security and higher financial assets. In part, this reflects cohort differences in the status of each group as they entered retirement, particularly the size of their stock of financial assets, the values of their homes, and their average earnings under Social Security. It also reflects the decline in Social Security income relative to wages as wage growth outpaces price growth over time.

Finally, these projections reveal wide differences between the economic status of those with the highest incomes and those with the lowest incomes. The mean total income of the highest quintile is seven times the mean of the lowest quintile, and the mean of the fourth quintile is four times that of the lowest quintile. Social Security

[14] The "other" group includes primarily native Americans and Asian Americans. The mean income of this group is affected strongly by the asset income of a few very wealthy individuals. When the wealthiest five percent of each cohort is excluded from the analysis, the mean income of this group is slightly below that of white, non-Hispanics.

income is distributed more equally than any other source, with a gap of two to one between the highest and lowest income groups. In the top quintile, defined benefit income is 20 times higher, asset income is 16 times higher, and earnings are 54 times higher than among the lowest quintile. By comparison, in the fourth quintile, defined benefit income is 12 times higher, asset income is 9 times higher, and earnings are 21 times higher than among the lowest quintile. When the top wealth holders are included, the top quintile has 30 times the asset income of the bottom quintile.

X. CO-RESIDENT INCOME

MINT3 also imputes the income and family characteristics of non-spouse co-resident family members. Table 9-12 shows the percent of the population age 62 to 89 who are projected to co-reside, that is, who will not live independently. It also shows the family income divided by the average wage of the co-resident families. The rate of co-residency declines with age from 15 percent at age 62 to 12 percent at age 79 and then increases through age 84. The decline reflects mostly the declining share of young-old whose older children have not left the household. The increase reflects the increase in the share of older individuals who need assistance from other members because of poor health or declining financial circumstances.

Individuals in the bottom per capita income quintile are more likely to co-reside than those in the top per capita income quintile (18 percent versus 11 percent); however, for the most part, the income of the co-resident members is lower among the wealthier aged. This reflects both the need of the co-resider and the ability of the co-resident family to support the aged individual. Using the poverty threshold to adjust income for family size, the income of co-resident family members improves the economic position of those in the lower income quintiles, but reduces slightly the economic position of the highest income group. Co-resident income among those in the bottom per capita income quintile raises family income relative to poverty from 1.32 to 3.11 while co-resident income reduces family income relative to poverty from 11.14 to 10.44 for those in the top per capita income quintile. It is important to consider, however, that co-residence is not always based on need. In many cases co-residence is the family social norm.

Including co-resident income in the measure of well-being increases family income divided by poverty for all education and racial groups, but it increases family well-being more for lower educated individuals compared to higher educated individuals, for African American and Hispanics compared to white, non-Hispanics, and for older individuals compared to younger individuals.

Table 9-12
Income of Co-resident Family Members in 2020 of Co-residing Individuals[a]

	Percent Co-residing	Income of Co-resident Family Members[b]	Family Income/Poverty (Exclude Co-resident Income)	Family Income/Poverty (Include Co-resident Income)
All	13%	0.73	4.49	5.48
By Education Attainment				
High School Dropout	21	0.85	2.52	4.15
High School Graduate	13	0.71	4.25	5.33
College Graduate	11	0.69	6.50	6.81
By Race/Ethnicity				
White, Non-Hispanic	11	0.68	4.95	5.89
African American	19	0.68	3.26	4.66
Hispanic	21	0.91	2.99	4.25
Other	25	1.00	4.80	5.19
Per Capita Income Quintile				
Bottom quintile	18	0.74	1.32	3.11
Second quintile	14	0.76	2.70	4.22
Third quintile	12	0.70	4.08	5.13
Fourth quintile	11	0.71	5.98	6.57
Top quintile	11	0.74	11.14	10.44
By Age				
62 to 64	15	0.70	5.17	5.82
65 to 69	13	0.69	4.51	5.38
70 to 74	13	0.74	4.44	5.47
75 to 79	12	0.75	4.01	5.28
80 to 84	14	0.83	3.82	5.28
85 to 89	14	0.82	4.33	5.57

a/ Includes all co-residing individuals including the top 5 percent of wealth holders.
b/ Total income of co-resident family members other than a spouse divided by the average wage.
Source: The Urban Institute projections from MINT3.

XI. MINT AND OCACT PROJECTIONS OF BENEFICIARIES AND BENEFIT LEVELS

Table 9-13 looks at the projected total number of OASDI beneficiaries and the annualized total benefits that will be paid to them.[15] The results compare projections from MINT with those from the SSA's Office of the Chief Actuary (OCACT). OCACT's projections are based on the Trustees' intermediate assumptions in 2002. OCACT projects a total of 69,602 thousand OASDI beneficiaries in 2020 – 58,459 thousand OASI beneficiaries and 11,143 thousand DI beneficiaries. MINT projects a total of 59,970 thousand OASDI beneficiaries in 2020 – 55,404 thousand OASI beneficiaries and 4,566 thousand DI beneficiaries.

MINT and OCACT project a similar number of retired worker and auxiliary OASI beneficiaries, except that MINT does not project child beneficiaries who account for 651 thousand of OCACT's OASI beneficiaries. MINT and OCACT also project a similar number of aged widows and widowers. OCACT projects 276 thousand disabled widow and widowers, 3 thousand parents, 1,857 thousand children, and 160 thousand widowed mother and fathers as survivors of deceased workers. MINT doesn't project benefits for these subgroups and so its projections of survivors of deceased workers are lower than those of OCACT. In total, OCACT projects 2,947 thousand OASI beneficiaries that MINT does not make projections of. When this number is subtracted from OCACT's total OASI beneficiary population, that number is reduced to 55,512 thousand beneficiaries – which is extremely close to MINT's projection of 55,405 thousand. Finally, MINT projects far fewer DI beneficiaries in 2020 than OCACT because MINT includes only birth cohorts through 1965. In 2020, this means that MINT captures only those DI beneficiaries who are at least 55 years old.

Annualized total OASI benefits projected to be paid out in 2020 are similar across most subgroups for MINT and OCACT (for the subgroups that MINT makes projections for). However, benefits paid to aged widows and widowers are projected to be much lower for MINT than for OCACT (compare $49,464 million for MINT with $86,558 million for OCACT). It turns out that the OCACT benefits for this subgroup include auxiliary benefits paid to dually entitled widow(er)s. For widows, this amount is projected to be approximately $28,923 million. MINT total benefits paid excludes auxiliary benefits paid to dually entitled widow(er)s – instead these benefits are counted in the retired workers subgroup. When we subtract $28,923 million from OCACT's benefits for aged widows and widowers, we get $57,635 million – an amount which is much closer to the MINT projected amount. Finally, annualized total DI benefits will be lower for MINT than for OCACT because MINT projections of DI beneficiaries in 2020 are much lower than OCACT projections.

[15] This table is based on Table III.A7 in the 2002 Annual Report of the Board of Trustees.

Table 9-13
Distribution of Benefit Payments by Type of Beneficiary or Payment in 2020

	MINT3		OCACT	
	Number of People (Thousands)	Annualized Total Benefits Paid (Millions)[1]	Number of People (Thousands)[2]	Annualized Total Benefits Paid (Millions)[1,2]
Total OASDI benefit payments	59,970	$740,869	69,602	$804,469
Total OASI benefit payments	55,404	681,190	58,459	684,263
Total DI benefit payments[3]	4,566	60,292	11,143	120,207
OASI benefit payments, total	55,404	681,190	58,459	684,263
Retired workers and auxiliaries	50,932	593,461	51,503	576,880
Retired workers	49,018	570,080	48,324	544,889
Wives and husbands	1,913	23,381	2,528	27,500
Children	-	-	651	4,491
Survivors of deceased workers	4,472	49,464	6,956	107,231
Aged widows and widowers[4]	4,472	49,464	4,660	86,558
Disabled widows and widowers	-	-	276	2,353
Parents	-	-	3	32
Children	-	-	1,857	16,778
Widowed mother and fathers	-	-	160	1,510
Lump-sum death payments	-	-	1,026	152
DI benefit payments, total[3]	4,566	60,292	11,143	120,207
Disabled workers	4,519	60,094	8,885	111,114
Wives and husbands	47	198	188	653
Children	-	-	2,070	8,440

[1] Expressed in 2000 dollars.

[2] As of 12/31/2020.

[3] In 2020, MINT includes only DI beneficiaries age 55 and older.

[4] OCACT total benefits paid includes auxiliary benefits paid to dually entitled widow(er)s. For widows, this amount is projected to be $50,830 million in 2020 dollars or approximately $28,923 million in 2000 dollars. MINT total benefits paid excludes auxiliary benefits paid to dually entitled widow(er)s.

Source: The Urban Institute projections from MINT3 and OCACT projections tabulated by Jason Schultz of the SSA's Office of the Chief Actuary and based on the intermediate assumptions of the 2002 Trustees' Report.

Table 9-14 describes the projected number of OASDI recipients and their average monthly benefits in 2020 by age, sex, and beneficiary status.[16] MINT projects more OASI retired worker beneficiaries in the 62-64 age group than does OCACT (compare 6,712 thousand for MINT with 4,966 thousand for OCACT), which could just reflect a higher take-up rate at these ages for MINT than for OCACT. The differences between MINT and OCACT projections, however, are much smaller among other age groups – with OCACT projecting slightly more retired workers ages 65 to 84 and slightly fewer retired workers ages 85 to 95. MINT and OCACT project very similar benefit levels for retired workers in all age groups – the difference being less than $100 per month.

MINT projects fewer male retired workers and more female retired workers than OCACT. The difference in the projections of female retired workers is largely attributable to MINT's projections of dually entitled widows. MINT projects 6,132 thousand dually entitled widows compared with only 3,985 thousand projected by OCACT. MINT and OCACT project similar benefit levels for retired women – where the benefit amount includes retired worker and auxiliary benefits for those who are dually entitled. However, MINT projects higher benefit levels for those receiving only retired worker benefits and lower benefit levels for dually entitled spouses and widows. MINT projects fewer wives and widows and more husbands and widowers who will receive only auxiliary benefits as spouses or widow(ers); however, the differences in the projected benefit levels are much smaller.

The differences described above could reflect differences between MINT and OCACT projections of lifetime earnings for men and women. It's likely that MINT projects lower lifetime male earnings than OCACT because of the lower benefit levels for retired men and auxiliary spouse and widow beneficiaries in MINT. It's also likely that MINT projects higher lifetime female earnings than OCACT because of the higher benefit levels for female retired worker only beneficiaries in MINT. If the projected relationship between the lifetime earnings of husbands and wives also differs between MINT and OCACT, this could explain why MINT classifies so many more widows as dually entitled than OCACT and why OCACT projects more auxiliary spouse and widow beneficiaries than MINT.

Finally, although MINT projects far fewer disabled workers than OCACT (compare 4,566 thousand for MINT with 8,885 thousand for OCACT), the projected benefit levels are very similar.

Table 9-15 looks at the number and average benefits of projected initial awards in 2020. MINT projects more newly entitled OASI retired worker beneficiaries in the 62-64 age group than does OCACT (compare 1,760 thousand for MINT with 1,338 thousand for OCACT). OCACT projects more newly entitled retired workers at age 63, fewer at age 64, and more at age 65 and 66. The differences in the projections for ages 67 through 70 are much smaller. Again, these differences may reflect differences in take-up rates estimated in MINT and assumed by OCACT.

[16] This table is based on Table 1-11 in the 2000 Green Book.

Table 9-14
Number of OASDI Recipients and Average Benefits, by Age, Sex, and Marital Status in 2020

	MINT3		OCACT	
	Number of Beneficiaries (Thousands)	Average Monthly Benefit Amount[1]	Number of Beneficiaries (Thousands)[2]	Average Monthly Benefit Amount[1,2]
Total OASDI beneficiaries	59,970	$1,030	69,602	$991
Total OASI beneficiaries	55,404	1,025	58,459	1,018
Total DI beneficiaries[3]	4,566	1,100	11,143	850
Age of OASI Retired Worker Beneficiary				
62-64	6,169	919	4,966	945
65-69	14,036	1,056	14,095	1,069
70-74	12,133	1,043	12,407	1,020
75-79	7,492	947	7,921	967
80-84	4,781	860	4,795	899
85-89	2,863	733	2,605	813
90-95	1,544	688	1,535	756
Retired workers[4]	49,018	969	48,324	986
Retired men	22,581	1,175	24,149	1,208
Retired women[5]	26,444	943	24,175	908
Retired women[4]	15,458	962	15,136	765
Dually Entitled Spouses	4,848	633	5,053	962
Dually Entitled Widows	6,132	1,139	3,985	1,380
Disabled workers[3]	4,566	1,100	8,885	991
Disabled men	2,375	1,202	4,644	1,109
Disabled women	2,191	991	4,242	862
Spouses of retired workers	1,913	475	2,528	536
Wives age 62 and over without entitled children	1,536	496	2,404	543
Husbands of retired workers	377	389	50	313
Spouses of disabled workers[3]	47	349	188	256
Wives of disabled workers	29	390	181	265
Husbands of disabled workers	18	282	7	221
Widows and widowers (nondisabled)	4,472	922	4,660	1,067
Widows (nondisabled)	3,911	943	4,612	1,071
Widowers (nondisabled)	561	776	48	765
Widows and widowers (disabled)	-	-	276	696
Widows (disabled)	-	-	267	704
Widowers (disabled)	-	-	9	476

[1] Expressed in 2000 dollars.
[2] As of 12/31/2020.
[3] In 2020, MINT includes only DI beneficiaries age 55 and older.
[4] Average benefit shown without auxiliary benefit amount for dually entitleds.
[5] Average benefit shown with auxiliary benefit amount for dually entitleds.

Source: The Urban Institute projections from MINT3 and OCACT projections tabulated by Jason Schultz of the SSA's Office of the Chief Actuary and based on the intermediate assumptions of the 2002 Trustees' Report.

Table 9-15
Number of OASDI Recipients and Average Benefits for Initial Awards, by Age, Sex, and Marital Status in 2020

	MINT3		OCACT	
	Number of Beneficiaries (Thousands)	Average Monthly Benefit Amount[1]	Number of Beneficiaries (Thousands)[2]	Average Monthly Benefit Amount[1,2]
Total Newly Entitled Worker Beneficiaries	3,122	$1,069	3,472	$1,123
Total Newly Entitled Retired Worker Beneficiaries	3,122	1,069	3,027	1,115
Total Newly Entitled Disabled Worker Beneficiaries	-	-	445	1,174
Age of OASI Newly Entitled				
62	1,761	886	1,338	922
63	295	1,024	422	1,017
64	466	1,172	225	1,120
65	260	1,320	448	1,315
66	132	1,685	424	1,489
67	90	1,883	37	1,496
68	26	1,880	34	1,387
69	61	1,664	38	1,411
70	31	1,360	62	1,363
Retired workers	3,122	1,069	3,027	1,115
Retired men	1,545	1,233	1,553	1,343
Retired women	1,577	907	1,475	876
Disabled workers	-	-	445	1,174
Disabled men	-	-	265	1,286
Disabled women	-	-	180	1,009

[1] Expressed in 2000 dollars.
[2] As of 12/31/2020

Source: The Urban Institute projections from MINT3 and OCACT projections tabulated by Jason Schultz of the SSA's Office of the Chief Actuary and based on the intermediate assumptions of the 2002 Trustees' Report.

Through age 65, MINT and OCACT project very similar benefit levels for retired workers. Between ages 65 and 69, the differences in the projections are much larger with MINT projecting higher benefits. These differences may also reflect the model of take-up rates in MINT, which predicts that those with higher income and earnings are more likely to delay retirement than those with lower income and earnings.

Looking at the entire group of newly entitled retired workers, MINT and OCACT projections of entitlements and benefit amounts are very similar. The difference between MINT and OCACT is larger for females than for males – with MINT projecting more newly entitled female retired workers than OCACT.

CHAPTER 9

APPENDIX TABLES

Table A9-1a
Percent of Individuals at Age 62, by Individual Characteristics and Cohort

Retirement Group	1995	2000	2005	2010	2015	2020	All
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
By Educational Attainment							
High School Dropout	24.3	19.6	15.2	10.4	9.4	10.8	13.5
High School Graduate	56.9	59.6	58.6	57.8	60.8	62.3	59.7
College Graduate	18.7	20.9	26.2	31.7	29.9	26.9	26.8
By Race/Ethnicity							
White, Non-Hispanic	82.1	81.2	81.0	78.9	77.7	75.0	78.7
African-American	8.8	8.7	8.8	8.9	9.8	10.6	9.4
Hispanic	5.7	6.9	6.6	7.7	8.6	10.0	7.9
Other	3.4	3.2	3.6	4.5	4.0	4.3	4.0
By Gender							
Female	52.7	51.9	52.4	51.4	51.6	51.8	51.9
Male	47.3	48.1	47.6	48.6	48.4	48.2	48.1
By Marital Status							
Never Married	4.3	4.7	5.0	5.5	6.8	7.3	5.9
Married	75.1	73.1	71.4	71.1	69.9	68.6	71.0
Widowed	10.3	7.8	7.9	6.8	6.7	7.0	7.5
Divorced	10.3	14.3	15.7	16.7	16.6	17.0	15.7

Source: The Urban Institute tabulations of MINT3.

Table A9-1b
Percent of Individuals at Age 67, by Individual Characteristics and Cohort

Retirement Group	1995	2000	2005	2010	2015	2020	All
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
By Educational Attainment							
High School Dropout	23.7	18.6	14.4	9.7	8.9	10.2	12.9
High School Graduate	57.2	59.9	58.8	57.9	60.6	62.3	59.7
College Graduate	19.2	21.5	26.8	32.4	30.5	27.5	27.3
By Race/Ethnicity							
White, Non-Hispanic	82.5	81.4	81.3	79.4	78.1	75.5	79.1
African-American	8.4	8.5	8.5	8.7	9.5	10.4	9.1
Hispanic	5.8	6.8	6.6	7.4	8.4	9.8	7.8
Other	3.3	3.3	3.6	4.6	4.0	4.3	4.0
By Gender							
Female	54.1	53.6	53.5	52.9	52.9	53.1	53.3
Male	45.9	46.4	46.5	47.1	47.1	46.9	46.7
By Marital Status							
Never Married	3.8	4.5	4.8	5.1	6.4	7.3	5.6
Married	70.2	68.8	67.5	67.3	66.0	63.9	66.8
Widowed	15.5	12.9	12.1	10.6	10.8	11.4	11.9
Divorced	10.5	13.8	15.6	17.1	16.8	17.3	15.7

Source: The Urban Institute tabulations of MINT3.

Table A9-2a
Percentage of Individuals Projected to be in Fair or Poor Health, by Cohort, Age, and Gender

Retirement Group		**1995**	**2000**	**2005**	**2010**	**2015**	**2020**	**All**
Year of Birth		1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
Females	50	.	.	6.2	5.4	5.6	6.1	5.8
	55	.	24.1	22.5	20.5	21.2	21.6	21.6
	60	29.7	27.4	25.4	24.1	24.2	24.4	25.2
	62	31.2	30.2	27.9	26.2	25.5	26.6	27.4
	67	33.8	31.3	29.7	28.5	26.7	30.6	29.7
Males	50	.	.	7.3	6.9	6.5	6.7	6.8
	55	.	18.7	15.7	14.5	17.5	17.0	16.5
	60	22.8	21.7	19.0	18.0	19.3	19.9	19.7
	62	24.3	23.1	19.7	20.2	21.3	22.1	21.6
	67	25.6	24.7	21.3	21.6	23.2	23.3	23.1

Source: The Urban Institute tabulations of MINT3.

Table A9-2b
Percent of Individuals Drawing Disability Benefits at Age 62, by Cohort, Race, and Gender

Retirement Group	1995	2000	2005	2010	2015	2020	All
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
All							
DI Only	9.40	10.70	9.70	10.60	11.10	12.10	10.80
SSI Only	1.80	1.60	1.00	0.70	0.60	0.80	1.00
Concurrent DI & SSI	1.20	0.80	0.40	0.30	0.40	0.20	0.50
Females							
DI Only	6.40	7.70	8.20	9.50	9.90	11.00	9.20
SSI Only	2.30	2.30	1.30	0.80	0.90	0.90	1.20
Concurrent DI & SSI	1.30	1.20	0.50	0.30	0.50	0.20	0.60
Males							
DI Only	12.70	14.00	11.40	11.90	12.40	13.40	12.60
SSI Only	1.10	0.80	0.70	0.60	0.40	0.70	0.70
Concurrent DI & SSI	1.10	0.30	0.20	0.30	0.40	0.30	0.40
White Non-Hispanic							
DI Only	9.10	10.30	8.70	9.60	9.90	10.90	9.80
SSI Only	1.00	1.00	0.70	0.50	0.40	0.50	0.60
Concurrent DI & SSI	0.60	0.60	0.30	0.20	0.20	0.10	0.30
Black Non-Hispanic							
DI Only	12.20	15.10	17.40	17.40	18.10	21.50	17.90
SSI Only	6.00	5.10	1.80	2.30	1.80	3.00	3.00
Concurrent DI & SSI	5.00	2.40	1.20	0.90	1.40	0.40	1.50
Hispanic							
DI Only	11.90	12.50	14.50	14.80	14.40	14.40	14.10
SSI Only	4.60	4.10	2.60	1.30	1.70	0.70	1.90
Concurrent DI & SSI	4.70	1.00	0.60	0.30	0.70	0.60	0.90
Other							
DI Only	7.00	6.30	5.40	8.70	10.00	6.20	7.50
SSI Only	4.00	2.40	3.70	0.20	1.00	0.50	1.50
Concurrent DI & SSI	0.60	0.40	0.60	0.50	1.00	0.40	0.60

Source: The Urban Institute tabulations of MINT3.

Table A9-3a
Projections of Age at Retirement, by Cohort and Gender

Retirement Group	**1995**	**2000**	**2005**	**2010**	**2015**	**2020**	**All**
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
All Workers							
% Retired at 55	27.0	34.9	41.2	41.0	36.5	36.2	36.7
% Retired at 60	45.3	54.8	63.0	60.3	58.5	57.7	57.4
% Retired at 62	58.1	65.2	72.2	69.2	67.5	67.0	67.1
% Retired at 65	78.7	82.4	84.7	82.8	80.9	80.5	81.7
% Retired at 67	87.7	88.3	90.1	87.9	86.6	86.4	87.7
% Retired at 70	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Females							
% Retired at 55	38.4	45.6	48.2	48.2	43.9	41.5	44.4
% Retired at 60	54.8	62.8	70.5	67.1	64.1	61.5	63.8
% Retired at 62	64.4	72.0	78.0	74.4	71.5	68.9	71.7
% Retired at 65	81.3	86.3	87.1	84.4	81.8	79.7	83.1
% Retired at 67	89.8	91.4	92.1	89.2	87.5	85.8	88.9
% Retired at 70	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Males							
% Retired at 55	13.3	22.7	33.1	32.9	28.2	30.1	27.9
% Retired at 60	33.7	45.5	54.3	52.7	52.2	53.5	50.1
% Retired at 62	50.5	57.3	65.6	63.4	63.1	64.8	61.8
% Retired at 65	75.5	78.0	81.7	80.9	79.9	81.5	80.0
% Retired at 67	85.2	84.8	87.7	86.4	85.6	87.1	86.3
% Retired at 70	100.0	100.0	100.0	100.0	100.0	100.0	100.0

NOTE: Retirement defined as either working 20 hours per week or less or having experienced a 50% earnings drop; persons not in the labor force (for reasons other than disability) at age 50 are considered retired by 55.persons not in the labor force (for reasons other than disability) at age 50 are considered retired by 55.

Table includes all never-disabled, non-institutionalized survivors.
Source: The Urban Institute tabulations of MINT3.

Table A9-3b
Projections of Age at Social Security Benefit Take-up, by Cohort and Gender

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
All Workers							
Takeup at ages 60-62	58.0	55.0	58.9	56.8	55.7	56.9	56.8
Takeup at age 63	7.0	8.9	9.3	8.6	9.2	9.3	8.8
Takeup at age 64	12.2	15.6	12.9	14.1	13.8	14.5	13.9
Takeup at age 65	13.4	13.9	9.8	8.0	8.9	8.4	9.9
Takeup at age 66	2.0	1.7	3.4	5.0	4.7	3.9	3.7
Takeup at age 67	1.6	1.3	2.0	2.9	3.3	3.0	2.5
Takeup at ages 68 and over	5.8	3.6	3.7	4.5	4.5	4.1	4.3
Males							
Takeup at ages 60-62	55.2	48.3	52.6	50.7	51.5	54.9	52.3
Takeup at age 63	8.3	9.7	9.4	8.8	9.7	9.3	9.3
Takeup at age 64	14.2	18.0	15.3	17.1	15.7	16.0	16.1
Takeup at age 65	15.5	17.4	12.1	9.1	9.8	9.3	11.4
Takeup at age 66	2.2	2.0	4.5	5.8	5.2	4.2	4.3
Takeup at age 67	1.5	1.7	2.2	3.6	3.3	2.6	2.6
Takeup at ages 68 and over	3.2	2.9	3.9	4.9	4.8	3.7	4.0
Females							
Takeup at ages 60-62	60.3	60.8	64.4	62.3	59.6	58.7	60.8
Takeup at age 63	5.9	8.2	9.2	8.5	8.7	9.2	8.5
Takeup at age 64	10.5	13.5	10.9	11.3	12.0	13.2	12.0
Takeup at age 65	11.7	11.0	7.9	7.1	8.1	7.6	8.5
Takeup at age 66	1.9	1.4	2.4	4.3	4.3	3.5	3.2
Takeup at age 67	1.8	0.9	1.8	2.3	3.3	3.3	2.4
Takeup at ages 68 and over	8.0	4.1	3.5	4.1	4.2	4.4	4.6

Note: Table includes all never-disabled individuals who take up Social Security by 2032.
Source: The Urban Institute tabulations of MINT3.

