A hobo syndrome? Mobility, wages, and job turnover

Lalith Munasinghe[a],*, Karl Sigman[b]

[a] *Department of Economics, Barnard College, Columbia University, 3009, Broadway, New York, NY 10027, USA*
[b] *Department of Industrial Engineering and Operations Research, Columbia University, USA*

Abstract

We present an analysis of labor mobility as a predictor of wages and job turnover. Data from the National Longitudinal Surveys of Youth show that workers with a history of less frequent job changes (stayers) earn higher wages and change jobs less frequently in the future than their more mobile counterparts (movers). These mobility effects on wages and turnover are stronger among more experienced workers, are highly robust across various model specifications, and persist despite corrections for unobserved individual fixed effects. In the second half of the paper we present a simple two period stochastic model of job mobility to study wages across movers and stayers. The model, incorporating salient features of human capital and job search, shows that whether stayers earn more than movers depend on the distribution of outside wage offers and firm-specific wage growth rate. Incorporating heterogeneity of wage growth rates among jobs increases the likelihood that stayers earn more than movers.
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1. Introduction

The relationship between the frequency of past job[1] changes (mobility) and other labor market outcomes, such as wages and future job changes (turnover), is a widely recognized phenomenon. In particular, the positive correlation between mobility and turnover, and the

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* Corresponding author. Tel.: +1-212-854-5652; fax: +1-212-854-8947.
E-mail address: lm25@columbia.edu (L. Munasinghe).
[1] Throughout the paper, job is synonymous with employer since we do not distinguish between job levels within firms and other internal labor market phenomena.

negative correlation between mobility and wages, are well-known empirical regularities across many disciplines. In the sociological literature these mobility patterns were explained by the so-called mover–stayer model (Blumen et al., 1955). The argument, in economic parlance, was based on "individual fixed effects:" some workers (identified as movers) are inherently more likely to move between jobs than some others (identified as stayers); and it was further presumed that movers are less productive than stayers. In the organizational psychology literature this same phenomenon was colorfully labelled the "hobo syndrome," and described as the "periodic itch to move from a job in one place to some other job in some other place" (Ghiselli, 1974). It was believed that the hobo's *wanderlust* derived from instinctive impulses.

Although these mobility facts have been extensively documented in the recent literature on job mobility and wages,[2] economic studies have yet to fully wrestle with the widely accepted view, even if only implicitly, that these empirical regularities are simply a consequence of an inherent "itch" or individual fixed effect. Since many of these mobility studies were based on cross-sectional data,[3] the more precise interpretive question is whether mobility effects on wages and turnover are a mere consequence of some unobserved individual characteristic or whether the history of job mobility reflects more fundamental search and investment processes that might be systematically linked to current labor market outcomes. As a consequence, the primary objective of this paper is to re-establish these mobility effects on current wages and turnover, and especially, to address whether these observed mobility patterns persist after accounting for individual fixed effects; or, put differently, to address whether heterogeneity of some unobserved individual characteristic can fully account for mobility effects on wages and turnover.

Data from the National Longitudinal Surveys of Youth (NLSY) are ideally suited to study the role of mobility in predicting wages and turnover. Since we observe the entire early work histories of the vast majority of our respondents and because information on the total number of jobs ever held is available, we can directly correlate frequency of past job changes with current wages and the likelihood of future job separations, respectively. In addition, the panel nature of the data allows us to implement econometric procedures to account for individual fixed effects. The NLSY data also contain rich information on a variety of individual, job, geographic, and other work related characteristics, and as a consequence, we include an extensive array of control variables in our regression analyses.

To preview our main findings: high mobility is associated with low wages, especially among more experienced workers. This negative effect persists despite corrections for individual fixed effects. The effects of mobility on turnover closely parallel the effects of mobility on wages. Mobility is positively associated with the likelihood of a future job separation. This positive effect is stronger among more experienced workers, is highly robust to various model specifications and corrections for individual fixed effects, and holds across both quits and layoffs. Hence, hypotheses based on individual fixed effects,

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[2] Mincer and Jovanovic (1981), Bartel and Borjas (1981), Light and McGarry (1998).

[3] Except for the Light and McGarry (1998) analysis, which is based on the National Longitudinal Surveys of Youth data, the same panel that we use in our study.

including the mover–stayer model and the hobo syndrome, are implausible explanations for mobility effects on wages and turnover.

A second concern of the paper is to develop a simple two period model of job mobility to compare wages across movers and stayers. The objective of this analytical effort is to ask whether a model based on job search and human capital can generate any implications for wages of movers versus stayers without appealing to individual heterogeneity of any stripe. The job search feature of the model is that workers search from a stationary distribution of outside wage offers and receive a single offer every period. Workers switch jobs if the outside wage offer is greater than the second period wage in the incumbent firm. And the human capital feature is that the second period wage is higher than the first period wage (in the incumbent firm) because of firm-specific wage growth. Although this simplistic model creates a systematic link between mobility and wages, the comparison of wages between movers and stayers remains indeterminate because whether stayers earn more than movers depend on the specifics of the distribution of wage offers and the wage growth rate. The intuition is straightforward. Indeed, movers do not receive wage increases due to within-job wage growth (as stayers do) because they move. But movers do receive wage increases because they move to more lucrative jobs. Hence, the precise wage differential between stayers and movers depends on which of these two effects dominate. However, introducing heterogeneity of wage growth rates among jobs increases the likelihood that stayers earn more than movers because those in high wage growth jobs are less likely to move and more likely to have higher second period wages.

The remainder of the paper is organized as follows. In the next section entitled "Related literature" we discuss in detail empirical and theoretical studies related to mobility, wages, and turnover. Section 3 in various subparts presents the details of the empirical analysis of mobility effects on wages and turnover. In Section 4 we present a simple two period model of job mobility to rationalize why stayers earn more than movers. Section 5 concludes. A bibliography is appended.

2. Related literature

The Achilles heal of the mover–stayer hypothesis is the claim that movers are less productive than stayers, and thus, movers earn less than stayers. In the fairly recent economics literature a variety of wage and turnover models have been designed to explicitly incorporate heterogeneity of mobility and search costs. These models typically lead to natural links between mobility and wages. For example, Black and Loewenstein (1991) develop a three-period model based on heterogeneity of mobility costs and self-enforcing contracts, and show, among various other results, that in the resulting equilibrium previous turnover increases the probability of subsequent turnover, and job changers systematically earn higher wages than job stayers. The authors argue that the latter finding may be consistent with some specialized labor markets, such as the labor market for academics. Note, however, that this prediction of their model is not supported by many studies, including the findings in our paper, that find past turnover is negatively correlated with wages.

Various other studies have modeled labor market outcomes, including wages and turnover, as a function of quit propensities across women and men. Although some of these papers, including Barron et al. (1993) and Kuhn (1993), are explicitly designed to investigate differences in gender outcomes due to differences in quit propensities, the models are easily adapted to study the links between mobility and wages due to heterogeneity of individual quit propensities.

Although these economic models go beyond the simple mover–stayer hypothesis in terms of endogenizing mobility and wages, two issues still remain. First, the theoretical predictions of these models do not square with all of the empirical evidence on mobility effects. Second, and more importantly, they are inconsistent with the recent empirical evidence that corrects for individual fixed effects. As we have mentioned earlier, many of the earlier studies on mobility (Mincer and Jovanovic, 1981; Bartel and Borjas, 1981) were based on cross-sectional data, and hence, the observed correlations could, in principle, be consistent with these models or the mover–stayer hypothesis. By contrast, recent econometric work on the effects of mobility on wages (Light and McGarry, 1998) and on turnover (Judge and Watanabe, 1995) have exploited the panel nature of their data to control for unobserved, time invariant individual characteristics. The fact that mobility remains a significant predictor of wages and turnover despite these heterogeneity corrections is *prima facie* evidence not only against the mover–stayer model and the hobo syndrome,[4] but also against these equilibrium models because the purported links between mobility, wages, and turnover are generated because of individual fixed effects— i.e., on account of individual heterogeneity in terms of mobility and search costs. As a consequence, a natural question to ask is whether there might be a structural relationship between past mobility and current labor market outcomes, such as wages and turnover, independently of unobserved individual fixed effects. As a consequence, our modeling effort is to ask whether the standard workhorse theories of labor—search and human capital—might have ramifications for mobility as a predictor of wages without appealing to heterogeneity of individual fixed effects.

