



Penn Institute for Economic Research
Department of Economics
University of Pennsylvania
3718 Locust Walk
Philadelphia, PA 19104-6297
pier@econ.upenn.edu
<http://www.econ.upenn.edu/pier>

PIER Working Paper 06-004

“The Role of Labor and Marriage Markets, Preference Heterogeneity and the Welfare System in the Life Cycle Decisions of Black, Hispanic and White Women”

by

Michael P. Keane and Kenneth I. Wolpin

<http://ssrn.com/abstract=889550>

The Role of Labor and Marriage Markets, Preference Heterogeneity and the Welfare System
in the Life Cycle Decisions of Black, Hispanic and White Women

by

Michael P. Keane

Yale University

and

Kenneth I. Wolpin

University of Pennsylvania

January, 2006

Abstract

Using data from the NLSY79, we structurally estimate a dynamic model of the life cycle decisions of young women. The women make joint and sequential decisions about school attendance, work, marriage, fertility and welfare participation. We use the model to perform a set of counterfactual simulations designed to shed light on three questions: (1) How much of observed minority-majority differences in behavior can be attributed to differences in labor market opportunities, marriage market opportunities, and preference heterogeneity? (2) How does the welfare system interact with these factors to augment those differences? (3) How can new cohorts that grow up under the new welfare system (TANF) be expected to behave compared to older cohorts?

The authors are grateful for support from NICHD under grant HD-34019 and from several grants from the Minnesota Supercomputer Institute. An early version of this work appeared under the title "Public Welfare and the Life Cycle Decisions of Young Women."

Keywords: female life cycle behavior, labor market opportunities, marriage market opportunities, public welfare.

JEL: J1, J2, J3

I. Introduction

The large differences in economic and demographic characteristics of majority (white) vs. minority (black and Hispanic) women are well documented. To get a picture of the extent of these differences, consider data drawn from the 1990 survey year of the NLSY79, when respondents were between the ages of 25 and 33. At the time of that survey, (i) the mean schooling of white women (13.4 years) exceeded that of black women by .6 years and that of Hispanic women by 1.3 years, (ii) 65 percent of white women, but only 32 percent of black women, and 55 percent of Hispanic women, were married and living with their spouse, (iii) the white women had borne, on average, 1.2 children, while blacks and Hispanics both had 1.7 children on average, (iv) 74 percent of the white women, 66 percent of the black women and 67 percent of the Hispanic women were employed, and (v) in the year prior to the survey, 4 percent of the white women, 20 percent of the black women and 11 percent of the Hispanic women had received some AFDC payments.

In this paper, we provide quantitative estimates of the relative importance of labor market opportunities, marriage market opportunities and preference heterogeneity in explaining these large minority-majority differences. We also ask whether government welfare programs interact with these three factors to augment these differences. Finally, we provide estimates of how recent major changes in welfare rules, such as the major expansion of the Earned Income Tax Credit (EITC) in 1994-96, and the 1996 welfare reform legislation establishing the Temporary Aid for Needy Families (TANF) program can be expected to alter the life cycle behavior of women entering adulthood in the new regime. In order to perform these assessments, we develop and estimate a life-cycle model that incorporates all the key behaviors of interest: welfare participation, labor supply, marriage, fertility and schooling.

Our work builds on a number of distinct literatures. One set of studies is concerned with the incentive effects of welfare programs. Extensive reviews of the literature can be found in Moffitt (1992, 1998). The prototypical study in that literature focuses on a select subsample of women, such as, low-income female household heads or female heads on welfare (treating marital status, fertility and prior human capital investments as given) and estimates the impact of welfare benefits on a subset of the key decisions facing single mothers, most commonly welfare

participation and either labor supply or marriage. The bulk of these studies are based on static models of behavior, although the behavioral model underlying the statistical work is not always made explicit.¹ Attention to the role of government welfare programs in accounting for minority-majority differences in labor supply and marital status is surprisingly rare.

A distinctly different literature, spanning both economics and sociology, has focused on minority-majority differences in rates of marriage, usually without considering the specific role of welfare. Wilson (1987) postulated that the much steeper decline since the 1960's in the marriage rate of black women relative to that of white women was due to a fall in the pool of marriageable, i.e, employed, black men.² Since then, numerous empirical studies based on economic models of marital sorting have attempted to determine the importance of marriage market opportunities, including the availability and characteristics of potential spouses, in explaining the minority-majority difference in marriage rates.³

Finally, we contribute to the literature on structural estimation of dynamic discrete choice models of female labor supply (see Blundell and MaCurdy (2004) for a recent survey). Almost all of that literature treats labor supply as the only choice, assuming that schooling, children and marital status are predetermined states.⁴ And, unlike here, welfare participation is generally

¹ Moffitt (1983) is an exception in that he explicitly specifies and structurally estimates a static model of labor supply and welfare participation. Fraker and Moffitt (1988) and Keane and Moffitt (1998) extend that framework to a consideration of multiple program participation. Other examples are Hoynes (1996) as well as several studies we cite below. Explicit models of demographic behavior and welfare participation are less common, although Rosenzweig (1999) is an exception. Rosenzweig (1999) and Keane and Wolpin (2002) provide a critical assessment of empirical issues that arise in this literature.

² Wood (1995) argues that male earnings is a better index of marriageability than employment.

³ Examples are Brien (1997) and Wood (1995). Wood includes AFDC benefits in the analysis, but finds that higher benefits increase marriage rates of black women, though it is imprecisely estimated. The most sophisticated studies model the marriage market equilibrium, for example, Seitz (2004). Seitz does not account for the decision to participate in welfare.

⁴ Vanderklaauw (1996) is an exception in that labor supply and marriage are treated as joint decisions.

ignored. Among the dynamic models that include welfare participation as a choice, Sanders (1993) and Miller and Sanders (1997) consider work and welfare participation, but do not model education, fertility and marriage. Fang and Silverman (2004) estimate a similar model, but allowing for time-inconsistent agents. Perhaps the most complete model to date linking the literatures on dynamic labor supply with the literature on welfare is Swann (2005). He estimates a dynamic model that, in addition to labor supply, includes also marriage and welfare participation decisions.

The model that we estimate significantly extends these diverse literatures. We augment the choice set to include schooling and fertility in addition to work, marriage and welfare participation. This extension enables a more complete analysis of existing anti-poverty programs. For instance, the EITC not only provides a subsidy to low earners, but, because the subsidy is much larger if one has children, is also strongly pronatalist. Thus, the program may have important effects on fertility, effects that would interact with decisions made jointly about marriage, schooling, work, and welfare participation.

In addition to considering a larger set of choices, the modeling framework with respect to these choices is generally richer. In our model, women make sequential decisions in each 6 month period, starting at age 14, about school attendance, work, fertility, and, starting at age 16, marriage. Employment may be either part- or full-time. In each period, with some probability a woman receives a part-time wage offer and, likewise, with some probability a full-time wage offer. In modeling fertility, it is assumed that a woman receives utility from children, but bears a time cost of rearing them that depends on their current age distribution. Sequential decisions about school attendance are governed by direct preferences and by the additional human capital, and thus wages, gained from schooling.

The marriage market is modeled in a search context. In each period a woman receives a marriage offer with some probability that depends on her current characteristics and on her past welfare participation. Gains from search, which induce delay, arise because the earnings potential of the person she meets contains a permanent component, drawn from a distribution that also depends on her characteristics. If the marriage offer is accepted, the husband's actual earnings evolve over time stochastically. The woman receives a fraction of the total of her

earnings and her husband's earnings. If a woman is not married, there is some probability, determined by current characteristics, that she co-resides with her parents. In that case, she receives a fraction of her parents' income that also depends on her characteristics.

Finally, we allow for unobserved permanent components of preferences and endowments that are person specific, as well as differences in preferences and endowments between minority and white women and across U.S. State of residence. Differences in labor market opportunities arise due to both differential skill "endowments" (at age 14) and discrimination against minorities. Minority women face different distributions of husband earnings than do white women, as well as different preferences for marriage (which may reflect, in part, differences in characteristics of the available men other than earnings capacity). And, there are also differences in preferences for leisure, school, fertility and welfare participation.

It is worth emphasizing that the welfare system could not by itself create differences between minority and white women in behavior (barring explicit differences in how the system treats them), unless there exist differences in preferences and constraints of the type that we allow for. But, if differences in preferences and constraints do exist, the welfare system can either enhance or mitigate their role in generating outcome differences.

We implement the model using 15 years of information from the 1979 youth cohort of the National Longitudinal Surveys of Labor Market Experience (NLSY79), supplemented with state level welfare benefit rules that we have collected for each state over a 23 year period prior to the new welfare reform. Benefit levels changed considerably over the decision-making period of the women in the NLSY79 sample. We develop simplified representations of state- and year-specific welfare benefit formulas to estimate forecasting rules for the agents that they are assumed to use in the decision model. The model was estimated on five of the largest states represented in the NLSY79 (California, Michigan, New York, North Carolina and Ohio).

Our estimates reveal that there are important differences among white, black and Hispanic women in their structural parameters. For example, black women value marriage the least and Hispanic women the most, but both of them draw from potential husband's earnings distributions with lower means than white women. Minority women also receive lower wage offers for given schooling and employment histories than do white women. Black women are

estimated to have the lowest welfare stigma, followed in order by white women and Hispanic women.

We perform a number of counterfactual experiments to determine the extent to which differences in the behaviors of minority women can be accounted for by differences in structural parameters. As an example, we find that if minority-majority wage offer distributions were equalized (eliminating differences in both age 14 endowments and wage discrimination), the black-white gap in employment would disappear. However, while marriage rates would also rise for black women, due the increase in their desirability as mates, only about 20 percent of the gap in the marriage rates would be eliminated.

We also consider the behavioral impact of counterfactual experiments in which welfare benefits and rules are altered. For example, eliminating all welfare (for women, based on their estimated type, that are most prone to be on welfare) would increase employment of minorities much more than of whites, essentially equalizing employment among the three groups. Thus, it appears that welfare exaggerates the differences in employment between whites and minorities that would arise solely due to differences in labor and marriage market opportunities and in preferences. Interestingly, although eliminating welfare must reduce the present value of utility calculated as of age 14, as there cannot be in this partial equilibrium framework a welfare gain from government policy that reduces benefits, it actually increases the present value of lifetime utility of all three groups calculated as of age 20.⁵ As a final exercise, we use data from the new NLSY97 cohort to see how much of the change in welfare participation and employment of 18-21 year olds, separated by about 20 years, is the result of the new welfare program, TANF, adopted in 1996.

The paper is organized as follows. The next section presents the model, followed by a discussion of the data. The estimation method is developed in section IV and the results are presented in section V. The last section summarizes and concludes.

⁵ This contrasts with the time-inconsistent model of Fang and Silverman (2004) in which government policy that reduces benefits can in principle bring about a utility gain. However, in fact, they do not find a gain when implementing time limits.

II. Model

In this section, we provide an outline of the model. A complete description with exact functional forms is provided in Appendix A. We consider a woman who makes joint decisions at each age “a” of her lifetime about the following set of discrete alternatives: whether or not to attend school, s_a , work part-time, h_a^p , or full-time, h_a^f , in the labor market (if an offer is received), be married (if an offer is received), m_a , become pregnant if the woman is of a fecund age, p_a , and receive government welfare if the woman is eligible, g_a . There are as many as 36 mutually exclusive alternatives that a woman chooses from at each age during her fecund life cycle stage and 18 during her infecund stage.⁶ The fecund stage is assumed to begin at age 14 and to end at age 45; the decision period extends to age 62. Decisions are made at discrete six month intervals up to age 45, i.e., semi-annually, and then annually up to age 62.⁷ A woman who becomes pregnant at age a has a birth at age a+1, with n_{a+1} representing the discrete birth outcome.⁸ Co-residence with parents, z_a , is also included as an outcome variable in the model, but is not treated as a choice. However, the probability of co-residence is determined by state variables that reflect prior choices. Consumption, C_a , is determined by the alternative chosen, and the woman’s state variables at age a.

The woman receives a utility flow at each age that depends on her consumption, as well as her five choices: (1) work, (2) school, (3) marriage, (4) pregnancy and (5) welfare participation. Utility also depends on past choices, as there is state dependence in preferences, on the number of children already born, N_a , and their current ages (which affect child-rearing time

⁶ Marriage only becomes an option at age 16. Married women face fewer choices because being married and receiving welfare is not an option. Although the AFDC-Unemployed Parent (AFDC-UP) program provided benefits for a family with an unemployed father, it accounts for only a small proportion of total spending on AFDC, so we do not consider it.

⁷ Allowing for a longer decision period at ages past 45 reduces the computational burden of the model (see Wolpin (1992)).

⁸ In keeping with the assumption that pregnancies can be perfectly timed, we only consider pregnancies that result in a live birth, i.e., we ignore pregnancies that result in miscarriages or abortions. We assume that a woman cannot become pregnant in two consecutive six month periods.

costs), and the current level of completed schooling, \mathbf{S}_a (which affects utility from attendance). Marriage and children shift the marginal utility of consumption. We also allow preferences to evolve with age, and to differ among individuals by birth cohort, race and U.S. State of residence.⁹ There is also a vector of 5 permanent unobservables, determined by a woman's latent "type," that shift her tastes for leisure, school, marriage, pregnancy and welfare participation. In addition, there are age-varying preference shocks to the disutility of time spent working, attending school, child-rearing or collecting welfare (i.e., non-leisure time), as well as the direct utilities or disutilities from school, pregnancy and welfare participation (unrelated to the time cost), and the fixed cost of marriage.¹⁰ Expressing the utility function in terms of the current set of alternatives, the utility of an individual at age a who is of type j is

$$(1) \quad U_a^j = U_a(C_a, s_a, m_a, p_a, g_a, h_a^p, h_a^f; \epsilon_a, I(\text{type}=j), \Omega_a^u),$$

where ϵ_a is the vector of five serially independent preference shocks (one associated with each of the 5 choices), $I(\text{type}=j)$ is an indicator function equal to one if the agent is type j , and Ω_a^u represents the subset of the state space (the set of past choices and fixed observables) that affects utility.

Monetary costs associated with particular choices, when unmeasured, are not generally distinguishable from psychic costs. It is thus somewhat arbitrary whether to include them in the utility function or the budget constraint. For example, we include in (1) (see Appendix A): (i) a fixed cost of working; (ii) a time cost of rearing children that varies by their ages; (iii) a time cost of collecting welfare (waiting at the welfare office); (iv) a school re-entry cost; and (v) costs of switching welfare and employment states.

The budget constraint, assumed to be satisfied each period, is given by:

⁹ In the model, we assume that women do not change their State of residence and restrict our estimation to a sample with that characteristic.

¹⁰ In the exact functional form that we specify (see Appendix A) agents receive disutility from the sum of all these sources of non-leisure time (as opposed to receiving utility from leisure).

$$(2) \quad C_a = y_a^o(1 - m_a)(1 - z_a)(1 - g_a) + [y_a^o + y_a^m]m_a\tau_a^m + [y_a^o + y_a^z\tau_a^z]z_a \\ + \beta_1 g_a b_a - [\beta_3 I(S_a \geq 12) - \beta_4 I(S_a \geq 16)]s_a,$$

where y_a^o is the woman's own earnings at age a , y_a^m husband's earnings and y_a^z parents income. The first term in (2) is a woman's income if she is unmarried ($m_a=0$), does not co-reside with parents ($z_a=0$) and does not receive welfare ($g_a=0$). The second term in (2) indicates that a woman who is married receives the share τ_a^m of the combined earnings of her and her spouse. The third term indicates that a woman who co-resides with parents receives her own earnings plus a share τ_a^z of her parents' income. Both τ_a^m and τ_a^z are estimated parameters. The fourth term is the income the woman receives from welfare, b_a , which is determined by a rather complex formula that we discuss in detail below. The parameter β_1 is a multiplier that converts welfare dollars into a monetary equivalent consumption value.¹¹ The last term reflects the tuition cost of attending college, β_3 , or graduate school, β_4 , with S_a the completed level of schooling at age a . Here, as in the rest of the paper, $I(\cdot)$ is an indicator function equal to unity when the argument in the parentheses is true.

Parental co-residence and marriage are treated as mutually exclusive states, as implicitly assumed in (2). A single woman lives with her parents according to a draw from an exogenous probability rule, π_a^z . We assume that the probability of co-residing with her parents, given the woman is unmarried, depends on her age and lagged co-residence status. The parents' income depends on education and race. The woman's share of her parents' income, when co-resident, depends on her age, her parents' schooling and whether she is attending post-secondary school. Thus, as in Keane and Wolpin (2001), more educated parents may make larger transfers to help children pay for college.

In each period a woman receives a part-time job offer with probability π^{wp} and a full-time job offer with probability π^{wf} . Each of these offer rates depends on the woman's previous-period work status. If an offer is received and accepted, the woman's earnings is the product of

¹¹ β_1 reflects the fact that welfare recipients are restricted in what they may purchase with welfare benefits, e.g., food stamps cannot be used to purchase tobacco products.

the offered hourly wage rate and the number of hours she works, $y_a^o = 500 \cdot w_a^p h_a^p + 1000 \cdot w_a^f h_a^f$. The hourly wage rate is the product of the woman's human capital stock, Ψ_a , and its per unit rental price, which is allowed to differ between part- and full-time jobs, r^j for $j=p, f$. Specifically, her log hourly wage is given by

$$(3) \ln w_a^j = r^j + \Psi(\cdot) + \epsilon_a^w, \quad j=p, f.$$

Her human capital stock is modeled as a function of completed schooling, the stock of accumulated work hours up to age a , H_a , whether or not the woman worked part- or full-time in the previous period, and her current age. Importantly, the level of human capital is also affected by her skill "endowment" at age 14. As with permanent preference heterogeneity, the skill endowment differs for black, Hispanic and white women, and by State of residence and unobserved type.¹² Along with the permanent heterogeneity in preferences for leisure, school, marriage, fertility and welfare, the skill endowment is the final element of the vector of latent variables that determines a woman's "type." The random shocks to a woman's human capital stock, ϵ_a^w , are assumed to be serially independent.

The marriage market is characterized by stochastic assortative mating. In each period a single woman draws an offer to marry with probability π_a^m , that depends on her age and welfare status. If the woman is currently married, with some probability that depends on her age and duration of marriage, she receives an offer to continue the marriage. If she declines to continue, the woman must be single for one period before receiving a new marriage offer.

A potential husband's earnings depends on his human capital stock, Ψ_a^m . Conditional on receiving a marriage offer, the husband's human capital is drawn from a distribution that depends on the woman's characteristics: on whether she is black, Hispanic or white, and on her schooling, age, state of residence and unobserved (to us) type. In addition, there is an iid random component to the draw of the husband's human capital that reflects a permanent characteristic of the husband unknown to the woman prior to meeting, μ^m . The woman can therefore profitably

¹² Differences in skill endowments cannot be distinguished from differences in skill rental prices due to discrimination against minority women.

search in the marriage market for husbands with more human capital, and can also directly affect the quality of her husband by the choice of her schooling. There is a fixed utility cost of getting married, which augments a woman's incentive to wait for a good husband draw before choosing marriage (we allow for a cohort effect in this fixed cost). After marriage, husband's earnings evolve with a fixed (quadratic) trend subject to a serially independent random shock, ϵ_a^m . Specifically,

$$(4) \quad \ln y_a^m = \mu^m + \Psi_{0a}^m(\cdot) + \epsilon_a^m$$

where Ψ_{0a}^m is the deterministic component of the husband's human capital stock.¹³

Welfare eligibility and the benefit amount for a woman residing in State s at calendar time t depends on her number of minor children (under the age of 18) and on her household income. In all cases, a woman must have at least one minor child to be eligible for benefits. Benefits are basically determined by a grant level that is increasing in the number of minor children, and which is taxed away if the woman has earnings or non-labor income. However, the welfare rules are State- and time-specific and are quite complex. Thus, in order to make estimation feasible, we approximate the rules by the following function:

$$(5) \quad \begin{aligned} b_t^s(N_{at}^{18}, y_{at}^o, y_{at}^z) &= b_{0t}^s + b_{1t}^s N_{at}^{18} - b_{3t}^s \beta_2 y_{at}^z z_{at} && \text{for } y_{at}^o < y_{at}^{s1}(N_a^{18}), \\ &= b_{2t}^s + b_{4t}^s N_{at}^{18} - b_{3t}^s [(y_{at}^o - y_{at}^{s1}) + \beta_2 y_{at}^z z_{at}] && \text{for } y_{at}^{s1}(N_a^{18}) < y_{at}^o < y_{at}^{s2}(N_a^{18}) \\ &= 0 && \text{otherwise.} \end{aligned}$$

As seen in the first line, the grant level is assumed to be linearly increasing in the number of minor children N_a^{18} and, in the case of a woman co-residing with her parents, to be linearly

¹³ The human capital rental price is impounded in this term. In addition, husband's labor supply is assumed to be exogenous.

declining in parents' income, y_a^z , at a rate α_9 .¹⁴

In general, benefits are taxed away if the woman has positive earnings, y_a^o . However, due to work expense deductions and child care allowances, the tax is not assessed until earnings exceed a (State- and time-specific) "disregard" level, which we denote as $y_{at}^{s1}(N_a^{18})$. The amount of benefits, once earnings exceed this level, is given by the second line segment in (5). The benefit tax rate or "benefit reduction" rate is given by the parameter b_{3t}^s . Finally, $y_{at}^{s2}(N_a^{18})$ is the level of earnings at which all benefits are taxed away and become zero.