Table A9-3c
Projections of Age at Social Security Benefit Take-up, by Cohort and AIME Quintile

Retirement Group Year of Birth	1995 1931-35	2000 1936-40	2005 1941-45	2010 1946-50	2015 1951-55	2020 1956-60	All All
Bottom AIME Quintile							
Takeup at ages 60-62	51.9	62.0	69.7	69.3	66.9	69.5	66.0
Takeup at age 63	4.4	7.2	5.8	6.3	7.8	8.7	7.0
Takeup at age 64	6.7	12.9	8.1	9.3	9.8	10.6	9.7
Takeup at age 65	10.3	4.3	4.4	4.6	5.2	3.1	5.0
Takeup at age 66	3.3	1.0	2.1	1.0	1.7	0.8	1.5
Takeup at age 67	3.0	1.7	1.1	0.7	1.1	1.1	1.3
Takeup at ages 68 and over	20.4	10.9	8.7	8.8	7.6	6.2	9.5
Second AIME Quintile							
Takeup at ages 60-62	69.1	65.7	71.3	69.1	66.1	66.8	67.9
Takeup at age 63	6.1	9.5	9.6	8.3	9.0	9.5	8.8
Takeup at age 64	8.2	13.8	10.8	12.0	12.9	12.3	11.9
Takeup at age 65	9.7	7.2	5.4	4.8	6.4	5.7	6.3
Takeup at age 66	1.3	1.4	0.7	1.5	2.0	1.5	1.4
Takeup at age 67	1.2	1.1	0.8	1.5	1.3	1.3	1.2
Takeup at ages 68 and over	4.3	1.2	1.3	2.8	2.3	2.9	2.5
Third AIME Quintile							
Takeup at ages 60-62	58.6	59.3	61.7	59.5	56.6	56.8	58.5
Takeup at age 63	7.9	8.8	10.5	9.9	10.4	10.2	9.8
Takeup at age 64	15.4	14.0	13.9	13.3	14.6	16.1	14.6
Takeup at age 65	13.3	13.3	8.4	7.6	9.3	8.0	9.5
Takeup at age 66	2.0	1.3	2.4	3.8	3.6	2.8	2.8
Takeup at age 67	1.4	1.0	1.4	3.4	3.0	3.5	2.5
Takeup at ages 68 and over	1.4	2.3	1.6	2.5	2.6	2.6	2.2
Fourth AIME Quintile							
Takeup at ages 60-62	58.6	47.8	55.1	49.8	50.3	53.1	52.2
Takeup at age 63	7.6	9.2	10.4	9.4	10.7	9.1	9.5
Takeup at age 64	14.5	18.4	14.4	16.4	14.4	15.3	15.5
Takeup at age 65	15.9	19.8	11.6	10.4	10.5	10.3	12.4
Takeup at age 66	1.5	1.9	3.3	6.9	6.0	5.4	4.7
Takeup at age 67	0.6	1.0	2.4	3.7	4.7	3.2	2.9
Takeup at ages 68 and over	1.2	1.9	2.8	3.4	3.3	3.6	2.9
Top AIME Quintile							
Takeup at ages 60-62	51.7	40.4	36.8	36.2	38.8	38.3	39.6
Takeup at age 63	8.8	9.7	10.0	9.5	8.0	8.9	9.0
Takeup at age 64	15.9	19.0	17.5	19.3	17.0	18.3	17.9
Takeup at age 65	17.9	25.1	19.3	12.7	13.1	15.0	16.4
Takeup at age 66	2.1	2.8	8.2	11.9	10.3	8.8	8.1
Takeup at age 67	1.9	1.6	4.3	5.4	6.2	5.8	4.6
Takeup at ages 68 and over	1.7	1.5	3.9	5.0	6.6	5.0	4.4

Notes: Table includes all never-disabled individuals who take up Social Security by 2032.
AIME quintiles are defined separately for each cohort
Source: The Urban Institute tabulations of MINT3.

Table A9-4a
Projections of Percentage of Non-Disabled Individuals, Age 62 and Over, With Positive Earnings, by Cohort and Gender

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
All							
At age 62	59.2	61.0	61.5	65.9	65.0	64.8	63.5
At age 65	42.3	44.6	43.9	47.2	47.3	47.4	45.9
At age 67	30.7	32.7	32.6	34.9	35.0	34.6	33.8
At age 70	20.8	22.3	22.2	23.9	23.9	24.2	23.2
Male							
At age 62	71.0	70.2	67.5	69.3	67.0	66.3	68.2
At age 65	50.3	52.5	50.0	50.4	50.7	48.9	50.3
At age 67	37.2	38.8	36.7	37.1	37.7	34.7	36.8
At age 70	25.5	25.2	25.1	25.2	24.8	24.5	25.0
Female							
At age 62	49.3	53.0	56.4	62.7	63.1	63.5	59.3
At age 65	35.7	37.8	38.7	44.2	44.2	46.0	42.0
At age 67	25.4	27.4	29.1	32.9	32.6	34.5	31.1
At age 70	16.9	19.9	19.7	22.7	23.1	23.9	21.6
All Beneficiaries							
At age 62	51.6	48.5	49.7	53.0	51.4	51.3	51.1
At age 65	43.1	44.2	41.4	42.5	42.8	43.3	42.9
At age 67	31.4	32.7	32.1	33.9	33.8	33.3	33.1
At age 70	20.8	22.3	22.2	23.9	23.9	24.2	23.2
All Male Beneficiaries							
At age 62	62.6	53.6	52.5	52.9	49.8	50.0	52.7
At age 65	49.5	51.7	46.8	45.0	46.0	45.0	46.8
At age 67	36.9	38.4	36.0	35.8	36.1	33.5	35.8
At age 70	25.5	25.2	25.1	25.2	24.8	24.5	25.0
All Female Beneficiaries							
At age 62	43.3	45.0	47.7	53.1	52.7	52.4	49.9
At age 65	37.6	37.6	37.0	40.3	40.0	41.7	39.4
At age 67	26.6	27.7	28.9	32.3	31.8	33.2	30.7
At age 70	16.9	19.9	19.7	22.7	23.1	23.9	21.6
All Non-Beneficiaries							
At age 62	69.6	76.3	78.4	82.7	82.0	82.6	79.7
At age 65	34.3	50.8	69.4	79.8	78.7	81.0	71.7
At age 67	19.6	33.2	44.6	55.6	60.8	64.5	49.5
All Male Non-Beneficiaries							
At age 62	81.4	85.8	84.1	86.2	85.2	86.2	85.1
At age 65	61.9	63.7	77.4	82.6	80.8	82.3	78.6
At age 67	36.9	38.4	36.0	35.8	36.1	33.5	35.8
All Female Non-Beneficiaries							
At age 62	58.5	65.6	72.0	78.6	78.5	79.2	73.9
At age 65	20.8	39.5	59.8	76.5	76.5	80.0	65.2
At age 67	10.8	21.1	35.4	47.4	51.6	63.0	39.8

Source: The Urban Institute tabulations of MINT3.

Table A9-4b
Percentage of Retirees With Positive Earnings Before Age of Benefit Entitlement, by Cohort and Gender

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
All							
At age 54 and 55	18.2	26.4	36.8	61.5	64.8	67.8	55.2
At age 56 and 57	21.8	32.8	44.7	57.8	58.1	58.1	51.6
At age 58 and 59	25.0	34.8	47.9	53.1	52.6	52.2	48.2
At age 60 and 61	27.1	36.3	49.0	51.4	50.1	51.4	47.1
Male							
At age 54 and 55	21.9	28.9	36.4	56.8	61.5	66.3	53.6
At age 56 and 57	25.0	36.8	43.0	56.4	57.9	58.7	51.9
At age 58 and 59	30.9	38.1	46.5	52.4	51.6	52.0	48.4
At age 60 and 61	33.4	36.8	47.8	50.3	49.1	48.9	46.4
Female							
At age 54 and 55	16.9	24.6	37.1	65.0	67.0	68.9	56.4
At age 56 and 57	20.2	29.4	46.2	58.9	58.2	57.5	51.3
At age 58 and 59	21.1	31.7	49.2	53.7	53.4	52.4	48.0
At age 60 and 61	22.0	35.9	50.1	52.3	51.0	53.7	47.7

Note: Retirees are never-disabled individuals with positive earnings at age 50 or older.
Source: The Urban Institute tabulations of MINT3.

Table A9-4c
Percent of Individuals Age 62 with Positive Earnings, by Cohort, Gender, and Social Security Receipt

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
All							
DI Beneficiaries							
Percent with Earnings	14.0	15.0	10.9	13.4	12.1	10.3	12.3
Mean Non-Zero Earnings	0.29	0.37	0.60	0.54	0.52	0.47	0.48
OASI Beneficiaries							
Percent with Earnings	51.3	48.6	49.8	52.7	51.3	51.3	51.0
Mean Non-Zero Earnings	0.52	0.51	0.49	0.48	0.50	0.50	0.50
Non-Beneficiaries							
Percent with Earnings	66.2	71.9	75.5	79.9	79.8	79.6	76.8
Mean Non-Zero Earnings	1.20	1.25	1.34	1.34	1.25	1.22	1.27
Females							
DI Beneficiaries							
Percent with Earnings	12.7	10.8	10.6	10.8	10.3	7.6	10.0
Mean Non-Zero Earnings	0.30	0.20	0.49	0.42	0.50	0.55	0.44
OASI Beneficiaries							
Percent with Earnings	42.8	45.3	48.1	52.8	52.5	52.2	49.9
Mean Non-Zero Earnings	0.43	0.44	0.42	0.43	0.45	0.45	0.44
Non-Beneficiaries							
Percent with Earnings	56.1	61.2	68.6	75.5	76.0	76.2	70.9
Mean Non-Zero Earnings	0.93	1.01	1.17	1.21	1.18	1.19	1.15
Males							
DI Beneficiaries							
Percent with Earnings	14.8	17.9	11.2	15.6	13.5	12.6	14.1
Mean Non-Zero Earnings	0.29	0.44	0.69	0.60	0.54	0.43	0.50
OASI Beneficiaries							
Percent with Earnings	62.2	53.5	52.3	52.6	49.7	50.3	52.5
Mean Non-Zero Earnings	0.60	0.58	0.57	0.55	0.57	0.55	0.57
Non-Beneficiaries							
Percent with Earnings	77.1	81.5	81.5	83.7	83.2	83.1	82.2
Mean Non-Zero Earnings	1.42	1.40	1.47	1.45	1.31	1.25	1.37

Source: The Urban Institute tabulations of MINT3.

Table A9-5a
Percentage of Individuals Covered by a Pension Plan at Age 62, by Cohort and Gender[a]

Year of Birth	Gender	Any Coverage	DB or DC Coverage	DB Coverage	DC Coverage	IRA Coverage	Keogh Coverage
1931-1935	Female	50.2%	33.3%	27.5%	9.8%	29.1%	0.8%
	Male	68.7%	57.0%	50.5%	15.8%	35.6%	1.7%
	All	58.9%	44.4%	38.3%	12.6%	32.2%	1.2%
1936-1940	Female	50.2%	35.1%	25.8%	14.9%	26.6%	0.5%
	Male	66.1%	55.0%	43.1%	24.1%	30.1%	0.8%
	All	57.8%	44.6%	34.1%	19.3%	28.3%	0.7%
1941-1945	Female	49.8%	36.4%	24.3%	18.2%	23.6%	0.6%
	Male	64.7%	54.0%	39.9%	26.7%	28.0%	1.4%
	All	56.8%	44.7%	31.7%	22.2%	25.7%	1.0%
1946-1950	Female	54.4%	43.2%	27.2%	24.1%	21.6%	0.6%
	Male	64.3%	53.6%	36.5%	30.1%	24.6%	1.0%
	All	59.1%	48.2%	31.7%	27.0%	23.0%	0.8%
1951-1955	Female	53.2%	44.4%	26.7%	27.5%	17.4%	0.4%
	Male	62.7%	54.3%	34.9%	34.0%	19.3%	1.0%
	All	57.8%	49.2%	30.7%	30.6%	18.3%	0.7%
1956-1960	Female	53.5%	47.7%	27.0%	31.9%	12.5%	0.4%
	Male	61.5%	56.3%	34.9%	38.2%	14.3%	0.6%
	All	57.3%	51.8%	30.8%	34.9%	13.4%	0.5%
All	Female	52.3%	41.5%	26.5%	23.1%	20.3%	0.5%
	Male	64.0%	54.9%	38.5%	30.1%	23.4%	1.0%
	All	57.9%	47.9%	32.2%	26.5%	21.8%	0.8%

a/ Excludes individuals whose asset income places them in the top 5 percent of their respective cohort.

Source: The Urban Institute projections from MINT3.

Table A9-5b
Percentage of Individuals Covered by a Pension Plan at Age 62, by Cohort and AIME Quintile[a]

Year of Birth	AIME Quintile	Any Coverage	DB or DC Coverage	DB Coverage	DC Coverage	IRA Coverage	Keogh Coverage
1931-1935	**1**	31.8%	17.0%	14.9%	3.4%	20.6%	0.2%
	2	43.0%	27.3%	24.0%	6.2%	24.9%	0.3%
	3	62.8%	48.5%	40.5%	13.9%	30.3%	1.6%
	4	71.9%	59.0%	51.2%	15.4%	31.7%	1.6%
	5	86.7%	72.0%	62.6%	24.8%	54.8%	2.4%
1936-1940	**1**	29.1%	16.2%	12.5%	5.6%	18.2%	0.3%
	2	43.4%	30.2%	21.4%	11.9%	22.6%	0.4%
	3	59.3%	47.0%	35.1%	19.3%	24.1%	0.5%
	4	72.2%	58.8%	47.1%	23.1%	30.7%	0.9%
	5	86.7%	72.3%	55.4%	37.8%	47.0%	1.4%
1941-1945	**1**	25.2%	12.6%	8.0%	5.9%	15.4%	0.0%
	2	39.5%	26.2%	17.5%	12.2%	19.4%	0.6%
	3	59.4%	48.0%	33.9%	20.9%	22.4%	1.0%
	4	74.2%	62.4%	45.1%	29.2%	30.8%	1.2%
	5	88.2%	76.9%	55.6%	44.7%	41.9%	2.4%
1946-1950	**1**	25.7%	12.6%	6.2%	8.0%	14.8%	0.5%
	2	41.5%	30.9%	19.4%	15.3%	15.4%	0.3%
	3	64.5%	53.4%	34.7%	28.6%	20.9%	0.6%
	4	79.0%	69.1%	47.2%	37.2%	26.3%	1.0%
	5	88.7%	78.9%	53.8%	48.7%	39.8%	1.6%
1951-1955	**1**	28.7%	19.5%	9.1%	13.4%	10.8%	0.3%
	2	39.7%	32.6%	18.4%	20.5%	11.1%	0.3%
	3	61.4%	52.6%	33.7%	28.0%	16.8%	0.4%
	4	76.5%	67.2%	43.4%	41.6%	22.6%	1.3%
	5	86.3%	77.7%	51.3%	52.5%	32.0%	1.5%
1956-1960	**1**	30.8%	25.5%	11.2%	19.6%	7.0%	0.2%
	2	45.9%	40.5%	23.7%	25.7%	8.6%	0.4%
	3	57.5%	52.7%	31.4%	33.1%	11.0%	0.4%
	4	72.5%	66.7%	41.5%	43.5%	16.4%	0.7%
	5	83.8%	77.3%	48.6%	55.8%	25.6%	0.9%
All	**1**	28.5%	17.9%	9.9%	10.8%	13.2%	0.3%
	2	42.2%	32.3%	20.6%	17.0%	15.3%	0.4%
	3	60.7%	51.0%	34.2%	25.8%	19.3%	0.6%
	4	74.7%	64.9%	45.2%	34.5%	25.0%	1.1%
	5	86.6%	76.4%	53.5%	46.6%	37.8%	1.6%

a/ Excludes individuals whose asset income places them in the top 5 percent of their respective cohort.
Source: The Urban Institute projections from MINT3.

Table A9-6a
Mean Projected Financial Wealth, by Age and Cohort
(Ratio of Wealth to the Economy-Wide Average Wage)

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
Defined Contribution Plan Plus IRA Wealth at Age:							
50	.	.	0.51	0.61	0.68	0.76	0.67
55	.	0.56	0.71	0.82	0.93	1.01	0.86
60	0.52	0.66	0.84	1.06	1.16	1.28	1.01
62	0.57	0.69	0.90	1.15	1.24	1.36	1.06
67	0.58	0.70	0.93	1.20	1.28	1.40	1.10
Non-Pension Financial Wealth at Age							
50	.	.	1.70	1.89	2.03	1.86	1.89
55	.	1.91	2.23	2.54	2.76	2.46	2.46
60	2.16	2.38	2.95	3.34	3.63	3.18	3.10
62	2.30	2.56	3.18	3.62	3.93	3.39	3.30
67	2.39	2.65	3.36	3.94	4.27	3.65	3.53
Total Financial Wealth (Excluding Defined Benefit Plans)							
50	.	.	2.21	2.50	2.71	2.61	2.56
55	.	2.47	2.93	3.36	3.69	3.48	3.32
60	2.68	3.04	3.80	4.40	4.79	4.47	4.11
62	2.88	3.25	4.07	4.76	5.16	4.75	4.37
67	2.97	3.35	4.29	5.14	5.55	5.05	4.63

Source: The Urban Institute tabulations of MINT3.

Table A9-6b
Mean Projected Financial Wealth, by Age and Cohort
(Ratio of Wealth to the Economy-Wide Average Wage)

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
Defined Contribution Plan Plus IRA Wealth at Age:							
50	.	.	0.43	0.52	0.56	0.61	0.55
55	.	0.46	0.59	0.70	0.76	0.81	0.71
60	0.44	0.56	0.71	0.90	0.95	1.03	0.84
62	0.48	0.57	0.75	0.96	1.01	1.09	0.87
67	0.48	0.58	0.77	1.00	1.02	1.11	0.89
Non-Pension Financial Wealth at Age							
50	.	.	1.00	1.09	1.11	1.05	1.07
55	.	1.22	1.37	1.47	1.48	1.39	1.41
60	1.46	1.55	1.80	1.92	1.92	1.80	1.79
62	1.57	1.67	1.92	2.09	2.06	1.91	1.91
67	1.61	1.72	1.97	2.16	2.12	1.94	1.96
Total Financial Wealth (Excluding Defined Benefit Plans)							
50	.	.	1.43	1.61	1.66	1.65	1.62
55	.	1.69	1.97	2.17	2.24	2.21	2.12
60	1.90	2.10	2.51	2.82	2.87	2.83	2.63
62	2.05	2.24	2.67	3.05	3.07	2.99	2.78
67	2.09	2.30	2.74	3.16	3.14	3.04	2.85

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort.
Source: The Urban Institute tabulations of MINT3.

Table A9-6c
Mean Projected Housing Wealth, by Age and Cohort
(Ratio of Wealth to the Economy-Wide Average Wage)

Retirement Group	**1995**	**2000**	**2005**	**2010**	**2015**	**2020**	**All**
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
ALL INDIVIDUALS							
Proportion with Positive Housing Wealth							
50	.	.	74.9	77.8	76.9	78.4	77.4
55	.	76.3	79.9	81.3	80.1	80.5	80.1
60	79.5	80.9	81.6	83.0	82.6	81.8	81.9
62	76.4	76.7	76.9	77.4	77.3	77.1	77.0
67	76.7	77.3	77.4	78.1	77.9	77.6	77.6
Mean Housing Wealth							
50	.	.	1.45	1.59	1.49	1.34	1.46
55	.	1.54	1.76	1.96	1.80	1.58	1.75
60	1.72	1.84	2.06	2.29	2.10	1.80	2.00
62	1.74	1.83	2.08	2.32	2.14	1.83	2.02
67	1.68	1.83	2.17	2.40	2.19	1.89	2.06
MARRIED INDIVIDUALS							
Proportion with Positive Housing Wealth							
50	.	.	83.4	86.4	85.4	87.3	86.0
55	.	84.0	87.7	88.9	87.6	88.9	87.9
60	87.0	88.2	88.7	89.8	89.2	89.0	88.9
62	82.5	82.4	81.7	81.8	81.5	81.6	81.8
67	81.5	82.2	81.4	81.4	81.3	81.3	81.4
Mean Housing Wealth							
50	.	.	1.48	1.63	1.48	1.25	1.45
55	.	1.55	1.78	2.00	1.78	1.50	1.74
60	1.68	1.81	2.02	2.29	2.06	1.70	1.95
62	1.68	1.80	2.01	2.29	2.05	1.68	1.94
67	1.54	1.74	2.00	2.29	2.07	1.69	1.92
SINGLE INDIVIDUALS							
Proportion with Positive Housing Wealth							
50	.	.	47.7	50.6	52.2	53.5	51.7
55	.	51.0	56.7	58.7	59.9	59.6	58.3
60	55.4	59.6	62.8	64.9	66.0	65.3	63.8
62	57.7	61.1	65.0	66.7	67.6	67.0	65.3
67	65.4	66.4	68.9	71.2	71.4	71.0	69.7
Mean Housing Wealth							
50	.	.	1.33	1.47	1.54	1.59	1.52
55	.	1.48	1.70	1.85	1.86	1.79	1.78
60	1.86	1.91	2.16	2.30	2.22	2.05	2.12
62	1.93	1.92	2.27	2.41	2.34	2.16	2.21
67	1.99	2.03	2.50	2.61	2.42	2.24	2.33

Source: The Urban Institute tabulations of MINT3.

Table A9-6d
Mean Projected Housing Wealth, by Age and Cohort
(Ratio of Wealth to the Economy-Wide Average Wage)

Retirement Group Year of Birth	1995 1931-35	2000 1936-40	2005 1941-45	2010 1946-50	2015 1951-55	2020 1956-60	All All
ALL INDIVIDUALS							
Proportion with Positive Housing Wealth							
50	.	.	73.8	76.9	75.9	77.5	76.4
55	.	75.5	79.4	80.5	79.4	80.0	79.5
60	78.9	80.4	81.1	82.4	82.0	81.2	81.3
62	75.9	76.2	76.5	76.8	76.8	76.4	76.5
67	76.2	77.0	77.1	77.6	77.5	77.0	77.1
Mean Housing Wealth							
50	.	.	1.37	1.50	1.39	1.23	1.37
55	.	1.45	1.66	1.85	1.68	1.45	1.63
60	1.63	1.74	1.95	2.13	1.94	1.64	1.86
62	1.66	1.72	1.97	2.15	1.96	1.66	1.87
67	1.59	1.71	2.05	2.21	2.01	1.70	1.90
MARRIED INDIVIDUALS							
Proportion with Positive Housing Wealth							
50	.	.	82.7	85.8	84.7	86.8	85.4
55	.	83.4	87.3	88.4	87.0	88.5	87.4
60	86.6	87.8	88.3	89.4	88.7	88.5	88.4
62	82.2	82.1	81.3	81.3	81.1	81.1	81.4
67	81.1	82.0	81.2	81.1	81.0	80.8	81.2
Mean Housing Wealth							
50	.	.	1.42	1.56	1.39	1.18	1.37
55	.	1.47	1.70	1.92	1.67	1.41	1.65
60	1.60	1.72	1.93	2.19	1.93	1.57	1.85
62	1.61	1.70	1.91	2.19	1.91	1.54	1.82
67	1.48	1.64	1.90	2.18	1.93	1.54	1.80
SINGLE INDIVIDUALS							
Proportion with Positive Housing Wealth							
50	.	.	46.1	48.9	50.8	51.7	50.1
55	.	49.7	56.2	57.4	59.2	58.7	57.4
60	54.5	59.1	62.3	64.0	65.4	64.6	63.1
62	57.1	60.5	64.5	65.7	67.0	66.2	64.6
67	64.7	65.9	68.5	70.3	70.6	70.3	69.1
Mean Housing Wealth							
50	.	.	1.21	1.33	1.39	1.37	1.35
55	.	1.37	1.55	1.64	1.68	1.57	1.59
60	1.73	1.79	1.99	1.97	1.98	1.80	1.90
62	1.82	1.79	2.12	2.07	2.08	1.91	1.99
67	1.87	1.86	2.34	2.25	2.15	1.97	2.09

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort.
Source: The Urban Institute tabulations of MINT3.

Table A9-7
Distribution of Per Capita Assets at Age 62 by Cohort
(Ratio of Wealth to the Economy-Wide Average Wage)

	Mean	20th Percentile	50th Percentile	80th Percentile	90th Percentile	95th Percentile	95th Percentile/ Mean	95th Percentile/ 80th Percentile
Year of Birth				**Per Capita DC Account Balance**				
1931-1935	0.57	0.00	0.00	0.91	1.78	2.67	4.66	2.94
1936-1940	0.69	0.00	0.03	1.07	2.09	3.18	4.61	2.98
1941-1945	0.90	0.00	0.05	1.37	2.79	4.39	4.89	3.20
1946-1950	1.15	0.00	0.13	1.73	3.45	5.58	4.88	3.24
1951-1955	1.24	0.00	0.16	1.85	3.70	5.94	4.81	3.21
1956-1960	1.36	0.00	0.23	2.04	3.88	6.53	4.79	3.20
				Per Capita Non-Pension Assets				
1931-1935	2.30	0.07	0.82	3.29	6.00	9.74	4.23	2.96
1936-1940	2.56	0.05	0.74	3.57	6.69	11.26	4.40	3.16
1941-1945	3.18	0.10	0.92	3.89	7.59	13.26	4.18	3.41
1946-1950	3.62	0.16	1.03	4.20	8.32	14.13	3.91	3.37
1951-1955	3.93	0.17	1.02	3.98	8.03	14.56	3.71	3.66
1956-1960	3.39	0.19	0.94	3.62	7.47	13.16	3.89	3.64
				Per Capita Financial Assets				
1931-1935	2.88	0.10	1.20	4.50	7.54	11.51	4.00	2.56
1936-1940	3.25	0.09	1.20	4.87	8.48	13.50	4.16	2.77
1941-1945	4.07	0.17	1.47	5.75	10.18	15.99	3.93	2.78
1946-1950	4.76	0.29	1.80	6.42	11.24	17.58	3.69	2.74
1951-1955	5.16	0.34	1.81	6.24	11.50	18.25	3.54	2.93
1956-1960	4.75	0.37	1.77	6.08	11.13	17.75	3.74	2.92
				Per Capita Housing Wealth				
1931-1935	1.74	0.01	1.20	2.82	4.02	5.72	3.29	2.02
1936-1940	1.83	0.10	1.23	2.94	4.31	5.96	3.26	2.03
1941-1945	2.08	0.14	1.20	3.25	4.99	6.85	3.29	2.11
1946-1950	2.32	0.20	1.16	3.43	5.60	8.45	3.64	2.46
1951-1955	2.14	0.16	0.99	2.98	4.97	7.68	3.60	2.58
1956-1960	1.83	0.15	0.79	2.50	4.31	6.87	3.75	2.74

Source: The Urban Institute tabulations of MINT3.