Although various adaptations of these workhorse theories are widely accepted as providing an explanation for why wages increase with job tenure (and work experience), and for why turnover rates decline with job tenure (and over the life cycle), neither search nor human capital considerations alone seem to generate systematic links between mobility and wages. A simple search model, where workers sample outside wage offers from the same distribution in each time period, predicts that current wages are independent of prior mobility (Burdett, 1978). That is, there is no systematic discrepancy between the expected wages of movers and stayers,[5] and thus also no systematic discrepancy between the future turnover outcomes of movers and stayers. The job matching model (Jovanovic, 1979a) may appear to predict a negative correlation between mobility and wages, but

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[4] Judge and Watanabe (1995) claim that their evidence—those who quit numerous jobs in the past were much less likely to survive on the job than those who quit few jobs (p. 220)—supports the hobo syndrome. However, given that they account for unobserved heterogeneity this conclusion seems unwarranted. If some individuals posses ''internal impulses to migrate,'' and if these impulses are time invariant, then accounting for individual fixed effects should in principle nullify the effect of past mobility on future mobility.

[5] This result, however, is not robust. As Weiss and Landau (1984) show, the introduction of a cost of mobility leads to a breakdown of this result.

Jovanovic explicitly notes in his article that the mismatch theory does not imply that movers should do worse than stayers.[6] Human capital theory predicts a negative relationship between job mobility and investments in job specific skills,[7] but these considerations do not yield any ex ante predictions about the relative wages of movers and stayers (Light and McGarry, 1998).

Since these considerations alone have never been developed into a model to explicitly study mobility effects,[8] our simple model in the paper attempts to formalize these basic ideas to address whether past mobility is related to current wages. Of course, since these ideas are not new, similar theoretical considerations have guided key empirical studies that try to obtain unbiased estimates of rates of return to tenure (Topel, 1991) and estimates of mobility wage gains (Antel, 1986). The first study argues that a comparison of wages of stayers and movers will underestimate the "true" return to tenure (due to firm specific training) because movers move to better paying jobs. The second study argues, conversely, that a comparison of wages of movers and stayers will underestimate "true" mobility wage gains (due to search effort) because wages of stayers grow due to firm specific training. Clearly, these two arguments are flip sides of the same coin. But neither study asks whether there is any systematic wage differential between stayers and movers, which of course is the key question for us.[9]

Given that our model is centered around the idea of firm-specific wage growth, it is important to address the recent empirical controversy about finding a tenure effect on wages. The early empirical support for wage increases with job seniority was based on evidence of positive cross-sectional association between seniority and earnings. However, as Abraham and Farber (1987) and Altonji and Shakotko (1987) argue, this evidence is insufficient to establish that earnings increase with seniority. For instance, if high wage jobs (due to say heterogeneity of worker–firm match quality) are more likely to survive than low wage jobs, then seniority will be positively correlated with high wages even though individual wages do not rise with seniority. Using longitudinal data and corrections for various potential sources of heterogeneity bias, both these studies find that the cross-sectional return to tenure is a statistical artifact of heterogeneity bias, and that the true wage return to tenure is small if not negligible. However, a later study by Topel (1991), also using longitudinal data and accounting for selection due to optimal mobility decisions, shows that wages do rise with seniority. A recent reassessment by Altonji and Williams (1997) concludes that Topel over estimates the returns, and that wage returns to tenure, across all these estimation procedures, are modest at best.[10] It is important to

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[6] See Jovanovic (1979a), footnote 11 on p. 982.

[7] See Becker (1975) and Jovanovic (1979b).

[8] The models mentioned earlier are of course based on similar considerations. However, mobility effects in these models are generated by explicitly assuming heterogeneity of search and mobility costs. Our objective is to ask whether mobility effects can be generated without appealing to any such individual effect.

[9] Note that the biases identified in each of the two studies remain in force whether stayers earn more than movers or *vice versa*. Simply, the issue of who earns more is equivalent to whether the within-job wage growth effect on the wages of stayers dominates the search effect on the wages of movers.

[10] Other empirical studies also seem to support the view that wage returns to tenure might be small. For example, Neal (1995) and Carrington (1993) present evidence to suggest that much of the tenure effect on wages may in fact be an industry as opposed to a firm effect.

note, however, that dynamically consistent models of wage determination can imply small wage returns to tenure despite substantial firm-specific skill accumulation (Munasinghe, 2001).

In an earlier paper, Munasinghe (2000) conjectured that in the presence of high and low wage growth jobs it would be more likely that stayers earn more than movers. Hence we extend our simple model with constant wage increase to incorporate heterogeneity of wage growth rates among jobs, a cornerstone of human capital theory.[11] The empirical evidence on heterogeneity of wage growth rates among jobs is also somewhat controversial. Abowd et al. (1999) find, using a large longitudinal French data source, that the estimated returns to tenure are small, but that there is substantial variation in these estimated tenure slopes across firms. Topel (1991) argues that heterogeneity of wage growth rates among jobs is empirically unimportant because there is no evidence of serial correlation of within-job wage increases. Note, however, that recent theoretical considerations show that serial correlation of wage increases is an inappropriate test for wage growth heterogeneity (Munasinghe, 2001). Perhaps more importantly, in a series of studies, Mincer (1986, 1988) found that stayers receive more job training than movers, and that movers, despite the gains to moving, do not catch up with wage levels of stayers. Although these are empirical observations, they do suggest that mobility related findings might possibly be explained by heterogeneous investments in firm specific human capital across individuals. We attempt to provide a theoretical basis for these observations by explicitly showing, in the context of our stochastic model, how heterogeneity of firm specific wage growth rates among jobs makes it more likely for stayers to earn more than movers. The point is that to explain wage differences across movers and stayers, heterogeneity of wage growth may be more relevant than the size of the tenure effect on wages.

3. Empirical analysis

Our objective in this two part empirical analysis is to study the role of mobility, defined as the ratio of jobs ever held to total labor market experience, as a predictor of current wages and future turnover, respectively. Given the extensive array of information available in the NLSY data, we can assess the net effect of mobility on wages and turnover after controlling for a variety individual, job and other characteristics. Further, since the NLSY is a panel data source, we can also make efforts to control for unobserved individual heterogeneity in our estimation procedures. We begin this section with a brief discussion of the estimation framework for analyzing the role of mobility in predicting wages and turnover. In Section 3.2 we describe the NLSY data, construction of key variables, and sample restrictions. The next subsection presents summary statistics and analysis of mobility correlates. In Sections 3.4 and 3.5 we present our main results from wage and turnover regressions, respectively, to study the effects of mobility on key labor market outcomes.

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[11] For example, see Becker's (1975) analysis of supply and demand for human capital for a variety of reasons why human capital investments differ among individuals.

3.1. Estimation framework

The following discussion outlines the estimation framework to analyze the effects of mobility on wages and turnover.[12] First, consider a standard cross-section human capital earnings equation augmented to include mobility as an additional explanatory variable:

$$w_i = X_i\beta + bm_i + \alpha + \varepsilon_i,$$

where w is log of real wages, X is a vector of observed worker, job and other characteristics, m is the mobility rate, ε is the error term, and all terms indexed by i pertain to worker i. Since each worker is observed at several points in time, we can consider an alternative specification of this regression model that explicitly incorporates heterogeneity or individual fixed effects:

$$w_{it} = X_{it}\beta + bm_{it} + z_i\alpha + \varepsilon_{it}.$$

The individual effect is $z_i\alpha$ where z_i includes a constant term and an unobserved, time-invariant individual specific variable. Hence the error component is composed of both an individual specific effect and a white noise component. This formulation allows a consideration of whether some unobserved individual characteristic is likely to be correlated with both our measure of mobility and wages, and thus lead to a biased estimate of the "true" mobility effect on wages under an OLS specification with pooled data. A key empirical issue to resolve is whether the observed negative effect of mobility on wages is simply due to a fixed individual effect, such as in the case of the mover–stayer hypothesis, or whether this observed correlation is indicative of a structural or causal linkage. The panel nature of our data allows us to get estimates of mobility effects after correcting for potential bias on account of individual fixed effects.