We will refer to $b_t^s(N_{at}^{18}, y_{at}^o, y_{at}^z)$ as the benefit rule and to the b_{kt}^s 's as the benefit rule parameters. The benefit rule parameters, and thus benefits themselves, change over time. Therefore, if women are forward-looking, they will incorporate their forecasts of the future values of the benefit rule parameters into their decision rules. We assume that benefit rule parameters evolve according to the following general vector autoregression (VAR) and that women use the VAR to form their forecasts of future benefit rules:

$$(6) \quad \mathbf{b}_t^s = \boldsymbol{\lambda}^s + \boldsymbol{\Lambda}^s \mathbf{b}_{t-1}^s + \mathbf{u}_t^s$$

where \mathbf{b}_t^s and \mathbf{b}_{t-1}^s are 5×1 column vectors of the benefit rule parameters, $\boldsymbol{\lambda}^s$ is a 5×1 column vector of regression constants, $\boldsymbol{\Lambda}^s$ is a 5×5 matrix of autoregressive parameters and \mathbf{u}_t^s is a 5×1 column vector of iid innovations drawn from a stationary distribution with variance-covariance matrix $\boldsymbol{\Xi}^s$. We call (6) the evolutionary rule (ER) and $\boldsymbol{\lambda}^s$, $\boldsymbol{\Lambda}^s$, $\boldsymbol{\Xi}^s$ the parameters of the ER. The evolutionary rule parameters are specific to the woman's state of residence.¹⁵ We estimated the ER parameters separately from the rest of the model, using a procedure we describe below.

¹⁴ The exact treatment of parents' income is quite complicated, varying among and within States (at the local welfare agency level) and over time. Rather than attempting to model the rules explicitly, as an approximation we instead treat the fraction of parents' income that is subject to tax as the parameter β_2 , which we will estimate.

¹⁵ As noted, it is assumed that a woman remains in the same location from age 14 on. Clearly, introducing the possibility of moving among states in a forward-looking model such as this would greatly complicate the decision problem.

Objective Function:

The woman is assumed to maximize her expected present discounted value of remaining lifetime utility at each age. The maximized value (the value function) is given by

$$(7) \quad V_a(\Omega_a) = \max E \left[\sum_{\tau=a}^{62} \delta^{\tau-a} U_{\tau}(\cdot) \mid \Omega_a \right],$$

where the expectation is taken over the distribution of future preference shocks, labor market, marriage and parental co-residence opportunities, and the distribution of the future innovations to the benefit ER. In (7), the state space Ω_a denotes the relevant factors known at age a that affect current or future utility or that affect the distributions of the future shocks and opportunities.

Decision Rules:

The solution to the optimization problem is a set of age-specific decision rules that relate the optimal choice at any age, from among the feasible choices, to the elements of the state space at that age. Casting the problem in a dynamic programming framework, the value function, $V_a(\Omega_a)$, can be written as the maximum over alternative-specific value functions, denoted as $V_a^j(\Omega_a)$, i.e., the expected discounted value of choice $j \in J$, that satisfy the Bellman equation, namely

$$\begin{aligned} V_a(\Omega_a) &= \max_{j \in J} [V_a^j(\Omega_a)] \\ (8) \quad V_a^j(\Omega_a) &= U_a^j + \delta E(V_{a+1}(\Omega_{a+1}) \mid j \in J, \Omega_a) \text{ for } a < A, \\ &= U_A^j \quad \text{for } a = A. \end{aligned}$$

A woman at each age a chooses the option j that gives the greatest expected present discounted value of lifetime utility. The value of option j depends on the current state Ω_a , which includes the State s in which she (permanently) resides, the current benefit rule parameters given by (5), the ER rule parameters given by (6), preference shocks, own and husband's earnings shocks,

parental income shocks, and labor market, marriage and parental co-residence opportunities.

Solution Method:

The solution of the optimization problem is in general not analytic. In solving the model numerically, one can regard its solution as consisting of the values of $E V_{a+1}(\Omega_{a+1} | j \in J, \Omega_a)$ for all j and elements of Ω_a . We refer to this as the “**Emax**” function for convenience. As seen in (8), treating these functions as known scalars for each value of the state space transforms the dynamic optimization problem into the more familiar static multinomial choice structure. The solution method proceeds by backwards recursion beginning with the last decision period.¹⁶

III. Data

The 1979 youth cohort of the National Longitudinal Surveys of Labor Market Experience (NLSY79) contains extensive information about schooling, employment, fertility, marriage, household composition, geographic location and welfare participation for a sample of over 6,000 women who were age 14-21 as of January 1, 1979. In addition to a nationally representative core sample, the NLSY79 contains oversamples of blacks and Hispanics. We use the annual interviews from 1979 to 1991 for women from the core sample and from the black and Hispanic oversamples.

The NLSY79 collects much of the relevant information, births, marriages and divorces, periods of school attendance, job spells, and welfare receipt, as dated events. This mode of collection allows the researcher the freedom to choose a decision period essentially as small as one month, i.e., to define the choice variables on a month-by-month basis. Although the exact choice of period length is arbitrary, we adopted as reasonable a decision period of six months. Periods are defined on a calendar year basis, beginning either on January 1 or on July 1 of any

¹⁶ Because the size of the state space is large, we adopt an approximation method to solve for the Emax functions. The Emax functions are calculated at a limited set of state points and their values are used to fit a polynomial approximation in the state variables consisting of linear, quadratic and interaction terms. See Keane and Wolpin (1994, 1997) for further details. As a further approximation, we let the Emax functions depend on the expected values of the next period benefit parameters, rather than integrating over the benefit rule shocks.

given year. We begin the analysis with data on choices starting from the first six month calendar period that the woman turned age 14 and ending in the second six month calendar period in 1990 (or, if the woman attrited before then, the last six-month period that data are available). The first calendar period observation, corresponding to that of the oldest NLSY79 sample members, occurs in the second half of 1971. There are fifteen subsequent birth cohorts who turned age 14 in each six month period through January, 1979. We restrict the sample to respondents residing in the five U.S. States that have the largest representations: California, Michigan, New York, North Carolina, Ohio.¹⁷ Consistent with the model, we include only respondents who resided continuously in the same state over the observation period, which is true for about 70 percent of the sample. There were significant numbers of Hispanics in only California and New York.

As noted, we consider the following choices: whether or not to (i) attend school (ii) work (part- or full-time), (iii) be married, (iv) become pregnant and (v) receive welfare (AFDC). The variables are defined as follows:

School Attendance: The NLSY79 collects data that permits the calculation of a continuous monthly attendance record for each women beginning as of January, 1979. A woman was defined to be attending school if she reported being in school each month between January and April in the first six-month calendar period and each month between October and December in the second calendar period.¹⁸ Given the sample design of the NLSY79, school attendance

¹⁷ Actually, Texas has a greater representation. However, in a companion paper described below, we used Texas respondents as a hold-out sample for the purpose of out-of-sample validation.

¹⁸ Beginning with the 1981 interview, school attendance was collected on a monthly basis for the prior calendar year. In the two prior interviews, attendance was ascertained at the interview date and, if not attending, the date of last attendance was obtained. If a woman was attending (not attending) at the time of the 1979 interview (which, in every case, took place during the first six months of 1979), and was also attending (not attending) in the first period of 1980, then the individual was coded as attending (not attending) in both periods of 1979. If attendance differed between the two years, enrollment was considered missing in the second half of 1979. We do not use the data prior to 1979 because only the last spell of non-attendance, and then only for individuals not attending at the 1979 interview, can be determined. In addition, because reported attendance and completed schooling levels were often longitudinally inconsistent, the attendance data was hand-edited to form a consistent attendance-highest grade completed profile.

records that begin at age 14 exist only for the cohort that turned 14 in January, 1979.

School attendance prior to age 14 is not explicitly treated as a choice. However, completed schooling at any age, including at age 14 (which we refer to as initial schooling), affects opportunities and thus choices. Given the sample design, we know initial schooling only for one of the cohorts. Thus, an estimation procedure has to deal with this serious missing initial conditions problem as well with the missing observations for many of the cohorts on schooling choices between age 14 and their age as of the first interview.

Employment Status: At the time of the first interview, an employment history was collected back to January 1, 1978, which provided details about spells of employment with each employer including the beginning and ending dates (to the week) of employer attachments, as well as gaps within employer-specific spells. Subsequent rounds collected the same information between interview dates. Using this information together with data on usual hours worked at each employer, we calculated the number of hours worked in each six month period. A woman was considered working part-time in the period (500 hours) if she reported working between 260 and 779 hours and full-time (1000 hours) if she reported working at least 780 hours during the period. As with school attendance, employment data does not extend back to age 14 for many of the cohorts. We assume that initial work experience, that is, at age 14, is zero.

Marital Status: The NLSY79 provides a complete event-dated marital history that is updated each interview. However, dates of separation are not reported. Therefore, for the years between 1979 and 1990, data on household composition was used to determine whether the woman was living with her spouse. But, because these data are collected only at the time of the interview, marital status is treated as missing during periods in which there were no interviews, in most cases for one six-month period per year. Marital event histories were used for the periods prior to 1979 even though it is uncertain from that data whether the spouse was present in the household.

Pregnancy Status: Although pregnancy rosters are collected at each interview, conception dates are noisy and miscarriages and abortions are under-reported. We ignore pregnancies that do not lead to a live birth, dating the month of the conception as occurring nine months prior to the month of birth. Except for misreporting of births, there is no missing

information on pregnancies back to age 14 for any of the cohort.

Welfare Receipt: AFDC receipt is reported for each month within the calendar year preceding the interview year, i.e., from January 1978. The respondent checks off each month from January through December that a payment was received. We define a woman as receiving welfare in a period if she reported receiving an AFDC payment in at least three of the six months of the period. As with school attendance and employment, data are missing back to age 14 for most of the cohorts. It is assumed that none of the women received welfare prior to age 14, as is consistent with the fact that none had borne a child by that time.

Descriptive Statistics:

Table 1 provides (marginals of) the sample choice distribution by full-year ages, separately for white, black and Hispanic women, aggregated over the five states. As seen, school attendance is essentially universal until age 16, drops about in half at age 18, the normal high school graduation age, and falls to around 10 percent at age 22. About 3 percent of the sample attends school at ages after 25.

Employment rates for white and Hispanic women (working either part- or full-time) increase rapidly through age 18 and then slowly thereafter, although they are higher for white women throughout by about 10-20 percentage points. Employment rates for black women rise more continuously, roughly doubling between age 18 and 25, and are comparable to that of Hispanic women at ages after 25.

Marriage rates rise continuously for white and Hispanic women, reaching 58.5 percent for whites and 47.2 percent for Hispanics by age 25. However, for black women, marriage rates more or less reach a plateau at about age 22, at between 20 and 25 percent. With respect to fertility, it is more revealing to look at cumulative children ever born rather than at pregnancy rates within six-month periods (as shown in the table). By age 20, white women in the sample on average had .28 live births, black women .47 live births and Hispanic women .40 live births. By age 27, the average number of live births by race are 1.06, 1.36 and 1.39, respectively, and by age 30, 1.54, 1.61 and 1.76. Viewed differently, the first age at which the sample women have had one child on average was 27 for white women, 24 for black women and 24.5 for Hispanic

women. Compared to white women, teenage pregnancies (leading to a live birth) are 68 percent higher for black women and 43 percent higher for Hispanic women.

Welfare participation naturally increases with age, at least through age 24, given the eligibility requirement of having had at least one child. Majority-minority differences are large; at its peak, participation reaches 7 percent for white women, 28 percent for black women and 17 percent for Hispanic women

Benefit Rules:

In order to estimate the benefit schedules (5) and the evolutionary rules governing changes in benefit parameters (6), we collected information on the rules governing AFDC and Food Stamp eligibility and benefits in each of the 50 states for the period 1967-1990. We then simulated a large data set of hypothetical women, with different numbers of children, and different levels of labor and non-labor income, and calculated their welfare benefits according to the exact rules in each State and year.¹⁹ We calculated the sum of monthly benefits from AFDC and Food Stamps, and expressed these monthly benefit amounts in 1987 New York equivalent dollars. The resulting simulated data was used to estimate the approximate benefit schedule given by (5) separately for each State and year. Thus, for each state, s , we obtain an estimate of the benefit rule parameters, $b_{w0}^s, b_{t1}^s, b_{t2}^s, b_{t3}^s, b_{t4}^s$, for each year t .²⁰ Given the estimates of the benefit rule parameters, we then estimated (6), the evolutionary rule.

For purposes of illustration, Table 2 transforms the benefit parameters obtained from the estimates of (5) into a more interpretable set of benefit measures, namely the total monthly benefits for women who have either one or two children, and who are either (i) not working (with zero non-earned income), (ii) have part-time monthly earnings of 500 dollars or (iii) have

¹⁹ Deductions for child care expenses and work expenses, as well as various other income disregards that existed under the AFDC program, were also factored into these calculations. EITC was also factored in, but this was quite trivial prior to the expansion in the 1993-94 period.

²⁰ The approximation given by (5) fits the monthly benefit data quite well, with R-squared statistics for the first line segment mostly above .99 and for the second, mostly about .95. These regressions are available on request.

full-time earnings of 1000 dollars.²¹ Referring to table 2, we see that, among the five states, NY, CA and MI are considerably more generous than NC and OH. Michigan is the most generous, with average benefits over the 24 years for a woman with one child being 654 (1987 NY) dollars per month. CA and NY were about equally generous on average (589 and 574 dollars) over the period as were NC and OH (480 and 489 dollars). Benefit reduction rates, net of child-care allowances, are fairly high. For example, a woman who had two children and earned 500 dollars per-month while working part-time would have lost 40 percent of the benefit.²²

As table 2 reveals, there was a steep decline in benefit amounts between the early 1970's and the mid 1980's, and relative constancy thereafter. For example, in Michigan monthly benefits fell from 912 dollars for a woman with no earnings and two children in 1975 to 705 dollars in 1985. For the same woman with 500 dollars in monthly earnings, benefits fell from 762 dollars in 1975 to 405 dollars in 1985, and then rose slightly to 484 dollars in 1990.

IV. Estimation Method:

The numerical solution to the agents' maximization problem provides (approximations to) the Emax functions that appear on the right hand side of (8). The alternative-specific value functions, V_a^j for $j=1, \dots, J$, which are sums of current payoffs and the discounted Emax functions, are known to the agents in the model. But the econometrician does not observe all the factors that enter the current payoff expressions U_a^j . In general, the econometrician does not observe the random preference shocks, the part- and full-time wage offer shocks, the earnings shock of the husband and the income shock of her parents. Whether particular alternatives are available depends on the implicit shocks governing whether a part- and/or full-time job offer is received,

²¹ See appendix table A.1 for summary statistics of the actual parameters themselves. Table A.2 shows the estimated parameters of the evolutionary rule.

²² Benefit reduction rates for AFDC and for Food Stamps were federally set. (This is no longer true under TANF). They differ across States in our approximation due to the fact that AFDC payments terminate at different income levels among the states while food stamp payments are still non-zero and the two programs have different benefit reduction rates. There is thus a kink in the schedule of total welfare payments with income that our approximation smooths over.

whether a marriage offer is received and whether a parental co-residence offer is received.

Thus, conditional on the deterministic part of the state space, the probability that an agent is observed to choose option k takes the form of an integral over the region of the several-dimensional error space such that k is the preferred option. The error space over which the econometrician must integrate depends on which option k the agent is observed to choose. For example, if the work option is chosen, then the wage offer is observed by us, and the wage shock is not in the subset over which we must integrate. In that case, the likelihood contribution for the observation also includes the density of the wage error. If the woman is married, then we observe the husband's income, we do not integrate over the husband's income shock, and the likelihood contribution includes the husband's income density.

As noted, the choice set contains as many as 36 elements, but our model imposes a factor structure where a much smaller number of errors (i.e., the wage shocks and the 5-element vector of preference shocks over leisure, school, marriage, fertility and welfare) determines choices.²³ It is well known that evaluation of choice probabilities is computationally burdensome when the number of alternatives is large. Recently, highly efficient smooth unbiased probability simulators, such as the GHK method (see, e.g., Keane (1993, 1994)), have been developed for these situations. Unfortunately, the GHK method, as well as other smooth unbiased simulators, rely on a structure in which each of the $J-1$ mutually exclusive alternatives have a value that is a strictly monotonic function of a single stochastic term, and that the $(J-1) \times (J-1)$ variance-covariance matrix of the error terms have full rank. This is not true here, because the alternatives have values that cannot be written as a strictly monotonic function of a single error.²⁴

²³ Note that, despite this factor structure, the likelihood is not “degenerate” (i.e., meaning that no feasible choice has zero probability). This is because each of the five discrete choices (work, school, fertility, marriage welfare participation) has an associated error term whose distribution (i.e., Normal) covers the real line. Thus, there always exists a configuration of the errors that can rationalize any 5-element vector of choices that might be observed in the data.

²⁴ One of us has written incorrectly elsewhere (see, e.g., Keane and Moffitt (1998)) that the GHK algorithm is only applicable when each alternative has a single error that is additive and the error covariance matrix is at least of rank $J-1$. A prime example is the multinomial probit model. But, additivity is in fact a much stronger condition than is required. Strict monotonicity is sufficient.

Furthermore, as discussed in Keane and Moffitt (1998), in estimation problems where the number of choices exceeds the number of error terms, the boundaries of the region of integration needed to evaluate a particular choice probability are generally intractably complex. Thus, given our model, the most practical method to simulate the probabilities of the observed choice set would be to use a kernel smoothed frequency simulator. These were proposed in McFadden (1989), and have been successfully applied to models with large choice sets in Keane and Moffitt (1998), Erdem (1996), Keane and Wolpin (1997) and Eckstein and Wolpin (1999).²⁵

However, in the present context, this approach is not feasible because of severe problems created by unobserved state variables. As noted, we do not always have complete histories of employment, schooling or welfare receipt for most of the cohorts back to age 14. Hence, the state variables of work experience, completed schooling and lagged welfare participation cannot always be constructed. In addition, parental co-residence and marital status are observed only once a year (every other period).

Further complicating the estimation problem, as we noted earlier, is that the youth's initial schooling level at age 14 is observed only for one of the 16 birth cohorts. It is well known that unobserved initial conditions, and unobserved state variables more generally, pose formidable problems for the estimation of dynamic discrete choice models (Heckman (1981)). If some or all elements of the state space are unobserved, then to construct conditional choice probabilities one must integrate over the distribution of the unobserved elements. Even in much simpler dynamic models than ours, such distributions are typically intractably complex.

In a previous paper (Keane and Wolpin (2001)), we developed a simulation algorithm that deals in a practical way with the problem of unobserved state variables. The algorithm is based on simulation of complete (age 14 to the terminal age) outcome histories for a set of artificial agents. An outcome history consists of the initial schooling level of the youth, \mathbf{S}_0 , parental schooling, \mathbf{S}^z , along with simulated values in all subsequent periods for all of the outcome variables in the model (school attendance, part- or full-time work, marriage, pregnancy,

²⁵ Kernel smoothed frequency simulators are, of course, biased for positive values of the smoothing parameter, and consistency requires letting the smoothing parameter approach zero as sample size increases.

welfare participation, the woman’s wage offer, the husband’s earnings, both permanent and transitory components, parental co-residence and income). The construction of an outcome history can be described compactly as follows:

At the current trial parameter value, we simulate histories as follows:

- 1) Draw the youth’s “type,” which includes both her skill endowment and 5-element vector of preference parameters, as well as her initial schooling and parent’s schooling, from a joint distribution;²⁶
- 2) Draw the relevant set of random shocks necessary to compute the alternative-specific value functions at age $a=1$;
- 3) Choose the alternative with the highest alternative-specific value function;
- 4) Update the state variables based on the choice in (3);
- 5) Repeat steps (2) – (4) for $a=2, \dots, A$;

We repeat steps (1) - (5) N times to obtain simulated outcome histories for N artificial persons. Denote by $\tilde{\mathbf{O}}^n$ the simulated outcome history for the n^{th} such person, so $\tilde{\mathbf{O}}^n = (\Omega_0^n, \tilde{\mathbf{O}}_{a=1}^n, \dots, \tilde{\mathbf{O}}_{a=A}^n)$, for $n = 1, \dots, N$.

