THE EFFECTS OF LABOR MARKET EXPERIENCE, JOB SENIORITY, AND JOB MOBILITY ON WAGE GROWTH

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I. INTRODUCTION

Because economic behavior is complex, data are limited, clean natural experiments are few, and controlled experiments usually are not possible, applied econometricians frequently estimate parameters of models that are not identified from sample information alone. A good example is research on why wages rise over a career. The accumulation of labor market experience, the accumulation of job tenure (seniority), and movement up the wage distribution through job mobility all play a role, but we have conflicting evidence on their relative importance.[1] Sorting out the contributions of the three factors with cross-section data is probably hopeless, for two main reasons. First, permanent differences across individuals in wage rates appear to be correlated with heterogeneity in mobility. Second, endogenous mobility decisions induce complicated correlations between labor market experience, job tenure, and job match quality. The situation is better in panel data. In panel data, one can use time differences to control for individual heterogeneity, and can

Research in Labor Economics, Volume 17, pages 233–276.

ISBN: 0-7623-0570-3

compare wages across jobs. However, job match heterogeneity is still a problem, since one must use variation in tenure across jobs to sort out the effects of experience and seniority.

In this paper we use prior information to help pin down the parameters of a wage growth model that is under identified based on sample information alone. The starting point is an equation in which wages depend on experience, tenure, a fixed individual specific error component, a fixed job match specific error component that changes only if the individual changes jobs, transitory error components, and other observed components. First differencing eliminates the fixed individual effect, but the change in the job match component remains for observations involving job changes. We replace the change in the job match components with expressions for their expectations conditional on a quit or layoff, tenure, and prior experience. The expressions are polynomial approximations to the true conditional expectations. Bias from fixed job match heterogeneity is eliminated. The coefficients on nonlinear terms are identified directly in the modified wage change equation. However, the coefficients on linear experience and tenure in the wage level equation, and the coefficients on the linear tenure terms in the polynomial approximations for the expected change in the job match components are under identified by one common parameter. Without additional information one cannot identify the returns to general capital, the returns to tenure, and the relationship between tenure and the gains from quits and layoffs. The first contribution of the paper is to provide a better understanding of what is identified in regression analyses of the wage changes of stayers, quits, and/or layoffs that are common in the literature.[2]

The second contribution is to make the case for a set of inequality restrictions on the parameters of the wage growth model that are helpful in obtaining bounds on the parameter estimates. The prior information is as follows. First, we argue that if the effect of tenure on wages is substantial, then the relationship between the change in the job match component and tenure at the time of a quit (layoff) will be positive (negative). The intuition for quits is that senior workers only quit if the job match gain is sufficient to compensate for the value of lost tenure. The intuition for layoffs is that jobs that workers choose to stay in for long periods tend be better than jobs that workers leave quickly.[3] The second piece of prior information is based on the fact that while the recent literature has been quite divided on the value of seniority, almost all research suggests that the return to general labor market experience is large. For example, Topel's (1991) 2-step estimates, Altonji and Shakotko's (1987) OLS estimates, and their IV estimates of the effect of 30 years of labor market experience on log wages are .428, .394, and .441, respectively. In view of this evidence and the fact that few researchers who believe that returns to seniority are important believe that general experience is unimportant, it is sensible to rule out a priori the possibility that the return is below a small positive value. We obtain upper bounds on the contribution of experience from OLS regressions of wages on experience with tenure terms *excluded*.[4] Finally, we treat the restriction that job match gains are 0 or negative for persons who are laid off with significant amounts of seniority as prior information, a restriction that is consistent with our model and one that we believe few labor economists would quarrel with.

The third contribution is to use a Bayes estimator due to Geweke (1986) to combine prior information in the form of inequality restrictions with sample information on the parameters of the model. We discuss both least squares estimates of the combinations of model parameters that are identified from the sample alone and formal Bayesian estimates. For our preferred wage measure the results suggest that 10 years of tenure raises the log wage by between .06 and .14. These estimates are far below the OLS estimate of .28. For purposes of comparison, Altonji and Shakotko's IV estimator is about .12, and Topel's 2-step estimator leads to estimates of .15. We compare the studies more fully below. We also provide a limited analysis of data from the National Longitudinal Survey of Youth (NLSY), and obtain results that are quite consistent with those for the PSID.

The paper proceeds as follows. In Section II we present an econometric model of wages and the gain from mobility. We justify a set of inequality priors in Section III. In Section IV we discuss the Bayes estimator and a few additional econometric issues. In Section V we discuss our samples from the 1975–1987 waves of the Panel Study of Income Dynamics. We present the results in Section VI. In Section VII we present the analysis of NLSY. We summarize our main empirical finding and discuss a research agenda in Section VIII.

II. AN ECONOMETRIC MODEL OF WAGES AND THE GAIN FROM MOBILITY

Following several papers, we assume that the log real wage W_{it} of person i in job j in period t is

$$W_{it} = Z_{it}\Gamma + \phi t + b_0 X_{it} + b_1 X_{it}^2 + b_2 T_{it} + b_3 T_{it}^2 + \varepsilon_i + \varepsilon_{ij(t)} + u_{it} + \nu_{ijt}, \qquad (2.1)$$

where Z_{it} is a set of other observed wage determinants, the parameter ϕ is an economy-wide trend in real wages, X_{it} is labor market experience, T_{it} is tenure with the employer, ε_i is a fixed individual specific error component, $\varepsilon_{ij(t)}$ is a fixed job match specific error component, u_{it} is an individual specific transitory error term, and ν_{ijt} is a transitory job match error component that is uncorrelated with u_{it}. In the empirical work we add the third and fourth powers of X_{it} and the third power of T_{it}.[5]

Wage growth over a career reflects accumulation of experience, growth in seniority within a given firm, and movement toward job matches with higher values of $\varepsilon_{ij(t)}$. Wage changes also reflect movements in the error component ν_{ijt}. For now we assume these latter movements are small or transitory and thus are not likely to have a strong relationship with turnover behavior, but we discuss this component more fully later.

Use of OLS to estimate the tenure and experience parameters of (2.1) is inappropriate for two well-known reasons. First, T_{it} will be positively correlated with ε_i in the likely event that individuals with low productivity (low ε_i) have high quit and layoff propensities.[6] Individual heterogeneity associated with ε_i will bias OLS estimates of the wage-tenure profile upward.

Second, the experience and tenure variables will be correlated with the fixed job match error component $\varepsilon_{ij(t)}$. The existence of differences in match quality across firm-worker pairs (Jovanovic, 1979; Johnson, 1978), the presence of noncompetitive elements in the wage structure, and differences across firms in the optimal compensation level for a given type (see Groshen, 1991 for evidence of firm specific wage components) all imply that individual workers face a distribution of wages. Workers will be less likely to quit high wage jobs than low wage jobs. Furthermore, the firm's share in the returns to a good match, $\varepsilon_{ij(t)}$, will be negatively correlated with the layoff probability. This suggests that tenure is positively correlated with $\varepsilon_{ij(t)}$. The positive correlation will tend to induce a positive bias in OLS estimates of the tenure coefficient in the wage equation. However, both job matching models and conventional search models (e.g., Burdett, 1978) imply that job shopping over a career will induce a positive correlation between X_{it} and $\varepsilon_{ij(t)}$. Since T_{it} and X_{it} are positively correlated, the overall effect of $\varepsilon_{ij(t)}$ on the tenure and experience slopes is unclear, but they are likely to be biased.

First differencing (2.1) and noting that ΔX_{it} equals 1 and ΔT_{it} is 1 for stayers and $T_{it} - T_{it-1}$ for movers leads to the wage growth equation for stayers

$$\Delta W_{it} = \Delta Z^*_{it}\Gamma^* + (b_0 + b_2) + b_1 \Delta X^2_{it} + b_3 \Delta T^2_{it} + \Delta u_{it} + \Delta \nu_{ijt}, \qquad (2.2a)$$

and for quits and layoffs

$$\Delta W_{it} = \Delta Z^*_{it}\Gamma^* + b_0 + b_1 \Delta X^2_{it} + b_2 \Delta T_{it} + b_3 \Delta T^2_{it} + \Delta \varepsilon_{ij(t)} + \Delta u_{it} + \Delta \nu_{ijt}, \qquad (2.2b)$$

where Z^*_{it} is the subvector of Z_{it} consisting of variables which change over time and Γ^* is the corresponding subvector of Γ. To simplify the exposition, we have omitted the trend term ϕ from (2.2a) and (2.2b) and proceed as if ϕ is known. (We will estimate ϕ from the wage level equation (2.1) in the empirical work.) Several papers have noted that conditional on ϕ only the sum of the linear tenure and experience slopes $b_0 + b_2$ and the nonlinear tenure and experience terms are identified from the stayers alone. Superficially at least, it would appear that all the tenure and experience coefficients in (2.1) are identified from (2.2b) alone or from joint estimation of (2.2a) and (2.2b). However, the term $\Delta\varepsilon_{ij(t)}$ is likely to cause problems because it may be nonzero if a worker quits or is laid off.

Let $E(\Delta\varepsilon_{ij(t)} | Q_{it}, X_{0ij(t-1)}, T_{it-1})$ be the expected value of $\Delta\varepsilon_{ij(t)}$ conditional on T_{it-1}, the level of experience at the start of job j ($X_{0ij(t-1)}$),[7] and a quit between $t-1$

and t ($Q_{it} = 1$). Let $E(\Delta\varepsilon_{ij(t)}|L_{it}, X_{0ij(t-1)}, T_{it-1})$ be the corresponding expectation in the event of a layoff ($L_{it} = 1$).

Then

$$\Delta\varepsilon_{ij(t)} = Q_{it}E(\Delta\varepsilon_{ij(t)}|Q_{it}, X_{0ij(t-1)}, T_{it-1})$$
$$+ L_{it}E(\Delta\varepsilon_{ij(t)}|L_{it}, X_{0ij(t-1)}, T_{it-1}) + Q_{it}\eta_{ij(t)} + L_{it}\xi_{ij(t)} \qquad (2.3)$$

where by the definition of an expectation $Q_{it}\eta_{ij(t)} + L_{it}\xi_{ij(t)}$ is uncorrelated with $X_{0ij(t-1)}$, T_{it-1}, Q_{it}, and L_{it}.[8] Assuming the conditional expectation functions are continuous, they can be approximated by polynomials in $X_{0ij(t-1)}$ and T_{it-1}. Suppose that the two conditional expectation functions are well approximated by

$$E(\Delta\varepsilon_{ij(t)} \mid Q_{it}, X_{0ij(t-1)}, T_{it-1})$$
$$= (d_0(X_{0ij(t-1)}) + d_1 + d_2T_{it-1} + d_3T^2_{it-1} + d_4T^3_{it-1})Q_{it} \qquad (2.4)$$

$$E(\Delta\varepsilon_{ij(t)} \mid L_{it}, X_{0ij(t-1)}, T_{it-1})$$
$$= (g_0(X_{0ij(t-1)}) + g_1 + g_2T_{it-1} + g_3T^2_{it-1} + g_4T^3_{it-1})L_{it} \qquad (2.5)$$

where the functions $d_0(X_{0ij(t-1)})$ and $g_0(X_{0ij(t-1)})$ are cubics in $X_{0ij(t-1)}$ in the empirical work. The terms on the right-hand side of these equations are uncorrelated with the error $Q_{it}\eta_{ij(t)} + L_{it}\xi_{ij(t)}$.[9] Since the change in the tenure variables are a function of past tenure, particularly for those who separate, and since the change in X^2_{it} will be correlated with past experience and tenure, one obtains biased estimates of the tenure and experience slopes using equations (2.2a) and (2.2b) unless one accounts for the fact that the expectation of $\Delta\varepsilon_{ij(t)}$ is a function of past tenure and experience for those who quit or are laid off. Furthermore, (2.2b) says nothing about how $\Delta\varepsilon_{ij(t)}$ depends on tenure and experience at the time of a quit or layoff, and so sheds little light on the contribution of mobility to wage growth. It is therefore natural to consider using (2.3), (2.4) and (2.5) to substitute out for $\Delta\varepsilon_{ij(t)}$ in (2.2b) and then examine what parameters are identified when the equation is combined with (2.2a). After performing the substitutions into (2.2b), combining the linear tenure terms, and adding and subtracting the terms b_2Q_{it} and b_2L_{it} from the right-hand side, using the identity $[Q_{it} + L_{it}]\ [T_{it}] = [Q_{it} + L_{it}][\underline{T} + T_{it} - \underline{T}]$ where $\underline{T}$ is the mean of T_{it} conditional on a job change in the preceding year, and then combining the resulting equation with (2.2a), we arrive at the combined equation for movers and stayers

$$\Delta W_{it} = \Delta Z^*_{it}\Gamma^* + (b_0 + b_2) + b_1\Delta X^2_{it} + b_3\Delta T^2_{it}$$
$$+ d_0(X_{0ij(t-1)})Q_{it} + d_3Q_{it}T^2_{it-1} + d_4Q_{it}T^3_{it-1}$$
$$+ g_0(X_{0ij(t-1)})L_{it} + g_3L_{it}T^2_{it-1} + g_4L_{it}T^3_{it-1}$$

$$+ [d_1 - b_2(1 - \underline{T})]Q_{it} + [g_1 - b_2(1 - \underline{T})]L_{it}$$

$$+ (b_2 - d_2)(-Q_{it}T_{it-1}) + (b_2 - g_2)(-L_{it}T_{it-1})$$

$$+ Q_{it}\eta_{ij(t)} + L_{it}\xi_{ij(t)} + b_2(Q_{it} + L_{it})(T_{it} - \underline{T}) + \Delta u_{it} + \Delta\nu_{ijt}. \quad (2.6)$$

The good news about (2.6) is that the tenure and experience terms are uncorrelated with the error term, ignoring complications associated with the error component $\Delta u_{it} + \Delta\nu_{ijt}$ which are discussed below. The information on stayers permits identification of the nonlinear experience and tenure terms. The information on movers permits identification of most of the job match gain parameters in equations (2.4) and (2.5). The bad news is that the linear experience slope b_0, the linear tenure slope b_2 and coefficients d_2 and g_2 on $Q_{it}T_{it-1}$ and $L_{it}T_{it-1}$ in (2.2), (2.4) and (2.5) are not identified in (2.6) unless one is prepared to rely on the variation in $[T_{it} - \underline{T}]$ in the event of a quit or a layoff. This variation is too small and too unreliable given measurement error in the first tenure observation on a new job for $[T_{it} - \underline{T}]$ to be used to identify the effect of ΔT_{it}. In most of our estimation we treat $[Q_{it} + L_{it}][T_{it} - \underline{T}]$ as part of the error term.[10] Thus, for practical purposes b_0, b_2, d_2 and g_2 are not separately identified. From the constant term one can obtain an estimate of the linear combination $b_0 + b_2$. The coefficients on $-Q_{it}T_{it-1}$ and $-L_{it}T_{it-1}$ provide estimates of $(b_2 - d_2)$ and $(b_2 - g_2)$, respectively.[11]

Equations similar to (2.6) have frequently been estimated on samples of job losers, quits and in some cases combined samples. The coefficients relating the wage gain to tenure and experience prior to the job change have been used to draw inferences about the returns to tenure.[12] However, it is clear from (2.6) that one cannot use wage change equations to decompose wage changes associated with layoffs into the effect of lost human capital, losses in the value of general human capital, the change in the value of the match specific component, and so forth. One cannot do so even if the layoffs are completely exogenous to the individual, as in the case of plant closings.