The two standard procedures to handle heterogeneity with panel data are the so called fixed and random effects models. In the former, the wage regression reduces to: $w_{it} = X_{it}\beta + bm_{it} + \alpha_i + \varepsilon_{it}$, where α_i is interpreted as an individual specific term that is constant over time. In the estimation of this model, the constant individual term can be correlated with the regressors, but it does not yield coefficient estimates for any of the time invariant variables. The random effects model on the other hand generates coefficient estimates for time invariant variables, but the restrictive assumption in this specification is that the unobserved individual effect is uncorrelated with the other regressors. Since our primary concern is to establish the mobility effect on wages, we present results from all three model specifications—OLS, fixed and random effects models—to assess the robustness of the mobility effect on wages.[13]

Estimating mobility effects on turnover raises further complications on account of the fact that the dependent variable is dichotomous—whether a job separation occurs or not.

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[12] For a more detailed discussion of the issues involved in using panel data to address heterogeneity, see Greene (2003).

[13] There are of course various tests to evaluate the fixed and random effects specification against the classical pooled regression—i.e. whether there are individual effects. Further, there is also a Hauseman test to discriminate between the fixed and random effects models. In Section 3.4 we discuss the implications of these test results for our wage analyses.

The standard models for limited dependent variables are the linear probability model and various nonlinear specifications, of which the Logit and Probit models are the best known. A key issue again is whether these models can account for individual fixed effects in the context of estimating a turnover model. Both the fixed effects and random effects models discussed earlier can be adopted and amended to accommodate the fact that the dependent variable is a dichotomous variable. Hence we use an extended binary choice framework and estimate an individual effects model for panel data.

$$y_{it}^* = X_{it}\alpha + \beta m_{it} + \mu_i + \varepsilon_{it}, \qquad i = 1, \ldots n, \ t = 1, \ldots T_i,$$

$$y_{it} = 1 \qquad \text{if } y_{it}^* > 0, \ \text{and 0 otherwise.}$$

The estimation of this model raises a few additional problems. For example, fixed effects models can only be estimated on observations that do not have only positive or negative outcomes. And since our data contain a large sample of individuals with such observations this procedure is infeasible. However, a random effects model, given the various caveats mentioned earlier, does not impose the same restriction and is thus feasible. In our regression analyses we present results from three model specifications, starting with a simple linear probability model, followed by a logit model, and finally a random effects specification of the logit model.

3.2. Data and sample restrictions

We use NLSY panel data from 1979 to 1994 to study the role of prior mobility in predicting current wages and future turnover rates. The NLSY tracks 12,686 young women and men first interviewed in 1979. The availability of work histories of early careers, including detailed information on job duration and separation, labor market experience, annual earnings, number of total employers a person has ever worked for, and other individual and job characteristics, make this data ideal for our empirical analyses of mobility, wages, and turnover.

We only consider Current Population Survey (CPS) designated jobs in the NLSY. Typically the CPS job is the main or more recent job, and more information is available about CPS jobs. Annual wages are deflated by the consumer price index from the Report of the President, where the base year is 1987. In the wage regression analyses we use the log transform of this real wage. Job turnover is based on whether a worker separates from the current employer by the next interview date. Hence the turnover models estimate the likelihood of an annual job separation rate. Information on the reasons for job separations allows us to analyze both voluntary and involuntary turnover rates, i.e. quits and layoffs, separately. The construction of total labor market experience and job tenure is based on actual weeks worked and the start and stopping dates of work with a specific employer, respectively.

Mobility rates for each individual is computed by taking the ratio of total jobs ever held to net labor market experience. Hence for each individual (at each survey point) we have a mobility rate that measures the average number of employers per year of actual labor market experience. Note that this variable is not fixed within the duration of a given

employment relationship since the denominator increases each year (and possibly also the numerator if a worker moves in and out of dual job holding).[14]

In our empirical analyses we use a host of other control variables, including job tenure and labor market experience, completed years of schooling, information about industry, required occupational training, union status, local unemployment rates, and Armed Forces Qualifying Test (AFQT) scores, to mention some of the key control variables. The required occupational training variable is constructed from data in the panel study of income dynamics (PSID). In the PSID, individuals are asked how long it takes for the average worker in their occupation to be fully qualified to perform his job. The question is asked in 1976 and 1978. We merge the 1978 means by the two-digit occupation code to the NLSY sample.

Our sample is restricted to the survey years from 1979 to 1993. We use information from the 1994 survey year to construct our separation variables for 1993 which is defined on the basis of whether a separation occurs between 1993 and 1994. By restricting our wage information to 1993 we are then able to use the same sample for both wage and turnover analyses. Our sample is also restricted to white males who are neither self employed nor employed in the agriculture or government sector. We further delete observations if the real wage (in 1987 dollars) is less than US$2 or greater than US$150, if mobility rate is greater than 6, and if net years of experience is less than a year. In the next subsection we provide summary statistics, and identify some key correlations with mobility rates as a prelude to our analysis of mobility as a predictor of wages and turnover.

3.3. Summary statistics and correlates of mobility

In Table 1 we list the main variables in our analyses, including a description and some basic summary statistics. The information highlights the young age of the NLSY sample. The mean age is approximately 26, and it ranges from 17 to 36 years. The mean labor market experience is a little over 7 years, and hence the majority of our sample is observed during the first decade of entering the labor market. The high separation rate (36%) and the high mobility rate (1.1 jobs per year) simply reflect the young age of our sample. Table 2 compares means of some key variables across a sample of stayers and movers. We define stayers and movers as those belonging to the left and right of the median value of our mobility variable (approximately .88 jobs per year of labor market experience), respectively.[15] Since turnover rates are much higher among younger workers, it is not surprising that mean experience, tenure, and age are much higher for stayers than movers. Also notice that wages are substantially higher, but completed years of schooling and AFQT scores are not much higher, among stayers compared to movers. Of course, the

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[14] If we define our measure of mobility to be fixed over the duration of any given employment relationship, then the variability of mobility will be restricted over time especially for individuals with a limited number of employment relationships. As a consequence, implementing a fixed effects model is likely to yield unreliable estimates of mobility effects. However by defining mobility for each period—i.e. as the ratio of total jobs ever held to total labor market experience in every period—we can implement a fixed effects model since this measure varies with time even within a given employment relationship.

[15] Since each individual can enter the sample multiple times, the same individual can be in both samples depending on their mobility rate at different points in time.

Table 1
Variable descriptions and summary statistics

Variable	Description	Mean	S.D.
Wage	Real wage in 1987 dollars	8.699	5.082
Separations	If separate by next interview date	0.355	0.479
Quits	If quit by next interview date	0.241	0.428
Layoffs	If layoff by next interview date	0.074	0.262
Experience	Net labor market experience	7.376	4.045
Tenure	Experience with current employer	2.781	2.965
AFQT	Armed forces qualifying tests scores	52.149	27.983
Prior Jobs	Total number of jobs ever held	6.436	4.334
Mobility	Prior number of jobs/Experience	1.102	0.842
Schooling	Completed years of schooling	12.844	2.367
Ed_LHS	Less than 9 years of schooling	0.036	0.187
Ed_SHS	Some high school	0.152	0.359
Ed_HS	High school graduate	0.405	0.491
Ed_SC	Some college	0.199	0.399
Ed_C	College graduate	0.142	0.349
Ed_PG	Post-graduate	0.065	0.246
Unemp	Local unemployment rate, six categories	3.069	1.054
Union	If wages set by collective bargaining	0.167	0.373
Age	Age in years	26.153	4.038
SMSA	If living in SMSA	0.733	0.442
Married	If married and living with spouse	0.444	0.497
Training	Required occupational training, years	1.236	0.660
North	If reside in north	0.180	0.385
North Central	If reside in north central	0.336	0.472
South	If reside in south	0.318	0.466
West	If reside in west	0.166	0.372

National Longitudinal Surveys of Youth, 1979–1993.
Number of observations = 19,366.

dramatically higher separation rates and lower wages among movers could simply reflect the fact that movers have been in the labor market for a much shorter time period.