In order to motivate the estimation algorithm, it is useful to ignore for now the complication that some of the outcomes are continuous variables and that there are observed initial conditions and unobserved types. Let \mathbf{O}^i denote the observed outcome history for person i , which may include missing elements. Then, an unbiased frequency simulator of the probability of the observed outcome history for person i , $\mathbf{P}(\mathbf{O}^i)$, is just the fraction of the N simulated histories that are consistent with \mathbf{O}^i . In this construction, missing elements of \mathbf{O}^i are counted as consistent with any entry in the corresponding element of $\tilde{\mathbf{O}}^n$. Note that the construction of this simulator relies only on unconditional simulations. It does not require evaluation of choice probabilities conditional on state variables. Thus, unobserved state variables do not create a

²⁶ We do not draw from the “correct” joint distribution. Instead, we draw from an incorrect “source” distribution and adjust the draws so obtained using importance sampling weights. The virtue of this procedure, similar to Keane (1993, 1994), will become apparent below. The key support condition for importance sampling is that the source distribution put positive mass on each possible type/initial school/parent’s school combination, which is easy to verify in this case.

problem for this procedure.

Unfortunately, this algorithm is not practical. Because the number of possible outcome histories is huge, consistency of a simulated history with an actual history is an extremely low probability event. Hence, simulated probabilities will typically be 0, as will be the simulated likelihood, unless an impractically large simulation size is used (see Lerman and Manski 1981). In addition, the method breaks down completely if any outcome is continuous (e.g., the woman's wage offer), regardless of simulation size, because agreement of observed with simulated wages is a measure zero event.

We solve this problem by assuming, as seems apt, that all observed quantities are measured with error. With measurement error there is a nonzero probability that any observed outcome history might be generated by any simulated outcome history. Denote by $\mathbf{P}(\mathbf{O}^i|\tilde{\mathbf{O}}^n)$ the probability that observed outcome history \mathbf{O}^i is generated by simulated outcome history $\tilde{\mathbf{O}}^n$. Then $\mathbf{P}(\mathbf{O}^i|\tilde{\mathbf{O}}^n)$ is the product of classification error rates on discrete outcomes (and measurement error densities for the continuous variables) that are needed to make \mathbf{O}^i and $\tilde{\mathbf{O}}^n$ consistent. Observe that $\mathbf{P}(\mathbf{O}^i|\tilde{\mathbf{O}}^n) > 0$ for any $\tilde{\mathbf{O}}^n$, given suitable choice of error processes. The specific measurement error processes that we assume are described below. The key point here is that $\mathbf{P}(\mathbf{O}^i|\tilde{\mathbf{O}}^n)$ does not depend on the state variables at any age a , but only depends on the outcomes.

Using N simulated outcome histories we obtain the unbiased simulator:

$$(9) \hat{\mathbf{P}}_N(\mathbf{O}^i) = \frac{1}{N} \sum_{n=1}^N \mathbf{P}(\mathbf{O}^i|\tilde{\mathbf{O}}^n).$$

Note that this simulator is analogous to a kernel-smoothed frequency simulator, in that $\mathbf{I}(\mathbf{O}^i = \tilde{\mathbf{O}}^n)$ is replaced with an object that is strictly positive, but that is greater if $\tilde{\mathbf{O}}^n$ is "closer" to \mathbf{O}^i . However, the simulator in (9) is unbiased because the measurement error is assumed to be present in the true statistical model.

It is straightforward to extend the estimation method to allow for unobserved heterogeneity. Assume that there are K types of women who differ in their permanent preferences for leisure, school, marriage, becoming pregnant and receiving welfare, as well as in

their human capital “endowment” at age 14.²⁷ In addition, women also differ in terms of their initial schooling (taking on 4 values) and parental schooling (taking on 14 values); initial schooling, as we have noted, is often unobserved. Thus, there are a total of $56 \cdot K$ possible initial conditions in simulation step (1) of the algorithm to generate histories. Let $k = 1, \dots, 56 \cdot K$ index these initial conditions, and define $\pi_{\mathbf{k}}$ as the probability a person has initial condition k given the joint distribution of unobserved type, initial schooling and parental schooling assumed in the model.²⁸ Also, define $\pi_{\mathbf{k}0}$ as the proportion of agents with initial condition k simulated in step 1, and let $k(n)$ denote the initial condition that was drawn in step 1 when simulating history n . Finally, let $\tilde{\mathbf{O}}_{\mathbf{k}}^n$ denote that the n^{th} outcome history, which is simulated under the assumption the agent has initial condition k . Then, we can form the unbiased simulator:

$$(10) \quad \hat{\mathbf{P}}_N(\mathbf{O}^i) = \frac{1}{N} \sum_{n=1}^N \mathbf{P}(\mathbf{O}^i | \tilde{\mathbf{O}}_{\mathbf{k}}^n) \frac{\pi_{\mathbf{k}(n)}}{\pi_{\mathbf{k}(n),0}}.$$

Observe that in (10), the conditional probabilities $\mathbf{P}(\mathbf{O}^i | \tilde{\mathbf{O}}_{\mathbf{k}}^n)$ are weighted by the ratio of the probability of agents with initial condition k according to the model, $\pi_{\mathbf{k}}$, to the probability of agents with initial condition k in the simulation, $\pi_{\mathbf{k}0}$. As we discuss in Appendix A, we construct the joint distribution of latent type, initial schooling, and parental schooling using (i) a multinomial logit (MNL) for initial schooling conditional on parents’ schooling, in conjunction with (ii) a MNL for type conditional on parent and initial schooling. Together, these logits generate the $\pi_{\mathbf{k}}$. It is important for probability simulators to be smooth functions of model parameters for several reasons.²⁹ The simulator in (10) is a smooth function of the MNL

²⁷ At a point in time, married women also differ in terms of the permanent unobservable component of their husband’s human capital, μ^m in (4), which is fixed for the duration of a marriage. But this is not part of a woman’s initial condition.

²⁸ Parental schooling and initial schooling are assumed to be exogenous conditional on type.

²⁹ As discussed in McFadden (19989) and Keane (1994), smoothness allows construction of derivatives, which both speeds the search for an optimum and permits calculation of numerical standard errors. It also typically leads to more efficient simulators, and avoids problems created by zero simulated probabilities (see Lerman and Manski (1981)).

parameters that determine the type proportions π_k , and this is a key virtue of using importance sampling in Step 1 of the algorithm for constructing histories.³⁰ Unfortunately, (10) is not a smooth function of the structural parameters that determine choice probabilities conditional on initial conditions. This is because $\mathbf{P}(\mathbf{O}^i|\tilde{\mathbf{O}}^n)$ will “jump” at points where a change in a model parameter causes the simulated outcome history $\tilde{\mathbf{O}}^n$ to change discretely. However, this simulator can be made smooth in these parameters by applying a second importance sampling procedure. The idea is to hold the simulated outcome histories fixed as the model parameters are varied, but to reweight them in an appropriate way.

Given an initial parameter vector θ_0 and an updated vector θ' , the appropriate weight to apply to sequence $\tilde{\mathbf{O}}^n$ is the ratio of the likelihood of simulated history n under θ' to that under θ_0 . Such weights have the form of importance sampling weights (i.e., the ratios of densities under the target and source distributions), and are smooth functions of the model parameters. Further, it is straightforward to simulate the likelihood of an artificial history $\tilde{\mathbf{O}}^n$ using conventional methods because the state vector is fully observed at all points along the history. The choice probabilities along a path $\tilde{\mathbf{O}}^n$ are simulated using a kernel smoothed frequency simulator. As this construction renders $\mathbf{P}(\mathbf{O}^i|\tilde{\mathbf{O}}^n)$ a smooth function of the model parameters, standard errors can be obtained using the BHHH algorithm.³¹

Lastly, it is necessary to describe our specific assumptions for the measurement error processes. First, we assume that discrete outcomes are subject to classification error. The structure we adopt is simply that there is some probability that the reported response category is

³⁰ Keane and Wolpin (1997, 2001) adopted the same approach to handling latent types.

³¹ Despite the smoothness of the simulated likelihood function, estimation of the model proved difficult, as it was common for the search algorithm to become “hung up” on local maxima. We thus alternated between BHHH, the simplex algorithm, and simply moving sets of parameters by hand, switching methods whenever it appeared that one method had gotten “hung up.” This laborious process ended when we were no longer able to find any further improvement in the likelihood using any method. At this point the in-sample fit of the model also appeared to be quite reasonable, in the sense of capturing well many key features of the data. Our companion paper Keane and Wolpin (forthcoming) provides much more detail on model fit.

the truth and some probability that it is not.³² Second, we assume that the continuous variables are also subject to normally distributed measurement error. In particular, we assume that these errors are additive in the woman's log wage offer equation and in the husband's log income equation, while we assume that the parental income error is additive in levels. All measurement/classification errors are assumed to be serially independent and independent of each other.

V. Empirical Results

A. Model Fit and External Validation:

Our companion paper, Keane and Wolpin (forthcoming), provides an extensive discussion of model fit and external validation of our model (in fact, the paper is entirely devoted to these issues), so we refer the reader to that paper for further discussion. There we argue that the within-sample fit of the structural model appears quite satisfactory, in the sense that it captures well many key features of the data, e.g., the choice frequencies for work, schooling, fertility, marriage and welfare participation for black, Hispanic and white women, for each of the five States, and over the life-cycle.

We note that our model contains 202 parameters (see Appendix A), which *prima facie* might seem profligate, leading to fears of over-fitting. However, in Keane and Wolpin (forthcoming) we compare our model to a simple reduced form MNL that attempts to fit only four of the discrete choices that we model, specifically, work, school, pregnancy and welfare, using latent indices that are simple linear functions of the main state variables of the model. This model actually has 240 parameters.³³ Yet, it does not attempt to fit marriage, full- vs. part-time

³² To ensure that the measurement error is unbiased, the probability that the reported value is the true value must be a linear function of the predicted sample proportion (see Appendix A for details). Obviously, measurement error cannot be distinguished from the other model parameters in a non-parametric setting. As in the model without measurement error, identification relies on a combination of functional form and distributional assumptions, and exclusionary restrictions. Keane and Sauer (2005) have applied this algorithm successfully with more general classification error processes

³³ This MNL model in principle attempts to fit $2^4=16$ alternatives, but 3 were combined due to small cell sizes, and one latent index of the model is normalized to zero. Thus, the model

work, wages, husband's income or living with parents, all of which are included in our model. Thus, viewed properly, one can see that our structural model is in fact very tightly parameterized.

In Keane and Wolpin (forthcoming) we show that the flexible MNL logit model and our structural model provide similar fits to the within-sample data (for those four choices where the MNL makes predictions). However, we show that the structural model outperforms the reduced form model in a set of external validation exercises. In one such exercise, we use both models to forecast the behaviors of women who resided in Texas, a state considerably less generous in terms of welfare benefits than the states used in the estimation. In another, we simulated what would happen if the estimation States in our sample (CA, MI, NY, NC, OH) adopted the Texas rules. We concluded that the structural model performed as well as or better than the MNL in these exercises.

B. Parameter Estimates:

Parameter estimates and standard errors are reported in Appendix table A.3. Many of the parameters are not themselves of direct interest, the behavioral patterns implied by the model as a whole being of central interest. Nevertheless, in this section we discuss the parameters that are of greatest interest, highlighting those related to differences among black, Hispanic and white women that are informative for the counterfactual experiments we perform below.

Utility function parameters:

Preferences for Leisure: The first column, labeled "Hours," reports estimates for the parameters that multiply hours of non-leisure time. A larger negative value means the women gets greater disutility from time spent in non-leisure activity, including work, time required to attend school or raise children, and time required to collect welfare benefits. The point estimates for black women, $\alpha_{1,10}$, and for Hispanic women, $\alpha_{1,11}$, are both negative, statistically insignificant and small. An extra 1000 hours of non-leisure time is equivalent to a reduction in

has 12 latent indices that depend on 20 variables each. These 20 state variables include lagged choices, State and black and Hispanic dummies, a measure of welfare benefits, age and its square, completed education and its square, the stock of children, parental education, and living in a two parent family at age 14.

consumption per period of \$117 more for black women and of \$15 more for Hispanic women than for white women.

School Attendance: The model also allows for a direct utility (or disutility) flow from school attendance. As seen in column 4, labeled “School,” the black and Hispanic women’s parameters are again statistically insignificant and small. Black women value attending school at \$49 more and Hispanic women at \$109 less, in terms of per-period consumption, than do white women

Marriage: The parameters in the column labeled “Marriage” represent a fixed utility cost of getting married. Relative to white women, black women have a fixed cost of marriage that is greater by \$2,500 and Hispanic women that is less by \$2,400, and these differences are statistically significant, and potentially of substantive significance.³⁴

Fertility: The preference parameters for pregnancy are in column 2. Note that $\alpha_{5,0}$, the base case, is normalized to zero, because the utility from pregnancy cannot be separately identified from the flow utility from children.³⁵ The parameter estimates imply that black and Hispanic women both get more utility from pregnancy than whites (which is equivalent to saying they get more utility from children in our model set up). Relative to a white woman, a pregnancy is worth \$1,352 more in per-period consumption to a black woman and \$1,735 more to a Hispanic woman.

Welfare stigma: The parameters in the fifth column, headed “Welfare,” measures the dollar equivalent disutility from welfare participation, sometimes referred to as “welfare stigma.” For the base case of whites in California, this stigma is estimated to be \$1,578 per 6-month period. Relative to white women, black women exhibit less stigma per period by \$290 and

³⁴ As noted earlier, the utility/disutility from getting married may reflect not just a woman’s taste from marriage, but also characteristics of the available pool of men (other than income) that differ by race. Unlike the other preference parameters, we do not let preferences for marriage differ across the 6 latent types that we include in the model. We tried to iterate on these parameters, but they never moved far from zero. The model appears to capture differences in marriage rates conditional on state, race and parental background quite well without the need for latent types.

³⁵ That is, eliminating the flow utility and adding its present value to the utility from pregnancy would not change behavior. This is not true in a more general setting where, e.g., pregnancy has uncertain outcomes.

Hispanic women more stigma by \$116 (not statistically significant).

Other Utility Function Parameters: The row labeled “non-leisure time” provides estimates for the equation for total non-leisure time (see Appendix A). Attending school is estimated to require 795 hours per 6-month period (half-way between full and part-time work). The relative time required to care for a newborn child is normalized to 1.0, which translates into 539 hours in each six-month period of the child’s first year of life. Older children require less time. The time required to collect AFDC (e.g., reporting to the welfare office, dealing with paperwork and caseworkers) is estimated to be 64 hours per period. This parameter is important, because in the simulations below, we interpret an increase in this parameter as equivalent to introducing a “work” requirements for welfare recipients.³⁶

The remaining parameters of the utility function are unsurprising given our earlier work on young men (see Keane and Wolpin (1997, 2001)). For instance, there is substantial state dependence in the form of a large fixed cost of returning to school once one has left ($\alpha_9 = -3.993$, implying a fixed cost of about \$4,000) and large increments to the utility of part- and full-time work if one had worked part- or full-time in the proceeding period (α_{15} and α_{16} utility increments of \$476 and \$1549 per period respectively.)

The age effects in the utility/disutility from pregnancy are specified as a flexible quartic function. The estimates imply a disutility of roughly \$600 at age 14, rising to a peak utility of \$1900 at age 18, and falling to roughly zero at 22. Disutility then gradually increases to roughly \$4200 at age 30, \$6300 at age 35, and \$14,100 at age 40. It then rapidly grows to \$38,000 at age 45, beyond which we assume women do not have further children.

Finally, we note that the model allows for substitutability/complementarity between consumption and leisure/non-leisure time (α_{21}), and for the degree of this interaction to differ with marriage (α_{27}) and number of children (α_{28}). These parameters turned out to be quantitatively large, statistically significant, and important for enabling the model to capture differences in choice behavior between married vs. single women and women with and without children. The estimates imply that total non-leisure time (comprised of hours of work, time

³⁶ As Fang and Keane (2004) discuss, “work” requirements under TANF do not literally mean work, as there are 14 “work activities,” such as skills training, that qualify. Thus, we feel that work requirements can best be interpreted as increasing the time cost of collecting welfare.

spent attending school, rearing children, etc.) and consumption are complements in utility, although the strength of the complementarity is reduced by marriage and children.³⁷

Labor market parameters: The log wage equation estimates are consistent with the literature. For instance, the education and education squared parameters imply that an additional year of schooling at grade level 12 increases the offered wage rate by 9.1 percent.³⁸ The estimates imply that black ($\omega_{0,10}$) and Hispanic ($\omega_{0,11}$) women, *ceteris paribus*, receive wage offers that are 12.5 and 5.6 percent lower than white women. These parameters reflect wage discrimination in the labor market, that is, lower skill rental prices for black and Hispanic women, and/or that black and Hispanic women have lower skill endowments at age 14 (independent of type).

Potential Husband's Earnings: The distribution of earnings of potential husbands from which black and Hispanic women draw have substantially lower means than that of white women (by 27 and 13 percent respectively). The estimates also imply a substantial degree of assortative mating, as the coefficient on the woman's skill endowment in the husband log wage offer function is nearly 2, and each additional year of education is estimated to increase the mean husband offer wage by about 3 percent.

Parental Income and Transfers: The estimates of the parental income function imply average parental (semi-annual) income of \$16,500 for white women who are age 18 and whose parents had 12 years of education.³⁹ Average parental income is about \$3,900 lower for comparable black women and \$2,000 lower for Hispanic women. Each additional year of parental education raises average parental income by about \$1000 per 6-month period.

The parental transfer function implies that a co-resident child over the age of 18 who is

³⁷ Thus, the marginal disutility of work effort is greater at higher consumption levels. This helps explain why, for example, women whose husbands have higher earnings tend to work less, *ceteris paribus*. And it helps to explain the relatively high hours of low wage women relative to high wage women.

³⁸Note that the education squared term, while statistically significant, is quantitatively quite small.

³⁹The age coefficient in the parental income equation is negative and statistically significant, but quantitatively small (i.e., about \$300 per year). The implication is that the typical parent is on the downside of their life-cycle earnings path during the child's life.

not in college receives a transfer equal to 21 percent of parental income.⁴⁰ The interaction term between college attendance and parental education is positive and significant, implying, for example, that a parent with 9 years of education transfers 30 percent of income, while a parent with 16 years of education transfers 36 percent of income to a child attending college. Consistent with our results in Keane and Wolpin (2001), these results imply that better educated and higher income parents provide larger transfers to youth to help them attend college. Because the parents of the black and Hispanic women tend to be lower income and less educated than the parents of the white women, black and Hispanic women receive, on average, lower transfers to help finance college.

Husband Transfer Function: The husband transfer function is simply a constant. Given the logistic form, the estimate ($\tau_0^m = .183$) implies that a woman receives 54.6 percent of household income when married.⁴¹

Error Rate Parameters: Error rate parameters are important in our estimation algorithm. To help interpret these parameters, consider, for example, the error rate parameter for schooling, $E_s = .785$. The value of that parameter implies that, in a period when the true probability of a youth attending school is 80 percent, a youth who attends will report that attendance correctly $.785 + (1 - .785)(.80) = 95.7$ percent of the time. Oppositely, a youth who does not attend will give a false positive report of attendance $(1 - .957)(.80/.20) = 17.2$ percent of the time. This formulation guarantees that the overall percentage of youth who report attendance is 80 percent, so classification error is unbiased. In contrast, in a period when only 20 percent of youth attend, attendance is correctly reported 82.8 percent of the time, and non-attendance is falsely reported as attendance only 4.3 percent of the time. Note that the probability of a false positive is 4 times smaller, because the probability of the event is four times smaller. This is precisely what must be true for classification error to be unbiased. Such a process is intuitive, since false positives for

⁴⁰This figure should be interpreted as including not only purely monetary transfers, but also the monetized value of room and board, clothing, etc.

⁴¹As a result, a woman needs to draw a husband with (average) earnings roughly equal to or greater than her own in order for marriage to raise her own consumption, although there is also a psychic value to being married. We experimented with including other state variables, like number of children, in the share equation, but they were not significant.

rare events must, almost tautologically, be rare.

Unobserved Heterogeneity: As in previous research (Keane and Wolpin (1997)) on men, we find that unobserved heterogeneity plays an important role in explaining differences in behavioral outcomes. We estimated a model with six latent types, finding that this number was sufficient for the model to provide a reasonable fit to all the key features of the data that we were interested in (again, see our companion paper Keane and Wolpin (forthcoming) for more details on model fit/validation). Because types are fundamentally unidentified without normalization (as they can always be interchanged without altering model fit), we imposed in estimation a ranking on the skill endowments, descending from type 1 (the highest) down to type 6 (the lowest).

We can see from the parameter estimates of several of the structural components of the model that types differ greatly. For instance, in the log offer wage equation, types 3 and 4 are estimated to have offer wages about 10 percent lower than either type 1 or 2, while types 5 and 6 have offer wages about 20 percent lower. Although types 1 and 2 have similar skill endowments, type 2's get greater disutility from non-leisure time ($\alpha_{1,5} = -.584$) and greater utility from pregnancy ($\alpha_{55} = 2.802$, or about \$2,800).

Types 5 and 6, having low skill endowments, comprise most of the high school dropout population. Type 6's have a slightly lower skill endowment than type 5's, get much greater disutility from non-leisure time, greater utility from pregnancy and exhibit less stigma from welfare participation. As a result, although types 5 and 6 are both low-skill, the type 6 women are most prone to teenage pregnancy and welfare participation.