There are two problems. First, there will be a relationship between initial experience and $\Delta\varepsilon_{ij(t)}$ even if general skill is unchanged when a separation occurs.[13] A relationship will arise because the conditional expectation of $\Delta\varepsilon_{ij(t)}$ is likely to depend upon how many years the person had the opportunity to search before finding the prior job. Second, d_2 and g_2 are not identified separately from b_2, so one cannot decompose the relationship between T_{it-1} and ΔW_{it} into the value of lost tenure and the change in the fixed job match specific wage component. One must have a model of quits and layoffs to identify the wage parameters needed to draw conclusions about what is responsible for the wage changes associated with job mobility, or about the nature of the bias when one uses the coefficients $b_2 - d_2$ and $b_2 - g_2$ as estimates of the linear component b_2 of the return to tenure.[14]

Our strategy is to combine sample information about the parameters identified in (2.6) with prior information about the parameters b_0, d_2, and g_2 in the model.[15]

III. WAGE CHANGES ASSOCIATED WITH QUITS AND LAYOFFS: THEORETICAL CONSIDERATIONS

In this section we argue for a set of prior restrictions on the parameters of the regression model (2.6). Sections III.A–III.C argue that the expected value of the change in the job match component $\Delta\varepsilon_{ij(t)}$ is an increasing function of tenure at the time of a quit and a decreasing function of tenure at the time of a layoff providing that one controls for experience at the start of the job. Differentiating (2.4) and (2.5), these conditions are

$$\partial E(\Delta\varepsilon_{ij(t)}|Q_{it}, X_{0ij(t-1)}, T_{it-1})/\partial T_{it-1} = d_2 + 2d_3T_{it-1} + 3d_4T^2_{it-1} > 0 \qquad (3.1)$$

and

$$\partial E(\Delta\varepsilon_{ij(t)}|L_{it}, X_{0ij(t-1)}, T_{it-1})/\partial T_{it-1} = g_2 + 2g_3T_{t-1} + 3g_4T^2_{it-1} < 0 \qquad (3.2)$$

for positive values of T_{it-1}. These equations place restrictions on d_2 and g_2 given the values of d_3, d_4, g_3, and g_4. In Sections III.A and III.B we justify the restrictions in the context of simple models of quits and layoffs. In Section III.C we discuss the robustness of these restrictions to a number of generalizations of our theoretical framework. In Section III.D we discuss prior information about job losses associated with layoffs and the return to experience. We argue that the expected value of the job match gain is negative for persons with substantial seniority who are laid off. This places additional restrictions on the parameters of (2.5) that appear in (2.6). We also obtain lower and upper bounds on the returns to experience based on empirical evidence.

A. The Relationship between Tenure and the Job Match Gain in the Case of Quits

Consider quits first. Ignoring the effects of the stochastic component ν_{ijt}, the wage equation (2.1) implies that the present value of a job is a positive function of T_{it} and $\varepsilon_{ij(t)}$. A worker quits between $t-1$ and t if

$$PV(X_{0ij'(t)}, 0, \varepsilon_{ij'(t)}) - PV(X_{0ij(t-1)}, T_{it-1}, \varepsilon_{ij(t-1)}) > M, \qquad (3.3)$$

where j' is the best alternative offer arriving between $t-1$ and t, M is mobility costs, $X_{0ij'(t)} = X_{0ij(t-1)} + T_{it-1} + 1$, and the PV function takes into account the discount rate as well as effects of future quits and layoffs on earnings.

The expected value of $\Delta\varepsilon_{ij(t)}$ in the event of a quit will tend to increase with T_{it-1} because the gain in $\Delta\varepsilon_{ij(t)}$ required to compensate for lost tenure rises with T_{it}. The strength of the relationship between T_{it} and $\Delta\varepsilon_{ij(t)}$ depends positively on the tenure slope of W_{it}.[16]

However, this is not the whole story. Since the probability that a worker will have received a better offer by tenure level T_{it-1} is negatively related to $\varepsilon_{ij(t-1)}$ for all tenure levels even if the true tenure effect on wages is 0, the distribution of $(\varepsilon_{ij(t-1)}|X_{0ij(t-1)}, T_{it-1})$ is stochastically increasing in T_{it-1}. The fact that jobs with high ε_{ij} tend to last and are hard to improve on means that T_{it-1} could be *negatively* related to $E(\Delta\varepsilon_{ij(t)}|Q_{it}, X_{0ij(t-1)}, T_{it-1})$ (assuming a log concave offer distribution). A net positive relationship will arise when the true tenure effect on wages (or the effect of T on mobility costs) is sufficiently positive. The requirement that ε_{ij} exceed $\varepsilon_{ij(t-1)}$ plus the tenure related wage component becomes more stringent at higher tenure levels in proportion to the return to tenure. It will offset the negative relationship induced by the outward shift in the distribution of $\varepsilon_{ij(t-1)}$ among the surviving jobs if the return to tenure is large.

B. The Relationship between Tenure and the Job Match Gain in the Case of Layoffs

We obtain a priori information about g_2, g_3, and g_4 by considering the relationship between $E(\Delta\varepsilon_{ij(t)})$ and tenure in the event of a layoff. Our argument is that both quit and layoff behavior select out the worst job matches as tenure accumulates. This leads to a positive association between $\varepsilon_{ij(t-1)}$ and T_{it-1} and a negative association between $E(\Delta\varepsilon_{ij(t)})$ and T_{it-1} in the event of a layoff.

Let V_{ijt} denote the value to firm j of not laying off worker i between $t-1$ and t. This is a function of layoff costs and the discounted expected value of current and future productivity net of wage payments to the worker, with future turnover taken into account. Productivity depends on X_{it} and T_{it}, a match component $\omega_{ij(t)}$, and a time varying component e_{ijt}. (We sometimes write $\omega_{ij(t)}$ as ω_{ij}.) As in the quit analysis, we assume that the general components of productivity are observable to other employers and as a result of competition are fully reflected in the wage components e_i and e_{it}. In this case, neither these components nor X_{it} affect V_{ijt} or layoffs. Firms and workers share the return to $\omega_{ij(t)}$. The wage component $\varepsilon_{ij(t)}$ is the worker's share s_ω of $\omega_{ij(t)}$. Consequently, V_{ijt} is a positive function of ω_{ij}. In general, workers and firms may also share in the returns to the time varying component e_{ijt}, and this sharing may be reflected in ν_{ijt}. However, because of risk aversion or costs of re-contracting and information (Hall & Lazear, 1984; Hashimoto & Yu, 1980) we assume that firms bear most of the risk associated with e_{ijt}. This implies that V_{ijt} is a positive function of e_{ijt}.

A layoff occurs if (1) e_{ijt} falls sufficiently below its value at the hiring date (given firing costs) and (2) the match had not already ended due to a quit or layoff. The odds of a layoff between $t-1$ and t fall with ω_{ij} regardless of the value of tenure at $t-1$. The distribution of ω_{ij} and $\varepsilon_{ij(t-1)}$ is increasing in prior experience, but we hold that constant. For any tenure value the odds of a quit between $t-1$ and t also declines with $\varepsilon_{ij(t-1)}$, and therefore, with ω_{ij}.[17] Consequently both quit and layoff behavior tend to weed out the lower values of ω_{ij} and $\varepsilon_{ij(t-1)}$ from the distribution of these variables conditional on prior experience. It follows that the distribution of ω_{ij} and thus $\varepsilon_{ij(t-1)}$ conditional on $X_{0ij(t-1)}$ and T_{it-1} is increasing in T_{it-1} for the subset of jobs which survive to $t-1$. The weeding out process will shift out the distribution of $\varepsilon_{ij(t-1)}$ with T_{it-1} among the jobs that end in a layoff between $t-1$ and t, as well as among the subset which survive additional periods. Following the layoff the worker locates a new job j'. Assuming that the offer distribution does not depend on T_{it-1} the discussion suggests that $E(\varepsilon_{ij'(t)} - \varepsilon_{ij(t-1)}|L_{it}, X_{0ij(t-1)}, T_{it-1})$ is a negative function of T_{it-1}.

The above discussion is not complete under the standard assumption that firms share in the returns to specific capital investment, which implies that V_{ijt} is a positive function of T_{it}.[18] In this case, productivity net of wages will be increasing in tenure holding everything else constant. Consequently, the higher tenure, the lower ω_{ij} and e_{ijt} must be for profits on the worker to become negative. Since ε_{ij} is positively related to ω_{ij}, the implication is that for a given value of e_{ijt} the critical value of ε_{ij} below which a layoff occurs will fall with tenure. This tends to induce a positive relationship between T_{it-1} and $E(\Delta\varepsilon_{ij(t)}|L_{it}, X_{0ij(t-1)}, T_{it-1})$. To the extent that the distribution of e_{ijt} spreads out with tenure, as relatively more permanent shocks accumulate, this selection effect is mitigated. It is also limited because job matches with values of ε_{ij} that would result in a layoff after tenure has been accumulated are likely to lead to a quit or layoff during the first few years of the match. Consequently, we expect that the outward shift in the distribution of ε_{ij} with T_{it-1} among the surviving jobs will dominate and lead to a negative relationship between T_{it-1} and $E(\Delta\varepsilon_{ij(t)}|L_{it}, X_{0ij(t-1)}, T_{it-1})$.

Simulation Results

In Altonji and Williams (1993) we simulate a version of the model discussed above for a variety of values of the tenure slope of productivity, the variance in the job match component of wages, and the sharing rules for the return to tenure, $\omega_{ij(t)}$, and e_{ijt}. The simulations indicate that the relationship between wage growth and tenure understates the returns to tenure in the event of a quit except when the return to tenure is close to 0. The return to the first year of tenure may be overstated. The relationship between wage growth and tenure will overstate the returns to tenure in the event of a layoff, except possibly at high tenure levels. Underlying these findings is the fact that the simulations confirm that $E(\Delta\varepsilon_{ij(t)}|L_{it}, X_{0ij(t-1)}, T_{it-1})$ depends negatively on T_{it-1} and that $E(\Delta\varepsilon_{ij(t)}| Q_{it}, X_{0ij(t-1)}, T_{it-1})$ depends positively on tenure when there is a positive effect of tenure on wages. Thus the simulations are basically consistent with the theoretical arguments made above.[19]

C. Generalizations of the Theoretical Framework

Variation in ν_{ijt}

Thus far, we have largely ignored the effects of changes in the firm and match specific productivity components captured in e_{iit}. Change in e_{iit} may affect wages through ν_{ijt} to the extent that firm or match specific productivity shifts are shared between the firm and worker. Also, the firm may gradually learn about the match specific component of productivity, which in our model could be interpreted as a shift in e_{ijt}. Changes within and across jobs in ν_{ijt} affect wage growth within jobs and the gains and losses from quits and layoffs.[20] Such changes may be important empirically, and so it is useful to speculate on how they affect interpretation of (2.6) and the restrictions (3.1) and (3.2).

One may add ν_{ijt} to the value function and use the quit condition to argue that the expected value of $\Delta\varepsilon_{ij(t)} - \Delta\nu_{ijt}$ is an increasing function of T_{it-1} in the event of a quit when the tenure slope of wages is substantial. In the case of layoffs the relationship between $\Delta\nu_{ijt}$ and T_{it-1} is ambiguous. First, to the extent that wages are heavily influenced by firm specific shocks to productivity, layoffs are less likely to result from them. Second, to the extent that firms insure workers against shocks which affect their productivity not only in the current firm but in other firms, $E(\Delta\nu_{ijt})$ could be a negative function of tenure, as wages in the spot market for new hires are not protected from a shift in product demand or productivity affecting an industry or occupation.

One may reinterpret the parameters $\{d_2, d_3, d_4\}$ and $\{g_2, g_3, g_4\}$ as measuring the effect of T_{it-1} on the conditional expectation of $(\Delta\varepsilon_{ij(t)} + \Delta\nu_{ijt})$ in the event of a quit and in the event of a layoff. If the combined effect of T_{it-1} on the two variables is positive for a quit and nonpositive for a layoff, then the restrictions (3.1) and (3.2) are valid. Simulations in Altonji and Williams (1993) support this.

Unfortunately, $\Delta\nu_{ijt}$ may also bias the combined return to a year of tenure and experience if the mean of $\Delta\nu_{ijt}$ is not zero for stayers. Job matches in which negative changes in ν_{ijt} occur will be more likely to end in a quit or a layoff. This suggests that the expected value of $\Delta\nu_{ijt}$ will tend to be positive *for stayers*. However, Bull and Jovanovic (1988) note that if workers tend to enter firms during periods of strong demand, ν_{ijt} tends to revert toward its mean of 0 as time goes on. In this case the expected value of $\Delta\nu_{ijt}$ for stayers could be negative.[21] Furthermore, Altonji and Shakotko (1987) note that the size of the decline in ν_{ijt} necessary to induce a quit (holding the value of the alternative offer fixed) increases with tenure if wages rise with tenure. Therefore, the expected value of $\Delta\nu_{ijt}$ conditional on continuation of the job may decline with T_{it}. Consequently, if the effect of tenure on wages and productivity is large, the expected value of $\Delta\nu_{ijt}$ for stayers may decline with tenure on the job. The estimates of the nonlinear tenure and experience terms in (2.6) will be biased if $E(\Delta\nu_{ijt})$ for stayers varies systematically with tenure.

The above discussion suggests that $E(\Delta\nu_{ijt})$ is likely to be positive for stayers but may decline with tenure. Simulations in Altonji and Williams (1993) indicate that wage growth within firms is indeed higher than that implied by the return to tenure, but the bias is small in magnitude. These results suggest that the consequences of ignoring the effects of $E(\Delta\nu_{ijt})$ on estimates of wage growth within jobs may be minor for our study and others, and if anything lead to an overstatement of the returns to seniority. However, they are based on a limited range of specifications, and we leave a full resolution of the issue to future research.

Robustness of the Priors to Other Factors

While the result that the job match gains will be positively related to tenure for quits and negatively related to tenure for layoffs is intuitively appealing, our theoretical framework excludes many factors that may be important. In this section we consider the robustness of the results to some modifications to the model.

Heterogeneity in Tenure Slopes. The wage model (2.1), like most empirical research on the returns to seniority, ignores differences across individuals and across job matches in tenure slopes. Differences in wage slopes might arise from variation across individuals, firms, and job matches in the optimal rate of specific human capital investment. Such variation has been emphasized in both formal and informal theoretical discussions of earnings dynamics.[22] Recent data sets which contain information on training suggest that these differences may be important.[23] We suspect that such heterogeneity, if unobserved when job matches start, would reinforce our analysis of quits. This is because jobs that survive will tend to be ones with a high return to seniority. Consequently, people who quit with substantial seniority will require larger compensation in the form of a job match gain to make the change. In the case of layoffs the heterogeneity might weaken or negate the positive relationship between $\varepsilon_{ij(t)}$ and T_{it-1} and therefore the negative relationship between $\Delta\varepsilon_{ij(t)}$ among the set of jobs that end in a layoff. Differences across matches in the odds that a job survives another period will depend on heterogeneity in $\varepsilon_{ij(t)}$ as well as heterogeneity in the tenure slope. However, the estimator will pick up the relationship between T_{it-1} and the sum of $\Delta\varepsilon_{ij(t)}$ and value of the lost tenure, and this relationship is likely to be negative. This would leave our prediction intact. Unfortunately, heterogeneity in tenure slopes is likely to lead to upward bias in the estimates of the relationship between seniority and wage growth within jobs. This is likely to lead to upward bias in estimated effects of seniority.

Layoffs and Lemons. Our analysis above and the simulations in Altonji and Williams (1993) assume that the general productivity component is always fully reflected in wage rates through the component $\varepsilon_i + u_{it}$. Gibbons and Katz (1991) consider a model in which firms learn about general productivity. The firms know that differentiating among workers on the basis of wage rates will reveal who the good workers are to other employers. Instead, employers may choose to lay off workers with low general productivity rather than adjust wages downward. Gibbons and Katz note that in this case layoffs may signal negative information about the general component of productivity. As a result, layoffs may be associated with negative values of the time varying person specific wage component Δu_{it}. Their analysis suggests that losses from layoffs might be negatively related to time in the labor market. We think that it also suggests that, conditional on prior labor market experience, the losses from layoffs may decline with tenure. The idea is that the *rate* at which firms acquire new information about the general labor market productivity of workers declines with the number of years the worker has been at the firm. Consequently, the proportion of "lemons" among the more senior workers who are laid off is lower. (The lemons have already been laid off.) Since our regression coefficients on the seniority-layoff interactions will pick up the relationship between T_{it-1} at the time of layoff and $\Delta\varepsilon_{ij} + \Delta u_{it}$, the result is a positive bias in the estimates. This weakens the case for treating equations (3.1) and (3.2) as prior information.

