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# DO WAGES RISE WITH JOB SENIORITY?

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## ABSTRACT

The extent to which wages rise with the accumulation of seniority (tenure) in a firm after one controls for total labor market experience is a fundamental question about the structure of earnings. A variety of studies have found a large, positive partial effect of tenure on wages. This paper re-examines the evidence using a simple instrumental variables scheme to deal with well known estimation biases which arise from the fact that tenure is likely to be related to unobserved individual and job characteristics affecting the wage. We use the variation of tenure over a given job match as the principal instrumental variable for tenure. The variation in tenure over the job, in contrast to variation in tenure across individuals and jobs, is uncorrelated by construction with the fixed individual specific and job match specific components of the error term of the wage equation. Our main finding is that the partial effect of tenure on wages is small, and that general labor market experience and job shopping in the labor market account for most wage growth over a career. The strong cross section relationship between tenure and wages is due primarily to heterogeneity bias.

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# Do Wages Rise With Job Seniority ?

## 1. INTRODUCTION

This paper measures the partial effects of labor market experience and job seniority (tenure) on wages. Prior researchers (see Mincer and Jovanovic (1981), Bartel and Borjas (1981), Borjas (1981), Cline (1979a) and Mellow (1981) among others) have established that tenure has a strong positive relationship with wage rates in a cross section or a cross section-time series of individuals. Furthermore, tenure has a strong negative association with job separation rates, quits, and layoffs (Mincer and Jovanovic, Cline (1979b), Borjas and Rosen (1981) among others). For example, Mincer and Jovanovic obtain coefficients of .0305 and -.0007 on tenure and tenure$^2$ in a cross sectional regression for the log wage over a sample of white males after controlling for the effects of labor market experience and schooling. They estimate the partial effects of tenure and tenure$^2$ on the separation probability to be -.0149 and .0004.* The decline of separations with tenure is about equally divided into a drop in the quit rate and a drop in layoffs.

The extent to which wages rise with tenure is important for several reasons. First and foremost, the wage-tenure profile is a fundamental question about the structure of earnings over careers. Second, it is a key determinant of the extent to which the earnings power of individuals is tied to specific jobs and thus is important for assessment of issues such as the losses suffered by "displaced" workers (Hamermesh (1984)). Third, evidence that wages rise with job tenure has been used as an explanation for the decline in quits with tenure, since the wage growth on the current job lowers the probability that the worker

*See Mincer and Jovanovic, Tables 1.6, 1.5. The results are based upon the 1976 cross section of white, out of school men under 64 from the Panel Study of Income Dynamics. The authors obtain slightly lower estimates of the tenure slope of wages when heterogeneity is controlled for using an index of prior job changes. They also report detailed results for the NLS samples of young and older men and obtain somewhat flatter tenure slopes for the sample of older men. Mellow's estimates of the tenure slope of wages from a sample based upon the Current Population Survey are also large.

will locate a superior alternative. In the theory of specific human capital (Oi (1962), Becker (1962), Mincer (1974), Parsons (1972), Kuratani (1973), and Hashimoto (1980)) the growth of wages with tenure (holding experience constant) is attributed to worker financed investment in skills which are specific to the firm. At the same time, firm financed investments in specific skills produce an increase in productivity relative to wages with time on the job and thus provide an explanation for the fall in the layoff probability with job tenure.[e]

More recently, a number of alternative explanations have been offered for the apparent growth of wages with tenure. In Lazear's (1981) supervision model of wage growth firms defer compensation as a means of inducing workers not to shirk duties, given that it is difficult to measure the output of workers directly. Freeman (1977) and Harris and Holmstrom (1982) provide an explanation for wage growth based upon an insurance motive. Harris and Holmstrom assume that workers are equally productive in all firms, mobility costs are zero, and the productivity of a given worker in future periods is uncertain. They show that firms will insure workers against low productivity outcomes later in their careers. The expected value of the wage in later periods exceeds the expected value of marginal product, and this gap is financed by an excess of expected marginal product over wages in early periods. Guasch and Weiss (1980, 1982) present an adverse selection model of wage growth. They assume that individuals

[e] The evidence that wages rise with tenure is also important in implicit contracts models of wages and employment. As Grossman (1977) pointed out and Rosen (1984) emphasizes in a recent survey article, contracts which insure workers against adverse swings in demand are feasible only if the worker cannot easily break the contract when conditions improve. The returns to the firm and the worker from shared investments in specific human capital would provide both parties with an incentive to maintain the job match despite fluctuations in marginal product and the alternative wage relative to the contract wage. It is clear from Hall(1982) and Mincer and Jovanovic (1981) that many workers end up in jobs which last for a long period of time. It is unclear whether this is due to a sharing in the rents from a good job match (see Jovanovic , 1979), a sharing in the returns from job specific training, or other barriers to quits and layoffs.

know more about their ability than do firms at the time that they are hired, and productivity is costly to observe. They show that in equilibrium firms may offer wages below marginal product in the initial period, during which workers are evaluated (at a cost), and a wage above marginal product in subsequent periods to those who meet a performance standard. The wage structure serves to discourage workers who know that they are relatively unproductive from applying.#

Although discussion of the link between these alternatives to the human capital model and empirical evidence have focussed on studies relating wages to total labor market experience, such as Mincer (1974), for the most part they offer an explanation for the partial effect of tenure on wages when experience is controlled for, rather than for the partial effect of total experience when tenure is controlled for. For example, within Lazear's supervision model firms should pay newly hired workers who have changed jobs after accumulating tenure in another firm a wage that is closer to that for new entrants. In Harris and Holmstrom's model, firms have no incentive to honor the wage guarantee the worker had with another firm if the worker's productivity (the same in all firms) turns out to be below the guarantee level. Starting wages may rise with prior experience, but only because the decline in the number of years until retirement and the decline in the residual uncertainty about the worker's productivity imply that the amount of insurance that the worker "buys" in the initial years on a job falls with experience. Presumably, this effect is small. The upshot is that the empirical basis for these models as important

#See also the related adverse selection models of Salop and Salop (1976) and Nickell (1976), in which the increase of wages with time on the job serves as a means of sorting out workers with a high propensity to quit. Parsons (1984) provides an excellent survey of the rapidly growing theoretical literature on of wage growth. Note that all three of the theories mentioned predict a decline in quits with tenure, as wages available in the firm rise above those available outside of the firm.

explanations of earnings patterns over the lifecycle rests heavily on the evidence that tenure has a substantial effect on wages.* Thus, a careful re-examination of whether wages do in fact rise with job tenure complements recent efforts by Medoff and Abraham(1980, 1981), Brown (1983), Mincer(1984) and others (see the conclusion) to provide more direct tests of the human capital model against alternatives which do not imply an increase in productivity with experience.

In summary, job tenure is a key variable in models of earnings determination. However, the studies of growth of wages with seniority have been accompanied by widespread recognition that unobserved heterogeneity across individuals and across job matches may produce large biases in estimates of the effect of tenure on wages as well as turnover. (See for example, Mincer and Jovanovic (1981), and Heckman (1981)). Indeed, the job matching models of Jovanovic (1979) and Johnson (1978) have stimulated a growing theoretical literature in which job match heterogeneity plays a central role in both turnover and wage growth.** Since tenure is a simple function of past quit and layoff decisions,*** it will be positively correlated with characteristics of individuals or of jobs which lead to lower quits and layoffs. These same characteristics are likely to be positively related to worker productivity and,

* Human capital theory and the other models mentioned are contributions to the search for a sound economic theory for why older workers are paid more than younger workers. The notion that they are paid more for cultural reasons would be particularly difficult to square with a finding that most of the increase is due to general labor market experience rather than tenure. Provided workers stay in the same job, the nonnegative profit condition does not tightly constrain the experience profile of wages. With mobility, it difficult to understand why firms are willing to pay a large experience premium to newly hired older workers (as the data indicate they routinely do), if older workers are not more productive than younger workers.

** Flinn (1982) implements the Jovanovic model for a sample of young men and finds that job match heterogeneity plays an important role in wage growth and mobility during first few years of work experience.

*** See equation (2) below.

in a competitive labor market, to wages.

The chief contribution of this paper is the development and implementation of a simple instrumental variables scheme for dealing with the problem of "heterogeneity bias" in analysis of the effects of tenure on wages. We use the variation of tenure over a given job match (along with the levels of the other variables which appear in the wage equation) to form an instrument for tenure. The variation in tenure over the job, in contrast to the variation in tenure across individuals and jobs, is uncorrelated with the fixed individual and job match components of the error term of the wage model. The methodology is inspired in part by Hausman and Taylor's (1981) treatment of analysis of covariance models in an instrumental variables framework. The approach is implemented for a sample of male heads of household from the Panel Study of Income Dynamics.

We also experiment with an error components type GLS version of the instrumental variables procedure to account for correlation in the wage errors for each person arising from the individual specific and job match specific component of the wage error. Use of the GLS versions of the instrumental variables and least squares procedures is complicated by the fact that the sample is unbalanced, with a large variation in the number of years of data on each individual and on each job match, and to our knowledge has never been implemented in such a situation. A secondary contribution of the paper is the derivation (in Appendix 1) of a simple formula to compute these estimators in the case of unbalanced data.

Our main finding is that the effect of seniority on wages (with the effects of general labor market experience and secular wage growth held constant) is small. The estimates from the instrumental variables procedure indicate that the first year of tenure raises wages by about 5 %, but additional years of tenure years of tenure contribute little to wage growth. The coefficient on the linear tenure term is actually slightly negative and the overall effect of the first 10 years of job tenure is to raise wages by only 3%. In contrast, general labor market experience results in a wage increase of 32% over the first 10 years and 87% over the first 30 years. It accounts for the lion's share of wage growth during a career,[#] although these estimates combine the wage effects of experience arising from general skill accumulation, which are stressed in human capital theory, and the wage increases due to labor market search, which are stressed in search and job matching models. The instrumental variables estimates of the tenure profile of wages are much flatter and the experience slopes are steeper than estimates based upon least squares or upon use of an index of prior job separations to control for individual heterogeneity.

Unfortunately, the instrumental variables estimates of the tenure slope are probably biased downward by job heterogeneity despite the fact that variance of tenure within a job is uncorrelated with the permanent component of the job match. As is explained below, the bias arises indirectly through the correlation of the job match component with labor market experience. Biases may also arise from measurement error in the tenure variable. Much of the empirical analysis is devoted to assessing the importance of these biases. We show that they are probably small.

We also present separate estimates for union and nonunion workers and for blacks as well as whites. Union-nonunion differences in the tenure profile of wages are dramatically reduced when heterogeneity is accounted for. Finally, we provide evidence that both the individual specific and match specific error components of the wage have negative associations with quits, layoffs and

[#] A time trend is used to control for secular growth in the economy, which is also an important factor in wage growth over the life of a worker.

separations, which tends to confirm a role for heterogeneity bias in least squares estimates of the wage equation.

The paper is organized as follows. Section 3 presents the econometric methodology. Section 4 (and Appendix 2) discusses the data. Section 5 presents the empirical analysis. The concluding section summarizes the results and their implications for models of wage growth and turnover over the work life, and provides an agenda for research. We begin with a brief review of why tenure is endogenous in the wage equation.

## 2. THE ENDOGENEITY OF TENURE IN THE WAGE EQUATION

Assume that the wage of individual i who is job j in period t is determined by the following equation.

(1) $$W_{ij(t)t} = b_0 X_{ij(t)t} + f(\ T_{ij(t)t}\ ) + \varepsilon_{ij(t)t}$$

The variable $W_{ij(t)t}$ is the log of the real wage, $X_{ij(t)t}$ is a vector characteristics of the person and the job and includes labor market experience, $T_{ij(t)t}$ is the number of years of person i has held job j as of time t, the function f(.) is the tenure profile of wages, and $\varepsilon_{ij(t)t}$ is the error term. In general, $\varepsilon_{ij(t)t}$ may consist of serially correlated components that are specific to worker i, job j(t) and the match between i and j(t).** The fact that worker i may change jobs during the sample period has been made explicit by writing the job subscript as j(t). For notational convenience we will often refer to j(t) simply as j.

Least squares estimates of the tenure profile will be biased upward if $T_{ijt}$ is positively correlated with $\varepsilon_{ijt}$. To see that this is likely to be the case,

** Without observations on several individuals in a given firm, it is not possible to decompose the job effects into firm effects (received by all workers in the firm) and job match effects. Below we use the term job match to refer to the sum of these separate effects.

consider the following simple model for $T_{ijt}$. One may show that $T_{ijt}$ is related to labor market experience and past quits and layoffs through the identity

$$(2) \quad T_{ijt} \equiv \sum_{\ell=0}^{EXP_{it}} \prod_{k=\ell}^{EXP_{it}} [1 - (Q_{ik} + L_{ik})] ,$$

where the quit indicator $Q_{ik}$ is 1 if the individual quit in period k and 0 otherwise, the layoff indicator $L_{ik}$ is 1 if the individual was laid off in period k and 0 otherwise, and $EXP_{it}$ is the labor market experience of person i in t. Workers quit if their best alternative is more valuable (in an intertemporal sense) than their present job given the option of future quits and expectations about future wages, nonpecuniary characteristics, mobility costs, and layoff behavior. Firms base layoff decisions upon a comparison of current and expected future wages to the current and future productivity of the worker plus the direct and indirect costs of terminating the him, given that the firm has the option of laying off the worker in the future and the worker has the option of quitting. We avoid detailed structural models of these decisions since they are not essential to our purposes and simply express the relationship between the arguments of the wage equation and $Q_{ik}$ and $L_{ik}$ as follows.

$$(3) \quad Q_{ik} = 1 \text{ if } U_{ij(k)k} = B_0 X_{ij(k)k} + g(T_{ij(k)k}) + u_{ij(k)k} < 0$$
$$= 0 \quad \text{otherwise}$$

$$(4) \quad L_{ik} = 1 \text{ if } V_{ij(k)k} = G_0 X_{ij(k)k} + G(T_{ij(k)k}) + v_{ij(k)k} < 0$$
$$= 0 \quad \text{otherwise}$$

$U_{ij(k)k}$ is the worker's valuation of job j(k) in period k relative to the worker's best alternative in k net of moving costs. The composite error component uij(k)k is a function of the unobserved characteristics of the individual, the job match and the worker's best alternative in period k.

$V_{ij(k)k}$ is the firm's valuation of the option of keeping the worker. It depends on the composite error component $v_{ij(k)k}$.

Equations (2), (3) and (4) together imply that $T_{ijt}$ depends upon the distribution of past values of the quit and layoff error components $\omega_{ij(k)k}$ and $v_{ij(k)k}$ and thus will be endogenous in the wage equation if these values are correlated with the wage error $\varepsilon_{ijt}$. This is likely to be the case for a number of reasons.:

i) Unmeasured individual differences in the quit propensity (due, for example, to differences across workers in the value of nonmarket time relative to the mean of their wage profile or to differences in drive and perseverance) are likely to be negatively correlated with the individual specific component in the wage equation. One would also expect low (high) productivity workers both to receive lower (higher) wages and to be more (less) susceptible to layoffs*.

ii) Individual differences in the value of leisure time are likely to be positively associated with quit rates into unemployment or out of the labor force. They are likely to be negatively related to productivity (through effort on the job and absenteeism) and wage rates.

iii) Optimal selection of jobs by workers in the presence of firm specific and match specific error components in the wage function will result in biases. Jovanovic (1979) argues that differences in the complementarity of the skills of workers with the requirements of particular jobs which are observable only through experience on the job results in substantial variation in the productivity and wages of workers across jobs. Noncompetitive elements in the wage structure or differences across firms in the optimal compensation policy (arising from differences in hiring costs, supervision costs, and other factors (see Pencavel (1972)) may also mean that workers face a distribution of wages for their skills. Workers who receive high wages relative to their alternatives will not quit, inducing a positive correlation between tenure and wages in a cross-section (see Jovanovic (1979)). Match heterogeneity in the layoff probability is also likely to be associated with match heterogeneity in the wage equation@. On the other hand, workers will quit to take an alternative job if and only if the alternatives are sufficiently high to compensate for the effect

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* This would be the case if total compensation, including wages and fringe benefits, does not vary one for one with productivity within a particular class of jobs.

@ Although we expect this to result in an overstatement of the tenure profile due to unmeasured productivity differences, workers with a given set of skills who enter job matches with high layoff probabilities might be expected to receive a compensating differential for layoff risk, especially in the presence of moving costs. This would tend to bias downward the estimates of the tenure slope. Note that the formal matching models such as Jovanovic(1979a) do not distinguish between layoffs and quits.

on wages of lost tenure. This results in a downward bias in the estimated wage-tenure profile. Use of a fixed effects or first differencing procedure to control for individual heterogeneity may amplify this downward bias, since with such a procedure changes in tenure associated with job changes identify the effect of tenure on wages.

Alternative means of dealing with these problems include the use of information on prior mobility as a control for individual heterogeneity (Mincer and Jovanovic (1981)), instrumental variables techniques, procedures to correct for sample selection (Borjas and Rosen (1981)), fixed effects procedures (Cline (1979a) and differencing (Bartel and Borjas (1981)). None of the earlier studies has simultaneously dealt with both individual heterogeneity and job heterogeneity. Ultimately, a joint analysis of quits, layoffs and wages rates which allows for both individual heterogeneity and job heterogeneity would be the most satisfactory way to deal with the endogeneity of tenure in the wage equation. However, there are many obstacles to such an analysis, including the lack of an accepted model of layoffs, and the econometric difficulties of estimating models based upon (3) and (4) once individual heterogeneity and job heterogeneity are admitted. For this reason, we focus upon single equation estimators for the wage equation.

## 3. USE OF VARIATION IN TENURE WITHIN THE JOB AS AN INSTRUMENTAL VARIABLE

We address the problems of both individual and job heterogeneity in the wage equation using an instrumental variables estimator, which we refer to as $IV_1$. The principal instrumental variable for tenure is the deviation of tenure around its mean for the sample observations on a given job match. The appeal of this variable is that it is uncorrelated by construction with both the individual specific error component of the wage equation and with the permanent job match component.

The details of the procedure and its formal justification are as follows.