Initial Conditions and Type Proportions: Two MNL functions, one expressing type probabilities as a function of parental education and initial schooling and the other expressing initial schooling as a function of parental schooling, together determine, in a parsimonious way, the complete joint multinomial distribution of parental schooling (14 levels), initial schooling (4 levels) and type (6 levels).⁴² We treat the parental schooling distribution for black, Hispanic and white women for each State as given, that is, these proportions are simply calculated from the data and not estimated. They are also reported in the table.

The estimates of the MNL functions imply that children of more educated parents are

⁴² Note that there are $14 \cdot 4 \cdot 6 = 336$ cells, but only 29 parameters in the two logits.

much more likely to be the high skill types. For instance, consider a women with initial schooling level 3 (which is the most common level and corresponds to being in 8th grade at age 14).⁴³ The estimates imply that if the parental schooling is at level 5 (which corresponds to 11 years of schooling), then 15.9 percent of the women are type 1 and 24.8 percent are type 6. But, if the parents have schooling level 10 (which corresponds to completing college), then 52.2 percent are type 1 and only a 4.6 percent are type 6.

Initial schooling level is also importantly related to type. For example, if a woman has completed only 7th grade by age 14 and her parents have 11 years of schooling, then 5 percent are type 1 and 27.7 percent are type 6. This is an 11 point lower probability of being type 1 than if the woman had completed 8th grade by age 14. The MNL for initial schooling further implies that parents schooling is also closely related to the woman's initial schooling.

The parents of minority women have substantially lower completed schooling levels than the parents of white women. For instance, in California, 13.2 percent of the parents of the white women are high-school drop outs, while 25.9 percent of the parents of black women and 56.3 percent of the parents of Hispanic women are dropouts. Conversely, 33.4 percent of the parents of white women in California have college degrees or post-graduate education, compared to only 10.3 percent and 5.7 percent of the parents of black and Hispanic women. Operating through the MNL functions that determine type, these differences imply that black and Hispanic women are substantially less likely to be high skill endowment types than are white women. For example, in California, the model estimates imply that the 6-element vector of type percentages is 21.3, 23.7, 11.7, 11.6, 14.6, 17.3 for white women, 17.3, 18.2, 12.0, 11.8, 18.1, 22.6 for black women, and 13.6, 14.1, 11.6, 11.9, 19.5, 29.4 for Hispanic women.⁴⁴ Thus, via the mechanism of determining type (which influences both skill endowments and preference parameters), differences in parental schooling may account for large behavioral differences between minority

⁴³ This level of initial schooling accounts for about three-quarters of the cases. Having completed only 7th grade accounts for nearly 15 percent of the cases (i.e., most of the remaining data).

⁴⁴ We also allow for skill and preference endowments to differ among the U.S. States. Minority-majority differences in skill and preference endowments, therefore, also emerge because minority women differ in their geographic distributions relative to white women.

and majority women.

C. Simulations of Type Differences in Behavior

In table 3, we compare the behaviors of the two extreme types, types 1 and 6, separately for white, black and Hispanic women. The differences are pronounced. Black women of type 6 have spent 7 more years on welfare by age 30 than have those of type 1, they have worked about 8 fewer years, have about 4 ½ years less education, and have 2 more children. Differences in welfare receipt between types are smaller for Hispanic and white women, but still substantial (i.e., about 5 and 3 years, respectively), and differences in work experience, schooling and fertility are about as large as for black women. Type 6's are a larger group than type 1's, by 10, 6 and 1 percentage points for black, Hispanic and white women, respectively. Indeed, type 6's are the largest group for all races.

Compared to other initial conditions, unobserved heterogeneity is by far the most important in accounting for the variance in behaviors. As seen in table 4, unobserved type alone accounts for 65 percent of the variation in completed schooling (by age 30). Whatever the process by which these unmeasured preferences and endowments are formed by age 14, they are critical in determining the completed schooling levels of these women. In contrast, the corresponding percentage associated with being black, Hispanic or white is only 2 percent, for state of residence 4 percent, and for parental schooling (which affects both type and parental income) 11 percent. Together, initial conditions account for 70 percent of the variance in completed schooling, with the other 30 percent due to idiosyncratic shocks up to age 30.

Welfare participation is more volatile. At age 30, only 33 percent of the variance in the total number of (6 month) periods on welfare is explained by type. At age 40 the comparable figure is 36 percent. Being black, Hispanic or white explains a smaller proportion of the variance, 7 and 9 percent at those two ages, respectively, while parental schooling explains 6 and 5 percent. The table also reports comparable figures for work experience, fertility, marriage, full-time wage offers and (potential) husband's income. Although the percentages of variance explained by the different initial conditions vary across these outcomes, in all cases except for years of marriage, type explains the largest percentage. In general, initial conditions explain a larger percentage of the variation for human capital outcomes, namely schooling, work

experience and wages, and a smaller percentage for demographic outcomes, namely children ever born, marriage duration and the income of potential husbands.

Finally, the last rows of Table 4 report the percent of variance in the present discounted value of lifetime utility explained by initial conditions both for black, Hispanic and white women separately and overall. Within each group, unobserved type, although by far the most important single characteristic, explains only 32 percent of the variance for white women, 9 percent for black women and 17 percent for Hispanic women. Interestingly, when the groups are pooled, type does not explain the greatest percentage of the variance; being black, Hispanic or white explains 24 percent, while type explains only 18 percent. And, all of the initial conditions taken together explain slightly less than one-half (47 percent) of the total variance in lifetime utility.

These results are seemingly quite different from those for white men, where we found (Keane and Wolpin (1997)) that type explained 90 percent of the variance in lifetime utility. However, that model only considered labor market outcomes. A more appropriate comparison would therefore be to the explained variance in full-time wage offers, which, as seen in table 4, is about 65 percent for women. Even that figure is not quite comparable because accumulated work experience and completed schooling, the determinants of full time wage offers, are affected by shocks to preferences related to demographic variables. It seems clear that the key reason that type explains less of the variance of lifetime utility for women in the present model than it did for men is because demographic outcomes, for example, whether a woman has a child, who one meets in the marriage market, etc., are governed by inherently more noisy processes than are labor market outcomes.

D. Counterfactual Experiments:

1. Accounting for Minority-Majority Differences in Outcomes:

In this section we use the model to address the first key question raised in the introduction: To what extent do differences in labor market opportunities, marriage market opportunities and tastes account for minority-majority differences in life-cycle choices and outcomes? To address this issue, we perform four counterfactual experiments corresponding to four of the categories of parameter estimates discussed above: those related to the marriage market, to the labor market, to welfare stigma and to parental schooling. Each experiment

answers the question of how close the outcomes for black and Hispanic women would be to the outcomes for white women if each category of parameters, taken one at a time, were set equal to those of white women.⁴⁵

Table 5a reports the results for black women and table 5b for Hispanic women. In each table, the first two columns show the baseline predictions from the model, and the following columns the counterfactual experiments.⁴⁶ The columns labeled (1) through (4) then show the effects on outcomes of (i) equalizing the preference for marriage and the (potential) husband's income, (ii) equalizing wage offers (through equalizing skill endowments and/or eliminating market discrimination), (iii) equalizing welfare stigma and (iv) equalizing (the distribution of) parental schooling.

Adopting the marriage market parameters of white women would have a large impact on the behavior of black women, for whom both the change in preferences and the improved husband's income distribution would increase the incentive to marry. But, it would have only a negligible impact on Hispanic women, for whom the two changes are offsetting. For black women, marriage rates increase almost to parity with white women (for example, from 28.5 percent to 55.7 percent at ages 26-29.5, compared to 65.4 percent for white women). Along with the rise in marriage rates, welfare participation falls, reducing the gap with white women by over a quarter at ages 22-25.5 and by over a third at ages 26-29.

Note that having a higher probability of marriage reduces the return to human capital investment by lowering the probability of being employed. As a result, black women's employment rates also fall along with the rise in marriage rates, doubling the gap with white women. Also reflecting the forward-looking nature of the model, mean schooling falls by a third of a year. However, fertility changes only marginally.

Providing black and Hispanic women with the same wage offer function as white women reduces welfare participation more than does equalizing marriage market parameters, closing 44

⁴⁵ In performing these counterfactuals, observations on minority women are weighted so as to replicate the geographic distribution across states of white women.

⁴⁶Note that the baselines for whites differ between Tables 5a and 5b, because 5b includes only California and New York (the only States where there were enough Hispanics for estimation), while Table 5a includes whites from all five States.

percent of the black-white gap and 34 percent of the Hispanic-white gap at ages 22 through 25. Employment rates rise for both minority groups, reaching parity with white women in the case of black women and closing about half of the gap in the case of Hispanic women. Marriage rates increase and fertility falls, especially for black women, although differences with white women are still large.

The effect on welfare participation of replacing the minority levels of welfare stigma with that of white women is relatively small for both blacks and Hispanics, although of opposite signs. Effects on other outcomes are also small. Thus, minority-majority differences in preferences for welfare participation appear to play little role in explaining differences in outcomes.

Unlike the other experiments, equalizing parental schooling distributions has a much larger effect on Hispanic women than on black women. This counterfactual has a larger effect on Hispanic women than any other experiment. Specifically, the Hispanic-white difference in welfare participation falls by over 50 percent, the employment difference falls by over 60 percent, and, perhaps most notable, mean schooling rises by .6 years, almost to parity with white women. Fertility rates fall slightly, leaving a still substantial difference with white women, and marriage rates actually drop slightly, increasing the difference.

Two conclusions emerge from these experiments. First, the difference in the behaviors of minority women and white women result from a complex combination of factors. Differences in marriage market opportunities, labor market opportunities, family background and underlying preferences all play some role, but no one of them is responsible for all of the behavioral differences. Second, the importance of these individual factors in explaining black-white differences are not the same as in explaining Hispanic-white differences. Labor market opportunities are of much greater significance for black women, while family background (parental schooling) is much more important for Hispanic women.

2. The Incentive Effects of Altering Welfare Rules:

In this section, we perform counterfactual simulations of the effects of various hypothetical changes in welfare rules on behavior. We report the results only for type 6 women, who are estimated to be the most likely to participate in welfare (see table 3); that is, the type

that has the set of preferences, endowments and opportunities that induce them to choose welfare more frequently than any other type. As shown in table 3, this type comprises 20 percent of white women, 25 percent of black women and 29 percent of Hispanic women.

Tables 6a, 6b and 6c report the counterfactual experiments for black, Hispanic and white women, respectively. The baseline outcomes under the welfare rules actually in effect for the sample are shown in column (1). As seen, about 65 percent of the black women, 40 percent of Hispanic women and 25 percent of white woman of type 6 are receiving welfare between the ages of 22 and 30.⁴⁷ Only about a fifth of black and Hispanic women, and a third of white women, are working at those ages. At ages 26-29.5, the marriage rate for white women is 58 percent, but for Hispanic women it is 45.5 percent and for black women only 21.8 percent. Fertility rates are high; the average number of children born by age 24 is 1.5 for black women, 1.4 for Hispanic women, and 1.2 for white women. The fraction of women who are high school dropouts ranges from 40 to 50 percent across the three groups. Welfare benefits, on average, comprise over 40 percent of the total income of black women between the ages of 26 and 29, about a quarter of the total income for Hispanic women, but only about 10 percent for white women.⁴⁸

The behavioral outcomes that result from eliminating welfare, the most extreme contrast, are shown in column (2).⁴⁹ The next two columns impose time limits, the first a strict 5-year limit and the second a 3-year limit after which benefits are reduced by a third. As Fang and Keane (2004) discuss, it has been extremely rare under TANF for States to literally impose a strict 5-

⁴⁷ Type 6 women account for 69 percent of all person-periods of welfare receipt for white women, 63 percent for black women and 76 percent for Hispanic women. Type 5 women account for most of the rest of the person-periods of welfare participation.

⁴⁸ Total income for an unmarried woman includes welfare benefits, earnings and the woman's share of parental income if she lives with her parents. For a married woman, for whom parental co-residence and welfare are precluded, her total income includes her share of her and her husband's earnings.

⁴⁹ The effects of this, and all other, experiments are partial equilibrium. They do not take into account equilibrium effects on the labor and marriage market relationships that we have estimated. Not only may labor supply effects alter skill prices, but, perhaps less obviously, as pointed out in Rosenzweig (1999), the existence and generosity of welfare may influence the behaviors of potential husbands in acquiring human capital.

year time limit on lifetime welfare receipt. Based on their analysis of State policies, we view the 1/3 benefit reduction after 3 years as a reasonable approximation to what most States have actually implemented.

Next, column (5) presents an experiment where benefits are reduced by 20 percent, and column (6) introduces a work requirement that in order to receive benefits a woman has to work, or engage in “work related activities,” for 25 hours per week after having been on welfare for six months. Again based on Fang and Keane (2004), this appears to be a reasonable approximation to the sort of work requirement policy that a typical State implemented under TANF.

Eliminating welfare is estimated to have a substantial impact on employment rates for all three groups. The percentage of black women who are working between the ages of 26 and 29 nearly triples, from 15.1 to 43.4 percent, while that for Hispanic women doubles, from 19.4 to 38.1 percent. There is a more modest increase for white women from 31.6 to 44.8 percent, implying that the gap in employment between majority and minority women in the group (i.e., type 6) most prone to welfare would be almost eliminated in a world without welfare. But, school completion levels increase by only slightly more for minority women when welfare is eliminated. The percentage of high school dropouts declines by 9 points for black women (from 45 to 36 percent), by 7 points for Hispanic women (from 52 to 45 percent) and by 5 points for white women (from 42 to 37 percent).

And finally, minority-majority differences in marriage and fertility remain much the same without welfare. Marriage rates do increase substantially for minority women, for example, from 22 to 37 percent for black women at ages 26 to 29, but the increase is of similar magnitude for white women as well. Fertility falls modestly for black and Hispanic women when welfare is eliminated (e.g., from 2.40 to 2.24 children born by age 30 for black women), but falls by essentially the same amount for white women.

Eliminating welfare must reduce well-being as measured by the expected present discounted value of lifetime utility (PDVU) calculated at age 14, the first decision period.⁵⁰ However, it need not reduce well-being calculated at later ages, as the state space at each age

⁵⁰ We ignore any tax savings, which would be negligible for type 6 women, and, as noted, also equilibrium effects on the labor and marriage markets.

reflects the new welfare environment. For example, elimination of welfare might lead to more human capital accumulation, which makes women better off at older ages. In fact, this seems to be the case. Calculated at age 14, there is a fall in the PDVU of 3.6 percent for black women, of 2.0 percent for Hispanic women and of 1.4 percent for white women. However, when calculated at age 18 the fall in PDVU is smaller, and there is a slight rise at age 22. Calculated at age 25, the PDVU actually increases by 6.8 percent for black women, 5.4 percent for Hispanic women, and 4.3 percent for white women. A social planner that placed more weight on the well-being of adults than teenagers, or who applied a higher discount factor than that used by the agents in the model (.93) might prefer a no welfare policy.

A strictly enforced five-year time limit (column (3)) reduces welfare participation negligibly at the younger ages, but by a large amount thereafter as the limit becomes binding. By age 26 through 29, the fall is from 68 to 17 percent for black women, from 40 to 15 percent for Hispanic women and from 35 to 13 percent for white women.⁵¹ Increases in employment follow the same age pattern, but are of smaller magnitude as marriage rates also increase with the imposition of the time limit. There is a negligible change in fertility and in schooling, and, unlike when welfare is eliminated, the PDVU falls at all ages. The weaker (and more realistic) time limit in column (4), where benefits are only partially reduced when the limit is reached, has only very small effects relative to the baseline. This is consistent with the findings in Fang and Keane (2004) that time limits as they have actually been applied under TANF can account for very little of the fall of welfare participation since 1996.

Reducing benefits by 20 percent (column (5)) has modest effects on behavior. For example, for black women, there is a decline in welfare participation of 9 percentage points between the ages of 22 and 25 (from 61 percent to 52 percent) and an increase in employment by 4 percentage points (from 21 to 25 percent). These changes are of the same magnitude for Hispanic and white women. Effects on fertility, marriage and school attainment are negligible. A finding of quantitatively small demographic effects of welfare policy changes of this magnitude is consistent with prior work (see Moffitt (1992)). It is worth noting that this is not inconsistent

⁵¹ Although not directly comparable, Swann (2005) obtains equally dramatic declines in welfare participation.

with the much larger effects we found above for the experiment of complete elimination of welfare.

Based on a reading of Fang and Keane (2004), a “work” requirement of 25 hours per week in order to be eligible to continue to receive welfare benefits beyond 6 months is rather typical of the sort of work requirements that have been implemented under TANF.⁵² Our model implies that such a policy, which we model as increasing the time cost of receiving welfare, would increase employment by 47 percentage points for black women at ages 26-29 (from 15 to 62 percent). But it would only reduce welfare receipt by 13 percentage points (from 68 to 55 percent). Thus, most of the women who are working after the imposition of the work requirement still remain eligible for welfare. However, welfare comprises, on average, only 25 percent of total income after the work requirement is introduced as opposed to 43 percent before, and earnings increases by a factor of 3. Like eliminating welfare, the PDVU declines at ages 14 and 18, but is higher thereafter. Results are qualitatively the same for Hispanic and white women.

3. The Effect of Increasing the Wage Rate

In column (7) of Tables 6a through 6c we report the impact of a 5 percent increase in the offer wages for black, Hispanic and white women. The experiment is implemented by increasing the intercept of the log offer wage function (a .05 increase in the skill rental price), which determines wage offers conditional on education and work experience. It is possible, with this experiment, to calculate the long-run wage elasticities of labor supply implied by our dynamic model. To the extent that the rental price increase induces women to invest more in human capital, unconditional offer wages will increase by more than 5 percent.

As seen in table 6, the 5 percent wage increase has a dramatic effect on behavior of type 6 women. For instance, for white women, the percent working at ages 22-29.5 increases from about 34 percent to about 50 percent. This is about a 45 percent increase in hours. In addition, mean completed schooling increases from 11.5 to 12.0 years, the percent of high school drop-

⁵²As we noted earlier, many activities qualify as “work,” including training of various sorts.

outs falls from 42.2 to 23.7 percent, children born by age 28 drops from 1.86 to 1.70, and welfare participation drops by about 5 percentage points, from about 25 to about 20 percent.

For black women the strong positive effect on work is similar, increasing from about 18 percent at ages 22-29.5 to about 27 percent. This 9 point increase is almost identical to that for white women in percentage terms (i.e., roughly 50%) but much smaller in absolute terms (9 points vs. 16 points). The effects on schooling and fertility are very similar to those for white women (half a year of school and .15 fewer children at age 28). However, the decline in welfare participation seems much more modest (from about 65 percent to 62 percent at ages 22-29.5). This drop is smaller than that for white women in absolute terms (3 points vs. 5 points) and is much smaller in percentage terms (only 5 percent vs. 20 percent).

The results for Hispanic women are similar to those for black and white women. If anything, there is a slightly larger increase in work, and schooling and fertility effects are almost identical. At ages 22-29.5, their rate of welfare participation drops from about 40 percent to about 36 percent. This is intermediate in both absolute and percentage terms between the white and black women.

It is interesting to examine the labor supply elasticities implied by the simulation. For whites, the 45 percent hours increase given a 5 percent wage increase implies a labor supply elasticity on the order of 9. This may seem unrealistically large, but it is important to recognize that this figure applies only to type 6 women. Considering women as whole at ages 25-25.5 (the last point at which we observe all 16 cohorts), the 5 percent increase in the skill rental price causes full-time work to increase from 57 percent to 65 percent, and part-time work to increase from 15 to 17 percent. These changes imply an increase in average weekly hours of 14 percent, from 25.8 to 29.4. Thus, the implied labor supply elasticity is roughly 2.8. This figure is very much in line with prior estimates for women, which have implied rather large labor supply elasticities (see e.g., Heckman and MaCurdy (1980)).

It is particularly interesting to examine how labor supply elasticities differ by type. For type 2's, the increase in weekly hours is from 33.0 to 35.0, or 6.1 percent. For type 3's we have an increase from 26.2 to 31.0, or 18.3 percent; for type 4's a 19.5 percent increase, from 26.6 to 31.8; For type 5's a 22.9 percent increase, from 21.8 to 26.8; and for type 6's a 45.9 percent increase, from 12.2 to 17.8. Thus, the vector of implied elasticities for types 1 through 6 is

roughly 0.6, 1.2, 3.7, 3.9, 4.6 and 9.2. Clearly, labor supply elasticities are greater for the less skilled types.

The very high elasticity for type 6 women is presumably due to the fact that the welfare system has an important impact on the budget constraint relevant for their decision making. As Keane and Moffitt (1998) discuss, the non-convex budget sets created by the AFDC/TANF type rules create a situation where women can be close to indifference between no work and working large positive hours. Then a small increase in the wage rate can induce a very large labor supply response, even when utility function parameters would imply much more modest elasticities were the woman maximizing subject to a standard linear budget set.