Compensating Differentials for Layoff Risk. If heterogeneity in the layoff risk of jobs is easily observable to workers, then it may be partially reflected in ε_{ij} as a compensating differential for risk. (Heterogeneity in layoff risk would arise if the variance of e_{ijt} differs across firms.) This would reduce the negative correlation between ε_{ij} and the probability that a job will survive, which underlies our argument that the job match gain is a negative function of seniority. However, we doubt if this is important empirically, because the large variance of wage changes across jobs in our sample as well as Groshen's (1991) evidence point to a very large variance in $\varepsilon_{ij(t)}$, while the limited evidence on the size of compensating differentials for unemployment risk suggests that they are only modest (Abowd and Ashenfelter, 1981).

Seniority Rules. Inverse seniority plays an important role in layoff decisions in many union firms and is probably a consideration in nonunion firms as well. These rules weaken the ability of firms to layoff senior workers on the basis of $\omega_{ij(t)} + e_{ijt}$. Consequently, they have the effect of weakening the connection between layoffs and the wage components $\varepsilon_{ij(t)}$ and ν_{ijt} assuming that productivity component $\omega_{ij(t)} + e_{ijt}$ is partially reflected in the wage. We have already noted in Section III.2 that a positive effect of tenure on productivity tends to lead to a decline with tenure in the minimum value of $\omega_{ij(t)}$ such that a firm would initiate a layoff. Inverse seniority rules would reinforce this decline. Assuming $\omega_{ij(t)}$ is reflected in wages through $\varepsilon_{ij(t)}$, the decline in the minimum $\omega_{ij(t)}$ with tenure would lead to a more positive relationship between $E(\Delta\varepsilon_{ij(t)})$ and tenure at the time of a layoff. This weakens our basic argument for a negative effect of tenure on the job match gain. On the other hand, inverse seniority rules might also intensify selection on the basis of $\omega_{ij(t)}$ for less senior workers, because layoffs will be more concentrated among the less senior workers and the firm will have a bigger stake in making sure that workers who accumulate seniority in the firm are well matched. Furthermore, quit behavior would continue to induce a positive relationship between $\varepsilon_{ij(t)}$ and T_{it-1} among the sample of stayers. It is thus not clear whether layoff costs that are related to seniority strengthens or weakens the negative relationship between $\varepsilon_{ij(t)}$ and T_{it-1}. The relationship might be strengthened when tenure is low and weakened when tenure is high.

Assuming that workers value job security, the accumulation of job security with tenure (or any other nonpecuniary job attribute that accumulates with tenure, such as vacations or pension rights) will reinforce the positive effect that T_{it-1} will have on the reservation value of $\Delta\varepsilon_{ij(t)}$ required to induce a quit, which strengthens the argument leading to (3.1).

To summarize, our analysis provides fairly strong support for the proposition that $E(\Delta\varepsilon_{ij}|Q_{it}, X_{0ij(t-1)}, T_{it-1})$ will be positively related to T_{it} if there is a substantial return to seniority. The intuition is that the improvement in $\varepsilon_{ij(t)}$ must compensate for the lost tenure. We have also argued that $E(\Delta\varepsilon_{ij}|L_{it}, X_{0ij(t-1)}, T_{it-1})$ is negatively related to T_{it-1}. The intuition is that the longer the job has survived, the higher the expected value of ε_{ij} and so the more negative $E(\Delta\varepsilon_{ij}|L_{it}, X_{0ij(t-1)}, T_{it-1})$ is if the next job is a random draw from the offer distribution. In what follows we will treat the predictions from our basic model as prior information. However, it should be kept in mind that we also informally considered a number of modifications. These leave our prediction about tenure and quits intact. The prediction for layoffs is weakened if layoffs at low tenure levels are a more negative signal than a layoff at a high tenure level or if firms offering unstable employment pay compensating differentials. The effect of inverse seniority rules governing layoffs on our prediction that job match losses rise with tenure in the event of a layoff is unclear.

D. Other Prior Information

The above framework also suggests that the expected value of the job match gain is negative for persons with substantial seniority who are laid off. This places additional restrictions on the parameters of (2.5) that appear in (2.6). In the empirical work we use the restriction

$$g_0(X_{0ij(t-1)}) + g_1 + g_2T_{it-1} + g_3T^2_{it-1} + g_4T^3_{it-1} < 0 \qquad (3.4)$$

for T_{it-1} large. The basic idea underlying (3.4) is that jobs that survive to high tenure levels are unusually good jobs. Rather than take the combination of (3.4) for various values of $X_{0ij(t-1)}$ and large values of T_{it-1} we use the restriction

$$\bar{g}_0(X_{0ij(t-1)}) + g_1 + g_1\,(.1836chtime2) + g_2 15 + g_3 15^2 + g_4 15^3 < 0 \qquad (3.5)$$

where we set T_{it-1} to 15, $\bar{g}_0(X_{0ij(t-1)})$ is an average of the polynomial function $g_0(X_{0ij(t-1)})$ evaluated over the distribution of $X_{0ij(t-1)}$ conditional on a layoff with $T_{it-1} > 10$, *chtime*2 is a dummy for whether there are two years between observations and .1836 is the fraction of layoffs for which *chtime*2 = 1. We include the *chtime*2 variable as an ad hoc adjustment for the fact that time between jobs is negatively related to wage growth in the event of a layoff even though our model does not deal with duration of nonemployment between jobs. In earlier drafts of the paper we excluded the dummy variable and obtained similar results.

We also make use of prior information on the return to labor market experience. We obtain prior information that the return to 30 years of labor market experience is larger than .10 from the fact that OLS estimates of (2.1) imply a large return to tenure as well as a return to experience of .3 or .4. Altonji and Shakotko (1987) and Topel (1991) also obtain returns to experience well above .10. We obtain an upper bound on the return to labor market experience of .78 by adding 2 standard errors to the estimate implied by OLS estimation of (2.1) with the tenure terms *excluded.* Since experience is positively correlated with both tenure and the job match error component, this estimate is an upper bound. In the quadratic case these restrictions imply

$$0.10 < b_0 30 + b_1 30^2 \text{ and} \tag{3.6a}$$

$$0.78 > b_0 30 + b_1 30^2 \tag{3.6b}$$

with an obvious modification for the fourth order polynomial in X_{it} used in the empirical work.

Putting the Restrictions in a Useable Form

We cannot impose constraints (3.1) and (3.2) on the parameters d_2, d_3, d_4, and g_2, g_3, g_4 because in the wage change equation (2.6), d_2 and g_2 only appear in combination with b_2. However, these constraints imply the constraints

$$(b_2 - d_2) - 2d_3 T_{it-1} - 3d_4 T^2_{it-1} \le b_2 \le (b_2 - g_2) - 2g_3 T_{it-1} - 3g_4 T^2_{it-1}. \tag{3.7}$$

and

$$0 \ge (g_2 - b_2) + 2g_3 T_{it-1} + 3g_4 T^2_{it-1}. \tag{3.8}$$

for any $T_{it-1} > 0$, where (3.8) follows from (3.2) and the assumption that the return to seniority is non-negative in the early years on the job ($b_2 > 0$). Some of our estimates make direct use of (3.7) and (3.8) for values of T_{it-1} from 0 to 10.[24] We do not go beyond $T_{it-1} = 10$ because there are relatively few quits and layoffs beyond $T_{it-1} = 10$ and so the tenure slopes of the layoff gain and quit gains are imprecisely estimated at high values of tenure. We do not want the prior information about what the derivatives should be for high values of T_{it-1} to dominate inference about the derivatives at the low values, although in practice our results are very similar when we use (3.7) and (3.8) for values of T_{it-1} from 0 to 15.[25] For the same reason, we also report estimates that use the average value of the expressions in (3.7) and (3.8) as T_{it-1} ranges from 0 to 10 and make these the focus of much of our discussion below. Equations (3.1) and (3.2) imply

$$b_2 - \bar{d}(d_2, d_3, d_4) < b_2 < b_2 - \bar{g}(g_2, g_3, g_4). \tag{3.9}$$

$$0 < \bar{g}(g_2, g_3, g_4) - b_2 \tag{3.10}$$

where

$$\bar{d}(d_2, d_3, d_4) = d_2 + 10d_3 + 100d_4 = \frac{1}{10}\int_0^{10} (d_2 + 2d_3T_{it-1} + 3d_4T_{it-1}^2)dT_{it-1} > 0 \tag{3.11}$$

$$\bar{g}(g_2, g_3, g_4) = g_2 + 10g_3 + 100g_4 = \frac{1}{10}\int_0^{10} (g_2 + 2g_3T_{it-1} + 3g_4T_{it-1}^2)dT_{it-1} < 0. \tag{3.12}$$

The above restrictions require that derivative restrictions (3.1) and (3.2) hold on average over the interval from 0 to 10 rather than at each point above 0.

Similarly, from (2.6) we can identify $(b_0 + b_2)$ but not b_0, and therefore we cannot work directly with the prior restrictions (3.6a) and (3.6b). However, we combine (3.6a) and (3.1) and combine (3.6b) and (3.2) to obtain the restrictions

$$30[(b_0 + b_2) - (b_2 - (d_2 + 2d_3T_{it-1} + 3d_4T_{it-1}^2))] + 30^2b_1 \geq .10$$

$$30[(b_0 + b_2) - (b_2 - (g_2 + 2g_3T_{it-1} + 3g_4T_{it-1}^2))] + 30^2b_1 \leq .78$$

for all $T_{it-1} > 0$. Given that our estimates of the job match gain and layoff gain parameters are noisy, we average the above restrictions over values of T_{it-1} from 0 to 10, which amounts to combining (3.6a) with (3.11) and (3.6b) with (3.12) to obtain

$$30[(b_0 + b_2) - (b_2 - \bar{d})] + 30^2b_1 \geq .10 \tag{3.13}$$

$$30[(b_0 + b_2) - (b_2 - \bar{g})] + 30^2b_1 \leq .78 \tag{3.14}$$

IV. ECONOMETRIC METHODS

A. Combining the Prior Information and Sample Information

We use a Bayesian estimator based on Geweke (1986) to combine the prior and sample information. Geweke's estimator combines the normal linear regression model with a prior that is the product of an uninformative distribution and an indicator function. The indicator function is 1 when the inequality constraints are satisfied and 0 otherwise. Since the procedure is not well-known in the labor literature we provide a brief description based closely on Geweke (1986).

Let β denote the parameter vector of (2.6). Let the prior distribution for β be the diffuse, possibly improper prior $q(\beta)$, which assigns equal probability to all values of β that satisfy the inequality constraints and 0 to values that do not. Let $L(\beta; Y)$

denote the likelihood function. Let $\gamma(\beta)$ be a vector of scalar valued functions of the parameters that we are interested in. For example, one of the functions might return a particular element of β, such as $b_2 - g_2$, and others might be linear combinations, such as $10(b_2 - g_2) + 100b_3 + 1000b_4$, where b_4 is the coefficient on the cubic term of tenure, which we suppressed in (2.1) and the subsequent equations. Let β^k, $k = 1, \ldots, n$ be a random draw from a p.d.f equal to $L(\beta; Y)$. Geweke proposes that Monte Carlo integration be used to evaluate the mean of the posterior distribution of $\gamma(\beta^k)$, using

$$E[\gamma(\beta)] = \sum_{k=1}^{n} \gamma(\beta^k)q(\beta^k)/\sum q(\beta^k) \tag{4.1}$$

where n is set large enough to insure numerical accuracy, and the sample likelihood for the normal regression model is used in place of $L(\beta; Y)$. The computation is straightforward. We first estimate the normal regression model (2.6) and obtain the parameter estimate $\hat{\beta}$ with estimated variance $\hat{\Omega}_\beta$. We then draw n random vectors from a multivariate normal $N(\hat{\beta}, \hat{\Omega}_\beta)$, compute $\gamma(\beta^k)$ and $q(\beta^k)$ for each draw, and evaluate (4.1).[26] From the draws for which $q(\beta^k)$ is 1 we can compute the standard deviations of the elements of $\gamma(\beta)$. In the empirical section below, we report the mean and standard deviation of the posterior distribution of the parameters of (2.6). We also report the means and standard deviations for the upper and lower bounds for the effects of seniority and experience based on these parameters.[27] This provides us with the posterior distribution of $b_2 - g_2$ and $b_2 - d_2$, and $b_0 + b_2$ as well as of all of the other parameters in (2.6) that incorporates the prior information in (3.7), (3.8), (3.13), and (3.14) or in (3.9), (3.10), (3.13), and (3.14) when we impose the prior information on the average of the derivatives rather the derivatives at each value of T_{it-1}. However, neither of these sets of restrictions makes full use of the prior information on b_2, g_2, and d_2. In using $b_2 - \bar{g}$ to compute tenure effects we are implicitly setting $\bar{g}$ to 0 and ignoring the fact that this value for $\bar{g}$, given β^k, may be inconsistent with (3.5) and (3.6a). Consequently, for each replication we also solve for the largest value of b_2 and the associated values of g_2 and $\bar{g}$ that are consistent with both a negative job match gain in the event of a layoff when tenure is 15 and a return to experience of .10 or more. Call these value $b_2^{\max}$ and $g_2^{\max}$. This amounts to adding a complicated function of β^k to the vector of functions $\gamma(\beta^k)$ in (4.1).[28] We compute the mean and standard deviation of the posterior for $b_2^{\max}$ and $g_2^{\max}$ and various functions of the model parameters that summarize the returns to experience and seniority.

In addition to the Bayes estimates, we simply report the sample estimates of $b_2 - \bar{g}$, $b_2 - \bar{d}$, $b_0 + b_2$, and the other parameters. Given sampling variation there is no guarantee, of course, that the sample estimate of $b_2 - \bar{g}$ will exceed $b_2 - \bar{d}$ *even if the prior information is correct.* We obtain upward biased and downward biased estimates of the return to tenure by using $b_2 - \bar{g}$ and $b_2 - \bar{d}$ (respectively) in place of b_2.

B. Other Econometric Issues

The above analysis is conditional on knowledge of the secular time trend ϕ. To guard against bias from changes in the sample composition of the PSID resulting from attrition or changes in cohort quality, we obtain ϕ by estimating equation (2.1) with the time trend treated as endogenous using the other variables in the equation (including the experience and tenure terms) and deviations from individual means of time as instruments.[29]

We use WLS throughout the paper because the error variances are larger for quit and layoff observations. The weights are proportional to the error variances of OLS residuals for the within job observations, the observations on quits, and the observations on layoffs. We report White standard errors for the WLS estimates. These allow for arbitrary person specific patterns of heteroskedasticity and serial correlation over time for each person. The Bayes estimator uses the WLS estimator of the regression coefficients and covariance matrix to evaluate the sample likelihood function.

V. DATA

Most of our analysis is based upon the 1975–1987 waves of the Panel Study of Income Dynamics (PSID). Our sample is limited to white male heads of household. For a given year the sample contains individuals who were between the ages of 18–60 inclusive, were employed, temporarily laid off, or unemployed at the time of the survey, were not from Alaska or Hawaii, and were household heads in that year. We excluded persons who were household heads in fewer than three years between 1975–1987 or who never worked at least 1,000 hours or were never employed at the survey date. After an individual retires, any further information is excluded from the analysis. All observations from a particular job are excluded if the worker ever reports being self-employed or employed by the government while on that job. Observations with missing data on the variables in the wage equation are excluded for the particular sample year. We exclude observations on job changes if the person spends more than two years between jobs.