It is always possible to decompose wage error term $\varepsilon_{ijt}$ into the sum of a fixed individual effect $\varepsilon_i$, a fixed job match component $\varepsilon_{ij(t)}$, and a transitory disturbance $\eta_{ijt}$ which may or may not be serially correlated, so that

$$\varepsilon_{ijt} = \varepsilon_i + \varepsilon_{ij(t)} + \eta_{ijt}.$$

One may decompose the transitory component $\eta_{ijt}$ as

$$\eta_{ijt} = \upsilon_{it} + \upsilon_{ijt} + \upsilon_t ,$$

where $\upsilon_{it}$ is an individual specific transitory error component that is uncorrelated across individuals, $\upsilon_{ijt}$ is a transitory match component that is uncorrelated with $\upsilon_{it}$, and $\upsilon_t$ is an economy wide wage disturbance. The individual specific component $\upsilon_{it}$ and the general time component $\upsilon_t$ may be freely correlated over time. However, we assume that the transitory match component $\upsilon_{ijt}$ is serially uncorrelated and/or has a small variance, an assumption which we will discuss below. After substituting for $\varepsilon_{ijt}$ and writing the tenure profile $f(T_{ijt})$ as the sum of terms involving $T_{ijt}$, $T_{ijt}^2$ and a dummy variable for tenure greater than 1, the wage equation (1) may be rewritten as

$$(5)\ W_{ijt} = b_0X_{ijt} + b_1T_{ijt} + b_2T_{ijt}^2 + b_3OLDJOB_{ijt} + \varepsilon_i + \varepsilon_{ij(t)} + \upsilon_{it} + \upsilon_{ijt} + \upsilon_t,$$

where $OLDJOB_{ijt}$ is 1 if $T_{ijt} > 1$ and 0 otherwise. The coefficient on $OLDJOB_{ijt}$ permits the first year on the job to have special importance. The variable would be expected to have a positive coefficient if specific capital investments associated with orientation and hiring are large and a substantial amount of information on the quality of the job match is revealed in the initial months on the job, or if investment in job specific skills is especially rapid at the beginning of a job. A large positive coefficient would also be consistent with Guasch and Weiss's emphasis on testing during the early months on the job.

Let $\overline{T}_{ij(t)}$ be the mean of tenure for individual i over the sample observations on the individual i in job j, where the fact that the job may change is again made explicit by writing j as a function of t. For example, if a person has been in a job for 3 years when the person enters the survey (t=1968) and remains on the job for 3 more years, then $\overline{T}_{ij(t)} = [3+4+5+6]/4$ as t ranges from 1968 to 1971.

Define $\tilde{T}_{ijt}$ to be the deviation of $T_{ijt}$ from the job mean, with $\tilde{T}_{ijt} = T_{ijt} - \overline{T}_{ij(t)}$. We now consider whether $\tilde{T}_{ijt}$ is a valid instrumental variable for $T_{ijt}$. Note that $\tilde{T}_{ijt}$ sums to 0 over the sample years in which the person is in job j. Consequently, it is orthogonal by construction to the error components $\varepsilon_i$ and $\varepsilon_{ij(t)}$, which are constant during job j and which embody permanent individual and job heterogeneity. That is, $\tilde{T}_{ijt}$ is unrelated to permanent heterogeneity across individuals and across job matches in the determinants of wage rates. If the transitory component $\eta_{ijt}$ is serially uncorrelated, then it will have only a weak relationship to $T_{ijt}$ and $\tilde{T}_{ijt}$, since $T_{ijt}$ depends upon past quit and layoff decisions, and a wage disturbance lasting only one period should have little weight in a mobility decision. Serial correlation in the individual specific and labor market wide subcomponents $\upsilon_{it}$ and $\upsilon_t$ should not pose a problem either, since in this case the resulting variation in the composite error $\varepsilon_{ijt}$ will not be related to movements in $T_{ijt}$ around its mean for a given job match. It follows that $\tilde{T}_{ijt}$ is a valid instrumental variable for $T_{ijt}$ as well as $T^2_{ijt}$ and $OLDJOB_{ijt}$. Basically, the tenure coefficients are estimated from the growth of tenure within each job. The same argument justifies use of $(\tilde{T}_{ijt})^2 = T_{ijt}{}^2 - \overline{T_{ij(t)})^2}$ and $\widetilde{OLDJOB}_{ijt} = OLDJOB_{ijt} - \overline{OLDJOB}_{ij(t)}$ as instrumental variables[&]. Note that this approach avoids bias in the tenure coefficients due to match heterogeneity, which would remain even

[&]The other variables in the wage equation are also used as instrumental variables.

after removal of individual effects.

It is natural to compare the $IV_1$ estimator to estimation using a fixed effect for each job match. This is equivalent to regressing the deviation of $W_{ijt}$ from the sample mean for job match ij on the deviations of the right hand side variables from their means for the match. The fixed job match effects estimator removes bias due to presence of $\varepsilon_i$ and $\varepsilon_{ij}(t)$. However, this is not feasible because the deviations from means of tenure and experience are perfectly correlated. Both advance by one each year during the course of a job.[9] Consequently, the tenure and experience coefficients are not separately identified.

## 3.1 Potential Sources of Bias in the $IV_1$ Estimates

In this section we discuss problems which may arise if (1) experience is correlated with $\varepsilon_{ij(t)}$, (2) tenure is measured with error, (3) the tenure slope varies across people and job matches, or (4) the assumption that the transitory part ($\upsilon_{ijt}$) of the match specific component of wages is serial uncorrelated or has a small variance is false.

Unfortunately, the fact that $\tilde{T}_{ijt}$, $\tilde{T}_{ijt}^2$, and $\tilde{OLDJOB}_{ijt}$ are uncorrelated with $\varepsilon_{ijt}$ is not sufficient to guarantee the consistency of the estimates of the tenure slopes given the presence of other variables in the model. Labor market experience will be correlated with $\varepsilon_{ij(t)}$. As a result, the $IV_1$ estimates of the experience slope of wages, as well as least squares estimates, combine the

[9] Our approach should be applicable to other problems in addition to the estimation of wage functions. One example is the analysis of the effects of time in residence and age of structure on the rental price of housing. The estimator falls within the general class of estimators considered by Hausman and Taylor (1981). They show how to estimate variance components models with endogenous time invariant right hand side variables using 1) exogenous time invariant right hand side variables and 2) the means and deviations from time means of exogenous time varying right hand side variables as instrumental variables. Note that they use their procedure to solve an identification problem which arises (in estimating the effects of schooling on wages) with a fixed effects approach.

effects of general skill accumulation on wages as well as the average change with time in the mean of $\varepsilon_{ij(t)}$. Jovanovic's(1979) job matching model and more conventional search models (eg. Burdett(1978)) imply that $\varepsilon_{ij(t)}$ is likely to be positively correlated with time in the labor market, since more experienced workers have had more time to locate and move to good jobs.* This positive effect is probably offset to some extent by the fact that a substantial fraction of job changes are layoffs (about 40% in our sample) or are motivated by nonpecuniary considerations and thus are not the response of workers to an offer of a job with a better match component in the wage. Nevertheless, the instrumental variables estimate of the coefficient on experience is likely to be upward biased as an estimate of the partial effect of experience (with $\varepsilon_{ij(t)}$ held constant) on wages. Unfortunately, the upward bias in experience is likely to induce a downward bias in the estimates of the tenure slope, since $\varepsilon_{ij(t)}$ does not in fact increase unless the job changes.** The downward bias arises as a partial correction for the overstatement of the effects of additional labor market experience on wages during years in which the job remains the same. We

* Much of the rise in wages with experience that is associated with moves through a sequence of jobs during a career is best interpreted as accumulation of general human capital rather than information on comparative advantage across jobs. A job may provide (worker financed) training that is more useful in a wide variety of alternative jobs than in the present job. See Rosen (1972). Apprenticeships are an extreme example of this phenomena.

** One might hypothesis that total labor market experience will be correlated with $\varepsilon_i$ if fixed individual characteristics which are negatively related to productivity are positively related to the amount of time persons spend out of the labor force or unemployed. We checked this possibility using the $IV_1$ procedure by treating the terms involving experience (EXP, $EXP^2$, $EXP^2$ and EXP·EDUC in Table 1) as endogenous variables along with the tenure variables in the wage equations and substituting (age - education + 5)·education and a cubic in (age - education + 5) for the variables involving experience in the first stage equations. The results are very similar to the $IV_1$ estimates reported in the table. We feel safe in ignoring possible bias in the coefficient on union status, health status, and other control variables in the wage equation arising from $\varepsilon_i$ because these variables are approximately orthogonal to $T_{ijt}$, $T_{ijt}^2$, and $OLDJOB_{ijt}$ and are also only weakly related to experience.

present evidence on the quantitative significance of the problem in Sections 5.4 and 5.5 below.

A second potential problem with the $IV_1$ concerns measurement error in the tenure variable. For the years prior to 1975 the tenure measure is bracketed. Also, since employer tenure is not asked in all years, it has been necessary to interpolate between some years using information on employer tenure for other years, reasons for job changes, evidence of changes of industry, and other variables. (See Appendix 2.) The resulting measurement error in the tenure variables is likely to bias downward both the least squares and the $IV_1$ estimates of the tenure profile. But the bias is likely to be more severe in the case of the $IV_1$ procedure, since removal of $\bar{T}_{ij(t)}$ in the construction of $\tilde{T}_{ijt}$ will amplify the relative importance of measurement error in the total variance of the instrument for $T_{ijt}$ used to estimate the wage equation.#  Sections 5.4 and 5.6 present evidence on the size of the bias from measurement error.

Thus far the discussion has ignored the possibility that the tenure profile of wages varies across people and jobs. Such variation might arise from differences in the amount of worker financed specific human capital which is appropriate given the characteristics of the job and the individual (See Borjas (1981) and Jovanovic (1979b)). This would add the component $b_{1ij}\ T_{ijt}$ to the error term of the wage equation, where $b_{1ij}$ is the deviation of the tenure slope for the match ij around $b_1$, and $b_1$ is redefined as the mean of the tenure slope $b_1$ over all job matches weighted by their relative frequency and duration (i.e.,

# This discussion assumes that the measurement error is not strongly serially correlated. Error in the level of tenure which is consistent from year to year within each job match will have little effect on the $IV_1$ and GLS-$IV_1$ estimates and a potentially strong (negative) effect on the OLS estimates. See Griliches (1984) for a recent survey on measurement error and other data problems.

the tenure slope of an observation chosen at random from the sample.) One would expect the level of tenure to be correlated with $b_{1ij}$, as workers in jobs which are suitable for large specific investments are more likely to stay in those jobs. Thus, if one estimates by OLS and ignores this component, the result is a biased estimate of the mean of the tenure slope. Unfortunately, one may show that the $IV_1$ estimate of the mean tenure slope is also likely to be upward biased.* We have not investigated remedies for this problem, in part because the very modest estimates of tenure slope based upon the $IV_1$ procedure indicate that the upward bias is not quantitatively important.

Finally, we discuss the assumption (pg. 11) of no serial correlation in $\upsilon_{ijt}$. There is reason to believe that some serial correlation will be present. For example, wages may vary with firm specific changes in product demand (especially with monopolistic competition in the product market) or production technology. Or serially correlated industry-wide productivity shocks may not affect the wages of workers in their present job (because of implicit contracts which smooth wages) but may alter the wages available to them

* In the simplified case in which $T_{ijt}$ is the only variable which enters the wage equation, one may show that the estimate of $b_1$ is equal to $b_1$ plus $\Sigma\, a_{ij}b_{1ij}$, where the summation is over ij pairs, the weights $a_{ij}$ are proportional to $\Sigma T_{ij(t)t}$, and the latter summation is over the values of t corresponding to the job match ij in the sample. One may show that $\Sigma T_{ij(t)t}$ is approximately equal to $(1/12)(n_{ij}-1)^3 + (1/4)(n_{ij}-1)^2+(1/6)(n_{ij}-1)$ where $n_{ij}$ is the number of sample observations corresponding to match ij. Thus, the weight $a_{ij}$ on the tenure parameter specific to match ij rises faster than the number of observations corresponding to ij. Since $n_{ij}$ is positively related to the duration of the job, and since almost any reasonable model of quits implies (ceteris paribus) that jobs with steeper tenure slopes have lower quit rates, we conclude that the estimate of $b_1$ is biased upward as an estimate of the tenure slope for an observation chosen at random from the sample. (The expression for $\Sigma T_{ij(t)t}$ is not exact because the starting date for jobs need not correspond exactly to the time of the survey, and because the time between surveys is not exactly one year. In deriving the above expressions one uses the facts that

$$\sum_{k=0,\ldots,n} k = n(n+1)/2 \quad \text{and} \quad \sum_{k=0,\ldots,n} k^2 = n(n+1)(2n+1)/6$$

for any positive integer n.)

elsewhere.[*] A decline in $\upsilon_{ijt}$ increases the probability that the worker will find a better alternative and quit, although the effect of a given change in $\upsilon_{ijt}$ on the worker's valuation of his job is small unless $\upsilon_{ijt}$ has a strong positive correlation. To see the implications of this for the estimate of the tenure profile, note first that the size of the decline in $\upsilon_{ijt}$ necessary to trigger a quit (for any given value of the alternative offer received) increases with $T_{ijt}$ if wages rise with $T_{ijt}$. This implies that the expected value of $\upsilon_{ijt}$ conditional on continuation of the job declines with $T_{ijt}$. Consequently, over the course of the job (i.e., conditional on no quit) $T_{ijt}$ is negatively correlated with the conditional expectation of $\upsilon_{ijt}$. Least squares estimates (with or without controls for individual heterogeneity) of the tenure slope will be downward biased. Part of this correlation will carry over to $\tilde{T}_{ijt}$ and bias downward the instrumental variables estimates of the tenure slope. On the other hand, a similar argument suggests that selection due to layoffs is likely to produce bias in the other direction, and so the two effects are partially offsetting. An analysis of the residuals does not provide evidence of strong positive autocorrelation in the residuals once individual and job effects have been taken into account, although it should be kept in mind that the residuals are affected by the selection process.[&] While there is no strong theoretical or

[*]/However, Altonji, Mincer and Shakotko (1984, ch. 4) find only minor differences by tenure level in the effect of the aggregate unemployment rate, state employment changes, or county unemployment rates on wages.

[&]/ The autocovariance function of residuals for the same individual across years in which the job is not the same is

| Lag: | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Covar: | .110 | .085 | .079 | .074 | .074 | .072 | .071 | .069 | .061 | .069 | .067 | .083 |

Ignoring an unimportant economy wide error component, the covariance at each lag is an estimate of $var(\varepsilon_i) + cov(\upsilon_{it}, \upsilon_{it-k})$ for $k > 0$. The autocovariance function of residuals for the same individual over years on the same job is

| Lag: | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Covar: | .110 | .101 | .094 | .092 | .090 | .090 | .088 | .091 | .093 | .090 | .085 | .072 |

This provides an estimate of $var(\varepsilon_i) + var(\varepsilon_{ij}) + cov(\upsilon_{it}, \upsilon_{it-k}) + cov(\upsilon_{ijt}, \upsilon_{ijt-k})$ for $k > 0$. Comparison of the patterns of decay of the two empirical presumption that this bias is important, further analysis is needed.

## 3.2 Treatment of Correlation of Errors Across Individuals and Jobs

Even if one assumes that $\eta_{ijt}$ is serially uncorrelated, the composite error term of the model is correlated over time as a result of the individual component and the job match components. Consequently, the $IV_1$ procedure is inefficient relative to a GLS (generalized least squares) version of the procedure. The same limitations apply to the OLS estimates of the model. Use of the GLS versions of the $IV_1$ and OLS procedures is complicated by the fact that the sample is unbalanced, with a large variation in the number of years of data on each individual and on each job match, and to our knowledge GLS has never been implemented in such a situation. The necessary formulae to compute GLS versions of the least squares and $IV_1$ procedures for the case of unbalanced data are derived in Appendix 1.*

covariance functions provides information on $\text{cov}(\upsilon_{ijt},\upsilon_{ijt-k})$, which plays a role only in the covariance of residuals over the same job. In making the comparison, one should keep in mind that the covariance of residuals across different jobs is overstated at lag 1 because the hourly wage variable is an average over the calendar year, and may combine information on the two jobs. Thus, the drop in the covariance between the first and second lags (.110 to .085) is overstated. The fact that the patterns of decay in the two autocovariance functions are very similar after the first lag suggests that $\upsilon_{ijt}$ is either white noise, a random walk, or has a very small variance. A regression analysis of squared residuals from wage equations in columns 3, 6, 9, and 12 of Table 1 indicates that if anything the error variance actually falls somewhat with tenure, which is inconsistent with the hypothesis that $\upsilon_{ijt}$ is a random walk. Thus, subject to the important caveat that the residuals themselves are affected by the job selection process discussed in the text, we find little evidence that $\upsilon_{ijt}$ plays an important of a role in the evolution of wages.

* The key to computation of the GLS versions of the least squares and $IV_1$ estimators is the analytical formula for the inverse of the covariance matrix of the wage errors for each individual in the sample, which we have derived under the assumption that $\eta_{ijt}$ is serially uncorrelated over time and across people. This inverse is a function of the number of observations on the individual in the sample, the number of jobs held, the number of years in each of the jobs, the covariances of the $\varepsilon_{ijt}$ across time periods on the same job and across different jobs for the same individual, and the variance of $\varepsilon_{ijt}$. Given the formula for the inverse of the covariance matrix, computation of the GLS versions of the least squares and $IV_1$ procedures is straightforward. We have ignored the effect of the common error component $\upsilon_t$ on covariance

In interpreting the GLS results below, readers should keep in mind that the standard justification for use of GLS is to improve efficiency and provide asymptotically valid standard errors rather than to reduce bias in the estimates. Since the calculated standard errors of the OLS estimates are very small (and are not likely to be understated by a large amount), large changes in the OLS results are not expected unless the wage model is misspecified. If the failure to control for heterogeneity is an important misspecification, then there is reason to expect substantial differences between the OLS and GLS estimates. To see this, note that when the instruments are not used in place of the tenure measures, the GLS estimator may be thought of as least squares applied to the wage model after subtracting from each of the variables in the equation: (1) a weighting factor times the average value of the variable for the sample years in which the person is in a given job, and (2) a second weight times the individual specific mean of the variable. The weighting factors depend in a complicated way upon the covariances mentioned above, the length of the job, the number of jobs held by the individual, and the number of years that the person is in the sample. Thus the GLS procedure uses less of the variation in the data across individuals and across jobs than does OLS. It is intermediate between use of an individual or job fixed effects procedure and OLS.* Consequently, the GLS estimates of the model may differ sharply from the OLS estimates if heterogeneity produces important biases in the OLS results. At the same time, one would expect the $IV_1$ and $IV_1$-GLS to give similar answers,

structure given that a time trend is added to the model and year dummies explain very little of the wage variance.