4. The Effect of the EITC:

Although the EITC has existed since 1975, spanning the time period of our estimation sample, real spending and the number of claimants were low and relatively constant until 1988. With reforms since 1986, the number of claimants doubled from 1987 to 1994 and real spending increased 5-fold (Hotz and Scholz (2002)). Table 7 reports the effect that introducing the EITC regulations in force as of 2004 would have had on the behavior of the type 6 women. We report both the one-period or short-run effect, assuming the program was a surprise and taking as given the state space at the introduction of the program, and the “full-adjustment” or long-run effect, assuming the program was in place at the beginning of the life cycle decision period, at age 14.⁵³ Unlike the one-period effect, which holds demographics (education, marriage, fertility) fixed, the “full-adjustment” simulation incorporates how the program influences the evolution of demographics from age 14 onward.

Consider first the one-period impact on the employment decisions of the type 6 women. For black women, employment at ages 22-25 would increase from 20.8 to 22.0 percent, 1.2 percentage points (6 percent), while employment at ages 26-29 would increase by 1.4 percentage

⁵³ The short-run impact is obtained from a regression based on pooling base line simulated data and data simulated after introducing the EITC. The regression controls for all the relevant state variables of the model, and also includes a dummy variable equal to one if the data come from the EITC simulation and zero otherwise. The coefficient on the EITC dummy is interpreted as the short-run effect.

points (9 percent). The same figures for Hispanic women are 1.3 percentage points (5 percent) and 2.2 percentage points (11 percent). The effects for white women are much smaller, 0.8 percentage points (2 percent) and 0.7 percentage points (2 percent). These estimates are consistent with the general findings in the literature (see the summary in Hotz and Scholz (2002)).

In the long-run simulations that assume EITC was in place from the start of the life-cycle, the impact on employment is reversed. At ages 22-25 employment rates fall by 2.7, 4.6 and 4.4 percentage points for black, Hispanic and white women. Correspondingly, at ages 26-29, employment rates fall by 1.8, 2.4 and 4.4 percentage points. Along with decreased employment, the EITC would increase the proportion of women receiving welfare receipt at all ages.

The reason for these surprising results is that the EITC is a strongly pronatalist policy. The maximum tax credit in 2004 for a married couple with earnings of 10,000 to 15,000 dollars was only 390 dollars if they were childless, but rose dramatically to \$2,604 if they had one child and \$4,300 if they had two children. As seen in table 7, pregnancy rates increase significantly, even at the earliest ages. By age 28, the increase in pregnancy rates imply that the EITC would have induced black women to have had .33 additional children, Hispanic women .24 additional children and white women .30 additional children. Along with increased fertility, it is optimal to reduce work and increase welfare participation.

It should be noted that these rather large fertility effects are specifically for type 6 women. If we look at the population as a whole, effects are more modest. For example, our model predicts that, by age 25.5, the total children for white women would increase from .88 to 1.05, an increase of .17. For the 6 types, the increases are .09, .13, .16, .21, .19 and .25, respectively. Thus, as we would expect, the impact of the EITC on fertility is much larger for the lower skilled women. However, it is not surprising that effects for the higher skilled women are non-negligible. EITC receipt is not nearly so concentrated among type 6 women as is welfare receipt.

5. The Effect of TANF:

The introduction of the NLSY97 cohort provides a way to assess the impact on behavior of the 1996 welfare reform legislation, replacing AFDC with TANF, that changed welfare rules

rather substantially. The female respondents of the NLSY97, who were age 12 to 16 as of December 31, 1997, have been subject only to the new program. Using the model estimates, it is possible to forecast how the 1979 cohort of women would have behaved if they had been subject to TANF starting at age 14. A comparison to the actual behaviors of the 1997 cohort, at the same ages, provides an estimate of how much of the inter-cohort changes can be accounted for by TANF.⁵⁴

Characterizing the changes made under TANF is not easy, because an essential feature of the reform was to give the States a great deal of leeway to implement State-specific policies, and a great deal of cross-State heterogeneity has in fact emerged. Based on the extensive analysis of the welfare policies implemented by all 50 U.S. States presented by Fang and Keane (2004), we have attempted to distill the essence of reform features that were implemented by the typical State. Thus, in performing this exercise, we assume that the change in welfare rules under TANF had the following characteristics: (1) a welfare benefit reduction of 20 percent;⁵⁵ (2) a 3 year time limit with a one-third reduction in benefits thereafter;⁵⁶ and (3) a 25 hours per week work requirement after being on welfare 6 months.

We perform these experiments under two alternative assumptions about EITC take-up, either full participation or no participation. As seen in table 8, women age 18 to 21 in the 1997 cohort reduced their welfare participation relative to women of the same ages in the 1979 cohort. The reduction was greatest for black women, 9.7 percentage points, followed by Hispanic women, 4.9 percentage points, and by white women, 3.4 percentage points. According to our

⁵⁴ As in the case of the counterfactual exercises, this assessment ignores general equilibrium effects induced by TANF. It also ignores macroeconomic factors that might have differed in the pre- and post-1996 periods.

⁵⁵ The typical State has left grant levels fixed in nominal terms at the level that prevailed in the mid-90s, and allowed real benefit levels to deteriorate with inflation. This led to about a 20 percent benefit reduction between our estimation cohorts and the NLSY97 cohort. We also simulate the subsequent deterioration of real benefits with inflation over time on an annual basis.

⁵⁶ As we have already discussed, Fang and Keane (2004) show that practically no State imposed the strict 5-year time limit followed by benefit termination that was a well publicized feature of the federal PRWORA legislation. The typical State actually impose a shorter time limit, but imposed only partial benefit reduction when it was reached, a reduction of about 25 to 33 percent being typical.

model estimates, assuming nothing else differed between the cohorts, imposing the above changes in welfare rules would have led to reductions of 10.1 to 10.8 percentage points for black women (depending on EITC take-up), 7.3 to 7.8 percentage points for Hispanic women, and 3.3 to 3.4 percentage points for white women. Thus, all of the fall in welfare participation can be accounted for by changes in welfare rules. Notice that the contribution of EITC to the fall is relatively small.

Other factors seem to have played a more important role in the changes in employment rates between the two cohorts, particularly in the case of black women. Although the employment rate for black women increased by 13.3 percentage points, the change in welfare rules can only explain between 3.9 and 6.6 percentage points of the increase. This leaves between 6.7 and 9.4 percentage points to be explained by other factors. In contrast, the difference between the actual change and that predicted by the changes in welfare rules is only between 3.3 and 6.1 percentage points for white women and between -1.8 and 2.1 percentage points for Hispanic women. Given these results, whatever other factors are responsible for these inter-cohort differences, overall the effect must be to increase employment, especially of black women, but to leave welfare participation essentially unchanged.

VI. Conclusions

In this paper, we have presented and structurally estimated a dynamic programming (DP) model of life-cycle decisions of young women. The model significantly extends earlier work on female labor supply, fertility, marriage, education and welfare participation by treating all five of these important decisions as being made jointly and sequentially within a life-cycle framework. We have used the model to perform a number of counterfactual experiments that shed light on how several key factors, specifically, labor and marriage market opportunities, preferences and the welfare system, influence life-cycle outcomes for young women, and lead to differences in outcomes across white, black and Hispanic women.

Wilson and Neckerman (1986) criticized the literature on welfare effects on female demographic outcomes like teenage births and single parenthood, arguing that “the recent trend among scholars and policy makers to neglect the role of male joblessness while emphasizing the role of welfare is ... questionable.” They argued that it was the decline in the number of “marriageable” men that primarily led to increases in female headed families, and the

concomitant growth of poverty and welfare receipt. In contrast, conservative social commentators like Murray (1984) have blamed the welfare system for a wide range of social “pathologies,” including dropping out of high school, teenage pregnancy, single motherhood, low marriage/high divorce rates, and a general “culture of poverty” that discourages work.

Unfortunately, prior work has not been able to quantitatively assess these competing arguments, because (i) studies of welfare effects on particular outcomes have generally viewed other outcomes as exogenously given (e.g., studies of the effect of welfare on marriage or fertility have treated education as given), and (ii) prior work has generally failed to allow for labor and marriage market opportunities and the welfare system to interact in jointly influencing life-cycle outcomes.

Our approach of modeling women’s sequential life-cycle decisions regarding schooling, marriage, fertility, welfare and work, contingent on both marriage opportunities as determined by the marriage market, and employment opportunities as determined by the labor market, allows us to directly address this debate. Our results suggest that, not surprisingly, both positions have some validity, but that both are greatly oversimplified. This can be seen from the following two counterfactual experiments.

In one experiment, we alter the marriage market facing black and Hispanic women so that they face the same distribution of potential husbands, in terms of their earnings opportunities, as do white women. This change would have the dramatic effect of doubling those black women’s marriage rates, bringing it nearly up to same rate as for white women. Nevertheless, black women’s welfare participation rates at ages 22-29 would only fall from about 28 percent to 21 percent. Although this is a substantial 25 percent drop, it still leaves them well above the white participation rate of about 7 percent.

In the second experiment, we eliminate the welfare system. This dramatic change does have important effects. For black women, it reduces the number of high school drop outs from 19.9 percent to 15.8 percent.⁵⁷ Average hours per week worked by black women at age 25 increases substantially, from 20.4 to 23.8, but this still remains below the baseline hours for white women of 25.8. Most notably, effects on female headship and teenage births are minor. The marriage rate at age 25 rises from 26 to 30 percent, which remains far below the baseline

⁵⁷ These figures are for all women, not only for the type 6 women as reported in table 6.

rate for white women of 58 percent. And the average number of children born before age 20 drops only slightly, from .48 to .44. Thus, although eliminating welfare may have a strong positive effect on employment for black women, and modestly increase their education, it does little to reduce the majority-minority difference in teenage pregnancies or the rate of marriage. More realistic experiments like reducing the generosity of welfare benefits have similar but even more modest effects. Results are basically similar for Hispanic women.

Therefore, although equalizing marriage market opportunities or eliminating (or reducing) welfare benefits would both lead to important changes in minority women's behavior, neither hypothetical intervention would come close to bridging the gap between their behavior and that of white women. A key factor separates minority from white women, namely differences in wage offers resulting from labor market discrimination and/or early (age 14) skill endowments.

For instance, our estimates imply that eliminating the difference in wage offers would raise the employment rate of black women at ages 22-29 from 57 percent to 71 percent, bringing it into parity with that of white women. It would also lower welfare participation from 28 percent to 19 percent (still well above the white rate of 7 percent), and lower teenage pregnancy from .47 to .41 children born before age 20 (also still well about the white rate of .31). Results for Hispanic women are in the same direction but more modest.

In previous work on young men (Keane and Wolpin (1997, 2000)), we identified the existence of substantial differences in a person's "type" or "skill endowment" at age 16 as a key determinant of differences in schooling and labor market outcomes among white men and of differences between white and black men. Similarly, here we find that the age 14 "type" is important for young women. This "type" may be interpreted as representing, in part, the cumulative outcome of human capital investments that have been made in a person, by parents, the school system, other relatives, the neighborhood, the person herself, etc., from conception up through age 14. According to our estimates, these skill endowment types differ substantially between minority and majority women. For instance, in CA, our estimates imply that 45 percent of white women but only 35 percent of black women are the "high" skill endowment types (which we label types 1 and 2). Similarly, 41 percent of black women but only 32 percent of white women are the "low" skill endowment types (which we label 5 and 6). The difference is even greater for Hispanic women, with 28 percent being the "high" skill types and 49 percent the

“low” skill types. Woman’s age 14 “type” explains 65 percent of the variance in highest grade completed, about 50 percent of the variance in work, and over 60 percent of the variance in wage offers.

According to our simulations, equalizing type proportions would raise employment rates for black women by about 5 points at ages 22-29 and for Hispanic women by about 10 points. Neither change is enough to bridge the gap with whites however. Levels of education for black women would actually surpass those for white women, while those for Hispanic women would be brought into parity.⁵⁸ These changes would not do much to reduce welfare participation rates for black and Hispanic women, because they continue to face worse marriage market opportunities and labor market discrimination.

One result that is clear is that differences in preferences for welfare participation between minority and majority women play almost no role in generating differences in welfare participation, labor supply or other outcomes. Our model implies that the much higher welfare participation rates for Hispanic and, especially, black women can be explained almost entirely by the worse labor market and marriage market opportunities that they face. Thus, it is unnecessary to resort to substantial differences in preferences for welfare to explain these differences in behavioral outcomes. Nevertheless, as noted above, the welfare system does differentially affect decisions and outcomes for minority relative to white women, precisely because they do face different constraints.

In summary, there is no simple answer to the question of what causes minority-majority differences in behaviors and outcomes. The estimates from our model imply that labor market opportunities, i.e., labor market discrimination and/or skill endowments in place by age 14, and marriage market opportunities, i.e., the earnings potential of prospective husbands, as well as the interaction of these differential constraints with the effects of the welfare system, all provide part of the explanation. As in our earlier work on young men (Keane and Wolpin (1997, 2000)), a key conclusion is that more work needs to be done on the determinants of investments in children at young ages that generate the age 14 skill “endowments” that appear to be so important for later outcomes.

⁵⁸ Note that, *ceteris paribus*, black women have a greater incentive to acquire education than whites because of their worse marriage market opportunities.

References

- Blundell, Richard and Thomas MaCurdy. "Labor Supply: A Review of Alternative Approaches." in O.C. Ashenfelter and D. Card eds., Handbook of Labor Economics 3A, Amsterdam: Elsevier Science Publishers, 1999, 1559-1689.
- Brien, Michael J. "Racial Differences in Marriage and the Role of Marriage Markets." Journal of Human Resources, 32, Winter 1997, 741-778.
- Erdem, Tülin. A Dynamic Analysis of Market Structure based on Panel Data, Marketing Science, 15, 1996, 359-378.
- Fang, Hanming and Michael Keane. "Assessing the Impact of Welfare Reform on Single Mothers." Brookings Paper on Economic Activity. 2004.
- Fang, Hanming and Dan Silverman. "Time-inconsistency and Welfare Program Participation: Evidence from the NLSY." mimeo, Yale University, 2004.
- Heckman, James J. "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process and Some Monte Carlo Evidence." in C. F. Manski and D. McFadden eds., Structural Analysis of Discrete Data with Econometric Applications, Cambridge, MA: MIT Press, 1981, 179-97.
- Heckman, James J. and Thomas MaCurdy. "A Life Cycle Model of Female Labour Supply." Review of Economic Studies, 47, January 1980, 47-74.
- Hotz, V, Joseph and Karl Scholz. "The Earned Income Tax Credit." Mimeo, UCLA, 2002.
- Hoynes, Hilary. Welfare Transfers in Two-Parent Families: Labor Supply and Welfare Participation Under AFDC-UP, Econometrica, 64, March 1996, 295-332.
- Keane, Michael P. "Simulation Estimation for Panel Data Models with Limited Dependent Variables." in G.S. Maddala, C.R. Rao and H.D. Vinod eds., Handbook of Statistics 11, Amsterdam: Elsevier Science Publishers, 1993, 545-572.
- _____. "A Computationally Practical Simulation Estimator for Panel Data." Econometrica, 62, January, 1994, 95-116.
- Keane, Michael P. and Robert Moffitt. "A Structural Model of Multiple Welfare Program Participation and Labor Supply." International Economic Review, 39, August 1998, 553-590.

- Keane, Michael P. and Robert Sauer. "A Computationally Practical Simulation Estimation Algorithm for Dynamic Panel Data Models With Unobserved Endogenous State Variables" Mimeo, Yale University, 2003.
- Keane, Michael P. and Kenneth I. Wolpin. "The Solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence." Review of Economics and Statistics, 76, November 1994, 684-672.
- _____. "The Career Decisions of Young Men." Journal of Political Economy, 105, June 1997, 473-522.
- _____. "Eliminating Race Differences in School Attainment and Labor Market Success." Journal of Labor Economics, 2000, 18:4, 614-652.
- _____. "Estimating Welfare Effects Consistent with Forward-Looking Behavior, Part I: Lessons From a Simulation Exercise." Journal of Human Resources, 37, Summer, 2001, pp. 600-622.
- _____. "The Effect of Parental Transfers and Borrowing Constraints on Educational Attainment." International Economic Review, 42, November 2001, 1051-1103.
- _____. "Exploring the Usefulness of a Non-Random Holdout Sample for Model Validation: Welfare Effects on Female Behavior," International Economic Review, forthcoming.
- Lerman Steven R. and Charles F. Manski. "On the Use of Simulated Frequencies to Approximate Choice Probabilities." in C. F. Manski and D. McFadden eds., Structural Analysis of Discrete Data with Econometric Applications, Cambridge, MA: MIT Press, 1981, 305-19.
- McFadden, Daniel. "A Method of Simulated Moments for Estimation of Discrete Response Models without Numerical Integration." Econometrica, 57, September, 1989, 995-1026.
- Miller, Robert A. And Seth G. Sanders. "Human Capital Development and Welfare Participation." Carnegie Rochester Conference Series on Public Policy, 46, 1997, 1-43.
- Moffitt, Robert. "An Economic Model of Welfare Stigma." American Economic Review, 73, 1983, 1023-35.
- _____. "Profiles of Fertility, Labor Supply and Wages of Married Women: A Complete Life Cycle Model." Review of Economic Studies, 51, April 1984, 263-278.

- _____. "Incentive Effects of the U.S. Welfare System: A Review." Journal of Economic Literature, 30, March 1992, 1-61.
- _____. "The Effect of Welfare on Marriage and Fertility: What Do We Know and What Do We Need to Know." in Robert Moffitt ed., The Effect of Welfare on the Family and Reproductive Behavior, Washington, D.C.: National Research Council, 50-97.
- Murray, Charles. Losing Ground: American Social Policy, 1950-1980. Basic Books, 1984, New York.
- Rosenzweig, Mark R. "Welfare, Marital Prospects, and Nonmarital Childbearing" Journal of Political Economy, 107, 1999, S3-S32.
- Sanders, Seth. "A Dynamic Model of Welfare and Work." Mimeo, Carnegie-Mellon University, 1993.
- Seitz, Shannon. "Accounting for Racial Differences in Marriage and Employment." Mimeo, Queens University, 2004.
- Swann, Christopher A. "Welfare Reform When Recipients Are Forward-Looking." Journal of Human Resources, 40, 2005, 31-56.
- Van der Klaauw, Wilbert. "Female Labour Supply and Marital Status Decisions: A Life-Cycle Model." Review of Economic Studies, 63, 1996, 199-235.
- Wilson, William J. The Truly Disadvantaged. Chicago: University of Chicago Press, 1987.
- Wilson, W. and K. Neckerman. "Poverty and Family Structure: The Widening Gap between Evidence and Public Policy Issues." In S. Danziger and D. Weinberg (eds.), Fighting Poverty: What Works and What Doesn't, Harvard University Press, 1986, Cambridge, 232-259.
- Wolpin, Kenneth I. "The Determinants of Black-White Differences in Early Employment Careers: Search, Layoffs, Quits and Endogenous Wage Growth." Journal of Political Economy, 100, June 1992, 535-560.
- Wood, Robert G. "Marriage Rates and Marriageable Men: A Test of the Wilson Hypothesis." Journal of Human Resources, 30, 1995, 163-193.

