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Abstract

Ever since Mincer (1974), years of labor market experience were used to approximate individual's general human capital, while years of seniority were used to approximate job specific human capital. This specification is restrictive because it assumes that starting wages at a new job depend only on job market experience. In this article I investigate the effects of human capital on wage growth by using a more flexible specification of the wage equation, which allows for rich set of information on past employment spells to affect the starting wages. In addition, I endogenize the labor mobility decision. In order to illuminate the effects of human capital accumulation patterns on wage growth, I compare counterfactual career paths for representative individuals.

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Key Words: Human Capital, Labor Mobility, Experience, Seniority.

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1 Introduction

Effects of human capital on wages have been investigated in numerous studies in the literature and are well summarized in Wößmann (2003) and Folloni and Vittadini (2010). There is a variety of methods proposed in the literature to measure human capital, including cost, income, and education based approaches, see e.g., a comprehensive overviews provided in Le, Oxley and Gibson (2003) and Oxley, Le, and Gibson (2008). However, most studies in Labor Economics start with a Mincer equation (Mincer 1974) and approximate the amount of general human capital, representing a set of skills transferable across jobs, by years of job market experience. In addition, a set of job-specific skills is approximated by the number of years of seniority at a given job. The assumption is that job-specific skills are lost when individuals decides to change jobs. In this paper I take another look at the effects of each type of human capital on wage growth, as well as the affects of timing of job changes.

The evolution of wages over an individual's career consists of the wage growth within and across jobs. While many studies have focused on the nature of wage evolution within a job, here I concentrate on the wage growth between jobs, specifically the effects of labor mobility on wages. In particular, I address three main questions: 1) What are the returns to labor mobility? 2) To what extent are these returns dependent on the level of schooling? 3) How are the returns to mobility affected by the amount of human capital?

Past explorations of labor mobility patterns include Farber (1999) and Mincer and Jovanovic (1981). These studies, however, differ from the current paper because they used a variety of models and approaches to explain mobility patterns observed in the data. Specifically, the authors analyze the effects of wages on mobility, whereas here I assess the impact of mobility on wages.

A large literature has concentrated on the return to seniority. Past studies in this area, namely Abraham and Farber (1987), Altonji and Shakotko (1987), Topel (1991), and Altonji and Williams (1997) faced an econometric problem of biases due to the unobserved heterogeneity of workers and the endogeneity of tenure. The authors choose different methods to eliminate these biases (see Farber (1999) for a comprehensive summary) and arrive at different estimates of the return to seniority. For example, Altonji and Shakotko (1987) use an instrumental variables approach, arguing that deviations of tenure variables from their means are uncorrelated *by construction* with unobserved heterogeneity components. They find that the return to seniority is small. Topel (1991), on the other hand, uses a two-step estimator that derives the return to seniority from the difference between total wage growth within a job, estimated in the first step, and the return to experience, estimated in the second step. He finds that a substantial return to tenure.

On the other end of the spectrum of the wage growth literature are the "on the job search" models (see Mortensen (1986) for a summary of earlier works in this field). The assumption in these models is that once a wage offer is accepted, wages stay constant and can only increase through labor mobility. Wolpin (1992) develops a dynamic optimization model that utilizes both the search and human capital accumulation aspects of labor dynamics.

Buchinsky et al. (2008) introduce a model that directly measures the worker's decisions that led to the observed combination of wages, experience and tenure. Another innovation of this model is the specification of initial wages at a new job. The starting wages are allowed to depend not only on experience, as in Topel (1991), but also on the other observed characteristics of the individual's labor history.

Here we employ a model similar to Buchinsky et al. (2008) to study the mobility-wage process for working individuals. The model consists of two equations, namely the mobility and wage equations. The approach used here improves on Abraham and Farber (1987), Altonji and Shakotko (1987), Topel (1991), and Altonji and Williams (1997) by jointly modeling mobility and wage processes and allowing for the rich set of past job market characteristics to affect not only the current wage at a firm but also the starting wage at a new job. I use a fully Bayesian framework that allows estimation of the exact small sample distribution of the parameters of the model. Once I have estimated the mobility-wage process, I can simulate various counterfactual labor transitions for a given individual using the posterior predictive distributions. The effects of past mobility on future wages can be inferred by comparing the counterfactuals labor trajectories.

Posterior predictive distributions have been used in past research in economics in Chamberlain and Hirano (1999) and Hansen (1998). Chamberlain and Hirano (1999) develop a mechanism of combining the individual's information with survey data to infer the distribution of the individual's future earnings. Hansen (1998) uses posterior predictive distributions to compare the counterfactual earnings distributions across different sectors in the context of the Roy selection model.

There are two main advantages to the use of posterior predictive distributions. First, it allows me to account for two types of uncertainty: the uncertainty incorporated in the model, and estimation uncertainty. Second, because the mobility decision is modeled here as a non-linear function of the covariates, the mean of the prediction would differ from the prediction based on the mean of the distribution of the parameters.

I use a sample of 2,741 working individuals from the Panel Study of Income Dynamics. The estimation is carried out separately for two education groups: high school graduates and college graduates. The results indicate that labor mobility has a strong effect on future wages, though the effects differ by career stage and education. In particular, the timing of a job change has a very strong effect on future earnings. Additionally, I find that the return to mobility is much higher for college graduates.

The rest of the paper is organized as follows. Section **??** presents the model and the stochastic assumptions, introduces the data set, and explains the estimation method. Section **??** discusses the results. Section **??** briefly explains the notion of the posterior predictive distributions. The simulations and their outcomes are presented in Section **??**, while Section **??** concludes.

2 Empirical Methodology

2.1 The Model

In this section I present a model that allows me to estimate the evolution of wages throughout an individual's career. I start by specifying a simple wage equation, similar to those used in Abraham and Farber (1987), Altonji and Shakotko (1987), Topel (1991), and Altonji and Williams (1997). The wage equation of an individual can be written in the following way:

$$W_{it} = E_{it}\beta_1 + T_{it}\beta_2 + X_{it}\beta_3 + e_{it},$$

where W_{it} denotes the observed (log) wage of individual i in year t, E_{it} is the individual's labor market experience at time t, T_{it} represents seniority (tenure with the same employer) and X_{it} is a set of other variables that affect current wages. The parameters of interest, β_1 and β_2, represent the returns to an additional year of experience and seniority, respectively. Note, that there is a direct connection between mobility decision and seniority: each time an individual changes jobs his seniority start from zero. In other words the value of seniority in each period is equal to the length of the sequence of unrealized past mobilities. The main problem encountered when estimating the return to seniority is the fact that seniority is endogenous in the sense that both seniority and the error term, e_{it}, might be jointly dependent on a common set of unobservables.

In this model I directly specify a separate equation to approximate the mobility decisions that led to the observed job changes. I directly model the latent utility of a job switch and the observed wages, as described below. One could follow the same logic to argue the endogeneity of experience. However, I do not specify an additional equation for the labor market participation decision because the analysis is restricted to only individuals working in every period (discussed in Section **??**).

Consider an individual i who makes a decision in each year, t, to either change jobs or keep an existing job. The individual changes jobs only if the utility from changing is higher than the utility from keeping the existing job. I denote this difference in utility levels as M^*_{it}. Following Buchinsky et al. (2008), I model the mobility-wage process for working individuals in the following way:

$$\begin{aligned} M^*_{it} &= X^m_{it}\beta^m + \mu^m_i + \epsilon^m_{it} \\ W_{it} &= X^w_{it}\beta^w + \mu^w_i + \epsilon^w_{it}, \; i = 1, \ldots, N; \; t = 2, \ldots, T_i; \end{aligned} \tag{1}$$

where X^m_{it} and X^w_{it} are the sets of individual-specific characteristics that affect mobility and wages, μ^m_i and μ^w_i are individual-specific random effects, while ϵ^m_{it} and ϵ^w_{it} are contemporaneous error terms. The researcher does not observe the latent utility, M^*, but only the decision to change jobs, $M_{it} = \mathbf{1}(M^*_{it} > 0)$, where $\mathbf{1}(\cdot)$ is the usual indicator function. The model in (**??**) is a selection model, where the first equation represents the individual's choice and the second equation represents the observed outcome in the form of wages.