*We were unable to derive an explicit formula relating the GLS procedure to these procedures. Our argument is by analogy to Maddala (1971), who provides an exact formula relating the GLS estimator to the OLS and fixed effect estimators for case of a fixed individual specific error component that is uncorrelated across people and a person specific serially uncorrelated transitory component, and the same number of observations per person.

since the $IV_1$ procedure is not sensitive to individual heterogeneity or job heterogeneity. The bottom line of this discussion is that we use the GLS version of the various estimators both to provide an informal specification test for heterogeneity bias and to improve efficiency.

**4. DATA**

The sample is based upon the 1968-1981 waves of the Panel Study of Income Dynamics. Most of the results below are for white male heads of households, although some findings for a corresponding sample of blacks are also presented. For a given year the sample contains individuals who were between the ages 18-60 inclusive, who were employed, temporarily laid off, or unemployed at the time of the survey, and who were not retired, permanently disabled, self employed, employed by the government in the current or past year, or from Alaska or Hawaii. Observations with missing data on the variables in wage equation are excluded for the particular sample year. The effective sample for whites covers the calendar years 1968-1980 and contains 15138 observations on 2163 individuals and 4334 job matches.

Most of the variables are standard. However, it is important to point out that there are ambiguities in the quit and job tenure measures, especially in the early years of the sample. This is because the questions about job changes in the early years do not distinguish clearly between promotions and quits, the tenure variable is bracketed in the early years, and in some years the tenure variable does not distinguish clearly between tenure with an employer and tenure in a position. We have used a number of cross checks to try to solve these problems, but some measurement error undoubtedly remains. The possibility that measurement error in the tenure variables has a serious effect on the results is investigated (and rejected) in Section 5.4 below.

The real wage measure is the log of labor earnings during the year divided by annual hours and is converted to real terms using the GNP implicit price deflator for consumption. The variables T, $T^2$ and OLDJOB and union status refer to the time of the survey in the corresponding year (typically in March or April).* ** The variable N/EXP is a measure of the number of jobs held by an individual up to the current year (N) divided by labor market experience (EXP). Table A.1 presents descriptive statistics on most of the variables used in the analysis. Appendix 2 provides additional discussion of the data.

## 5. RESULTS

The results are organized as follows. Section 5.1 presents the least

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* Since the earnings and hours questions refer to the previous calendar year, this data was matched to information on union status and tenure from the prior survey. The quit, layoff, and separation indicators refer to the 12 months prior to the current survey and are matched to data on union status and tenure from the previous survey.

** Note that for those who change jobs during the year the wage is presumably an average of the wage on each of the jobs weighted by the portion of the year spent in each. Thus, use tenure at the time of the survey rather than the average of tenure over the calendar year may lead to an understatement of the effect of the first year of tenure on wages. One alternative is to construct a weighted average from tenure in adjacent survey years. Preliminary analysis using such a measure lead to results very similar to those reported below. The second alternative is to use the reported hourly wage for the job held at the time of the survey as the wage measure. The main disadvantages of this variable are (1) it only available for hourly workers prior to the 1976 survey (2) it is truncated at $9.98 prior to 1978, and (3) it underestimates wage growth to the extent that paid vacations and holidays rise with tenure and experience. The truncation of the data and the fact that the mean of the average hourly earnings of hourly workers is 25.7% below the corresponding figure for salary workers will bias to some extent the experience and tenure coefficients. When these factors are taken into account the results using the reported wage are very similar to those using the average hourly wage. For example, when the sample is restricted to the years 1978-1981 (when neither of the first two problems are present), the parameter estimates (with uncorrected standard errors) corresponding to column 6 of Table 1 are

$$W = \underset{(.011)}{-.0012}\,T + \underset{(.0005)}{.00021}\,T^2 + \underset{(.0273)}{.0363}\,\text{OLDJOB} + \underset{(.0096)}{.0393}\,\text{EXP} \underset{(.004)}{-.0140}\,\text{EXP}^2/10$$

$$+ \underset{(.005)}{.0013}\,\text{EXP}^3/100 + \underset{(.0003)}{.0005}\,\text{EDUC} \cdot \text{EXP} + \text{other variables.}$$

squares and $IV_1$ estimates of the wage equation for white males. Section 5.2 examines whether both individual heterogeneity and job heterogeneity are present. Section 5.3 discusses the GLS versions of the least squares and IV estimators. Section 5.4 compares the OLS and IV methods from the standpoint of predictive accuracy. Sections 5.5 and 5.6 assess the possibility of biases in our estimates. Section 5.7 compares results for blacks and whites and union and nonunion workers. Section 5.8 shows that both $\varepsilon_i$ and $\varepsilon_{ij(t)}$ have a strong positive association with the quit and separation probabilities. Our main conclusion is that job tenure plays only a small role in the wage equation, and that heterogeneity bias dominates the cross-sectional relationship between tenure and wages.

## 5.1 Basic OLS and $IV_1$ Estimates of the Wage Equation for White Males

Table 1 reports various estimates of the coefficients on years of education, experience, and tenure. To reduce the possibility of bias in the tenure and experience profiles from an overly restrictive specification of the education-experience polynomial, we include education, education$^2$, EXP, EXP$^2$, and EXP$^3$, and the product of education and EXP. The equations also contain controls for marital status, union membership, health status, city size and residence in an SMSA, time, and region, although the parameter estimates for these variables are not displayed.* Most previous studies have used either T or T and $T^2$ as the specification of the tenure profile. We report results for these specifications but focus the discussion on the results with T, $T^2$ and the dummy variable OLDJOB, which is defined to be 1 if $T \geq 1$ and 0 otherwise, all included in the equation.

The OLS estimates (columns 1-3) and the $IV_1$ estimates (columns 4-6) of the

* The full set of estimates for columns 3 and 6 of Table 1 and columns 3 and 6 of Table 2 are reported in Table A3.

wage parameters tell very different stories about the tenure profile of wages.* The OLS estimates indicate that OLDJOB has a large positive effect on wages, with a point estimate of .111 (Col. 3) and a standard error of .012. In contrast, the $IV_1$ estimate of the OLDJOB coefficient is only .050 with a standard error of .009. The $IV_1$ coefficient estimates for T and $T^2$ are -.0041 and .002 with small standard errors. (See col. 6; note that T has a coefficient of .0016 with a t-value of 1.14 when it is entered by itself.) The corresponding OLS estimates are .0178 and -.0003 with tiny standard errors.

In general, the OLS estimates are typical of those obtained from cross sectional analyses of the wage equation. They indicate a substantial growth of wages with tenure, with much of the growth occurring in the first year on the job. By constrast, the $IV_1$ estimates indicate substantially smaller first year growth and a virtually flat tenure profile thereafter. The relationship between tenure and wages is usefully summarized by calculating the effect of the first 10 years of tenure on the wage. This is reported at the bottom of the columns of Table 1. The $IV_1$ estimates imply that the accumulation of the first 10 years of tenure (including the first year effect) results in a wage increase of .0268 (with a standard error of .016). Since the wage is in logs this corresponds to a percentage increase of 2.7%. This is only 1/11th of the corresponding OLS estimate of the contribution of 10 years of tenure to wages (30%). These results indicate that the strong correlation between wages and tenure observed in previous studies is primarily due to heterogeneity bias. Evidently, the permanent individual component of wages is positively correlated with the

* The first stage equation for the tenure variables are reported in Table A2,columns 1-3. The standard errors in Tables 1, 5 and 6 have been corrected for the effects of correlation across observations on the same individual and on the same job match arising from the error components $\varepsilon_i$ and $\varepsilon_{ij(t)}$. They are asymptotically correct under the assumption that $\eta_{ijt}$ is serially uncorrelated.

propensity to quit or suffer layoffs, and/or individuals who enter into job matches which are at the low end of the wage distribution (for the individual) quickly move on to other positions. The findings are consistent with Jovanovic's matching model as well as with a potentially large role for individual heterogeneity.

Accompanying the much smaller $IV_1$ estimates of the tenure slope is an increase in the estimated experience profile. This is expected since the strong positive correlation between experience and tenure implies that the upward bias in the tenure profile resulting from heterogeneity will result in a downward bias in the experience profile. The OLS estimates indicate that total labor market experience raises wages by 31.7% during the first ten years of work and 48.2% during the first 30 years. (Note that these estimates are very precise.) The corresponding figures based upon the $IV_1$ estimates are 53.7% and 86.6%. Since the tenure effects on wages must be multiplied by approximately .25 or .3 (the derivative of the mean of tenure with respect to experience) to estimate the contribution of tenure to growth in wages over a career, the $IV_1$ estimates indicate that the role of tenure is trivial relative to labor market experience in explaining the gross increase in wages with labor market experience.

It is useful to compare the $IV_1$ results with those based upon the addition of N/EXP, the ratio of prior separations to experience, to the wage equation as a control for individual heterogeneity. The results for this approach to the problem of heterogeneity bias, which is due to Mincer and Jovanovic (1981), are reported in columns 10-13 and are similar to the OLS results discussed above.*

*Compare columns 10-12 with 1-3. The variable makes less of difference in our results than in Mincer and Jovanovic's, who used the 1976 panel from the PSID, measure N as the number of separations between 1968 and 1975, and work with N directly or with the product of N and experience. This is not surprising, since the link between current tenure and number of separations in the previous 8 years is closer to being definitional than the link between tenure and our estimates of the total number of prior separations divided by

The estimated tenure profile over the first 10 years is about 10 times steeper than that using $IV_1$. The prior separation index does not appear to be an adequate control for heterogeneity bias. One possible reason is that N/EXP variable does not control for job match heterogeneity. A second reason is that N/EXP the variable is a noisy control for individual heterogeneity. In part, this may be due to problems with the measure of N, and in part it is due to the fact that for any given true separation probability the observed separation rate has a considerable variance when EXP is low. The noise in N/EXP may have a complicated effect on the results because of the presence of EXP, $EXP^2$ and $EXP^3$ in the model and the fact that EXP is correlated with T.

5.2 Extensions: Individual Heterogeneity Versus Job Heterogeneity

An interesting alternative estimator is obtained by adding the deviation of $\overline{T}_{ij(t)}$ from the individual mean $\overline{T}_i$ to the list of instrumental variables ($IV_2$). $\overline{T}_{ij(t)} - \overline{T}_i$ will be uncorrelated with the wage disturbance if the job effects $\varepsilon_{ij(t)}$ are 0 or are not related to separations. Note that since $T_{ijt}-\overline{T}_i = \tilde{T}_{ijt} + \overline{T}_{ij(t)} - \overline{T}_i$, use of both $\tilde{T}_{ijt}$ and $\overline{T}_{ij(t)} - \overline{T}_i$ in the first stage equations is similar to estimation using $T_{ijt} - \overline{T}_i$. Similarly, one may add $\overline{T_{ij(t)}^2} - \overline{T_i^2}$ and $\overline{OLDJOB}_{ij(t)} - \overline{OLDJOB}_i$ to the

experience. They report a reduction in the tenure profile of about 15% when N $\cdot$ EXP is added. They find virtually no reduction for the NLS sample of young men but a 40% reduction for the NLS sample of older men. Note that the experience coefficients in columns 10-12 are not comparable with those in 1-3 because N/EXP falls over the lifetime for a typical worker. See Mincer and Jovanovic and Mincer(1984) for a detailed analysis of this variable.

first stage equations for the tenure variables. (The first stage equations for the $IV_2$ estimator are reported in columns 4-6 of Table A2.)

The $IV_2$ parameter estimates are displayed in columns 7-9 of Table 1. predicted values. The use of the variation in the tenure means across jobs leads to a modest changes in the estimates of the tenure slopes when $T_{ijt}$, $T_{ijt}^2$ and $OLDJob_{ijt}$ are all present in the wage equation (compare columns 6 and 9). The extra effect of the first year of tenure rises to .073, and the overall effect of 10 years of tenure is about 7.5%. This exceeds the $IV_1$ estimate of 2.7 by about 3 standard errors, but is far below the OLS estimate of 30%. A formal Hausman type test of the null hypothesis of exogeneity of $\overline{T}_{ij(t)} - \overline{T}_i$, $\overline{T_{ij(t)}^2} - \overline{T_i^2}$ and $\overline{OLDJOB}_{ij(t)} - \overline{OLDJOB}_i$ lead to rejection the hypothesis at the .001% level .*

In summary, both the $IV_1$ and $IV_2$ results indicate that tenure plays only a modest role in wage growth, with general labor market experience accounting for most of the growth. The tenure estimates lie considerably below estimates based upon least squares and use of a prior mobility index as a control for individual

* Following Newey (1984, pg.26) we performed the exogeneity test by testing for the joint significance in the wage equation of the residuals from regressions of the three additional instrumental variables against the maintained set of instrumental variables. The covariance matrix of the parameter estimates of the wage equation used in forming the test statistic was calculated using the $IV_2$ (Table 1, column 9) estimate of the residual variance and with the correlation in the errors across observations on the same individual and the same job match taken into account.

The fact that the $IV_2$ estimates of the tenure profiles are much closer to the $IV_1$ results than to the OLS results does not provide clear evidence on the relative importance of individual heterogeneity and job match heterogeneity in biasing the OLS results. To see this, note that about 1/2 of the observations come from individuals who held only one job during the years in which they are in the sample. For these observations, the additional instrumental variables $[\overline{T}_{ij(t)} - \overline{T}_i, \overline{T_{ij(t)}^2} - \overline{T_i^2}, \overline{NewJob}_{ij(t)} - \overline{NewJob}_i]$ used in the $IV_2$ procedure are identically 0 and add nothing to the instruments for the tenure variables. Adding the deviations from individual means has little impact on the $R^2$'s of the first stage equations for the T and $T^2$ but does make a substantial difference in the equation for OLDJOB. See Table A2.

heterogeneity.

5.3 GLS Estimates

The columns of Table 2 report GLS estimates which correspond to the OLS results in columns 1-3 and 10-13 of Table 1 as well as $IV_1$-GLS and $IV_2$-GLS estimates which correspond to the $IV_1$ and $IV_2$ estimates of columns 4-6 and 7-9. The estimates of the covariance matrix of the residuals for each individual used in the GLS calculations are based upon the correlation of the wage residuals for a given individual across different jobs and upon the correlation for a given individual in the same job. These estimates equal 0.46 and 0.59 respectively and were calculated from the $IV_1$ equation estimate in column 6 of Table 1. Very similar estimates were obtained using the residuals from the OLS estimates,* and so we have employed the same residual correlation matrix in computing all of the results in Table 2.

Comparison of columns 3 and 12 of the two tables indicates that GLS produces a dramatic reduction in the least squares estimates of the wage-tenure profile, regardless of whether one controls for prior job mobility. For example, OLS estimates of the model with T, $T^2$, and OLDJOB imply that 10 years of tenure are associated with an increase in wages of about 30%, while the

* Using the $IV_1$ equation from Table 1 (Col. 6), the corresponding correlation estimates are (0.42, 0.57). Using the $IV_2$ equation (Col. 9), the correlation estimates are (0.45, 0.59). Using the N/EXP equation (Col. 12), the correlation estimates are (0.42, 0.58).For the $IV_1$ equation, the estimates of the variances of $\eta_{ijt}$, $\varepsilon_i$ and $\varepsilon_{ij}$ are .069, .077, and .022. (The estimate of the variance of $\eta_{ijt}$ is exaggerated by the presence of serially uncorrelated measurement error in the wage, although this has no bearing on estimation of the wage of equation.) Thus, the job match component accounts for substantial fraction of the error variance. This is consistent with Cline(1979a). Note that the estimates above as well as the estimates for nonunion workers and blacks used in correcting the standard errors of tables 5 and 6 are based upon the residual variance, the average of the cross products of residuals between periods in which the individual held different jobs, and the average of the cross products between periods in which the individual held the same job. The variance decomposition is based upon the assumption that $\eta_{ijt}$ is serially uncorrelated.

corresponding GLS estimate is only 13.1%. The GLS estimates of the coefficients on T and OLDJOB are .0044 and .074 (respectively), which are well below the OLS estimates of .0178 and .111. The reduction in the estimated tenure slope is accompanied by a large offsetting increase in the experience slope.

The impact of GLS is far too large to be explained by sampling error. As was explained earlier, it is fully consistent with the presence of strong heterogeneity bias in the OLS estimates. This interpretation is strongly supported by comparison of the $IV_1$ estimates in columns 4-6 of Table 1 with the $IV_1$-GLS results in columns 4-6 of the Table 2. The GLS transformation has only a small effect on the $IV_1$ estimates, although the point estimates of the coefficients on individual coefficients in the education-experience polynomial change somewhat. The tenure coefficients are virtually unchanged. The $IV_1$-GLS estimate in column 6 implies that 10 years of tenure produces a wage increase of 2.2%, while the corresponding $IV_1$ estimate is 2.7%. The experience profiles are also very close. Since the $IV_1$ procedure does not use variation in tenure across jobs and across individuals to identify the tenure effect, it is less sensitive to GLS. The $IV_2$ estimates using deviations from individual means as well as deviations from job means as instrumental variables also change by only a small amount.

5.4 Evaluating the Performance of OLS and $IV_1$ in Predicting Wage Changes.

The most natural check on the OLS and $IV_1$ estimates of the tenure slope is to compare their performance in predicting the change in the wage across years in which the job does not change (stayers) and for observations with a job change (movers). If the $IV_1$ tenure slope is correct, then one would expect the predicted wage changes based on the OLS coefficients to be greater than the actual wage changes for stayers, and to be less than the actual wage changes for job changers. The $IV_1$ estimates should be accurate for both groups.

Furthermore, the OLS prediction errors should be systematically related with the change in tenure from year to year. Roughly speaking, this is what we find.