Table 1
Choice Distributions by Age: Estimation Sample of the Combined Five States

Age	Attending School			Working (PT or FT)			Married			Becomes Pregnant			Receives AFDC		
	W	B	H	W	B	H	W	B	H	W	B	H	W	B	H
14	100	93.3	100	14.3	10.5	12.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15	97.7	100	100	11.4	9.9	5.2	0.0	0.0	0.0	1.0	3.4	1.0	1.0	1.3	0.0
16	88.3	87.5	90.3	30.0	14.5	19.3	3.0	1.0	2.9	3.1	3.8	2.1	1.0	1.0	1.0
17	84.6	80.7	79.2	50.0	26.9	32.4	8.7	1.4	6.4	5.6	5.3	2.5	1.3	2.5	2.3
18	42.8	50.9	41.5	63.0	32.6	50.7	16.4	3.7	11.9	3.7	4.5	6.7	2.6	9.0	3.3
19	32.5	32.1	27.1	65.6	43.4	51.2	24.9	7.1	19.9	4.5	8.6	5.6	3.6	15.6	6.8
20	23.8	22.2	18.8	67.5	46.4	52.2	31.5	11.7	27.1	4.3	6.0	4.9	5.4	17.3	10.3
21	19.4	12.3	12.2	69.6	49.2	58.3	37.1	14.4	34.2	6.0	7.9	6.3	5.1	21.2	13.7
22	10.8	8.3	7.7	70.0	52.5	60.6	37.5	20.3	35.9	4.5	5.3	5.7	6.1	25.6	15.1
23	4.2	6.2	3.9	72.0	54.2	58.5	49.1	22.3	39.7	5.9	6.1	5.3	6.2	27.2	15.3
24	3.8	5.4	4.6	72.7	55.4	57.7	54.1	22.8	45.7	6.6	6.9	7.9	7.0	27.8	17.2
25	4.0	5.9	2.9	73.8	62.8	55.6	58.5	20.9	47.2	7.6	7.0	7.2	6.4	26.8	16.0
26-29	3.2	3.6	2.2	71.5	61.1	56.7	63.6	25.6	52.1	5.8	4.4	5.8	5.0	25.7	15.4
30-33	4.5	2.3	2.6	72.6	63.3	64.9	72.8	32.0	56.7	4.3	2.3	5.3	2.6	22.3	14.5

Table 2
Summary Statistics of Total Monthly Benefits By Numbers of Children and Earnings by State: 1967-1990

		Monthly Earnings					
		Zero		\$500		\$1000	
		One child	Two children	One child	Two children	One child	Two children
CA							
	μ	589	724	351	517	87	196
	σ	60	67	85	91	89	151
	1970	459	568	416	560	297	440
	1975	652	794	441	620	132	311
	1980	617	757	405	560	156	311
	1985	596	730	260	414	0	46
	1990	594	728	303	476	0	110
MI							
	μ	654	809	429	621	150	304
	σ	92	106	161	179	158	215
	1970	671	830	585	799	302	516
	1975	735	912	551	762	273	483
	1980	660	808	424	602	152	330
	1985	561	705	235	405	0	58
	1990	551	694	293	484	0	156
NY							
	μ	574	718	334	514	92	204
	σ	52	71	126	152	98	189
	1970	562	726	469	685	189	406
	1975	635	798	443	643	172	372
	1980	552	679	322	473	61	211
	1985	524	644	189	334	0	0
	1990	528	649	230	393	0	31

Table 2, continued

NC							
	μ	480	566	274	384	35	132
	σ	48	58	68	82	40	66
	1970	455	513	348	432	143	227
	1975	570	679	356	502	50	197
	1980	462	553	260	364	31	134
	1985	454	543	199	295	0	69
	1990	438	530	249	367	13	131
OH							
	μ	489	607	270	414	87	128
	σ	34	43	69	88	36	87
	1970	460	565	361	511	106	256
	1975	552	688	339	514	27	202
	1980	499	619	284	423	11	151
	1985	459	570	185	305	0	0
	1990	455	566	218	346	0	0

Table 3: Behavioral Differences by Unobserved Type for Black, Hispanic and White Women

	Black Women		Hispanic Women		White Women	
	Type 1	Type 6	Type 1	Type 6	Type 1	Type 6
Number of Years Receiving Welfare By Age 30	0.1	7.1	0.0	4.7	0.0	2.8
Number of Years of Work Experience By Age 30	9.7	1.9	10.6	2.5	10.3	3.5
Number of Years of Schooling Completed By Age 30	15.9	11.5	15.1	11.2	15.4	11.6
Number of Years of Marriage By Age 30	2.6	2.7	5.6	4.5	6.5	5.7
Number of Children By Age 30	0.8	2.7	0.8	2.6	0.6	2.1
Percent of Sample	15.8	25.5	13.8	29.3	19.2	20.4

Table 4
Proportion of Variance Explained by Initial Conditions^a

	Type	B,W,H	State	Parent Schooling	All (With Interactions)
Highest Grade Completed					
By Age 30	.65	.02	.04	.11	.70
Years on Welfare					
By Age 30	.33	.07	.01	.06	.49
40	.36	.09	.01	.05	.55
Years of Work Experience					
By Age 30	.43	.03	.03	.06	.52
40	.51	.03	.03	.07	.60
50	.49	.02	.04	.07	.60
Children Ever Born					
By Age 30	.22	.04	.01	.05	.28
40	.26	.06	.01	.05	.34
Years of Marriage					
By Age 30	.03	.12	.04	.01	.23
40	.02	.17	.05	.01	.27

Table 4 continued

	Type	B,W,H	State	Parent Schooling	All (With Interactions)
Full Time Wage Offer					
At Age 20	.44	.06	.02	.08	.54
30	.61	.04	.01	.11	.65
40	.65	.04	.01	.15	.70
50	.64	.04	.01	.11	.68
Potential Husband's Earnings					
At Age 20	.18	.16	.08	.06	.44
30	.25	.14	.11	.10	.47
40	.28	.14	.10	.10	.49
Present Discounted Value of Utility					
White Women	.32	-	.00	.09	.36
Black Women	.09	-	.04	.03	.20
Hispanic Women	.17	-	.02	.05	.23
All	.18	.24	.03	.11	.47

a. All determinants created as categorical. There are 6 type, 3 race, 5 state, and 13 parent schooling categories.

Table 5a: Accounting for Difference in Outcomes Between White and Black Women

	Baseline		Counterfactuals			
	White	Black ^a	(1)	(2)	(3)	(4)
Pct. Receiving Welfare						
Age 15-17.5	1.3	5.1	5.4	4.1	4.1	4.2
18-21.5	4.7	16.8	15.1	12.5	14.0	14.3
22-25.5	7.1	26.5	20.9	17.9	22.8	23.3
26-29.5	7.1	29.7	21.4	19.6	26.4	26.1
Pct. In School						
Age 15-17.5	85.3	84.4	80.7	87.7	84.2	85.2
18-21.5	29.8	29.6	25.0	30.6	29.8	33.1
22-25.5	8.3	8.1	6.0	9.0	8.1	9.0
26-29.5	3.4	3.5	2.6	3.7	3.5	3.9
Pct. Working						
Age 15-17.5	28.3	16.9	15.5	31.0	17.0	16.3
18-21.5	63.8	51.9	42.4	68.5	52.8	53.0
22-25.5	70.3	57.4	44.7	71.2	59.1	61.6
26-29.5	69.8	55.7	42.3	70.2	57.3	60.5
Pct. Pregnant						
Age 15-17.5	1.9	3.0	3.2	2.6	2.9	2.8
18-21.5	4.8	6.7	7.0	5.9	6.6	6.5
22-25.5	5.1	7.4	7.6	6.7	7.3	7.3
26-29.5	4.9	6.8	6.9	6.3	6.7	6.5

a. Black women assigned same geographic distribution as white women.

1. Black women have same marriage market as white women.
2. Black women have same wage offer function as white women.
3. Black women have same welfare stigma as white women.
4. Blacks women same parent schooling as white women.

Table 5a continued

	White	Baseline Black ^a	(1)	Counterfactuals (2)	(3)	(4)
Pct. Married						
Age 15-17.5	5.0	1.1	3.6	1.7	1.1	1.0
18-21.5	28.2	9.6	24.6	12.7	10.0	8.7
22-25.5	52.3	21.7	45.1	27.3	22.5	20.6
26-29.5	65.4	28.5	55.7	36.5	29.4	27.6
Pct. Living with Parents						
Age 15-17.5	93.6	97.6	95.0	96.9	97.6	97.6
18-21.5	56.2	71.5	60.0	68.8	71.3	72.4
22-25.5	19.6	33.2	22.4	30.5	32.9	34.1
26-29.5	10.5	23.2	13.9	20.4	22.9	23.8
Children Ever Born Before						
Age 20	.31	.47	.51	.41	.47	.45
24	.72	1.04	1.09	.91	1.02	1.00
28	1.14	1.65	1.71	1.47	1.63	1.59
Highest Grade Completed by Age 24						
	13.08	12.97	12.62	13.17	12.99	13.22

a. Black women assigned same geographic distribution as white women.

1. Black women have same marriage market as white women.
2. Black women have same wage offer function as white women.
3. Black women have same welfare stigma as white women.
4. Black women have same parent schooling as white women.

Table 5b: Accounting for Difference in Outcomes Between White and Hispanic Women

	White ^a	Baseline Hispanic ^b	(1)	(2)	Counterfactuals (3)	(4)
Pct. Receiving Welfare						
Age 15-17.5	1.0	4.1	4.1	3.1	4.5	2.0
18-21.5	3.6	10.6	10.6	9.0	11.5	6.1
22-25.5	5.7	14.7	15.0	11.6	16.0	9.5
26-29.5	5.6	15.7	15.6	11.9	16.9	10.1
Pct. In School						
Age 15-17.5	85.5	80.2	79.6	82.7	80.1	84.1
18-21.5	31.1	22.5	21.8	23.4	22.4	30.6
22-25.5	8.7	6.4	6.0	7.0	6.4	8.3
26-29.5	3.7	2.9	2.6	2.9	2.9	3.8
Pct. Working						
Age 15-17.5	30.2	25.5	25.7	33.6	25.5	24.7
18-21.5	69.0	58.8	57.5	66.1	58.4	63.0
22-25.5	76.1	58.9	56.5	66.5	58.1	69.8
26-29.5	75.8	56.5	53.1	65.0	55.9	68.8
Pct. Pregnant						
Age 15-17.5	1.6	3.1	3.1	2.9	3.1	2.5
18-21.5	4.1	6.4	6.5	6.1	6.4	5.8
22-25.5	4.5	7.0	6.9	6.6	7.0	6.3
26-29.5	4.3	6.6	6.5	6.4	6.6	5.9

a. California and New York only.

b. Hispanic women assigned same geographic distribution as white women.

1. Hispanic women have same marriage market as white women.
2. Hispanic women have same wage offer function as white women.
3. Hispanic women have same welfare stigma as white women.
4. Hispanic women have same parent schooling as white women.

Table 5b continued

	White ^a	Baseline Hispanics ^b	(1)	Counterfactuals (2)	(3)	(4)
Pct. Married						
Age 15-17.5	4.1	3.1	3.2	3.7	3.1	2.8
18-21.5	23.8	22.4	22.9	23.9	22.4	19.0
22-25.5	47.8	42.6	43.6	44.6	42.4	40.7
26-29.5	61.6	53.9	55.9	56.6	53.4	52.9
Pct. Living with Parents						
Age 15-17.5	94.5	95.6	95.5	95.0	95.6	95.7
18-21.5	60.1	60.9	60.0	59.4	60.9	64.1
22-25.5	21.8	23.3	22.9	22.5	23.4	24.9
26-29.5	11.9	14.5	13.9	13.4	14.8	15.1
Children Ever Born Before						
Age 20	.27	.47	.47	.44	.47	.39
24	.62	1.01	1.01	.95	1.01	.89
28	.99	1.59	1.59	1.51	1.60	1.41
Highest Grade Completed by Age 24						
	13.18	12.48	12.41	12.61	12.46	13.10

a. California and New York only.

b. Hispanic women assigned same geographic distribution as whites.

1. Hispanic women have same marriage market as white women.
2. Hispanic women have same wage offer function as white women.
3. Hispanic women have same welfare stigma as white women.
4. Hispanic women have same parent schooling as white women.

Table 6a : The Effect of Welfare and Wages on Outcomes: Black Women (type 6)

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pct. Receiving Welfare							
Age 15-17.5	13.2	0.0	13.0	13.2	9.6	8.0	10.9
18-21.5	39.6	0.0	36.4	39.9	30.6	27.2	35.3
22-25.5	61.2	0.0	35.6	60.5	52.2	45.2	57.2
26-29.5	68.1	0.0	16.5	66.5	61.8	55.1	66.5
Pct. In School							
Age 15-17.5	70.1	72.8	70.2	70.1	71.1	70.9	79.2
18-21.5	8.9	10.9	8.9	8.8	9.5	9.1	13.1
22-25.5	3.7	5.2	4.5	4.0	4.3	3.9	5.1
26-29.5	1.1	1.6	1.5	1.3	1.4	1.3	1.7
Pct. Working							
Age 15-17.5	9.5	10.4	9.6	9.6	9.7	11.9	11.3
18-21.5	26.9	36.5	27.2	26.7	29.1	42.6	36.8
22-25.5	20.8	42.7	25.9	21.4	24.7	54.1	29.7
26-29.5	15.1	43.4	31.2	18.1	18.9	62.2	23.8
Pct. Pregnant							
Age 15-17.5	5.0	4.5	5.2	5.2	4.9	4.9	4.4
18-21.5	9.5	8.8	9.5	9.6	9.4	9.3	8.9
22-25.5	10.1	9.7	10.3	10.3	10.1	10.1	9.8
26-29.5	9.2	8.8	9.4	9.3	9.1	9.1	8.7

1. Baseline.

2. No Welfare.

3. 5-Year Time Limit – no benefits thereafter

4. 3-Year Time Limit – 1/3 reduction in benefits.

5. Welfare Benefit Reduction of 20 percent.

6. 25 hours/week work requirement after six months on welfare

7. Wage offers 5 percent higher.

Table 6a continued

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pct. Living with Parents							
Age 15-17.5	98.2	98.0	98.2	98.1	98.1	98.1	98.2
18-21.5	73.1	70.7	73.0	73.1	72.5	71.9	73.9
22-25.5	34.4	31.1	33.6	34.3	33.7	33.4	35.2
26-29.5	26.3	21.0	23.6	26.0	25.6	25.4	27.2
Pct. Married							
Age 15-17.5	0.4	0.5	0.4	0.4	0.4	0.4	0.3
18-21.5	7.8	10.6	8.0	7.8	8.6	9.0	6.9
22-25.5	16.5	25.3	19.0	16.8	18.3	18.9	14.7
26-29.5	21.8	36.6	28.9	22.6	23.9	25.0	14.2
Children Ever Born Before							
Age 20	0.76	0.68	0.78	0.78	0.75	0.74	0.67
24	1.50	1.38	1.52	1.53	1.48	1.47	1.38
28	2.40	2.24	2.43	2.44	2.37	2.37	2.25
Highest Grade Completed by							
Age 24	11.4	11.6	11.5	11.4	11.5	11.5	11.9
Pct. High School Dropouts	45.4	36.2	44.0	45.2	42.2	43.7	27.0

1. Baseline.

2. No Welfare.

3. 5-Year Time Limit – no benefits thereafter.

4. 3-Year Time Limit – 1/3 reduction in benefits.

5. Welfare Benefit Reduction of 20 percent.

6. 25 hours/week work requirement after six months on welfare.

7. Wage offers 5 percent higher.

Table 6a continued

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Welfare Benefits (÷ 1000)							
Age 15-17.5	0.16	0.00	0.15	0.16	0.08	0.09	0.13
18-21.5	0.63	0.00	0.57	0.62	0.38	0.40	0.56
22-25.5	1.42	0.00	0.76	1.20	0.98	0.89	1.31
26-29.5	1.88	0.00	0.39	1.36	1.35	1.25	1.78
Earnings (÷ 1000)							
Age 15-17.5	0.15	0.16	0.15	0.15	0.15	0.18	0.19
18-21.5	0.63	0.86	0.64	0.62	0.69	0.90	0.96
22-25.5	0.70	1.43	0.84	0.75	0.84	1.40	1.11
26-29.5	0.61	1.77	1.13	0.69	0.77	1.77	1.04
Total Income (÷ 1000)							
Age 15-17.5	7.13	6.98	7.13	7.14	7.06	7.10	7.15
18-21.5	6.03	5.56	5.98	6.02	5.82	6.03	6.31
22-25.5	4.33	3.68	3.83	4.13	4.03	4.50	4.63
26-29.5	4.35	3.86	3.50	3.92	4.00	4.91	4.65
PDV Utility (÷ 1000)							
From Age 14	58.2	56.1	58.1	58.2	57.7	57.9	5.98
18	62.1	60.9	61.6	61.8	61.8	61.9	66.5
22	55.5	56.1	54.7	54.9	55.4	56.0	62.2
25	52.8	55.2	52.2	52.2	53.1	54.2	60.0

1. Baseline.
2. No Welfare.
3. 5-Year Time Limit – no benefits thereafter.
4. 3-Year Time Limit – 1/3 reduction in benefits.
5. Welfare Benefit Reduction of 20 percent.
6. 25 hours/week work requirement after six months on welfare.
7. Wage offers 5 percent higher.

Table 6b : The Effect of Welfare and Wages on Outcomes: Hispanic Women (type 6)

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pct. Receiving Welfare							
Age 15-17.5	12.1	0.0	11.8	12.0	6.4	6.2	9.3
18-21.5	28.8	0.0	26.4	28.9	18.7	18.1	25.4
22-25.5	39.6	0.0	26.4	38.8	30.5	27.4	36.2
26-29.5	40.3	0.0	15.3	38.3	31.1	29.1	35.3
Pct. In School							
Age 15-17.5	65.4	68.8	65.5	65.4	66.5	66.2	75.2
18-21.5	6.7	8.5	6.7	6.7	7.3	7.0	10.9
22-25.5	2.9	4.3	3.5	3.0	3.3	3.0	4.4
26-29.5	0.9	0.8	1.0	0.9	1.0	0.9	1.1
Pct. Working							
Age 15-17.5	13.2	14.9	13.4	13.2	14.4	15.7	17.7
18-21.5	34.5	44.4	35.1	34.5	37.8	45.3	46.5
22-25.5	25.4	42.8	29.7	26.4	30.1	45.4	37.7
26-29.5	19.4	38.1	28.4	21.4	24.0	45.2	32.1
Pct. Pregnant							
Age 15-17.5	4.9	4.7	5.0	5.0	4.8	4.9	4.5
18-21.5	8.9	8.4	8.9	8.9	8.8	8.8	8.4
22-25.5	9.8	9.3	10.0	10.0	9.8	9.7	9.2
26-29.5	8.7	8.6	8.9	8.9	8.7	8.7	8.5

1. Baseline.

2. No Welfare.

3. 5-Year Time Limit – no benefits thereafter

4. 3-Year Time Limit – 1/3 reduction in benefits.

5. Welfare Benefit Reduction of 20 percent.

6. 25 hours/week work requirement after six months on welfare

7. Wage offers 5 percent higher.

Table 6b continued

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pct. Living with Parents							
Age 15-17.5	97.3	97.0	97.4	97.4	97.2	97.3	97.6
18-21.5	63.1	59.7	62.9	63.0	61.4	60.8	65.3
22-25.5	25.9	22.5	25.5	25.8	24.4	24.8	27.0
26-29.5	17.7	12.4	15.4	17.2	15.6	15.9	18.5
Pct. Married							
Age 15-17.5	1.2	1.5	1.2	1.2	1.4	1.3	1.0
18-21.5	19.7	23.0	19.9	19.7	21.3	21.5	16.7
22-25.5	35.3	45.0	37.0	35.7	38.3	38.2	31.6
26-29.5	45.5	58.8	51.5	46.7	49.2	49.8	43.0
Children Ever Born Before							
Age 20	0.74	0.68	0.75	0.76	0.73	0.72	0.66
24	1.42	1.33	1.43	1.44	1.40	1.39	1.31
28	2.29	2.18	2.31	2.32	2.27	2.26	2.14
Highest Grade Completed by							
Age 24	11.1	11.4	11.2	11.1	11.2	11.2	11.7
Pct. High School Dropouts	51.9	45.0	51.4	51.8	49.0	51.1	35.4

1. Baseline.

2. No Welfare.

3. 5-Year Time Limit – no benefits thereafter.

4. 3-Year Time Limit – 1/3 reduction in benefits.

5. Welfare Benefit Reduction of 20 percent.

6. 25 hours/week work requirement after six months on welfare.

7. Wage offers 5 percent higher.

Table 6b continued

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Welfare Benefits (÷ 1000)							
Age 15-17.5	0.15	0.00	0.15	0.15	0.05	0.07	0.11
18-21.5	0.50	0.00	0.45	0.48	0.27	0.32	0.44
22-25.5	1.03	0.00	0.67	0.90	0.65	0.62	0.94
26-29.5	1.24	0.00	0.44	0.94	0.79	0.76	1.08
Earnings (÷ 1000)							
Age 15-17.5	0.25	0.28	0.25	0.25	0.27	0.28	0.34
18-21.5	0.98	1.26	0.99	0.97	1.07	1.18	0.43
22-25.5	1.03	1.70	1.17	1.05	1.23	1.51	1.67
26-29.5	0.96	1.87	1.28	1.02	1.20	1.71	1.71
Total Income (÷ 1000)							
Age 15-17.5	8.15	8.02	8.16	8.16	8.06	8.11	8.22
18-21.5	6.67	6.32	6.63	6.66	6.46	6.60	7.13
22-25.5	4.85	4.56	4.65	4.74	4.67	4.93	5.34
26-29.5	4.97	4.83	4.61	4.75	4.79	5.29	5.52
PDV Utility (÷ 1000)							
From Age 14	69.5	68.1	69.4	69.5	69.1	69.2	71.4
18	76.8	76.4	76.5	76.5	76.8	76.9	81.7
22	72.5	74.4	72.0	72.0	73.1	73.7	79.5
25	69.9	73.7	69.8	70.3	70.8	71.5	78.1

1. Baseline.
2. No Welfare.
3. 5-Year Time Limit – no benefits thereafter.
4. 3-Year Time Limit – 1/3 reduction in benefits.
5. Welfare Benefit Reduction of 20 percent.
6. 25 hours/week work requirement after six months on welfare.
7. Wage offers 5 percent higher.