The variables that affect the mobility decision include the information available to the individual at the time of the job change, such as lagged experience and seniority, last year's mobility and a set of other variables discussed in Section **??**. To insure that the model is semi-parametrically identified (Heckman 1990), I include a set of variables that affect the mobility decision but not wages, such as family composition and other family income.[1] In the wage equation, I include variables that affect wage growth both within a given job and across jobs. Variables affecting within job wage growth are the current levels of experience and seniority, while wage growth across jobs depends on a set of variables that affect initial wages at a new job. Other variables included in the wage equation are discussed in Section **??**.

In the year an individual changes jobs, wages can change discontinuously because the wage changes across jobs follow a different trajectory than within a job. To account for these changes in the wage function, I incorporate a set of variables that include information about the individual's labor market history. This specification allows me to account for wage changes at different levels of seniority and experience, as well

[1] See Millimet (2000) and Millimet et al. (2010) for evidence of the impact of children on labor market decisions.

as the amount of times an individual changed jobs in the past, and helps me control for the quality of job match and job shopping behavior. The decision to change jobs is affected by both labor demand and the current human capital composition. Antonelli et al. (2010) provide some recent evidence of the effects of labor demand on human capital formation.

To complete the likelihood specification I make the following distributional assumptions:

$$\mu_i = (\mu_i^m, \mu_i^w)' \overset{iid}{\sim} N_2(0, \Gamma),$$

$$\epsilon_{it} = (\epsilon_{it}^m, \epsilon_{it}^w)' \overset{iid}{\sim} N_2(0, \Sigma),$$

where Γ is a full covariance matrix, Σ is restricted as follows

$$\Sigma = \begin{pmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{pmatrix},$$

and $N_2(a, B)$ denotes bivariate normal distribution with mean vector a and covariance matrix B. The variance of the ϵ_{it}^m is restricted to one for the usual identification reasons in a probit model.

One can write down the likelihood function of the labor transitions of individual i for periods 2 through T conditional on the observed data in year 1 in the following way:

$$\begin{aligned} l\left\{(M_{it}, W_{it})_{t=2,\ldots T} \left| \mu_i, X_{it}, \theta \right.\right\} &= l\left\{(M_{iT}, W_{iT}) \left| \mu_i, X_{iT}, X_{iT-1}, \theta, M_{iT-1} \right.\right\} \\ &\times l\left\{(M_{iT-1}, W_{iT-1}) \left| \mu_i, X_{iT-1}, X_{iT-2}, \theta, M_{iT-2} \right.\right\} \\ &\times \ldots \times l\left\{(M_{i2}, W_{i2}) \left| \mu_i, X_{i2}, X_{i1}, \theta, M_{i1} \right.\right\}, \end{aligned} \tag{2}$$

where

$$\theta = \{\beta, \Gamma, \rho, \sigma^2\}, \tag{3}$$

and $X_{it} = (X_{it}^m, X_{it}^w)$.

The likelihood function is conditional on the initial values, M_{i1}. Alternatively, one could specify an initial conditions equation to describe the mobility process in the first year (e.g., Heckman 1981). This is the route taken in Buchinsky et al. (2008). However, here I use the likelihood specification conditioning on the observed initial values, similar to Lancaster (2000). The conditional likelihood specification allows me to simulate the predictive distributions, described below, in a more efficient way.

The posterior distribution is proportional to the product of the likelihood function and the prior. The elements of the parameter vector, θ, are assigned the conjugate prior distributions, that is $\beta \sim N(b_0, V_0)$, $\Gamma \sim IW(v_0, R_0 v_0)$, $\rho \sim N(0, c)\mathbf{1}[-1, 1]$, and $\sigma^2 \sim IG(a_1, a_2)$, respectively.[2] As detailed below, I use the conditional posterior densities to obtain the marginal distributions of the parameters. The values of the hyperparameters, $(b_0, V_0, R_0, v_0, c, a_1, a_2)$, are set to reflect the prior knowledge about the parameters. I work with rather dispersed prior distributions, thereby allowing the data to dictate the distribution of the parameters.

This model differs from the specification used in Abraham and Farber (1987), Altonji and Shakotko (1987), Topel (1991), and Altonji and Williams (1997). The models used in these studies specify a single wage equation that includes experience and seniority. They allow for unobserved heterogeneity to affect both wages and seniority and try to control for it using various methods. Abraham and Farber (1987) argue that if completed job duration is included in the earning function it will eliminate the correlation of tenure with the error component. Altonji and Shakotko (1987) present an instrumental variable solution, using within-job variation in tenure as an instrument. Topel (1991), on the other hand, uses a two-step estimation procedure that yields an estimate of the lower bound of the return to tenure that is much higher than the results of the other two studies mention above. In this model, the correlation between the seniority and the unobserved heterogeneity component is controlled for by means of explicitly modeling the mobility decision and allowing for the random effects to be correlated in across the mobility and wage equations.

A second difference is that, unlike Topel (1991) who assumes the starting wages to be a function of only past experience, I allow starting wages to vary with the level of past seniority as well. The reason for doing so is that while experience measures the amount of general human capital that is completely transferable across jobs, seniority measures not only job-specific human capital, but also human capital that may be transferable to some jobs but not others (e.g., industry-specific human capital). Neal (1995) investigates the existence of the industry-specific human capital using the Displaced Workers Survey. He argues that a complete explanation of the relationship between wages and seniority must involve factors that are specific to a particular job, but also industry- or occupation-specific skills. This specification allows me to measure

[2] A conjugate prior distribution leaves the posterior distribution in the same form as the prior (Gelman et al. 1995). *IW* and *IG* denote Inverse Wishart and Inverse Gamma distribution functions, respectively.

both the returns to seniority within a job and the effect of accumulated industry-specific human capital on the initial wages at a new job.

2.2 Data

Following previous studies of the returns to seniority mentioned above (Abraham and Farber 1987; Altonji and Shakotko 1987; Topel 1991; Altonji and Williams 1997; Buchinsky et al. 2008), I use the data from the Panel Study of Income Dynamics (PSID). This data set is particularly attractive for longitudinal research of labor transitions for a number of reasons.[3] First, individuals are followed for very long periods of time; particular efforts were made to follow individuals even when they change place of residence. Second, information is collected on a wide range of topics, including information about an individual's jobs and family composition. Third, the families are followed across generations; when children of original sample members leave home, they remain in the sample.

I use 18 waves of the PSID, spanning the years 1975 through 1992. The sample used in this study is restricted to household head between the ages of 18 and 60, are in the sample for at least three consecutive years, and participate in the labor force in every year they appear in the sample. All observations from the poverty sub-sample are excluded. In addition, because the sample is restricted to individuals who work in each year they appear in the sample, high school dropouts are excluded from the estimation as this restriction severely affected (by more than 50%) the size of this group. The resulting data set includes 2,741 individuals with 12 or more years of education.

Particular effort has been made to cross-check and validate the constructed variables related to experience and seniority. Topel (1991) gives a detailed explanation of the problematic features of the data, especially the tenure data. For example, tenure variables are sometimes recorded in wide intervals, are missing, or are inconsistent with participation and mobility data. Consequently, the data were thoroughly checked.[4]

I estimate the model separately for two education groups (high school and college graduates) to allow for the human capital accumulation process to vary with education level. The dependent variables are the logarithm of the real annual income, W_{it}, expressed in 1987 US dollars and adjusted for full-time work (if the number of weeks the person worked was less than 50, earnings are adjusted), and an indicator of labor

[3]See Hill (1992) for a detailed description of the PSID.