Table A9-8a
Per Capita Income by Source at Age 62, by Gender and Cohort
(Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
All Individuals							
Total Income	0.88	0.86	0.90	0.95	0.92	0.88	0.90
Social Security Benefits	0.17	0.15	0.16	0.16	0.16	0.17	0.16
Financial Income	0.11	0.11	0.14	0.15	0.15	0.15	0.14
DB Pension Income	0.14	0.09	0.07	0.06	0.05	0.05	0.07
Earned Income	0.42	0.45	0.48	0.51	0.48	0.46	0.47
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
Males							
Total Income	0.91	0.90	0.94	0.97	0.92	0.89	0.92
Social Security Benefits	0.14	0.13	0.14	0.14	0.15	0.16	0.15
Own benefits	0.12	0.11	0.11	0.11	0.11	0.11	0.11
Wife's benefits	0.02	0.02	0.02	0.03	0.04	0.04	0.03
Financial Income	0.11	0.12	0.14	0.16	0.16	0.16	0.15
DB Pension Income	0.12	0.08	0.07	0.06	0.05	0.05	0.07
Earned Income	0.48	0.52	0.53	0.55	0.50	0.47	0.51
Own earnings	0.33	0.37	0.37	0.37	0.34	0.32	0.35
Wife's earnings	0.15	0.15	0.16	0.18	0.16	0.16	0.16
Imputed Rental Income	0.05	0.05	0.06	0.06	0.06	0.05	0.06
Females							
Total Income	0.86	0.82	0.87	0.93	0.91	0.87	0.88
Social Security Benefits	0.19	0.18	0.18	0.18	0.18	0.17	0.18
Own benefits	0.10	0.10	0.11	0.11	0.11	0.10	0.10
Husband's benefits	0.10	0.08	0.08	0.07	0.07	0.07	0.08
Financial Income	0.10	0.11	0.13	0.15	0.15	0.14	0.13
DB Pension Income	0.15	0.10	0.07	0.06	0.06	0.05	0.07
Earned Income	0.36	0.38	0.43	0.47	0.47	0.45	0.44
Own earnings	0.21	0.24	0.28	0.31	0.32	0.32	0.29
Husband's earnings	0.14	0.14	0.15	0.16	0.15	0.13	0.14
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort
Source: The Urban Institute tabulations of MINT3.

Table A9-8b
Per Capita Income by Source at Age 62, by Marital Status and Cohort
(Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
All Individuals							
Total Income	0.88	0.86	0.90	0.95	0.92	0.88	0.90
Social Security Benefits	0.17	0.15	0.16	0.16	0.16	0.17	0.16
Financial Income	0.11	0.11	0.14	0.15	0.15	0.15	0.14
DB Pension Income	0.14	0.09	0.07	0.06	0.05	0.05	0.07
Earned Income	0.42	0.45	0.48	0.51	0.48	0.46	0.47
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
Never Married Individuals							
Total Income	0.72	0.70	0.80	0.80	0.89	0.88	0.83
Social Security Benefits	0.15	0.14	0.14	0.14	0.16	0.14	0.15
Financial Income	0.08	0.09	0.10	0.10	0.14	0.12	0.11
DB Pension Income	0.12	0.06	0.05	0.05	0.05	0.06	0.06
Earned Income	0.33	0.36	0.46	0.46	0.50	0.51	0.46
Imputed Rental Income	0.03	0.03	0.04	0.04	0.04	0.04	0.04
Married Individuals							
Total Income	0.89	0.87	0.91	0.97	0.92	0.88	0.91
Social Security Benefits	0.17	0.15	0.15	0.16	0.16	0.17	0.16
Financial Income	0.12	0.13	0.14	0.16	0.16	0.16	0.15
DB Pension Income	0.13	0.09	0.07	0.06	0.06	0.05	0.07
Earned Income	0.43	0.45	0.49	0.52	0.48	0.46	0.48
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
Widowed Individuals							
Total Income	0.95	0.84	0.87	0.88	0.89	0.81	0.87
Social Security Benefits	0.18	0.20	0.23	0.22	0.22	0.21	0.21
Financial Income	0.07	0.09	0.12	0.16	0.14	0.15	0.13
DB Pension Income	0.28	0.13	0.09	0.07	0.07	0.04	0.10
Earned Income	0.34	0.36	0.33	0.35	0.36	0.34	0.35
Imputed Rental Income	0.07	0.07	0.09	0.09	0.09	0.07	0.08
Divorced Individuals							
Total Income	0.83	0.86	0.91	0.94	0.92	0.88	0.90
Social Security Benefits	0.16	0.14	0.16	0.17	0.16	0.15	0.16
Financial Income	0.07	0.08	0.11	0.13	0.13	0.13	0.12
DB Pension Income	0.09	0.06	0.06	0.05	0.05	0.04	0.05
Earned Income	0.44	0.51	0.52	0.54	0.53	0.50	0.51
Imputed Rental Income	0.05	0.05	0.06	0.06	0.06	0.06	0.06

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort

Source: The Urban Institute tabulations of MINT3.

Table A9-8c
Per Capita Income by Source at Age 62, by Race and Cohort
(Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
All Individuals							
Total Income	0.88	0.86	0.90	0.95	0.92	0.88	0.90
Social Security Benefits	0.17	0.15	0.16	0.16	0.16	0.17	0.16
Financial Income	0.11	0.11	0.14	0.15	0.15	0.15	0.14
DB Pension Income	0.14	0.09	0.07	0.06	0.05	0.05	0.07
Earned Income	0.42	0.45	0.48	0.51	0.48	0.46	0.47
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
White, Non-Hispanics							
Total Income	0.92	0.91	0.96	1.01	0.98	0.95	0.96
Social Security Benefits	0.17	0.16	0.16	0.17	0.17	0.17	0.17
Financial Income	0.12	0.13	0.15	0.17	0.17	0.17	0.16
DB Pension Income	0.14	0.09	0.07	0.06	0.06	0.05	0.07
Earned Income	0.43	0.47	0.51	0.54	0.52	0.50	0.50
Imputed Rental Income	0.05	0.06	0.07	0.07	0.07	0.06	0.06
African-Americans							
Total Income	0.72	0.63	0.64	0.69	0.67	0.61	0.66
Social Security Benefits	0.16	0.14	0.17	0.17	0.17	0.17	0.17
Financial Income	0.04	0.04	0.06	0.07	0.07	0.07	0.06
DB Pension Income	0.16	0.10	0.07	0.06	0.05	0.05	0.07
Earned Income	0.32	0.31	0.31	0.37	0.35	0.30	0.33
Imputed Rental Income	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Hispanics							
Total Income	0.66	0.59	0.58	0.66	0.65	0.65	0.64
Social Security Benefits	0.15	0.13	0.13	0.14	0.15	0.15	0.14
Financial Income	0.05	0.05	0.07	0.07	0.08	0.09	0.08
DB Pension Income	0.07	0.05	0.03	0.04	0.04	0.03	0.04
Earned Income	0.33	0.32	0.30	0.37	0.35	0.34	0.34
Imputed Rental Income	0.04	0.03	0.04	0.04	0.03	0.03	0.03

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort
Source: The Urban Institute tabulations of MINT3.

Table A9-8d
Per Capita Income by Source at Age 62, by Educational Attainment and Cohort
(Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
All Individuals							
Total Income	0.88	0.86	0.90	0.95	0.92	0.88	0.90
Social Security Benefits	0.17	0.15	0.16	0.16	0.16	0.17	0.16
Financial Income	0.11	0.11	0.14	0.15	0.15	0.15	0.14
DB Pension Income	0.14	0.09	0.07	0.06	0.05	0.05	0.07
Earned Income	0.42	0.45	0.48	0.51	0.48	0.46	0.47
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
High School Dropouts							
Total Income	0.59	0.52	0.52	0.51	0.49	0.48	0.52
Social Security Benefits	0.17	0.15	0.15	0.15	0.14	0.14	0.15
Financial Income	0.05	0.05	0.05	0.05	0.05	0.06	0.05
DB Pension Income	0.07	0.04	0.04	0.03	0.03	0.02	0.04
Earned Income	0.26	0.25	0.25	0.24	0.24	0.22	0.24
Imputed Rental Income	0.03	0.03	0.03	0.03	0.03	0.02	0.03
High School Graduates							
Total Income	0.91	0.86	0.86	0.87	0.85	0.80	0.85
Social Security Benefits	0.18	0.16	0.17	0.17	0.17	0.17	0.17
Financial Income	0.11	0.11	0.12	0.13	0.13	0.13	0.12
DB Pension Income	0.15	0.09	0.07	0.06	0.05	0.05	0.07
Earned Income	0.42	0.44	0.44	0.45	0.44	0.41	0.43
Imputed Rental Income	0.05	0.05	0.06	0.06	0.05	0.04	0.05
College Graduates							
Total Income	1.23	1.22	1.26	1.26	1.22	1.25	1.24
Social Security Benefits	0.14	0.13	0.14	0.15	0.16	0.16	0.15
Financial Income	0.18	0.19	0.22	0.23	0.24	0.24	0.23
DB Pension Income	0.20	0.13	0.08	0.07	0.06	0.06	0.08
Earned Income	0.63	0.70	0.73	0.72	0.68	0.71	0.70
Imputed Rental Income	0.07	0.07	0.09	0.10	0.09	0.08	0.09

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort
Source: The Urban Institute tabulations of MINT3.

Table A9-8e
Per Capita Income by Source at Age 62, by Per-Capita Income Quintile and Cohort
(Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group	**1995**	**2000**	**2005**	**2010**	**2015**	**2020**	**All**
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
All Individuals							
Total Income	0.88	0.86	0.90	0.95	0.92	0.88	0.90
Social Security Benefits	0.17	0.15	0.16	0.16	0.16	0.17	0.16
Financial Income	0.11	0.11	0.14	0.15	0.15	0.15	0.14
DB Pension Income	0.14	0.09	0.07	0.06	0.05	0.05	0.07
Earned Income	0.42	0.45	0.48	0.51	0.48	0.46	0.47
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
Bottom Quintile							
Total Income	0.25	0.22	0.22	0.22	0.22	0.22	0.22
Social Security Benefits	0.13	0.12	0.12	0.12	0.12	0.12	0.12
Financial Income	0.02	0.03	0.03	0.03	0.03	0.04	0.03
DB Pension Income	0.02	0.01	0.01	0.01	0.01	0.01	0.01
Earned Income	0.04	0.03	0.03	0.03	0.03	0.03	0.03
Imputed Rental Income	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Quintile 2							
Total Income	0.54	0.50	0.50	0.54	0.51	0.49	0.51
Social Security Benefits	0.20	0.19	0.20	0.20	0.20	0.20	0.20
Financial Income	0.07	0.07	0.08	0.08	0.08	0.08	0.08
DB Pension Income	0.08	0.05	0.04	0.04	0.04	0.03	0.04
Earned Income	0.15	0.15	0.14	0.18	0.17	0.14	0.16
Imputed Rental Income	0.04	0.04	0.04	0.04	0.04	0.03	0.04
Quintile 3							
Total Income	0.80	0.78	0.80	0.86	0.82	0.77	0.81
Social Security Benefits	0.20	0.18	0.19	0.20	0.19	0.19	0.19
Financial Income	0.11	0.11	0.13	0.14	0.14	0.13	0.13
DB Pension Income	0.16	0.10	0.08	0.07	0.06	0.06	0.08
Earned Income	0.29	0.33	0.36	0.39	0.38	0.36	0.36
Imputed Rental Income	0.05	0.05	0.06	0.06	0.05	0.04	0.05
Quintile 4							
Total Income	1.17	1.14	1.22	1.30	1.26	1.18	1.22
Social Security Benefits	0.18	0.16	0.17	0.16	0.17	0.17	0.17
Financial Income	0.15	0.15	0.18	0.21	0.20	0.20	0.19
DB Pension Income	0.21	0.14	0.10	0.08	0.08	0.07	0.10
Earned Income	0.56	0.63	0.70	0.77	0.72	0.67	0.69
Imputed Rental Income	0.06	0.06	0.07	0.08	0.07	0.06	0.07
Top Quintile							
Total Income	1.85	1.87	2.01	2.09	2.04	1.99	1.99
Social Security Benefits	0.14	0.11	0.12	0.12	0.13	0.13	0.13
Financial Income	0.20	0.24	0.29	0.35	0.36	0.35	0.31
DB Pension Income	0.25	0.16	0.12	0.11	0.10	0.09	0.13
Earned Income	1.18	1.27	1.36	1.38	1.32	1.30	1.31
Imputed Rental Income	0.08	0.09	0.12	0.14	0.13	0.11	0.12

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort.
Source: The Urban Institute tabulations of MINT3.

Table A9-8f
Per Capita Income by Source at Age 62, by Per-Capita Income Quintile and Cohort
(Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group	**1995**	**2000**	**2005**	**2010**	**2015**	**2020**	**All**
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
All Individuals							
Total Income	0.94	0.93	0.99	1.06	1.05	0.99	1.00
Social Security Benefits	0.17	0.15	0.16	0.16	0.16	0.17	0.16
Financial Income	0.15	0.16	0.20	0.24	0.25	0.23	0.22
DB Pension Income	0.14	0.09	0.07	0.06	0.06	0.05	0.07
Earned Income	0.43	0.46	0.49	0.53	0.51	0.48	0.49
Imputed Rental Income	0.05	0.06	0.06	0.07	0.06	0.06	0.06
Bottom Quintile							
Total Income	0.25	0.22	0.22	0.22	0.22	0.22	0.22
Social Security Benefits	0.13	0.12	0.12	0.12	0.12	0.12	0.12
Financial Income	0.02	0.03	0.03	0.03	0.03	0.04	0.03
DB Pension Income	0.02	0.01	0.01	0.01	0.01	0.01	0.01
Earned Income	0.04	0.03	0.03	0.03	0.03	0.03	0.03
Imputed Rental Income	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Quintile 2							
Total Income	0.54	0.50	0.50	0.54	0.51	0.49	0.51
Social Security Benefits	0.20	0.19	0.20	0.20	0.20	0.20	0.20
Financial Income	0.07	0.07	0.08	0.08	0.08	0.08	0.08
DB Pension Income	0.08	0.05	0.04	0.04	0.04	0.03	0.04
Earned Income	0.15	0.15	0.14	0.18	0.17	0.14	0.16
Imputed Rental Income	0.04	0.04	0.04	0.04	0.04	0.03	0.04
Quintile 3							
Total Income	0.80	0.78	0.80	0.86	0.82	0.77	0.81
Social Security Benefits	0.20	0.18	0.19	0.20	0.19	0.19	0.19
Financial Income	0.11	0.11	0.13	0.14	0.14	0.13	0.13
DB Pension Income	0.15	0.10	0.08	0.07	0.06	0.06	0.08
Earned Income	0.29	0.33	0.36	0.39	0.38	0.36	0.36
Imputed Rental Income	0.05	0.05	0.06	0.06	0.05	0.04	0.05
Quintile 4							
Total Income	1.17	1.14	1.22	1.30	1.26	1.18	1.22
Social Security Benefits	0.18	0.16	0.17	0.17	0.17	0.17	0.17
Financial Income	0.18	0.18	0.21	0.22	0.21	0.21	0.21
DB Pension Income	0.20	0.13	0.10	0.08	0.08	0.07	0.10
Earned Income	0.54	0.60	0.68	0.76	0.72	0.66	0.68
Imputed Rental Income	0.06	0.06	0.07	0.08	0.07	0.06	0.07
Top Quintile							
Total Income	1.96	1.99	2.20	2.39	2.45	2.31	2.26
Social Security Benefits	0.14	0.12	0.13	0.13	0.14	0.14	0.14
Financial Income	0.35	0.43	0.58	0.70	0.81	0.72	0.64
DB Pension Income	0.24	0.16	0.12	0.11	0.10	0.10	0.12
Earned Income	1.14	1.18	1.25	1.30	1.26	1.23	1.24
Imputed Rental Income	0.08	0.10	0.12	0.15	0.14	0.12	0.12

Table includes all non-institutionalized survivors including top wealth holders.
Source: The Urban Institute tabulations of MINT3.

Table A9-9a
Per Capita Income by Source at Age 67, by Gender and Cohort
(Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group	**1995**	**2000**	**2005**	**2010**	**2015**	**2020**	**All**
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
All Individuals							
Total Income	0.72	0.71	0.75	0.80	0.78	0.74	0.76
Social Security Benefits	0.25	0.27	0.28	0.29	0.29	0.28	0.28
Financial Income	0.12	0.13	0.16	0.18	0.18	0.17	0.16
DB Pension Income	0.15	0.11	0.09	0.08	0.07	0.07	0.09
Earned Income	0.15	0.15	0.16	0.18	0.18	0.17	0.17
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
Males							
Total Income	0.75	0.76	0.78	0.81	0.80	0.75	0.78
Social Security Benefits	0.25	0.27	0.28	0.29	0.29	0.28	0.28
Own benefits	0.19	0.20	0.21	0.21	0.21	0.20	0.20
Wife's benefits	0.10	0.09	0.10	0.10	0.10	0.09	0.10
Financial Income	0.12	0.12	0.15	0.17	0.17	0.16	0.15
DB Pension Income	0.15	0.11	0.08	0.08	0.07	0.06	0.09
Earned Income	0.19	0.19	0.18	0.20	0.19	0.17	0.18
Own earnings	0.10	0.11	0.11	0.12	0.12	0.10	0.11
Wife's earnings	0.09	0.08	0.07	0.07	0.07	0.07	0.07
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
Females							
Total Income	0.70	0.68	0.72	0.78	0.76	0.73	0.74
Social Security Benefits	0.26	0.26	0.28	0.29	0.29	0.28	0.28
Own benefits	0.16	0.17	0.18	0.19	0.20	0.19	0.19
Husband's benefits	0.10	0.09	0.10	0.10	0.10	0.09	0.10
Financial Income	0.12	0.12	0.15	0.17	0.17	0.16	0.15
DB Pension Income	0.15	0.11	0.08	0.08	0.07	0.06	0.09
Earned Income	0.12	0.13	0.15	0.17	0.17	0.17	0.16
Own earnings	0.07	0.08	0.10	0.12	0.12	0.13	0.11
Husband's earnings	0.05	0.05	0.05	0.05	0.05	0.04	0.05
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.06	0.06

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort
Source: The Urban Institute tabulations of MINT3.

Table A9-9b
Per Capita Income by Source at Age 67, by Marital Status and Cohort
(Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
All Individuals							
Total Income	0.72	0.71	0.75	0.80	0.78	0.74	0.76
Social Security Benefits	0.25	0.27	0.28	0.29	0.29	0.28	0.28
Financial Income	0.12	0.13	0.16	0.18	0.18	0.17	0.16
DB Pension Income	0.15	0.11	0.09	0.08	0.07	0.07	0.09
Earned Income	0.15	0.15	0.16	0.18	0.18	0.17	0.17
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
Never Married Individuals							
Total Income	0.61	0.60	0.65	0.66	0.71	0.68	0.67
Social Security Benefits	0.21	0.22	0.25	0.25	0.27	0.24	0.24
Financial Income	0.10	0.10	0.12	0.13	0.16	0.14	0.13
DB Pension Income	0.15	0.09	0.07	0.07	0.06	0.07	0.07
Earned Income	0.10	0.13	0.16	0.17	0.19	0.18	0.17
Imputed Rental Income	0.03	0.03	0.04	0.04	0.04	0.04	0.04
Married Individuals							
Total Income	0.72	0.72	0.76	0.81	0.79	0.74	0.76
Social Security Benefits	0.25	0.26	0.28	0.29	0.29	0.28	0.28
Financial Income	0.13	0.14	0.17	0.19	0.18	0.18	0.17
DB Pension Income	0.14	0.11	0.09	0.08	0.08	0.07	0.09
Earned Income	0.16	0.16	0.17	0.18	0.18	0.16	0.17
Imputed Rental Income	0.04	0.05	0.06	0.07	0.06	0.05	0.05
Widowed Individuals							
Total Income	0.80	0.73	0.77	0.80	0.78	0.75	0.77
Social Security Benefits	0.29	0.30	0.32	0.33	0.33	0.32	0.32
Financial Income	0.10	0.12	0.15	0.18	0.17	0.16	0.15
DB Pension Income	0.22	0.13	0.09	0.07	0.07	0.07	0.10
Earned Income	0.12	0.11	0.11	0.12	0.12	0.13	0.12
Imputed Rental Income	0.07	0.07	0.10	0.10	0.09	0.07	0.08
Divorced Individuals							
Total Income	0.64	0.69	0.72	0.80	0.78	0.77	0.75
Social Security Benefits	0.26	0.28	0.29	0.30	0.30	0.28	0.29
Financial Income	0.09	0.10	0.13	0.15	0.16	0.16	0.14
DB Pension Income	0.10	0.09	0.07	0.08	0.06	0.06	0.07
Earned Income	0.13	0.15	0.17	0.21	0.20	0.20	0.19
Imputed Rental Income	0.05	0.05	0.06	0.06	0.06	0.06	0.06

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort
Source: The Urban Institute tabulations of MINT3.

Table A9-9c
Per Capita Income by Source at Age 67, by Race and Cohort
(Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group	**1995**	**2000**	**2005**	**2010**	**2015**	**2020**	**All**
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
All Individuals							
Total Income	0.72	0.71	0.75	0.80	0.78	0.74	0.76
Social Security Benefits	0.25	0.27	0.28	0.29	0.29	0.28	0.28
Financial Income	0.12	0.13	0.16	0.18	0.18	0.17	0.16
DB Pension Income	0.15	0.11	0.09	0.08	0.07	0.07	0.09
Earned Income	0.15	0.15	0.16	0.18	0.18	0.17	0.17
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
White, Non-Hispanics							
Total Income	0.75	0.76	0.79	0.85	0.84	0.80	0.81
Social Security Benefits	0.26	0.28	0.29	0.30	0.30	0.30	0.29
Financial Income	0.14	0.15	0.17	0.20	0.20	0.19	0.18
DB Pension Income	0.15	0.11	0.09	0.09	0.08	0.08	0.09
Earned Income	0.15	0.16	0.17	0.19	0.19	0.18	0.18
Imputed Rental Income	0.05	0.06	0.07	0.07	0.07	0.06	0.06
African-Americans							
Total Income	0.59	0.53	0.54	0.57	0.55	0.52	0.55
Social Security Benefits	0.22	0.23	0.26	0.26	0.27	0.24	0.25
Financial Income	0.04	0.05	0.07	0.08	0.08	0.07	0.07
DB Pension Income	0.16	0.11	0.07	0.07	0.07	0.06	0.08
Earned Income	0.12	0.10	0.11	0.13	0.10	0.11	0.11
Imputed Rental Income	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Hispanics							
Total Income	0.53	0.48	0.50	0.55	0.54	0.53	0.53
Social Security Benefits	0.22	0.22	0.22	0.23	0.24	0.23	0.23
Financial Income	0.06	0.06	0.08	0.08	0.09	0.10	0.08
DB Pension Income	0.09	0.06	0.04	0.07	0.05	0.04	0.05
Earned Income	0.11	0.11	0.12	0.13	0.12	0.13	0.12
Imputed Rental Income	0.04	0.03	0.04	0.04	0.03	0.03	0.03

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort

Source: The Urban Institute tabulations of MINT3.

Table A9-9d
Per Capita Income by Source at Age 67, by Level of Educational Attainment and Cohort (Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
All Individuals							
Total Income	0.72	0.71	0.75	0.80	0.78	0.74	0.76
Social Security Benefits	0.25	0.27	0.28	0.29	0.29	0.28	0.28
Financial Income	0.12	0.13	0.16	0.18	0.18	0.17	0.16
DB Pension Income	0.15	0.11	0.09	0.08	0.07	0.07	0.09
Earned Income	0.15	0.15	0.16	0.18	0.18	0.17	0.17
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
High School Dropouts							
Total Income	0.50	0.44	0.44	0.43	0.43	0.41	0.44
Social Security Benefits	0.22	0.22	0.22	0.21	0.21	0.21	0.22
Financial Income	0.06	0.05	0.06	0.06	0.06	0.07	0.06
DB Pension Income	0.08	0.05	0.05	0.04	0.03	0.03	0.05
Earned Income	0.09	0.08	0.08	0.09	0.09	0.07	0.08
Imputed Rental Income	0.03	0.03	0.03	0.03	0.03	0.02	0.03
High School Graduates							
Total Income	0.73	0.71	0.71	0.74	0.72	0.69	0.71
Social Security Benefits	0.26	0.27	0.29	0.29	0.29	0.28	0.28
Financial Income	0.12	0.13	0.14	0.15	0.15	0.15	0.14
DB Pension Income	0.15	0.11	0.09	0.08	0.07	0.07	0.09
Earned Income	0.15	0.15	0.15	0.16	0.16	0.15	0.15
Imputed Rental Income	0.05	0.05	0.06	0.06	0.05	0.04	0.05
College Graduates							
Total Income	1.00	0.98	1.03	1.03	1.04	1.02	1.02
Social Security Benefits	0.27	0.29	0.31	0.32	0.32	0.32	0.31
Financial Income	0.21	0.22	0.26	0.27	0.27	0.27	0.26
DB Pension Income	0.22	0.16	0.11	0.10	0.09	0.09	0.11
Earned Income	0.23	0.25	0.25	0.25	0.26	0.25	0.25
Imputed Rental Income	0.07	0.07	0.09	0.10	0.09	0.08	0.09

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort
Source: The Urban Institute tabulations of MINT3.

Table A9-9e
Per Capita Income by Source at Age 67, by Per-Capita Income Quintile and Cohort (Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group Year of Birth	**1995** 1931-35	**2000** 1936-40	**2005** 1941-45	**2010** 1946-50	**2015** 1951-55	**2020** 1956-60	**All** All
All Individuals							
Total Income	0.72	0.71	0.75	0.80	0.78	0.74	0.76
Social Security Benefits	0.25	0.27	0.28	0.29	0.29	0.28	0.28
Financial Income	0.12	0.13	0.16	0.18	0.18	0.17	0.16
DB Pension Income	0.15	0.11	0.09	0.08	0.07	0.07	0.09
Earned Income	0.15	0.15	0.16	0.18	0.18	0.17	0.17
Imputed Rental Income	0.05	0.05	0.06	0.07	0.06	0.05	0.06
Bottom Quintile							
Total Income	0.24	0.23	0.24	0.24	0.23	0.23	0.23
Social Security Benefits	0.16	0.16	0.17	0.16	0.17	0.16	0.16
Financial Income	0.02	0.02	0.03	0.03	0.03	0.03	0.03
DB Pension Income	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Earned Income	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Imputed Rental Income	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Quintile 2							
Total Income	0.46	0.45	0.45	0.47	0.46	0.43	0.45
Social Security Benefits	0.25	0.27	0.27	0.27	0.27	0.26	0.27
Financial Income	0.06	0.06	0.07	0.08	0.08	0.08	0.07
DB Pension Income	0.07	0.04	0.04	0.04	0.03	0.03	0.04
Earned Income	0.04	0.04	0.04	0.05	0.04	0.03	0.04
Imputed Rental Income	0.04	0.04	0.04	0.04	0.03	0.03	0.04
Quintile 3							
Total Income	0.67	0.64	0.67	0.71	0.68	0.64	0.67
Social Security Benefits	0.27	0.28	0.30	0.31	0.32	0.30	0.30
Financial Income	0.12	0.12	0.13	0.15	0.14	0.14	0.13
DB Pension Income	0.14	0.10	0.08	0.08	0.07	0.06	0.08
Earned Income	0.09	0.09	0.10	0.11	0.11	0.10	0.10
Imputed Rental Income	0.05	0.05	0.06	0.06	0.05	0.04	0.05
Quintile 4							
Total Income	0.93	0.92	0.97	1.04	1.02	0.96	0.98
Social Security Benefits	0.29	0.30	0.33	0.34	0.35	0.33	0.33
Financial Income	0.19	0.20	0.23	0.26	0.25	0.24	0.23
DB Pension Income	0.22	0.15	0.13	0.12	0.11	0.10	0.13
Earned Income	0.18	0.21	0.20	0.23	0.23	0.22	0.22
Imputed Rental Income	0.06	0.06	0.08	0.08	0.08	0.07	0.07
Top Quintile							
Total Income	1.50	1.53	1.65	1.78	1.76	1.69	1.67
Social Security Benefits	0.31	0.34	0.38	0.40	0.39	0.38	0.37
Financial Income	0.26	0.31	0.38	0.43	0.44	0.43	0.39
DB Pension Income	0.35	0.27	0.20	0.19	0.17	0.18	0.21
Earned Income	0.50	0.51	0.56	0.61	0.62	0.59	0.57
Imputed Rental Income	0.08	0.10	0.13	0.15	0.14	0.12	0.12

Note: To minimize the effects of outliers, estimates exclude individuals whose financial income is in the top 5 percent of their cohort.
Source: The Urban Institute tabulations of MINT3.