Table 3 reports the difference between the actual and predicted values of $\Delta W_{ijt}$ as a function of tenure in period t-1. For purposes of comparison, Table 3 also reports OLS and $IV_1$ estimates (based upon the tenure coefficients in Table 1) of the contribution of the change in tenure between t-1 and t to the expected value of $\Delta W_{ijt}$ given tenure in period t-1. On average, the OLS equation predicts that $\Delta W_{ijt}$ will equal .046, while the mean of $\Delta W_{ijt}$ is .026, an overprediction of .020. Furthermore, a comparison of columns 3 and 4 reveals that the prediction errors are systematically related to the estimated contribution of tenure to the wage change. On the other hand the $IV_1$ procedure slightly overestimates wage growth for stayers. The $IV_1$ prediction errors are small at all tenure levels.

For movers, OLS dramatically underpredicts $\Delta W_{ijt}$. The average prediction error is .095, which compares to the average value of $\Delta W_{ijt}$ is .058. Since the tenure coefficients have little effect on the average of the predicted wage change for persons with $T_{ijt-1}$ between 0 and 1, it is useful to compute the average prediction error for persons with $T_{ijt-1}$ greater than 1. For this group, OLS underpredicts $\Delta W_{ijt}$ by .169. Comparison of columns 3 and 4 reveals that the prediction error is systematically related to the OLS estimate of the contribution of the change in tenure to the wage growth. In contrast, the $IV_1$ prediction errors average only .029 and are not systematically related to tenure level.

Table 3 also reports separate results for quits and layoffs. They show that the OLS equation performs very poorly for both groups, and that the prediction errors are systematically related to the OLS estimate of the contribution of the change in tenure to the wage change. The $IV_1$ estimates perform much better than the OLS estimates for both quits and layoffs, although the $IV_1$ estimates underpredict by .058 and .015 for quits and layoffs respectively. (The latter figure is not significantly different from zero.) The prediction errors are not systematically related to $T_{ijt-1}$.

In summary, the results of the prediction tests are basically favorable to the $IV_1$ estimates and indicate that the OLS estimates of the tenure slope are seriously overstated. These tests cast serious doubt on the view that measurement error in the tenure variable is responsible for the difference between the OLS and $IV_1$ results. The sample means of the changes in tenure for each initial tenure level underly the predictions. Random measurement error in the tenure variables should have little effect on these. However, the fact that $IV_1$ estimator tends to underpredict for quits by a constant amount is consistent with the notion that the job shopping process leads to an increase in $\varepsilon_{ij(t)}$ with experience. As was explained earlier, the resulting correlation of $\varepsilon_{ij(t)}$ with experience would produce a downward bias in the tenure slope which offsets an upward bias in the experience slope. It seems unlikely that these biases are large given the poor performance of the OLS equation, the fact that the $IV_1$ prediction errors are not related to tenure level and are very small for layoffs, and the fact that the the $IV_1$ procedure actually overpredicts wage growth (slightly) for stayers. In any event, we provide additional analysis of the possible biases which arise from job shopping and from measurement error in the next two sections.

## 5.5 Analysis of Bias from Omission of $\varepsilon_{ij(t)}$

Let the $IV_1$ instruments for $T_{ijt}$, $T^2_{ijt}$ and $OLDJOB_{ijt}$ be denoted by $\hat{T}_{ijt}$, $\hat{T}^2_{ijt}$ and $OLD\hat{J}OB_{ijt}$ respectively, and let $\hat{\underline{T}}_{ijt}'$ denote the vector $[\hat{T}_{ijt}, \hat{T}^2_{ijt}, OLD\hat{J}JOB_{ijt}]$. $\hat{\underline{T}}_{ijt}'$ is determined by the system of first stage equations

$$\hat{\underline{T}}_{ijt} = X_{ijt}\hat{\Pi}_1 + [\tilde{T}_{ijt}, \tilde{T}^2_{ijt}, OL\tilde{D}JOB_{ijt}]\hat{\Pi}_2$$

where $\hat{\Pi}_1$ and $\hat{\Pi}_2$ are the matrices of coefficients of the first stage equations for $T_{ijt}$, $T^2_{ijt}$, and $OLDJOB_{ijt}$ reported in Table A2. From the Theil-Griliches formula for the analysis of bias due to an omitted variable (See Theil (1971), Ch. 12), the bias $\hat{B}_{bias}$ in the coefficients of the wage equation which arises from the presence of $\varepsilon_{ij(t)}$ in the error term of the model, is equal to the column vector

(6) $\hat{B}_{bias} = \text{plim}[\sum_{ijt}(Z_{ijt}'Z_{ijt})]^{-1}[\sum_{ijt}[X_{ijt},\underline{\hat{T}}_{ijt}]'\varepsilon_{ij(t)}]$

where $Z_{ijt} = [X_{ijt}, \underline{\hat{T}}_{ijt}]$.

In most multivariate contexts, one cannot even sign the elements of $\hat{B}_{bias}$, let alone assess them quantitatively. Since the omitted variable $\varepsilon_{ij(t)}$ is not observed, it cannot be used directly to estimate the term $\sum_{ijt}[X_{ijt},\hat{T}_{ijt}]'\varepsilon_{ij(t)}$, which is the cross product of the included regressors with the omitted variable and is required to evaluate the bias formula.

In the present case, however, one may infer a great deal about these cross products. First, and most important, $\tilde{T}_{ijt}$, $\tilde{T}^2_{ijt}$ and $O\tilde{L}DJOB_{ijt}$ are orthogonal to $\varepsilon_{ij(t)}$ <u>by construction</u>. Consequently, $\sum_{ijt}[X_{ijt}, \underline{\hat{T}}_{ijt}]'\varepsilon_{ij(t)}$ reduces to $\sum_{ijt}[X_{ijt}, X_{ijt}\hat{\Pi}_1]'\varepsilon_{ij(t)}$. Second, many of the elements of $X_{ijt}$ such as schooling, region, SMSA are not likely to directly influence $\varepsilon_{ij(t)}$, given that $\varepsilon_{ij(t)}$ is defined to be net of the fixed individual characteristics such schooling. The problem of bias arises primarily because $\varepsilon_{ij(t)}$ is correlated with experience as a result of job shopping over the course of a career. For this reason, we assume that correlations of $\varepsilon_{ij(t)}$ with the other variables in the model arise only to the extent that they are correlated with experience. In this case, one can estimate the crossproducts between $\varepsilon_{ij(t)}$ and the explanatory variables in the model if one can estimate the conditional expectation of $\varepsilon_{ij(t)}$ given experience, which we denote by $[\hat{\varepsilon}_{ij(t)}|EXP_{it}]$. If $[\hat{\varepsilon}_{ij(t)}|EXP_{it}]$ is known, one may then compute $\hat{B}_{bias}$ as

(7) $\hat{B}_{bias} = \text{plim}[\sum_{ijt}[(Z_{ijt}'Z_{ijt})]]^{-1}\ [\sum_{ijt}[X_{ijt},\ X_{ijt}\hat{\Pi}_1]'[\hat{\varepsilon}_{ij(t)}|EXP_{it}]]$

We obtain a set of estimates of $[\hat{\varepsilon}_{ij(t)}|EXP_{it}]$ by combining information on the experience profile of quits with a range of assumptions about the expected value of the wage change resulting from a quit. The very small errors of the $IV_1$ estimator in predicting wage growth for those who quit, and evidence on the total growth in wages arising labor market experience over a career provide a check on the plausibility of the assumptions about wage gains per quit. We ignore layoffs under the conservative assumption that on average they result in a zero change in $\varepsilon_{ij(t)}$. If they are associated with negative changes, then consideration of layoffs would result in even smaller estimates of the bias than those reported below.

Let $Jobs_{it}$ equal the expected number of times a typical worker has quit conditional on the experience $EXP_{it}$ of the worker in time t. $Jobs_{it}$ may be approximated as

$$Jobs_{it} = \sum_{X=0}^{EXP_{it}} P_Q(X)$$

where $P_Q(X)$ is the probability that a worker with experience X will quit during the year. We estimate $P_Q(X)$ from a logit model relating the quit probability to a constant, EXP, $EXP^2$, and $EXP^3$.* Finally, we estimate $[\hat{\varepsilon}_{ij(t)}|EXP_{it}]$ as the product of $Jobs_{ijt}$ and an assumed value for the average change in $\varepsilon_{ij(t)}$ per quit and use (6) to compute $\hat{B}_{bias}$. The assumed value for the change in $\varepsilon_{ij(t)}$ ranges from .025 to .100. We consider .100 to be an upper bound for the change in $\varepsilon_{ij(t)}$ per quit for two reasons. First, if one assumes that the average change in $\varepsilon_{ij(t)}$ associated with layoffs is less than or equal to zero, then the difference .046 (with a standard error of .023) between the means of the actual change in $\Delta W_{ijt}$ for quits and for layoffs provides an upper bound on the average

* The implied probability of a quit in the first, 5th, 10th, 20th, and 30th years in the labor market are .394, .191, .120, .056 and .035 respectively.

gain in $\varepsilon_{ij(t)}$ associated with a quit. (This comparison requires the assumption that the sample distributions of quits and layoffs by experience and tenure levels are the same, which is approximately true.) In view of this figure, our preferred estimate of the gain per quit is .05. Second, as we shall see momentarily, the assumption that the average gain per quit is .100 implies that, for the average worker, 55.9 % of the gain in wages associated with labor market experience is due to increases in $\varepsilon_{ij(t)}$ resulting from job shopping and 44.1 % is due to the direct effect of experience.

The upper panel of Table 4 reports estimates of $\hat{B}_{bias}$ under the various assumptions about the average gain per quit. If the gain is .05 , then the bias in the estimate of the returns to 10 years of tenure on the log wage is biased downward by .0375. The "corrected" coefficients on T, $T^2$ and OLDJOB are .0005, .0012, and .0435 respectively, and the "corrected" estimates of the effects of 10 years of tenure and 30 years of experience on the log wage are .0643 and .4405. The implied average growth in $\varepsilon_{ij(t)}$ over 30 years of experience is .1835. When the gain per quit is assumed to be .100, the "corrected" estimates of the effect of 10 years of tenure and 30 years of experience are .1019 and .2570 respectively, and the average growth in $\varepsilon_{ij(t)}$ over 30 years is .325.*

In summary, the analysis of bias in the $IV_1$ arising from the correlation of experience with $\varepsilon_{ij(t)}$ suggests that the percentage gain in the wage from 10 years of tenure might be as large as 10.7 %, although our preferred estimate is 6.6 %.

An alternative way to analyze the important of bias arising from failure to control for $\varepsilon_{ij(t)}$ is to compare the $IV_1$ estimates to estimates obtained using a

* If one were to assume the gain is .150 per quit, the revised estimate of the effects of 10 years of tenure is only .139, which is still only half of the OLS estimate in in Table 1, column 3. We do not consider this case in the text in part because the it implies a corrected estimate for the direct effect of 30 years of experience and growth in $\varepsilon_{ij(t)}$ equal to only .074.

fixed effect for each job to control for both $\varepsilon_{ij(t)}$ and $\varepsilon_i$. As was noted earlier, only the sum of the coefficients on EXP, T, and the time trend are identified when the "job effects" estimator is used. However, one may use the test procedure suggested by Hausman and Taylor (1981) to compare the subset of experience and tenure parameters which are identified using the job effects estimator with the corresponding $IV_1$ estimates. In practice, we use the $IV_1$-GLS estimates in place of the $IV_1$ estimates in performing the test, since we were unable to find a way to adopt Hausman and Taylor's test to the case in which neither estimator is efficient under the null hypothesis. The relevant subset of the coefficient estimates from the $IV_1$-GLS and the job effects procedures are displayed below.

| | Coefficient on | | | | | |
|---|---|---|---|---|---|---|
| Estimator: | EXP+T+Time | $T^2$ | OLDJOB | Ed · EXP | $EXP^2/10$ | $EXP^3/100$ |
| JOB EFFECTS. | .0642 | .00004 | .0461 | -.00026 | -.0153 | .00153 |
| | (.0052) | (.00003) | (.0072) | (.00025) | (.0020) | (.00031) |
| $IV_1$-GLS | .0633 | .00018 | .0470 | .00016 | -.0185 | .00187 |
| | (.0045) | (.00007) | (.0088) | (.00018) | (.0019) | (.00028) |

The point estimates are very close relative to the standard errors, and a formal test of equality of the coefficient vectors passes.# It should be noted that

# The standard errors of the job effects estimates reported in the text are based upon an estimate of the variance of the transitory error component $\eta_{ijt}$ which equals .047. (The loss of degrees of freedom which arises from addition of the job constants to the model was taken into account in calculating this figure.) This estimate is well below the corresponding estimate based upon the $IV_1$ and $IV_1$-GLS procedures. We do not have a good explanation for why the variance estimates differ. It may be related to the fact jobs lasting only one period have no effect on the job effects estimator of the residual variance. As a result, two of the diagonal elements in the difference between the covariance matrices of the job effects estimator and the $IV_1$-GLS estimator are actually negative if one uses the .047 figure to compute the covariance matrix of the subset of job effects parameter estimates used in the test. Unfortunately, the specification test is based upon $c_1' [\Sigma_1 - \Sigma_2]^{-1} c_1$, where $c_1$ is the difference in the job effects and $IV_1$-GLS parameter estimates reported in the text and $\Sigma_1$ and $\Sigma_2$ are the covariance matrices of the job effects and $IV_1$-GLS parameter estimates (respectively ). estimate $[S_1 - S_1]$ of the covariance of $c_1$ (a problem which frequently arises in computing Hausman test statistics) and computes the test statistic, one obtains 6.8, which is not significant at the 10 % level. We used the $IV_{1-GLS}$ estimate of the variance of $h_{ijt}$ in computing $S_1$. In this case, all diagonal elements of $[S_1-S_2]$ are positive and the test statistic is 2.99.

this test may not be sufficiently powerful to detect a small degree of bias in the $IV_1$-GLS estimates, especially since the downward bias in the linear tenure term is likely to be offset by an upward bias in the linear experience term. Also, the point estimates from the Job Effects and the $IV_1$ estimators do not match up quite as closely. Nevertheless, Job Effects estimates are additional evidence that the $IV_1$ and $IV_1$-GLS results are in the right ballpark.

### 5.6 Analysis of Effects of Measurement Error in Tenure

As was explained earlier, a second potentially important source of bias in the $IV_1$ estimates is measurement error in the tenure variables. The fact that the GLS estimates are based on partial differencing of the wage equation is likely to make them more sensitive than the OLS estimates to the problem of measurement error for the same reasons that they are less sensitive to upward bias due to heterogeneity.

The results of the prediction tests in Table 3 are strong evidence against the hypothesis that measurement error offers an alternative to heterogeneity bias as the main explanation for the large reduction in tenure slopes when $IV_1$ is used and when GLS is substituted for OLS. However, we have performed a additional checks on the measurement error problem in an attempt to improve upon the $IV_1$ estimates. First, the wage equations were re-estimated with observations for years prior to 1975 (the years in which tenure was bracketed) excluded. The results for both OLS and the IV procedure are very close to those in Table 1*. Second, an analysis of the frequency of the first difference of

* For example, the estimates of the effect of 10 years of tenure on the log wage data implied by the OLS, $IV_1$ and $IV_2$ results for post 1974 sample are .2654, -.0252 and .0392 respectively. The corresponding values for the full sample (from Table 1, col. 3, 6, and 9) are .2627, .0268, and .0741.

$\tilde{T}_{ijt}$ indicates that most of the observations lie in a plausible range. Third, when the sample is restricted to observations over the post 1975 sample for which the change in $T_{ijt}$ is between .9 and 1.1 (unless a separation took place between surveys)**, the coefficients on T, $T^2$ and OLDJOB are -.0083, .00013, and .0439. These are very close to the corresponding $IV_1$ estimates on the full sample in Table 1, col 6, as are the implied estimates of the effects of 10 years of tenure and 10 years of experience. These results suggest that the effects of measurement error are small.

In addition, an attempt was made to construct $\tilde{T}_{ijt}$ using information only on the number of sample observations corresponding to a particular match, the number of years between observations, and that fact tenure on a continuing job should rise by one each year. It is not necessary to know the level of tenure in a given year to construct $\tilde{T}_{ijt}$, since displacement of the tenure values in all of the years by a constant makes no difference in $\tilde{T}_{ijt}$. For the most part, this information is based on whether or not an individual indicated that he had been on his current job for less than a year. It does not depend directly on the specific number of years reported for tenure, although some dependence will arise as a result of the procedures used to impute tenure values (see Appendix 2). Hopefully, measurement error in the alternative $\tilde{T}_{ijt}$ measure will be weakly related to measurement error in $T_{ijt}$. Unfortunately, it is necessary to know the tenure level to construct $(\tilde{T}_{ijt})^2$ and $\tilde{\text{OLDJOB}}_{ijt}$. We used $\tilde{\text{OLDJOB}}_{ijt}$ as is, since measurement error in $\text{OLDJOB}_{ijt}$ should not be much more of a problem for the $IV_1$ procedure than for OLS. To construct $(\tilde{T}_{ijt})^2$, we took the tenure observations corresponding to a given job and fit a least squares regression of

**This excludes some good observations on individuals who started jobs less than .9 years before the survey and who were unemployed at the time of the prior survey.

tenure against an intercept and time, with the time slope constrained to 1. Separate regressions were run for each job match in the sample. The squares of the predicted values of tenure from the reqressions were used as measures of $T_{ijt}^2$ for purposes of constructing $(\tilde{T}_{ijt})^2$. The $IV_1$ procedure was implemented using the new measures of $\tilde{T}_{ijt}$ and $(\tilde{T}_{ijt})^2$ and the old measure of $\widetilde{OLDJOB}_{ijt}$ as instrumental variables for the tenure variables. The coefficients on T, $T^2$, and OLDJOB for the specification corresponding to Table 1, Col 6 are -.0024, .00017, and -.046. These estimates imply that wages rise by 4% after 10 years of tenure, which is slightly above the earlier estimate of 2.7%.

Finally, it is important to keep in mind that even if the $IV_1$ estimates are biased downward by a factor of 3, (with measurement error accounting for 2/3 of the variance in the $IV_1$ instrument for tenure), most of the difference between the $IV_1$ and OLS estimates of the tenure profile would remain.[@] The evidence above suggests that the bias from measurement error is small.