[4]For more details on the algorithm of data cleaning and variable construction, see Buchinsky et al. (2008).

mobility, M_{it}, which is set to be one (job change occurred in year t) if the person changed employers in the year $t-1$, but worked in the new job less than half the amount of time he was employed in that year, or if he moved in the first six months (for full time) of the year t.

Summary statistics are presented in Table 1. Several changes over time can be observed, such as an increase in both sample size and annual income. Despite a modest amount of sample attrition the sample size increases over the years for two reasons: First, children of the originally surveyed families became household heads and are added to the sample. Second, new families were added to the sample. The annual income increases over time, a fact that can be explained by the sample restriction rule. While the average experience and seniority increases, the education level does not change, which is consistent with following individuals over time. The proportion of individuals who change jobs each year ranges from 8% to 20% and decreases over time.

The data set used in Topel (1991) was based on the earlier waves of the PSID, 1968-1983. In comparison with the data used in his study, individuals in the sample, on average, have more years of education: 14.5 versus 12.6 years. This difference can be explained by the exclusion of high school dropouts. At the same time, the experience and seniority are lower in the sample (17 and 6 years of experience and seniority versus 20 and 10, respectively).

Looking at the demographic variables, we can see that about 20% of the sample are African-American, while only four percent are Hispanic. The fraction of Hispanics in the sample increases between 1988 and 1990 as a result of efforts made by the PSID to collect information for individuals who left the sample in the previous years. The proportion of small children in the sample decreases over time, while the amount of children remains roughly constant. Geographic location variables indicate a certain degree of geographic mobility. The proportion of older individuals decreases over time, while the proportion of younger individuals increases, as is evident from the cohort variables.

2.3 Estimation Procedure

The goal in estimating the model is to summarize the marginal posterior distribution of the model parameters. The complexity of the model does not allow me to analytically derive marginal posterior distributions of the elements of the parameter vector, θ. Hence, I estimate the posterior distribution of the parameters of the model using the Markov Chain Monte Carlo simulation method, specifically the Gibbs sampler (Gelfand and Smith 1990; Casella and George 1992) and the Metropolis-Hastings algorithm (Hastings

1970; Chib and Greenberg 1995).

The Gibbs sampler allows me to obtain a sample of draws from the marginal posterior distributions of the parameters by sequentially sampling from the posterior distributions, conditional on the latest draws of the other parameters. The derivation of the conditional densities is additionally complicated by the fact that both M^*_{it} and μ_i are unobserved. I follow Chib and Greenberg (1998) and augment the parameter vector, θ, to include both the latent M^*, and the random effects, μ, so that $\theta = \{\beta, \Sigma, \Gamma, M^*, \mu\}$.

I obtain a sample of draws from the posterior density of the parameters by sequentially sampling from the following conditional densities:

$$p(\beta|y, \theta_{-\beta}), \tag{4}$$

$$p(M^*|y, \theta_{-M^*}), \tag{5}$$

$$p(\mu|y, \theta_{-\mu}), \tag{6}$$

$$p(\Gamma|\mu), \tag{7}$$

$$p(\Sigma|y, \theta_{-\Sigma}), \tag{8}$$

where y denotes the observed data and $\theta_{-(\cdot)}$ denotes all the elements of θ other than $(\cdot)$. The exact conditional posterior densities are presented in Appendix A. The first four conditional densities, (**??**)-(**??**), have known density functions and can be easily simulated by direct sampling. The conditional density in (**??**) does not belong to any known class of distributions and is approximated using the Metropolis-Hastings algorithm.

The Gibbs sampler was run for 7,000 iterations, and the first 2,000 iterations were discarded. The length of the chains is chosen to insure convergence and have a sufficient number of draws from the post-burn-in run. Convergence and mixing of the chains is discussed in Appendix A.

One of the goals of this paper is to learn to what extent the amount of schooling affects wage growth. To answer this question the estimation was carried out for two education groups, referred to as "high school graduates" and "college graduates", having 12 to 16 years of education and more than 16 years of education, respectively.

The variables included in the mobility equation include: a constant, education, lagged experience and its square, lagged seniority and its square, other family income, county unemployment rate, number of children in the family, number of children younger than two years old, and between two and five years old, three region dummies, an SMSA dummy, dummies for African-American and Hispanic, a dummy for married, and cohort effects measured using age categories in 1975 (less than 15, 16 to 25, 26 to 35, and 36 to 45), and calendar year dummies.[5]

The variables included in the wage equation are: a constant, education, experience and its square, seniority and its square, a set of variables to allow for discontinuous wage changes associated with labor mobility[6], county unemployment rate, three region dummies, an SMSA dummy, dummies for African-American and Hispanic, and cohort effects measured using age categories in 1975 (less than 15, 16 to 25, 26 to 35, and 36 to 45), and calendar year dummies.

3 Results

3.1 Parameter Estimates

The results of the model estimation are presented in Tables 2 through 7—I first present the results for mobility equation for both education groups, followed by results for the wage equation, and then the results for covariance matrices. In all the tables I omit the results for geographical, cohort, and year dummies for brevity. Since estimation of the model's parameters is only an intermediate step of this paper, and the simulation of the counterfactuals is the actual goal I only devote a small part of the paper to the discussion of parameter estimates.

I start by comparing the results from the mobility equation across education groups. High school graduates are slightly more likely than college graduates to change jobs over the sample period—the probability of a job change evaluated at the mean of the regressors is 14.69% for high school graduates and 13.36% for college graduates. The elasticity of the probability of a job change with respect to experience and seniority is 0.37 and 0.45 for high school graduates, respectively, and 0.50 and 0.79 for college graduates. This finding is consistent with Mincer and Jovanovich (1981), who claim that the fact that seniority has a stronger effect than experience on labor mobility "the most firmly established fact about labor mobility."

[5] I include a set of 16 year dummy variables (the omitted year is 1992) to control for economy wide trends in wages and mobility.

[6] These variables are constructed in the following way. I divide the level of seniority at the end of the last job into four groups—up to one year, two to five years, six to ten years and more than ten years. The groups are denoted by $j = 1, \dots, 4$, respectively. Each time an individual changes jobs I update the j's group of variables in the following way: d_j, the number of job changes, increases by one, s_j is set at the level of seniority on the last job and e_j is set at the level of experience at the time of job change.

An additional year of seniority decreases the probability of a job change by 8% for high school graduates and 13%, and college graduates. Family income that is not from work has a negative effect on both education groups, but more so on high school graduates. The probability of a job change in two consecutive years is much lower for college graduates. Labor mobility decreases the probability of a job change in the next year by 75% and 84% for high school graduates and college graduates, respectively. This could indicate better job matches or a greater cost to repetitive job changes for college graduates.

Looking at the parameter estimates for the wage equation, we can see that wages on average are lower for high school graduates; the constant and the return to education are smaller in the less educated group. The return to experience, defined as a partial derivative of wages with respect to experience, is lower for high school graduates than for college graduates, while the return to seniority is higher. The return to ten years of seniority increases wages by approximately 30% and 20% for high school and college graduates, respectively, which is comparable to Topel's estimate of 25% for the "typical worker". These results are consistent with the predictions of the theory of human capital which states that the more educated individuals would have higher returns to the general human capital (measure by experience), while less educated individuals would have higher returns to firm specific human capital (measured by seniority).

The fact that high school graduates exhibit higher returns to seniority while college graduates exhibit higher returns to experience, can be explained by different levels of initial human capital – accumulated prior to entering the labor force and measured by the level of schooling – that sort the individuals into different labor markets resulting in different accumulation of transferable and job-specific skills.