To get a better sense of the net correlations between mobility and these other factors, in Table 3 we present mobility regression results that control for experience, tenure, and age. The three columns show coefficient estimates from different model specifications—OLS, fixed effects, and random effects models—respectively. Unsurprisingly, experience and tenure are strongly negatively correlated with mobility across all specifications. The net positive coefficient on age simply says that controlling for labor market experience and completed years of schooling, increase in age is associated with a higher mobility rate. A higher ratio of age to labor market experience is likely to imply employment gaps and thus a higher mobility rate.

A few other correlations also appear to be robust. First, high school graduates have the lowest mobility rate.[16] Second, AFQT scores and required occupational training are

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[16] Since we select our sample when individuals enter the labor market after completion of school, our education variables are constant over time for each individual and thus the fixed effects model does not yield coefficient estimates. The same is true for AFQT scores.

Table 2
Variable means across stayers and movers

Variable	Stayers	Movers
Wage	9.720	7.679
Schooling	12.922	12.767
AFQT	54.413	49.886
Experience	9.074	5.678
Tenure	4.260	1.302
Age	27.327	24.980
Separations	0.217	0.493
Quits	0.149	0.333
Layoffs	0.042	0.106
Training	1.281	1.191
Married	0.542	0.345
Union	0.193	0.141
SMSA	0.729	0.737
Unemp	3.040	3.097
North	0.189	0.172
North Central	0.362	0.311
South	0.309	0.326
West	0.140	0.191
Number of observations	9694	9672

negatively correlated across all specifications. Perhaps, occupations with higher training requirements and complementarities between AFQT scores and training may lead to more durable jobs and thus lower overall mobility rates. Individuals living in Standard Metropolitan Statistical Area (SMSA) have higher mobility rates possibly due to lower search costs on account of greater work opportunities. As expected, marital status and union coefficients are negative in the OLS specification; however, in the fixed and random effects specifications the sign reverses on marital status and the union coefficient becomes insignificant. Note that all models include 15 industry and four region indicator variables.

The tests for fixed and random effects highlights the fact that a large fraction of the variation in mobility is indeed due to individual fixed effects.[17] However, the many correlations that remain significant after such corrections for individual fixed effects suggest that mobility may be systematically related to factors that are especially associated with mobility and search costs. In the next subsection we present results from wage regressions to assess the role of mobility in predicting wages.

3.4. Mobility and wages

Table 4 presents estimates from various human capital earnings functions with mobility as the key explanatory variable. The first two columns in the table are from OLS models. The second column includes, in addition to the mobility variable, an interaction term between mobility and experience to test whether mobility effects on wages differ systematically

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[17] The reported "Rho" in the second and third columns of Table 3 is around 0.8, implying that about 80% of the variance is due to individual fixed effects. Note further that a Hauseman test rejects the Random effects model assumption that individual effects are uncorrelated with the other regressors in the model.

Table 3
Mobility regressions

Variable	Coefficient estimates (standard errors)		
	OLS	Fixed effects	Random effects
Tenure	− 0.214	− 0.099	− 0.107
	(0.005)	(0.003)	(0.003)
Tenure^2	0.012	0.006	0.006
	(0.0004)	(0.0002)	(0.0002)
Experience	− 0.235	− 0.295	− 0.292
	(0.005)	(0.006)	(0.005)
Experience^2	0.007	0.010	0.010
	(0.0003)	(0.0002)	(0.0002)
Age	0.061	0.072	0.072
	(0.002)	(0.005)	(0.004)
Ed_SHS	0.012		0.031
	(0.027)		(0.067)
Ed_HS	− 0.171		− 0.228
	(0.026)		(0.066)
Ed_SC	− 0.073		− 0.041
	(0.029)		(0.072)
Ed_C	− 0.098		− 0.076
	(0.031)		(0.078)
Ed_PG	− 0.090		− 0.0001
	(0.034)		(0.084)
AFQT	− 0.002		− 0.003
	(0.0002)		(0.001)
Married	− 0.038	0.024	0.017
	(0.010)	(0.007)	(0.007)
Unemp	− 0.037	− 0.006	− 0.009
	(0.005)	(0.003)	(0.003)
Training	− 0.029	− 0.015	− 0.017
	(0.007)	(0.005)	(0.005)
SMSA	0.024	0.031	0.029
	(0.011)	(0.012)	(0.011)
Union	− 0.058	− 0.006	− 0.012
	(0.013)	(0.009)	(0.009)
No. of observations	19,366	19,366	19,366
Adjusted R^2	0.442	0.382	0.404
Rho		0.837	0.793

Standard errors in parenthesis.

across experience levels. The last two columns show coefficient estimates from fixed effects and random effects models. The question addressed here is whether the mobility effect in the OLS specification could be due to some unobserved, time invariant individual effect. Hence an estimate of a significant mobility effect in the last two specifications would cast doubt on explanations based on individual fixed effects, such as an inherent individual turnover propensity or a hobo's periodic "itch" to move from one job to another job.

Most of the signs of our coefficient estimates are widely established in the literature, and thus unremarkable. Hence our discussion will focus primarily on the effect of mobility on wages. In the first column mobility has a strong and significant negative effect on

Table 4
Wage regressions

Variable	OLS		Fixed effects	Random effects
Mobility	− 0.027	− 0.010	− 0.019	− 0.016
	(0.004)	(0.006)	(0.006)	(0.006)
Mobility*Experience		− 0.004	− 0.005	− 0.005
		(0.001)	(0.001)	(0.001)
Tenure	0.050	0.047	0.043	0.045
	(0.003)	(0.003)	(0.002)	(0.002)
Tenure^2	− 0.003	− 0.003	− 0.003	− 0.003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Experience	0.024	0.032	0.044	0.040
	(0.003)	(0.004)	(0.003)	(0.003)
Experience^2	− 0.0003	− 0.001	− 0.001	− 0.001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Ed_SHS	0.021	0.020		0.032
	(0.015)	(0.015)		(0.027)
Ed_HS	0.075	0.074		0.078
	(0.015)	(0.015)		(0.027)
Ed_SC	0.122	0.122		0.109
	(0.016)	(0.016)		(0.029)
Ed_C	0.233	0.232		0.213
	(0.017)	(0.017)		(0.032)
Ed_PG	0.248	0.247		0.209
	(0.019)	(0.019)		(0.035)
AFQT	0.002	0.002		0.003
	(0.0001)	(0.0001)		(0.0002)
Married	0.086	0.085	0.057	0.065
	(0.006)	(0.006)	(0.006)	(0.006)
Union	0.191	0.191	0.138	0.153
	(0.007)	(0.007)	(0.007)	(0.007)
Training	0.098	0.098	0.043	0.056
	(0.004)	(0.004)	(0.004)	(0.004)
Unemp	− 0.019	− 0.019	− 0.021	− 0.022
	(0.003)	(0.003)	(0.003)	(0.003)
No. of observation	19,366	19,366	19,366	19,366
Adjusted R^2	0.432	0.432	0.336	0.425
Rho			0.584	0.442

Standard errors in parenthesis.

wages. Including the interaction of mobility and experience shows that the negative mobility effect is much stronger among more experienced workers. The fact that these results are robust across fixed and random effects specifications[18]—in fact, the negative

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[18] The *F* statistic for testing the joint significance of the individual effects in the fixed effects model specification is highly significant suggesting strong evidence of individual effects in the data. Similarly, the Lagrange Multiplier test statistic in the context of the random effects model also strongly rejects the OLS specification with a single constant term. The Hauseman specification test for the random effects model, however, rejects the assumption that individual effects are uncorrelated with the other regressors in the model. Hence the data favors the fixed effects model to the random effects model. The key point, however, is that under both these specifications the mobility effects are fairly similar and highly significant implying that mobility effects persist despite corrections for individual effects.

mobility effect on wages appears to be slightly stronger under these model specifica-
tions—suggest that the explanation is unlikely to be on account of some unobserved and
time invariant individual effect.[19]

One important question to ask is why the negative mobility effect on wages might be
stronger among more experienced workers. In the conclusion we conjecture that a possible
explanation may have to do with the optimal sequencing of investments in job search and
firm specific skills over the life cycle. However, from a statistical point of view it is
important to note that our measure of mobility increases in precision with labor market
experience. Since mobility is the ratio of jobs ever held to net labor market experience, this
variable is clearly less noisy for those with longer labor market experience.