### 5.7 Differences between Blacks and Whites and Union and Nonunion Workers

Columns 1 and 2 of Table A4 report OLS estimates of the wage equation for samples of white men and black men respectively, and Column 3 reports the difference between the two groups in the coefficients. Corresponding $IV_1$ estimates are reported in columns 3-6. The OLS results suggest that the tenure profile of wages is about a 15% less steep for blacks than for whites. The growth of wages with experience in the labor market is less than half as steep for blacks than for whites.

The small racial differential in the tenure profile disappears when the $IV_1$ is used to correct for heterogeneity, and both groups have very flat tenure profiles. Thirty years of experience results in a wage increase of 86.7% for

[@] If one triples the $IV_1$ estimate of the effect of 10 years of tenure on the log of the wage, one obtains .084. This compares to the OLS estimate of .263.

whites and 35.5% for blacks. In summary, the evidence is that the effects of tenure are relatively small for both groups and are much less important than differences in wage growth with labor market experience in explaining racial differences in wages.

Table 6 compares estimates of the wage equation for the samples of union and nonunion white workers. The OLS results indicate that the OLDJOB effect on wages is smaller for union than nonunion workers (.03 and .09 respectively). The tenure slope for union workers is also significantly flatter, which confirms earlier studies. As shown in the Table 6, these estimates imply that during the first ten years on the job wages rise by about 24% for nonunion workers and 10% for union workers, and this difference is highly significant. The experience profiles are very similar.

Once again, the $IV_1$ results tell a different story. The estimates of the tenure profile decline sharply for both groups, but the decline is much larger for nonunion workers than for union workers. No significant difference in the effects of tenure on wages remains once heterogeneity is controlled for using the $IV_1$ procedure. The decline in the estimated difference in the tenure profile is accompanied by a substantial increase in the experience profile for both groups. The effect of 10 years of experience on wages is very similar for the two groups, but 30 years of experience is associated with a 89.7 % increase for nonunion workers and a 70.2% increase for union workers. It reflects an increase in the estimated experience profile for nonunion workers when $IV_1$ is used.[@]

The differential impact of $IV_1$ on the union and nonunion samples is consistent with the notion that union jobs and union workers are more heterogenous than nonunion jobs and workers. The mean squared errors of the $IV_1$ wage equations in Tables 4 are about .109 for the union sample and .185 for the nonunion sample. It may also be attributed to the fact that union jobs are more desirable than alternative jobs for broad classes of workers, which reduces heterogeneity bias resulting from quits in the first few years on the job by workers for whom the job is a poor match. Finally, it is consistent with the notion that union contracts (1) restrict the extent to which wages received by individual workers reflect the quality of the job match and (2) restrict the extent to which employers may selectively layoff workers who are below average in productivity.*

## 5.8 Effects of Individual Specific and Match Specific Wage Components on Quits, Layoffs and Separations

[@] Note that the effect of education on the wage for union workers is much smaller than for nonunion, which is consistent with many previous studies. The coefficient on the interaction of education and experience is positive for nonunion members and negative for union members. The overall similarity of the OLS estimates of the experience profiles for union and nonunion workers is somewhat surprising, since other studies (for example Freeman (1980, Table 3) using CPS data on blue collar workers without controls for tenure, Mincer (1983, Table 12) using the 1968-1978 PSID data with controls for tenure) have obtained a flatter experience slope for union workers. The difference between our results and Mincer's are related to the fact that Mincer obtains a flatter tenure slope for nonunion workers than for union workers, while we obtain a much steeper nonunion slope when OLS is used. Most prior studies (See Mellow (1981) and Block and Kushkin) obtain flatter tenure profiles for union than for nonunion workers. There are many differences between Mincer's study and ours, but we do not have a good explanation the difference in these results. When we exclude tenure from the model and estimate by OLS, the nonunion experience slope is indeed steeper than the union slope. As is discussed in the text, the $IV_1$ results indicate that the experience slope is steeper for nonunion than union workers.

*Freeman (1980) provides evidence that unions reduce wage dispersion associated with both observed and unobserved characteristics of jobs and workers.

Table 7 provides some direct evidence on the role of unobserved heterogeneity in the job mobility equations. The fact that consistent estimates of the wage parameters may be obtained using the $IV_1$ procedure permits estimation of the individual component $\varepsilon_i$ as the mean $\hat{\varepsilon}_i$ of the wage residuals for a given individual and estimation of $\varepsilon_{ij(t)}$ as the deviation of the wage residuals over a given job match from the individual mean $\hat{\varepsilon}_i$. The estimates $\hat{\varepsilon}_i$ and $\hat{\varepsilon}_{ij(t)}$ are then added to logit models for quits, layoffs and separations to see if the individual components and job components are in fact related to job mobility, both with and without controls for tenure. The table reports the implied estimates of the partial derivatives of the quit, layoff and separation probabilities with respect to these variables (evaluated at the mean quit, layoff, and separation probabilities). The point estimates should be treated with caution for a number of reasons. Both $\hat{\varepsilon}_i$ and $\hat{\varepsilon}_{ij(t)}$ are subject to sampling error from the averages of the transitory wage component $\eta_{ijt}$. Since relatively few job spells are observed for most individuals, the estimate of $\varepsilon_i$ is subject to sampling error due to the match components $\varepsilon_{ij(t)}$. Finally, the tenure coefficients may be biased by heterogeneity which is not control for by individual specific and job specific wage components.

Despite these problems, the qualitative results are quite interesting. $\hat{\varepsilon}_i$ has a negative coefficient in the quit, layoff and separation equations. A one standard deviation (0.33) increase in this variable is associated with a fall of 0.05 in the separation rate when tenure is not controlled for .032 when it is controlled for. $\hat{\varepsilon}_{ij(t)}$ has a large negative coefficient in the quit and separation equations, a smaller negative coefficient in the layoff equation.[@] Overall, the results indicate that the individual component and job match

[@] Note that the effect of $\hat{\varepsilon}_{ij(t)}$ on layoffs reflects variation across matches in wages <u>relative</u> to productivity since unobserved productivity differences are not controlled.

components are both negatively related to the separation rate and thus positively correlated with job tenure. These findings support our earlier conclusion that the OLS estimates of the tenure profile suffer from a substantial upward bias.

## 6. CONCLUDING REMARKS

The instrumental variables estimates of the wage equation indicate that tenure has a modest effect on wage growth, with total labor market experience accounting for most of the growth during a career. Holding the effect of total experience constant, wages rise by slightly under 5 percent in the first year on the job and decline slightly thereafter. The accumulation of 10 years of tenure is responsible for a wage increase of 2.7 %. Our analysis indicates that this estimate is probably downward biased as a result of correlation between experience and the job match error component and as a result of measurement error in tenure. We would not rule out the possibility that the true effect of 10 years of tenure is 2 or 3 time as large as the 2.7% figure and would use choose 6.6% as our preferred estimate. However, it is clear that heterogeneity bias is responsible for the much larger least squares estimates of the tenure profile discussed in the introduction. The evidence indicates that positive bias in the least squares estimates arises from individual heterogeneity and job match heterogeneity. The large change in the least squares estimates when GLS is used, the fact that the results for nonunion workers (presumed to be more heterogenous and in more heterogenous jobs) are more sensitive to the estimation procedure, and the fact that the estimates of the individual specific and job match specific error components are negatively related to mobility is further evidence that heterogeneity is important. Our findings are fully consistence with the fact that estimates of the tenure slope based upon the relationship regressions with fixed effects for each individual and regresssions of the change in the wage upon the change in tenure and the usual controls are almost always well below those obtained by regressing the level of the wage against tenure, although the individual fixed effects and first difference methods do not deal adequately with job heterogeneity.

Our results have important implications for models of wage growth and job mobility. First, they suggest that worker specific financed investments in human capital may be too small to explain the decline in quits with tenure that is observed in simple least squares or logit estimates of the quit function. However, they leave open the possibility that most of the returns to the investments are received as fringe benefits rather than wages,* and that the tenure slope of total compensation is sufficiently steep to explain most of the drop in quits. The results also leave open the possibility that firm financed specific human capital investments are large, since such investments would not show up in wage growth, and thus the small tenure effect on wages does not speak directly to the issue of whether the strong negative partial correlation of tenure and layoffs is due to heterogeneity bias. A drop in the layoff probability is likely to increase the value a worker places on his job and thus to reduce the quit probability as well. Conclusions about the role of specific capital accumulation in the layoff and quit profiles will require further research.

Second, the estimates of the effects of total labor market experience are consistent with the view that worker financed investments in general training

$Studies by Mitchell (1984) and Bartel(1982) indicate that fringe benefits rise with time on the job and that these play a role in the quit decision. We have not consider these factors, in part, for lack of data. This is an important research question. Note that in assessing the links among tenure, fringe benefits, and mobility it will be necessary to deal with the problems of individual heterogeneity and job heterogeneity which have been the focus of this study.

are important.

Third, our finding that most wage growth is associated with total labor market experience rather than seniority contradicts the supervision, sorting, and risk aversion models of wage growth discussed in the introduction. This is because these theories are primarily explanations for an increase in compensation for the current job relative to the worker's alternatives. Consequently, the results tend to support growth in productivity with experience, as emphasized in human capital theory, as the dominant explanation for overall effect of experience on earnings, although they are consistent with an important role for job matching and labor market search.

A long research agenda remains. A number of limitations of the present study have been mentioned in the text. It would be desireable to attempt to encorporate unobserved differences in experience and tenure slopes (this will not be easy) and to implement the procedures using an alternative data set. Recent studies by Brown (1983), Duncan and Hoffman (1979) and Mincer (1984) have used information on the occurrence of training on the job to study directly the links among training, experience, and wages. The results indicate that growth in wages on a given job is much higher during the training period than after, lending support to the human capital hypothesis. The findings of the present study are consistent with these training effects only if most of the wage growth carries over to other jobs (the training is general).* This remains to be determined.** It is also unclear whether our results or those of the above

*Duncan and Hoffman's(1979) finding that black men are less likely to be receiving training than white men is consistent with the finding that the experience profile for these workers is flatter than that of white workers.

**Mincer finds a negative association between the training measure and mobility. Taken at face value, this result suggests that some of the training is firm specific. However, it is possible that it is due to heterogeneity bias may explain it. Reference should also be made to the work of Bishop(1979).

studies can be reconciled with the work of Medoff and Abraham (1980, 1981), who find that wages of workers within the same grade level improve with seniority and prior experience while performance evaluations do not. Techniques similar to the instrumental variables procedures of the present study may provide a useful way to address possible biases due to individual heterogeneity and job heterogeneity in sorting out the effects of training on the current and subsequent jobs.

Finally, it would be useful to go beyond the limited evidence presented in Table 3 of the paper and decompose our estimates of the returns to total experience for the average worker into the direct effects of experience and the gains from job matching and search. Our results are consistent with a substantial role for both. However, a full solution to this problem would seem to require joint estimation of the wage model, a quit model, and a layoff model. This will be a difficult undertaken given the complexity of the quit and layoff decisions and the severe econometric problems arising from job heterogeneity and individual heterogeneity.

## Appendix 1 : Inversion of the Error Covariance Matrix

A standard result in matrix algebra is that for

$$\text{(A.1)} \quad H = A + BDC \ ,$$

H, A, and D all being square, non-singular matrices, then

$$\text{(A.2)} \quad H^{-1} = A^{-1} - A^{-1}B(D^{-1} + CA^{-1}B)^{-1}CA^{-1} \ .$$

It is apparent that this formula for the analytic inverse of a sum of matrices is most useful when the inverse of A is known (or easily calculated), and when D is of sufficiently small dimension to make evaluation of the second term in (A.2) relatively easy. Indeed, this formula is a cornerstone of traditional variance components analysis, such as that developed by Wallace and Hussein (1969), for example. In its absence, the computational requirements for GLS in these models would be too onerous to be generally practical.

Henderson and Searle (1981) investigate special cases and extensions of (A.1) in terms of identifying the inverse, and particularly those special cases which have statistical applications. Our purpose in this appendix is to derive the inverse for one of the cases not considered by Henderson and Searle, but one which has wide applicability in analyses of panel data. Suppose a particular individual i in a panel is observed to hold J different jobs over a period of T years. Suppose further that the residual in a wage equation can be written as the sum of three mutually independent components

$$\varepsilon_{ijt} = \varepsilon_i + \varepsilon_{ij} + \varepsilon_{it} \quad , \quad j=1,2,\ldots,J \quad , \quad t=1,2,\ldots,T \quad ,$$

where $\varepsilon_i$ is an individual effect, $\varepsilon_{ij}$ is a job-specific effect, and $\varepsilon_{it}$ is a white noise error. Let the variances of the components be denoted by $\sigma_i^2$, $\sigma_j^2$ and $\sigma_t^2$. Then it is easily verified that the TxT covariance matrix of residuals for each individual can be written

$$\Sigma = \sigma_t^{\,2} I + \sigma_i^{\,2} \ell\ell' + \sigma_j^{\,2} GG'$$

where $\ell$ is a column vector (of length T) of units, and $G$ is a TxJ matrix such that a typical element $g_{tj}=1$ if job j was held in year t, and $g_{tj}=0$ otherwise. The corresponding correlation matrix, which is a scalar multiple of $\Sigma$, is given by

$$\text{(A.3)} \quad \Omega = (1-\rho_1-\rho_2)I + \rho_2 \ell\ell' + \rho_1 GG'$$

where $\rho_1$ and $\rho_2$ are respectively the intertemporal residual correlations due to the job effect and the individual effect. It should be noted, moreover, that the structure of $\Omega$ is individual-specific, because, first of all, of the different numbers of jobs and tenure length in each job, and second, because of ragged panels (i.e. different T for each individual). This makes it all the more imperative to compute an analytic inverse for $\Omega$.

The key to the inversion of $\Omega$ is to note that (A.2) can be applied sequentially to (A.3). Rewriting (A.3), let $\Omega = A_1 + A_2 + A_3$ , where

$$\text{(A.4)} \quad \begin{aligned} A_1 &\equiv \phi I \\ A_2 &\equiv \rho_2 \ell\ell' \\ A_3 &\equiv \rho_1 GG' \qquad \text{and} \\ \phi &\equiv (1-\rho_1-\rho_2) \ . \end{aligned}$$

Define $A \equiv A_1 + A_2$ ; then, it follows directly from (A.2) and (A.4) that

$$\text{(A.5)} \quad A^{-1} = \frac{1}{\phi}\left[I - \frac{\rho_2}{\phi+T\rho_2}\ \ell\ell'\right] \ .$$

Now, $\Omega = A + A_3$ , so that again from (A.2) and (A.4)

$$\text{(A.6)} \quad \Omega^{-1} = A^{-1} - A^{-1}G\left(\frac{1}{\rho_1} I + G'A^{-1}G\right)^{-1} G'A^{-1} \ .$$

Consider first the matrix $G'A^{-1}G$, whose elements, because of the structure of G, consist of sums of elements of $A^{-1}$. Define $Y_j$ to be the number of years that the individual is observed to be in job j, and define $\Psi \equiv G'A^{-1}G$. Then, typical elements of $\Psi$ are

$$\psi_{jj} = \frac{1}{\phi}\left(Y_j - \frac{Y_j^2\rho_2}{\phi+T\rho_2}\right) \qquad \text{and}$$

$$\psi_{jk} = -\frac{1}{\phi}\frac{Y_jY_k\rho_2}{\phi+T\rho_2} \quad .$$

Now define $S \equiv \frac{1}{\rho_1} I + \Psi$, whose dimension is JxJ, and whose typical elements can be written

$$s_{jj} = \frac{1}{\phi}\left(Y_j + \frac{\phi}{\rho_1} - \frac{Y_j^2\rho_2}{\phi+T\rho_2}\right) \qquad \text{and}$$

$$s_{jk} = -\frac{1}{\phi}\frac{Y_jY_k\rho_2}{\phi+T\rho_2} \quad .$$

Note that S can be written as the sum of a diagonal matrix and a matrix of rank one. Defining $y' = [\ Y_1\ Y_2\ \ldots\ Y_J\ ]$, then

$$\text{(A.7)} \qquad S = \frac{1}{\phi}\left(Y_j + \frac{\phi}{\rho_1}\right)_{\text{diag}} - \frac{1}{\phi}\frac{\rho_2}{\phi+T\rho_2}\, yy' \quad .$$

Now using (A.2) to invert (A.7),

$$\text{(A.8)} \qquad S^{-1} = \left(\frac{\phi\rho_1}{\phi+\rho_1Y_j}\right)_{\text{diag}} - \left(\frac{\phi\rho_1}{\phi+\rho_1Y_j}\right)_{\text{diag}} y\,P\,y' \left(\frac{\phi\rho_1}{\phi+\rho_1Y_j}\right)_{\text{diag}} ,$$

where P is a scalar defined as

$$P \equiv \left( -\frac{\phi(\phi+T\rho_2)}{\rho_2} + \sum_{j=1}^{J} \frac{\phi\rho_1Y_j^2}{\phi+\rho_1Y_j} \right)^{-1} .$$

Therefore, typical elements of $S^{-1}$ can be written

$$s^{jj} = \frac{\phi\rho_1Y_j}{\phi+\rho_1Y_j} - P\left(\frac{\phi\rho_1Y_j}{\phi+\rho_1Y_j}\right)^2$$

$$s^{jk} = -P\left(\frac{\phi\rho_1Y_j}{\phi+\rho_1Y_j}\right)\left(\frac{\phi\rho_1Y_k}{\phi+\rho_1Y_k}\right) , \qquad j \neq k \ .$$

But from (A.6) and the definition of S,

(A.6)' $\Omega^{-1} = A^{-1} - A^{-1}G\, S^{-1}G'A^{-1}$ .

With $A^{-1}$ given by (A.5), and $S^{-1}$ by (A.8), the exact analytic inverse of $\Omega$ is simple to calculate from (A.6)'.