The effects of mobility on wages depend on a number of factors, such as the level of experience and seniority. The estimates of the model parameters can be used to infer the immediate effect of a job change conditional on particular values of the parameters. However, to infer the effect of past mobility on future wages, I need to iterate the process and compare the distribution of wages for different mobility scenarios. In the next section, I introduce the notion of the posterior predictive distribution and explain how I use the estimates of the parameters of the model to provide information about the effects of mobility in one period on wages in subsequent years.

3.2 Posterior Predictive Distributions

One of the advantages of the Bayesian approach is that it allows me to summarize the implications of the model by the use of the *posterior predictive distribution* (PPD). It uses the knowledge obtained from the analysis of the data to make inferences about unknown observables (Gelman et al. 1995). For example, consider a model in which a set of observables, y, is a function of the parameters, θ. After estimating the model, I can make a prediction about an unknown observable, $\tilde{y}$, which summarizes the overall implication of the estimated model on the variables of interest. The PPD of $\tilde{y}$ is as follows:

$$\begin{aligned} p(\tilde{y}|y) &= \int p(\tilde{y}, \theta|y) d\theta \\ &= \int p(\tilde{y}|\theta, y) p(\theta|y) d\theta \\ &= \int p(\tilde{y}|\theta) p(\theta|y) d\theta. \end{aligned} \tag{9}$$

The last line of (**??**) presents the predictive distribution as an average of the conditional prediction over the posterior density of θ. The Monte Carlo approximation of (**??**) is given by

$$\frac{1}{J} \sum_{j=1}^{J} p(\tilde{y}|\theta^{(j)}),$$

where $\theta^{(j)}$ represents the jth draw, $j = 1, \ldots, J$, of the parameter vector.

To obtain a draw from this distribution, I first draw $\theta^{(j)}$ from the posterior density of θ, $p(\theta|y)$, and then draw a predicted value $\tilde{y}^{(j)}$ from the conditional predictive density, $p(\tilde{y}|\theta = \theta^{(j)})$. In the context of this model, I can simulate both the mobility decisions and the corresponding wages for given values of the exogenous variables from the posterior predictive distribution, $p(M, W|y)$.

One of the reasons I use the PPD is to account for uncertainty. There are two types of uncertainty associated with predicting the outcomes. First, there exists the uncertainty that is a part of the model, represented by the variance components. Second, there is the posterior uncertainty of the parameters, θ, due to the fact that the sample is finite. This means that when I make predictions about mobility and wages, I need to account both for uncertainty of the model given the parameters, and the parameter uncertainty (Buchinsky and Leslie 2000). The use of the PPD allows me to account for both sources of uncertainty.

The second reason for using the PPD is the non-linearity of the mobility equation. An alternative strategy could be to simulate mobility and wages conditional on the point estimates of the parameters of the model—"plug-in" prediction. The expected value of the PPD and the "plug-in" prediction are equivalent for linear functions. However, the fact that I use a non-linear function in the mobility equation rules out the possibility of correctly predicting mobility conditional on the point estimates of the parameters.

After simulating the joint distribution of mobility and wages, I can directly compare particular alternatives. For example, I can compare the wages in later periods conditional on different mobility paths in earlier periods, M_1 and M_2, by comparing $p(W|M_1)$ and $p(W|M_2)$. The next section describes this process with respect to the simulations performed.

3.3 Simulations

The following sets of simulations explore the mobility-wage process by means of comparing simulated alternatives. The simulations are computed for a given set of values of the exogenous variables, chosen to be representative of the data set.

I chose two sets of independent variables by fixing all the exogenous (with respect to mobility) variables.[7] The value of experience in the starting year has a mean of ten years. In each education group, I simulate the mobility-wage process for two different individuals, one with 14 years of experience and five years of seniority in the initial year, and the other with four years of experience and one year of seniority in the initial year. As a result, I create four sets of independent variables referred to as follows: High school graduate with five years of experience, high school graduate with 15 years of experience, college graduate with five years of experience, and college graduate with 15 years of experience. The simulations for individuals with 12 years of education and 16 years of education are done using the draws from the corresponding distributions of the parameters.

The 17 sample years, for which the simulations are computed, are divided into two stages—the primary stage, years one through five, and the secondary stage, years six through 17. For most of the simulations, I compare the mean of the wage distribution in the secondary stage that corresponds to a particular mobility pattern in the primary stage.

A few words are needed to describe the treatment of the value of the random effects in both equations. The simulations presented below are computed conditional on the value of the random effects set to zero. If I treat the individual-specific heterogeneity as a parameter and sample different values of the random effect from its predictive distribution, I would end up comparing different individuals. In that case, the effect of

[7] The independent variables reflect the following individual characteristics: 12 (16) years of education, depending on the education group, resident of an SMSA in the western region of the USA, married with one child.

mobility on wages would be confounded with differences in the individual heterogeneity component.

I present two sets of simulations. First, simulations computed with no restriction on the mobility process. Second, simulations for which I fix *a priori* the mobility pattern in the primary stage. The simulation algorithm is presented in Appendix B.

3.3.1 Unrestricted Simulations

The first set of simulations is created without imposing any restrictions on mobility. From the computed draws of mobility and wages, I choose the sets of simulations that correspond to specific mobility patterns in the primary stage and compare the means of the wages in the secondary stage across sets. The resulting values are the Monte Carlo approximation of $E(W|M_1)$ and $E(W|M_2)$, where M_1 and M_2 are alternative mobility paths in the primary stage. This set of simulations is used for exploration of mobility-wage patterns, while more rigorous analysis is provided in the next section.

Figure 1 presents the mean of the log wages in years six through 17 associated with mobility paths that result in one job change in the primary stage that occurs during year 1, 3, or 5. For example, the "M1_3" curve represents the mean of wages, conditional on one job change in the primary stage that took place in year 3. I find all the simulations that have a particular mobility pattern and compute the mean over those simulations only, so each curve corresponds to a mean of wages over a different number of simulations.

We can see that the timing of the job switch affects the mean wage differently for individuals with five and 15 years of starting experience. While the wages of younger individuals (five years of starting experience) increase if they delay the job change from year 1 to year 5, the older individuals (15 years of starting experience) receive higher wages if they move in year 1 as opposed to year 5. A possible reason for may be the form of dependence of the initial wages at a new job on general and specific human capital. These results seem to indicate that returns to mobility are time contingent and suggest that there is an optimal timing for a job change. I investigate this assertion further in the next section.

Figure 2 illustrates the means of wages for a different number of job changes during the primary stage, ranging from zero to four job changes. I first compare the results for individuals with five years of starting experience. One job change, compared to no job changes, in the primary stage, increases the average wage of a high school graduate by approximately 10% in year 6, while the wages of a college graduate increase by 20%. The wage differential is almost constant over the 12 years of the secondary stage.

We can see that more frequent job changes increase wages. Mobility patterns resulting in three job changes lead to wages that are increased by approximately 20% and 32% for the high school graduate and the college graduate, respectively. For older individuals (15 years of starting experience) the relationship between the number of job changes and wages is similar, although the magnitude is different. Three job changes during the primary stage increase the annual wages of a high school graduate by only 6%, while wages of college graduate increase by 32%.

While job changes seem to increase future wages, the probability of these mobility paths is lower for a higher number of job changes. The probability of an individual changing jobs four times in first five years ranges from 0.02% to 0.2%, while the probability of one job change is between 33% and 42%.

3.3.2 Simulations for Exogenous Mobility Paths

In the second set of simulations, I utilize a different approach. Instead of simulating the mobility decisions in the primary stage, I fix them *a priori* and allow the model to determine both mobility and wages in the secondary stage. The three simulated mobility paths in the primary stage (first five years) are: no labor mobility, only one job change in year 1, and only one job change in year 5. We can think of these mobility paths as pertaining to different job contracts that restrict labor mobility.