We work with three different samples. The first sample is based on the wage measure (WAGE1), which is the log of the reported hourly wage for the job held at the time of the survey (deflated by the implicit price deflator with a base year of 1982). WAGE1 is only available for hourly workers in 1975, is truncated at \$9.98 prior to 1978, and underestimates wage growth to the extent that paid vacations and holidays rise with tenure and experience. When WAGE1 is used T_{it} and union status refer to the same survey date as the reported wage. The second sample uses the log of real labor earnings during the preceding year divided by annual hours as the wage measure (WAGE2). For the average hourly earnings sample T_{it} refers to the time of the survey in the preceding year (typically in March or April). For job changers, average hourly earnings is presumably an average of the wage on each of the jobs weighted by the portion of the year spent in each. This may potentially lead to serious biases in the analysis of a first difference equation such as (2.6). For this reason, we strongly prefer WAGE1 to WAGE2. To minimize the impact of the top coding on WAGE1 we replaced the top-coded values for 1975–1977 with imputed values from a regression of WAGE1 on WAGE2 in 1978 for the sample in which WAGE1 exceeds the topcoat value of $9.98. We work with both measures primarily to facilitate comparison to the many previous studies, including Mincer and Jovanovic (1981), Altonji and Shakotko (1987), Abraham and Farber (1987), and Topel (1991) that have used WAGE2.[30]

Our third sample, which we will call the "combined" sample, combines observations based on the two wage samples, which are often overlapping. In the combined sample we do not use WAGE2 when it refers to the first year on job or the last year on a job. For job changes the wage change measure based on WAGE2 is typically the difference in the wage one year after the new job begins and the wage one year prior to the end of the previous job.[31] We are able to construct such wage change measures for only 127 of the 1,151 observations on the job changes in the WAGE2 sample and for 6,947 of 9,326 observations on stayers.[32] Our idea in using the combined sample is that we have two noisy, unbiased observations on the actual wage change, so we can improve efficiency over the WAGE1 sample by using both while avoiding problems in using WAGE2 when it is likely to be an average across two jobs.

The PSID does not allow employers to be precisely identified across surveys, so employer tenure, quits, and layoffs must be inferred. Briefly, we determine the starting and stopping dates of all jobs held by the individual from data on the reason for leaving the previous employer, employment status, and other variables indicating a change in employers.[33] Although within a job tenure should increase one for one with time, the reported data often fail to satisfy this criterion as tenure sometimes remains constant, falls, or jumps dramatically from one survey to the next. We attack this problem in three steps. First, we weight the reported data within a job with a measure of how consistent the data point is with the tenure reports on the job. Second, we estimate the initial tenure on a job using the weighted data. Third, we increase tenure by one year for each subsequent year of the job. If this process results in an estimate of initial tenure less than zero, initial tenure is set to one month. If this process results in an estimate of initial tenure which is greater than two years, the current job and all subsequent jobs are excluded from the sample. We implemented this last rule to exclude jobs with large tenures which we have identified as starting during the sample period. This might have occurred due to an inability to identify a return to a previous employer. When the reason for job changes is unavailable or we are unable to classify the job change into a quit or a layoff based on the reason given, we have excluded the observation. Despite our efforts, there is probably still significant measurement error in our estimates of the level of tenure, and we probably miss some separations entirely and infer some separations that never happened. The resulting measurement error in the tenure variables is likely to bias downward both least squares estimates based on equation (2.1) and estimates based on (2.6). The bias will be more severe for (2.6).[34] We doubt, however, that measurement error is likely to be much more serious for our estimator than for the estimators used in Topel and Altonji and Shakotko.

We are also concerned with the possibility that persons were laid off from the job held at survey in $t-1$ found another one, quit it, and obtained another job by the survey in t. Our methodology would classify the move from the job held at the survey in $t-1$ to the job held at the survey in t as a quit, while from the point of view of our model it should be classified as a layoff because the job held at $t-1$ ended in a layoff. Misclassifications of this sort weaken the case that we have bounds.

To provide a further check on whether data quality is an important issue, we also report the results of a limited analysis based on the National Longitudinal Survey of Youth (NLSY) through 1992. The NLSY has better data on tenure and separations because respondents are asked to name their employers, which makes it much easier to track tenure across surveys. Recent studies by Light and McGarry (1993) and Parent (1995) obtain low returns to seniority using methods similar to Altonji and Shakotko. However, the mean of seniority for the young men in these studies is less than three years, and so one must extrapolate outside of sample to draw inferences about the value of 10 years of seniority from NLSY. In Section VII we apply our methods using the NLSY data and obtain estimates of the returns to tenure that are similar to those for our preferred wage measure from the PSID. This suggests that measurement error is not dominating our PSID results.

In the PSID we construct current experience as follows. First, we estimate the initial level of experience in the year before the worker entered the sample. This is done using reported accumulated years of experience for workers in the year they became a head, and in 1974, 1976, and 1985 if these years follow the year the worker became a head. Current experience is then obtained by incrementing initial experience whenever the individual is observed to be employed, which ensures that within a job, current experience and tenure increment identically.[35]

We use a number of standard control variables from the PSID that do not require discussion. We set education to the mean of the values reported for the person.

VI. RESULTS FOR THE PSID

A. Some Descriptive Statistics

The WAGE1 sample consists of 9,961 wage change observations on 1,802 individuals and 2,683 job matches.[36] In the entire sample 63.3% of the individuals never change jobs, 22.7% change jobs once, and the remaining 14.0% change jobs more than once. 72.0% of the sample never quit, 19.7% quit once, and 8.3% quit more than one job. Similarly, 85.5% of the sample is never laid off, 11.0% are laid off once, and 3.6% are laid off more than once.[37,38] Appendix Table A-1 presents the means for the full sample, for stayers, for quits, for all layoffs, and for layoffs due to a plant closing. The annual quit rate, layoff rate, and layoff rate due to plant closing are .0710, .0344, and .0111. The overall mean of ΔWAGE1 (the change in the reported wage at the survey) is .0247. The mean (standard error) is .0383 (.0105) for movers and .0231 (.0017) for stayers. After a quit there is a mean wage increase of .0719 (.0123), while a layoff reduces wages by −.0310 (.0194). The mean wage growth for WAGE1 is lower for stayers and higher for movers than for WAGE2.

B. Wage Growth by Experience and Tenure

Before turning to the econometric analysis, we use Table 1a–c to present the means (standard errors of the means) of the change in the log wage, ΔWAGE1, by experience and tenure category for stayers, quits, and layoffs. Consider first wage growth for stayers in Table 1a. When lagged tenure is less than 1 the wage growth for stayers falls from .056 when experience is between 0 and 5 to .013 for experience greater than 20. This is consistent with a strong effect of experience on wages that diminishes with time in the labor market. The pattern is similar in the 1–3 and 3–6 tenure categories. The pattern is also similar in Table 2a, which uses ΔWAGE2. Wage growth within jobs has a weak negative relationship with tenure holding experience constant. These results are potentially consistent with a substantial but relatively constant return to each year of additional tenure. Assuming the effect of experience is substantial, then the effect of tenure would seem to be much smaller than the value implied by the OLS estimates of (2.1) that we present below.

In the case of quits in Table 1b, wage growth drops dramatically with experience when tenure at the end of the previous job is less than 1 but does not vary much with experience in the higher tenure categories relative to the standard errors of the cell means. For layoffs in Table 1c there is also a drop in wage growth at higher experience levels when tenure is between 0 and 1 or 1 and 3 but not in the 3 to 6 category. Overall, Tables 1a–c indicate that wage growth within and across jobs tends to fall as experience increases, holding tenure constant.

Holding experience constant and reading across the rows, we observe that mean wage growth for quits shows a decline with tenure holding experience constant. For example, in the 5 to 10 year experience category, wage growth is .136 (.031) if tenure on the previous job is less than 1 and .012 (.089) if tenure is between 6 and 15 years. The theoretical analysis suggests that this relationship will understate the partial effect of tenure on wage levels. For layoffs in the bottom panel we observe a similar modest decline in wage growth with previous tenure. The theory suggests that this relationship will overstate the return to tenure. (The standard errors are quite large for some of the cells.)

Table 1. Log Wage Change (ΔWage1) by Lagged Tenure and Experience

A: STAYERS

Experience Level	*Tenure in Previous Year* $0 \le T_{it-1} < 1$	$1 \le T_{it-1} < 3$	$3 \le T_{it-1} < 6$	$6 \le T_{it-1} < 15$	$T_{it-1} \ge 15$
$0 \le X_{it} < 5$	0.0563 (0.0164)	0.0828 (0.0126)	0.0709 (0.0282)		
$5 \le X_{it} < 10$	0.0502 (0.0098)	0.0627 (0.0067)	0.0352 (0.0065)	0.0047 (0.0107)	
$10 \le X_{it} < 20$	0.0379 (0.0134)	0.0303 (0.0062)	0.0286 (0.0057)	0.0158 (0.0038)	–0.0009 (0.0139)
$X_{it} \ge 20$	0.0132 (0.0205)	0.0188 (0.0089)	0.0173 (0.0088)	0.0043 (0.0052)	0.0079 (0.0037)

B: QUITS

Experience Level	*Tenure in Previous Year* $0 \le T_{it-1} < 1$	$1 \le T_{it-1} < 3$	$3 \le T_{it-1} < 6$	$6 \le T_{it-1} < 15$	$T_{it-1} \ge 15$
$0 \le X_{it} < 5$	0.2561 (0.0559)	–0.0168 (0.0811)	0.0324 (0.1301)		
$5 \le X_{it} < 10$	0.1364 (0.0313)	0.1031 (0.0409)	–0.0131 (0.0566)	0.0120 (0.0889)	
$10 \le X_{it} < 20$	0.0418 (0.0289)	0.0664 (0.0364)	0.0286 (0.0394)	0.0237 (0.0443)	0.0055 (0.3002)
$X_{it} \ge 20$	0.1132 (0.0449)	0.0569 (0.0640)	0.0259 (0.0867)	–0.0676 (0.0689)	–0.0527 (0.1135)

C: LAYOFFS

Experience Level	*Tenure in Previous Year* $0 \le T_{it-1} < 1$	$1 \le T_{it-1} < 3$	$3 \le T_{it-1} < 6$	$6 \le T_{it-1} < 15$	$T_{it-1} \ge 15$
$0 \le X_{it} < 5$	0.0273 (0.0677)	–0.0516 (0.1266)			
$5 \le X_{it} < 10$	0.0147 (0.0478)	–0.0099 (0.0677)	–0.1635 (0.0746)		
$10 \le X_{it} < 20$	0.0948 (0.0538)	–0.0695 (0.0564)	–0.1671 (0.0762)	–0.0673 (0.0654)	
$X_{it} \ge 20$	–0.0582 (0.0812)	–0.1405 (0.0871)	–0.0373 (0.1282)	–0.0415 (0.0839)	–0.1810 (0.0839)

Notes: The upper number in each cell of the table is the mean wage change, while the number in parentheses is the standard error of the mean. There are a total of 9,961 wage change observations, with 8,911 of these being stayers, 707 quits, and 343 layoffs. The standard errors are computed under the assumption that the variance is constant within three experience-lagged tenure cells: i) experience is less than 10; ii) lagged tenure is less than 1 and experience is greater than or equal to 10; iii) tenure is greater than or equal to one and experience is greater than or equal to 10.

Table 2. Log Earnings Change (ΔWage2) by Lagged Tenure and Experience

A: STAYERS

Tenure in Previous Year

Experience Level	$0 \leq T_{it-1} < 1$	$1 \leq T_{it-1} < 3$	$3 \leq T_{it-1} < 6$	$6 \leq T_{it-1} < 15$	$T_{it-1} \geq 15$
$0 \leq X_{it} < 5$	0.1028 (0.0242)	0.0771 (0.0190)	0.0048 (0.0445)		
$5 \leq X_{it} < 10$	0.0697 (0.0143)	0.0718 (0.0101)	0.0358 (0.0099)	0.0248 (0.0169)	
$10 \leq X_{it} < 20$	0.0375 (0.0159)	0.0444 (0.0086)	0.0308 (0.0080)	0.0123 (0.0054)	0.0364 (0.0206)
$X_{it} \geq 20$	0.0881 (0.0236)	0.0213 (0.0125)	0.0188 (0.0120)	0.0085 (0.0072)	0.0147 (0.0053)

B: QUITS

Tenure in Previous Year

Experience Level	$0 \leq T_{it-1} < 1$	$1 \leq T_{it-1} < 3$	$3 \leq T_{it-1} < 6$	$6 \leq T_{it-1} < 15$	$T_{it-1} \geq 15$
$0 \leq X_{it} < 5$	0.1325 (0.0678)	–0.1506 (0.1014)	0.0555 (0.1756)		
$5 \leq X_{it} < 10$	0.1034 (0.0386)	0.1428 (0.0523)	–0.0209 (0.0774)	–0.1170 (0.1200)	
$10 \leq X_{it} < 20$	0.0358 (0.0316)	0.0601 (0.0438)	–0.0150 (0.0441)	–0.0226 (0.0553)	
$X_{it} \geq 20$	0.1043 (0.0542)	0.0261 (0.0690)	0.0324 (0.1081)	–0.0799 (0.0782)	–0.2365 (0.1081)

C: LAYOFFS

Tenure in Previous Year

Experience Level	$0 \leq T_{it-1} < 1$	$1 \leq T_{it-1} < 3$	$3 \leq T_{it-1} < 6$	$6 \leq T_{it-1} < 15$	$T_{it-1} \geq 15$
$0 \leq X_{it} < 5$	–0.0176 (0.0833)	–0.1574 (0.1418)			
$5 \leq X_{it} < 10$	–0.0026 (0.0599)	–0.0239 (0.0819)	–0.2799 (0.1003)	–0.3960 (0.4485)	
$10 \leq X_{it} < 20$	0.0667 (0.0496)	–0.0274 (0.0687)	–0.1383 (0.0960)	–0.1960 (0.0876)	
$X_{it} \geq 20$	0.0191 (0.0685)	–0.0806 (0.1109)	–0.2810 (0.1623)	0.0113 (0.1294)	–0.3279 (0.1109)

Notes: See Table 1. There are a total of 10,477 earnings change observations, with 9,326 of these being stayers, 784 quits, and 367 layoffs.

The results using ΔWAGE2 are similar to those using ΔWAGE1 in the case of stayers. (Compare Table 1a and Table 2a). The main difference is that growth rates in the first year on the job are higher in Table 2a. This may be related to the fact that ΔWAGE2 is a mixture of wages on the old job and the new job for jobs that have been in progress for less than one year. In Table 2c wage losses in the event of a layoff appear to be larger and more negatively related to seniority than those in Table 1c.

Overall, the evidence is potentially consistent with a modest positive return to tenure. The layoff results seem inconsistent with the large OLS estimates of the return to tenure reported below and in other studies.

C. Estimates of the Return to Seniority Based on OLS, Altonji and Shakotko, and Topel

In Altonji and Williams (1997) we present estimates of the returns to various amounts of tenure and experience based on OLS, Altonji and Shakotko's (IV1), and Topel's estimators. We do this for various samples, including those used by Altonji and Shakotko and Topel, and the WAGE1 and WAGE2 samples used here. We discuss these briefly to provide background for the results based on the approach of the present paper.[39] In Table 3 we present the basic results for the WAGE1, WAGE2, and the combined samples. Columns 2, 6, and 10 report OLS estimates. For WAGE1 and WAGE2 the return to 10 years of seniority is .277 (.01) and .351 (.01), respectively. These estimates are almost three times as large as those based on AS's IV1 estimator (columns 3, 7, and 11) and almost two times as large as the estimates for Topel's estimator (columns 4, 8, and 12). In contrast, Topel (1991) found that the OLS estimates are only slightly larger. As noted above, Altonji and Williams (1997) argue that Topel's results for his estimator and especially for the AS estimator are biased upward by the use of a real wage trend based on the CPS and by the fact that his seniority measure and his wage measure do not refer to the same year. However, the OLS results and the IV1 results for WAGE2 are larger than the OLS and IV1 estimates reported by AS using this wage measure. This difference across samples may be due to greater measurement error in AS's and Topel's tenure data and/or to increases over time in the return to seniority. The latter would be in keeping with large increases in the return to schooling and experience.

Finally, note that the returns to seniority are somewhat higher for WAGE2 than WAGE1, with the results for the combined sample in between. The insensitivity of the OLS estimates of the return to 30 years of experience with the tenure measure excluded (columns 1 and 5) suggests that only the partition of the returns between tenure and experience is sensitive to the use of the time averaged wage measure. There are good reasons to prefer the WAGE1 measure on a priori grounds, but it should be kept in mind when comparing across studies that it does lead to somewhat smaller tenure estimates.

We now turn to the formal econometric analysis based on (2.6).