Table A9-9f
Per Capita Income by Source at Age 67, by Per-Capita Income Quintile and Cohort
(Income as a Percentage of the Economy-Wide Average Wage)

Retirement Group	**1995**	**2000**	**2005**	**2010**	**2015**	**2020**	**All**
Year of Birth	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60	All
All Individuals							
Total Income	0.79	0.79	0.85	0.93	0.94	0.88	0.88
Social Security Benefits	0.26	0.27	0.29	0.30	0.30	0.29	0.29
Financial Income	0.17	0.19	0.24	0.28	0.31	0.28	0.26
DB Pension Income	0.15	0.11	0.09	0.08	0.08	0.07	0.09
Earned Income	0.16	0.16	0.17	0.19	0.20	0.18	0.18
Imputed Rental Income	0.05	0.06	0.07	0.07	0.07	0.06	0.06
Bottom Quintile							
Total Income	0.24	0.23	0.24	0.24	0.23	0.23	0.23
Social Security Benefits	0.16	0.16	0.17	0.16	0.17	0.16	0.16
Financial Income	0.02	0.02	0.03	0.03	0.03	0.03	0.03
DB Pension Income	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Earned Income	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Imputed Rental Income	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Quintile 2							
Total Income	0.46	0.45	0.45	0.47	0.46	0.43	0.45
Social Security Benefits	0.25	0.27	0.27	0.27	0.27	0.26	0.27
Financial Income	0.06	0.06	0.07	0.08	0.08	0.08	0.07
DB Pension Income	0.07	0.04	0.04	0.04	0.03	0.03	0.04
Earned Income	0.04	0.04	0.04	0.05	0.04	0.03	0.04
Imputed Rental Income	0.04	0.04	0.04	0.04	0.03	0.03	0.04
Quintile 3							
Total Income	0.67	0.64	0.67	0.71	0.68	0.64	0.67
Social Security Benefits	0.27	0.28	0.30	0.31	0.32	0.30	0.30
Financial Income	0.12	0.12	0.13	0.15	0.14	0.14	0.13
DB Pension Income	0.14	0.10	0.08	0.08	0.07	0.06	0.08
Earned Income	0.09	0.09	0.10	0.11	0.11	0.10	0.10
Imputed Rental Income	0.05	0.05	0.06	0.06	0.05	0.04	0.05
Quintile 4							
Total Income	0.93	0.92	0.97	1.04	1.02	0.96	0.98
Social Security Benefits	0.29	0.30	0.32	0.34	0.35	0.33	0.33
Financial Income	0.20	0.20	0.23	0.26	0.25	0.24	0.23
DB Pension Income	0.22	0.15	0.13	0.12	0.11	0.10	0.13
Earned Income	0.18	0.21	0.20	0.23	0.23	0.22	0.22
Imputed Rental Income	0.06	0.06	0.08	0.08	0.08	0.07	0.07
Top Quintile							
Total Income	1.65	1.69	1.94	2.20	2.32	2.13	2.05
Social Security Benefits	0.31	0.34	0.37	0.40	0.39	0.38	0.37
Financial Income	0.47	0.56	0.76	0.91	1.03	0.91	0.82
DB Pension Income	0.32	0.24	0.18	0.18	0.16	0.17	0.19
Earned Income	0.47	0.46	0.51	0.56	0.59	0.54	0.53
Imputed Rental Income	0.08	0.10	0.13	0.16	0.15	0.13	0.13

Table includes all non-institutionalized survivors including top wealth holders.
Source: The Urban Institute tabulations of MINT3.

Table A9-10a
Percent of Population Ages 62 to 89 in 2020, by Individual Characteristics

Age in 2020	62 to 64	65 to 69	70 to 74	75 to 79	80 to 84	85 to 89	ALL
ALL	100.0	100.0	100.0	100.0	100.0	100.0	100.0
By Educational Attainment							
High School Dropout	10.4	9.0	9.0	12.2	13.6	15.6	10.6
High School Graduate	62.5	60.7	57.9	59.3	63.1	61.7	60.5
College Graduate	27.1	30.4	33.1	28.5	23.3	22.7	28.9
By Race/Ethnicity							
White, Non-Hispanic	74.6	78.1	79.9	82.8	83.7	85.6	79.5
African American	10.7	9.4	8.2	8.0	7.2	7.1	8.8
Hispanic	10.1	8.4	7.2	5.8	5.7	4.7	7.6
Other	4.6	4.1	4.7	3.5	3.4	2.6	4.1
By Gender							
Female	52.3	52.8	55.6	59.4	62.4	69.1	56.2
Male	47.7	47.2	44.4	40.6	37.6	30.9	43.8
By Marital Status							
Never Married	7.1	6.4	4.8	4.0	3.8	3.4	5.4
Married	67.7	66.0	61.9	57.1	53.0	45.6	61.7
Widowed	8.2	10.9	16.0	23.3	29.4	39.8	16.8
Divorced	17.0	16.6	17.3	15.6	13.8	11.2	16.1
By SS Benefit Status							
OASI Recipient	57.5	81.0	88.2	89.5	90.3	89.9	80.7
DI Recipient	11.7	11.6	9.3	7.3	5.7	5.4	9.5
SSI Recipient	0.9	1.3	1.6	2.1	2.7	3.5	1.7
Not Receiving SS Benefits	29.9	6.1	0.9	1.1	1.3	1.2	8.1

Source: The Urban Institute tabulations of MINT3.

Table A9-10b
Average Per Capita Income in 2020, by Individual Characteristics and Income Source
(Income as a Percentage of the Economy-Wide Average Wage)[a]

	Percent of Individuals	Total Income[b]	Social Security Benefits	SSI Benefits	DB Pensions	Income From Financial Assets	Earnings	Imputed Rental Income
ALL	100.0%	0.88	0.27	0.00	0.08	0.29	0.17	0.06
By Educational Attainment								
High School Dropout	10.6%	0.43	0.21	0.01	0.03	0.07	0.07	0.03
High School Graduate	60.5%	0.74	0.27	0.00	0.07	0.20	0.15	0.05
College Graduate	28.9%	1.33	0.30	0.00	0.10	0.57	0.26	0.10
By Race/Ethnicity								
White, Non-Hispanic	79.5%	0.94	0.28	0.00	0.08	0.33	0.18	0.07
African American	8.8%	0.56	0.24	0.00	0.07	0.09	0.12	0.03
Hispanic	7.6%	0.55	0.22	0.00	0.05	0.11	0.13	0.04
Other	4.1%	0.98	0.24	0.01	0.06	0.38	0.22	0.08
By Gender								
Female	56.2%	0.84	0.27	0.00	0.08	0.27	0.16	0.07
Male	43.8%	0.94	0.27	0.00	0.08	0.33	0.19	0.06
By Marital Status								
Never Married	5.4%	0.88	0.23	0.01	0.08	0.29	0.22	0.05
Married	61.7%	0.89	0.27	0.00	0.08	0.30	0.18	0.06
Widowed	16.8%	0.87	0.31	0.00	0.08	0.30	0.08	0.09
Divorced	16.1%	0.87	0.27	0.00	0.07	0.26	0.20	0.06
By Age								
62 to 64	19.6%	0.98	0.20	0.00	0.06	0.25	0.42	0.06
65 to 69	27.9%	0.93	0.29	0.00	0.07	0.30	0.20	0.07
70 to 74	22.5%	0.89	0.31	0.00	0.09	0.32	0.10	0.07
75 to 79	14.5%	0.81	0.29	0.00	0.08	0.31	0.06	0.07
80 to 84	9.6%	0.73	0.27	0.00	0.09	0.29	0.03	0.06
85 to 89	6.0%	0.72	0.25	0.00	0.10	0.30	0.02	0.05
By SS Benefit Status								
OASI Recipient	80.7%	0.88	0.30	0.00	0.09	0.30	0.13	0.07
DI Recipient	9.5%	0.62	0.30	0.00	0.06	0.16	0.06	0.05
SSI Recipient	1.7%	0.18	0.06	0.10	0.01	0.00	0.00	0.02
Not Receiving SS Benefits	8.1%	1.38	0.05	0.00	0.04	0.47	0.76	0.07
By Per-Capita Income Quintile								
Bottom quintile	20.0%	0.23	0.16	0.01	0.01	0.03	0.01	0.02
Second quintile	20.0%	0.44	0.26	0.00	0.03	0.08	0.04	0.04
Third quintile	20.0%	0.66	0.29	0.00	0.07	0.14	0.10	0.05
Fourth quintile	20.0%	0.97	0.31	0.00	0.11	0.27	0.21	0.08
Top quintile	20.0%	2.10	0.34	0.00	0.16	0.96	0.50	0.14

a/ Table includes all non-institutionalized survivors including top wealth holders.
b/ Total income does not include co-resident income.
Source: The Urban Institute tabulations of MINT3.

Table A9-13a
Average Family Total Income as a Percent of the Poverty Threshold in 2020, by Age and Individual Characteristics

Age in 2020	62 to 64	65 to 69	70 to 74	75 to 79	80 to 84	85 to 89	ALL
ALL	6.50	6.05	5.68	5.11	4.62	4.48	5.69
By Educational Attainment							
High School Dropout	3.29	3.09	2.87	2.87	2.76	2.81	2.98
High School Graduate	5.47	5.03	4.76	4.35	4.23	4.12	4.83
College Graduate	10.13	8.94	8.05	7.65	6.77	6.60	8.46
By Race/Ethnicity							
White, Non-Hispanic	7.06	6.52	6.08	5.38	4.87	4.70	6.06
African American	4.29	3.72	3.43	3.33	2.88	3.08	3.65
Hispanic	4.28	3.93	3.66	2.97	3.11	3.06	3.77
Other	7.49	6.67	5.93	6.24	4.90	3.45	6.34
By Gender							
Female	6.25	5.75	5.25	4.63	4.21	4.03	5.27
Male	6.78	6.38	6.21	5.81	5.31	5.47	6.22
By Marital Status							
Never Married	4.68	4.63	4.48	3.41	3.29	3.82	4.36
Married	7.29	6.78	6.49	6.05	5.48	5.63	6.57
Widowed	5.00	4.75	4.47	4.02	3.71	3.51	4.21
Divorced	4.86	4.52	4.21	3.71	3.65	3.40	4.29
By SS Benefit Status							
OASI Recipient	5.84	5.94	5.98	5.33	4.82	4.70	5.63
DI Recipient	4.43	4.18	3.93	3.92	3.20	2.97	4.06
SSI Recipient	1.31	1.34	1.36	1.46	1.32	1.42	1.37
Not Receiving SS Benefits	8.73	11.95	1.81	2.22	4.27	3.38	8.98
By Per-Capita Income Quintile							
Bottom quintile	1.76	1.76	1.74	1.74	1.76	1.72	1.75
Second quintile	3.29	3.12	2.99	2.73	2.66	2.59	2.99
Third quintile	4.98	4.49	4.32	3.81	3.62	3.55	4.31
Fourth quintile	7.56	6.59	6.14	5.44	5.07	4.92	6.27
Top quintile	14.93	14.27	13.19	11.83	10.02	9.61	13.12

Source: The Urban Institute tabulations of MINT3.

Table A9-13b
Percent of Individuals in Poverty in 2020, by Age and Individual Characteristics

Age in 2020	62 to 64	65 to 69	70 to 74	75 to 79	80 to 84	85 to 89	ALL
ALL	4.6	4.1	4.0	4.0	3.9	4.7	4.2
By Educational Attainment							
High School Dropout	12.6	10.8	10.7	13.0	12.5	12.5	11.9
High School Graduate	4.2	4.1	4.0	3.2	2.8	3.9	3.8
College Graduate	2.5	2.2	2.1	1.9	1.8	1.6	2.1
By Race/Ethnicity							
White, Non-Hispanic	3.5	3.1	2.9	3.0	3.0	3.7	3.1
African American	10.1	9.4	10.9	9.2	11.2	11.9	10.1
Hispanic	6.8	7.1	8.8	10.1	7.8	8.3	7.8
Other	5.4	5.3	3.3	6.0	3.7	13.5	5.1
By Gender/Marital Status							
All Females	5.1	4.8	4.8	4.9	5.4	6.0	5.0
Never Married Females	14.4	12.3	18.6	20.5	24.4	23.9	16.5
Married Females	1.8	1.4	1.2	1.1	1.2	1.2	1.4
Widowed Females	4.8	5.2	5.2	4.6	5.6	5.6	5.2
Divorced Females	12.1	12.0	9.8	11.0	9.4	13.9	11.2
All Males	4.1	3.3	3.0	2.8	1.4	1.9	3.1
Never Married Males	10.9	11.9	17.9	16.8	12.1	24.9	13.5
Married Males	2.3	2.2	1.3	1.2	0.9	1.1	1.7
Widowed Males	3.0	2.5	5.0	3.0	1.4	3.7	3.2
Divorced Males	10.7	6.0	6.7	8.3	2.6	.	7.2
By SS Benefit Status							
OASI Recipient	2.5	2.3	2.5	2.2	2.0	2.2	2.3
DI Recipient	2.5	4.4	4.7	6.2	8.7	11.7	4.7
SSI Recipient	56.5	59.1	55.4	56.4	47.7	56.8	55.5
Not Receiving SS Benefits	8.1	15.4	49.6	36.0	24.7	9.0	11.5

Source: The Urban Institute tabulations of MINT3.

Table A9-13c
Percent of 62- to 89-Year-Old Population, Average Family Income as a Percent of Poverty and Percent of 62- to 89-Year-Olds Below Poverty in the Early 1990s and 2020, by Individual Characteristics

	Percent of Retirees		Average Family Income/Poverty Threshold			Percent of Retirees Below Poverty		
			Census Measure	UI Measure		Census Measure	UI Measure	
	Early 1990s	2020	Early 1990s	Early 1990s	2020	Early 1990s	Early 1990s	2020
ALL	100%	100.0%	3.33	3.47	5.69	8.2%	7.8%	4.2%
By Educational Attainment								
High School Dropout	39.8%	10.6%	2.30	2.42	2.98	14.9%	14.4%	11.9%
High School Graduate	47.5%	60.5%	3.57	3.71	4.83	4.3%	3.9%	3.8%
College Graduate	12.7%	28.9%	5.63	5.80	8.46	2.0%	2.1%	2.1%
By Race/Ethnicity								
White, Non-Hispanic	85.5%	79.5%	3.50	3.65	6.06	6.1%	5.7%	3.1%
African American	7.6%	8.8%	2.13	2.19	3.65	23.8%	23.5%	10.1%
Hispanic	4.7%	7.6%	2.25	2.33	3.77	20.1%	19.4%	7.8%
Other	2.2%	4.1%	3.18	3.30	6.34	10.4%	11.9%	5.1%
By Gender								
Female	57.5%	56.2%	3.05	3.16	5.27	10.8%	10.3%	5.0%
Male	42.5%	43.8%	3.71	3.90	6.22	4.7%	4.3%	3.1%
By Marital Status								
Never Married	4.6%	5.4%	2.69	2.68	4.36	17.6%	17.0%	15.3%
Married	59.2%	61.7%	3.88	4.07	6.57	2.6%	2.5%	1.6%
Widowed	29.2%	16.8%	2.50	2.55	4.21	15.1%	14.4%	4.8%
Divorced	7.0%	16.1%	2.53	2.61	4.29	20.8%	20.2%	9.8%
By Age								
62 to 64	16.1%	19.6%	4.17	4.29	6.50	6.1%	6.1%	4.6%
65 to 69	27.9%	27.9%	3.55	3.65	6.05	6.4%	6.1%	4.1%
70 to 74	22.9%	22.5%	3.19	3.30	5.68	7.8%	7.5%	4.0%
75 to 79	16.6%	14.5%	3.01	3.15	5.11	9.5%	9.0%	4.0%
80 to 84	12.1%	9.6%	2.67	2.84	4.62	12.8%	12.4%	3.9%
85 to 89	4.3%	6.0%	2.62	2.83	4.48	11.8%	10.7%	4.7%
By SS Benefit Status								
OASI Recipient	76.6%	80.7%	3.29	3.42	5.63	5.6%	5.2%	2.3%
DI Recipient	6.5%	9.5%	2.43	2.53	4.06	12.5%	12.2%	4.7%
SSI Recipient	4.9%	1.7%	1.41	1.43	1.37	49.1%	48.9%	55.5%
Not Receiving SS Benefits	12.0%	8.1%	4.83	5.06	8.98	5.7%	5.6%	11.5%

Income from assets is based on reported income from assets in the Census measure and annuitized assets in the UI measure.
All poverty rates use the 65 and older poverty thresholds.
Source: The Urban Institute tabulations of MINT3 and the 1990 to 1993 SIPP.

Table A9-13d
Contribution of Individual Characteristics to Poverty Rates in Early 1990s and 2020
(UI Measures of Poverty Level Income)

	Percent of Retirees		Percent of Retirees Below Poverty		Contribution to Poverty	
	Early 1990s	2020	Early 1990s	2020	Early 1990s	2020
ALL	100.0%	100.0%	7.8%	4.2%	7.8%	4.2%
By Educational Attainment						
High School Dropout	39.8%	10.6%	14.4%	11.9%	5.7%	1.3%
High School Graduate	47.5%	60.5%	3.9%	3.8%	1.9%	2.3%
College Graduate	12.7%	28.9%	2.1%	2.1%	0.3%	0.6%
By Race/Ethnicity						
White, Non-Hispanic	85.5%	79.5%	5.7%	3.1%	4.9%	2.5%
African American	7.6%	8.8%	23.5%	10.1%	1.8%	0.9%
Hispanic	4.7%	7.6%	19.4%	7.8%	0.9%	0.6%
Other	2.2%	4.1%	11.9%	5.1%	0.3%	0.2%
By Gender						
Female	57.5%	56.2%	10.3%	5.0%	5.9%	2.8%
Male	42.5%	43.8%	4.3%	3.1%	1.8%	1.4%
By Marital Status						
Never Married	4.6%	5.4%	17.0%	15.3%	0.8%	0.8%
Married	59.2%	61.7%	2.5%	1.6%	1.5%	1.0%
Widowed	29.2%	16.8%	14.4%	4.8%	4.2%	0.8%
Divorced	7.0%	16.1%	20.2%	9.8%	1.4%	1.6%
By Age						
62 to 64	16.1%	19.6%	6.1%	4.6%	1.0%	0.9%
65 to 69	27.9%	27.9%	6.1%	4.1%	1.7%	1.1%
70 to 74	22.9%	22.5%	7.5%	4.0%	1.7%	0.9%
75 to 79	16.6%	14.5%	9.0%	4.0%	1.5%	0.6%
80 to 84	12.1%	9.6%	12.4%	3.9%	1.5%	0.4%
85 to 89	4.3%	6.0%	10.7%	4.7%	0.5%	0.3%
By SS Benefit Status						
OASI Recipient	76.6%	80.7%	5.2%	2.3%	4.0%	1.9%
DI Recipient	6.5%	9.5%	12.2%	4.7%	0.8%	0.4%
SSI Recipient	4.9%	1.7%	48.9%	55.5%	2.4%	0.9%
Not Receiving SS Benefits	12.0%	8.1%	5.6%	11.5%	0.7%	0.9%

NOTE: Contribution to poverty of any group is equal to the product of its share in the population and its own poverty rate

Source: The Urban Institute tabulations of MINT3 and 1990 to 1993 SIPP.

CHAPTER 10

PROJECTIONS OF POVERTY IN 2020

I. OVERVIEW

In this chapter we present MINT projections of poverty in 2020. We begin in Section II by defining our measure of poverty. In Section III, we show the economic status of the aged population in the early 1990s. We look at sources of income, family income divided by poverty, poverty rates, and the marginal contribution each income source has on family well-being. In Section IV, we report MINT projections of income and poverty in 2020 and contrast them with those of the early 1990s. We find that the overall poverty rate is projected to decline by nearly half between the early 1990s and 2020; however, despite increased earnings of women and projected real wage growth, some sub-groups of the population will continue to experience persistently high poverty rates in the future. Finally, in Section V we consider how economic, demographic, and policy changes might contribute to poverty rates in 2020. Specifically, we examine how projections of future poverty rates are influenced by: 1) Social Security benefits, which are reduced by the scheduled increase in the Normal Retirement Age (NRA), 2) the proportion of retirees who are unmarried, 3) average relative earnings for post-1950 birth cohorts, and 4) earnings inequality for post-1950 birth cohorts. We find that poverty rates of future retirees are highly influenced by rising real wages. Poverty rates are influenced much more by changes in the NRA and marriage patterns than by changes in earnings patterns. We include in the Appendix a comparison of these MINT results with earlier findings and describe the source of the differences.

II. MEASURING POVERTY

We measure poverty rates using the official poverty thresholds of the U.S. Bureau of the Census. These thresholds vary with family size; the poverty threshold for a married couple age 65 and over is 1.26 times the poverty rate of a single individual. To avoid an arbitrary change in poverty status when someone's age increases from 64 to 65, we use the age 65 and over poverty thresholds to calculate the ratio of income to poverty levels for all individuals age 62 and over.[1]

We modify the definition of income used by the Census Bureau for measuring poverty in several ways. First, we impute income from assets by multiplying projected wealth by a real return of 3 percent. This discount rate is meant to represent an estimate of the long-run yield on high-quality bonds. The Census Bureau, in contrast, measures people's income from assets directly, but their income measure is conceptually different from the one we use. Census

[1] In 2000, the poverty threshold for a couple age 65 and older was $10,419 and $8,259 for a single individual age 65 and older (Dalaker 2001). A couple with combined income of $12,000 would have income that is 115 percent of poverty (above the poverty threshold). A single individual with half of the couples' income ($6,000) would have income that is 73 percent of poverty (below the poverty threshold). On a per capita basis, the well-being of these single and married individuals is the same. On a poverty equivalent basis, the single individual is considerably worse off.

measures nominal income, which includes both the real return on assets and the portion of income that merely compensates asset owners for the decline in the value of their principal due to inflation. We would have higher investment incomes, and therefore lower poverty, if we were to impute a *nominal* return to projected wealth.[2] We use a measure of real income instead of nominal income because we do not want to show people's economic status improving or declining over time due to changes in nominal incomes attributable to changes in forecasts of the inflation rate. Changes that alter only nominal incomes do not affect living standards.

A second difference between our income measure and that used by the Census Bureau is that we include the return of capital as a part of the income from financial assets, while the Census includes only the interest and dividends from assets. Census does, however, include the full amount of annual payments from private defined benefit pension plans and Social Security in their definition of income, even though some of the payments from these and other annuities represent a return of contributions instead of income from wealth. To ensure consistency between the treatment of annuities and other assets, we also count the potential annual annuity payments from other assets as income.

An issue, of course, is how to measure the potential annuity payments from other assets. If each person knew how long he or she would live or could purchase an actuarially fair annuity, we could calculate the annual consumption that his or her wealth could finance after age 62. In reality, individuals must set aside part of their wealth to self-insure against the risk of outliving their assets if they are unwilling to purchase an annuity at the rates available to them in private markets. To measure income from assets, we calculate an actuarially fair annuity, using life expectancy projections in MINT (Panis and Lillard, 1999) that are based on age, gender, race, educational attainment, and disability status.[3] We include only 80 percent of this annuity value in income from assets. The reduction factor we apply in measuring income is meant to approximate an adjustment for the risk of living beyond one's life expectancy.

We include return of capital from financial assets that people hold in the form of defined contribution wealth and assets outside of pension plans in our measure of retirement income to minimize the effect on measured poverty rates of the projected shift from DB to DC retirement plans. Without this adjustment, individuals would appear poorer from the shift in wealth from DB plans (where the Census income measure includes return of capital) to DC plans (where the Census measure excludes return from capital.)

Years of persistent real wage growth will inevitably increase incomes relative to the price-adjusted poverty threshold and lower poverty rates. The poverty thresholds increase annually with increases in prices as measured by the Consumer Price Index (CPI). If wages increase faster than the CPI, virtually all individuals with Social Security entitlement will eventually have incomes above poverty since the Social Security initial benefit grows with

[2] We would also impute a higher investment yield if we used a rate of return that reflected the average return on a more representative portfolio of stocks and bonds. But, working in the other direction, Census understates the nominal yield on assets because their measure of income excludes certain sources of income, most notably capital gains, and also undercounts income from dividends and interest relative to incomes reported to the IRS.

[3] MINT3 adjusts the Panis and Lillard (1999) mortality projections to include disability status based on mortality differentials estimated from Zayatz (1999).

wages. To test the sensitivity of the poverty projections, we also consider what poverty rates would be if the thresholds were wage-adjusted rather than price-adjusted. We expect that wage adjusting the poverty thresholds will increase projected poverty rates in 2020.

III. RETIREMENT INCOME IN THE EARLY 1990S

In this section, we describe average per capita family income by income source, average family-size-adjusted income using family income divided by the poverty threshold, and poverty rates of 62- to 89-year-olds in the early 1990s by subgroup. We also show how important specific sources of income are for reducing poverty. These results are based on tabulations of aged families from the 1990 to 1993 SIPP panels.

1. Per Capita Income by Source

For the 62- to 89-year-olds in the early 1990s, average per-capita income was 87 percent of the average economy-wide wage in 1990 (Table 10-1). On average, Social Security benefits were 24 percent of the average wage, income from financial assets (defined contribution pension plans, IRAs, and other savings) 11 percent, income from earnings 14 percent, income from private defined benefit pension plans 12 percent, and imputed income from owner-occupied homes 5 percent.[4] In addition, other non-spouse family members (co-residents) contributed about 15 percent of the average wage to family income. SSI was only 1 percent of the average wage, co-resident income was 15 percent of the average wage, and other incomes not projected in MINT (veterans benefits, railroad retirement, life insurance annuities, other cash, lump sum payments, alimony, unemployment compensation, and miscellaneous other sources) added about 4 percent of the average wage to family income.[5]

Per-capita total income of the 62- to 89-year-olds varies by educational attainment, race, gender, marital status, and age. Income of college graduates age 62 and over was about 133 percent of the average wage, while income of high school dropouts was about 68 percent. Income of white non-Hispanics was 89 percent of the average wage, compared with 68 percent for blacks and 72 percent for Hispanics. Income of males was slightly higher as a percentage of the average wage (89 percent) than income of females (86 percent). Among gender-marital status groups, per-capita income was highest among widowed and divorced males (near or over 100 percent of the average wage) and lowest among married women (about 80 percent of the average wage). Without co-resident income, unmarried women would have the lowest per capita income.