Figure 3 depicts the means of wages for each set of simulations and the mean of the unrestricted simulations for all individuals. We can see that the wage trajectory is very different across individuals. For the younger individuals (five years of starting experience), wages start at roughly the same level and are increasing, but the trajectory is steeper for the college graduate which indicates higher overall wage growth associated with a higher level of schooling. If both individuals keep their existing jobs (no job changes in the primary stage), during the 12 years the college graduate would have accumulated almost twice the annual income of the high school graduate in year 6. Older individuals (15 years of starting experience) have flatter wage profiles, but the wages of the college graduate are strictly higher than the wages of the high school graduate.

Comparing the wage profiles of younger individuals, we can see that both benefit from job changes, but in different ways. The effect of mobility is more pronounced for the college graduate. The highest wage level of those simulated is achieved by switching jobs in year 5. The high school graduate benefits less from job changes. The unrestricted path yields the highest wage level, but a later job switch still increases his earnings more than the earlier mobility.[8] The job change in year 1 increases the wages (compared to no

[8]The unrestricted simulations lead to higher wages because the average wage is computed over all mobility patterns in the

job switches in the primary stage) by 4% and 11% for the high school graduate and the college graduate, respectively. Alternatively, the job change in year 5 increases the wage by 9% and 26% for the high school graduate and college graduate, respectively. One plausible explanation is that it is advantageous to accumulate seniority before a job switch at the early stages of an individual's career.

The wage profiles are different for older individuals (15 years of starting experience). Both receive higher wages if they move earlier, in year 1. However, while the later move increases the wages of the college graduate in comparison to no mobility scenario, the high school graduate suffers wage losses if he switches jobs in year 5. The job change in year 1 increases wages (compared to no job switches in the primary stage) by 9% and 19% for the high school graduate and the college graduate, respectively. Alternatively, the job change in year 5 decreases the wage of the high school graduate by 10% and increases wages of the college graduate by only 1%. These results suggest that a non-linear dependence between the timing of a job change and the returns to mobility, which is examined below.

I find that during the 12 years the college graduate with five years of starting experience accumulates more than four times the annual income of the high school graduate in year 6, given that both change jobs in year 5. That means that during these 12 years the college graduate accumulates more than the opportunity cost of college education, measured by forgone income.

To check the hypothesis that returns to mobility are dependent on the timing of the job change, an additional set of simulations is computed. For both younger individuals, wages are simulated for 15 mobility paths that were exogenously fixed in *all* years. Each path includes only one job change in a different year, for years 1 through 15. Figure 4 presents the mean of wages in year 17 corresponding to the year of the job change for both individuals. The graphs are concave; wages increase for later job changes in years 1 through 5, and decrease for later years. We can see that in both cases there is an optimal time for a job change (around year 5).

The findings presented above have a number of important economic implications. The fact that the effects of mobility on wages differ by education informs us that schooling, or initial human capital, affects not only the wage growth within a job, through the returns to experience and seniority, but also the wage growth across jobs. Specifically, the returns to mobility are much more pronounced for the college graduate. This provides us with additional information about the returns to schooling and their structure.

From the individual's point of view, we can see that it is important to take into account the effects of

primary stage, including more than one job change.

the timing of labor mobility on future wages. For example, if an individual is considering a job change in the upcoming years, he can change his future wages by choosing the optimal time to move. In other words, if individuals recognize the labor market opportunities and constraints they face in each period, these constraints can be altered by past behavior. The effects of the timing of labor mobility become even more important when signing job contracts. On one hand, an individual is not allowed to quit during the period covered by the contract, but on the other hand the contract provides him with an insurance policy from being fired. The analysis above shows that the length and timing of contracts should depend on optimal mobility. For instance, younger individuals, considered above, could benefit from signing a contract for years 1 through 5, as well as a contract for later years.

The most common interpretation of experience and seniority in the literature is that they represent the amounts of general and specific human capital, respectively. While general human capital increases the marginal productivity of individuals by the same amount across firms, some training increases the productivity more in firms that provided the training than in other firms. It has been pointed out in Becker (1962) that much of the training provided by a firm is neither completely specific nor completely general. In this study, I find that the initial wages at a new job depend non-linearly on the level of an individual's seniority at the last job. A possible explanation is that seniority measures not only specific, or non-transferable, human capital, but also human capital that is transferable to some jobs, but not necessarily all (e.g., industry-specific human capital as argued in Neal (1995)).

4 Conclusions

In this paper I investigate the effects of human capital accumulation on wages. I use a selection model to specify the dependence between labor mobility and wages. This model is estimated using a fully Bayesian framework that allows me to sample from the exact small sample distribution of the model parameters.

The parameters of the model do not directly, or fully, inform us of the effects of labor mobility on wages because of the sequential nature of the dependence between mobility and wages. However, I can infer these effects by predicting future wages that correspond to alternative mobility scenarios, and thus different patterns of human capital accumulation. This is accomplished by simulating posterior predictive distributions of mobility and wages. This approach allows me to take into account two sources of uncertainty: uncertainty within the model and estimation/prediction uncertainty.

I estimate the model using working individuals from the PSID. The model is estimated separately for high school and college graduates to allow for differential effects of post-schooling human capital accumulation on wages. For each group I pick two hypothetical "representative" individuals, corresponding to different stages of one's career, and simulate the mobility-wage paths for those individuals. The effects of labor mobility are inferred by comparing wage outcomes in later periods, corresponding to alternative past mobility paths.

This study presents a number of new findings. First, I find that the labor mobility has a strong effect on the distribution of wages in later periods for both education groups and both stages of an individual's career. Second, I find that these effects are much larger for college graduates than for high school graduates. In all of the simulations, only one mobility scenario leads to a wage loss (compared to the no mobility alternative). Third, I show that both the magnitude and the direction of the effects of labor mobility on wages are strongly dependent on the timing of the job change. I find that one job change at an optimal time can increase the wages of a young high school graduate by 9% and the wages of a young college graduate by as much as 26%. These results indicate that further investigation of the effects of human capital on the wage growth is in order, as well as construction of new measures of human capital that reflect skills that are transferable across some, but not all jobs.

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Appendix A—Posterior Sampling

The model in (**??**) can be written in matrix notation as

$$Z = X\beta + \mu + \epsilon, \tag{10}$$

where Z, X, μ, ϵ are the stacked vectors of $Z_{it} = (M^*_{it},\ W_{it})'$, $X_{it} = \begin{pmatrix} X^m_{it} & 0 \\ 0 & X^w_{it} \end{pmatrix}$, μ_i and ϵ_{it}.