3.5. Mobility and job turnover

Tables 5–7 present evidence of the role of mobility in predicting future turnover—i.e.
the likelihood that a worker will change employers between now and the next interview
date, approximately a year later. Table 5 present regression results where the dependent
variable is an overall job separation rate. Tables 6 and 7 duplicate the same analyses for
voluntary and involuntary job separations, respectively. The three columns in each table
represent different model specifications—a linear probability model, a nonlinear logit
model, and a random effects logit model that exploits the panel nature of our data and
hence explicitly accounts for unobserved individual effects.

The remarkable finding is that across all model specifications and different types of
turnover, mobility has a positive effect on future turnover and this positive effect is much
stronger among more experienced workers, as indicated by the positive coefficient of the
interaction between mobility and experience. Of course, the "hobo syndrome" would
predict precisely such a positive correlation between prior mobility and future job
turnover in a simple pooled OLS regression. However, the fact that this effect is stronger
among older workers and the robustness of this positive mobility effect after correcting
for individual fixed effects, suggests, as in the earlier wage analyses, that the relation
between past mobility and future mobility is more systematic than a spurious link due
unobserved heterogeneity. Note further that all the regression analyses control for current
wages. Thus a simple interpretation based on the wage analysis that shows lower wages
among more mobile workers, is clearly also insufficient to explain these turnover
patterns.

Disaggregation of total turnover into quits and layoffs reveal some interesting mobility
patterns. First, tenure and experience always have their negative effect across both quits
and layoffs. The negative effect of marriage on turnover is stronger for quits than it is for
layoffs. High school graduates have lower quit rates but not so noticeably lower layoff
rates. Wages are strongly negatively correlated with quits but positively correlated with
layoffs, as is union status. In a parallel manner, the local unemployment rate is negatively
correlated with quits and positively correlated with layoffs. Thus the insignificant effect of

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[19] Light and McGarry (1998) also show a very similar result. In their study they not only control for
individual fixed effects but also for job specific effects. Hence they rule out not only individual effects but also
job specific effects as the possible culprit for why stayers earn more than movers.

Table 5
Turnover regressions

Variable	Linear Probability Model	Logit model	Random effects logit
Mobility	0.062	0.198	0.234
	(0.008)	(0.042)	(0.044)
Mobility*Experience	0.007	0.047	0.040
	(0.001)	(0.008)	(0.009)
Log Wages	− 0.101	− 0.537	− 0.581
	(0.009)	(0.048)	(0.052)
Tenure	− 0.069	− 0.366	− 0.327
	(0.003)	(0.019)	(0.021)
Tenure^2	0.004	0.021	0.019
	(0.000)	(0.002)	(0.002)
Experience	− 0.011	− 0.065	− 0.060
	(0.005)	(0.025)	(0.026)
Experience^2	0.0002	0.001	0.001
	(0.0002)	(0.001)	(0.001)
Ed_SHS	− 0.006	− 0.009	0.008
	(0.018)	(0.093)	(0.105)
Ed_HS	− 0.050	− 0.223	− 0.235
	(0.018)	(0.092)	(0.104)
Ed_SC	− 0.006	0.006	0.012
	(0.020)	(0.100)	(0.113)
Ed_C	− 0.026	− 0.087	− 0.091
	(0.021)	(0.110)	(0.124)
Ed_PG	0.015	0.122	0.141
	(0.023)	(0.122)	(0.137)
AFQT	− 0.0004	− 0.002	− 0.002
	(0.0002)	(0.001)	(0.001)
Married	− 0.029	− 0.160	− 0.071
	(0.007)	(0.037)	(0.040)
Union	− 0.017	− 0.100	− 0.111
	(0.009)	(0.050)	(0.052)
Training	− 0.013	− 0.062	− 0.066
	(0.005)	(0.028)	(0.029)
Unemp	0.002	0.006	0.002
	(0.003)	(0.018)	(0.019)
No. of observation	19,366		

Standard errors in parenthesis.

local unemployment rates on overall turnover simply masks these differences across quits and layoffs. The negative wage effect on overall quits simply reflects the fact that the negative wage effect on quits dominates the relative weaker positive effect of wages on layoffs.

3.6. Stochastic dominance of wages of stayers

Table 8 presents some preliminary but novel evidence to address the question of whether wages of stayers stochastically dominate wages of movers—i.e., whether a higher

Table 6
Quit regressions

Variable	Linear Probability Model	Logit model	Random effects logit
Mobility	0.041	0.100	0.125
	(0.007)	(0.041)	(0.043)
Mobility*Experience	0.003	0.033	0.029
	(0.001)	(0.008)	(0.008)
Log Wages	− 0.101	− 0.615	− 0.677
	(0.008)	(0.052)	(0.056)
Tenure	− 0.044	− 0.290	− 0.258
	(0.003)	(0.021)	(0.023)
Tenure^2	0.003	0.016	0.015
	(0.000)	(0.002)	(0.002)
Experience	− 0.003	− 0.035	− 0.029
	(0.004)	(0.028)	(0.028)
Experience^2	− 0.0001	− 0.0003	− 0.001
	(0.0002)	(0.001)	(0.001)
Ed_SHS	0.001	0.020	0.041
	(0.017)	(0.097)	(0.109)
Ed_HS	− 0.024	− 0.143	− 0.144
	(0.017)	(0.097)	(0.109)
Ed_SC	0.023	0.144	0.168
	(0.018)	(0.105)	(0.118)
Ed_C	0.013	0.103	0.123
	(0.020)	(0.116)	(0.130)
Ed_PG	0.045	0.276	0.308
	(0.022)	(0.128)	(0.143)
AFQT	− 0.00002	− 0.0004	− 0.0003
	(0.0001)	(0.001)	(0.001)
Married	− 0.014	− 0.099	− 0.106
	(0.007)	(0.041)	(0.043)
Union	− 0.043	− 0.361	− 0.373
	(0.008)	(0.058)	(0.061)
Training	− 0.009	− 0.043	− 0.046
	(0.005)	(0.030)	(0.031)
Unemp	− 0.017	− 0.110	− 0.117
	(0.003)	(0.019)	(0.020)
No. of observation	19,366		

Standard errors in parenthesis.

percent of stayers than of movers have wages above any given wage cutoff level. The motivation for presenting this evidence is based on an example we present in the next section where we show that wages of stayers stochastically dominate the wages of movers. This simple analysis, using the same NLSY data as before, seems to support this conjecture.