Table 3. OLS, IV1 and Topel Estimators

	Wage1 Sample				*Wage2 Sample*				*Combined Sample*			
	OLS	*OLS*	*IV1*	*Topel*	*OLS*	*OLS*	*IV1*	*Topel*	*OLS*	*OLS*	*IV1*	*Topel*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
2 Years of Tenure		0.0825	0.0350	0.0458		0.1041	0.0437	0.0699		0.0905	0.0400	0.0554
		(0.0041)	(0.0080)	(0.0075)		(0.0044)	(0.0088)	(0.0100)		(0.0034)	(0.0066)	(0.0067)
10 Years of Tenure		0.2768	0.1026	0.1459		0.3513	0.1206	0.2020		0.3065	0.1132	0.1828
		(0.0106)	(0.0232)	(0.0226)		(0.0114)	(0.0255)	(0.0286)		(0.0090)	(0.0194)	(0.0207)
15 Years of Tenure		0.3189	0.1118	0.1635		0.4077	0.1236	0.2052		0.3558	0.1177	0.2122
		(0.0111)	(0.0290)	(0.0265)		(0.0120)	(0.0323)	(0.0327)		(0.0093)	(0.0239)	(0.0246)
10 Years of Experience	0.4342	0.2871	0.3581	0.3744	0.4280	0.2459	0.3368	0.3165	0.4694	0.2904	0.3823	0.3571
	(0.0285)	(0.0282)	(0.0306)	(0.0474)	(0.0331)	(0.0296)	(0.0323)	(0.0639)	(0.0249)	(0.0246)	(0.0268)	(0.0449)
30 Years of Experience	0.7074	0.4492	0.5777	0.4869	0.7218	0.3871	0.5798	0.3794	0.7476	0.4441	0.6181	0.4758
	(0.0262)	(0.0268)	(0.0406)	(0.0492)	(0.0300)	(0.0277)	(0.0440)	(0.0602)	(0.0231)	(0.0235)	(0.0351)	(0.0487)

Notes: Columns 1 to 4 contain results when the WAGE1 sample is used. The sample size in columns 1–3 is 12,609. For the Topel two-step estimator used in column 4, the first-step within-job sample contains 8,911 observations, while the second-step sample contains 12,609 observations. Columns 5 to 8 contain results when the Wage2 sample is used. The sample size in columns 5–7 is 13,108. For the Topel estimator used in column 8, the within-job sample contains 9,326 observations, while the second-step sample contains 13,108 observations. Columns 9 to 12 report results for the "combined" sample. The sample size in columns 9–11 is 21,385. For the Topel estimator used in column 12, the within-job sample contains 15,858 observations, while the second-step sample containse 21,385 observations. Estimates in columns 1, 2, 5, 6, 9, and 10 are based on OLS which includes an exogenous time trend. The IV1 results in columns 3, 7, and 11 treat both the time trend and the tenure variables as endogenous. The deviation of the tenure variables from their job means are used as instruments, along with the deviation of time from its mean for each individual. The estimates in columns 4, 8, and 12 are based on Topel's two-step estimator. The time trend estimate is taken from an IV specification where time is instrumented with the deviations of time from each individuals mean. The basic specification in all columns includes a quartic in experience and the interaction of experience with education. A cubic specification in tenure is used, except in columns 1, 5, and 9. Other variables included in the OLS, IV1, and Topel's second-step include an intercept, education, and dummies for marital status, residence in an SMSA, residence in large city, disability status, membership in a union, and 3 regional dummies.

D. Estimates of the Wage Growth Equations

In column 1 of Table 4 we report weighted least squares (WLS) estimates of (2.6) using ΔWAGE1 as the dependent variable (White standard errors in parentheses). In column 2 we report the Bayes estimates. All equations in the table include the time interval between the first differenced observations (always 1 for stayers), the change in the square, cube, and quartic of experience, the change in the square and cubic of tenure, quit and layoff dummies, the dummy variable $Q_{it}chtime2$ equal to 1 if a quit occurred and the time gap between observations is two years, and a similar dummy for layoffs.[40] Since the change in education minus 12 times experience is also included, the coefficient on time is the sum of the effect of an additional year of experience, an additional year of tenure, and the secular time trend for an individual with 12 years of education.[41] We include interactions between T_{it-1}, T^2_{it-1}, and T^3_{it-1} and both Q_{it} and L_{it} in (2.6). We also include interactions between Q_{it} and L_{it} and the level, square and cube of $X_{0ij(t-1)}$.

Table 4. Wage Change Equations (Equation 2.6)

	ΔWAGE1		ΔWAGE2		Combined	
	WLS	*Bayes*	*WLS*	*Bayes*	*WLS*	*Bayes*
Variable	*1*	*2*	*3*	*4*	*5*	*6*
ΔTime	0.0898	0.0891	0.1080	0.1080	0.0889	0.0864
	(0.0095)	(0.0106)	(0.0129)	(0.0149)	(0.0089)	(0.0091)
$\Delta T^2_{it}/10$	−0.0134	−0.0132	−0.0230	−0.0230	−0.0146	−0.0150
	(0.0029)	(0.0036)	(0.0043)	(0.0041)	(0.0025)	(0.0026)
$\Delta T^3_{it}/100$	0.0024	0.0023	0.0041	0.0041	0.0026	0.0027
	(0.0005)	(0.0007)	(0.0009)	(0.0011)	(0.0005)	(0.0005)
$\Delta X^2_{it}/10$	−0.0386	−0.0381	−0.0458	−0.0456	−0.0341	−0.0314
	(0.0085)	(0.0100)	(0.0117)	(0.0139)	(0.0079)	(0.0080)
$\Delta X^3_{it}/100$	0.0106	0.0105	0.0135	0.0134	0.0093	0.0084
	(0.0028)	(0.0035)	(0.0039)	(0.0048)	(0.0026)	(0.0027)
$\Delta X^4_{it}/1000$	−0.0011	−0.0011	−0.0014	−0.0014	−0.0010	−0.0009
	(0.0003)	(0.0004)	(0.0004)	(0.0006)	(0.0003)	(0.0003)
$\Delta\{X^*_{it}(Educ-12)\}$	0.0014	0.0015	0.0030	0.0029	0.0015	0.0015
	(0.0006)	(0.0007)	(0.0007)	(0.0010)	(0.0005)	(0.0005)
Q_{it}	0.0816	0.0742	−0.0414	−0.0459	0.0855	0.0939
	(0.0397)	(0.0404)	(0.0539)	(0.0511)	(0.0397)	(0.0440)
L_{it}	−0.0592	−0.0345	−0.1739	−0.1618	−0.0393	−0.0044
	(0.0548)	(0.0579)	(0.0717)	(0.0705)	(0.0585)	(0.0725)
$Q^*_{it}\Delta Time2$	−0.0393	−0.0406	−0.0858	−0.0865	−0.0523	−0.0637
	(0.0370)	(0.0400)	(0.0548)	(0.0504)	(0.0379)	(0.0461)
$L^*_{it}\Delta Time2$	−0.1851	−0.1812	−0.2244	−0.2223	−0.1946	−0.1974
	(0.0422)	(0.0472)	(0.0692)	(0.0581)	(0.0410)	(0.0437)

(continued)

Table 4. Continued

	ΔWAGE1		*ΔWAGE2*		*Combined*	
	WLS	*Bayes*	*WLS*	*Bayes*	*WLS*	*Bayes*
Variable	*1*	*2*	*3*	*4*	*5*	*6*
$Q^*_{it}T_{it-1}$	−0.0351	−0.0324	−0.0150	−0.0133	−0.0346	−0.0340
	(0.0116)	(0.0122)	(0.0132)	(0.0140)	(0.0113)	(0.0131)
$Q^*_{it}T^2_{it-1}/10$	0.0211	0.0247	−0.0193	−0.0199	0.0179	0.0147
	(0.0126)	(0.0154)	(0.0144)	(0.0163)	(0.0118)	(0.0128)
$Q^*_{it}T^3_{it-1}/100$	−0.0061	−0.0061	0.0033	0.0033	−0.0052	−0.0043
	(0.0029)	(0.0040)	(0.0032)	(0.0037)	(0.0027)	(0.0030)
$Q^*_{it}X_{0ij(t-1)}$	0.0043	0.0048	0.0216	0.0220	0.0027	0.0010
	(0.0091)	(0.0098)	(0.0130)	(0.0130)	(0.0092)	(0.0104)
$Q^*_{it}X^2_{0ij(t-1)}/10$	−0.0077	−0.0079	−0.0170	−0.0170	−0.0065	−0.0051
	(0.0066)	(0.0071)	(0.0096)	(0.0097)	(0.0067)	(0.0076)
$Q^*_{it}X^3_{0ij(t-1)}/100$	0.0019	0.0019	0.0036	0.0036	0.0017	0.0016
	(0.0013)	(0.0014)	(0.0020)	(0.0020)	(0.0013)	(0.0015)
$L^*_{it}T_{it-1}$	−0.0380	−0.0488	−0.0440	−0.0492	−0.0421	−0.0480
	(0.0152)	(0.0140)	(0.0175)	(0.0177)	(0.0160)	(0.0183)
$L^*_{it}T^2_{it-1}/10$	0.0271	0.0334	0.0101	0.0131	0.0294	0.0342
	(0.0164)	(0.0163)	(0.0181)	(0.0199)	(0.0182)	(0.0209)
$L^*_{it}T^3_{it-1}/100$	−0.0073	−0.0082	−0.0034	−0.0038	−0.0083	−0.0098
	(0.0042)	(0.0039)	(0.0044)	(0.0047)	(0.0048)	(0.0053)
$L^*_{it}X_{0ij(t-1)}$	0.0179	0.0158	0.0458	0.0449	0.0120	0.0036
	(0.0152)	(0.0155)	(0.0178)	(0.0187)	(0.0156)	(0.0188)
$L^*_{it}X^2_{0ij(t-1)}/10$	−0.0118	−0.0105	−0.0300	−0.0295	−0.0083	−0.0034
	(0.0104)	(0.0116)	(0.0132)	(0.0139)	(0.0107)	(0.0126)
$L^*_{it}X^3_{0ij(t-1)}/100$	0.0022	0.0019	0.0056	0.0055	0.0016	0.0009
	(0.0020)	(0.0023)	(0.0027)	(0.0028)	(0.0020)	(0.0023)
b_2^{max}	NA	0.0178	NA	0.0365	NA	0.0187
		(0.0057)		(0.0069)		
$b_2 - \bar{a}$	0.0201	0.0181	0.0310	0.0298	0.0220	0.0205
	(0.0046)	(0.0047)	(0.0061)	(0.0065)	(0.0044)	(0.0047)
$b_2 - \bar{g}$	0.0182	0.0235	0.0373	0.0399	0.0209	0.0259
	(0.0063)	(0.0051)	(0.0080)	(0.0073)	(0.0063)	(0.0070)

Notes: [1]The ΔWage1 sample size is 9,961 in columns 1–2, the ΔWage2 sample in columns 3–4 is 10,477, and the combined wage and earnings sample excluding possible job mixtures in columns 5–6 is 17,035. The R^2 in columns 1, 3, and 6 are .0433, .0309, and .0368. These refer to the weighted data. The equations are variants of equation (2.6).

[2]The equations in columns 1, 3, and 5 are estimated by weighted least squares using the OLS residuals to estimate weights for the within job observations, quits and layoffs. White standard errors from the weighted least squares regression are in parentheses. For the merged sample, separate GLS weights are estimated for the wage and earnings observations. See the text for a description of the Bayes estimates in columns 2, 4, and 6. These combine the sample information summarized in the WLS estimates with a set of inequality priors on the parameters. Standard deviations of the posterior distribution are in parentheses.

Since the models are highly nonlinear we summarize what the estimates imply about the returns to tenure and experience in Table 5 rather than dwell on the specific coefficients in Table 4. However, we begin by discussing the estimates of $b_2 - \bar{d}$ and $b_2 - \bar{g}$, which are reported at the bottom of the Table 4. The WLS estimator used in column 1 does not incorporate the prior information that $b_2 - \bar{d} < b_2 - \bar{g}$, while the Bayes1 and Bayes2 estimators do. The Bayes1 estimator incorporates the restrictions on the average derivatives (3.9), (3.10) as well as (3.13) and (3.14), while the Bayes2 estimator replaces (3.9) and (3.10) with the restriction that (3.7), (3.8) are satisfied at every value of T_{it-1} between 0 and 10 rather than on average between 0 and 10. To save space, we only report the full set of parameter estimates for the Bayes1 estimator, which for reasons discussed above we prefer to Bayes2.[42]

The estimate of $b_2 - \bar{d}$ in column 1 is .0201 (.0046). Recall that $\bar{d}$ is the average derivative of the conditional mean of the change in the job match component $\varepsilon_{ij(t)}$ in the event of a quit. We argued above that $\bar{d}$ will be positive unless the true effect of tenure on wages and mobility costs is small. The parameter $\bar{g}$ is the average derivative of the conditional mean of the change in the job match component $\varepsilon_{ij(t)}$ in the event of a layoff. We have argued that $\bar{g} < 0$. The estimate of $b_2 - \bar{g}$ is .0182 (.0063), which is slightly below the estimate of .0201 for $b_2 - \bar{d}$ even though the theoretical analysis implies that $b_2 - \bar{d} < b_2 - \bar{g}$. Although the point estimates violate the theoretical restriction on the tenure slopes of the job match gain in the event of a quit and a layoff, the point estimates are close in size and only about 1/3 of a standard error apart so there is little evidence against the model.

In column 2 we report that the Bayes1 estimates of the mean (standard deviation) of the posterior for $b_2 - \bar{d}$ is .0181 (.0047). The corresponding values for $b_2 - \bar{g}$ are .0235 (.0051). The posterior for $b_2^{\max}$ has a mean (standard deviation) of 0.0178 (.0057) which naturally is below $b_2 - \bar{g}$ and is about equal to the WLS estimate of $b_2 - \bar{g}$.[43] The incorporation of the prior information leads to small changes in the other coefficients as well. The relatively small changes in the coefficients that are mainly identified from within job wage growth is not surprising, because only the priors (3.13) and (3.14) about the return to experience directly affect these coefficients. The relatively small difference between the sample estimates and the posteriors for $b_2 - \bar{d}$ and $b_2 - \bar{g}$ reflect the fact that the data are reasonably concordant with the priors.

In columns 3 and 4 we report WLS and Bayes1 estimates using ΔWAGE2. The WLS point estimates of $b_2 - \bar{d}$ and $b_2 - \bar{g}$ are .0310 (.0061) and .0373 (.0080), respectively, which satisfy the restrictions $\bar{d} > 0$ and $\bar{g} < 0$. When the prior information is incorporated the mean (standard deviation) of the posterior for $b_2 - \bar{d}$ falls to .0298 (.0065) while $b_2 - \bar{g}$ rises to .0399 (.0073). The posterior of $b_2^{\max}$ has a mean of .0365.

The estimates for the combined sample are in between those for the separate samples (columns 5 and 6). The WLS point estimates of $b_2 - \bar{d}$ and $b_2 - \bar{g}$ are very close (column 5).