Sampling the Latent Variable M^*

The conditional distribution of Z is

$$Z_{it}|\theta \sim N(X_{it}\beta + \mu_i, \Sigma).$$

From this joint distribution we can infer the conditional univariate distribution of interest, $\Pr(M^*_{it}|W_{it}, \theta)$, which is truncated univariate normal, with the truncation region depending on the values of M_{it}

Sampling the Regression Coefficients β

It can be shown (see Chib and Greenberg (1998) for details) that if the prior distribution of β is given by

$$\beta \sim N(\beta_0, B_0),$$

then the posterior distribution of β, conditional on all other parameters is

$$\beta|\theta_{-\beta} \sim N(\hat{\beta}, B),$$

where

$$\hat{\beta} = B\left(B_0^{-1}\beta_0 + \sum_{i=1}^{N}\sum_{t=1}^{T} X'_{it}\Sigma^{-1}(Z_{it} - \mu_i)\right)$$

and

$$B = \left(B_0^{-1} + \sum_{i=1}^{N}\sum_{t=1}^{T} X'_{it}\Sigma^{-1}X_{it}\right)^{-1}.$$

Sampling the Individuals' Random Effects μ_i

The conditional likelihood of the random effects for individual i is as follows

$$l(\mu_i) \propto \Sigma^{-T/2} \exp\left\{-.5\sum_{t=1}^{T}(Z_{it} - X_{it}\beta - \mu_i)'\Sigma^{-1}(Z_{it} - X_{it}\beta - \mu_i)\right\},$$

The prior distribution for the random effects is $N(0, \Gamma_i)$, so that the posterior distribution of μ_i is

$$\mu_i \sim N(\hat{\mu}_i, V_{\mu_i}),$$

where

$$V_{\mu_i} = \left(\Gamma_i^{-1} + T\Sigma^{-1}\right)^{-1},$$

and

$$\hat{\mu}_i = V_{\mu_i}(\iota_T \otimes \Sigma^{-1})(Z_i - X_i\beta)$$

Sampling the Covariance Matrix Σ

Recall that the covariance matrix of the idiosyncratic error terms, ϵ_{it}, is given by $\Sigma = \begin{pmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{pmatrix}$. Since the conditional distribution of Σ is not a standard known distribution, it is impossible to sample it directly. Instead, we sample the elements of Σ using the Metropolis-Hastings (M-H) algorithm (see Chib and Greenberg, 1995). The target distribution here is the conditional posterior of Σ, that is,

$$p(\Sigma|\theta_{-\Sigma}) \propto l(\Sigma|\theta_{-\Sigma},)p(\sigma^2)p(\rho).$$

The likelihood component is given by

$$l(\Sigma|\theta_{-\Sigma}) = |\Sigma|^{-NT/2}\exp\left\{\sum_{i=1}^{N}\sum_{t=1}^{T} A_{it}'\Sigma^{-1}A_{it}\right\},$$

where, $A_{it} = Z_{it} - X_{it}\beta - \mu_i$ and the prior distribution on ρ and σ^2 is chosen to be the conjugate distribution, truncated over the relevant regions, namely

$$p(\rho) = N_{[-1,1]}(0, V_\rho)$$

and

$$p(\sigma^2) = N_{(0,\infty)}(\mu_{\sigma^2}, V_{\sigma^2}).$$

The candidate generating function is chosen to be of the autoregressive form, $q(x', x^*) = x^* + v_i$, where v_i is a random normal disturbance. The tuning parameter for ρ and σ^2 is the variance of $v_i's$.

Sampling the Covariance Matrix Γ

Given the prior distribution $IW(v_0, R_0 v_0)$, the posterior distribution of Γ, conditional on all other parameters is:

$$\Gamma \sim IW(N + v_0, R_0 + \sum_{i=1}^{N}(\mu_i \mu_i').$$

Appendix B—Simulating the Predictive Distribution

Start from choosing a set of exogenous right-hand-side variables and a value of the random effect. For each simulation repeat the following steps. These steps result in two $1 \times T$ vectors of M and W.

1) Pick ρ, σ^2 from the Gibbs sequence and compose Σ

2) Simulate ϵ from $f(\epsilon|\Sigma)$

3) Pick β from the Gibbs sequence

4) Compute M_t^* and M_t from (**??**)

5) Update the mobility dependent variables (i.e. seniority, J variables and lagged mobility)

6) Compute W_t from (**??**)

Table 1: Summary Statistics for the PSID Extract for Selected Years, 1976–1992

	Variable	Year			
		1976	1980	1986	1992
Individual and Family Characteristics:					
	Observations	1,028	1,384	1,735	2,066
1.	Mobility	0.0759	0.1828	0.1055	0.0774
		(0.2649)	(0.3866)	(0.3073)	(0.2674)
2.	Log Wages	10.1452	10.1527	10.2482	10.2631
		(0.6353)	(0.6433)	(0.7190)	(0.7228)
3.	Education	14.6255	14.4588	14.7499	14.7231
		(1.9880)	(1.9416)	(1.8326)	(1.7845)
4.	Experience	13.5136	14.3559	16.9879	20.5765
		(8.9736)	(8.9566)	(9.3086)	(9.5802)
5.	Seniority	4.4839	4.1220	6.3074	8.2615
		(5.2849)	(5.3954)	(5.9456)	(7.2034)
6.	Black	0.1654	0.2038	0.2035	0.1805
		(0.3717)	(0.4029)	(0.4027)	(0.3847)
7.	Hispanic	0.0360	0.0332	0.0340	0.0542
		(0.1864)	(0.1793)	(0.1813)	(0.2265)
8.	Married	0.8434	0.7847	0.8052	0.8103
		(0.3636)	(0.4112)	(0.3962)	(0.3922)
9.	Family Other Income	0.8640	1.7059	2.9469	4.8468
		(4.8345)	(7.0220)	(10.1179)	(24.3498)
10.	Northeast	0.1420	0.0853	0.0594	0.0779
		(0.8576)	(1.0580)	(1.1634)	(1.0365)
11.	North Central	0.2023	0.1467	0.0968	0.1162
		(0.8803)	(1.0800)	(1.1769)	(1.0513)
12.	South	0.2597	0.2413	0.2213	0.2817
		(0.8977)	(1.1065)	(1.2124)	(1.0977)
13.	Living in SMSA	0.7529	0.7392	0.6219	0.6234
		(0.4315)	(0.4393)	(0.4851)	(0.4846)
14.	County Unempl. rate	7.6733	6.8274	6.3164	6.6595
		(2.9995)	(2.4642)	(2.5440)	(2.0723)
15.	Age 15 or less in 1975	0.0447	0.2045	0.3873	0.5426
		(0.2068)	(0.4035)	(0.4873)	(0.4983)
16.	Age 16 to 25 in 1975	0.2646	0.3100	0.2755	0.2144
		(0.4413)	(0.4626)	(0.4469)	(0.4105)
17.	Age 26 to 35 in 1975	0.4446	0.3194	0.2282	0.1684
		(0.4972)	(0.4664)	(0.4198)	(0.3743)
18.	Age 36 to 45 in 1975	0.1508	0.1062	0.0726	0.0513
		(0.3580)	(0.3082)	(0.2596)	(0.2207)

Table 2: Mobility Equation for College Graduates

	Variable	Participation			
		Mean	St. Dev.	Range	
				Min	Max
1.	Constant	-0.5973	0.2708	-1.1338	-0.0796
2.	Education	0.0035	0.0116	-0.0182	0.0272
3.	Lagged Experience	-0.0446	0.0082	-0.0605	-0.0284
4.	Lagged Experience Squared	0.0007	0.0002	0.0003	0.0011
5.	Lagged Seniority	-0.0747	0.0091	-0.0930	-0.0571
6.	Lagged Seniority Squared	0.0017	0.0004	0.0009	0.0025
7.	Lagged Mobility	-0.9193	0.0600	-1.0403	-0.8041
8.	Black	0.0598	0.0517	-0.0452	0.1608
9.	Hispanic	-0.0230	0.1191	-0.2702	0.1972
11.	Number of children	-0.0721	0.0224	-0.1156	-0.0284
12.	Children 1 to 2	0.0452	0.0363	-0.0260	0.1157
13.	Children 3 to 5	0.0089	0.0407	-0.0731	0.0885
14.	Married	-0.0636	0.0444	-0.1525	0.0226
15.	Family Other Income	-0.0090	0.0021	-0.0131	-0.0046