By "Mob" we designate a categorical prior mobility variable that takes values from 1 to 3, representing groups with increasing mobility rates. The "Exp" variable represents different labor market experience groups in increasing order, and the "$P(W>x)$" terms denote the percent of workers who have wages above x, where x represents four (real)

Table 7
Layoff regressions

Variable	Linear Probability Model	Logit model	Random effects logit
Mobility	0.010	− 0.076	− 0.071
	(0.005)	(0.059)	(0.061)
Mobility*Experience	0.003	0.068	0.068
	(0.001)	(0.012)	(0.013)
Log Wages	0.010	0.086	0.094
	(0.005)	(0.083)	(0.085)
Tenure	− 0.022	− 0.405	− 0.393
	(0.002)	(0.039)	(0.040)
Tenure^2	0.001	0.019	0.018
	(0.0002)	(0.004)	(0.004)
Experience	− 0.008	− 0.176	− 0.183
	(0.003)	(0.044)	(0.045)
Experience^2	0.0003	0.006	0.006
	(0.0001)	(0.002)	(0.002)
Ed_SHS	− 0.003	− 0.034	− 0.036
	(0.011)	(0.139)	(0.149)
Ed_HS	− 0.014	− 0.126	− 0.133
	(0.011)	(0.140)	(0.149)
Ed_SC	− 0.009	− 0.048	− 0.056
	(0.012)	(0.156)	(0.166)
Ed_C	− 0.025	− 0.439	− 0.451
	(0.013)	(0.187)	(0.197)
Ed_PG	− 0.011	− 0.071	− 0.070
	(0.014)	(0.205)	(0.216)
AFQT	− 0.0001	− 0.003	− 0.003
	(0.0001)	(0.001)	(0.001)
Married	− 0.006	− 0.099	− 0.097
	(0.004)	(0.064)	(0.067)
Union	0.034	0.491	0.496
	(0.005)	(0.074)	(0.077)
Training	− 0.002	− 0.043	− 0.044
	(0.003)	(0.048)	(0.049)
Unemp	0.015	0.222	0.225
	(0.002)	(0.028)	(0.029)
No. of observation	19,366		

Standard errors in parenthesis.

wage levels starting from 6 and increasing to 24 in intervals of 6.[20] Hence the numbers in the columns represent the percent of workers who have wages above the specified wage level. The decrease in these numbers for any given experience group, as prior mobility increases, i.e., going down a column for a given experience group, seems to suggest that wages of stayers stochastically dominate wages of movers. Not surprisingly, given our earlier results on the differential impact of mobility on the wages of older and younger

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[20] We experimented with various other cutoff points with similar results.

Table 8
Stochastic dominance of wages of stayers

Exp	Mob	Observation	$P(W>6)$	$P(W>12)$	$P(W>18)$	$P(W>24)$
All	All	15,965	0.701	0.178	0.032	0.008
All	1	6136	0.821	0.247	0.048	0.010
All	2	7177	0.691	0.164	0.028	0.007
All	3	2652	0.451	0.055	0.009	0.003
1	1	236	0.521	0.102	0.008	0.000
1	2	705	0.590	0.096	0.010	0.004
1	3	514	0.446	0.089	0.008	0.004
2	1	1177	0.764	0.184	0.026	0.003
2	2	2027	0.670	0.166	0.022	0.006
2	3	922	0.436	0.049	0.009	0.002
3	1	1649	0.841	0.278	0.055	0.009
3	2	2037	0.735	0.179	0.037	0.009
3	3	673	0.483	0.048	0.012	0.004
4	1	1614	0.853	0.275	0.071	0.015
4	2	1482	0.742	0.192	0.033	0.008
4	3	355	0.462	0.056	0.008	0.000
5	1	1460	0.859	0.254	0.038	0.014
5	2	926	0.638	0.133	0.024	0.006
5	3	188	0.410	0.021	0.000	0.000

The numbers in the cells represent the percentage of wage observations that are greater than the specified wage level in the last four columns for different experience and prior mobility categories.

workers, this result of stochastic dominance of stayers' wages seems especially strong for the high experience groups.

4. A simple model

In this section we present a simple stochastic model of mobility and wages as a first step toward rationalizing some of our empirical findings. The motivation here is to provide a framework to link past mobility to current wages without appealing to any sort of unobserved individual heterogeneity. In particular, we ask whether human capital and search considerations alone can help explain why stayers earn more than movers.

4.1. Within-job wage growth, mobility, and wages

Consider a model where workers live for two periods. In each period a worker receives a wage offer from the same distribution. In a simple search framework, workers change jobs if and only if they receive a second period wage offer that exceeds the first period wage. Human capital considerations are introduced to this framework by assuming that first period wages increase in the second period; in which event, workers change jobs if and only if the second period wage offer exceeds the first period wage plus the wage increase. Since the wage offer distribution is the same in both periods the increase in first period wages is interpreted as a firm specific wage increase.

Let W_1 and W_2 denote first period and second period wage offers, respectively, assumed independent random variables from the same *wage offer* distribution. Further assume that first period wages increase by c, such that the wage at the end of the first period is simply $W_1 + c$. If a worker stays in the first job then the second period wage is $W_1 + c$, and if the worker moves, then the second period wage is W_2. The optimal decision criterion is: if $W_1 + c > W_2$, then the worker stays, else the worker moves. In the absence of a first period wage increase, the order of arrival of offers does not affect the expected value of the second period wage. That is, by symmetry the expected wage of movers and stayers is the same:

$$E(W_2 \mid W_2 > W_1) = E(W_1 \mid W_1 > W_2) \tag{1}$$

This is a well known result. If, however, the first period wage increases by c then the expected second period wage of movers is clearly greater than the expected first period wage of stayers:

$$E(W_2 \mid W_2 > W_1 + c) > E(W_1 \mid W_1 + c > W_2) \tag{2}$$

In turn, Eq. (2) implies that:

$$E(W_1 + c \mid W_1 + c > W_2) - E(W_2 \mid W_2 > W_1 + c) < c \tag{3}$$

The above result says that a comparison of second period wages of stayers and movers will underestimate the within-job wage increase c (see Topel, 1991). What is more interesting from the point of view of mobility effects on wages is that the relative second period wages of stayers and movers cannot be unambiguously signed. The second period wages of stayers could be either greater or lesser than the second period wages of movers:

$$E(W_1 + c \mid W_1 + c > W_2) \lessgtr E(W_2 \mid W_2 > W_1 + c) \tag{4}$$

The fact that the sign can reverse illustrates that a simple search model with a constant firm specific wage increase does not lead to a clear-cut prediction between mobility and wages.[21] Whether stayers earn more than movers or the other way around depends on the exact distribution of wage offers and on the value of c. For example, it can be demonstrated that if wage offers come from a uniform distribution, then stayers earn more than movers for all positive values of c (see the first example in Section 4.2 below). This result in turn could explain why stayers are less likely to move in the future. Note, however, as the counterexample in Section 4.3 illustrates that with another

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[21] The within-job wage growth parameter c can be viewed more generally as a mobility cost. However, if we model it as such then the wages of movers will always exceed the wages of stayers since the inequality in Eq. (2) will now apply not only to the second period wages of movers but also to the second period wages of stayers. However, since our objective is to rationalize the finding that stayers earn more than movers, we characterize mobility costs more precisely as a firm-specific wage growth rate because then this parameter of wage growth not only determines the mobility decision but it also contributes to the second period wages of stayers, and thus makes it possible for stayers to earn more than movers.

wage offer distribution and for some specific values of c movers can earn more than stayers.[22]

Despite the fact that stayers experience wage increases, the reason why they do not necessarily earn more than movers is due to two other countervailing forces. First, a wage increase in the first period implies that acceptable second period wage offers must be relatively high. So movers must receive second period wages that are higher than what they would have to be if first period wages did not increase. Second, even though the first period wage increases, lower wage offers in the first period survive because of the wage increase. It is precisely these considerations that explain why stayers do not necessarily do better than movers. Therefore, the relative performance of stayers and movers depends on the distribution of wage offers and on c, the firm specific wage increase. The point is that this simple rendition of the workhorse theories of labor economics is not silent regarding the effects of mobility on wages; rather, for the reasons given, it cannot make the unambiguous prediction that stayers earn more than movers.

4.2. An example: stayers earn more

In this subsection we present a detailed example of wage comparisons between stayers and movers when the outside wage offer distribution is uniform. We show that stayers do better than movers for all positive values of wage increases, and do so by stochastically dominating wages of movers. These results hold for both fixed wage increases and percentage wage increases. Empirical evidence that support these implications was presented earlier in Section 3.6.