Per-capita income was higher for the younger (below age 70) than for the older elderly, with the difference attributable primarily to higher earnings of those under age 70 (many of whom have not retired, have a non-retired spouses, or continue to work while receiving Social

[4] Imputed rental income is based on a 3 percent real rate of return on the family's home equity.

[5] Veterans benefits, railroad retirement, life insurance annuities, other retirement pensions are the major sources of non-MINT income. They amount for about 70 percent of non-MINT income.

Table 10-1
Average Per Capita Income as a Percent of the Average Wage in the Early 1990s by Income Source

	Percent of Retirees	Total	Social Security	Financial Asset Income[1]	Earnings	DB Pension Income	Imputed Rental Income	SSI	Co-resident Income	Other Income
Total	100.0%	0.87	0.24	0.11	0.14	0.12	0.05	0.01	0.15	0.04
Educational Attainment										
High School Dropout	40.7%	0.68	0.23	0.05	0.07	0.06	0.04	0.01	0.18	0.03
High School Graduate	46.6%	0.91	0.25	0.13	0.15	0.14	0.06	0.00	0.14	0.04
College Graduate	12.7%	1.33	0.24	0.25	0.34	0.26	0.08	0.00	0.10	0.06
Race										
White, non-Hispanic	85.4%	0.89	0.26	0.13	0.15	0.13	0.06	0.00	0.13	0.04
Black	7.7%	0.68	0.19	0.01	0.11	0.09	0.03	0.02	0.20	0.02
Hispanic	4.7%	0.72	0.18	0.03	0.10	0.07	0.04	0.03	0.26	0.02
Asian/Native American	2.2%	1.09	0.15	0.06	0.17	0.08	0.04	0.05	0.50	0.04
Gender										
Female	58.6%	0.86	0.25	0.11	0.12	0.10	0.05	0.01	0.19	0.04
Male	41.4%	0.89	0.24	0.12	0.18	0.15	0.05	0.00	0.10	0.04
Marital Status by Gender										
Never Married Male	2.0%	0.92	0.22	0.13	0.11	0.14	0.04	0.02	0.21	0.05
Married Male	32.1%	0.84	0.22	0.12	0.20	0.14	0.05	0.00	0.07	0.04
Widowed Male	4.5%	1.14	0.32	0.16	0.11	0.18	0.06	0.01	0.26	0.05
Divorced Male	2.7%	0.98	0.25	0.08	0.24	0.15	0.04	0.01	0.15	0.06
Never Married Female	2.6%	0.94	0.23	0.11	0.09	0.16	0.04	0.03	0.27	0.03
Married Female	27.9%	0.80	0.24	0.12	0.17	0.13	0.05	0.00	0.05	0.04
Widowed Female	23.8%	0.92	0.28	0.10	0.05	0.07	0.06	0.01	0.32	0.04
Divorced Female	4.4%	0.85	0.20	0.06	0.15	0.07	0.04	0.02	0.26	0.03
Age										
62 to 64	15.5%	1.01	0.14	0.09	0.39	0.13	0.06	0.01	0.16	0.05
65 to 69	27.8%	0.89	0.23	0.10	0.19	0.14	0.06	0.01	0.14	0.04
70 to 74	23.2%	0.83	0.27	0.11	0.08	0.14	0.05	0.01	0.13	0.04
75 to 79	16.7%	0.83	0.29	0.13	0.05	0.11	0.05	0.01	0.15	0.03
80 to 84	12.4%	0.80	0.28	0.12	0.03	0.08	0.05	0.01	0.20	0.04
85 to 89	4.5%	0.81	0.28	0.13	0.01	0.07	0.05	0.01	0.24	0.03
Per-Capita Income Quintile										
1	20.0%	0.54	0.17	0.02	0.01	0.01	0.02	0.03	0.26	0.01
2	20.0%	0.61	0.25	0.05	0.04	0.05	0.04	0.00	0.16	0.02
3	20.0%	0.74	0.27	0.08	0.07	0.10	0.05	0.00	0.14	0.03
4	20.0%	0.95	0.27	0.13	0.15	0.17	0.07	0.00	0.13	0.04
5	20.0%	1.51	0.26	0.28	0.44	0.27	0.10	0.00	0.08	0.09

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on 1990-1993 SIPP.

Security benefits). As individuals age, Social Security benefits increase and earnings decrease as individuals replace earnings with benefits.

Social Security benefits are projected to be the largest source of income for the overall population, but the relative importance of different income sources varies among sub-groups. Income from assets is the largest income source for those in the highest per-capita income quintile. Here, the per capita income quintile is based solely on the aged unit; it does not include co-resident income. Asset income is also a relatively more important income source for those in higher economic status groups in general (college graduates and whites). Pension income is also concentrated among those in the top income quintile, but pension income is more evenly distributed among different racial groups than asset income is.

Co-resident income is an important source of income for aged individuals. Co-resident income is higher among older individuals compared to younger individuals, higher for unmarried individuals compared to married individuals, and higher for females compared to males. It is also higher for individuals with the lowest per capita income. Interestingly, however, co-resident income is still a relatively large source of income for individuals in the top per capita income quintile. As a word of caution, the co-resident income shown here is the total family co-resident income divided by the number of people in the aged unit. It is not really a "per-capita" measure because the co-resident income supports more individuals than just the aged unit.

Non-MINT sources of income are evenly distributed across all subgroups. The non-MINT income monotonically increases by per capita income quintile of the aged unit. This implies that higher income individuals also have more non-MINT income. In many cases, non-MINT income is a very important source of income for the family well-being.

2. Family Income Divided by Poverty

We divide family income by the family poverty threshold to adjust income for differences in family size. As with Census, we do not include imputed rent in the income measure we use to determine poverty rates. The poverty threshold accounts for both the size and composition of the family in determining family need. This measure is a commonly used equivalence measure. Average family income of the 62 and over population in the early 1990s was about 3.5 times the poverty level (Table 10-2).[6] Income in relation to the poverty level will be higher for relatively younger individuals than for older individuals. Individuals between ages 62 and 64 in the early 1990s had about 46 percent higher poverty adjusted income than those between ages 85 and 89. This reflects three trends. First, that younger individuals have higher earnings than older individuals. Second, the impact of wage growth on new Social Security benefits, and third, higher marriage rates among younger individuals than among older individuals who are mostly widowed.

[6] Recall that the ratio of family income to the poverty level depends on both the level of income of individuals and their marital status. If two individuals age 65 and over who each have income at the poverty level marry, their per-capita income remains constant, but their combined income rises to 1.59 times the poverty level. This change in the ratio of income to the poverty level reflects the fact that the poverty threshold for a married couple is 1.26 times as high as the poverty threshold for a single individual.

Table 10-2
Average Family Income as a Percent of Poverty in the Early 1990s, by Age

	All	Age 62-64	65-69	70-74	75-79	80-84	85-89
Total	3.46	4.28	3.60	3.33	3.22	2.89	2.93
Educational Attainment							
High School Dropout	2.45	2.85	2.48	2.36	2.39	2.32	2.38
High School Graduate	3.72	4.39	3.81	3.55	3.57	3.09	3.15
College Graduate	5.77	6.89	5.78	5.48	5.12	5.37	5.04
Race							
White, non-Hispanic	3.64	4.54	3.82	3.48	3.39	3.05	3.07
Black	2.18	2.81	2.27	2.16	1.86	1.73	1.87
Hispanic	2.33	2.74	2.51	2.08	1.98	2.09	2.00
Asian/Native American	3.31	4.05	3.04	3.96	2.68	2.43	2.19
Gender							
Female	3.19	3.97	3.40	3.04	2.97	2.62	2.76
Male	3.85	4.68	3.87	3.72	3.58	3.38	3.31
Marital Status by Gender							
Never Married Male	2.68	3.04	2.60	2.82	2.62	2.31	2.29
Married Male	4.07	4.92	4.09	3.86	3.84	3.56	3.57
Widowed Male	3.31	4.73	3.40	3.41	2.96	3.17	3.08
Divorced Male	3.02	3.58	2.97	3.00	2.37	2.49	1.92
Never Married Female	2.63	2.66	2.74	2.43	2.78	2.53	2.71
Married Female	4.01	4.67	4.00	3.71	3.86	3.57	3.53
Widowed Female	2.46	2.88	2.49	2.36	2.42	2.34	2.64
Divorced Female	2.27	2.52	2.20	2.20	2.18	2.20	2.29
Per-Capita Income Quintile							
1	1.53	1.65	1.50	1.52	1.49	1.44	1.67
2	2.17	2.65	2.28	2.09	1.98	1.85	1.85
3	2.88	3.67	3.09	2.77	2.64	2.27	2.05
4	3.85	5.01	4.10	3.67	3.43	3.03	3.01
5	6.89	8.45	7.05	6.59	6.56	5.88	6.11

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on 1990-1993 SIPP.

Because of the differences in the poverty threshold between couples and singles, married couples improve their measured well-being controlling for family size compared to the per capita income measure. The opposite is true for unmarried individuals. In the per capita measure, married couples had lower relative standing compared to singles. In the family income divided by poverty measure, married couples have higher well-being compared to singles.

As expected, average income relative to poverty was higher for more educated than for less educated individuals, higher for white non-Hispanics than for blacks and Hispanics, and higher for males than for females. While poverty adjusted income was over 4 times higher for individuals in the top per capita income quintile compared to those in the bottom per capita quintile, the dispersion widens as age decreases (mostly due to the increase in earnings at younger ages).

3. Poverty Rates

Using the income measure described above in Section II, we find that 7.8 percent of 62- to 89-year-olds will have incomes below the poverty level in 1990 (Table 10-3). Poverty rates among older individuals vary by educational attainment, race, gender, and marital status. Poverty rates were much higher among high school dropouts (13.7 percent) than among high school graduates (4.0 percent) and college graduates (2.5 percent). They were also higher among blacks and Hispanics (23.8 percent and 18.8 percent, respectively) than among non-Hispanic whites (5.6 percent).

Poverty rates increase with age. As with family income, much of the age differential occurs because loss of earnings is not offset by an equal increase in Social Security benefits as individuals age. Poverty rates also increase as individuals switch from being married to widowed (changing their poverty threshold from couple-based to single-person-based). In addition, many defined benefit pensions are not updated for increases in prices, and have no provision for paying survivor benefits. As a consequence, pension incomes decline with age.

4. Contribution to Poverty Rate by Sub-Group

The contribution of any sub-group of the population to the overall poverty rate can be measured by the product of the group's poverty rate and its share of the 62- to 89-year-old population. A sub-group of the population will contribute more to overall poverty if its share in the population is large and its own poverty rate is high (Table 10-4).

Among educational sub-groups, high school dropouts contributed 5.6 percentage points to the 62- to 89-year-old poverty rate in the early 1990s, high school graduates contributed 1.9 points, and college graduates contributed only 0.3 points, for a total poverty rate of 7.8 percent. Non-Hispanic whites contribute more to the overall poverty (4.8 percentage points) than other ethnic groups because, although their poverty rates are the lowest, they represent over 85 percent of the population. Females contributed more to poverty among the elderly than males (compare 5.9 percentage points for females with 1.9 percentage points for males) because they comprised 58.6 percent of the aged population and their poverty rates were more than twice as high.

Table 10-3
Percent of Individuals in Poverty in the Early 1990s, by Age

		Age					
	All	62-64	65-69	70-74	75-79	80-84	85-89
Total	7.8%	6.2%	6.4%	7.1%	8.7%	11.6%	11.2%
Educational Attainment							
High School Dropout	13.7%	12.3%	12.2%	13.4%	15.1%	15.0%	15.8%
High School Graduate	4.0%	3.7%	3.3%	3.4%	3.7%	8.4%	6.4%
College Graduate	2.5%	1.4%	2.8%	1.9%	2.9%	3.6%	3.5%
Race							
White, non-Hispanic	5.6%	4.4%	4.2%	4.8%	6.2%	9.6%	9.1%
Black	23.8%	16.3%	20.6%	22.8%	30.8%	29.9%	32.6%
Hispanic	18.8%	18.6%	16.6%	22.5%	21.0%	16.0%	18.1%
Asian/Native American	11.8%	5.3%	13.3%	12.3%	16.4%	13.6%	14.5%
Race by Education							
Non-Black							
High School Dropout	11.2%	10.1%	9.6%	10.9%	12.1%	12.6%	13.3%
High School Graduate	3.4%	3.4%	2.7%	2.8%	3.0%	7.6%	5.8%
College Graduate	2.4%	1.5%	2.9%	2.0%	2.7%	3.1%	3.7%
Black							
High School Dropout	29.5%	26.1%	25.8%	29.7%	34.6%	30.8%	35.2%
High School Graduate	14.3%	8.4%	12.4%	16.0%	18.3%	25.4%	21.6%
College Graduate	3.3%	0.0%	2.0%	0.0%	6.6%	18.9%	0.0%
Gender							
Female	10.1%	8.1%	7.7%	9.5%	11.7%	14.7%	13.3%
Male	4.5%	3.8%	4.8%	3.7%	4.2%	6.0%	6.6%
Marital Status by Gender							
Never Married Male	15.9%	11.1%	16.4%	13.2%	17.3%	26.0%	17.6%
Married Male	2.3%	2.2%	2.6%	1.9%	1.7%	3.4%	3.2%
Widowed Male	8.0%	5.1%	9.1%	6.8%	7.5%	9.8%	7.1%
Divorced Male	15.2%	11.8%	14.7%	16.7%	19.8%	9.4%	49.4%
Never Married Female	20.5%	39.2%	20.5%	21.3%	17.8%	10.4%	18.2%
Married Female	2.4%	1.7%	2.4%	2.2%	2.2%	5.4%	3.3%
Widowed Female	15.3%	12.7%	12.3%	15.5%	16.6%	17.5%	14.4%
Divorced Female	24.4%	25.5%	24.4%	23.1%	26.0%	23.3%	21.2%

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on 1990-1993 SIPP.

Table 10-4
Contributions of Subgroups to Poverty in the Early 1990s

	Percent of Retirees	Poverty	Contribution to Poverty
Total	100.0%	7.8%	7.8%
Educational Attainment			
High School Dropout	40.7%	13.7%	5.6%
High School Graduate	46.6%	4.0%	1.9%
College Graduate	12.7%	2.5%	0.3%
Race			
White, non-Hispanic	85.4%	5.6%	4.8%
Black	7.7%	23.8%	1.8%
Hispanic	4.7%	18.8%	0.9%
Asian/Native American	2.2%	11.8%	0.3%
Gender			
Female	58.6%	10.1%	5.9%
Male	41.4%	4.5%	1.9%
Marital Status			
Never Married	4.6%	18.5%	0.9%
Married	60.0%	2.3%	1.4%
Widowed	28.2%	14.2%	4.0%
Divorced	7.2%	20.9%	1.5%
Marital Status by Gender			
Never Married Male	2.0%	15.9%	0.3%
Married Male	32.1%	2.3%	0.7%
Widowed Male	4.5%	8.0%	0.4%
Divorced Male	2.7%	15.2%	0.4%
Never Married Female	2.6%	20.5%	0.5%
Married Female	27.9%	2.4%	0.7%
Widowed Female	23.8%	15.3%	3.6%
Divorced Female	4.4%	24.4%	1.1%
Age			
62 to 64	15.5%	6.2%	1.0%
65 to 69	27.8%	6.4%	1.8%
70 to 74	23.2%	7.1%	1.6%
75 to 79	16.7%	8.7%	1.5%
80 to 84	12.4%	11.6%	1.4%
85 to 89	4.5%	11.2%	0.5%

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on 1990-1993 SIPP.

Widow(er)s contributed 4.0 percentage points to the overall poverty rate in the early 1990s – more than any other marital group. Though they did not comprise the largest share of the aged population and their poverty rate was not the highest, they represented 28.2 percent of the 62- to 89-year old population and 14.2 percent of them were in poverty. Widows contributed 9 times more to the overall poverty (3.6 percentage points) rate than widowers (0.4 percentage points). Finally, for each successive age group among the 65- to 84 year population, the share of retirees decreased and poverty rates increased – the result being that the contribution to overall poverty also decreased.

5. Importance of Sources of Income in Reducing Poverty

In order to evaluate the importance of various sources of income for reducing poverty, we calculate poverty rates including only Social Security income and earnings. Then we individually add other income sources and measure the marginal impact of each income source on family poverty rates. First we add defined benefit pension income, then financial income, SSI, co-resident income, and finally income not calculated in MINT. The latter component is some indication of any bias in the MINT projections for not projecting all sources of retirement income.[7]

If aged families in the early 1990s only received their Social Security income and earnings, poverty rates would have been 28.4 percent (Table 10-5). When we add pension income, poverty rates decline to 20 percent (a 30 percent reduction). When we add financial income, poverty rates decline to 15.6 percent (another 22 percent reduction). When we add SSI, poverty rates decline to 14.4 percent (another 8 percent reduction). When we add co-resident income, poverty rates decline to 10 percent (a 31 percent reduction). Finally, when we add non-MINT income, poverty rates decline to 7.8 percent (another 22 percent reduction).

While Social Security and earnings are the main-stay of income of the aged, they are not enough to keep almost one-third of this population out of poverty. Even after adding pensions and financial income, nearly one in 6 aged individuals will be in poverty. Non-MINT income is a very important source of income for about 2 percent of the population. This income mostly reflect types of pensions that MINT will project as either Social Security (for railroad retirement) or DB survivor pensions (for other retirement income and life insurance annuities). Veterans benefits, unemployment benefits, and miscellaneous cash and lump sum payments are more problematic, but they represent a small amount of income for a small share of the population. Co-resident income, on the other hand, is an extremely important source of income for reducing poverty of the aged. If we give individuals their non-MINT income first, co-resident income reduces poverty by 33 percent. While some individuals choose co-residency for reasons other than poverty, it is clearly a determining factor for many needy aged.

[7] We use the poverty threshold for the aged unit when considering only aged unit income. When we add co-resident income, we use the full family poverty threshold.

Table 10-5
Marginal Contributions of Income Sources to Poverty in the Early 1990s[1]

	Social Security and Earnings	Add Pensions	Add Financial Income	Add SSI	Add Co-resident Income	Add Other Income
Total	28.4%	20.0%	15.6%	14.4%	10.0%	7.8%
Educational Attainment						
High School Dropout	38.1%	31.6%	26.1%	24.0%	16.7%	13.7%
High School Graduate	22.4%	13.2%	9.1%	8.5%	5.7%	4.0%
College Graduate	19.4%	7.8%	5.5%	5.1%	3.7%	2.5%
Race						
White, non-Hispanic	24.5%	16.1%	11.3%	10.7%	7.6%	5.6%
Black	52.7%	42.2%	40.5%	38.1%	27.7%	23.8%
Hispanic	50.8%	42.7%	39.7%	34.7%	21.6%	18.8%
Asian/Native American	49.8%	45.9%	41.4%	31.5%	14.2%	11.8%
Gender						
Female	33.6%	25.2%	19.6%	18.3%	12.3%	10.1%
Male	21.0%	12.7%	9.9%	8.8%	6.6%	4.5%
Marital Status by Gender						
Never Married Male	53.6%	40.1%	31.5%	29.0%	20.4%	15.9%
Married Male	15.6%	8.3%	6.2%	5.3%	4.0%	2.3%
Widowed Male	34.5%	22.3%	16.5%	15.3%	11.3%	8.0%
Divorced Male	38.8%	29.4%	26.5%	24.5%	20.1%	15.2%
Never Married Female	55.6%	42.0%	37.0%	35.0%	21.6%	20.5%
Married Female	15.0%	8.1%	5.8%	5.0%	3.8%	2.4%
Widowed Female	48.7%	39.5%	30.0%	28.8%	18.4%	15.3%
Divorced Female	57.1%	46.1%	40.0%	35.9%	27.8%	24.4%
Age						
62 to 64	24.0%	16.0%	13.4%	12.4%	7.9%	6.2%
65 to 69	24.5%	16.6%	13.5%	12.3%	8.6%	6.4%
70 to 74	26.8%	17.8%	13.8%	12.6%	9.4%	7.1%
75 to 79	29.6%	20.7%	16.3%	15.2%	10.8%	8.7%
80 to 84	38.9%	30.9%	22.3%	21.2%	14.1%	11.6%
85 to 89	43.6%	34.5%	24.0%	21.7%	13.5%	11.2%
Percentage Point Reduction		-8.4%	-4.4%	-1.2%	-4.4%	-2.2%
Percent Reduction		-29.6%	-22.0%	-7.7%	-30.6%	-22.0%

[1]Poverty rates are calculated first including only Social Security and earnings. We add pensions, financial income, SSI, and co-resident income one at a time to measure the marginal impact of each income source to alleviating poverty.

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on 1990-1993 SIPP.

IV. RETIREMENT INCOME IN 2020

In this section, we report MINT projections of per capita family income, family income divided by the poverty threshold, and poverty rates in 2020 among the population aged 62 to 89 and its sub-groups. As with 1990, we describe how important various income sources are for the economic well-being of current retirees. After describing the projections, we compare the 2020 projections with the observed values in the early 1990s. These results are based on projections of aged families in MINT3.

1. Per Capita Income by Source

The ratio of per capita income to the average wage is projected to be 10 percent higher in 2020 than in the early 1990s (compare 87 percent in the early 1990s to 96 percent in 2020 – Table 10-6). Between the two periods, it's expected that Social Security benefits will increase to 27 percent of the average wage (from 24 percent), income from financial assets will more than double to 29 percent (from 11 percent), income from earnings will increase to 17 percent (from 14 percent), income from private defined benefit pension plans will decrease to 8 percent (from 12 percent), and imputed income from owner-occupied homes will increase slightly to 6 percent (from 5 percent). In addition, income from other non-spouse family members will decrease by almost half to 8 percent (from 15 percent). While always a small program, SSI will mostly disappear (compare 1 percent in the early 1990s to less than 1 percent in 2020).

Part of the difference between the early 1990s and 2020 in the ratio of per capita income to the average wage reflects differences in the relative sizes of subgroups. The remainder of the gain reflects increases in per-capita income relative to the average wage within subgroups. Between the two periods, the share of high school dropouts is expected to decline by nearly 75 percent (from 40.7 percent to 10.6 percent) and the share of college graduates is expected to more than double (from 12.7 percent to 28.9 percent). Total income for high school dropouts is projected to decrease from 68 percent to 57 percent of the average wage, while total income for college graduates is projected to increase from 133 percent to 139 percent of the average wage.

Per-capita income is expected to increase for non-Hispanic whites (from 89 percent to 100 percent) and Asian/Native Americans (from 109 percent to 116 percent) and to decrease for Hispanics (from 72 percent to 70 percent). For blacks, per-capita income is projected to decrease slightly from 68 to 67 percent. Among gender/marital groups, the largest increases in total income are projected for divorced males (from 98 percent to 118 percent), never married males (from 92 percent to 108 percent), and married females (from 80 percent to 91 percent).

There will be a larger share of younger elderly in 2020 compared to the early 1990s and a smaller share of older elderly. This increases the share of those with higher incomes (the young) and reduces the share of those with lower incomes (the old). In addition, total income is projected to increase for all age groups. The biggest gain in per-capita income is projected for 70- to 74-year-olds (16.9 percent – from 83 percent to 97 percent), while the smallest gain in per-capita income is projected for 85- to 89-year-olds (1.2 percent – from 81 percent to 82 percent).

Table 10-6
Average Per Capita Income as a Percent of the Average Wage in 2020 by Income Source

	Percent of Retirees	Total	Social Security	Financial Asset Income[1]	Earnings	DB Pension Income	Imputed Rental Income	SSI	Co-resident Income
Total	100.0%	0.96	0.27	0.29	0.17	0.08	0.06	0.00	0.08
Educational Attainment									
High School Dropout	10.6%	0.57	0.21	0.07	0.07	0.03	0.03	0.01	0.14
High School Graduate	60.5%	0.82	0.27	0.20	0.15	0.07	0.05	0.00	0.07
College Graduate	28.9%	1.39	0.30	0.57	0.26	0.10	0.10	0.00	0.06
Race									
White, non-Hispanic	79.5%	1.00	0.28	0.33	0.18	0.08	0.07	0.00	0.06
Black	8.8%	0.67	0.24	0.09	0.12	0.07	0.03	0.00	0.11
Hispanic	7.6%	0.70	0.22	0.11	0.13	0.05	0.04	0.00	0.14
Asian/Native American	4.1%	1.16	0.24	0.38	0.22	0.06	0.08	0.01	0.18
Gender									
Female	56.2%	0.93	0.27	0.27	0.16	0.08	0.07	0.00	0.09
Male	43.8%	0.99	0.27	0.33	0.19	0.08	0.06	0.00	0.05
Marital Status by Gender									
Never Married Male	2.1%	1.08	0.25	0.46	0.17	0.08	0.05	0.01	0.07
Married Male	32.8%	0.92	0.26	0.30	0.20	0.08	0.06	0.00	0.03
Widowed Male	3.1%	1.26	0.33	0.45	0.13	0.11	0.09	0.00	0.15
Divorced Male	5.8%	1.18	0.30	0.39	0.22	0.09	0.07	0.00	0.11
Never Married Female	3.3%	0.96	0.22	0.19	0.26	0.07	0.05	0.01	0.15
Married Female	28.8%	0.91	0.27	0.30	0.17	0.08	0.06	0.00	0.03
Widowed Female	13.7%	0.98	0.30	0.27	0.07	0.08	0.09	0.00	0.17
Divorced Female	10.4%	0.91	0.26	0.19	0.19	0.06	0.06	0.00	0.15
Age									
62 to 64	19.6%	1.05	0.20	0.25	0.42	0.06	0.06	0.00	0.07
65 to 69	27.9%	0.99	0.29	0.30	0.20	0.07	0.07	0.00	0.07
70 to 74	22.5%	0.97	0.31	0.32	0.10	0.09	0.07	0.00	0.08
75 to 79	14.5%	0.88	0.29	0.31	0.06	0.08	0.07	0.00	0.07
80 to 84	9.6%	0.83	0.27	0.29	0.03	0.09	0.06	0.00	0.10
85 to 89	6.0%	0.82	0.25	0.30	0.02	0.10	0.05	0.00	0.10
Shared AIME Quintile at 62									
1	20.0%	0.48	0.15	0.10	0.06	0.03	0.03	0.01	0.11
2	20.0%	0.65	0.24	0.14	0.10	0.04	0.04	0.00	0.09
3	20.0%	0.81	0.28	0.19	0.14	0.07	0.06	0.00	0.07
4	20.0%	1.11	0.32	0.36	0.20	0.10	0.08	0.00	0.06
5	20.0%	1.73	0.36	0.69	0.36	0.15	0.12	0.00	0.06
Per-Capita Income Quintile									
1	20.0%	0.34	0.16	0.03	0.01	0.01	0.02	0.01	0.11
2	20.0%	0.53	0.26	0.08	0.04	0.03	0.04	0.00	0.09
3	20.0%	0.72	0.29	0.14	0.10	0.07	0.05	0.00	0.06
4	20.0%	1.04	0.31	0.27	0.21	0.11	0.08	0.00	0.06
5	20.0%	2.16	0.34	0.96	0.50	0.16	0.14	0.00	0.06

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.