Table 3: Mobility Equation for High School Graduates

	Variable	Participation			
		Mean	St. Dev.	Range	
				Min	Max
1.	Constant	-0.9904	0.2975	-1.5777	-0.3940
2.	Education	0.0264	0.0146	-0.0017	0.0554
3.	Lagged Experience	-0.0294	0.0083	-0.0458	-0.0127
4.	Lagged Experience Squared	0.0004	0.0002	0.0000	0.0008
5.	Lagged Seniority	-0.0831	0.0083	-0.0993	-0.0669
6.	Lagged Seniority Squared	0.0019	0.0003	0.0013	0.0025
7.	Lagged Mobility	-0.7449	0.0580	-0.8574	-0.6296
8.	Black	0.0459	0.0425	-0.0378	0.1290
9.	Hispanic	0.0419	0.0750	-0.1007	0.1921
11.	Number of children	-0.0053	0.0203	-0.0459	0.0327
12.	Children 1 to 2	0.0430	0.0368	-0.0285	0.1157
13.	Children 3 to 5	-0.0467	0.0380	-0.1202	0.0277
14.	Married	-0.0614	0.0462	-0.1480	0.0298
15.	Family Other Income	-0.0198	0.0046	-0.0291	-0.0112

Table 4: Wage Equation for High School Graduates

	Variable	Participation			
		Mean	St. Dev.	Range	
				Min	Max
1.	Constant	8.2835	0.1566	7.9838	8.5999
2.	Education	0.0428	0.0057	0.0319	0.0542
3.	Experience	0.0536	0.0034	0.0469	0.0604
4.	Experience Squared	-0.0010	0.0001	-0.0012	-0.0009
5.	Seniority	0.0283	0.0035	0.0214	0.0353
6.	Seniority Squared	-0.0002	0.0001	-0.0004	0.0001
7.	Black	-0.1944	0.0283	-0.2507	-0.1404
8.	Hispanic	0.0059	0.0506	-0.0945	0.1026
	No. Of Jobs that Lasted:				
9.	Up to 1 Year	0.1001	0.0149	0.0707	0.1287
10.	2 to 5 Years	0.1514	0.0216	0.1086	0.1939
11.	6 to 10 Years	0.2900	0.0674	0.1566	0.4197
12.	Over 10 Years	0.0784	0.0904	-0.0984	0.2516
	Seniority at the Last Job Change that Lasted:				
13.	2 to 5 Years	0.0263	0.0073	0.0120	0.0405
14.	6 to 10 Years	0.0050	0.0090	-0.0122	0.0226
15.	Over 10 Years	0.0201	0.0062	0.0079	0.0326
	Experience at the Last Job Change that Lasted:				
16.	Up to 1 Year	-0.0051	0.0017	-0.0085	-0.0017
17.	2 to 5 Years	-0.0035	0.0017	-0.0070	-0.0001
18.	6 to 10 Years	-0.0101	0.0029	-0.0157	-0.0045
19	Over 10 Years	-0.0006	0.0040	-0.0084	0.0072

Table 5: Wage Equation for College Graduates

	Variable	Participation			
		Mean	St. Dev.	Range	
				Min	Max
1.	Constant	8.8138	0.1565	8.5111	9.1259
2.	Education	0.0568	0.0055	0.0458	0.0671
3.	Experience	0.0692	0.0036	0.0622	0.0760
4.	Experience Squared	-0.0014	0.0001	-0.0016	-0.0013
5.	Seniority	0.0183	0.0040	0.0107	0.0262
6.	Seniority Squared	0.0000	0.0001	-0.0002	0.0002
7.	Black	-0.2088	0.0405	-0.2924	-0.1290
8.	Hispanic	0.0620	0.0813	-0.0938	0.2195
	No. Of Jobs that Lasted:				
9.	Up to 1 Year	0.1405	0.0194	0.1021	0.1784
10.	2 to 5 Years	0.1465	0.0203	0.1067	0.1860
11.	6 to 10 Years	0.2089	0.0684	0.0757	0.3413
12.	Over 10 Years	0.2519	0.0970	0.0631	0.4404
	Seniority at the Last Job Change that Lasted:				
13.	2 to 5 Years	0.0535	0.0071	0.0399	0.0678
14.	6 to 10 Years	-0.0046	0.0096	-0.0231	0.0146
15.	Over 10 Years	0.0020	0.0079	-0.0138	0.0171
	Experience at the Last Job Change that Lasted:				
16.	Up to 1 Year	-0.0031	0.0019	-0.0068	0.0008
17.	2 to 5 Years	-0.0095	0.0018	-0.0130	-0.0058
18.	6 to 10 Years	0.0012	0.0029	-0.0044	0.0068
19	Over 10 Years	-0.0056	0.0036	-0.0129	0.0015

Table 6: Estimates of the Stochastic Elements for High School Graduates

Variable		Mean	St. Dev.	Range	
				Min	Max
Covariance Matrix of White Noises (element of Σ):					
1.	Σ_{11}	1.0000	0.0000	1.0000	1.0000
2.	Σ_{12}	-0.0219	0.0068	-0.0350	-0.0085
3.	Σ_{22}	0.1511	0.0021	0.1467	0.1552
Covariance of Individual Specific Effects (elements of Γ):					
4.	Γ_{11}	0.0506	0.0103	0.0336	0.0734
5.	Γ_{12}	-0.0338	0.0083	-0.0515	-0.0181
6.	Γ_{22}	0.1792	0.0082	0.1641	0.1957

Table 7: Estimates of the Stochastic Elements for College Graduates

Variable		Mean	St. Dev.	Range	
				Min	Max
Covariance Matrix of White Noises (element of Σ):					
1.	Σ_{11}	1.0000	0.0000	1.0000	1.0000
2.	Σ_{12}	-0.0105	0.0069	-0.0248	0.0025
3.	Σ_{22}	0.1601	0.0020	0.1559	0.1640
Covariance of Individual Specific Effects (elements of Γ):					
4.	Γ_{11}	0.0592	0.0115	0.0411	0.0839
5.	Γ_{12}	-0.0569	0.0095	-0.0771	-0.0396
6.	Γ_{22}	0.2401	0.0104	0.2206	0.2619