Accordingly, the GLS estimator, given a random sample of N individuals each observed for $T_i$ years, for a linear model of the form

$$y_i = X_i\beta + \varepsilon_{ijt} \quad ,$$

where $E[\varepsilon_i\varepsilon_i'] \sim \Omega_i$ (of dimension $T_i \times T_i$), is

(A.9) $$\hat{\beta}_{GLS} = \left(\sum_{i=1}^{N} X_i'\Omega_i^{-1}X_i\right)^{-1}\left(\sum_{i=1}^{N} X_i'\Omega_i^{-1}y_i\right) \quad .$$

If consistent estimates of $\rho_1$ and $\rho_2$ are available (as might be obtained from OLS, for example), an estimate of $\Omega$ can be derived and used in (A.9) to calculate the GLS estimates. If an instrumental variables procedure is used, $X_i$ is replaced in (A.9) by $Z_i$, where $Z_i$ is the matrix of predicted values of $X_i$ obtained from projection of $Z_i$ on the set of instrumental variables.

Finally, it should be pointed out that there is no readily apparent or simple data transformation consistent with $\Omega^{-1}$ which will simplify the calculations in (A.9), i.e. a matrix $\Theta_i$ such that $X_i^* = \Theta_i X_i$ and $(X_i'\Omega_i^{-1}X_i) = (X_i^{*\prime}X_i^*)$. This feature has been frequently noted in similar variance components contexts.

## Appendix 2: Data

The data are from the 1968-1981 Michigan Panel Study of Income Dynamics individuals tape. A few variables are based upon other sources, which are identified below. Two working data sets were constructed, one for white male heads of households and one for black male heads of households. The data sets contain one observation for each person in each year the person was in the sample. Although the survey starts in 1968, many individuals entered the survey in later years. Individuals were excluded entirely if they were not household heads in 1979, 1980 and 1981. Data for an individual were included for a given year only if the following criteria were met:

1) The individual was employed, temporarily laid off, or unemployed in that year, and had been employed, temporarily laid off, unemployed, a student, or not in the survey in the previous year;

2) The individual was not soley self-employed, a government worker, or from Alaska or Hawaii in the current year or in the previous year;

3) The individual was between the ages of 18 and 60, inclusive.

Persons with missing data on the variables in the wage equation were excluded from the wage equation for that year.

### NOTES ON THE VARIABLES

1) Education: Number of grades completed. This variable can take on values from 0 to 17. Due to a programming error, education in 1975 was left out of the data set. For this year it was assigned the mean of education in 1974 and 1976. Education was bracketed in the Michigan survey prior to 1975. Consequently, an individual's value of education in 1976 was assigned to all earlier years if the individual was over 28 years old in 1976.

2) Experience: Number of years worked since age 18. The Michigan Survey asked this question only from 1974 to 1981, and asked it only of new heads of households in 1975 and 1977-1981. Experience was imputed for years in which it was missing in the following way. First, an individual was imputed to have a year of work experience if hours worked in that year was greater than 100. Then, years worked since age 18 was computed by counting backwards or forwards from a year in which the experience question was actually asked. For example, if an individual reported 20 years of experience in 1974, and reported 500 hours of work in 1973, experience in 1973 was given a value of 19. Also, experience was set to missing if it was greater than (age-education-5).

3) Union Membership: The variable is equal to 1 if the individual is a member of a labor union, and 0 if not. This variable is missing from the data in 1973; it was imputed for this year by averaging the 1972 and 1974 values, or by assigning the non-missing value if either the 1972 or 1974 value was missing.

4) Marital Status: 1=Married, 0=Single, Widowed or Divorced.

5) Health Limitation: This variable is equal to 1 if the individual indicates that he has a health problem which affects his ability to work, and is equal to 0 if not.

6) Wage Measure: This variable is the log of annual earnings divided by

annual hours on the person's main job. The measure is deflated by the personal consumption fix-weight price index (Source: 1983 Economic Report of the President) and put into log form.

7) <u>Quit, Layoff, and Separation Indicators</u>: The PSID contains information on tenure and separations for the years 1968-1981. However, the questions relating to these items and the coding of the responses are not consistent over the years, making it necessary to re-construct accurate measures of employer tenure, quits and layoffs. Three major problems with the data required attention. First, tenure levels are bracketed from 1968-1974. This presents a problem for individuals with higher tenure levels, since the bracketing at higher levels is coarse. Second, in the years 1969-1974, quits are not distinguished from promotions. Third, the tenure question refers to tenure with employer only in 1968, 1976, 1977, 1978 (for individuals under the age of 45), and 1981. In the other years, the tenure question relates to tenure "on the job" (1969-1975) or tenure in position (1978 for individuals 45 or older, 1979-1980).

A lengthy computer program was written to handle these problems. The program, which will be provided upon request, filled in missing tenure data, separated quits form promotions by cross-checking against other variables, and constructed measures of employer tenure in years when this information was not available. The following comments summarize the more important sections of the program:

I. Tenure levels in 1968-1974 are set to the midpoints of the brackets. A response of "over 19-1/2 years" is set to 23.

II. Tenure levels in 1978 (for individuals over 45 years and older), 1979, and 1980 are imputed by adding 1 to the previous year's tenure if no separation between years was indicated, and setting tenure to .5 if a separation was indicated. This process is performed sequentially, using 1977 tenure to impute 1978 tenure, then 1978 tenure to impute 1979 tenure, etc.

III. For individuals who reported quits/promotions in 1969-1974, the following method is used to determine whether a quit or promotion had occurred. A promotion is inferred if no unemployment had occurred in the previous year, if there had been no change in the major industry group reported by the individual, and if at least one of the following conditions was true:

1) Employer tenure reported in 1976 is greater than 2 plus the number of years between the survey year and 1976. For example, if an individual reported a quit/promotion in 1973, but reported in 1976 that tenure with employer was greater than 5, it is assumed that the individual had been promoted in 1973.

2) Employer tenure reported in 1977 is greater than 2 plus the number of years between the survey year and 1977.

3) The tenure reported in the year following the survey year is greater than 3.

4) The tenure reported two years after the survey year is greater than 4.

IV. Next, any missing data for tenure is filled in. First, if the missing value for tenure occurred in a year in which the person was employed, and if tenure reported in the following year is greater than 1, current tenure is set to next year's tenure minus 1.* Second, if last year's tenure was not missing and if the individual was in the labor force in the current year, had experienced no unemployment in the previous year, and did not indicate that a separation had taken place between the last and current year, current tenure is set to last period's tenure plus 1. If a separation had been indicated, or if the individual had been out of the labor force or experienced unemployment in the previous year, current tenure is set to .5.

V. Next, for years in which "tenure with employer" is not specifically asked, a check is made to see whether reported tenure represents time in position or time with employer. An imputed value for tenure is created for the years in which tenure with employer was not asked by extrapolating backwards from years in which tenure with employer was asked. The imputed tenure value is created simply by letting current imputed tenure equal next year's imputed tenure minus 1. For example, since 1976 tenure represents years with employer, tenure in 1975 is set to tenure in 1976 minus 1, and imputed tenure in 1974 is set to imputed tenure in 1975 minus 1. Since tenure with employer must be greater than or equal to tenure in position, a value of imputed tenure which is greater than reported tenure in any "non-employer tenure" year serves as an indication that reported tenure represents time in position rather than time with employer. If imputed tenure is greater than current tenure plus 2, current tenure is set to imputed tenure. If a separation had occurred between the current year and the next year in which an employer tenure question was asked, imputed tenure would lie below reported tenure and so reported tenure would not be changed.

This procedure also partially takes care of the problems created by the bracketing of tenure in 1968-1974. Individuals with higher tenure levels in these years will have large jumps in tenure as they move from one bracket to the next. These jumps in tenure will be smoothed out. However, the procedure does not compeletely smooth out tenure when an individual stays in the same bracket for several years; tenure will be smoothed only when it lies more than two years below imputed tenure.

VI. The last step of the program creates the separation, quit and layoff variables. The separation variable is given a value of 1 if the individual worked at least 200 hours in the previous year, and if one of the following conditions is true:

* Actually, tenure is set to next year's tenure minus one only if next year's tenure is greater than 1, and either no separation occurred in the between the current and last year or next year's tenure was less than 2. If a separation occurred between the last and current year, the missing value for tenure would get filled in by the next step of the procedure. Likewise, a tenure value of less than 2 in the next year indicates that the individual is in a new job in the current year, and so the missing value would get filled in the second step of the procedure.

1) Tenure is less than 2 and the question "what happened to your last job?"[1] has a non-missing response which is other than "promoted" (including "inferred promotion" created in step III of the program) or "no previous job".

2) The individual is currently unemployed or out of the labor force and the question "what happened to your last job?" has a non-missing response other than "no previous job".

3) Tenure is between 0 and 1 and the question "what happened to your last job"[2] has a missing value.

Finally, for those who report that their job ended due to a quit or a layoff and who are unemployed at the time of the survey there is some ambiguity as to whether the separation occurred within the previous 12 month. For example, an individual may have been laid off 2 years ago and suffered a long spell of unemployment, which raises the possibility that the same layoff may be counted in two consecutive surveys. To minimize this possibility, we employ a variety of checks using separations, unemployment, and hours worked in prior years.

The quit variable is given a value of 1 if the separation variable is equal to 1 and the reason for the separation is either "quit" or "was self-employed before this". The layoff variable is given a value of 1 if a separation is indicated and the reason for the separation is given as "business failure", "strike, lockout", "laid off, fired", "other, incuding military" or "seasonal or temporary job". Finally, if tenure was greater than experience, it was set to missing.

8) Area Dummy Variables: The area indicators refer to residence in the 9 Census regions. Area1 is the Pacific region. Area2 is the Mountain region. Area3 is the West North Central region. Area4 is the East North Central region. Area5 is the West South Central region. Area6 is the East South Central region. Area7 is the South Atlantic region. Area8 is the Mid Atlantic region. The omitted category is New England.

1 This question is asked of currently employed individuals with raw tenure of less than 1. Possible responses are: 1) business failure, 2) strike, lockout, 3) laid off, fired, 4) quit, was self-employed before (1975-1981), 5) no previous job, 6) was self-employed before (1968-1974), 7) other, including military, 8) seasonal or temporary job, 9) don't know, 10) promoted (1975-1981), 11) inferred promotion (1968-1974, created in step III of program).

2 This question was asked of individuals currently unemployed or out of the labor force. The coding is the same as given in footnote 1, except codes 10 and 11 are not possible.

Table 1

Effects of Education, Experience and Tenure on the Log Wage : White Males

ESTIMATION METHOD[a] (Standard Errors in Parentheses)

| | OLS | | | $IV_1$ | | | $IV_2$ | | | OLS | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Education | .0188 (.0192) | .0198 (.0191) | .0179 (.0191) | .0164 (.0199) | .0163 (.0199) | .0155 (.0198) | .0171 (.0197) | .0171 (.0197) | .0158 (.0197) | .0157 (.0193) | .0171 (.0192) | .0163 (.0192) |
| $Education^2$ | .0018 (.0007) | .0017 (.0007) | .0017 (.0007) | .0019 (.0007) | .0019 (.0007) | .0019 (.0007) | .0019 (.0007) | .0018 (.0007) | .0019 (.0007) | .0019 (.0007) | .0018 (.0007) | .0018 (.0007) |
| Experience | .0491 (.0064) | .0397 (.0065) | .0335 (.0066) | .0468 (.0066) | .0480 (.0070) | .0449 (.0071) | .0474 (.0065) | .0464 (.0070) | .0427 (.0070) | .0387 (.0071) | .0320 (.0072) | .0288 (.0072) |
| $Experience^2/10$ | -.0180 (.0030) | -.0150 (.0030) | -.0119 (.0030) | -.0146 (.0032) | -.0150 (.0032) | -.0135 (.0033) | -.0156 (.0031) | -.0152 (.0032) | -.0132 (.0032) | -.0139 (.0032) | -.0119 (.0032) | -.0100 (.0032) |
| $Experience^3/100$ | .0019 (.0005) | .0016 (.0005) | .0012 (.0005) | .0014 (.0005) | .0014 (.0005) | .0012 (.0005) | .0015 (.0005) | .0015 (.0005) | .0012 (.0005) | .0014 (.0005) | .0012 (.0005) | .0009 (.0005) |
| Ed . Exper | .0003 (.0003) | .0004 (.0003) | .0004 (.0003) | .0005 (.0003) | .0005 (.0003) | .0005 (.0003) | .0004 (.0003) | .0004 (.0003) | .0005 (.0003) | .0003 (.0003) | .0004 (.0003) | .0004 (.0003) |
| T[a] | .0137 (.0012) | .0280 (.0026) | .0178 (.0031) | .0016 (.0014) | .0001 (.0021) | -.0041 (.0022) | .0050 (.0011) | .0062 (.0019) | -.0014 (.0021) | .0130 (.0012) | .0264 (.0027) | .0174 (.0031) |
| $T^2$ [a] | | -.0006 (.0001) | -.0003 (.0001) | | .0001 (.0001) | .0002 (.0001) | | .0001 (.0001) | .0002 (.0001) | | -.0005 (.0001) | -.0003 (.0001) |
| OLD Job[a] | | | .1113 (.0126) | | | .0501 (.0094) | | | .0729 (.0089) | | | .1037 (.0126) |
| | | | | | | | | | | -.0935 (.0242) | -.0747 (.0242) | -.0501 (.0245) |
| S.E. | .405 | .403 | .402 | .411 | .411 | .410 | .408 | .408 | .407 | .404 | .403 | .402 |
| $R^2$ | .366 | .371 | .376 | .342 | .342 | .343 | .346 | .346 | .348 | .368 | .372 | .376 |
| Effect of 10 years of T on the log wage.[b] | .1368 (.0119) | .2419 (.0180) | .2627 (.0176) | .0163 (.0138) | .0074 (.0159) | .0268 (.0162) | .0500 (.0110) | .0565 (.0136) | .0741 (.0137) | .1300 (.0121) | .2127 (.0182) | .2522 (.0178) |
| Effect of 10 years of experience on log wage for high school grads.[b] | .3666 (.0305) | .3069 (.0318) | .2756 (.0319) | .3938 (.0308) | .4008 (.0335) | .4300 (.0340) | .3862 (.0308) | .3813 (.0336) | .3635 (.0339) | .3037 (.0356) | .2610 (.0362) | .2468 (.0362) |
| Effect of 30 years of experience on log wage for high school grads.[b] | .4736 (.0319) | .4123 (.0327) | .3935 (.0327) | .6282 (.0335) | .6332 (.0349) | .6240 (.0349) | .5846 (.0381) | .5872 (.0333) | .5773 (.0332) | .4041 (.0371) | .3621 (.0374) | .3592 (.0374) |

a/Treated as endogenous in columns 4 - 9. In columns 4 - 6 the instrumental variables include all variables in wage equation (except T, $T^2$ and New Job) and the deviations of T, $T^2$ and OLDJob from their respective means over the sample observations on the worker's current job. In columns 6 - 9 the difference between the individual means of T, $T^2$, and OLDJob and the job means of these variables are also added to the instrumental variables list. The first stage equations are reported in Table A2. Observations = 15138
Other variables in the equations are a time trend and dummy variables for 8 Census regions, union membership, disability, residence in an SMSA, and residence in a city with more than 500,000 people.

b/Calculated from the regression coefficients. The estimates of the percentage effects of 10 years of tenure and 10 and 30 years experience on the wage reported in the text are based on the antilogs of the figures in the tables for the effects on the log wage.

TABLE 2

Effects of Education, Experience and Tenure on the Log Wage: White Males

ESTIMATION METHOD[a] (Standard errors in Parentheses

| | GLS | | | $IV_1$-GLS | | | $IV_2$- GLS | | | GLS | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Education | .0514 (.0057) | .0524 (.0057) | .0624 (.0058) | .0484 (.0058) | .0475 (.0058) | .0541 (.0059) | .0498 (.0058) | .0501 (.0058) | .0590 (.0059) | .0629 (.0062) | .0634 (.0062) | .0696 (.0062) |
| $\text{Education}^2$ | .0007 (.0003) | .0006 (.0003) | .0002 (.0003) | .0008 (.0003) | .0008 (.0003) | .0006 (.0003) | .0007 (.0003) | .0007 (.0003) | .0004 (.0003) | .0003 (.0003) | .0002 (.0003) | -.0000 (.0003) |
| Experience | .0602 (.0034) | .0577 (.0035) | .0543 (.0035) | .0613 (.0035) | .0632 (.0038) | .0601 (.0038) | .0624 (.0035) | .0618 (.0038) | .0578 (.0038) | .0537 (.0037) | .0518 (.0038) | .0503 (.0038) |
| $\text{Experience}^2/10$ | -.0204 (.0017) | -.0198 (.0017) | -.0171 (.0017) | -.0202 (.0018) | -.0207 (.0018) | -.0186 (.0019) | -.0217 (.0017) | -.0210 (.0018) | -.0180 (.0018) | -.0172 (.0018) | -.0168 (.0018) | -.0151 (.0018) |
| $\text{Experience}^3/100$ | .0022 (.0003) | .0022 (.0003) | .0017 (.0003) | .0022 (.0003) | .0022 (.0003) | .0019 (.0003) | .0023 (.0003) | .0023 (.0003) | .0018 (.0003) | .0018 (.0003) | .0018 (.0003) | .0015 (.0003) |
| Ed. Exper | .0001 (.0001) | .0001 (.0001) | -.0000 (.0001) | .0002 (.0001) | .0001 (.0001) | .0001 (.0001) | .0001 (.0001) | .0001 (.0001) | .0000 (.0001) | -.0000 (.0001) | -.0000 (.0001) | -.0001 (.0001) |
| T a/ | .0084 (.0007) | .0119 (.0014) | .0044 (.0016) | .0014 (.0011) | -.0003 (.0017) | -.0043 (.0019) | .0043 (.0009) | .0048 (.0016) | -.0017 (.0018) | .0080 (.0007) | .0111 (.0014) | .0042 (.0016) |
| $T^2$ a/ | | -.0002 (.0001) | .0001 (.0001) | | .0001 (.0001) | .0002 (.0001) | | -.0000 (.0001) | .0002 (.0001) | | -.0001 (.0001) | .0001 (.0001) |
| New Job a/ | | | -.0735 (.0077) | | | -.0465 (.0088) | | | -.0645 (.0080) | | | -.0700 (.0078) |
| N/Exp | | | | | | | | | | -.0715 (.0150) | -.0685 (.0150) | -.0487 (.0152) |
| S.E. | .411 | .411 | .410 | .418 | .418 | .417 | .416 | .415 | .415 | .411 | .411 | .410 |
| $R^2$ | .343 | .345 | .349 | .323 | .323 | .326 | .332 | .332 | .335 | .346 | .347 | .350 |
| Effect of 10 years of T on the log wage. b/ | .0837 (.0072) | .1035 (.0099) | .1233 (.0100) | .0142 (.0105) | .0045 (.0129) | .0222 (.0134) | .0427 (.0092) | .0456 (.0115) | .0623 (.0116) | .0801 (.0072) | .0978 (.0099) | .1183 (.0102) |
| Effect of 10 years of experience on log wage for high school grads. b/ | .4255 (.0180) | .4095 (.0188) | .3880 (.0189) | .4524 (.0180) | .4637 (.0201) | .4448 (.0204) | .4478 (.0180) | .4440 (.0200) | .4214 (.0201) | .3780 (.0206) | .3530 (.0204) | .3581 (.0211) |
| Effect of 30 years of experience on log wage for high school grads. b/ | .5749 (.0219) | .5608 (.0224) | .5546 (.0224) | .6660 (.0241) | .6750 (.0250) | .6674 (.0250) | .6305 (.0233) | .6265 (.0238) | .6229 (.0238) | .5273 (.0243) | .5243 (.0249) | .5235 (.0245) |

a,b/ See Table 1.

c/ For a discussion of the GLS procedures, see the text and Appendix 2.