Source: Authors' calculations based on MINT3.

Between the early 1990s and 2020, total income is projected to decline for the three lowest per-capita income quintiles and to increase for the two highest per-capita income quintiles. For the lowest quintile, total income will decline by 37.0 percent (from 54 percent to 34 percent of the average wage). For the highest quintile, total income will increase by 43.1 percent (from 151 percent to 216 percent of the average wage).

Social Security benefits increase as a percent of the average wage between the early 1990s and 2020 for the younger aged, but decrease for the older aged. The increase for the younger aged reflects higher benefits paid to women as they increase their lifetime employment. It also reflects earlier benefit take-up among the younger aged in 2020 compared to the younger aged in the 1990s. The decrease in benefits at older ages reflects the decline in the share of older retirees who are widowed in 2020 compared with 1990. Widows receiving survivor benefits typically receive higher per capita Social Security benefits than do married women who largely received spousal benefits or lower worker benefits, especially among the earlier cohorts.

In 2020 a larger share of income comes from financial assets and a smaller share from DB pensions compared to 1990. This reflects the dramatic shift from defined benefit pensions to defined contribution pensions and other retirement savings over the 30-year period. The increase in financial assets between 1990 and 2020 is largest for the younger aged since they have had a longer time to contribute to retirement accounts.[8] While the gain in financial assets is greater than the decline in DB pensions, most of the gain is for individuals in the top income groups. Asset income is typically very unevenly distributed, and retirements saving accounts accentuate this inequality.

2. Family Income Divided by Poverty

Average family income as a ratio of poverty is projected to increase between the early 1990s and 2020 by 62.7 percent (from 3.46 to 5.69 times the poverty level – Table 10-7). These findings are highly influenced by the future wage growth assumptions in the model. Because wages are expected to grow faster than prices, poverty-adjusted family income (where poverty thresholds increase by the CPI and incomes increase by wage growth) will be higher in the future. Even after adjusting income for family size, which this measure does, total income is projected to increase for all subgroups.

3. Poverty Rates

Because total income for all income levels is expected to increase between the early 1990s and 2020, overall poverty rates will decrease by 46.2 percent (from 7.8 percent to 4.2 percent – Table 10-8). This decline is largely attributable to the growth in real earnings over time, which raises real Social Security benefits and other retirement income relative to poverty. Older retirees in 2020 (young retirees today) had higher real earnings over their lifetimes than older retirees in the 1990s, while younger retirees in 2020 are projected to have higher real earnings in the next 20 years than their counterparts who retired in the 1990s.

[8] Many of the 62- to 64-year-olds have not yet retired and are still contributing to their retirement accounts.

Table 10-7
Average Family Income as a Percent of Poverty in 2020, by Age

	All	Age					
		62-64	65-69	70-74	75-79	80-84	85-89
Total	5.69	6.50	6.05	5.68	5.11	4.62	4.48
Educational Attainment							
High School Dropout	2.98	3.29	3.09	2.87	2.87	2.76	2.81
High School Graduate	4.83	5.47	5.03	4.76	4.35	4.23	4.12
College Graduate	8.46	10.13	8.94	8.05	7.65	6.77	6.60
Race							
White, non-Hispanic	6.06	7.06	6.52	6.08	5.38	4.87	4.70
Black	3.65	4.29	3.72	3.43	3.33	2.88	3.08
Hispanic	3.77	4.28	3.93	3.66	2.97	3.11	3.06
Asian/Native American	6.34	7.49	6.67	5.93	6.24	4.90	3.45
Gender							
Female	5.27	6.25	5.75	5.25	4.63	4.21	4.03
Male	6.22	6.78	6.38	6.21	5.81	5.31	5.47
Marital Status by Gender							
Never Married Male	4.88	4.56	5.20	5.11	4.12	4.82	5.17
Married Male	6.58	7.29	6.72	6.62	6.11	5.50	5.58
Widowed Male	5.36	6.29	5.55	5.37	5.24	4.29	5.22
Divorced Male	5.14	5.36	5.36	4.79	4.97	5.01	4.82
Never Married Female	4.03	4.77	4.21	4.10	3.04	2.70	3.42
Married Female	6.55	7.29	6.85	6.34	5.99	5.45	5.69
Widowed Female	3.96	4.59	4.48	4.22	3.74	3.62	3.36
Divorced Female	3.81	4.50	3.99	3.89	3.15	3.17	3.02
Shared AIME Quintile at 62							
1	2.57	2.42	2.46	2.37	2.81	3.08	2.84
2	3.67	3.94	3.69	3.66	3.45	3.55	3.46
3	4.78	5.28	5.02	4.85	4.23	4.11	4.13
4	6.92	7.90	7.45	7.09	6.14	5.39	5.02
5	10.50	12.98	11.62	10.42	8.91	6.99	6.94
Per-Capita Income Quintile							
1	1.75	1.76	1.76	1.74	1.74	1.76	1.72
2	2.99	3.29	3.12	2.99	2.73	2.66	2.59
3	4.31	4.98	4.49	4.32	3.81	3.62	3.55
4	6.27	7.56	6.59	6.14	5.44	5.07	4.92
5	13.12	14.93	14.27	13.19	11.83	10.02	9.61

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on MINT3.

Table 10-8
Percent of Individuals in Poverty in 2020, by Age

	All	Age					
		62-64	65-69	70-74	75-79	80-84	85-89
Total	4.2%	4.6%	4.1%	4.0%	4.0%	3.9%	4.7%
Educational Attainment							
High School Dropout	11.9%	12.6%	10.8%	10.7%	13.0%	12.5%	12.5%
High School Graduate	3.8%	4.2%	4.1%	4.0%	3.2%	2.8%	3.9%
College Graduate	2.1%	2.5%	2.2%	2.1%	1.9%	1.8%	1.6%
Race							
White, non-Hispanic	3.1%	3.5%	3.1%	2.9%	3.0%	3.0%	3.7%
Black	10.1%	10.1%	9.4%	10.9%	9.2%	11.2%	11.9%
Hispanic	7.8%	6.8%	7.1%	8.8%	10.1%	7.8%	8.3%
Asian/Native American	5.1%	5.4%	5.3%	3.3%	6.0%	3.7%	13.5%
Race by Education							
Non-Black							
High School Dropout	10.4%	10.6%	10.2%	9.2%	11.8%	10.9%	10.2%
High School Graduate	3.3%	3.6%	3.4%	3.3%	3.0%	2.4%	3.6%
College Graduate	1.9%	2.2%	2.1%	1.8%	1.7%	1.7%	1.7%
Black							
High School Dropout	19.0%	24.3%	13.5%	17.6%	18.5%	20.7%	28.1%
High School Graduate	8.6%	8.3%	8.9%	10.7%	5.4%	7.6%	7.7%
College Graduate	4.8%	5.6%	3.9%	6.8%	4.5%	3.3%	0.0%
Gender							
Female	5.0%	5.1%	4.8%	4.8%	4.9%	5.4%	6.0%
Male	3.1%	4.1%	3.3%	3.0%	2.8%	1.4%	1.9%
Marital Status by Gender							
Never Married Male	13.5%	10.9%	11.9%	17.9%	16.8%	12.1%	24.9%
Married Male	1.7%	2.3%	2.2%	1.3%	1.2%	0.9%	1.1%
Widowed Male	3.2%	3.0%	2.5%	5.0%	3.0%	1.4%	3.7%
Divorced Male	7.2%	10.7%	6.0%	6.7%	8.3%	2.6%	0.0%
Never Married Female	16.5%	14.4%	12.3%	18.6%	20.5%	24.4%	23.9%
Married Female	1.4%	1.8%	1.4%	1.2%	1.1%	1.2%	1.2%
Widowed Female	5.2%	4.8%	5.2%	5.2%	4.6%	5.6%	5.6%
Divorced Female	11.2%	12.1%	12.0%	9.8%	11.0%	9.4%	13.9%

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on MINT3.

While poverty rates decline for all age groups, the poverty rates for the younger age groups do not decline as much as for older age groups. Between the early 1990s and 2020, the prevalence of poverty is projected to decrease from 6.2 percent to 4.6 percent for 62- to 64-year-olds (a 26 percent reduction) and from 11.2 percent to 4.7 percent for 85-89 year olds (a 58 percent reduction).

Poverty rates are projected to decrease for all educational groups; however, the impact will be greatest in absolute terms for those without a high school degree (from 13.7 percent to 11.9 percent). Poverty rates are also projected to decline for all ethnic groups, but they will decline more for blacks (from 23.8 percent to 10.1 percent) and Hispanics (from 18.8 percent to 7.8 percent) than for non-Hispanic whites (from 5.6 percent to 3.1 percent). Overall poverty will decline for both men and women, but women's poverty rates decline more (from 10.1 percent to 5.1 percent) than men's rates do (from 4.5 percent to 3.1 percent). Despite the reduction in poverty for women, the prevalence of poverty among women will remain higher than among men. Poverty rates are projected to decline among all marital status groups, but will remain very high among those who have never married.

4. Contribution to Poverty Rate by Sub-Group

Between the early 1990s and 2020, the poverty rate among high school dropouts in the 62- to 89-year-old population is projected to decrease from 13.7 percent to 10.6 percent, and high school dropouts will be a much smaller share of this population (40.7 percent in the early 1990s compared with 10.6 percent in 2020). Consequently, high school dropouts will contribute 4.3 percentage points less to the poverty rate in 2020 (Table 10-9) than they did in the early 1990s (compare 5.6 percentage points in the early 1990s with 1.3 percentage points in 2020). The contribution of high school graduates to poverty will increase (from 1.9 percentage points to 2.3 percentage points), however, because both their poverty rate and their share of the total population rise. The contribution of college graduates to poverty will also increase (from 0.3 percentage points to 0.6 percentage points). Although their poverty rate remains just over 2 percent between the early 1990s and 2020, their share of the population is projected to rise from 12.7 percent to 28.9 percent.

The contributions to poverty of all ethnic groups are projected to decline between the periods, but they decline more in absolute terms for non-Hispanic whites (from 4.8 percentage points to 2.5 percentage points) than for other ethnic groups. The larger poverty reductions among minorities compared to non-Hispanic whites are offset by increases in their population share, yielding only small reductions in the contribution to poverty among minorities. Non-Hispanic whites have both declining poverty rates and declining population share for a larger overall reduction in their contribution to poverty.

Females will contribute far less to overall poverty among the elderly in 2020 than in the 1990s (from 5.9 percentage points to 2.8 percentage points), while the male contribution to poverty will decline only slightly (compare 1.9 percentage points in the early 1990s with 1.4 percentage points in 2020). This is the consequence of a large decline in the poverty rate of females and a slight decline in the poverty rate of males; population shares of the two groups change only slightly. Males will become a slightly larger share of the population because, as the

Table 10-9
Contributions of Subgroups to Poverty in 2020

	Percent of Retirees	Poverty	Contribution to Poverty
Total	100.0%	4.2%	4.2%
Educational Attainment			
High School Dropout	10.6%	11.9%	1.3%
High School Graduate	60.5%	3.8%	2.3%
College Graduate	28.9%	2.1%	0.6%
Race			
White, non-Hispanic	79.5%	3.1%	2.5%
Black	8.8%	10.1%	0.9%
Hispanic	7.6%	7.8%	0.6%
Asian/Native American	4.1%	5.1%	0.2%
Gender			
Female	56.2%	5.0%	2.8%
Male	43.8%	3.1%	1.4%
Marital Status			
Never Married	5.4%	15.3%	0.8%
Married	61.7%	1.6%	1.0%
Widowed	16.8%	4.8%	0.8%
Divorced	16.1%	9.8%	1.6%
Marital Status by Gender			
Never Married Male	2.1%	13.5%	0.3%
Married Male	32.8%	1.7%	0.6%
Widowed Male	3.1%	3.2%	0.1%
Divorced Male	5.8%	7.2%	0.4%
Never Married Female	3.3%	16.5%	0.5%
Married Female	28.8%	1.4%	0.4%
Widowed Female	13.7%	5.2%	0.7%
Divorced Female	10.4%	11.2%	1.2%
Age			
62 to 64	19.6%	4.6%	0.9%
65 to 69	27.9%	4.1%	1.1%
70 to 74	22.5%	4.0%	0.9%
75 to 79	14.5%	4.0%	0.6%
80 to 84	9.6%	3.9%	0.4%
85 to 89	6.0%	4.7%	0.3%

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on MINT3.

group with the shorter life expectancy, projected increases in longevity increase their numbers in a given age range by relatively more than those for females.

Contributions to elderly poverty among different marital groups are projected to change dramatically for widow(er)s (from 4.0 percentage points to 0.8 percentage points). The reduced importance of widowhood in explaining elderly poverty occurs for two reasons. First, due both to greater longevity and an increase in the share of the young elderly in 2020 that reflects the large baby boomer cohorts, the share of the 62- to 89-year-old population that is widowed will decline from 28.2 percent to 16.8 percent. Second, poverty rates will decline among widow(er)s from 14.2 percent to 4.8 percent. This decline in poverty reflects overall economic growth, the increased lifetime earnings of married women, increased Social Security coverage rates, and an increased prevalence of joint and survivor pensions in later cohorts. Between the early 1990s and 2020, the poverty rate among divorced individuals is projected to fall by more than 50 percent (from 20.9 percent to 9.8 percent); however, their share of the aged population poverty is projected to increase sharply from 7.2 percent to 16.1 percent. As a result, divorced individuals will contribute slightly more to overall poverty in 2020 than in the early 1990s (compare 1.5 percentage points in the early 1990s with 1.6 percentage points in 2020).

Finally, the contribution to poverty of all age groups will decline between the early 1990s and 2020, but will decline more for older age groups. Both the oldest and youngest age groups increase their share of the age 62- to 89-year-old population between the early 1990s and 2020, due to increased longevity and the baby boom cohorts moving into retirement. Seventy- to 84-year-olds decrease their share of the of the population and have lower poverty rates in 2020 compared to the early 1990s. These middle age groups have larger reductions in their contributions to poverty than do the younger and oldest age groups.

5. Importance of Sources of Income in Reducing Poverty

As with 1990, to evaluate the importance of various sources of income for reducing poverty, we calculate poverty rates including only Social Security income and earnings. Then we individually add other income sources and measure the marginal impact of each income source on family poverty rates.

If aged families in 2020 only received their Social Security income and earnings, poverty rates would be 10.4 percent (Table 10-10). When we pension income, poverty rates decline to 8.8 percent (a 15 percent reduction). When we add financial income, poverty rates decline to 5.8 percent (another 34 percent reduction). When we add SSI, poverty rates decline to 5.4 percent (another 7 percent reduction). When we add co-resident income, poverty rates decline to 4.02percent (a 22 percent reduction).

With increases in Social Security benefits through wage growth and increased Social Security coverage rates, Social Security and earnings alone are projected to keep all but 10.4 percent of the aged population out of poverty in 2020 (compared with 28.4 percent in the early 1990s). After adding pensions and financial income, 5.8 percent of aged individuals will be in poverty (compared with 15.6 percent in the early 1990s). While SSI is a small program in 2020, it still reduces poverty by 7 percent to 5.4 percent (compared with 14.4 percent in the early

Table 10-10
Marginal Contributions of Income Sources to Poverty in 2020[1]

	Social Security and Earnings	Add Pensions	Add Financial Income	Add SSI	Add Co-resident Income
Total	10.4%	8.8%	5.8%	5.4%	4.2%
Educational Attainment					
High School Dropout	25.2%	22.9%	18.2%	16.4%	11.9%
High School Graduate	9.2%	7.7%	5.0%	4.8%	3.8%
College Graduate	7.4%	6.1%	2.8%	2.7%	2.1%
Race					
White, non-Hispanic	8.2%	6.7%	4.0%	3.8%	3.1%
Black	19.2%	16.6%	14.0%	13.6%	10.1%
Hispanic	19.3%	17.8%	12.6%	11.0%	7.8%
Asian/Native American	17.3%	15.6%	9.9%	8.1%	5.1%
Gender					
Female	12.3%	10.4%	7.0%	6.6%	5.0%
Male	7.8%	6.7%	4.1%	3.9%	3.1%
Marital Status by Gender					
Never Married Male	28.3%	25.8%	19.2%	18.7%	13.5%
Married Male	4.9%	4.0%	2.2%	2.1%	1.7%
Widowed Male	12.6%	10.7%	5.5%	4.7%	3.2%
Divorced Male	14.8%	12.9%	8.6%	8.2%	7.2%
Never Married Female	34.1%	30.4%	25.3%	24.2%	16.5%
Married Female	4.7%	3.8%	2.0%	1.7%	1.4%
Widowed Female	14.9%	11.9%	7.5%	6.8%	5.2%
Divorced Female	23.2%	20.7%	14.6%	14.3%	11.2%
Age					
62 to 64	10.1%	9.0%	6.1%	5.9%	4.6%
65 to 69	8.7%	7.9%	5.5%	5.2%	4.1%
70 to 74	9.7%	8.6%	5.5%	5.2%	4.0%
75 to 79	11.1%	9.4%	5.6%	5.2%	4.0%
80 to 84	13.3%	9.5%	6.0%	5.1%	3.9%
85 to 89	15.4%	11.0%	6.7%	5.9%	4.7%
Percentage Point Reduction		-1.6%	-3.0%	-0.4%	-1.2%
Percent Reduction		-15.4%	-34.1%	-6.9%	-22.2%

[1]Poverty rates are calculated first including only Social Security and earnings. We add pensions, financial income, SSI, and co-resident income one at a time to measure the marginal impact of each income source to alleviating poverty.

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on MINT3.

1990s). Co-resident income remains an extremely important source of income for reducing poverty of the aged. When co-resident income is added, poverty is reduced to 4.2 percent (compared with 10.0 percent in the early 1990s).

V. EFFECTS OF USING DIFFERENT INCOME AND POVERTY MEASURES

The general trends in estimated income and poverty remain about the same when one uses different income measures (Tables 10-11, 10-12, and 10-13). In Table 10-11 we show two separate measures of poverty for the early 1990s. The first measure, labeled "Census Measure," uses the Census definition of income from assets (based on nominal income from interest, dividends, and other property income). In the second measure, labeled "UI Measure," we use our definition of asset income (based on a real annuity income from 80 percent of financial assets). Because the latter measure includes a return on capital, it increases poverty-adjusted family income by 0.16 and reduces poverty by 0.2 percentage points. While income for all subgroups is higher for the UI measure than the Census measure, poverty isn't lower for all subgroups. With the UI measure, poverty is higher for college graduates, Hispanics and Asian/Native Americans, never married females, and the youngest age group.

If we assume that people can spend down all of their wealth in retirement instead of only 80 percent of wealth and count this additional return of capital as income, then measured incomes are higher and poverty rates lower – for all subgroups, except divorced males (Table 10-12). But the trend in poverty is about the same – the overall poverty rate drops over from 7.8 percent to 7.5 percent. Using the alternative measure would have the largest impact, in absolute terms, on high school dropouts, Asian/Native Americans, the never married, and the oldest age groups.

If one does not count any return on capital from financial assets in measured income, then overall measured income is lower and the poverty rate is higher (Table 10-13). By this alternative measure, the overall poverty rate for the 62- to 89-year-old population would be 8.4 percent (compared with 7.8 percent for the UI measure). While income for all subgroups is lower for the alternative measure than the UI measure, poverty isn't higher for all subgroups. College graduates and the youngest age group would have lower poverty rates if we used the alternative measure.

If poverty thresholds were increased by wage growth rather than price growth, the overall poverty rate in 2020 would be 9.9 percent, rather than 4.2 percent – a difference of 5.7 percentage points (Table 10-14). For all subgroups, poverty rates would be higher if they were wage-adjusted instead of price-adjusted. This is because wages are projected to increase by 3.5 times between the early 1990s and 2020, while prices are projected to increase by only about 2.3 times.[9] Many retirees have enough income to put them just above the price-adjusted poverty

[9] Based on the intermediate assumptions in Table V.B1 of the 2002 OASDI Trustees Report.

Table 10-11
Average Family Income as a Percent of Poverty and Percent of Retirees Below Poverty in the Early 1990s
(Comparison of Census and UI Measure)

	Average Family Income / Poverty Threshold			Percent of Retirees Below Poverty		
	Census Measure[1]	UI Measure[2]	Difference	Census Measure[1]	UI Measure[2]	Difference
Total	3.30	3.46	0.16	8.0%	7.8%	-0.2%
Educational Attainment						
High School Dropout	2.31	2.45	0.14	14.4%	13.7%	-0.7%
High School Graduate	3.55	3.72	0.17	4.0%	4.0%	0.0%
College Graduate	5.53	5.77	0.23	1.9%	2.5%	0.6%
Race						
White, non-Hispanic	3.46	3.64	0.18	5.8%	5.6%	-0.2%
Black	2.12	2.18	0.06	24.4%	23.8%	-0.6%
Hispanic	2.26	2.33	0.07	18.7%	18.8%	0.1%
Asian/Native American	3.22	3.31	0.10	11.1%	11.8%	0.7%
Gender						
Female	3.04	3.19	0.15	10.4%	10.1%	-0.3%
Male	3.67	3.85	0.19	4.6%	4.5%	-0.1%
Marital Status						
Never Married	2.57	2.65	0.08	17.9%	18.5%	0.6%
Married	3.85	4.04	0.20	2.4%	2.3%	-0.1%
Widowed	2.47	2.59	0.13	14.8%	14.2%	-0.6%
Divorced	2.46	2.56	0.10	21.1%	20.9%	-0.2%
Marital Status by Gender						
Never Married Male	2.58	2.68	0.10	16.0%	15.9%	-0.1%
Married Male	3.88	4.07	0.19	2.4%	2.3%	-0.1%
Widowed Male	3.10	3.31	0.21	8.3%	8.0%	-0.3%
Divorced Male	2.85	3.02	0.17	15.7%	15.2%	-0.5%
Never Married Female	2.56	2.63	0.07	19.3%	20.5%	1.2%
Married Female	3.80	4.01	0.20	2.5%	2.4%	-0.1%
Widowed Female	2.35	2.46	0.11	16.0%	15.3%	-0.7%
Divorced Female	2.22	2.27	0.05	24.5%	24.4%	-0.1%
Age						
62 to 64	4.14	4.28	0.14	5.8%	6.2%	0.4%
65 to 69	3.48	3.60	0.12	6.6%	6.4%	-0.2%
70 to 74	3.19	3.33	0.13	7.4%	7.1%	-0.3%
75 to 79	3.05	3.22	0.17	8.9%	8.7%	-0.2%
80 to 84	2.65	2.89	0.24	12.2%	11.6%	-0.6%
85 to 89	2.52	2.93	0.41	11.8%	11.2%	-0.6%

Notes:
[1] The Census measure uses nominal income from interest, dividends, and other property income to represent income from assets. It also excludes imputed rental income from total family income.
[2] The UI measure uses a real discount rate of 3.0% to convert 80% of wealth to asset income. It also excludes imputed rental income from total family income.

Source: Authors' calculations based on 1990-1993 SIPP.

Table 10-12
Average Family Income as a Percent of Poverty, and Percent of Retirees Below Poverty in the Early 1990s (Comparison of Annuitization of 80% and 100% of Asset Income)

	Average Family Income / Poverty Threshold			Percent of Retirees Below Poverty		
	UI Measure[1] (80%)	Alternative Measure[2] (100%)	Difference	UI Measure[1] (80%)	Alternative Measure[2] (100%)	Difference
Total	3.46	3.81	0.35	7.8%	7.5%	-0.3%
Educational Attainment						
High School Dropout	2.45	2.62	0.17	13.7%	13.3%	-0.4%
High School Graduate	3.72	4.11	0.39	4.0%	3.8%	-0.2%
College Graduate	5.77	6.53	0.76	2.5%	2.2%	-0.3%
Race						
White, non-Hispanic	3.64	4.04	0.39	5.6%	5.3%	-0.3%
Black	2.18	2.23	0.05	23.8%	23.5%	-0.3%
Hispanic	2.33	2.42	0.10	18.8%	18.6%	-0.2%
Asian/Native American	3.31	3.49	0.18	11.8%	11.4%	-0.4%
Gender						
Female	3.19	3.50	0.31	10.1%	9.8%	-0.3%
Male	3.85	4.26	0.41	4.5%	4.2%	-0.3%
Marital Status						
Never Married	2.65	2.77	0.11	18.5%	17.8%	-0.7%
Married	4.04	4.55	0.51	2.3%	2.1%	-0.2%
Widowed	2.59	2.71	0.12	14.2%	13.8%	-0.4%
Divorced	2.56	2.64	0.08	20.9%	20.6%	-0.3%
Marital Status by Gender						
Never Married Male	2.68	2.82	0.13	15.9%	15.1%	-0.8%
Married Male	4.07	4.55	0.48	2.3%	2.1%	-0.2%
Widowed Male	3.31	3.49	0.18	8.0%	7.8%	-0.2%
Divorced Male	3.02	3.12	0.11	15.2%	15.4%	0.2%
Never Married Female	2.63	2.73	0.10	20.5%	20.0%	-0.5%
Married Female	4.01	4.54	0.54	2.4%	2.2%	-0.2%
Widowed Female	2.46	2.57	0.11	15.3%	15.0%	-0.3%
Divorced Female	2.27	2.34	0.06	24.4%	23.9%	-0.5%
Age						
62 to 64	4.28	4.60	0.32	6.2%	5.9%	-0.3%
65 to 69	3.60	3.95	0.34	6.4%	6.3%	-0.1%
70 to 74	3.33	3.68	0.35	7.1%	6.7%	-0.4%
75 to 79	3.22	3.61	0.39	8.7%	8.4%	-0.3%
80 to 84	2.89	3.22	0.33	11.6%	11.1%	-0.5%
85 to 89	2.93	3.27	0.34	11.2%	10.7%	-0.5%

Notes:
[1] The UI measure uses a real discount rate of 3.0% to convert 80% of wealth to asset income. It also excludes imputed rental income from total family income.
[2] The alternative measure uses a real discount rate of 3.0% to convert 100% of wealth to asset income. It also excludes imputed rental income from total family income.