Figure 1: Mean of Wages for One Job Change—Unrestricted

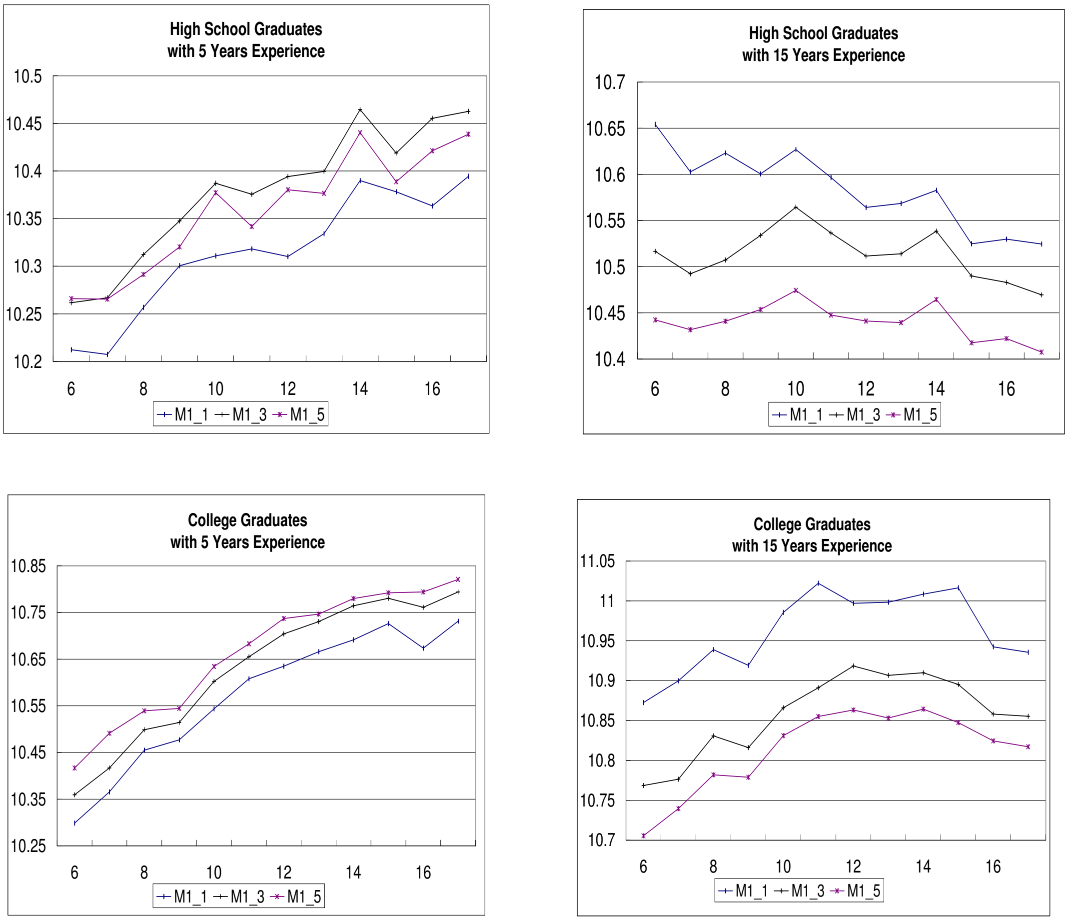

Figure 2: Mean of Wages for Different Number of Job Changes

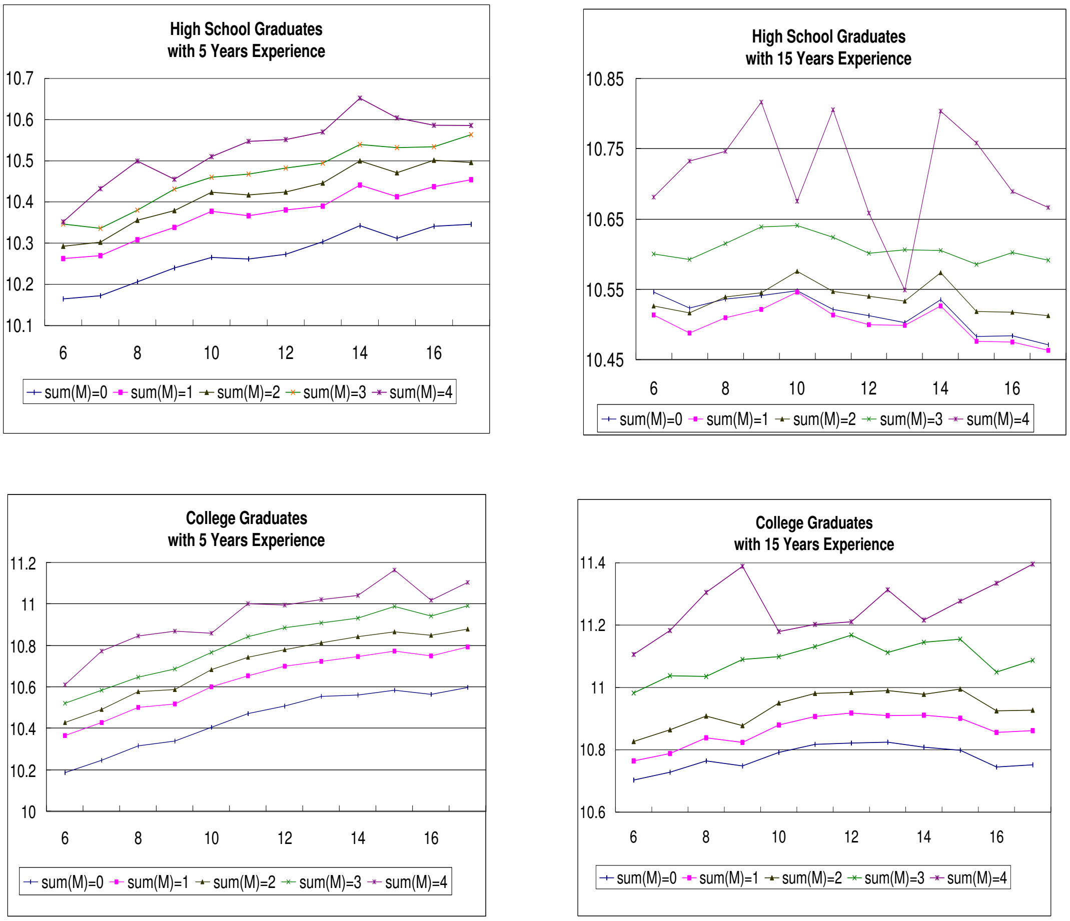

Figure 3: Mean of Wages for One Job Change—Restricted

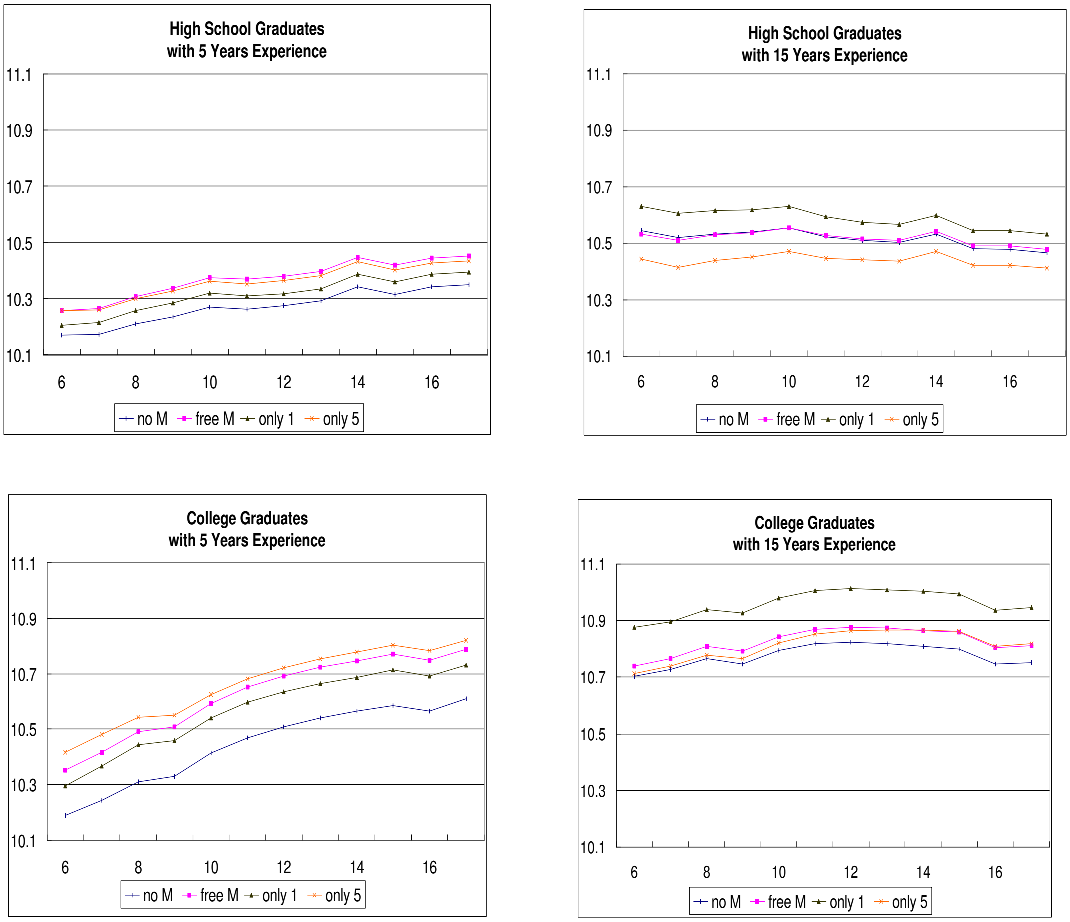

Figure 4: Timing of Job Change and Wages in the Last Year