Table 6c : The Effect of Welfare and Wages on Outcomes: White Women (type 6)

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pct. Receiving Welfare							
Age 15-17.5	4.6	0.0	4.4	4.4	2.1	2.9	3.4
18-21.5	15.2	0.0	14.3	15.0	9.5	10.5	12.4
22-25.5	25.0	0.0	19.6	24.6	18.2	18.2	20.7
26-29.5	24.6	0.0	12.6	23.5	18.2	18.4	20.4
Pct. In School							
Age 15-17.5	69.5	72.3	69.7	69.6	70.3	70.4	79.0
18-21.5	9.4	10.5	9.4	9.3	9.6	9.4	12.9
22-25.5	4.6	4.9	4.7	4.4	4.8	4.5	5.7
26-29.5	1.2	1.2	1.2	1.1	1.3	1.1	1.6
Pct. Working							
Age 15-17.5	15.4	15.9	15.5	15.6	15.7	16.0	19.4
18-21.5	40.8	48.3	41.2	43.6	43.2	47.1	54.4
22-25.5	35.5	47.7	37.5	44.5	38.8	48.6	50.6
26-29.5	31.6	44.8	36.0	44.0	35.1	46.5	49.1
Pct. Pregnant							
Age 15-17.5	3.6	3.1	3.6	3.6	3.5	3.5	2.9
18-21.5	7.7	7.2	7.8	7.8	7.6	7.6	7.1
22-25.5	8.0	7.5	8.1	8.0	7.9	8.0	7.6
26-29.5	7.3	6.9	7.4	7.4	7.2	7.3	6.8

1. Baseline.

2. No Welfare.

3. 5-Year Time Limit – no benefits thereafter

4. 3-Year Time Limit – 1/3 reduction in benefits.

5. Welfare Benefit Reduction of 20 percent.

6. 25 hours/week work requirement after six months on welfare

7. Wage offers 5 percent higher.

Table 6c continued

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pct. Living with Parents							
Age 15-17.5	95.3	95.2	95.4	95.4	95.3	95.3	95.7
18-21.5	57.7	56.4	57.8	57.8	57.0	57.0	60.0
22-25.5	21.8	20.0	21.6	21.8	21.1	21.3	23.4
26-29.5	12.4	9.4	11.2	12.2	11.3	11.4	13.5
Pct. Married							
Age 15-17.5	3.2	3.4	3.1	3.2	3.3	3.2	3.4
18-21.5	25.4	27.3	25.3	25.3	26.1	26.1	25.7
22-25.5	45.8	52.7	46.8	46.0	47.9	47.7	47.1
26-29.5	58.0	66.2	61.2	58.7	60.7	60.3	59.8
Children Ever Born Before							
Age 20	0.55	0.49	0.56	0.56	0.54	0.54	0.48
24	1.18	1.08	1.19	1.19	1.16	1.16	1.07
28	1.86	1.72	1.88	1.88	1.83	1.88	1.70
Highest Grade Completed by							
Age 24	11.5	11.7	11.5	11.5	11.5	11.5	12.0
Pct. High School Dropouts	42.2	36.8	41.6	42.1	40.3	41.2	23.7

1. Baseline.

2. No Welfare.

3. 5-Year Time Limit – no benefits thereafter.

4. 3-Year Time Limit – 1/3 reduction in benefits.

5. Welfare Benefit Reduction of 20 percent.

6. 25 hours/week work requirement after six months on welfare.

7. Wage offers 5 percent higher.

Table 6c continued

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Welfare Benefits (\div 1000)							
Age 15-17.5	0.04	0.00	0.04	0.04	0.01	0.02	0.03
18-21.5	0.25	0.00	0.23	0.24	0.14	0.17	0.20
22-25.5	0.57	0.00	0.43	0.52	0.35	0.35	0.46
26-29.5	0.63	0.00	0.30	0.50	0.39	0.39	0.50
Earnings (\div 1000)							
Age 15-17.5	0.30	0.31	0.30	0.30	0.30	0.31	0.39
18-21.5	1.22	1.46	1.23	1.22	1.29	1.35	1.79
22-25.5	1.52	2.06	1.60	1.53	1.67	1.87	2.39
26-29.5	1.58	2.36	1.79	1.61	1.76	2.07	2.73
Total Income (\div 1000)							
Age 15-17.5	10.5	10.4	10.5	10.5	10.4	10.5	10.6
18-21.5	8.09	8.01	8.08	8.08	8.00	8.09	8.69
22-25.5	5.72	5.79	5.69	5.69	5.66	5.87	6.42
26-29.5	5.83	6.07	5.75	5.75	5.79	6.09	6.65
PDV Utility (\div 1000)							
From Age 14	84.6	83.4	84.5	84.6	84.3	84.4	86.9
18	94.2	94.1	94.0	94.1	94.1	94.2	99.6
22	92.8	94.7	92.6	92.6	93.2	93.5	100.8
25	92.3	96.3	92.3	92.1	93.1	93.5	101.4

1. Baseline.
2. No Welfare.
3. 5-Year Time Limit – no benefits thereafter.
4. 3-Year Time Limit – 1/3 reduction in benefits.
5. Welfare Benefit Reduction of 20 percent.
6. 25 hours/week work requirement after six months on welfare.
7. Wage offers 5 percent higher.

Table 7 : The Effect of EITC on Outcomes: Type 6

Outcome	Black Women			Hispanic Women			White Women		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Pct. Receiving Welfare									
Age 15-17.5	13.2	12.8	15.8	12.1	11.8	14.3	4.6	4.6	5.9
18-21.5	39.6	39.3	43.2	28.8	28.0	31.1	15.2	14.8	16.9
22-25.5	61.2	61.0	62.9	39.6	39.3	41.0	25.0	24.7	26.9
26-29.5	68.1	68.2	69.3	40.3	40.5	41.6	24.6	24.9	27.4
Pct. In School									
Age 15-17.5	70.1	68.7	67.0	65.4	63.4	61.3	69.5	68.0	66.3
18-21.5	8.9	8.3	7.4	6.7	6.1	5.0	9.4	8.7	7.9
22-25.5	3.7	3.2	2.8	2.9	2.4	2.1	4.6	4.0	3.7
26-29.5	1.1	1.0	0.9	0.9	0.7	0.7	1.2	1.1	1.0
Pct. Working									
Age 15-17.5	9.5	9.4	9.1	13.2	12.9	12.5	15.4	15.5	14.9
18-21.5	26.9	27.2	23.4	34.5	34.2	28.8	40.8	41.0	36.6
22-25.5	20.8	22.0	18.1	25.4	26.7	20.8	35.5	36.3	31.0
26-29.5	15.1	16.5	13.3	19.4	21.6	17.0	31.6	32.3	27.2
Pct. Pregnant									
Age 15-17.5	5.0	6.1	6.0	4.9	6.2	6.0	3.6	4.5	4.4
18-21.5	9.5	10.8	10.6	8.9	10.7	10.5	7.7	9.0	8.9
22-25.5	10.1	11.5	11.5	9.8	10.4	10.5	8.0	9.2	9.2
26-29.5	9.2	10.0	10.3	8.7	9.6	9.9	7.3	8.1	8.2

1. Baseline.

2. Short-Run: One-period ahead forecast with same states as baseline at each age.

3. Long-Run.

Table 8: Actual and Predicted Changes in Welfare Participation and Employment Between NLSY79 and NLSY97 Cohorts at Ages 18-21

NLSY79-NLSY97 Change in	Actual	White Women		Actual	Black Women		Actual	Hispanic Women	
		EITC	Predicted No EITC		EITC	Predicted No EITC		EITC	Predicted No EITC
Pct. Receiving Welfare	-3.4	-3.3	-3.4	-9.7	-10.1	-10.8	-4.9	-7.3	-7.8
Pct. Working	-2.3	+1.0	+3.8	+13.3	+3.9	+6.6	+3.6	+1.8	+5.7

Appendix A:

In this equation we present the specific functional forms for equations 1, 3 and 4 in the main text, as well as the mathematical expressions for some aspects of the model that were only described verbally in Sections II and IV.

I. Utility Function:

$$\begin{aligned}
 U_a = & C_a + \alpha_{1a}h_a + \alpha_2h_a^2 + \alpha_3N_a + \alpha_4N_a^2 + \alpha_{5a}P_a \\
 & + \alpha_{6a}m_a(1 - m_{a-1}) + \alpha_{7a}s_a + \alpha_{8a}g_a + \alpha_9s_a(1 - s_{a-1}) \\
 & + \alpha_{10}m_a m_{a-1} + \alpha_{11}h_a^f s_a + \alpha_{12}h_a^p s_a + \alpha_{13}g_a g_{a-1} \\
 & + \alpha_{14}p_a s_a + \alpha_{15}h_a^p h_{a-1}^p + \alpha_{16}h_a^f h_{a-1}^f + \alpha_{17}p_a a \\
 (A.1) \quad & + \alpha_{18}p_a a^2 + \alpha_{19}p_a a^3 + \alpha_{20}p_a a^4 + \alpha_{21}h_a C_a + \alpha_{22}s_a I(a < 16) \\
 & + \alpha_{23}s_a I(a < 18) + \alpha_{24}p_a I(a < 18) + \alpha_{25}m_a I(a < 21) + \alpha_{26}m_a I(a < 25) \\
 & + \alpha_{27}h_a m_a C_a + \alpha_{28}h_a C_a N_a + \alpha_{29}h_a^f s_a I(S_a < 12) \\
 & + \alpha_{30}h_a^p s_a I(S_a < 12) + \alpha_{31}h_a^p I(16 \leq a < 18) \\
 & + \alpha_{32}COHORT * m_a(1 - m_a)
 \end{aligned}$$

where the α_{ja} , $j=1, 5, 6, 7, 8$, are the utilities or disutilities from (the linear term) in non-leisure time, a pregnancy, getting married, school attendance and welfare participation. They are given by:

$$\alpha_{ja} = \alpha_{j,0} + \sum_{q=1}^4 \alpha_{j,q} I(\text{State} = q + 1) + \sum_{q=5}^9 \alpha_{j,q} I(\text{type} = q - 3) + \sum_{q=10}^{11} \alpha_{j,q} I(r = q - 8) + \epsilon_{j,a}^u$$

for $j = 1, 5, 6, 7, 8$,

where $r=2$ denotes Black and $r=3$ denotes Hispanic. Notice that these five preference parameters, which correspond to the five choice alternatives in the model, are allowed to differ by observed initial conditions and by the latent “type”. In addition, each has an associated preference shock $\epsilon_{j,a}^u$ that we assume is normally distributed (see below). Having one shock associated with each choice alternative assures that likelihood is not degenerate.

Non-leisure time consists of the time required to raise the “effective” or age-weighted number of children existing at age a (which we denote by N_a^*), along with school time, the time

required to collect welfare, a fixed time-cost of work, and actual work hours, as follows:

$$h_a = \alpha_{2,1} N_a^* + \alpha_{2,2} s_a + \alpha_{2,3} g_a + \alpha_{2,4} I(h_a^p + h_a^f = 1) + 500 h_a^p + 1000 h_a^f,$$

The formula for the “effective” number of children is given by :

$$N_a^* = n_a + \alpha_{3,1} N_a^{1,6} + \alpha_{3,2} N_a^{7,13} + \alpha_{3,3} N_a^{14,17},$$

where n_a denotes a newborn child at age a (which results from a pregnancy at age $a-1$, $p_{a-1}=1$). The time required to care for a newborn is the numeraire (i.e., n_a has a coefficient of 1), and we estimate the time required for other children relative to that required for a newborn. For this purpose, we group children into three age categories: 1 to 6, 7-13, and 14-17. Thus, for example, the time required to care for a newborn is $\alpha_{2,1}$, while that required to care for a 5 year old is $\alpha_{2,1} \cdot \alpha_{3,1}$.

II. Labor Market:

A. Wage Function:

$$(A.2) \quad \ln w_a = \omega_0 + \omega_1 S_a + \omega_2 S_a^2 + \omega_3 H_a + \omega_4 H_a^2 + \omega_5 h_{a-1}^p + \omega_6 h_{a-1}^f \\ + \omega_7 a + \omega_8 I(a < 16) + \omega_9 I(a < 22) + \omega_{10} I(a < 25) + \omega_{11} h_a^p + \epsilon_a^w$$

Note that ω_{11} shifts the intercept in the part-time wage equation relative to that for full-time wages. The stochastic term ϵ_a^w is assumed normal, and the type specific intercept (or “skill endowment”) ω_{0k} is given by

$$\omega_{0k} = \omega_{00} + \sum_{q=1}^4 \omega_{0q} I(\text{State} = q + 1) + \sum_{q=5}^9 \omega_{0q} I(\text{type} = q - 3) + \sum_{q=10}^{11} \omega_{0q} I(r = q - 8) \\ = \omega_{00} + \overline{\omega}_{0k}$$

Here, ω_{00} represents the skill endowment in the baseline case (a type 1 white woman in California), while $\overline{\omega}_{0k}$ represents the skill endowments of women with the other combinations of initial conditions (IC). Note that $k=1, \dots, 90$, since there are 90 possible combinations of $S/r/type$, and that $\overline{\omega}_{01} = 0$.

B. Full and Part-Time Job Offer Probability Functions:

$$(A.3) \quad \begin{aligned} \pi_a^{wp} &= \Pr(\text{Receive PT Job Offer}) = \exp(x_a \pi^p) / (1 + \exp(x_a \pi^p)) \\ \pi_a^{wf} &= \Pr(\text{Receive FT Job Offer}) = \exp(x_a \pi^f) / (1 + \exp(x_a \pi^f)) \end{aligned}$$

$$x_a \pi^p = \pi_0^p + \pi_1^p h_{a-1}^f$$

$$x_a \pi^f = x_a \pi^p + \pi_1^f + \pi_2^f I(a < 22)$$

III. Marriage Market

The woman receives marriage offers each period with a probability that depends on her state variables. If she receives an offer, it can be thought of as consisting of two parts (i) the shock to the woman's fixed cost of marriage, which may capture the non-earnings qualities of the potential mate, and (ii) the earnings capacity of the potential mate. The earnings capacity of the potential husband is drawn from a distribution that depends on the woman's state variables, including her human capital level $\bar{\omega}_{0k}$, as follows:

A. Husband's Income Function:

$$(A.4) \quad \ln y_a^m = \gamma_{0ka}^m + \gamma_1^m S_a + \gamma_2^m a + \gamma_3^m a^2 + \gamma_4^m (a - a_m) + \gamma_5^m (a - a_m)^2$$

where

$$\gamma_{0ka}^m = \gamma_{00}^m + \gamma_0^m \sum_{k=1}^{90} \bar{\omega}_{0k} I(IC = k) + \sum_{q=1}^4 \gamma_{0q}^m I(\text{State} = q + 1) + \sum_{q=5}^6 \gamma_{0q}^m I(r = j - 3) + \mu^m + \epsilon_a^m,$$

Note that in A.4, the skill endowment enters through the intercept, while offers are also allowed to depend on the woman's schooling, age and the duration of the marriage. The quadratic in duration is meant to capture movement of the husband along his life-cycle wage path.

Note that whether a woman is black or Hispanic and State of residence are allowed to enter in addition to $\bar{\omega}_{0k}$. This may appear redundant, since $\bar{\omega}_{0k}$ already depends on these variables. However, the idea here is that, even controlling for her skill endowment, schooling and age, it may be the case that, e.g., a white woman in New York draws from a better husband income distribution than a black woman in North Carolina.

The parameter μ^m is a permanent part of the husband earnings function which the woman knows at the time she decides on a marriage offer, and which, should she accept the offer, remains fixed for the duration of the marriage. On the other hand, ϵ_a^m is a stochastic component of husband earnings that will fluctuate from period-to-period during the marriage (and which the woman cannot anticipate in advance). Both are assumed to be normally distributed with mean zero

and standard deviations σ_μ and σ_{ϵ^m} respectively.

B. Marriage Offer Probability Function:

$$(A.5) \quad \pi_a^m = \Pr(\text{Receive Marriage Offer}) = \exp(x_a \pi^m) / (1 + \exp(x_a \pi^m))$$

where

$$\begin{aligned} x_a \pi^m = & \pi_0^m + \pi_1^m m_{a-1} + \pi_2^m a + \pi_3^m a^2 + \pi_4^m m_a (a - a_m) \\ & + \pi_5^m (1 - m_{a-1}) I(a \geq 30) + \pi_6^m g_{a-1} (1 - m_{a-1}) \end{aligned}$$

Notice that the probability of receiving a marriage offer depends on lagged marital status. Already married women may, or may not, receive offers. Thus, in the model, divorce may be initiated by the husband (no offer is made) or by the wife (an offer is received but rejected). Note, however, that the fixed cost of marriage is only borne at the start of a marriage, not when an already married woman accepts an offer to continue a marriage.

C. Husband's Transfer Function:

If married, the woman receives a share of total household income according to:

$$(A.6) \quad \tau_a^m = \exp(\tau_0^m) / (1 + \exp(\tau_0^m))$$

where τ_0^m is simply a constant.

IV. Parental-Residence, Parental Income, and Parental Transfers:

Co-residence is not a choice, but is rather determined by a simple stochastic process that depends on age. Co-resident or dependent children receive transfers from parents that depend both on (i) parental income, and (ii) a sharing rule, which depends on the child's decisions, such as college attendance:

A. Parental Co-Residence Probability Function:

$$(A.7) \quad \pi_a^z = \Pr(\text{Receive Parental Co-Residence Offer}) = \exp(x_a \pi^z) / (1 + \exp(x_a \pi^z))$$

where

$$x_a \pi^z = \pi_0^z + \pi_1^z a + \pi_2^z I(a < 18) + \pi_3^z I(a < 22) + \pi_4^z I(a < 25)$$

B. Parents' Income Function:

$$(A.8) \quad y_a^z = \gamma_0^z + \gamma_1^z S^z + \gamma_2^z a + \sum_{j=3}^4 \gamma_j^z I(r=j-1) + \epsilon_a^z$$

where S^Z denotes the parents' schooling level (determined as the highest of the two parents if the youth is from a two parent household).

C. Parents' Transfer Function:

$$(A.9) \quad \tau_a^Z = \exp(x_a \tau^Z) / (1 + \exp(x_a \tau^Z))$$

where

$$x_a \tau^Z = \tau_0^Z + \tau_1^Z I(a < 16) + \tau_2^Z I(a < 18) + \tau_3^Z s_a I(S_a \geq 12) + \tau_4^Z s_a I(S_a \geq 12) S^Z$$

V. Initial Conditions

The parental schooling level is taken as given, and it determines both the probability of one of four possible initial schooling levels that the youth might have at the start of the year when they first age 14 (i.e., 6th through 9th grade), and the probability that the youth is one of six latent skill/preference types, according to the following MNL equations:

A. Initial Schooling Distribution:

$$(A.10) \quad \Pr(S_0 = j) = \exp(x_a \pi_j^S) / (1 + \exp(x_a \pi_j^S))$$

where

$$\begin{aligned} x_a \pi_j^S &= \pi_{0j}^S + j \pi_1^S S^Z \quad \text{for } j = 2, 3, 4, \\ &= \pi_1^S S^Z \quad \text{for } j = 1 \end{aligned}$$

B. Type Probabilities:

$$(A.11) \quad \begin{aligned} \Pr(\text{type} = j) &= \exp(x_a \pi_j^t) / (1 + \exp(x_a \pi_j^t)) \quad \text{for } j = 2, 3, 4, 5, 6 \\ &= 1 - \sum_{j=1}^5 \Pr(\text{type} = j) \quad \text{for } j = 1 \end{aligned}$$

where

$$x_a \pi_j^t = \pi_{j0}^t + \pi_{j1}^t S_0 + \pi_{j2}^t S^Z + \pi_{j3}^t I(S_a^Z \geq 16)$$

VI. Measurement Error:

Our estimation procedure described in section IV requires us to assume that all discrete and continuous variables in the model are measured with error.

A. Classification Error Rates for Discrete Outcomes:

We specify the classification error process in such a way that aggregate choice frequencies are unbiased. To see how this works, consider first the classification error process for school attendance:

Π_{0a}^s = probability that school attendance is correctly recorded at age a.

Π_{1a}^s = probability that school attendance is reported when person did not attend school.

Then we assume that:

$$\Pi_{0a}^s = E s + (1 - E s) f(s_a = 1)$$

$$\Pi_{1a}^s = (1 - \Pi_{0a}^s) f(s_a = 1) / [1 - f(a_t = 1)]$$

where $f(s_a = 1) = \frac{1}{N} \sum_{i=1}^N I(s_a = 1)$ is the probability in the simulation (i.e., the “true” aggregate

choice frequency for school at age a, up to simulation error) and $E s$ is an error rate parameter to be estimated. With this measurement error process, the model’s prediction for the aggregate frequency with which school will be observed at age a is:

$$\Pi_{0a}^s f(s_a = 1) + \Pi_{1a}^s (1 - f(s_a = 1)) = f(s_a = 1)$$

Thus, the model makes the same prediction for the “true” aggregate rate of school attendance at age a, and for the “observed” aggregate rate of school attendance at age a. Similar classification error processes are assumed for all the other discrete variables in the model: hours (which recall, is either part of full time), pregnancy, welfare receipt, marriage, living with parents, initial schooling and parents’ schooling. Following previous notation, the corresponding parameters are $E_h, E_b, E_g, E_m, E_p, E S_0, E S^z$.