The uniform density on (a, b) is defined by

$$f(x) = \begin{cases} \frac{1}{b-a}, & x \in (a, b) \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

and has mean $E(W) = \int_a^b xf(x)\mathrm{d}x = (a+b)/2$.

Given two random variables X and Y, we say that X is *stochastically larger* than Y, denoted by $X \geq_{st} Y$, if $P(X > x) > P(Y > x)$ for all x. It is easily seen that such an ordering implies that $E(X) \geq E(Y)$. Such an ordering is actually an ordering on the distributions of X and Y; in particular their tails. Our objective in this section is to show that for the uniform distribution, stayers always do better than movers. We prove the result in a stochastic ordering sense which therefore includes the corresponding expected value result (e.g. as in Eq. (4)).

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[22] We were interested in obtaining a more general characterization of the role of outside wage offer distributions in predicting the wages across movers and stayers. For example, we considered whether there might be some class of distributions for which stayers always did better than movers (or *vice versa*). In particular, we tried to use only beta distributions with density on $(0, 1)$ of the form $f(x) = x^n(1-x)^m$, but even here we could not obtain general results that only depend upon the parameters n and m. It appears that these kind of results are sensitive to more complex properties of distributions.

Given a r.v. X and an event A, by $(X|A)$ we denote a r.v. with the conditional distribution of X given A. Of particular interest to us are the pairs

$$(W_1 + c \mid W_1 + c > W_2) \text{ and } (W_2 \mid W_2 > W_1 + c),$$

$$((1 + \alpha)W_1 \mid (1 + \alpha)W_1 > W_2) \text{ and } (W_2 \mid W_2 > (1 + \alpha)W_1).$$

Proposition 4.1. *If wages are distributed as the uniform density on (a, b), then for each $c \in (0, b - a)$, and each $\alpha \in (0, 1)$*

$$((1 + \alpha)W_1 \mid (1 + \alpha)W_1 > W_2) \geq_{st} \quad (W_2 \mid W_2 > (1 + \alpha)W_1)$$

$$(W_1 + c \mid W_1 + c > W_2) \geq_{st} \quad (W_2 \mid W_2 > W_1 + c).$$

Proof. We prove only the percentage increase case (1), and do so for $a = 0$ and $b = 1$; the fixed increase case and general $0 \leq a < b$ being handled similarly. Throughout we use $F(x)$ to denote the probability that W is less than or equal to x and $1 - \bar{F}(x)$ as the probability that W is greater than x. Let

$$P_1(y) \overset{\text{def}}{=} P((1 + \alpha)W_1 > y \mid (1 + \alpha)W_1 > W_2),$$

$$P_2(y) \overset{\text{def}}{=} P(W_2 > y \mid W_2 > (1 + \alpha)W_1)$$

Note that when $1 \leq y < 1 + \alpha$, $P(W_2 > y) = 0$, thus, the result holds trivially for such y and we need only consider $0 \leq y < 1$. Thus we need to show that $P_1(y) \geq P_2(y)$, $y \in (0, 1)$.

$$P_1(y) = P((1 + \alpha)W_1 > y \mid (1 + \alpha)W_1 > W_2)$$

$$= \frac{P((1 + \alpha)W_1 > y, (1 + \alpha)W_1 > W_2)}{P((1 + \alpha)W_1 > W_2)} = \frac{N_1}{D_1},$$

where N_1 and D_1 denote the numerator and denominator, respectively. Then conditioning on $W_2 = x$ yields

$$D_1 = \int_0^1 \bar{F}\left(\frac{x}{1 + \alpha}\right) f(x) dx.$$

Similarly, conditioning on $W_2 = x \leq y$ and $W_2 = x > y$ yields

$$N_1 = \bar{F}\left(\frac{y}{1 + \alpha}\right) F(y) + \int_y^1 \bar{F}\left(\frac{x}{1 + \alpha}\right) f(x) dx.$$

Thus

$$P_1(y) = \frac{\bar{F}\left(\dfrac{y}{1+\alpha}\right)F(y) + \displaystyle\int_y^1 \bar{F}\left(\dfrac{x}{1+\alpha}\right)f(x)\mathrm{d}x}{\displaystyle\int_0^1 \bar{F}\left(\dfrac{x}{1+\alpha}\right)f(x)\mathrm{d}x} \tag{6}$$

On the other hand,

$$P_2(y) = P(W_2 > y \mid W_2 > (1+\alpha)W_1) = \frac{P(W_2 > y, W_2 > (1+\alpha)W_1)}{P(W_2 > (1+\alpha)W_1)} = \frac{N_2}{D_2},$$

where N_2 and D_2 denote numerator and denominator. We need only condition on $W_1 = x < 1/(1+\alpha)$ because $P(W_2 > (1+\alpha)x) = 0$ when $x \geq 1/(1+\alpha)$. Doing so yields

$$D_2 = \int_0^{1/(1+\alpha)} \bar{F}((1+\alpha)x)f(x)\mathrm{d}x.$$

Similarly, conditioning on $W_1 = x \leq y/(1+\alpha)$ and $W_1 = x > y/(1+\alpha)$ yields

$$N_2 = \bar{F}(y)F\left(\frac{y}{1+\alpha}\right) + \int_{y/(1+\alpha)}^{1/(1+\alpha)} \bar{F}((1+\alpha)x)f(x)\mathrm{d}x.$$

Thus

$$P_2(y) = \frac{\bar{F}(y)F\left(\dfrac{y}{1+\alpha}\right) + \displaystyle\int_{y/(1+\alpha)}^{1/(1+\alpha)} \bar{F}((1+\alpha)x)f(x)\mathrm{d}x}{\displaystyle\int_0^{1/(1+\alpha)} \bar{F}((1+\alpha)x)f(x)\mathrm{d}x} \tag{7}$$

The denominator D_1 in Eq. (5) becomes

$$D = \int_0^1 \left(1 - \frac{x}{1+\alpha}\right)\mathrm{d}x = (1+\alpha)^{-1}\int_0^1 (1+\alpha-x)\mathrm{d}x = (1+\alpha)^{-1}\left(\alpha + \frac{1}{2}\right).$$

The numerator N_1 becomes

$$N = (1+\alpha)^{-1}\{(1+\alpha-y)y + \int_y^1 (1+\alpha-x)\mathrm{d}x\} = (1+\alpha)^{-1}\left(\alpha + \frac{1}{2} - \frac{y^2}{2}\right).$$

Thus

$$P_1(y) = \frac{N_1}{D_1} = 1 - \frac{y^2}{2\left(\alpha + \dfrac{1}{2}\right)}.$$

Similar computations yield the denominator D_2 in Eq. (7) as

$$D_2 = \{2(1+\alpha)\}^{-1},$$

and numerator N_2 as

$$N_2 = (1+\alpha)^{-1}\{(1-y)y + \frac{1}{2}(1-2y+y^2)\} = \{2(1+\alpha)\}^{-1}(1-y^2).$$

Thus

$$P_2(y) = \frac{N_2}{D_2} = 1 - y^2,$$

and it is interesting to note that is does not depend on α.

Finally,

$$P_1(y) - P_2(y) = \frac{2\alpha}{2\alpha+1}y^2 \geq 0. \qquad \square$$

4.3. Counterexample: movers earn more

Here we present a counterexample where movers earn more than stayers, illustrating that in general, the results for the uniform distribution do not extend to all outside wage offer distributions.

Consider the following wage offer distribution: $P(W=1)=0.1$ and $P(W=10)=0.9$. Suppose workers sample job offers from this same distribution in both periods. Further assume, consistent with our model of within-job wage growth, that first period wages increase by some constant $0 < c < 9$. Denote by W_1 and W_2 the independent random wage draws from this distribution. Then the expected second period wages of movers and stayers are given by

$$E(W_2 \mid W_2 > W_1 + c) = 10$$

and

$$E(W_1 + c \mid W_1 + c > W_2) = \frac{(0.1)^2(1+c) + (0.9)(10+c)}{(0.1)^2 + 0.9} = 9.9011 + c.$$

respectively. Thus for $c < 0.0989$ movers earn more than stayers.