Source: Authors' calculations based on 1990-1993 SIPP.

Table 10-13
Average Family Income as a Percent of Poverty,
And Percent of Retirees Below Poverty in the Early 1990s
(Comparison of Income With and Without a Return of Capital)

	Average Family Income / Poverty Threshold			Percent of Retirees Below Poverty		
	UI Measure[1] (With)	Alternative Measure[2] (Without)	Difference	UI Measure[1] (With)	Alternative Measure[2] (Without)	Difference
Total	3.46	3.26	-0.21	7.8%	8.4%	0.6%
Educational Attainment						
High School Dropout	2.45	2.29	-0.16	13.7%	14.9%	1.2%
High School Graduate	3.72	3.51	-0.21	4.0%	4.5%	0.5%
College Graduate	5.77	5.43	-0.33	2.5%	2.3%	-0.2%
Race						
White, non-Hispanic	3.64	3.41	-0.23	5.6%	6.3%	0.7%
Black	2.18	2.12	-0.05	23.8%	24.5%	0.7%
Hispanic	2.33	2.27	-0.06	18.8%	19.2%	0.4%
Asian/Native American	3.31	3.22	-0.10	11.8%	12.0%	0.2%
Gender						
Female	3.19	2.99	-0.20	10.1%	11.1%	1.0%
Male	3.85	3.64	-0.22	4.5%	4.7%	0.2%
Marital Status						
Never Married	2.65	2.38	-0.27	18.5%	20.7%	2.2%
Married	4.04	3.88	-0.16	2.3%	2.3%	0.0%
Widowed	2.59	2.29	-0.30	14.2%	16.0%	1.8%
Divorced	2.56	2.38	-0.18	20.9%	22.0%	1.1%
Marital Status by Gender						
Never Married Male	2.68	2.37	-0.31	15.9%	17.7%	1.8%
Married Male	4.07	3.91	-0.17	2.3%	2.3%	0.0%
Widowed Male	3.31	2.80	-0.50	8.0%	8.8%	0.8%
Divorced Male	3.02	2.77	-0.25	15.2%	16.2%	1.0%
Never Married Female	2.63	2.39	-0.24	20.5%	22.9%	2.4%
Married Female	4.01	3.86	-0.15	2.4%	2.4%	0.0%
Widowed Female	2.46	2.20	-0.26	15.3%	17.3%	2.0%
Divorced Female	2.27	2.14	-0.14	24.4%	25.6%	1.2%
Age						
62 to 64	4.28	4.21	-0.08	6.2%	6.1%	-0.1%
65 to 69	3.60	3.50	-0.11	6.4%	6.7%	0.3%
70 to 74	3.33	3.15	-0.18	7.1%	7.5%	0.4%
75 to 79	3.22	2.93	-0.28	8.7%	9.5%	0.8%
80 to 84	2.89	2.50	-0.39	11.6%	13.8%	2.2%
85 to 89	2.93	2.35	-0.59	11.2%	13.7%	2.5%

Notes:
[1] The UI measure uses a real discount rate of 3.0% to convert 80% of wealth to asset income. It also excludes imputed rental income from total family income.
[2] The alternative measure does not include any return on capital from asset income. It also excludes imputed rental income from total family income.

Source: Authors' calculations based on 1990-1993 SIPP.

Table 10-14
Price-Adjusted and Wage-Adjusted Poverty Rates in 2020

	Price-Adjusted Poverty	Wage-Adjusted Poverty	Difference
Total	4.2%	9.9%	5.7%
Educational Attainment			
High School Dropout	11.9%	25.4%	13.5%
High School Graduate	3.8%	9.6%	5.8%
College Graduate	2.1%	4.8%	2.7%
Race			
White, non-Hispanic	3.1%	7.7%	4.6%
Black	10.1%	21.4%	11.3%
Hispanic	7.8%	18.5%	10.7%
Asian/Native American	5.1%	11.9%	6.8%
Gender			
Female	5.0%	11.8%	6.8%
Male	3.1%	7.5%	4.4%
Marital Status			
Never Married	15.3%	25.8%	10.5%
Married	1.6%	4.5%	2.9%
Widowed	4.8%	14.4%	9.6%
Divorced	9.8%	20.4%	10.6%
Marital Status by Gender			
Never Married Male	13.5%	22.5%	9.0%
Married Male	1.7%	4.8%	3.1%
Widowed Male	3.2%	10.4%	7.2%
Divorced Male	7.2%	15.9%	8.7%
Never Married Female	16.5%	28.0%	11.5%
Married Female	1.4%	4.3%	2.9%
Widowed Female	5.2%	15.3%	10.1%
Divorced Female	11.2%	22.9%	11.7%
Age			
62 to 64	4.6%	9.2%	4.6%
65 to 69	4.1%	9.6%	5.5%
70 to 74	4.0%	9.6%	5.6%
75 to 79	4.0%	10.4%	6.4%
80 to 84	3.9%	11.1%	7.2%
85 to 89	4.7%	11.8%	7.1%

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on MINT3.

threshold, but not enough income to put them above the wage-adjusted poverty threshold. The difference in poverty rate measures is largest for high school dropouts, blacks and Hispanics, females, the never married, and older retirees. This is not surprising since these groups also had the highest price-adjusted poverty rates.

VI. CONTRIBUTIONS OF ECONOMIC, DEMOGRAPHIC, AND POLICY CHANGES TO POVERTY IN 2020

In this section we consider how projections of future poverty rates are influenced by changes in the Social Security NRA, the proportion of retirees who are unmarried, and average relative earnings and earnings inequality for post-1950 birth cohorts. For the reader's reference, we present results for both price-adjusted and wage-adjusted poverty rates; however, our discussion will focus on how the simulations impact wage-adjusted poverty rates.

1. Effects of Changes in the Normal Retirement Age

First, we consider what the poverty rate in 2020 would be if the NRA were not scheduled to increase. Under Social Security rules, individuals are paid their full Social Security benefit if they delay retirement until the NRA. Individuals may take up benefits before the NRA (beginning at age 62), but annual benefits are then reduced to adjust for the fact that early retirees receive benefits over a longer period.

The NRA is 65 for retirees born before 1938, and is scheduled to increase for those born in the year 1938 or later. Table 10-15 describes how the NRA changes by year of birth. As long as individuals wait until their NRA to collect Social Security benefits, they will receive the full amount of their benefits. Currently, most individuals do not wait until age 65 to collect Social Security retirement benefits. In 1999, more than half of the benefits awarded were to retirees who opted to begin receiving Social Security benefits at age 62 – despite the reduction in benefits (Social Security Administration, 2000, Table 6.A4).[10] For individuals who retired in 1999 (born prior to 1938), annual benefits can be reduced by as much as 20 percent for early retirement. As Table 10-15 shows, the annual benefit reduction for take-up at age 62 will be even greater for retirees born in 1938 or later. Early retirees in the 2020 population will have their benefits reduced by as much as 28.3 percent. Those born in 1960 or later will have their benefits reduced by as much as 30 percent.

To simulate the effects of changes in the NRA, we calculate the effect of restoring the NRA to age 65, so that the benefits of those who retire at age 62 will be reduced by only 20 percent. In this simulation, we continue to incorporate the MINT projections of changes among cohorts in their lifetime earnings patterns and demographic characteristics. Though it is not realistic, we also assume that individuals do not change their retirement behavior in response to a change in the NRA. The result should give us the marginal effect on 2020 poverty of changes in the NRA for more recent birth cohorts. We expect that restoring the NRA to age 65 will reduce

[10] This figure represents retired-worker benefits only and includes conversions from nondisabled widow(er)'s benefits to higher retired-worker benefits.

Table 10-15
NRA and Social Security Reduction Factors by Year of Birth

Birthyear	NRA	Reduction for Take-up at Age 62
1926-1937	65	20.0%
1938	65.17	20.8%
1939	65.33	21.7%
1940	65.50	22.5%
1941	65.67	23.3%
1942	65.83	24.2%
1943-1954	66	25.0%
1955	66.17	25.8%
1956	66.33	26.7%
1957	66.50	27.5%
1958	66.67	28.3%
1959	66.83	29.2%
1960+	67	30.0%

Source: Social Security Administration (2000).

projected poverty rates in 2020 by raising Social Security benefits for those born in 1938 or later.[11]

This is, in fact, the result we find. If the NRA were restored to 65, overall wage-adjusted poverty in 2020 would be 9.3 percent – 0.6 percentage points lower than the baseline poverty rate that MINT projects (Table 10-16). Poverty rates would fall for all sub-groups of the population. While the NRA remains unchanged for individuals age 82 and older, some of these older individuals have younger spouses receiving reduced benefits, and so their poverty is still slightly decreased by the simulation.

Changes in the NRA have differential effects on poverty rates among different sub-groups of the retiree population. Among racial and ethnic groups, the impact of increasing the NRA is larger for Hispanic retirees (from 18.5 percent to 17.4 percent) and for Asian/Native American retirees (from 11.9 percent to 11.1 percent). Among marital status/gender groups, divorced women and never married and divorced men are projected to experience the largest absolute decline in their poverty rates. Divorced female poverty rates shift from 22.9 percent under current law to 21.8 percent without the increase in the NRA. Never married male poverty rates shift from 22.5 percent to 21.1 percent and divorced male poverty rates shift from 15.9 percent to 14.7 percent. These results suggest that the reduction in the current law Social Security replacement rate will push a greater proportion of individuals with the lowest incomes below the poverty line (note that Social Security benefits are actually rising over time under current law because of wage indexing; the increase in the NRA, however, lowers the ratio of benefits to AIME).

[11] If individuals retire earlier in response to a reduction in the NRA, then the lower NRA will not raise their incomes, or reduce poverty, by as much as we estimate in the absence of this behavior.

Table 10-16
Simulation of the NRA at Age 65

	Price Adjusted Poverty			Wage Adjusted Poverty		
	Base	Sim.	Impact	Base	Sim.	Impact
Total	4.2%	3.9%	-0.3%	9.9%	9.3%	-0.6%
Educational Attainment						
High School Dropout	11.9%	11.5%	-0.4%	25.4%	24.2%	-1.2%
High School Graduate	3.8%	3.5%	-0.3%	9.6%	8.9%	-0.7%
College Graduate	2.1%	2.0%	-0.1%	4.8%	4.6%	-0.2%
Race						
White, non-Hispanic	3.1%	2.9%	-0.2%	7.7%	7.2%	-0.5%
Black	10.1%	9.6%	-0.5%	21.4%	20.7%	-0.7%
Hispanic	7.8%	7.2%	-0.6%	18.5%	17.4%	-1.1%
Asian/Native American	5.1%	5.0%	-0.1%	11.9%	11.1%	-0.8%
Gender						
Female	5.0%	4.7%	-0.3%	11.8%	11.2%	-0.6%
Male	3.1%	2.9%	-0.2%	7.5%	6.8%	-0.7%
Marital Status						
Never Married	15.3%	14.8%	-0.5%	25.8%	25.0%	-0.8%
Married	1.6%	1.4%	-0.2%	4.5%	4.0%	-0.5%
Widowed	4.8%	4.6%	-0.2%	14.4%	14.0%	-0.4%
Divorced	9.8%	9.0%	-0.8%	20.4%	19.3%	-1.1%
Marital Status by Gender						
Never Married Male	13.5%	12.7%	-0.8%	22.5%	21.1%	-1.4%
Married Male	1.7%	1.6%	-0.1%	4.8%	4.3%	-0.5%
Widowed Male	3.2%	2.9%	-0.3%	10.4%	9.7%	-0.7%
Divorced Male	7.2%	6.6%	-0.6%	15.9%	14.7%	-1.2%
Never Married Female	16.5%	16.1%	-0.4%	28.0%	27.5%	-0.5%
Married Female	1.4%	1.2%	-0.2%	4.3%	3.8%	-0.5%
Widowed Female	5.2%	5.0%	-0.2%	15.3%	14.9%	-0.4%
Divorced Female	11.2%	10.3%	-0.9%	22.9%	21.8%	-1.1%
Age						
62 to 64	4.6%	4.5%	-0.1%	9.2%	8.7%	-0.5%
65 to 69	4.1%	3.7%	-0.4%	9.6%	8.8%	-0.8%
70 to 74	4.0%	3.7%	-0.3%	9.6%	8.9%	-0.7%
75 to 79	4.0%	3.6%	-0.4%	10.4%	9.6%	-0.8%
80 to 84	3.9%	3.8%	-0.1%	11.1%	11.0%	-0.1%
85 to 89	4.7%	4.7%	0.0%	11.8%	11.8%	0.0%

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
4) No behavioral response to the change in the normal retirement age.
Source: Authors' calculations based on MINT3.

2. Effects of Changes in Marital Composition of Retirees Between Early 1990s and 2020.

Second, we consider what the poverty rate in 2020 would be if the marital composition of retirees in 2020 looked like that of retirees in 1990. Table 10-17 compares the marital composition of retirees in the early 1990's computed from SIPP data with the projected marital composition of retirees in 2020 using the MINT projections. The findings suggest that future retirees are more likely than their predecessors to be never married or divorced and less likely to be widowed. The projected change is more pronounced for female retirees than for male retirees. The share of divorced females in the 2020 retiree population is nearly 2.5 times higher than it was for their counterparts in the 1990s retiree population. Furthermore, the proportion of widowed females in the 2020 retiree population is projected to be 60 percent of what it was in the 1990s retiree population. Finally, a larger share of female retirees in 2020 will not have ever married. There are also pronounced differences in the marital composition of age groups. While the proportion of both widows and widowers increase at older ages, at all ages females are much more likely to be widowed than males. For the oldest age group, 35.9 percent of males were widowed in the early 1990s compared to 80.6 percent of females. These large differences are also expected for the future. These projections have implications for Social Security benefits, private pensions, and economic well-being in retirement.

The Social Security Administration pays retired-worker benefits, which are based on an individual's earnings history, to insured retirees. Because of auxiliary benefits, marital history also plays an important role in the computation of Social Security benefits. Individuals who are not insured based on their earnings may still be eligible for auxiliary benefits as (ex-)spouses or surviving (ex-)spouses of retired workers. These benefits are based on the earnings history of a living or deceased (ex-)spouse. When she becomes widowed, a woman may receive up to twice as much in auxiliary benefits as she did when she was married. The same is true for a divorced woman when her ex-husband dies. However, in order to qualify for any auxiliary benefits, divorced individuals must have been married to their living or deceased ex-spouses for at least ten years. Finally, because auxiliary benefits are paid only to those currently or previously married, individuals who never married are only eligible for retired-worker benefits at retirement. As the marital composition of retirees shifts toward more never married and divorced individuals, auxiliary benefits received will decline, for any given amount of a worker's own earnings. Therefore, we expect projected changes in the marital composition of the population to increase poverty rates among future retirees, particularly women.

The simulation we perform re-weights the 2020 population to produce the same marital composition within each sex and age group as existed in the early 1990s, holding constant average earnings and the distribution of average earnings in 2020. In most sex/age groups, this involves increasing the share of retirees who are married or widowed and decreasing the share of retirees who are never married or divorced. With this simulation we incorporate the projected changes across cohorts in the NRA and lifetime earnings patterns. The result gives us the marginal effect on 2020 poverty of changes in mortality and marital status for more recent birth cohorts. We expect poverty to be lower under the simulation because there will be fewer unmarried retirees.

Table 10-17
Marital Status of Retirees in 1990 and 2020, by Age and Sex

	Male		Female	
	1990	2020	1990	2020
All				
Never Married	4.9%	4.8%	4.4%	5.8%
Married	77.7%	75.0%	47.5%	51.3%
Widowed	10.8%	7.1%	40.5%	24.4%
Divorced	6.6%	13.1%	7.5%	18.4%
All	100.0%	100.0%	100.0%	100.0%
62-64				
Never Married	4.6%	6.6%	3.2%	7.6%
Married	80.9%	74.6%	61.4%	61.5%
Widowed	4.6%	4.1%	23.4%	11.8%
Divorced	9.9%	14.7%	11.9%	19.1%
All	100.0%	100.0%	100.0%	100.0%
65-69				
Never Married	6.1%	5.7%	4.4%	7.0%
Married	79.7%	74.8%	57.5%	58.2%
Widowed	6.2%	5.8%	28.8%	15.5%
Divorced	7.9%	13.7%	9.2%	19.2%
All	100.0%	100.0%	100.0%	100.0%
70-74				
Never Married	4.1%	4.0%	4.4%	5.3%
Married	80.2%	74.3%	47.9%	52.0%
Widowed	10.7%	7.7%	41.2%	22.6%
Divorced	5.0%	13.9%	6.6%	20.0%
All	100.0%	100.0%	100.0%	100.0%
75-79				
Never Married	4.8%	3.4%	4.6%	4.4%
Married	74.4%	74.1%	36.1%	45.5%
Widowed	16.1%	10.6%	53.5%	31.9%
Divorced	4.8%	11.9%	5.8%	18.1%
All	100.0%	100.0%	100.0%	100.0%
80-84				
Never Married	3.5%	2.8%	5.4%	4.4%
Married	67.7%	77.3%	21.9%	38.3%
Widowed	24.9%	10.3%	68.4%	41.0%
Divorced	3.8%	9.6%	4.3%	16.3%
All	100.0%	100.0%	100.0%	100.0%
85+				
Never Married	3.4%	2.5%	5.1%	3.8%
Married	58.9%	79.5%	11.2%	30.5%
Widowed	35.9%	10.5%	80.6%	52.9%
Divorced	1.8%	7.6%	3.2%	12.9%
All	100.0%	100.0%	100.0%	100.0%

Source: Authors' calculations based on 1990-1993 SIPP and MINT3 data.

If the marital composition of the 2020 retiree population were identical to that of the 1990's retiree population, the result is that overall wage-adjusted poverty in 2020 would be 9.4 percent – 0.5 percentage points lower than the baseline projection (Table 10-18). The simulation has the greatest impact on never married females whose poverty rates increase 1.3 percentage points - from 28.0 percent under the baseline projections to 29.3 percent under the simulation. The simulation decreases the share of younger never married females – those with higher

incomes and lower poverty rates – and increases the share of older never married females – those with lower incomes and higher poverty rates – to reflect the 1990 composition (see Table 10-17). The result is an increase in the overall poverty rate of never married females. A similar story explains the simulation's projected increase in the poverty rates of never married men.

Finally, poverty rates for retirees aged 75 do not decline with the simulation - most likely because this age group is comprised largely of widows. The simulation increases the proportion of widows in the 2020 retiree population and because their poverty rates tend to be relatively high, the result is that the poverty rate for this sub-group increases.

3. Effects of Changes in Relative Earnings for Post-1950 Birth Cohorts

Third, we consider what the poverty rate in 2020 would be if those born after 1950 had the same relative earnings as those born before 1950.[12] Table 10-19 reports projected average relative lifetime earnings by cohort in the MINT data. The data suggest that average lifetime earnings in relation to the national average wage will increase for retirees in each successive cohort through the 1946-50 cohort, after which average lifetime earnings will decline slightly. The data also underscore changes between male and female earnings patterns. Male retirees in the post-1945 cohorts are projected to have lower average lifetime earnings than do their predecessors, while female retirees in the post-1945 cohorts are projected to have higher average lifetime earnings than their predecessors.

The simulation is to make the average earnings of male and female retirees in the post-1950 cohorts look like the average earnings of their counterparts in the 1946-50 cohort. To do this, we increase average lifetime earnings for male retirees in the post-1950 cohorts and decrease average lifetime earnings for female retirees in the post-1950 cohorts. We continue to incorporate projected changes in the NRA, the dispersion of earnings within cohorts, and demographic characteristics. The result gives us the marginal effect on 2020 poverty of undoing changes in average lifetime earnings relative to the national average wage for more recent birth cohorts.

Table 10-20 reports the results of the simulation. We find that giving post-1950 birth cohorts the same relative average lifetime earnings as those born before 1950 would have no impact on the overall wage-adjusted poverty rate. This finding may appear counterintuitive because the simulation raises lifetime earnings of the entire population by undoing the decline in

[12] As discussed above in the methodology section, MINT projects the ratio of earnings to the national average wage.

Table 10-18
Simulation Holding the Marital Composition of 1990 Constant

	Percent of Retirees		Price Adjusted Poverty			Wage Adjusted Poverty		
	Base	Sim.	Base	Sim.	Impact	Base	Sim.	Impact
Total	100.0%	100.0%	4.2%	3.7%	-0.5%	9.9%	9.4%	-0.5%
Educational Attainment								
High School Dropout	10.6%	11.1%	11.9%	11.0%	-0.9%	25.4%	25.1%	-0.3%
High School Graduate	60.5%	60.5%	3.8%	3.3%	-0.5%	9.6%	8.8%	-0.8%
College Graduate	28.9%	28.3%	2.1%	1.8%	-0.3%	4.8%	4.3%	-0.5%
Race								
White, non-Hispanic	79.5%	79.3%	3.1%	2.7%	-0.4%	7.7%	7.1%	-0.6%
Black	8.8%	8.7%	10.1%	9.3%	-0.8%	21.4%	20.9%	-0.5%
Hispanic	7.6%	7.7%	7.8%	7.0%	-0.8%	18.5%	17.8%	-0.7%
Asian/Native American	4.1%	4.3%	5.1%	5.5%	0.4%	11.9%	12.3%	0.4%
Gender								
Female	56.2%	56.2%	5.0%	4.4%	-0.6%	11.8%	11.3%	-0.5%
Male	43.8%	43.8%	3.1%	2.8%	-0.3%	7.5%	6.9%	-0.6%
Marital Status								
Never Married	5.4%	4.6%	15.3%	15.9%	0.6%	25.8%	26.6%	0.8%
Married	61.7%	59.6%	1.6%	1.6%	0.0%	4.5%	4.4%	-0.1%
Widowed	16.8%	28.7%	4.8%	4.7%	-0.1%	14.4%	14.2%	-0.2%
Divorced	16.1%	7.2%	9.8%	9.8%	0.0%	20.4%	19.8%	-0.6%
Marital Status by Gender								
Never Married Male	2.1%	2.1%	13.5%	13.7%	0.2%	22.5%	23.5%	1.0%
Married Male	32.8%	33.9%	1.7%	1.7%	0.0%	4.8%	4.6%	-0.2%
Widowed Male	3.1%	4.8%	3.2%	2.9%	-0.3%	10.4%	10.1%	-0.3%
Divorced Male	5.8%	2.9%	7.2%	7.4%	0.2%	15.9%	15.7%	-0.2%
Never Married Female	3.3%	2.5%	16.5%	17.7%	1.2%	28.0%	29.3%	1.3%
Married Female	28.8%	25.6%	1.4%	1.4%	0.0%	4.3%	4.2%	-0.1%
Widowed Female	13.7%	23.8%	5.2%	5.1%	-0.1%	15.3%	15.1%	-0.2%
Divorced Female	10.4%	4.3%	11.2%	11.3%	0.1%	22.9%	22.5%	-0.4%
Age								
62 to 64	19.6%	19.6%	4.6%	3.8%	-0.8%	9.2%	8.1%	-1.1%
65 to 69	27.9%	27.9%	4.1%	3.4%	-0.7%	9.6%	8.7%	-0.9%
70 to 74	22.5%	22.5%	4.0%	3.5%	-0.5%	9.6%	8.4%	-1.2%
75 to 79	14.5%	14.5%	4.0%	3.6%	-0.4%	10.4%	10.4%	0.0%
80 to 84	9.6%	9.6%	3.9%	4.1%	0.2%	11.1%	12.3%	1.2%
85 to 89	6.0%	6.0%	4.7%	5.2%	0.5%	11.8%	13.2%	1.4%

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on MINT3.

Table 10-19
Average Lifetime Earnings, by Cohort

	1931-35	1936-40	1941-45	1946-50	1951-55	1956-60
All	0.67	0.72	0.75	0.80	0.79	0.78
Male	1.05	1.08	1.08	1.06	1.01	0.97
Female	0.32	0.38	0.45	0.55	0.58	0.60

Note: Average lifetime earnings are computed as the average of relative earnings from age 22 through age 62.
Source: Authors' calculations based on the MINT3 data.

Table 10-20
Simulation Holding Earnings Constant Between Cohorts

	Price Adjusted Poverty			Wage Adjusted Poverty		
	Base	Sim.	Impact	Base	Sim.	Impact
Total	4.2%	4.2%	0.0%	9.9%	9.9%	0.0%
Educational Attainment						
High School Dropout	11.9%	11.8%	-0.1%	25.4%	25.0%	-0.4%
High School Graduate	3.8%	3.9%	0.1%	9.6%	9.6%	0.0%
College Graduate	2.1%	2.2%	0.1%	4.8%	5.0%	0.2%
Race						
White, non-Hispanic	3.1%	3.2%	0.1%	7.7%	7.7%	0.0%
Black	10.1%	10.1%	0.0%	21.4%	21.5%	0.1%
Hispanic	7.8%	8.0%	0.2%	18.5%	18.3%	-0.2%
Asian/Native American	5.1%	5.3%	0.2%	11.9%	12.2%	0.3%
Gender						
Female	5.0%	5.1%	0.1%	11.8%	11.8%	0.0%
Male	3.1%	3.1%	0.0%	7.5%	7.4%	-0.1%
Marital Status						
Never Married	15.3%	15.7%	0.4%	25.8%	25.7%	-0.1%
Married	1.6%	1.6%	0.0%	4.5%	4.5%	0.0%
Widowed	4.8%	4.8%	0.0%	14.4%	14.3%	-0.1%
Divorced	9.8%	9.9%	0.1%	20.4%	20.5%	0.1%
Marital Status by Gender						
Never Married Male	13.5%	12.7%	-0.8%	22.5%	21.6%	-0.9%
Married Male	1.7%	1.7%	0.0%	4.8%	4.7%	-0.1%
Widowed Male	3.2%	3.0%	-0.2%	10.4%	10.2%	-0.2%
Divorced Male	7.2%	7.2%	0.0%	15.9%	15.8%	-0.1%
Never Married Female	16.5%	17.6%	1.1%	28.0%	28.3%	0.3%
Married Female	1.4%	1.4%	0.0%	4.3%	4.3%	0.0%
Widowed Female	5.2%	5.2%	0.0%	15.3%	15.2%	-0.1%
Divorced Female	11.2%	11.4%	0.2%	22.9%	23.0%	0.1%
Age						
62 to 64	4.6%	4.7%	0.1%	9.2%	9.1%	-0.1%
65 to 69	4.1%	4.2%	0.1%	9.6%	9.5%	-0.1%
70 to 74	4.0%	4.0%	0.0%	9.6%	9.5%	-0.1%
75 to 79	4.0%	4.0%	0.0%	10.4%	10.5%	0.1%
80 to 84	3.9%	3.9%	0.0%	11.1%	11.1%	0.0%
85 to 89	4.7%	4.8%	0.1%	11.8%	11.8%	0.0%

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on MINT3.

relative earnings for those born after 1950. But the decrease in poverty from the increase in earnings of males is almost entirely offset by the increase in poverty from the decrease in earnings of females. This is because women contribute more to the overall poverty rate in 2020 than men by constituting a larger share of the population and by being nearly twice as likely as to be poor in retirement (Table 10-9). Restoring the average earnings of earlier cohorts to those of later cohorts has the greatest adverse impact on Asian/Native Americans and never married females – increasing their poverty rates by 0.3 percentage points. The simulation has the greatest positive impact on never married males – decreasing their poverty rate by 0.9 percentage points.