Table 5. Estimates of the Return to Tenure and Experience[1]

Panel A: Wage1 Sample

	WLS,[2] b_2 set to $b_2 - \bar{d} = .0201$	WLS,[2] b_2 set to $b_2 - \bar{g} = .0182$	Bayes1,[3] b_2 set to $b_2 - \bar{d} = .0181$	Bayes1,[3] b_2 set to $b_2 - \bar{g} = .0235$	Bayes1,[3] b_2 set to $b_2^{max} = .0178$	Bayes2,[4] b_2 set to $b_2 - \bar{d} = .0173$	Bayes2,[4] b_2 set to $b_2 - \bar{g} = .0254$	Bayes2,[4] b_2 set to $b_2^{max} = .0191$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2 years of tenure	0.0350	0.0312	0.0312	0.0420	0.0305	0.0293	0.0456	0.0329
	(0.0085)	(0.0122)	(0.0086)	(0.0094)	(0.0105)	(0.0085)	(0.0092)	(0.0080)
10 years of tenure	0.0906	0.0718	0.0723	0.1262	0.0690	0.0604	0.1417	0.0782
	(0.0376)	(0.0585)	(0.0352)	(0.0400)	(0.0410)	(0.0364)	(0.0411)	(0.0312)
15 years of tenure	0.0798	0.0516	0.0528	0.1336	0.0478	0.0331	0.1550	0.0598
	(0.0571)	(0.0886)	(0.0537)	(0.0608)	(0.0584)	(0.0558)	(0.0629)	(0.0460)
5 years of experience	0.2681	0.2774	0.2751	0.2482	0.2854	0.2814	0.2408	0.2725
	(0.0393)	(0.0438)	(0.0398)	(0.0400)	(0.0458)	(0.0396)	(0.0398)	(0.0375)
10 years of experience	0.4137	0.4325	0.4290	0.3751	0.4323	0.4416	0.3603	0.4238
	(0.0596)	(0.0726)	(0.0581)	(0.0595)	(0.0615)	(0.0583)	(0.0595)	(0.0532)
30 years of experience	0.6369	0.6932	0.6855	0.5238	0.6954	0.7271	0.4833	0.6737
	(0.1287)	(0.1849)	(0.1210)	(0.1294)	(0.1274)	(0.1249)	(0.1334)	(0.1043)

Panel B: Wage2 Sample

	WLS,[2] b_2 set to $b_2-\bar{d}=.0301$	WLS,[2] b_2 set to $b_2-\bar{g}=.0373$	Bayes1,[3] b_2 set to $b_2-\bar{d}=.0298$	Bayes1,[3] b_2 set to $b_2-\bar{g}=.0399$	Bayes1,[3] b_2 set to $b_2^{max}=.0365$	Bayes2,[4] b_2 set to $b_2-\bar{d}=.0287$	Bayes2,[4] b_2 set to $b_2-\bar{g}=0.0418$	Bayes2,[4] b_2 set to $b_2^{max}=.0400$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2 years of tenure	0.0531	0.0656	0.0507	0.0709	0.0641	0.0484	0.0748	0.0711
	(0.0113)	(0.0153)	(0.0065)	(0.0135)	(0.0124)	(0.0118)	(0.0132)	(0.0118)
10 years of tenure	0.1204	0.1832	0.1094	0.2101	0.1761	0.0985	0.2302	0.2114
	(0.0483)	(0.0710)	(0.0474)	(0.0583)	(0.0470)	(0.0474)	(0.0566)	(0.0044)
15 years of tenure	0.0848	0.1790	0.0687	0.2198	0.1687	0.0525	0.2502	0.2219
	(0.0737)	(0.1074)	(0.0728)	(0.0890)	(0.0688)	(0.0727)	(0.0866)	(0.0652)
5 years of experience	0.2696	0.2382	0.2741	0.2238	0.2408	0.2988	0.2329	0.2420
	(0.0520)	(0.0579)	(0.0569)	(0.0589)	(0.0560)	(0.0559)	(0.0570)	(0.0541)
10 years of experience	0.3996	0.3368	0.4093	0.3085	0.3426	0.4588	0.3271	0.3460
	(0.0774)	(0.0927)	(0.0833)	(0.0891)	(0.0815)	(0.0819)	(0.0857)	(0.0779)
30 years of experience	0.6217	0.4333	0.6511	0.3488	0.4510	0.8001	0.4048	0.4615
	(0.1627)	(0.2255)	(0.1695)	(0.1965)	(0.1585)	(0.1686)	(0.1872)	(0.1487)

(continued)

Table 5. Continued

	Panel [illegible]: "Combined" Sample							
	WLS,[2] b_2 set to $b_2 - \bar{d} = .0220$	WLS,[2] b_2 set to $b_2 - \bar{g} = .0209$	Bayes1,[3] b_2 set to $b_2 - \bar{d} = .0205$	Bayes1,[3] b_2 set to $b_2 - \bar{g} = .0259$	Bayes1,[3] b_2 set to $b_2^{max} = .0187$	Bayes2,[4] b_2 set to $b_2 - \bar{d} = .0194$	Bayes2,[4] b_2 set to $b_2 - \bar{g} = .0270$	Bayes2,[4] b_2 set to $b_2^{max} = .0218$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2 years of tenure	0.0383 (0.0083)	0.0363 (0.0124)	0.0355 (0.0078)	0.0461 (0.0087)	0.0317 (0.0089)	0.0330 (0.0078)	0.0484 (0.0089)	0.0366 (0.0076)
10 years of tenure	0.1002 (0.0372)	0.0899 (0.0594)	0.0857 (0.0375)	0.1389 (0.0374)	0.0669 (0.0358)	0.0733 (0.0334)	0.1494 (0.0396)	0.0907 (0.0293)
15 years of tenure	0.0900 (0.0562)	0.0746 (0.0895)	0.0682 (0.0498)	0.1480 (0.0563)	0.0399 (0.0516)	0.0488 (0.0504)	0.1630 (0.0596)	0.0749 (0.0423)
5 years of experience	0.2440 (0.0373)	0.2491 (0.0432)	0.2664 (0.0354)	0.2398 (0.0539)	0.2758 (0.0359)	0.2730 (0.0356)	0.2349 (0.0369)	0.2640 (0.0339)
10 years of experience	0.3786 (0.0570)	0.3889 (0.0726)	0.4249 (0.0521)	0.3717 (0.5393)	0.4438 (0.0537)	0.4379 (0.0527)	0.3617 (0.0564)	0.4205 (0.0489)
30 years of experience	0.5690 (0.1250)	0.5999 (0.1860)	0.7116 (0.1085)	0.5520 (0.1180)	0.7682 (0.1125)	0.7516 (0.1107)	0.5231 (0.1266)	0.6994 (0.0946)

Notes: [1]The tenure coefficient b_2 is set to the parameter estimate in the column heading. The linear experience coefficient b_0 is set to the coefficient on (ΔTime) – ϕ – b_2, where ϕ is the time trend. The time trend for the wage sample is –0.0[illegible]06. The time trend for the earnings sample is 0.0034. The time trend for the wage and earnings sample is 0.0033.

[2]In columns 1 and 2 the nonlinear tenure and experience coefficients used to evaluate the tenure and experience effects are taken from column 1 of Table 4 in the case of Panel A, from column 3 of Table 4 in the case of Panel B, and from column 5 of Table 4 in the case of Panel C. White standard errors are in parentheses.

[3]The Bayes1 estimator uses the restrictions (3.9), (3.10) as inequality priors along with (3.13) and (3.14). In columns 3, 4, and 5 the nonlinear tenure and experience coefficients used to evaluate the tenure and experience effects are taken from column 2 of Table 4 in the case of Panel A, from column 4 in the case of Panel B, and from column 6 in the case of Panel C. Standard deviations of the posterior distribution are in parentheses.

[4]The Bayes2 estimator uses the restrictions (3.7) and (3.8) for T_{ij-1} between 0 and 10 as inequality priors along with (3.13) and (3.14). The coefficient estimates underlying the estimates in the table are available from the authors. Standard deviations of the posterior distribution are in parentheses.

In Table 5 we measure the contribution of experience and tenure to wage growth by evaluating the experience and tenure coefficients in Table 4 at various values. As noted above, the linear experience coefficient b_0, the linear tenure coefficient b_2, the job match gain parameters d_2 and g_2, and the time trend are not separately identified. Consequently, in Table 5 we present estimates of the value of experience and tenure by combining the sample information with extreme assumptions about d_2 and g_2 that are consistent with the prior information discussed above. As discussed above, the estimate of the time trend parameter ϕ is based on IV estimation of (2.1) with time treated as endogenous.[44]

The first two columns of Table 5, Panel A are based on column 1 of Table 4, where ΔWAGE1 is the dependent variable. In column 1 we set b_2 to the estimate .0201 of $b_2 - \bar{d}$. Since $\bar{d}$ is positive using $b_2 - \bar{d}$ in place of b_2 leads to a downward biased estimate of the return to tenure. The implied estimate of the linear experience slope is .0703, which we obtain by subtracting the estimates of b_2 and the time trend (–.0006) from the coefficient on the change in time. The results indicate that two years of tenure raise the log wage by .035 (.009). Ten years are worth .0906 (.038). For a high school graduate 10 years of experience are worth .4137 (.0596) and 30 years are worth .6369 (.1287). These are estimates of the effect of experience on wages holding the job match constant. That is, they do not include the increase in $\varepsilon_{ij(t)}$ over a career.

In the second column of Panel A we set the linear slope b_2 to the estimate of $(b_2 - \bar{g})$, which amounts to setting $\bar{g}$ set to 0. These results imply that the effects of 10 years of tenure and 30 years of experience are .0718 and .6932 respectively.

In column 4 we report results based on the Bayes1 estimates of the parameters, with the Bayes1 estimate of the posterior distribution of $b_2 - \bar{g}$ evaluated at $\bar{g}$ equal to 0. The implied return to 10 years of tenure is .126 (.040).

In column 5 we set b_2 to the value of b_2^{max} for each point in the posterior distribution (see note 28). The mean of b_2^{max} should still lie above the parameter b_2. The estimated effect of 10 year of tenure declines to .069 (.041), which is close to the value obtained using the WLS estimate $b_2 - \bar{g}$ with $\bar{g}$ set to 0. In column 3 we report a lower bound based on the posterior distribution of $b_2 - \bar{d}$, with $\bar{d}$ set to 0. (We did not compute the even lower estimates that would result if at each point in the posterior distribution we set $\bar{d}$ to the smallest value that is consistent with all of the prior information.) The mean of the posterior of the effects of 10 years of tenure is .072 (.035), which is below the estimate based on $b_2 - \bar{d}$.

Columns 6–8 report estimates based on the Bayes2 estimator, which uses the inequality priors (3.7) and (3.8) for $0 \leq T_{it-1} \leq 10$. The estimated effect of 10 years of tenure based on $b_2 - \bar{d}$, $b_2 - \bar{g}$, and b_2^{max} are .0604, .1417, and .0782, respectively. Not surprisingly, the gap between the lower bound and upper bound estimates is a bit wider in the case of Bayes2. The estimate based on b_2^{max} is slightly higher.

In Table 5 Panel B we repeat the analysis for the WAGE2 measure using the specifications in Table 4, columns 3 and 4. The results point to somewhat larger estimates of the return to seniority. Using the estimate of $b_2 - \bar{d}$ with $\bar{d}$ set to 0 the estimate of the return to 10 years of seniority is .120 (.048) but the estimated return to 15 years of tenure is only .085 (.074). Using $b_2 - \bar{g}$ with $\bar{g}$ set to 0 we obtain .183. This estimate is only half the OLS estimate of .35, a bit below the result for the Topel estimator (.196), but substantially above the AS estimator (.121). When we use the Bayes1 estimate of $b_2 - \bar{g}$, setting $\bar{g}$ to 0, the upper bound estimate of the effect of 10 years of tenure is .210 (.058). However, the Bayes1 estimate using $b_2^{\max}$ is .176 (.047). The Bayes2 estimate using $b_2^{\max}$ is .2114, so using the Bayes2 inequality restrictions rather than the averaged restrictions in Bayes1 makes more difference for the WAGE2 sample than for the WAGE1. We do not know why.

In Panel C we repeat the analysis using the combined sample. The results lie in between those for the separate wage measures, with the Bayes1 procedure yielding estimates of .086 using the posterior of $b_2 - \bar{d}$ and setting $\bar{d}$ to 0, .139 using the posterior of $b_2 - \bar{g}$ with $\bar{g}$ set to 0, and .070 when $b_2^{\max}$ is used. The Bayes2 estimates are very similar.

The results based on the WAGE1 sample suggest the value of 10 years of tenure is between .07 and .14, and the estimates for the combined sample are similar. The estimates are higher in WAGE2 sample, ranging from a value of .099 based on the Bayes2 estimate of $b_2 - \bar{d}$ to .230 based on the Bayes2 estimate of $b_2 - \bar{g}$. All of these estimates are well below the corresponding OLS results of .27, .31, and .35 for the WAGE1, combined, and WAGE2 samples, respectively. The OLS estimation of (2.1) appears to substantially overstate the return to tenure.

To help reduce the range of plausible estimates, we examine what they imply about the wage changes associated with quits and layoffs. Specifically, we computed the implied estimates of the change in the job match component $\Delta\varepsilon_{ij(t)}$ for quits and layoffs at various values of $X_{0ij(t-1)}$ and T_{it-1}. To do this we evaluate (2.4) and (2.5) using the estimates of the parameters of (2.4) and (2.5) that are directly identified from (2.6) and the fact that an estimate of b_2 implies a choice for d_2 and g_2. For example, if we set b_2 to the coefficient $(b_2 - \bar{g})$ and set $\bar{g}$ to 0, this implies that

$$g_2 = \bar{g}(g_2, g_3, g_4) - 10g_3 - 100g_4 = -10g_3 - 100g_4$$

We computed estimates for various values of experience prior to the job $X_{0ij(t-1)}$ and T_{it-1} but space precludes a detailed presentation of the results, which have substantial standard errors (or standard deviations of the posterior in the Bayes cases). The results generally show substantial job match gains from quits that rise with tenure but decline at high tenure levels. However, they also show that when b_2 is set to either the WLS, Bayes1 or Bayes2 estimate of $b_2 - \bar{g}$, the implied estimate of the mean of $\Delta\varepsilon_{ij(t)}$ for layoffs takes on a substantial positive value in many cases. For example, when WAGE2 is used the WLS estimates in column 3 of Table 4 imply a job match gain of .056 when $X_{0ij(t-1)}$ is 10 and tenure is 15. At these levels of $X_{0ij(t-1)}$ and T_{it-1} the model implies that the combined effect of the change in experience, tenure, and $\Delta\varepsilon_{ij(t)}$ lead to a wage loss of only –.117. Consequently, the positive estimate of the mean of $\Delta\varepsilon_{ij(t)}$ arises to balance the wage loss of .179 associated with the loss of 15 years of tenure (see Table 5, Panel B, column 2). When $X_{0ij(t-1)}$ is 10 and T_{it-1} is 15 the Bayes1 estimator implies a job match gain of .081 (.089). A similar problem arises when WAGE1 is used and b_2 is set to the Bayes posterior of $b_2 - \overline{g}$ with $\overline{g}$ set to 0. In the Bayes1 case the estimate of the job match gain is .129 (.069). These results reflect a feature of the data that is apparent in cross tabulations in Table 2—the wage losses associated with layoffs at high tenure levels are too small to accommodate both large wage losses due to tenure and a job match loss. This suggests that either the returns to seniority are modest or that the returns to tenure are large and persons who have several years of seniority when they are laid off find jobs with higher job match components than their previous ones. The latter interpretation seems implausible to us. We have not investigated a third possibility, which is that the returns to tenure are large but the stochastic wage component ν_{ijt} is negative prior to a layoff for workers with several years of seniority.[45]

The Bayes estimates based on b_2^{max} incorporate the prior information that the job match gain be negative. This is reflected in the more negative estimates of the mean of $\Delta\varepsilon_{ij(t)}$ in the event of a layoff (not shown) as well as in smaller estimates of the return to tenure in Table 5. For example, the Bayes1 estimates based on b_2^{max} imply that $\Delta\varepsilon_{ij(t)}$ in the event of a layoff when $X_{0ij(t-1)}$ is 10 and T_{it-1} is 15 is 0.0 in the WAGE1 sample and .025 in the WAGE2 sample. (The corresponding Bayes2 estimates are 0.010 and .018.) We conclude that the estimates of the return to tenure based on the WLS or Bayes estimates of $b_2 - \overline{g}$ are overstated.

The above discussion highlights the importance of the link between tenure and layoff losses in our analysis. Is the evidence on the link consistent with other evidence? Topel (1990) used the PSID and found little relationship between tenure and the wage losses of people who are laid off. A careful study by Carrington (1993) reports wage growth equations using several panels of the Displaced Worker Survey. His models are parameterized in terms of experience and tenure at the time of displacement rather than prior experience and tenure, but for purposes of comparisons we used his estimates to evaluate the effect of tenure holding prior experience constant. His estimates imply that the wage loss is about .16 larger for a person with 10 years of seniority than a person with 0 years (see his Table 7, column 1). This number is not directly comparable to ours, because we use the stayers to estimate the nonlinear tenure effects and experience effects on wage levels, while Carrington's estimates reflect the combined effect of tenure and experience on the wage level given the job match component and on the change in the job match component. In any case, the .16 estimate is higher than our results for WAGE1 but lower than our estimates for WAGE2. Neal's (1995) results for industry stayers and industry changes work with the same data and appears to support a similar conclusion. His finding that the value of tenure before and after a dislocation is about the same is consistent with only a small return to firm seniority.