B. Measurement Error in Continuous Outcomes:

For hourly wages, we assume the same measurement error variance in both the full-time and part time wage equations. Thus, we have:

$$w_a^{f, \text{observed}} = w_a^f \exp\{\epsilon_a^{w,m}\}$$

$$w_a^{p, \text{observed}} = w_a^p \exp\{\epsilon_a^{w,m}\}$$

$$\epsilon_a^{w,m} \sim N(0, \sigma_{w,m}^2)$$

Similarly, husband's income is assumed to be measured with log normal measurement error, with standard deviation σ_{mm} , while parent's income in levels is assumed to be measured with normal measurement error with standard deviation σ_{mm} .

Suppose that, according to simulated choice history $\tilde{\mathbf{O}}^n$, a person true choice at age a was not working, or not married, or not living with parents. Yet, in the data, \mathbf{O}^i we observed that the person is working, or is married, or is living with parents. Our method described in section IV reconciles the two via classification error, and, for the discrete outcomes, the appropriate likelihood contribution is trivial: it is simply the probability the person is observed to work, be married or be living with parents, when in truth they are not. This probability is simply a function of the classification error rates constructed above.

But a more subtle problem arises in a case where the simulated history says a person was not working, or not married, or not living with parents, and, in the data, we not only observe a different discrete outcome, but also observe a wage, or husband earnings or parent's income. What is the density of an observed wage conditional on the person not actually working? We make the simple assumption that such "falsely reported" continuous outcomes are drawn from the same distribution as that which governs the "true" continuous outcomes, except for a mean shift parameter that we estimate. We denote these mean shift parameters $\kappa-w$, $\kappa-m$, and $\kappa-z$ for the woman's offer wage function, husband earnings function and parent's income function respectively. During estimation, $\kappa-w$ never departed to any significant extent from zero, so we eventually pegged it at zero and report only $\kappa-m$, and $\kappa-z$ in Table A3.

Table A.1
Summary Statistics of Parameters of Benefits Rules by State: 1967-1990 (a,b)

		b ₀	b ₁	b ₂	b ₃	b ₄
CA	μ	454	134	503	.64	166
	σ	53	9	47	.15	12
	Min	332	108	393	.24	143
	Max	517	148	579	.89	286
MI	μ	498	155	553	.63	193
	σ	78	16	118	.11	19
	Min	389	130	391	.53	146
	Max	649	181	744	.92	221
NY	μ	430	144	472	.63	179
	σ	38	24	65	.13	32
	Min	374	117	384	.48	142
	Max	522	182	590	.92	234
NC	μ	393	86	423	.52	110
	σ	42	18	83	.11	20
	Min	332	48	295	.41	84
	Max	462	111	545	.82	148
OH	μ	371	118	415	.58	143
	σ	26	12	71	.10	23
	Min	337	100	308	.47	114
	Max	415	143	539	.88	183

a. 1987 NY dollars

b. Based on Monthly AFDC plus Food Stamp Benefits

Table A.2
Evolutionary Rules for Benefit Parameters^a

	CA					MI				
	b _{0t}	b _{1t}	b _{2t}	b _{3t}	b _{4t}	b _{0t}	b _{1t}	b _{2t}	b _{3t}	b _{4t}
b _{0,t-1}	.834 (.104)	.051 (.032)	-	-.00039 (.0006)	-	-.120 (.280)	-.086 (.050)	-.547 (.286)	-	-
b _{1,t-1}	.840 (.590)	.227 (.185)	-	-.00047 (.0034)	-	.446 (.903)	.774 (.164)	-.524 (.924)	-	-
b _{2,t-1}	-.322 (.130)	.041 (.040)	.640 (.128)	-.00040 (.0007)	-	.514 (.203)	.078 (.036)	1.04 (.207)	-	-
b _{3,t-1}	59.4 (19.4)	9.52 (6.12)	-	.673 (.114)	-	166.9 (67.6)	27.4 (12.3)	60.5 (69.1)	.614 (.117)	-
b _{4,t-1}	.496 (.404)	-.236 (.133)	-	.00601 (.002)	.469 (.152)	.468 (.870)	-.070 (.163)	1.71 (.896)	-	.800 (.101)
Constant	83.3 (55.3)	105.5 (18.4)	178.7 (64.8)	-.749 (.317)	87.6 (25.4)	216.2 (124.8)	65.6 (23.9)	28.6 (129.3)	-.233 (.075)	38.1 (19.6)
R ²	.88	.53	.48	.60	.23	.89	.84	.94	.50	.74
P. Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
Mean	454	134	503	.64	166	498	155	553	.63	193
RMSE	17.1	5.9	33.5	.087	10.3	25.9	6.2	28.5	.065	10.0

Table A.2, continued

	NY					NC				
	b _{0t}	b _{1t}	b _{2t}	b _{3t}	b _{4t}	b _{0t}	b _{1t}	b _{2t}	b _{3t}	b _{4t}
b _{0,t-1}	.851 (.065)	-	-	-	-	1.72 (.134)	.236 (.064)	2.18 (.328)	-.00249 (.0007)	.533 (.137)
b _{1,t-1}	-	.891 (.031)	-	-	-	-2.59 (.449)	.267 (.216)	-5.85 (1.10)	.00230 (.0026)	-.829 (.462)
b _{2,t-1}	-	-	.856 (.072)	-	-	-.446 (.090)	-.079 (.043)	-.619 (.221)	.00090 (.0005)	-.203 (.092)
b _{3,t-1}	-	-	-	.665 (.105)	-	201.0 (25.6)	77.3 (12.3)	144.1 (62.9)	.360 (.149)	86.7 (26.4)
b _{4,t-1}	-	-	-	-	.860 (.041)	1.38 (.381)	.287 (.183)	3.27 (.934)	-.00055 (.002)	1.07 (.392)
Constant	64.7 (28.6)	13.1 (4.70)	63.3 (35.2)	-.202 (.068)	22.1 (7.75)	77.1 (27.1)	14.1 (13.1)	37.1 (66.6)	.141 (.158)	-14.3 (27.9)
R ²	.61	.92	.73	.54	.91	.97	.95	.95	.75	.86
P. Value	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Mean	430	144	472	.63	179	393	86	423	.52	110
RMSE	22.9	6.4	33.3	.074	8.7	7.3	3.5	17.8	.042	7.5

Table A.2, continued

	OH				
	b_{0t}	b_{1t}	b_{2t}	b_{3t}	B_{4t}
$b_{0,t-1}$	-.623 (.218)	.019 (.069)	-.045 (.312)	-	-
$b_{1,t-1}$	-.242 (.805)	.539 (.256)	-2.79 (1.15)	-	-
$b_{2,t-1}$	-.022 (.168)	-.027 (.053)	.126 (.241)	-	-
$b_{3,t-1}$	5.02 (32.3)	23.5 (10.3)	-144.6 (46.2)	.552 (.116)	-
$b_{4,t-1}$	1.19 (.560)	.230 (.181)	2.93 (.801)	-	.904 (.082)
Constant	261.8 (49.7)	38.9 (16.6)	195.6 (71.0)	-.243 (.069)	12.5 (12.0)
R^2	.79	.75	.94	.48	.84
P. Value	0.00	0.00	0.00	0.00	0.00
Mean	371	118	415	.58	143
RMSE	11.4	5.7	16.0	.056	9.0

Table A.3 Parameter Estimates

Utility Function^a										
	Hours		Pregnancy		Marriage		School		Welfare	
Intercept	$\alpha_{1,0}$	-2.266 (.321)	$\alpha_{5,0}$	0.000 -----	$\alpha_{6,0}$	-16.985 (2.772)	$\alpha_{7,0}$	3.202 (.516)	$\alpha_{8,0}$	-1.578 (1.023)
State Effects	$\alpha_{1,1}$	-0.710 (.109)	$\alpha_{5,1}$	1.174 (.260)	$\alpha_{6,1}$	-2.555 (1.045)	$\alpha_{7,1}$	0.915 (.167)	$\alpha_{8,1}$	0.801 (.189)
	$\alpha_{1,2}$	-0.333 (.091)	$\alpha_{5,2}$	-0.080 (.196)	$\alpha_{6,2}$	-5.723 (.912)	$\alpha_{7,2}$	0.786 (.138)	$\alpha_{8,2}$	-0.400 (.122)
	$\alpha_{1,3}$	1.007 (.128)	$\alpha_{5,3}$	-0.946 (.304)	$\alpha_{6,3}$	8.463 (1.082)	$\alpha_{7,3}$	-0.451 (.185)	$\alpha_{8,3}$	-0.437 (.174)
	$\alpha_{1,4}$	0.039 (.083)	$\alpha_{5,4}$	0.448 (.199)	$\alpha_{6,4}$	0.861 (.870)	$\alpha_{7,4}$	0.241 (.148)	$\alpha_{8,4}$	-0.409 (.131)
Type	$\alpha_{1,5}$	-0.584 (.181)	$\alpha_{5,5}$	2.802 (.301)			$\alpha_{7,5}$	-0.229 (.224)	$\alpha_{8,5}$	0.013 (.984)
	$\alpha_{1,6}$	-0.110 (.182)	$\alpha_{5,6}$	3.176 (.342)			$\alpha_{7,6}$	-2.584 (.321)	$\alpha_{8,6}$	-0.041 (.863)
	$\alpha_{1,7}$	0.002 (.191)	$\alpha_{5,7}$	2.983 (.342)			$\alpha_{7,7}$	-2.447 (.279)	$\alpha_{8,7}$	-0.025 (.887)
	$\alpha_{1,8}$	0.400 (.205)	$\alpha_{5,8}$	3.180 (.397)			$\alpha_{7,8}$	-3.058 (.315)	$\alpha_{8,8}$	0.710 (.893)
	$\alpha_{1,9}$	-0.108 (.206)	$\alpha_{5,9}$	4.944 (.437)			$\alpha_{7,9}$	-3.006 (.292)	$\alpha_{8,9}$	1.420 (.869)
Black	$\alpha_{1,10}$	-0.117 (.098)	$\alpha_{5,10}$	1.352 (.236)	$\alpha_{6,10}$	-2.499 (.693)	$\alpha_{7,10}$	0.049 (.133)	$\alpha_{8,10}$	0.290 (.136)
Hispanic	$\alpha_{1,11}$	-0.015 (.089)	$\alpha_{5,11}$	1.735 (.203)	$\alpha_{6,11}$	2.401 (.846)	$\alpha_{7,11}$	-0.109 (.139)	$\alpha_{8,11}$	-0.116 (.129)

Non-leisure Time	$\alpha_{2,1-N}^*$	0.539 (.074)	$\alpha_{2,2-S}$	0.795 (.081)	$\alpha_{2,3-A}$	0.064 (.069)	$\alpha_{2,4-FC}$	0.056 (.031)	$\alpha_{3,1-N1,6}$	0.800 (.152)	$\alpha_{3,2-N7,13}$	0.349 (.088)	$\alpha_{3,3-N14,18}$	0.349 (.145)
Other parameters	$\alpha_2\text{-Hrs}^2$	-0.00071 (.00004)	$\alpha_{10}\text{-LM}$	0.625 (.226)	$\alpha_{14}\text{-B,S}$	-1.202 (.243)	$\alpha_{18}\text{-B,a}^2$	-0.281 (.057)	$\alpha_{22}\text{-S,16}$	0.473 (.239)	$\alpha_{26}\text{-M25}$	6.005 (1.247)	$\alpha_{30}\text{-P,S12}$.793 (.116)
	$\alpha_3\text{-Kids}$	0.815 (.171)	$\alpha_{11}\text{-F,S}$	-0.795 (.277)	$\alpha_{15}\text{-LP}$	0.476 (.049)	$\alpha_{19}\text{-B,a}^3$	0.0164 (.0046)	$\alpha_{23}\text{-S,18}$	0.619 (.128)	$\alpha_{27}\text{-hCM}$	1.435 (.151)	$\alpha_{31}\text{-P,16-17}$.000 (.048)
	$\alpha_4\text{-Kds}^2$	-0.449 (.027)	$\alpha_{12}\text{-P,S}$	-0.489 (.132)	$\alpha_{16}\text{-LF}$	1.549 (.135)	$\alpha_{20}\text{-B,a}^4$	-0.00032 (.00013)	$\alpha_{24}\text{-B,18}$	-0.597 (.520)	$\alpha_{28}\text{-hCN}$	0.330 (.084)	$\alpha_{32}\text{-C,M}$	-0.195 (.048)
	$\alpha_9\text{-LS}$	-3.993 (.3273)	$\alpha_{13}\text{-LA}$	1.063 (.211)	$\alpha_{17}\text{-B,a}$	1.361 (.343)	$\alpha_{21}\text{-h*C}$	-3.962 (.220)	$\alpha_{25}\text{-M,21}$	3.403 (.691)	$\alpha_{29}\text{-F,S12}$	2.283 (.236)		

^a Utility function parameters should be multiplied by 1000, and can be interpreted in thousands of dollars per period.

Table A.3: Cont.

Wage Function			Other Parameters		
Constant	$\omega_{0,0}$	7.555 (.034)		ω_1 -Educ	0.0928 (.0037)
State Effects	$\omega_{0,1}$	0.0001 (.0095)		ω_2 -Ed ² /100	-0.0075 (.0013)
	$\omega_{0,2}$	0.0008 (.0078)		ω_3 -Hours	0.0131 (.0011)
	$\omega_{0,3}$	-0.0709 (.0099)		ω_4 -Hrs ² /100	-0.0090 (.0034)
	$\omega_{0,4}$	-0.0594 (.0079)		ω_5 -LPT	0.0300 (.0040)
	Type Differences in Skill Endowment	$\omega_{0,5}$	-0.0009 (.0081)		ω_6 -LFT
	$\omega_{0,6}$	-0.094 (.0093)		ω_7 -Age	0.0065 (.0006)
	$\omega_{0,7}$	-0.100 (.0101)		ω_8 -Age<16	-0.1159 (.0478)
	$\omega_{0,8}$	-0.200 (.0117)		ω_9 -Age<22	-0.1039 (.0111)
	$\omega_{0,9}$	-0.224 (.0115)		ω_{10} -Age<25	-0.0625 (.0102)
Black	$\omega_{0,10}$	-0.125 (.0076)		ω_{11} -PT	-0.1053 (.0103)
Hispanic	$\omega_{0,11}$	-0.056 (.0069)		$\sigma_{\varepsilon w}$.1708 (.0046)

Husband Offer Wage Function							
Constant	γ_{00}^m	7.004 (.160)	Black	γ_{05}^m -B	-0.270 (.026)	γ_3^m -Age ² /100	-0.084 (.028)
State Effects	γ_{01}^m -MI	0.097 (.027)	Hispanic	γ_{06}^m -H	-0.130 (.027)	γ_4^m -DUR	0.040 (.004)
	γ_{02}^m -NY	0.052 (.027)	Other Parameters	γ_0^m - Skill	1.947 (.116)	γ_5^m -DUR ² /100	-0.040 (.011)
	γ_{03}^m -NC	-0.194 (.033)		γ_1^m -ED	0.029 (.004)	σ_μ -permanent	0.390 (.007)
	γ_{04}^m -OH	0.099 (.025)		γ_2^m -Age	0.084 (.013)	σ_μ -transitory	0.211 (.014)

Table A.3: Cont.

Parents' Income Function					
<i>Constant</i>	γ_0^z	9.497 (.144)	Black	γ_1^z -B	-3.921 (.014)
Other Parameters	γ_1^z -PS	1.042 (.019)	Hispanic	γ_1^z -H	-2.030 (.131)
	γ_2^z -Age	-305 (.014)	Error Term	σ_{ε^z}	2.662 (.046)

Note: Parameters are in thousands of dollars per 6-month period.

Parental Co-Residence													
π_0^z	-0.229 (.320)	π_1^z -Age	-0.0800 (.0109)	π_2^z -A18	2.0897 (.2356)	π_3^z -A22	0.5964 (.1330)	π_4^z -A25	-0.2837 (.1260)	π_5^z -LP	3.988 (.0976)		
Job Offer Probabilities													
π_0^p	2.147 (.041)	π_1^p -LF	1.801 (.079)	π_1^f	-1.801 (.062)	π_2^f -A22	-0.570 (.052)						
Marriage Offer Probabilities													
π_0^m	-1.853 (.051)	π_1^m -LM	4.228 (.075)	π_2^m -Age	0.126 (.009)	π_3^m -Age ²	-0.0034 (.0006)	π_4^m -DUR	0.040 (.008)	π_5^m -A30	-0.667 (.215)	π_6^m -LA	-0.749 (.104)
Parents' Transfer Function													
τ_0^z	-1.297 (.111)	τ_1^z -A16	-0.182 (.218)	τ_2^z -A18	-0.203 (.143)	τ_3^z -COL	0.065 (.169)	τ_4^z -C*PS	0.043 (.015)				
Husband's Transfer Function						Welfare Benefit Parameters							
τ_0^m	0.183 (.127)					β_1	.7475 (.0731)	β_2	.3760 (.0019)				

Note: The parent transfer function parameters enter the latent index of a logit model, that determines the share of parent income devoted to the co-resident child's consumption. In contrast, the husband transfer parameter enters a latent index that determines the share of total household income that the woman receives.

Table A.3: Cont.

Standard Deviations of Taste Shocks											
Leisure		School		Marriage		Birth		Welfare			
σ_1	1.025 (.104)	σ_2	1.748 (.171)	σ_3	2.635 (.384)	σ_4	9.473 (.537)	σ_5	0.656 (.198)		
Cost of Attending School				Discount Factor							
β_3	3079 (380)	β_4	2603 (698)	δ	.93 ----						
Measurement Error Parameters											
A. Continuous Outcomes											
σ_{wm}	0.3949 (.0014)	σ_{mm}	0.5582 (.0030)	σ_{zm}	0.400 (.0020)	$\kappa\text{-m}$	-0.309 (.029)	$\kappa\text{-z}$	-0.785 (.023)		
B. Discrete Outcomes											
E_S	0.785 (.009)	E_H	0.838 (.003)	E_B	0.863 (.008)	E_G	0.923 (.004)	E_M	0.934 (.003)	E_P	0.898 (.005)
E_{S0}	0.936 (.009)	E_{SP}	0.865 (.017)								

Type Probabilities: MNL Parameters										
		Type 2		Type 3		Type 4		Type 5		Type 6
Constant	π_{20}^t	3.199 (1.892)	π_{30}^t	4.209 (1.858)	π_{40}^t	4.801 (1.754)	π_{50}^t	5.673 (1.617)	π_{60}^t	6.043 (1.653)
Initial School	π_{21}^t	-0.784 (.600)	π_{31}^t	-1.180 (.557)	π_{41}^t	-1.540 (.519)	π_{51}^t	-1.458 (.477)	π_{61}^t	-1.271 (.491)
Parents' School	π_{22}^t	-0.187 (.158)	π_{32}^t	-0.172 (.159)	π_{42}^t	-0.095 (.164)	π_{52}^t	-0.209 (.161)	π_{62}^t	-0.357 (.149)
Parents' College	π_{23}^t	1.228 (.944)	π_{33}^t	0.071 (1.016)	π_{43}^t	-0.190 (.976)	π_{53}^t	-0.356 (.964)	π_{63}^t	0.190 (.915)
Initial School Distribution Conditional on Parents' School: MNL Parameters										
	π_{02}^s	1.809 (.855)	π_{03}^s	3.153 (.537)	π_{04}^s	3.467 (.336)	$\pi_{1^s\text{-PS}}$	0.157 (.042)		

Note: As a location normalization, in the MNL for type, the latent index for type one is normalized to zero. In the MNL for initial schooling, the constant for level 1 (the lowest level) is set to zero.

Table A.3: Cont.

Parents' Schooling Distribution (by Race and State)

GRADES	STATE	White	Black	Hispanic
<HS (7-11)	CA	.1320	.2590	.5630
	MI	.2380	.2940	
	NY	.1190	.3550	.5580
	NC	.4090	.6550	
	OH	.1800	.4000	
HS (12)	CA	.3380	.4810	.3190
	MI	.4750	.3530	
	NY	.4780	.4350	.2620
	NC	.4850	.3140	
	OH	.5230	.4360	
SC (13-15)	CA	.2061	.1671	.0609
	MI	.1719	.2061	
	NY	.1641	.1290	.1311
	NC	.0450	.0150	
	OH	.0939	.1299	
COL (16)	CA	.2210	.0560	.0470
	MI	.0900	.0880	
	NY	.1340	.0320	.0480
	NC	.0300	.0100	
	OH	.1250	.0100	
COL+ (17-20)	CA	.1130	.0369	.0100
	MI	.0251	.0589	
	NY	.1049	.0490	.0010
	NC	.0310	.0060	
	OH	.0781	.0241	

Note: The parent education proportions are not estimated jointly with the structural parameters of the model. They were calculated directly from the NLSY data. Note that there are 14 levels of education, with 4 categories within <HS, 3 categories with SC, and 4 categories within COL+. We assume parents are distributed evenly across the subcategories within each of these levels. For example, for whites in CA, we assume that $13.20 \div 5 = 2.64\%$ of parents are in each of the categories from 7 to 11. Small sample sizes preclude us from reliably estimating the size of each cell separately.