TABLE 3

Comparison of Actual and Predicted Wage Changes for Movers and Stayers

| | | | OLS | | $IV_1$ | |
|---|---|---|---|---|---|---|
| Initial Tenure ($T_{ijt-1}$) | Sample Size[b] (1) | Mean of Actual $\Delta W_{ijt}$ (2) | Mean of Actual $\Delta W_{ijt}$ - Predicted $\Delta W_{ijt}$ (3) | Estimated[a] Contribution of $\Delta$ Tenure to $\Delta W_{ijt}$ (4) | Mean of Actual $\Delta W_{ijt}$ - Predicted $\Delta W_{ijt}$ (5) | Estimated Contribution of $\Delta$ Tenure to $\Delta W_{ijt}$ (6) |
| **STAYERS** | | | | | | |
| **Average** | 10804 | .026 (.003) | -.020 (.003) | --- | -.006 (.003) | --- |
| 0-1 | 1779 | .065 (.008) | -.081 (.008) | .129 | -.011 (.008) | .046 |
| 1-2 | 878 | .034 (.010) | -.016 (.010) | .017 | -.002 (.010) | -.004 |
| 2-3 | 1307 | .021 (.007) | -.029 (.007) | .016 | -.011 (.007) | -.003 |
| 3-5 | 746 | .030 (.011) | -.007 (.012) | .015 | .001 (.012) | -.003 |
| 5-7 | 1760 | .028 (.006) | .000 (.006) | .014 | .001 (.006) | -.002 |
| 7-10 | 807 | -.002 (.009) | .030 (.009) | .013 | -.023 (.009) | -.001 |
| 10-15 | 1509 | .007 (.007) | -.007 (.007) | .010 | -.009 (.007) | .001 |
| 15-25 | 1530 | .015 (.006) | .008 (.006) | .006 | .004 (.006) | .004 |
| 25+ | 488 | .009 (.011) | .001 (.011) | --- | -.006 (.011) | --- |
| **MOVERS** | | | | | | |
| **Average** | 2169 | .058 (.011) | .095 (.011) | --- | .029 (.011) | --- |
| 0-1 | 1253 | .085 (.014) | .040 (.014) | 0 | .031 (.014) | 0 |
| 1-2 | 268 | .009 (.032) | .105 (.032) | -.129 | .011 (.032) | -.046 |
| 2-3 | 263 | .053 (.029) | .163 (.030) | -.150 | .051 (.030) | -.043 |
| 3-5 | 95 | .050 (.049) | .189 (.048) | -.178 | .042 (.048) | -.039 |
| 5-7 | 170 | -.030 (.037) | .156 (.036) | -.207 | -.022 (.036) | -.035 |
| 7-10 | 27 | .190 (.080) | .393 (.082) | -.241 | .182 (.082) | -.030 |
| 10-15 | 64 | .019 (.066) | .319 (.069) | -.287 | .049 (.069) | -.033 |
| 15-25 | 24 | -.044 (.094) | .325 (.092) | -.339 | .011 (.092) | -.050 |
| 25+ | 5 | --- | --- | --- | --- | --- |

TABLE 3
(Continued)

| Initial Tenure ($T_{ijt-1}$) | Sample Size[b] (1) | Mean of Actual $\Delta W_{ijt}$ (2) | OLS: Mean of Actual $\Delta W_{ijt}$ - Predicted $\Delta W_{ijt}$ (3) | OLS: Estimated[a] Contribution of $\Delta$ Tenure to $\Delta W_{ijt}$ (4) | $IV_1$: Mean of Actual $\Delta W_{ijt}$ - Predicted $\Delta W_{ijt}$ (5) | $IV_1$: Estimated Contribution of $\Delta$ Tenure to $\Delta W_{ijt}$ (6) |
|---|---|---|---|---|---|---|
| **QUITS** | | | | | | |
| Average | 1094 | .079 (.013) | .126 (.013) | --- | .058 (.013) | --- |
| 0-1 | 602 | .116 (.018) | .078 (.018) | 0 | .068 (.019) | 0 |
| 1-2 | 147 | .038 (.035) | .136 (.035) | -.129 | .043 (.035) | -.046 |
| 2-3 | 139 | .068 (.038) | .194 (.038) | -.150 | .081 (.038) | -.043 |
| 3-5 | 56 | -.024 (.066) | .127 (.067) | -.178 | -.018 (.066) | -.039 |
| 5-7 | 93 | -.023 (.034) | .170 (.035) | -.207 | -.008 (.035) | -.035 |
| 7-10 | 16 | .163 (.096) | .404 (.104) | -.241 | .188 (.105) | -.030 |
| 10-15 | 31 | .022 (.065) | .306 (.065) | -.287 | .036 (.065) | -.033 |
| 15-25 | 9 | .189 (.184) | .537 (.182) | -.339 | .222 (.182) | -.050 |
| 25+ | 1 | --- | --- | --- | --- | --- |
| **LAYOFFS** | | | | | | |
| Average | 759 | .033 (.019) | .074 (.019) | --- | .015 (.019) | --- |
| 0-1 | 486 | .067 (.023) | .036 (.023) | 0 | .029 (.023) | 0 |
| 1-2 | 80 | -.019 (.076) | .092 (.075) | -.129 | -.000 (.024) | -.046 |
| 2-3 | 78 | -.044 (.054) | .072 (.056) | -.150 | -.043 (.056) | -.043 |
| 3-5 | 25 | .092 (.079) | .240 (.075) | -.178 | .088 (.075) | -.039 |
| 5-7 | 42 | -.024 (.087) | .180 (.086) | -.207 | -.001 (.086) | -.035 |
| 7-10 | 8 | -.014 (.124) | .208 (.131) | -.241 | -.007 (.135) | -.030 |
| 10-15 | 22 | -.008 (.123) | .333 (.130) | -.287 | .070 (.130) | -.033 |
| 15-25 | 14 | -.178 (.094) | .207 (.093) | -.339 | -.106 (.094) | -.050 |
| 25+ | 4 | --- | --- | --- | --- | --- |

[a]The estimated contribution of $\Delta$Tenure to $\Delta W_{ijt}$ is calculated from the tenure coefficients in Table 1, column 3, for OLS and Table 1, column 6, for $IV_1$. The tenure contribution is evaluated at the midpoint of all initial tenure categories except 25+. For this group, $T_{ijt-1}$ is set to 28. For movers, $T_{ijt}$ is set to .5 and $OLDJOB_{ijt} = 0$ in calculating the contribution of the change in tenure.

[b]Sample sizes for quits and layoffs do not sum to the totals for all Movers because reason for separation is unavailable in some cases.

Table 4

Estimates of Bias in Tenure and Experience Slopes

Arising From Failure to Control for Job Shopping

| Assumption About Average Gain in $\epsilon_{ij(t)}$ Per Quit | Implied Average[c] Growth in $\epsilon_{ij(t)}$ over 30 Years | $T_{ijt}$ | $T^2_{ijt}$ | $OLDJOB_{ijt}$ | $EXP_{it}$ | $EXP^2_{it}/10$ | $EXP^3_{it}/100$ | $Ed \cdot EXP_{it}$ | Effect of 10 Years of T on the Log Wage | Effect of 30 Years Experience on Log Wage for High School Grads |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Estimates of Bias**[a] | | | | | |
| .025 | .0813 | -.0023 | .00003 | .0016 | .0055 | -.00122 | .000107 | .000022 | -.00188 | .09174 |
| .050 | .1626 | -.0047 | .00006 | .0033 | .0110 | -.00244 | .000214 | .000043 | -.03754 | .18349 |
| .075 | .2439 | -.0070 | .00009 | .0049 | .0165 | -.00366 | .000321 | .000065 | -.05631 | .27523 |
| .100 | .3252 | -.0094 | .00012 | .0065 | .0220 | -.00488 | .000428 | .000086 | -.07508 | .36697 |
| | | | | | **"Corrected" $IV_1$ Estimates**[b] | | | | | |
| .025 | .0813 | -.0018 | .00015 | .0484 | .0394 | -.0123 | .00106 | .00048 | .0456 | .5322 |
| .050 | .1626 | .0005 | .00012 | .0467 | .0339 | -.0111 | .00096 | .00045 | .0643 | .4405 |
| .075 | .2439 | .0029 | .00009 | .0451 | .0284 | -.0099 | .00085 | .00043 | .0831 | .3488 |
| .100 | .3252 | .0052 | .00006 | .0435 | .0229 | -.0087 | .00074 | .00041 | .1019 | .2570 |

[a] The estimates of bias are elements of $\hat{B}_{bias}$ corresponding to the variables listed, where $\hat{B}_{bias} = [\sum (Z_{ijt}' Z_{ijt}]^{-1} [\sum [X_{ijt}, X_{ijt} \hat{\pi}_1]' [\hat{\epsilon}_{ij(t)} | EXP_{it}]]$, where $Z_{ijt}$, $\hat{\pi}_1$ and $[\hat{\epsilon}_{ij(t)} | EXP_{it}]$ are defined in the text.

The "corrected" estimates are equal to the $IV_1$ coefficients reported in Table 1, column 8, minus the bias estimates reported in the upper panel of the table.

[c] The implied average growth in $\epsilon_{ij(t)}$ over 30 years is equal to the expected number of quits after 30 years of experience implied by the logit model (3.252 quits times the assumption about the average gain in $\epsilon_{ij(t)}$ per quit listed in column 1 of the table.

# TABLE 5

Differences between White and Black Males in the effects of Experience and Tenure on the Log Hourly Wage
(Standard errors in parentheses)

Estimation Method[a]

| Variable | OLS Whites (1) | OLS Blacks (2) | OLS White-Black Differential (3) | $IV_1$ Whites (4) | $IV_1$ Blacks (5) | $IV_1$ White-Black Differential (6) |
|---|---|---|---|---|---|---|
| Education | .0179 | .0129 | .0050 | .0155 | .0097 | .0058 |
| | (.0191) | (.0267) | (.0329) | (.0198) | (.0276) | (.0340) |
| Education$^2$ | .0017 | .0033 | -.0016 | .0019 | .0035 | -.0016 |
| | (.0007) | (.0011) | (.0013) | (.0007) | (.0011) | (.0013) |
| Experience | .0335 | .0301 | .0034 | .0449 | .0429 | .0020 |
| | (.0067) | (.0100) | (.0120) | (.0071) | (.0106) | (.0128) |
| Experience$^2$/10 | -.0119 | -.0037 | -.0082 | -.0135 | -.0073 | -.0062 |
| | (.0030) | (.0045) | (.0054) | (.0033) | (.0047) | (.0057) |
| Experience$^3$/100 | .0012 | .0000 | .0012 | .0012 | .0003 | .0009 |
| | (.0005) | (.0007) | (.0008) | (.0005) | (.0010) | (.0009) |
| Ed. Exper. | .0004 | -.0012 | .0016 | .0005 | -.0017 | .0006 |
| | (.0003) | (.0004) | (.0005) | (.0003) | (.0004) | (.0005) |
| T[a/] | .0178 | .0120 | .0058 | -.0041 | .0035 | -.0076 |
| | (.0031) | (.0058) | (.0059) | (.0022) | (.0039) | (.0045) |
| $T^2$[a/] | -.0003 | -.0003 | .0000 | .0002 | -.0001 | .0003 |
| | (.0001) | (.0002) | (.0002) | (.0001) | (.0001) | (.0002) |
| OLDJOB | .1113 | .1388 | -.0275 | .0501 | .0002 | .0499 |
| | (.0126) | (.0199) | (.0235) | (.0095) | (.0166) | (.0191) |
| Effect of 10 years of T on the log wage. | .2627 | .2326 | .0301 | .0268 | .0281 | -.0013 |
| | (.0176) | (.0266) | (.0319) | (.0162) | (.0266) | (.0311) |
| Effect of 10 years of experience on log wage for high school graduates. | .2756 | .1246 | .1510 | .3851 | .2212 | .1639 |
| | (.0319) | (.0471) | (.0569) | (.0340) | (.0450) | (.0564) |
| Effect of 30 years of experience on log wage for high school graduates. | .3939 | .1462 | .2473 | .6244 | .3045 | .3199 |
| | (.0327) | (.0528) | (.06[illegible]1) | (.0349) | (.0576) | (.0674) |

a/ Treated as endogenous in columns 3 and 4. The instrumental variables include all variables in wage equation (except T, $T^2$ and New Job) and the deviations of T, $T^2$ and New Job from their respective means over the sample observations on the worker's current job. Other variables in the equations are a time trend, dummy variables for 8 Census regions, disability, residence in an SMSA, and residence in a city with more than 500,000 people. The $\bar{R}^2$ is for columns 1, 2, 4, and 5 are .38, .35, .34 and .33. The standard errors are .40, .43, .41 and .44. The White and black samples contain 15138 and 6551 observations respectively. The coefficient standard errors have been calculated under the assumption that the error structure consists of a fixed job component, a fixed individual component, and a serially uncorrelated component.

b/ See Table 1, footnote b.

Table 6
Union-NonUnion Differences in Effects of Experience and Tenure on the log hourly wage
(Standard Errors in parentheses)

Estimation Method[a]

| Variable | OLS Union (1) | OLS Nonunion (2) | OLS [Union]-[Nonunion] (3) | $IV_1$ Union (4) | $IV_1$ Nonunion (5) | $IV_1$ [Union]-[Nonunion] (6) |
|---|---|---|---|---|---|---|
| Education | .0095 (.0304) | .0318 (.0227) | -.0223 (.0380) | .0128 (.0313) | .0250 (.0235) | -.0122 (.0391) |
| $Education^2$ | .0015 (.0011) | .0013 (.0008) | .0002 (.0014) | .0015 (.0011) | .0016 (.0008) | -.0001 (.0014) |
| Experience | .0453 (.0103) | .0306 (.0079) | .0147 (.0130) | .0578 (.0109) | .0396 (.0086) | .0182 (.0139) |
| $Experience^2/10$ | -.0133 (.0045) | -.0123 (.0038) | -.0010 (.0058) | -.0161 (.0047) | -.0129 (.0040) | -.0032 (.0062) |
| $Experience^3/100$ | .0014 (.0007) | .0013 (.0006) | .0002 (.0009) | .0016 (.0007) | .0011 (.0006) | .0005 (.0010) |
| Ed. Exper. | -.0005 (.0004) | .0006 (.0003) | -.0011 (.0005) | -.0005 (.0004) | .0009 (.0003) | -.0014 (.0005) |
| T a/ | .0117 (.0042) | .0223 (.0040) | -.0106 (.0058) | -.0046 (.0034) | -.0035 (.0030) | .0011 (.0045) |
| $T^2$ a/ | -.0002 (.0001) | -.0004 (.0001) | .0002 (.0002) | .0002 (.0001) | .0001 (.0001) | .0001 (.0002) |
| OLDJOB | .0649 (.0200) | .1122 (.0155) | -.0473 (.0253) | .0287 (.0247) | .0549 (.0121) | -.0262 (.0202) |
| Effect of 10 years of T on the log wage. | .1641 (.0246) | .2989 (.0219) | -.1348 (.0329) | .0053 (.0265) | .0303 (.0216) | -.0250 (.0342) |
| Effect of 10 years of experience on log wage for high school graduates. | .2753 (.0492) | .2716 (.0382) | .0037 (.0622) | .3693 (.0525) | .3822 (.0408) | -.0129 (.0665) |
| Effect of 30 years of experience on log wage for high school graduates. | .3715 (.0498) | .3809 (.0387) | -.0094 (.0631) | .5321 (.0567) | .6408 (.0429) | -.1087 (.0711) |

a/ Treated as endogenous in columns 3 and 4. The instrumental variables include all variables in wage equation (except T, $T^2$ and New Job) and the deviations of T, $T^2$ and New Job from their respective means over the sample observations on the worker's current job. Other variables in the equations are a time trend, dummy variables for 8 Census regions, disability, residence in an SMSA, and residence in a city with more than 500,000 people. The $R^2$ for columns 1, 2, 4, and 5 are .23, .42, .21 and .38. The standard errors are .33, .42, .33 and .43. The union sample contains 4649 observations and the non union sample contains 10,364. The standard errors of the coefficients have been corrected for correlation arising from fixed individual specific and job specific error components. The estimates of the variances of the individual specific, job specific, and transitory error components used in correcting the standard errors for the union sample are based upon the pooled union-nonunion sample, since a negative estimate of the variance of the job specific component was obtained for the union sample. The estimates of the variances for the nonunion sample were calculated from the residuals for the nonunion sample.

b/ See Table 1, footnote b.