E. Other Results

Since one might expect the gains and losses from turnover to be related to labor market conditions, in preliminary work we added the current and lagged value of unemployment and the interactions of these variables with Q_{it} and L_{it} to the models in Table 4. This made little difference. When ΔWAGE2 is the dependent variable none of the unemployment variables are significant. When ΔWAGE1 is the dependent variable the coefficient on $-Q_{it}T_{it-1}$ is .005 and the coefficient on $-L_{it}T_{it-1}$ is .0015. Our main conclusions are unchanged.[46]

VII. RESULTS FOR THE NLSY

In this section we provide a limited set of results for a sample of white men from the NLSY. To be included in a given year the person must have been out of school for at least one year, worked at least 15 hours per week, held a private sector job and not been self-employed. The specification of (2.6) is the same as for the PSID, except that we use quadratic rather than cubic specifications for the effects of tenure on the wage level and for the effects of tenure on the job match gains from a quit and a layoff. We also exclude ΔX_{it}^4 from the analysis. We do this because the range of variation in tenure is quite limited in the NLSY. We revise the definitions of $\overline{d}$ and $\overline{g}$ in (3.10) and (3.11) to be the average of the derivative of the job match gain over the range $T_{it-1} = 0$ to $T_{it-1} = 7$ rather than $T_{it-1} = 10$. Our restriction of the functional form to a quadratic plays a large role in the estimates of the effect of 10 years of tenure, because only 23 quits and 2 layoffs are observed at value of $T_{it-1} >$ than 8.

The implied estimates of the return to tenure and experience are reported in Table 6.[47] Note that the point estimates of $b_2 - \overline{g}$ exceed those for $b_2 - \overline{d}$, so the point estimates are consistent with the sign restriction $\overline{d} - \overline{g} > 0$, although the standard errors overlap. In column 1a we report estimates of the lower bound of the tenure effect, with b_2 set to $b_2 - \overline{d}$. The estimate of the value of 7 years of tenure is .138 (.036). The estimate of the value of 10 years of tenure is .106 (.051). These estimates are a bit above the corresponding PSID estimates based on WAGE1. The upper bound estimate using $b_2 - \overline{g}$ as the estimate of b_2 is .157 (.055) for 7 years of tenure and .132 (.079) for 10 years of tenure. This estimate for 10 years is well above the estimate of .072 obtained using WAGE1 but is within sampling error of it. It is close to the Bayes1 estimate of .126. We have not computed Bayes1 estimates using the NLSY but our experience with the PSID suggests that the posterior for the upper bound would exceed the sample estimate by a small amount if we did. The estimates of the return to experience are higher than the PSID estimates, but part of this is due to the fact that the NLSY measure is a count of weeks worked, which increases more slowly with potential experience than the PSID measure.

In columns 2a and 2b adding $Q_{it}(T_{it} - \underline{T})$ and $L_{it}(T_{it} - \underline{T})$ to the equation as additional controls makes little difference. Restricting the sample to observations

Table 6. Estimates of the Return to Tenure and Experience[1], NLSY[2]

	$Q_{it}T_{it}$ and $L_{it}T_{it}$ *excluded*		$Q_{it}T_{it}$ and $L_{it}T_{it}$ *included*	
	WLS, b_2 set to $b_2 - \bar{d}$ = .0412 (.006)	*WLS, b_2 set to $b_2 - \bar{g}$ = .0439 (.009)*	*WLS, b_2 set to $b_2 - \bar{d}$ = .042 (.006)*	*WLS b_2 set to $b_2 - \bar{g}$ = 0.044 (.009)*
	(1a)	*(1b)*	*(2a)*	*(2b)*
2 years of tenure	.070 (.011)	.075 (.017)	.071 (.011)	.076 (.016)
5 years of tenure	.129 (.026)	.143 (.040)	.131 (.026)	.145 (.040)
7 years of tenure	.138 (.036)	.157 (.055)	.140 (.035)	.160 (.055)
10 years tenure	.106 (.051)	.132 (.079)	.107 (.051)	.136 (.079)
5 years of experience	.321 (.042)	.308 (.052)	.320 (.041)	.305 (.052)
10 years of experience	.560 (.061)	.534 (.087)	.558 (.061)	.529 (.087)
15 years of experience	.673 (.082)	.633 (.124)	.669 (.082)	.626 (.124)

Notes: [1]The estimates in the columns 1a and 1b of the table are computed using the WLS coefficient estimates of a version of equation (2.6) in manner analogous to columns 1 and 2 of Table 5. White standard error estimates are in parentheses. See the text for a definition of $\bar{g}$ and $\bar{d}$. The specification is the same as in Table 4, with the exception that the terms ΔX^4_{it}, $L_{it}T^3_{it-1}$, $Q_{it}T^3_{it-1}$, and ΔT^3_{it} are dropped to accommodate the fact that the NLSY is a young sample and the range of variation in X_{it} and T_{it} is limited. The tenure coefficient b_2 is set to the parameter estimate in the column heading. In computing the experience effects the linear experience coefficient b_0 is set to the coefficient on (ΔTime) – ϕ – b_2, where ϕ is the time trend. The time trend is estimated to be –.0189 using the same approach taken with the PSID. The estimates in columns 2a and 2b are computed from a wage growth model that includes $Q_{it}T_{it}$ and $L_{it}T_{it}$ among the controls.

[2]The NLSY sample contains 10,567 observations on 2,356 white men in 4,274 job matches. The observations are from 1981 to 1992. The mean of time is 1987.0. Quits and layoffs constitute 17.5 and 5.9 percent of the observations, respectively. For stayers the mean and 95th percentile value of X_{it} are 8.45 and 14.14. The corresponding mean and 95th percentile value for T_{it} are 4.15 and 10.10. For quits the means of X_{0it-1}, T_{it-1} and X_{it} (experience following the quit) are 4.6, 1.4, and 7.25. For layoffs the corresponding means are 4.74, 1.24, and 7.01. The mean of ΔW_{it} is .046 for stayers, .087 for quits, and –.058 for layoffs.

in which the person worked an average of at least 35 hours per week over the preceding years decreases the upper bound estimate of the effect of 10 years of tenure to .144. We view the NLSY results as broadly consistent with our PSID findings.

VIII. DISCUSSION AND CONCLUSIONS

In this paper we estimate the returns to seniority, the returns to experience, and the relationship between changes in the match specific component of wages and experience and seniority at the time of a quit or layoff. The word "estimate" is a bit misleading, since Section II shows that these returns are not identified in regression models relating the wage changes of stayers, quits, and layoffs to tenure and experience that we and others have used. Specifically, the coefficients on the linear experience and tenure terms in the wage level equation and the coefficients on the linear tenure and linear experience terms in the polynomial approximations for the expected change in the job match components in the event of a quit or layoff are all under identified by one common parameter.

We deal with the identification problem by using "a priori" information on the unidentified parameters. We obtain the information by analyzing a simple structural model of wages, quits, and layoffs and from the relationship between wages and experience when tenure is excluded. Our approach of working out the implications of an under identified model that reflects the complexity of a problem may be preferable in many circumstances to imposing arbitrary 0 restrictions onto the data to achieve nominal identification.

We use a Bayes estimator due to Geweke (1986) to combine prior information in the form of inequality restrictions with sample information on the parameters of the model. The prior information is as follows. We argue that if the effect of tenure on wages is substantial, then the relationship between the change in the job match component and tenure at the time of a quit will be positive, while the relationship between the change in the job match component and tenure at the time of a layoff will be negative. We also use the fact that almost all research suggests that there is a substantial return to general labor market experience, and that few researchers would argue that persons laid off with substantial tenure would typically experience a job match gain.

The empirical analysis suggests the following conclusions. First, there is a large return to general labor market experience that is independent of job shopping. Second, the weight of the evidence suggests an economically significant tenure effect on the log wage that is above the .07 estimate suggested by Altonji and Shakotko (1987), but far below OLS estimates for our sample and also below Topel's (1991) of .246 for an earlier sample. The range from .07 to .17 seems most reasonable to us based on the present paper, particularly since the PSID estimates based on our preferred wage measure and the combined sample lie in the .07 to .14 range. The range of estimates that we present reflects the fact that our model is fundamentally under identified as well as differences across the choice of dependent variable. Estimates of the return to tenure that are above our "bounds" estimates imply that senior workers who lose their jobs experience job match gains, which we find counterintuitive. Furthermore, the range is quite consistent with the sample estimates of .10 and .14 for the lower and upper bounds on the returns to 10 years obtained using NLSY.

There is a long research agenda. First, we have identified a number of shortcomings of our empirical specification that should be investigated. Explicit treatment of the stochastic job specific error component should be high on the list. Second, the adequacy of the tenure and mobility measures need further investigation. Third, the behavior of the Bayes procedure in applications requires further investigation. Fourth, additional investigation of the robustness of our a priori restrictions to alternative models of turnover requires additional investigation. We noted earlier that if layoffs are a more negative signal for low tenure than high tenure workers, then tenure might have a negative relationship with the job match loss, which would undermine one of the a priori restrictions we rely on. Fifth, with advances in computational power, it may now be worth trying to develop and estimate an empirical version of the model sketched in Section III and simulated in Altonji and Williams (1993). Finally, it would be interesting to follow up on research work by Carrington (1993), Neal (1995), and Parent (1995) suggesting that industry specific experience is as or more important than firm specific experience by using our methods to obtain bounds on the returns to industry specific experience.[48]

Table A-1. Summary Statistics for ΔWAGE1 Regression Sample

Variable	*Overall*	*Mover*	*Stayer*	*Quit*	*Layoff*
Wage1	2.2835 (0.4425)	2.0216 (0.4816)	2.3143 (0.4272)	2.0591 (0.4868)	1.9444 (0.4617)
ΔWage1	0.0247 (0.1904)	0.0383 (0.3409)	0.0231 (0.1637)	0.0719 (0.3267)	–0.0310 (0.3592)
ΔWage2	0.0283 (0.2504)	0.0189 (0.4101)	0.0293 (0.2259)	0.0532 (0.3991)	–0.0530 (0.4242)
X_{it-1}	16.9627 (10.3312)	11.9865 (8.1452)	17.5490 (10.4038)	11.5458 (7.4950)	12.8949 (9.2898)
$X_{0ij(t-1)}$	8.4028 (7.7001)	9.3190 (7.6445)	8.2948 (7.6999)	9.0719 (7.2644)	9.8284 (8.3619)
T_{it-1}	8.5599 (8.6184)	2.6675 (4.0655)	9.2542 (8.7470)	2.4739 (3.3585)	3.0665 (5.2130)
$(\text{Education} - 12)_i$	0.7378 (2.5046)	0.7875 (2.4128)	0.7319 (2.5153)	1.0170 (2.4533)	0.3145 (2.2578)
Union_{it-1}	0.2921 (0.4548)	0.1200 (0.3251)	0.3124 (0.4635)	0.0919 (0.2891)	0.1778 (0.3829)
Married_{it-1}	0.8755 (0.3302)	0.8086 (0.3936)	0.8834 (0.3210)	0.8048 (0.3966)	0.8163 (0.3878)
$(\text{Resident SMSA})_{it-1}$	0.6303 (0.4828)	0.5990 (0.4903)	0.6339 (0.4818)	0.6110 (0.4879)	0.5743 (0.4952)
$(\text{Resident City} > 500{,}000)_{it-1}$	0.2412 (0.4103)	0.1914 (0.3936)	0.2169 (0.4122)	0.1853 (0.3888)	0.2041 (0.4036)
N	9961	1050	8911	707	343

Notes: The upper number in each cell is the mean, while the lower number in parentheses is the standard deviation. The statistics for ΔWAGE2 are computed from the cases with nonmissing data that are in the ΔWAGE1 sample. For ΔWAGE2 N is 8,971 overall, 8,079 for stayers, 892 for movers, 604 for quits and 288 for layoffs.

ACKNOWLEDGMENTS

Support from the Institute for Policy Research, Northwestern University, and the computer centers at Northwestern and the University of Cincinnati are gratefully acknowledged. We also thank D. Bernhardt, John Geweke, M. Hashimoto, H. van Ophem, Reed Olsen, Yoram Weiss, two anonymous referees, participants in conferences at Vrije University (January 1991) and University of Montreal (June 1991), and seminar participants at the University of Chicago, Cornell University, Florida State University, Northwestern University and University of Cincinnati for helpful comments. We thank Nachum Sicherman for assisting us with the NLSY data and Charles Pierret for excellent research assistance. This paper is a drastically revised version of our working paper, Altonji and Williams (1992). The simulation analysis and detailed descriptive statistics on mobility and wage growth from that paper are presented in Altonji and Williams (1993).

NOTES

1. See Mincer and Jovanovic (1981), Altonji and Shakotko (1987), Abraham and Farber (1987), Brown (1989), Williams (1991) and Topel (1991), to name just a few of the studies. Devine and Kiefer (1991) survey much of the literature relevant to the present paper. The recent surveys by Carmichael (1989) and Hutchens (1989) discuss the empirical literature on returns to seniority and mobility and the theoretical implications of this work.

2. Recent examples that examine the wage losses from layoffs and discuss the distinction between the value of lost seniority and the job match loss include Hamermesh (1987), Addison and Portugal (1989), Kletzer (1989), Topel (1990), Carrington (1993), Ruhm (1991), and Neal (1995). Jacobson, LaLonde, and Sullivan (1993) survey the literature on dislocated workers. They also provide a detailed analysis of the earnings losses of job changers using panel data from the unemployment insurance system of the state of Pennsylvania. Other studies treat job separations as voluntary quits and estimate the gain from quitting. Devine and Kiefer (1991) survey this literature.

3. This is true conditional on years of labor market experience prior to the start of the job. The theoretical framework for our analysis of quits and layoffs draws on Hall and Lazear (1984) and Hashimoto and Yu (1980).

4. These are upper bounds because experience is positively correlated with seniority and workers with more experience have had more time to shop for good jobs.

5. In an earlier draft we used a quadratic in tenure and a dummy for tenure greater than 1. We also estimated models with a quartic in tenure. Our results were not very sensitive to these changes.

6. Altonji and Shakotko (1987) present evidence that estimates of ε_i and $\varepsilon_{ij(t)}$ enter logit models for both quits and layoffs with negative signs. Abraham and Farber (1987) find that completed job tenure has a strong positive association with the level of wages on a job. See also Bishop (1990).

7. $X_{0ij(t-1)} = X_{it-1} - T_{it-1}$.

8. This does not rule out the possibility that η and ξ are correlated with turnover behavior prior to the start of job $ij(t-1)$. Also, we should probably distinguish between types of layoffs. Our sample is too small to do this.

9. Note that if $Q_{it} = L_{it} = 0$, the equation states that $\Delta\varepsilon_{ij(t)} = 0$, which reflects the fact that $\varepsilon_{ij(t)}$ is fixed over the course of a job.

10. Adding $Q_{it}(T_{it} - \underline{T})$ and $L_{it}(T_{it} - \underline{T})$ as control variables to the models in Table 4 makes little difference. See below.

11. There are a number of reasons why the tenure slopes might depend upon experience, and why one might expect the relationship between tenure on the previous job and $E(\Delta\varepsilon_{ij(t)})$ to depend on experience. It is natural, therefore, to consider adding the change in the product of $X_{0ij(t-1)}$ and T_{it} into

the wage equation and the products of $X_{0ij(t-1)}$, T_{it-1} and the quit and layoff indicators into the change in the job match equations. Unfortunately, these effects are not separately identified when total experience accumulates continuously. To see this, note first that the coefficient on the change in $X_{0ij(t-1)}T_{it}$ is not identified from stayers alone if ΔX_{it}^2 and ΔT_{it}^2 are also included in the equation, because $\Delta(X_{0ij(t-1)}T_{it})$ is equal to $(X_{0ij(t-1)}1)$ and ΔX_{it}^2 is equal to $2X_{0ij(t-1)} + \Delta T_{it}^2$. Furthermore, $\Delta(X_{0ij(t-1)}T_{it})$ across jobs is equal to $X_{0ij(t-1)}T_{it-1}$ (abstracting from variation in tenure at the time the first job is initially observed.). The effects are identified if one uses spells of nonemployment as a source of variation in experience, but we think it is unwise to rely on this variation in a sample of male heads of household. One can also identify the interaction terms in the wage level equation if one excludes them from (2.4) and/or (2.5), and one can identify interactions terms in (2.4) and (2.5) if one excludes them from (2.1). We have not pursued this strategy.