4. Effects of Changes in the Earnings Distribution for Post-1950 Birth Cohorts

Finally, we examine what would happen to the poverty rate in 2020 if those born after 1950 had the earnings distribution of those born before 1950. Projections of average lifetime earnings in the MINT data indicate that the earnings distribution will be less dispersed for post-1950 cohorts than it was for earlier cohorts – suggesting less earnings inequality among post-1950 cohorts (Table 10-21). The findings also highlight changes in the lifetime earnings distributions between male and female retirees. The distribution of average lifetime earnings is projected to be more dispersed for male retirees in the post-1950 cohorts (more inequality) and less dispersed for female retirees in the post-1950 cohorts (less inequality).

The simulation is to make the earnings distribution of male and female retirees in the post-1950 cohorts look like the earnings distribution of their counterparts in the 1946-50 cohort, holding average earnings within each cohort constant. For male retirees in the post-1950 cohorts, this means increasing the average lifetime earnings of those in the bottom quintiles and decreasing the average lifetime earnings of those in the top quintiles. For female retirees in the post-1950 cohorts, this means decreasing the average lifetime earnings of those in the bottom quintiles and increasing the average lifetime earnings of those in the top quintiles. Within each cohort, we hold average lifetime earnings constant. With this simulation we incorporate the changes between cohorts in their NRA, average lifetime earnings, and demographic characteristics that MINT projects. The result gives us the marginal effect on 2020 poverty of changes in the distribution of lifetime earnings for more recent birth cohorts.

We find that changes in the lifetime earnings distribution have no impact on the overall wage-adjusted poverty rate (Table 10-22). For most sub-groups of the population, the impact of the simulation is negligible. The simulation slightly increases the poverty rates of college graduates (from 4.8 to 4.9 percent) and Asian/Native American retirees (from 11.9 to 12.1 percent). This suggests that the distribution of average lifetime earnings of members of these sub-groups has changed since the 1946-50 cohort – with fewer of their members located in the bottom income quintile. As a result, imposing a 1946-50 lifetime earnings distribution on these cohorts pushes a number of these people into poverty.

Table 10-21
Distribution of Average Lifetime Earnings, by Cohort

Ratio of Fifth to First Quintile	1926-35	1936-40	1941-45	1946-50	1951-55	1956-60
All	13.90	11.82	12.39	13.04	13.09	12.56
Male	9.71	8.37	9.26	10.49	11.08	10.77
Female	104.13	50.78	28.48	20.36	17.49	16.09

Note: Average lifetime earnings are computed as the average of relative earnings from age 22 through age 62.
Source: Authors' calculations based on the MINT data.

Table 10-22
Simulation Holding the Earnings Distribution Constant Between Cohorts

	Price Adjusted Poverty			Wage Adjusted Poverty		
	Base	Sim.	Impact	Base	Sim.	Impact
Total	4.2%	4.3%	0.1%	9.9%	9.9%	0.0%
Educational Attainment						
High School Dropout	11.9%	11.9%	0.0%	25.4%	25.3%	-0.1%
High School Graduate	3.8%	3.9%	0.1%	9.6%	9.6%	0.0%
College Graduate	2.1%	2.2%	0.1%	4.8%	4.9%	0.1%
Race						
White, non-Hispanic	3.1%	3.2%	0.1%	7.7%	7.7%	0.0%
Black	10.1%	10.1%	0.0%	21.4%	21.4%	0.0%
Hispanic	7.8%	7.9%	0.1%	18.5%	18.2%	-0.3%
Asian/Native American	5.1%	5.4%	0.3%	11.9%	12.1%	0.2%
Gender						
Female	5.0%	5.1%	0.1%	11.8%	11.7%	-0.1%
Male	3.1%	3.2%	0.1%	7.5%	7.5%	0.0%
Marital Status						
Never Married	15.3%	15.7%	0.4%	25.8%	25.8%	0.0%
Married	1.6%	1.6%	0.0%	4.5%	4.5%	0.0%
Widowed	4.8%	4.9%	0.1%	14.4%	14.3%	-0.1%
Divorced	9.8%	9.9%	0.1%	20.4%	20.3%	-0.1%
Marital Status by Gender						
Never Married Male	13.5%	13.4%	-0.1%	22.5%	22.4%	-0.1%
Married Male	1.7%	1.8%	0.1%	4.8%	4.8%	0.0%
Widowed Male	3.2%	3.0%	-0.2%	10.4%	10.4%	0.0%
Divorced Male	7.2%	7.4%	0.2%	15.9%	15.8%	-0.1%
Never Married Female	16.5%	17.2%	0.7%	28.0%	27.9%	-0.1%
Married Female	1.4%	1.4%	0.0%	4.3%	4.2%	-0.1%
Widowed Female	5.2%	5.3%	0.1%	15.3%	15.2%	-0.1%
Divorced Female	11.2%	11.3%	0.1%	22.9%	22.8%	-0.1%
Age						
62 to 64	4.6%	4.9%	0.3%	9.2%	9.2%	0.0%
65 to 69	4.1%	4.1%	0.0%	9.6%	9.5%	-0.1%
70 to 74	4.0%	4.0%	0.0%	9.6%	9.5%	-0.1%
75 to 79	4.0%	4.0%	0.0%	10.4%	10.4%	0.0%
80 to 84	3.9%	3.9%	0.0%	11.1%	11.1%	0.0%
85 to 89	4.7%	4.8%	0.1%	11.8%	11.8%	0.0%

Notes:
1) Uses a real discount rate of 3.0% to convert wealth to asset income.
2) Annuitizes 80% of wealth.
3) Imputed rental income is excluded from total family income.
Source: Authors' calculations based on MINT3.

VII. CONCLUSIONS

The Social Security Administration's Model of Income in the Near Term (MINT) projects that the overall price-adjusted poverty rate of the aged population will decline from 7.8 percent in the early 1990s to 4.2 percent in 2020 (a 46 percent reduction). For most sub-groups of the 2020 retiree population, poverty rates are projected to be lower than for their predecessors; however, despite increased earnings of women and projected real wage growth, some sub-groups of the population will continue to experience persistently high poverty rates in the future. With increases in Social Security benefits through wage growth and increased Social Security coverage rates, Social Security and earnings alone are projected to keep all but 10 percent of the aged population out of poverty in 2020 – a drop from 28 percent in the early 1990s.

This chapter examines the factors affecting the projected changes in poverty among 62- to 89-year olds between the early 1990s and 2020. We focus on five possible factors: changes in wage growth, scheduled increases in the NRA, changes in the marital composition of future retirees, and changes in the level and distribution of earnings among more recent birth cohorts. Not surprisingly, projections of overall real wage growth – determined outside of MINT – have the largest effect on poverty rates in 2020. When we assume that poverty thresholds increase with wages, instead of prices, overall poverty rates in 2020 increase by 5.7 percentage points to 9.9 percent (which is 27 percent higher than the early 1990s poverty rate of 7.8 percent). The hardest hit were those who were already at risk of poverty – high school dropouts, blacks and Hispanics, women, the unmarried, and the oldest of the aged population.

Controlling for wage growth, we find that projected changes in poverty rates were affected much more by projected changes in the NRA and marriage patterns than by changes in earnings patterns. When we restored the NRA to age 65, thereby reducing the early retirement penalty to Social Security benefits, we found that overall wage-adjusted poverty rates decreased by 0.6 percentage points. By imposing the gender/age/marital status composition of the early 1990s retirees on the 2020 retirees, we found that overall wage-adjusted poverty rates decreased by 0.5 percentage points. Changes in the distribution of earnings between and within cohorts had no effect on future poverty rates.

It was somewhat surprising how little impact that changes in the level and distribution of earnings had on future poverty rates. On the other hand, the progressive Social Security payment formula replaces a greater share of earnings for those in the bottom of the earnings distribution. It also caps payments at the top of the distribution. The progressive payment formula makes the distribution of retirement income much more equal than it otherwise would be. Also our findings suggest, though, that a large part of the increase in female earnings was offset by decreases in male earnings.

Finally, we note several limitations of MINT that may affect the results. MINT does not model behavioral responses to policy changes. MINT directly measures the experiences of survey respondents up to the early 1990s and statistically projects their characteristics into the future, adjusting for expected demographic and socioeconomic changes. The model implicitly assumes that future populations will behave the same way as past populations with regard to such choices as educational attainment, marriage partners, job types, and the decision to work.

Furthermore, MINT assumes that the interdependence of the outcomes from such choices, like education and earnings, will remain unchanged in the near future.

MINT does not project immigration, so, while it includes immigrants captured in the SIPP, it does not represent who immigrated after the survey and those will immigrate in future years. Because immigrants have lower average income than native-born Americans, MINT understates true poverty by not including them. Projected immigration might be included in future modeling work. Also, MINT does not project all sources of income. While these non-imputed sources in aggregate are small, they can be very important for measuring the numbers who fall below a fixed poverty threshold.

Finally, MINT does not include all the elderly. In 2020, it is missing those age 90 and over. These oldest old have historically had the highest poverty rates. MINT understates aged poverty rates by omitting them. Although this group is very small and therefore contributes little to the aggregate poverty rate, it is growing over time.

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APPENDIX TO CHAPTER 10

COMPARISON WITH MINT1 POVERTY RATES

Smith and Toder (1999) used projections from MINT1 to project poverty rates among the retired population in 2020. The authors estimated that the poverty rate among retirees would increase from 7.9 percent in the early 1990s (about the same as the 7.8 percent poverty estimate in the same period in this chapter) to 8.5 percent in 2020. Thus, Smith and Toder (1999) project poverty rates in 2020 that are about 4.3 percentage points above the poverty rates we project using MINT3.

Although changes in methodology in MINT3 account for some of the difference between these results and those of Smith and Toder (1999), the main source of the more optimistic projection of future poverty rates is the use of updated data on the growth in economy-wide wages. The actual growth in productivity and real wages in the late 1990s was much greater than the projected wage growth used in MINT1; the higher baseline wages raise the level of 2020 average earnings currently projected by OCACT. This change in economic assumptions is external to MINT. The large productivity gains of the late 1990s have made prospects for future retirees look much better than they appeared even a few years ago.[13]

A second major difference in these projections compared to Smith and Toder (1999) is that these projections include all individuals age 62 to 89. MINT1 projected retirement to begin at either age 62 or 67. Individuals in the later cohorts who did not retire at age 62 were not included in the analysis because of a limitation in the model. MINT3 projects incomes from age 50 (or the SIPP interview age if older than 50) until death. MINT3 includes many more individuals who work. These workers tend to have higher incomes and lower poverty rates compared to non-workers. Including these workers lowers the aggregate poverty rates in 2020.

A third major difference in these projections compared to Smith and Toder (1999) is that MINT3 projects two additional sources of incomes: SSI and non-spouse co-resident income. SSI spending is extremely small, but half of SSI recipients get benefits high enough to lift them out of poverty. Co-resident income is much more substantial and is always poverty reducing. About 14 percent of individuals age 62 to 89 are projected to co-reside and about three percent will receive SSI. Omitting co-resident income increases poverty rates in 2020 from 4.2 percent to 5.4 percent. Omitting both co-resident income and SSI increases poverty rates in 2020 to 5.8 percent.

[13] The average earnings in 2020 in MINT1 was $69,334 and the poverty threshold for a couple was $21,426 (31 percent of the average wage). In MINT3, the average earnings in 2020 is $75,209 and the poverty threshold for a couple is $19,672 (26 percent of the average wage). A couple projected to have family income between 26 and 31 percent of the average earnings would be in poverty in MINT1, but not in MINT3.

CHAPTER 11

CONCLUDING COMMENTS

I. PROJECTIONS FOR POLICY ANALYSIS

MINT3 produces a micro dataset suitable for projecting the distributional consequences of current population and economic trends and for analyzing the impact of changes both in Social Security policy and in other important components of the income security system. It incorporates behavioral responses to policy and economic changes by making the decision to retire, claim Social Security benefits and continue to work after retirement endogenous. It also introduces explicit consideration of the living arrangements of the elderly and their claiming of Supplemental Security Income benefits.

Table 11-1 explores the role that MINT3 could play in analyzing a number of Social Security policy changes that have been suggested recently. As noted, MINT3 is capable of analyzing both the labor supply and distributional impacts of many of these proposals, particularly those involving changes in the benefit formula and in the structure of dependents' benefits. In many other cases, MINT3 is able to inform the analysis of a particular policy impact, even though it may be necessary to supplement the MINT3 model with some assumptions about savings or other impacts not modeled in MINT3.

II. POTENTIAL AREAS FOR FUTURE MODEL DEVELOPMENT

The validation and sensitivity tests revealed several areas in which the MINT model might be improved. One particularly promising area involves the use of additional information found in the Detailed Earnings file in constructing the matched earnings records, including earnings above the taxable maximum, earnings in employment not covered by Social Security, and the division of earnings into earnings from self-employment and those from employment. The addition of this information to the MINT matched earnings records should allow improved estimates of many of the income sources and of retirement decisions.

Estimates of earnings above the maximum would allow us to generate better estimates of the pension and asset income that will be available to the highest earners in the MINT sample and of their earnings after age 50. In turn, these improvements should lead to better estimates of retirement decisions. Estimates of earnings from employment not covered by Social Security should improve our ability to estimate pension income from noncovered employment and the asset holdings of people who have noncovered earnings. Each of these improvements would also help improve estimates of the retirement decision. Finally, generating separate estimates of income from self-employment should allow us to take better account of the tendency of workers to shift to self-employment as they approach retirement age and thereby produce better estimates of

Table 11-1
Simulating Policy Changes with MINT 3

Policy Change	Suitability of MINT3 for Analysis	
	Distributional Impacts	**Behavioral Impacts**
Financing Changes:		
Raise payroll tax rates	Not particularly suited	No built-in behavioral impacts
Increase income taxation	Could analyze impact on retirement income, but would first have to add income tax module and ability to track taxability of different assets, deductions for itemizers.	No built-in behavioral impacts. Could analyze distributional impact of assumptions about savings response.
Raise taxable maximum	Could analyze impact on benefit distribution, but would first have to add earnings above the current maximum.	No built-in behavioral impacts. Could analyze distributional impact of assumptions about savings response.
Invest Trust Fund in equities	Not particularly suited	No obvious behavioral impacts that model could simulate.
Coverage Changes:		
Cover remaining state and local employees	Could analyze impact on retirement income, but would first have to add earnings from employment not now covered by Social Security	No obvious behavioral impacts that model could simulate.
Entitlement Changes:		
Raise early retirement age or age of first eligibility for widow(er)'s benefits.	Can analyze impact of alternatives assumptions about behavioral impact on retirement income, given assumptions about impact on disability incidence.	Predicting change in retirement or savings behavior would require projecting outside of current data observations. Model could simulate SSI claiming and other labor supply effects, given retirement and savings behavior.
Relax disability definition for certain age groups	Can analyze impact on retirement income of different assumptions about changes in disability incidence rates.	Current version not set up to predict DI or SSI benefit claiming response to changes in disability rules.
Individual Accounts		
Mandatory (carve out or add on)	Can analyze impact on retirement income given assumptions about net returns to accounts.	Can estimate OASI & SSI claiming and labor supply responses, given assumptions about savings responses and net returns; can estimate distributional impact of different assumptions about savings response.

Table 11-1 Continued

Policy Change	Suitability of MINT3 for Analysis	
	Distributional Impacts	Behavioral Impacts
Voluntary (carve out or add on)	Can analyze impact on retirement income given assumptions about net returns to accounts and participation patterns.	Can estimate OASI & SSI claiming and labor supply responses, given assumptions about participation rates, savings responses and net returns; can estimate distributional impact of different assumptions about savings response.
Government matching contribution for low income workers	Can analyze impact on retirement income given assumptions about net returns to accounts and participation patterns.	Can estimate OASI & SSI claiming, and labor supply responses, given assumptions about participation rates, savings responses and net returns; can estimate distributional impact of different assumptions about savings response.
Worker Benefit Changes:		
Raise normal retirement age	Can analyze impact on retirement incomes, given assumptions about impact on disability incidence.	Can estimate OASI & SSI claiming and labor supply response of the nondisabled, given assumptions about savings responses. Can analyze impact of different assumptions about disability response.
Reduce COLA or increase the DRC	Can analyze impact on retirement incomes.	Can estimate OASI & SSI claiming and labor supply response.
Increase actuarial reduction	Can analyze impact on retirement incomes, given assumptions about impact on disability incidence.	Can estimate changes in OASI & SSI claiming and the labor supply response of the nondisabled. Can analyze impact of different assumptions about disability response.
Change benefit formula brackets & marginal rates	Can analyze impact on retirement incomes.	Can estimate OASI & SSI claiming and labor supply response.
Increase averaging period	Can analyze impact on retirement incomes.	Can estimate OASI & SSI claiming and labor supply response.
Award child care drop out years	Depending on specifics of proposal, should be able to analyze impact on retirement incomes. (Have information on number and ages of children.)	Can estimate OASI & SSI claiming and labor supply response of any particular proposal that model can simulate.
Add minimum benefit or increase the special minimum	Can analyze impact on retirement incomes.	Can estimate OASI & SSI claiming and labor supply response.

Table 11-1 Continued

Policy Change	**Suitability of MINT3 for Analysis**	
	Distributional Impacts	**Behavioral Impacts**
Income test benefits	Depending on specifics of proposal, should be able to analyze impact on retirement incomes, given alternative assumptions about impacts on savings behavior.	Can estimate impact on OASI & SSI claiming. Impact on labor supply may be complicated, depending on structure of proposal. Would have to make alternative assumptions about savings impacts.
Auxiliary Benefit Changes:		
Reduce spouses' benefit	Can analyze impact on retirement incomes.	Can estimate OASI & SSI claiming and labor supply response.
Base widow(er)'s benefit on combined earnings	Can analyze impact on retirement incomes.	Can estimate OASI & SSI claiming and labor supply response.
Introduce earnings sharing at divorce	Can analyze impact on retirement incomes.	Can estimate OASI & SSI claiming and labor supply response.
Eliminate children's benefits for living workers or reduce maximum family benefit	Model does not now estimate children's benefits.	
Means-test auxiliary benefits	Depending on specifics of proposal, should be able to analyze impact on retirement incomes.	Can estimate OASI & SSI claiming and labor supply response.
SSI Changes		
Increase national guarantee	Can analyze impact on retirement incomes	Can estimate impact on SSI eligibility and take-up rates.
Eliminate asset test; impute asset income	Can analyze impact on retirement incomes	Can estimate impact on SSI eligibility and take-up rates
Reduce age of eligibility to 62	Can analyze impact on retirement incomes	Can estimate impact on SSI eligibility and take-up rates
Change benefit reduction rates	Can analyze impact on retirement incomes	Can estimate impact on SSI eligibility and take-up rates

the split between employment and self-employment among future cohorts. Better modeling of this shift will also improve our predictions of pension and asset income by allowing explicit recognition of the different asset accumulation patterns and pension arrangements of the self-employed.

Our sensitivity tests suggested that these data elements could be added to the earnings matching process without significant difficulties. Their addition did not appear to make finding good donors for each target record more difficult. Before a new baseline is created using these additional data elements, however, a more careful review is needed of the quality of the data currently found in these additional data elements. Our work did not turn up any serious quality issues, other than those already known, but we also did not specifically look for data problems. In addition, more careful analysis will be needed of the implications of different strategies generating matches using earnings above the taxable maximum. Using the current matching algorithm will substantially increase the size of the adjustments needed to equalize five-year average earnings variables among the highest earners, with unknown consequences for the quality of the resulting career earnings records. Changing to an algorithm that matched to the nearest neighbor would reduce this problem, but would not eliminate it, and could introduce other problems, such as finding that one record was being overused as a donor. Introducing any of these additional data elements will also require reestimation of many of the asset, pension, earnings and retirement decision equations.

A second potential improvement involves adding future immigrants to the MINT population. Our sensitivity tests suggested that inserting additional records to represent future immigrants was not a particularly difficult computational step. The larger challenge may be the development of the assumptions about the number and source of future immigrants. The addition of future immigrants will probably produce more accurate estimates of the distribution of future benefits and the size of the future population in poverty. It should also provide more realistic estimates of the future SSI caseload, although projecting the impact of the current restrictions on immigrant eligibility will be a challenge.

The implications of our test of an alternative treatment of marital status are less clear. Implementing the alternative approach to creating the matched earnings records required a six-fold multiplication in the number of donor pools, undoubtedly reducing the quality of some of the matches. The alternative approach did not increase the correlation between husband's and wife's earnings, but probably did improve the link between changes in marital status and changes in labor force behavior. Determining the net impact of all of these changes on the quality of the resulting earnings records probably requires more analysis than we were able to do under this contract.

The pension chapter notes three areas where additional work could improve the MINT model. One is an improved job history module that ties job tenure and job changes more closely to the earnings projections. A second is the development of a more sophisticated mechanism for determining the characteristics of the pension plans in which state and local workers participate. Ideally, an alternative should be developed that uses an approach similar to that now used to assign plan characteristics to private sector workers. Finally, it would be desirable to simulate the formation of future IRAs for current cohort members. The model currently handles all IRAs that exist at the time of the SIPP interview and, indirectly, all IRAs subsequently created through rollovers from employer-sponsored pension plans. It does not, however, allow for new IRAs that are created with new money after the SIPP interview date.

Another area of potential improvement is the treatment of defined benefit pensions in divorces. The current model makes no adjustment to either the financial assets or the future defined benefit pension income of parties to a divorce as long as the divorce occurs prior to the receipt of pension benefits. Pensions in payment status are divided equally. Although the future value of a defined benefit pension may in fact be ignored in most current divorce proceedings, it is surely an oversimplification of the situation when long-term marriages end in divorce near to the retirement age of one or both partners. By ignoring the adjustments made in these latter cases, we are underestimating the income of divorced women and overestimating the income of divorced men, although we don't know by how much. While improving the treatment of defined benefit pensions in divorce is desirable, it may require additional research on current practices and is likely to involve some moderately challenging changes in the structure of the computer processing.

As noted in the discussion of the retirement equations, the model appears to over predict slightly the incidence of Social Security benefit take-up at age 64 and under predict slightly the incidence of retirement at age 65. In the course of estimating the retirement equations, we noticed that self-reports of age at retirement often differed slightly from administrative records. It may be useful at some future date to explore the reasons for this difference. In particular, one might explore whether the administrative records tend to show slightly lower retirement ages than either self-reports or data on the actual age at benefit award because of a tendency for individuals to back date claims and obtain lump-sum retroactive payments, when their situation allows.

Several minor categories of adult beneficiaries are not now projected by MINT. Probably, the two most important are disabled widow(er)s and surviving spouses entitled by the presence of entitled children. As part of a future package of MINT modifications, it may be desirable to add these two categories of beneficiaries. In principle, the information needed to simulate each category is currently being generated in the MINT projection process. We are already estimating the number of children ever born and using the results in the simulation of living arrangements. The same estimates ought to provide a basis for projecting entitlement among surviving spouses caring for entitled children. Before adding disabled widow(er)s to the MINT simulations it would be necessary to evaluate the accuracy of the disability assignments growing out of the earnings matches. Assuming these were producing plausible results, the addition of the benefit category would not be difficult. Explicit recognition of disabled widow(er) beneficiaries would allow simulations of the impact of proposals to liberalize the treatment of these beneficiaries. It would also provide a more accurate projection of the benefit after age 62 of persons who had previously received disabled widow(er)s benefits.

A final issue meriting attention is the unification of the benefit calculators. At present, MINT employs two benefit calculators. One is used to project alternative measures of Social Security wealth for the purposes of simulating retirement behavior. The other is used to calculate the actual Social Security benefit received. The use of the two separate calculators complicates somewhat the simulation of benefit changes that might affect the retirement decision, since it requires that the change be separately programmed into each calculator. In principle, the calculator used for final benefit calculations could also be used for simulating the retirement decision, although converting to the alternative calculator would require reestimating the retirement equations.

III. CONCLUDING OBSERVATIONS

MINT3 builds on the work previous done under the MINT1 contract by researchers from the Brookings Institution, RAND, and the Urban Institute. In some cases, MINT3 adds new simulation capability that was not present in MINT1. In other cases, it introduces refinements to the projection techniques used to construct MINT1. The need for many of these refinements only became clear after the initial MINT1 results could be carefully analyzed.

The major changes introduced in MINT3 include:

- A new technique for generating individual earnings records that relies on statistical matching to preserve a greater degree of individual variation in earnings experience, produce more realistic distributions of lifetime earnings patterns and better link lifetime earnings with key demographic factors, such as ethnicity and education.

- A new technique for determining which workers become disabled and tracking the earnings of disabled workers after the onset of disability. The new technique allows the incidence of disability among each birth cohort and age group to be adjusted to match external assumptions, particularly those used in Social Security cost projections.

- A new technique for determining mortality which links the mortality projections to the actual experience of workers at different education and earnings levels. This technique also allows total mortality in the projected population to be adjusted to external control totals, such as those contained in the Trustees' Report.

- A new procedure for modeling the retirement decision which separates the decision to retire from the career job from the decision to file for Social Security benefits, providing a more satisfactory way of handling bridge jobs and other mechanisms for phasing in retirement. The new model also incorporates current pension entitlements and the impact of continued work on future entitlements into the retirement decision.

- New pension modules that provide more accurate estimates of both defined benefit and defined contribution pension plans. Individual workers projected to be covered by defined benefit plans are assigned to one of a number of different plans through a new procedure that recognizes the variety of different defined benefit arrangements now in existence and reproduces the approximate distribution of workers among such different plan types. Similarly, those participating in defined contribution plans are assigned different combinations of employer and employee contribution rates and are assumed to make different asset allocation decisions in accordance with actual distributions of each variable.

- A new asset accumulation module that relates better controls for differences in actual and projected initial wealth holdings, better controls for life-time earnings and retirement, and better controls for private pensions.

- A new procedure to simulate living arrangements of the elderly, SSI eligibility and the SSI take-up decision. This is an entirely new module for the MINT model and allows the analysis of more complex policy proposals that combine changes in the insurance program with enhancements of the safety net provided by the companion assistance program.

- A new procedure to simulate the characteristics and income of co-resident family members to allow better measures of the well-being of co-residing retirees.

Each of these is a valuable addition to the MINT model. Together, they substantially strengthen MINT's ability to project the future status of the aged and simulate the impact that Social Security policy changes will have on the economic status of the aged.