TABLE 7

Partial Derivatives of the Quit, Layoff and Separation Probabilities with Respect to Individual Specific and Match Specific Wage Components

(standard errors in parentheses)

| Partial Derivatives of the QUIT, LAYOFF and SEPARATION Probabilities with Respect to: | QUIT EQUATION | | LAYOFF EQUATION | | SEPARATION EQUATION | |
|---|---|---|---|---|---|---|
| $\hat{\varepsilon}_i$ | -.0787<br>(.0069) | -.0527<br>(.0073) | -.0565<br>(.0058) | -.0298<br>(.0062) | -.1587<br>.0098 | -.0984<br>(.0101) |
| $\hat{\varepsilon}_{ij}$ | -.0898<br>(.0121) | -.0660<br>(.0110) | -.0303<br>(.0102) | -.0128<br>(.0088) | -.1471<br>(.0174) | -.0991<br>(.0158) |
| T | | -.0135<br>(.0021) | | -.0166<br>(.0017) | | -.0314<br>(.0025) |
| $T^2$ | | .00015<br>(.00010) | | .00038<br>(.000059) | | .00061<br>(.00010) |
| OLDJOB | | -.0259<br>(.0074) | | -.0372<br>(.0063) | | -.0743<br>(.0096) |

[a] The equations also include education, education$^2$, education x experience, a cubic in experience, marital stutus, the lag of union membership, health status, dummies for SMSA and residence in a city of more than 500,000, and a time trend. Observations = 15133.

$\hat{\varepsilon}_i$ is the mean of the residuals from the wage equation (Table 1, column 6) for each individual in the sample. $\hat{\varepsilon}_{ij}$ was calculated as the difference between the residuals from the wage equation for a particular job match and the individual mean $\hat{\varepsilon}_i$ .

The partial derivatives of the quit, layoff, and separation probabilities are based upon the logistic regression parameters. They were evaluated at the mean quit, layoff and separation probabilities respectively. The point estimates should be treated very cautiously given the measurement problems mentioned in the text and the endogeneity of tenure. The detailed logit results are available from the authors.

TABLE A1

MEANS AND STANDARD ERRORS

| VARIABLE | ALL WHITES MEAN | ALL WHITES STANDARD DEVIATION | WHITE UNION MEMBERS MEAN | WHITE UNION MEMBERS STANDARD DEVIATION | WHITE NONUNION MEMBERS MEAN | WHITE NONUNION MEMBERS STANDARD DEVIATION | ALL BLACKS MEAN | ALL BLACKS STANDARD DEVIATION |
|---|---|---|---|---|---|---|---|---|
| EARNINGS | 1.5307 | 0.5079 | 1.6279 | 0.3718 | 1.4887 | 0.5529 | 1.1061 | 0.56 |
| EDUC | 12.5133 | 2.9107 | 11.5251 | 2.5482 | 12.9555 | 2.9570 | 10.0842 | 3.16 |
| EDUC2 | 165.0556 | 70.0970 | 139.3188 | 58.8205 | 176.5885 | 71.7095 | 111.7350 | 59.31 |
| EXP | 17.7536 | 10.7576 | 19.5502 | 10.8832 | 16.9768 | 10.6003 | 17.5346 | 11.12 |
| EXP2 | 430.9078 | 445.4148 | 500.6300 | 466.5806 | 400.5687 | 432.0215 | 431.2129 | 472.93 |
| EXP3 | 12296.6807 | 16905.5969 | 14727.8514 | 18002.3160 | 11233.2433 | 16276.9627 | 12154.6030 | 18312.680 |
| EDUC.EXP | 214.0318 | 133.3789 | 216.6425 | 122.7082 | 213.2216 | 137.9233 | 157.6524 | 97.91 |
| MARRIED | 0.9008 | 0.2990 | 0.9307 | 0.2539 | 0.8875 | 0.3160 | 0.7858 | 0.41 |
| UNION | 0.3112 | 0.4608 | | | | | 0.3270 | 0.46 |
| HEALTH | 0.0823 | 0.2748 | 0.0955 | 0.2939 | 0.0760 | 0.2651 | 0.1027 | 0.30 |
| CITY>500000 | 0.2694 | 0.4437 | 0.2867 | 0.4523 | 0.2615 | 0.4395 | 0.4430 | 0.49 |
| SMSA | 0.6513 | 0.4766 | 0.6885 | 0.4631 | 0.6353 | 0.4814 | 0.7311 | 0.44 |
| TIME | 8.7471 | 3.6916 | 8.6059 | 3.7333 | 8.8314 | 3.6881 | 9.1355 | 3.61 |
| AREA1 | 0.1231 | 0.3286 | 0.1306 | 0.3370 | 0.1195 | 0.3244 | 0.0601 | 0.23 |
| AREA2 | 0.0419 | 0.2005 | 0.0260 | 0.1592 | 0.0489 | 0.2157 | 0.0043 | 0.06 |
| AREA3 | 0.1096 | 0.3124 | 0.1297 | 0.3360 | 0.1008 | 0.3011 | 0.0253 | 0.15 |
| AREA4 | 0.2085 | 0.4062 | 0.2592 | 0.4382 | 0.1859 | 0.3891 | 0.1210 | 0.32 |
| AREA5 | 0.0815 | 0.2736 | 0.0323 | 0.1767 | 0.1034 | 0.3045 | 0.1614 | 0.36 |
| AREA6 | 0.0775 | 0.2674 | 0.0873 | 0.2823 | 0.0734 | 0.2608 | 0.1169 | 0.32 |
| AREA7 | 0.1423 | 0.3494 | 0.0811 | 0.2730 | 0.1700 | 0.3757 | 0.4464 | 0.49 |
| AREA8 | 0.1639 | 0.3702 | 0.2056 | 0.4042 | 0.1452 | 0.3523 | 0.0610 | 0.23 |
| T | 7.6580 | 8.0343 | 9.4004 | 8.5417 | 6.9093 | 7.6809 | 6.4754 | 7.16 |
| T2 | 123.1904 | 215.6558 | 161.3126 | 242.3478 | 106.7284 | 200.7767 | 93.3048 | 176.53 |
| OLDJOB | 0.7778 | 0.4222 | 0.8449 | 0.3620 | 0.7352 | 0.4412 | 0.7218 | 0.44 |
| N/EXP | 0.3694 | 0.3161 | 0.3323 | 0.2575 | 0.3844 | 0.3359 | | |
| QUIT | 0.0874 | 0.2824 | 0.0467 | 0.2110 | 0.1044 | 0.3058 | 0.0816 | 0.27 |
| LAYOFF | 0.0635 | 0.2438 | 0.0566 | 0.2310 | 0.0662 | 0.2486 | 0.1089 | 0.31 |
| SEPARATION | 0.1566 | 0.3635 | 0.1054 | 0.3071 | 0.1775 | 0.3821 | 0.1970 | 0.39 |
| $\widehat{T}_{ijt}$ | 0.0000 | 2.8307 | 0.0000 | 2.9369 | 0.0000 | 2.6525 | 0.0000 | 2.77 |
| $(\tilde{T}_{ijt})^2$ | 0.0000 | 80.3766 | 0.0000 | 89.0943 | 0.0000 | 73.4594 | 0.0000 | 72.48 |
| $\widetilde{OLDJOB}_{ijt}$ | 0.0000 | 0.2686 | 0.0000 | 0.2215 | 0.0000 | 0.2709 | 0.0000 | 0.27 |
| NUMBER OF OBSERVATIONS | 15138 | | 4649 | | 10364 | | 6551 | |

TABLE A2

INSTRUMENTAL REGRESSIONS FOR TENURE VARIABLES*

WHITE MALES

(t-statistics in parens.)

DEPENDENT VARIABLE

| | T (1) | $T^2$ (2) | Old Job (3) | T (4) | $T^2$ (5) | Old Job (6) | T** (7) | $T^{2}$** (8) | Old Job** (9) |
|---|---|---|---|---|---|---|---|---|---|
| INTERCEPT* | 3.4969 | 63.7267 | -.8861 | 3.5118 | 61.2299 | -.8154 | -.1562 | 29.5679 | -1.1786 |
| | (3.71) | (2.41) | (18.62) | (3.86) | (2.35) | (27.74) | (.15) | (1.05) | (18.50) |
| EDUC | -.0569 | 2.8870 | .0116 | -.0710 | 2.2458 | .0138 | -.2053 | -3.6472 | .0076 |
| | (.49) | (.88) | (1.98) | (.63) | (.70) | (2.97) | (1.64) | (1.04) | (.96) |
| $EDUC^2$ | .0017 | -.2010 | .0002 | .0017 | -.1875 | .0001 | .0066 | -.0178 | .0004 |
| | (.41) | (1.78) | (.85) | (.45) | (1.69) | (.39) | (1.53) | (.15) | (1.45) |
| EXP | -.2637 | -20.0356 | .0639 | -.3703 | -21.1659 | .0469 | -.1973 | -22.1964 | .0945 |
| | (5.14) | (13.94) | (24.73) | (7.47) | (14.91) | (22.93) | (3.61) | (14.50) | (27.38) |
| $EXP^2$ | .0315 | 1.3024 | -.0021 | .0359 | 1.3333 | -.0013 | .0280 | 1.2610 | -.0035 |
| | (12.81) | (18.88) | (17.05) | (15.08) | (19.56) | (12.85) | (10.66) | (17.12) | (21.10) |
| $EXP^3$ | -.0005 | -.0184 | .0000 | -.0006 | -.0184 | .0000 | -.0004 | -.0159 | .0000 |
| | (13.40) | (16.97) | (12.28) | (15.10) | (17.25) | (7.77) | (10.77) | (13.79) | (16.58) |
| EDUC·EXP | .0133 | .3821 | -.0002 | .0139 | .3997 | -.0002 | .0157 | .5195 | -.0002 |
| | (7.83) | (8.05) | (1.89) | (8.54) | (8.57) | (2.33) | (8.63) | (10.23) | (1.61) |
| MARRIED | .8374 | 16.4776 | .0724 | .8519 | 16.6861 | .0741 | .8703 | 18.1008 | .0718 |
| | (5.37) | (3.77) | (9.21) | (5.67) | (3.88) | (11.96) | (5.20) | (3.86) | (6.79) |
| UNION | 1.4408 | 28.2501 | .0826 | 1.3183 | 26.4995 | .0690 | 1.4438 | 28.0567 | .0878 |
| | (13.67) | (9.56) | (15.54) | (12.98) | (9.12) | (16.47) | (12.76) | (8.85) | (12.29) |
| HEALTH | -.9852 | -18.4859 | -.0852 | -.9611 | -18.22 | -.0818 | -.8477 | -15.0470 | -.0777 |
| | (5.89) | (3.94) | (10.10) | (5.96) | (3.95) | (12.30) | (4.72) | (3.00) | (6.84) |
| CITY>500,000 | -.0618 | -.1976 | -.0094 | -.0850 | -.6562 | -.0118 | -.0360 | .6173 | -.0101 |
| | (.50) | (.06) | (1.51) | (.72) | (.19) | (2.42) | (.27) | (.17) | (1.21) |
| SMSA | .7841 | 24.1788 | .0032 | .7845 | 24.45 | .0029 | .7755 | 23.4181 | .0041 |
| | (7.17) | (7.88) | (.58) | (7.44) | (8.12) | (.68) | (6.60) | (7.11) | (.55) |
| TIME | -.3372 | -6.[illegible]362 | -.0132 | -.2657 | -5.0421 | -.0122 | .0698 | 2.7591 | .0013 |
| | (22.32) | (15.31) | (17.39) | (18.01) | (11.95) | (20.13) | (5.18) | (7.31) | (1.50) |
| AREA 1 | -1.018 | -27.9043 | -.0131 | -1.0476 | -28.45 | -.0159 | -.0936 | -28.1601 | -.0114 |
| | (4.26) | (4.16) | (1.09) | (4.55) | (4.32) | (1.68) | (3.07) | (3.01) | (.70) |
| AREA 2 | -.9732 | 23.9743 | -.0001 | -.9675 | -24.2949 | .0017 | -1.079 | -28.3470 | .0034 |
| | (3.22) | (2.83) | (.01) | (3.33) | (2.92) | (.14) | (3.33) | (3.12) | (.17) |
| AREA 3 | 1.3137 | 35.9967 | .0418 | 1.3022 | 35.9326 | .0370 | 1.3618 | 37.1923 | .0421 |
| | (5.37) | (5.25) | (3.39) | (5.53) | (5.33) | (3.81) | (5.18) | (5.05) | (2.54) |
| AREA 4 | 1.6323 | 42.8739 | .0537 | 1.6058 | 42.6438 | .0470 | 1.6191 | 42.2834 | .0556 |
| | (7.26) | (6.80) | (4.73) | (7.42) | (6.88) | (5.26) | (6.71) | (6.25) | (3.65) |
| AREA 5 | .2004 | 10.2026 | .0038 | .1599 | 9.6834 | -.0028 | .1552 | 8.3412 | .0057 |
| | (.77) | (1.41) | (.29) | (.64) | (1.36) | (.27) | (.56) | (1.07) | (.32) |
| AREA 6 | 1.8346 | 46.3140 | .0744 | 1.8072 | 45.8322 | .0714 | 1.7856 | 44.4421 | .0726 |
| | (6.94) | (6.25) | (5.58) | (7.10) | (6.29) | (6.79) | (6.29) | (5.59) | (4.05) |
| AREA 7 | .3955 | 4.0687 | .0448 | .3940 | 4.0613 | .0407 | .5137 | 7.3351 | .0450 |
| | (1.67) | (.61) | (3.75) | (1.73) | (.62) | (4.32) | (2.02) | (1.03) | (2.80) |
| AREA 8 | .0868 | 3.0491 | .0154 | .0978 | 3.2282 | .0141 | .1100 | 4.1108 | .0144 |
| | (.37) | (.47) | (1.32) | (.44) | (.51) | (1.53) | (.44) | (.59) | (.91) |
| $\overline{\text{Old Job}}_{ij(t)}-\overline{\text{Old Job}}_{i}$ | | | | -.1843 | -4.6915 | .9915 | | | |
| | | | | (.46) | (.41) | (60.39) | | | |
| $\bar{T}_{ij(t)}-\bar{T}_{i}$ | | | | 1.0894 | 4.4302 | -.0066 | | | |
| | | | | (9.67) | (1.37) | (1.43) | | | |
| $\bar{T}^2_{ij(t)}-\bar{T}^2_{i}$ | | | | -.0024 | .9121 | .0001 | | | |
| | | | | (.44) | (5.84) | (.57) | | | |
| $\text{Old Job}_{ijt}$ | .1846 | 6.9634 | .9863 | .1806 | 6.4363 | .9920 | | | |
| | (.95) | (1.28) | (100.81) | (.96) | (1.20) | (128.66) | | | |
| $\tilde{T}_{ijt}$ | .9059 | -1.4363 | -.0064 | .8709 | -2.1574 | -.0061 | | | |
| | (23.54) | (1.33) | (3.32) | (23.49) | (2.03) | (4.03) | | | |
| $\tilde{T}^2_{ijt}$ | .0019 | .9415 | .0004 | .0009 | .9217 | .0003 | | | |
| | (1.52) | (26.64) | (5.92) | (.76) | (26.52) | (6.57) | | | |
| $R^2$ | .52 | .47 | .55 | .55 | .49 | .72 | .45 | .41 | .16 |
| SE | 5.59 | 156.83 | .28 | 5.39 | 154.16 | .22 | 6.33 | 187.01 | .33 |

*Columns 1-3 are the first stage equations for Table 1 col. 4-6. Columns 4-6 are the first stage equations for Table 1 col. 6-9. Observations = 15,138.

** Columns 7-9 exclude the deviations from tenure means and are provided for the sake of reference.

TABLE A3

UNREPORTED COEFFICIENTS FROM TABLES 1 AND 2.*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| INTERCEPT | 0.304124 | 0.215382 | 0.135084 | 0.096346 |
| | (4.448) | (3.047) | (1.2083) | (0.8555) |
| MARRIED | 0.114956 | 0.130359 | 0.041401 | 0.040430 |
| | (10.254) | (11.313) | (3.6676) | (3.5508) |
| UNION | 0.154398 | 0.178917 | 0.105642 | 0.109247 |
| | (20.246) | (22.201) | (12.2974 | (12.4631 |
| HEALTH | -0.096599 | -0.113230 | -0.012208 | -0.00989434 |
| | (8.028) | (9.163) | (1.1613) | (0.9331) |
| CITY>500000 | 0.085146 | 0.083463 | 0.035998 | 0.038038 |
| | (9.660) | (9.270) | (3.0747) | (3.2339) |
| SMSA | 0.142306 | 0.149108 | 0.081553 | 0.082947 |
| | (18.084) | (18.342) | (7.8886) | (7.9572) |
| TIME | 0.008775501 | 0.009156271 | 0.007554073 | 0.008645422 |
| | (9.723) | (9.819) | (8.9621) | (9.9773) |
| AREA1 | 0.051049 | 0.041136 | 0.073531 | 0.069915 |
| | (2.971) | (2.336) | (2.5147) | (2.3790) |
| AREA2 | 0.010597 | -0.000206222 | 0.008989408 | 0.003059989 |
| | (0.488) | (0.009) | (0.2507) | (0.0849) |
| AREA3 | -0.027874 | -0.012032 | 0.002929507 | 0.008764124 |
| | (1.585) | (0.666) | (0.0966) | (0.2873) |
| AREA4 | 0.052027 | 0.072068 | 0.085552 | 0.094767 |
| | (3.219) | (4.321) | (3.0833) | (3.3941) |
| AREA5 | -0.086292 | -0.086267 | -0.105387 | -0.105740 |
| | (4.640) | (4.539) | (3.4602) | (3.4553) |
| AREA6 | -0.063452 | -0.039685 | -0.044953 | -0.036906 |
| | (3.338) | (2.026) | (1.3653) | (1.1139) |
| AREA7 | -0.043701 | -0.032952 | -0.042791 | -0.038478 |
| | (2.568) | (1.893) | (1.4766) | (1.3212) |
| AREA8 | -0.014672 | -0.013215 | 0.033042 | 0.035757 |
| | (0.881) | (0.777) | (1.1554) | (1.2444) |

* COLUMNS 1 AND 2 CONTAIN THE COEFFICIENTS NOT REPORTED IN TABLE 1 COLUMNS 3 AND 6. COLUMNS 3 AND 4 CONTAIN THE COEFFICIENTS NOT REPORTED IN TABLE 2 COLUMNS 3 AND 6.

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