12. Recent examples include Carrington (1993), Addison and Portugal (1989), and Topel (1990). See note 2.

13. By general skill we mean the location of the distribution of the wages faced by the individual.

14. See Mortensen (1988) for a theoretical model of wages and quits which incorporates a stochastic job specific wage component but does not distinguish between quits and layoffs. Topel (1986) estimates a model that is similar to Mortensen's and obtains a very small return to tenure. See also Marshall and Zarkin (1987), who estimate a joint model of wage offers and separations with cross-section data.

15. The alternative used by both Altonji and Shakotko (1987) and Topel (1991) is to make selective use of the cross-sectional variation underlying (2.1) in combination with the information on stayers in (2.2a). Abstract from the nonlinear tenure and experience terms in (2.1) and rewrite the equation as

$$W_{ijt} - \hat{\phi}t - \hat{b}_{02}T_{ijt} = X_{0it}b_0 + \varepsilon_i + \varepsilon_{ij(t)} + u_{it} + \nu_{ijt} + (\phi - \hat{\phi})t + (b_{02} - \hat{b}_{02})T_{ijt}$$

where X_{0it} is prior experience and $\hat{b}_{02}$ is the estimate of the sum of b_0 and b_2 obtained from OLS estimation of (2.2a) given an estimate of ϕ. Topel estimates the above equation by OLS, using cross sectional variation in X_{0it} to identify b_0 and thus $b_2 = b_{02} - b_0$. The problem with this (discussed in Topel) is that X_{0it} is likely to be correlated with both ε_i and $\varepsilon_{ij(t)}$. In the linear case AS's estimator amounts to using an equation similar to (2.2a) (but in deviation from job means form rather than first differences) to estimate b_{02}. They estimate b_0 by using X_{it} as an instrument for X_{0it} in the above equation. As AS point out, X_{it} is likely to be correlated with $\varepsilon_{ij(t)}$. AS's use of evidence on the gains from mobility and the experience profile of quits to correct the bias has some of the flavor of the analysis in the present paper. See Altonji and Williams (1997) for a detailed discussion of the AS and Topel estimators. Note that we also make selective use of (2.1) in developing our priors about the return to experience below and to estimate the time trend ϕ.

16. The relationship is re-enforced if mobility costs rise with total experience in a given geographic location. In this case, X_{it} might have a positive partial effect on the expectation of $\Delta\varepsilon_{ij(t)}$ in the event of a quit. The tenure term will pick up the effect on the expectation of $\Delta\varepsilon_{ij(t)}$ of any increase in mobility costs with tenure or with experience. This is because we control for the level of prior experience rather than current experience, which increases one for one with tenure. Note also that we have abstracted from worker preferences for nonwage attributes of jobs that are match specific (such as location). If these are present, then the combined value of the gain in $\varepsilon_{ij(t)}$ and the nonwage attribute must exceed the value of lost tenure. The presence of nonpecuniary match specific factors will weaken the strength of the relationship between T_{it-1} and $\Delta\varepsilon_{ij(t)}$ but will not change the sign. The result is to tighten the lower bound implied by the relationship between wage gains and tenure at the time of a quit.

17. The reduction in the quit probability raises V_{ijt}, reinforcing the direct effect of ω_{ij} on the layoff probability, and the reduction in the layoff probability leads to an increase in the present value of earnings associated with job j and reinforces the direct effect of $\varepsilon_{ij(t-1)}$ and ω_{ij} on the quit probability.

18. This positive relationship will be re-enforced if layoff costs are on average positively related to T_{it} due to inverse seniority layoff rules and/or tenure based severance pay rules that are present in some firms, and also because the seniority premium leads to a decline in the quit probability with T_{it}.

19. In some experiments we increase the slope of the relationship between productivity and tenure, while reducing the worker's share of the investment so as to hold the wage slope of tenure constant. These experiments are similar to the effect of increasing the effect of tenure on layoff costs. In the case of layoffs we found a negative relationship between T_{it-1} and both $\Delta\varepsilon_{ij(t)}$ and $\Delta\varepsilon_{ij(t)} + \Delta\nu_{it}$ for a fairly wide range of parameter values.

20. If ν_{ijt} is serially uncorrelated, then this variable will not have much effect on earnings over a career or mobility decisions, since it has a small effect on the present value of the earning stream associated with a particular job. Here we focus on persistent change in ν_{ijt}.

21. They do not provide evidence on the quantitative significance of this. The assumptions about productivity underlying the simulations in Altonji and Williams (1993) imply that ν_{ijt} is either 0 or a random walk with initial condition 0 at the start of the job, so there is no reversion to the mean. Topel (1991) finds support in the PSID for the assumption that the sum $u_{it} + \nu_{ijt}$ is a random walk plus a white noise component.

22. See, for example, Mincer and Jovanovic (1981), Jovanovic (1979) and Bartel and Borjas (1981).

23. See, for example, Barron, Black, and Loewenstein (1989), Brown (1989), Altonji and Spletzer (1991) and Lynch (1992).

24. Combining (3.1) for all positive values of T_{it-1} leads to the condition

$$d_2 > \left[\max_{T_{it-1}} (-2d_3T_{it-1} - 3d_4T^2_{it-1})\right] > 0 \qquad \text{over the range } 0 \le T_{it-1} \le 10.$$

There is a similar expression for (3.2). In practice, it is easier to simply check (3.1) and (3.2) for values of T_{it-1} from 0 to 10 at discrete intervals. In the empirical work we use intervals of 0.5.

25. The priors are uniform from 0 to infinity on one side of the inequality. The more noisy the parameter estimates the greater the effect of the prior on the posterior, and the more important it becomes to balance the priors about the sign of the derivatives with a restriction on how large in absolute value they can reasonably be. We have not done this for (3.7) and (3.8) or (3.9) and (3.10).

26. We use the multivariate normal distribution rather than the multivariate t-distribution (which would be more appropriate given that the error variance is estimated) because our sample sizes are very large and the computations are much faster with the normal. We set n to 10,000 and also make use of the "antithetic" replications, for a total of 20,000 replications.

27. For example, we report the means and standard deviation of the posterior distribution of $10(b_2 - \bar{g}) + 100b_3 + 1000b_4$ and $10(b_2 - \bar{d}) + 100b_3 + 1000b_4$. These functions are lower and upper bounds of the effects of 10 years of seniority.

28. Specifically, $b_2^{\max}(\beta^k) = (b_2 - \bar{g})^k - \max(0, H(\beta^k), X(\beta^k))$

$$H(\beta^k) = \frac{1}{15}([(g_2 - b_2)^k + (b_2 - \bar{g})^k]\ 15 + \bar{g}_0^k(X_{0ij(t-1)}) + g_1^k + g_1^k(.1836chtime_2) + g_3^k 15^2 + g_4^k 15^3)$$

$$X(\beta^k) = -\frac{1}{30}(30[(b_0 + b_2)^k + (\bar{g} - b_2)^k] + 30^2 b_1^k - .10)$$

where k denotes the k^{th} Monte Carlo replication. In the empirical specification, we add terms involving third and fourth powers of X to (2.1), and these also appear in $X(\beta^k)$. To understand $H(\beta^k)$ note that when $\bar{g}$ is set to 0, the term $[(g_2 - b_2)^k + (b_2 - \bar{g})^k]$ is g_2 and $H(\beta^k)$ is one fifteenth of the average job match gain for person laid off when tenure equals to 15. If this gain is positive, then $\bar{g}$ and g_2 are decreased by $H(\beta^k)$, which is enough to make the job match gain 0, and b_2 is decreased by the same amount. $X(\beta^k)$ checks that when $\bar{g}$ is set to 0 the implied value of b_0 is such that the return to 30 years of experience exceeds .10. We could replace $(b_2 - \bar{g})^k$ with largest value of $b_2 - g_2$ for replication k that is consistent with (3.8) for the values of T_{it-1} over the range 0 to 10 or 0 to 15. We choose not to because sampling error in this value is very large.

29. In Altonji and Williams (1997) we provide a detailed discussion of alternative ways of estimating the time trend. We show that, at least for the 1968–1982 period, the CPS real wage index based on the 1989 draft of Murphy and Welch (1992) used by Topel (1991) understates real wage growth experienced

by members of the PSID sample. Altonji and Williams show that imposing the wrong time trend on the PSID leads to serious bias in the IV1 estimator and to a lesser extent in the Topel estimator. When we implement Topel's 2 step estimator below, we use the time trend from the IV estimator with the time trend endogenous. When we implement Altonji and Shakotko's IV1 estimator, we simply treat the time trend as endogenous and add its deviation from the individual mean to the instrument list. Treating the time trend as exogenous or replacing the time trend with endogenous year dummies has little effect on the results. In Table 3 we report OLS estimates with the time trend exogenous.

30. To reduce the influence of measurement error and outliers, we have set the wage rates to missing when they are less than 1.50 in 1982 dollars. We have set the wage changes involving an increase of 800% or a fall to less than 1/8th of the previous years value to missing as well.

31. Variables such as ΔX_{it}^2 are measured between the same periods as ΔW_{it}. However, the variables from the job match change equations, such as $Q_{it}T_{it-1}$ refer to tenure at the end of the job.

32. The breakdown of the combined sample is as follows:

	Layoffs	Quits	*Stayers*
WAGE1	343	707	891
WAGE2	40	87	6947
Both WAGE1 and WAGE2	383	794	15858

33. Altonji and Williams (1992) provides an appendix documenting the procedures used to infer employer tenure, quits, and layoffs. This appendix and our computer programs will be made available from the authors upon request.

34. Difficulties with the tenure data are well-known. Brown and Light (1992) provide a thorough and somewhat harrowing account of the quality of the data on job seniority and job mobility from the PSID, although they also emphasize the many advantages of this data set. Altonji and Shakotko (1987) use a complicated but quite different procedure to construct the tenure and job separation used in their study. However, they use data from 1968–1974, during which the tenure values were bracketed and did not smooth the tenure responses, although they did eliminate large changes in tenure in some instances. They report that smoothing the tenure values or limiting their analysis to 1975–1981 did not make much difference in their estimates in absolute terms, and this finding is confirmed in Altonji and Williams (1997). Brown and Light (1992) report obtaining results similar to Altonji and Shakotko's for various treatments of the tenure data, although they criticize Altonji and Shakotko's methodology. Topel (1991) argues that measurement error in the Altonji and Shakotko tenure series is a major source of the discrepancy between his findings and Altonji and Shakotko's. In Altonji and Williams (1997) we show that it is the interaction between the effects of measurement error and the effects of other differences between the two studies that is responsible for the discrepancies.

35. Unfortunately, our procedures do not guarantee that the initial experience must increase between jobs. In 60 job changes it falls by a small amount. The results change little when these observations are eliminated. Note also that the change in experience is likely to be less than one for many job changes but our experience measure increments by one for persons who work in year t. If the dispersion in the true change in experience around the mean for quits and layoffs is related to T_{it-1}, bias may result. We have been able to show that this bias will be very small given the size of the effect of experience on wages, the variance in T_{it-1} for movers, and the fact that the true change in experience is between 0 and 1. Also, the specifications that control for $Q_{it}(T_{it} - \underline{T})$ and $L_{it}(T_{it} - \underline{T})$ should pick up part of the effect of experience. These lead to results that are very close to those in the tables. See note 42.

36. The 10th percentile, the mean, and the 90th percentile of the number of observations per person are 1, 5.52, and 11, respectively. The mean number of wage change observations per job is 3.70.

37. Of the 549 individuals with eight or more observations, 66.7% never change jobs, 17.7% change jobs once, and 14.6% move more than once. Separations that we could not classify into a quit or a layoff are excluded, so our descriptive statistics understate quits and layoffs.

38. The WAGE2 sample has 1,931 individuals who have 2,895 job matches. The average number of observations on each person is 5.43 with an average of 3.62 observations per job. 62.5% of the individuals never change jobs, 22.9% change jobs once, and 15.6% change jobs more than once. The combined sample has 1,865 individuals who have 2,768 job matches. The average number of observations per person is 9.13 with an average of 6.15 observations per job. 63.8% of this sample never change jobs, 18.6% change jobs once, and 17.7% change jobs more than once.

39. It should be kept in mind that there are problems with both AS's and Topel's approaches. For example, the AS estimator is probably downward biased because of correlation between ε_{ij} and experience and Topel's approach is biased upward by correlation between ε_i and prior experience. Altonji and Shakotko (1987) and Altonji and Williams (1997) discuss bias corrections.

40. All of the equations also include as control variables the change in three location variables, the change in union membership, the change in marital status, the change in the SMSA dummy, the change in city size dummy, and the change in a dummy for health limitation, but coefficients on these variables are not displayed.

41. The coefficient on the education times the change in experience should be interpreted as the sum of an interaction between education and a time trend and education and experience.

42. When we add the controls $Q_{it}(T_{it} - \underline{T})$ and $L_{it}(T_{it} - \underline{T})$ to the model, the coefficients on $Q_{it}(T_{it} - \underline{T})$ and $L_{it}(T_{it} - \underline{T})$ are .0203 (.030) and .022 (.044) and the estimates of $b_2 - \overline{d}$ and $b_2 - \overline{g}$ are .0183 and .0197 which is very similar to what we obtain without these controls. The estimates of the effects of 10 years of tenure in Table 5 change very little. The results in Table 4 and 5 for ΔWAGE2 and the combined sample are also insensitive to adding $Q_{it}(T_{it} - \underline{T})$ and $L_{it}(T_{it} - \underline{T})$ to the wage growth model. We regard the fact that in the ΔWAGE1 case the estimated value of b_2 based on $Q_{it}(T_{it} - \underline{T})$ and $L_{it}(T_{it} - \underline{T})$ are so close to the estimates of $b_2 - \overline{d}$ and $b_2 - \overline{g}$ as a lucky coincidence rather than a vindication of our approach.

43. The Bayes2 estimates of $(b_2 - \overline{d})$, $(b_2 - \overline{g})$, and $b_2^{\max}$ are .0173, .0254, and .0191. For the ΔWAGE2 sample the corresponding Bayes2 estimates are .0287, .0418, and .0400. The full set of Bayes2 estimates are available from the authors.

44. The estimates are –0.0006 for WAGE1, .0034 for WAGE2, and –.00016 for the combined sample. The time trend estimates based on AS's IV estimator with the trend treated as endogenous are similar.

45. Hamermesh (1987) finds little evidence of this in the PSID for the early years of our sample. Topel (1991) does not find a link between wage growth and years remaining on a job in the PSID. Jacobson, LaLonde, and Sullivan (1993) do find that earnings growth is lower prior to a separation, but reductions in work hours could drive these results.

46. The specifications and samples correspond to those in Altonji and Williams (1992). The equations include interactions of a dummy for tenure greater than one and T_{it-1} with both Q_{it} and L_{it}. Carrington (1993) reports detailed results on the effects of labor market conditions on the wage losses of displaced workers. He find wages losses are greater for workers displaced from shrinking industries, but also find that the effect of job tenure on the wage loss is not that sensitive to labor market conditions. See also Topel (1990) and Jacobson and colleagues (1993).

47. We provide a few descriptive statistics in the notes to Table 6. The details of how we handled the data are available from the authors.

48. The Carrington and Neal studies use data from the BLS Dislocated Workers Surveys and find, particularly Neal (1995), that the wage losses are more strongly related to tenure for dislocated workers who change industries than for stayers. Parent (1995) confirms these results using data from NLSY and the PSID. He also shows using both a GLS estimator and an estimator similar to that of Altonji and Shakotko that adding industry tenure to wage equations containing tenure eliminates most of the firm tenure effect.

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