4.4. Heterogeneity of wage growth rates

In an earlier paper, Munasinghe (2000) conjectured that heterogeneity of firm specific wage growth rates among jobs could possibly explain: the negative relationship between prior mobility and current wages, and the positive relationship between prior mobility and current turnover. The idea was that high prior mobility could imply both a lower current

job value and, as a result, a higher current turnover rate because prior mobility is a proxy for wage growth rates of prior jobs. The reason is that the value of low wage-growth jobs increases less rapidly than the value of high wage-growth jobs (with time on the job). As a consequence, prior jobs with low wage growth rates lead to higher prior mobility and relatively low job value.

This idea of heterogeneous wage growth rates is readily incorporated into our two period model. Stayers do not unambiguously earn more than movers, but they are more likely to earn higher wages if wage increases are random than if wage increases are constant across all jobs. The intuition is straightforward. If a worker moves then it is more likely for that worker to have received a smaller wage increase; and conversely, if a worker stays then it is more likely that the worker received a higher wage increase. These conclusions follow because a firm specific wage increase unambiguously reduces the likelihood of moving.

To introduce heterogeneity of wage growth rates, assume that workers in the first period make draws, independently, from two distributions: first from a wage offer distribution, and second from a wage growth (increase) distribution. C denotes this random wage increase, and for simplicity, we assume that the first period wage either increases in the second period by constant amount $c>0$ or that it does not, that is, $P(C=c)+P(C=0)=1$. We provide simple analytics to compare the expected second period wages of stayers with the expected second period wages of movers. The main objective here is to show that if firm specific wage growth rates differ among workers or jobs then stayers have a better chance of doing better than movers than they would otherwise (under constant wage growth). The randomized wage growth version of Eq. (4) takes the form

$$E(W_1 + C \mid W_1 + C > W_2) \lesseqgtr E(W_2 \mid W_2 > W_1 + C). \tag{8}$$

We first present an example in which movers do better under constant wage growth c, but stayers do better under random wage growth C; it switches. We start with the example from Section 4.3 with $c<0.0989$, so that movers do better.

We now use a random wage growth C with $P(C=c)=P(C=0)=0.5$, and will show that there are values of $c<0.0989$ for which stayers do better. To set up the problem precisely, note that when $C=0$ we need to handle the possibility of a match, $W_1=W_2$. (We could avoid this by using continuous distributions, but then the computations would be more involved.) We hereby assume that whenever this happens, the worker will stay or move with probability 0.5, that is, it is determined by the independent flip of a fair coin. Let $T=1$ if the coin lands heads (stay), $T=0$ if it lands tails (move). Then by symmetry, given $C=0$, the probability to stay equals one half, the same as to move. Let S denote the event "stay," and let M denote the event "move."

Proposition 4.2. *There exist values of $c<0.0989$ such that*

$$E(W_1 + C \mid S) - E(W_2 \mid M) > 0 \tag{9}$$

even though

$$E(W_1 + c \mid W_1 + c > W_2) - E(W_2 \mid W_2 > W_1 + c) < 0.$$

To prepare for the proof we first see that each of S and M is the union of three events describing how each event could occur,

$$S = \{C = c, W_1 + c > W_2\} \cup \{C = 0, W_1 > W_2\} \cup \{C = 0, W_1 = W_2, T = 1\}$$

$$M = \{C = c, W_1 + c < W_2\} \cup \{C = 0, W_1 < W_2\} \cup \{C = 0, W_1 = W_2, T = 0\}.$$

Probabilities and conditional probabilities can then be easily computed:

$$P(S) = P(C = c)[0.91] + P(C = 0)[0.5]$$

$$P(M) = P(C = c)[0.09] + P(C = 0)[0.5]$$

$$p \overset{\text{def}}{=} P(C = 0 \mid S) = \frac{P(C = 0)[0.5]}{P(C = c)[0.91] + P(C = 0)[0.5]}$$

$$P(C = c \mid S) = 1 - P(C = 0 \mid S)$$

$$P(C = c \mid S) = \frac{P(C = c)[0.91]}{P(C = c)[0.91] + P(C = 0)[0.5]}$$

$$q \overset{\text{def}}{=} P(C = 0 \mid M) = \frac{P(C = 0)[0.5]}{P(C = c)[0.09] + P(C = 0)[0.5]}$$

$$P(C = c \mid M) = 1 - P(C = 0 \mid M)$$

$$P(C = c \mid M) = \frac{P(C = c)[0.09]}{P(C = c)[0.09] + P(C = 0)[0.5]}.$$

For example,

$$P(C = c, W_1 + c > W_2) = P(C = c)[P(W_1 = 1, W_2 = 1) + P(W_1 = 10)]$$
$$= P(C = c)[(0.1)^2 + 0.9] = P(C = c)[0.91],$$

and

$$P(C = 0, W_1 > W_2) + P(C = 0, W_1 = W_2, T = 1) = P(C = 0)0.5,$$

by symmetry.

Proof. We can express each of the desired expectations as weighted sums,

$$E(W_1 + C \mid S) = pE(W_1 \mid S, C = 0) + (1 - p)E(W_1 + c \mid S, C = c)$$

$$E(W_2 \mid M) = qE(W_2 \mid M, C = 0) + (1 - q)E(W_2 \mid M, C = c).$$

By symmetry $E(W_1|S, C=0)=E(W_2|M, C=0)=P(W_1>W_2)+(0.5)P(W_1=W_2)=9.91$ so the difference in Eq. (9) is given by

$$(p - q)(9.91) + (1 - p)E(W_1 + c \mid S, C = c) - (1 - q)E(W_2 \mid M, C = c).$$

Each of the expected values is easily computed directly yielding the difference as

$$\begin{aligned} E(W_1 + C \mid S) - E(W_2 \mid M) &= (p - q)(9.91) + (1 - p)(9.9011 + c) - (1 - q)10 \\ &= (1 - p)(c - 0.0089) - (1 - q)(0.09), \end{aligned}$$

where we have used the basic fact that $p+(1-p)=1$ and $q+(1-p)=1$.

It is at this point that we plug in $P(C=0)=P(C=c)=0.5$ into the formulas for p and q getting $1-p=0.6450$, $1-q=0.1525$ so that $E(W_1+C|S)-E(W_2|M)=0.645c-0.0195$, and we see that for $c>0.0323$, the difference is strictly positive. □

We now present another general result and we assume for simplicity that wage distributions are continuous (to avoid ties):

Proposition 4.3. *If stayers do better than movers under constant c wage growth, then they continue doing better under random wage growth C; $E(W_1+ C|W_1+ C>W_2)>E(W_2|W_2> W_1+ C)$ if $E(W_1+ c|W_1+ c>W_2)>E(W_2|W_2>W_1+ c)$.*

Proof. Using the assumption that $E(W_1+c|W_1+c>W_2)>E(W_2|W_2>W_1+c)$ we can express the difference $d=E(W_1+C|W_1+C>W_2)-E(W_2|W_2>W_1+C)$ as

$$\begin{aligned} d = {}&(p - q)E(W_1 \mid W_1 > W_2) + (1 - p)E(W_1 + c \mid W_1 + c > W_2) \\ &- (1 - q)E(W_2 \mid W_2 > W_1 + c) > (p - q)E(W_1 \mid W_1 > W_2) + ((1 - p) \\ &- (1 - q))E(W_2 \mid W_2 > W_1 + c) \geq [(p - q) + ((1 - p) - (1 - q))] \\ &\times E(W_1 \mid W_1 > W_2) = 0, \end{aligned}$$

where, in the $\geq$ line we have used the fact that $E(W_2|W_2>W_1+c) \geq E(W_2|W_2>W_1)=E(W_1| W_1>W_2)$ and that $(1-p)-(1-q) \geq 0$ (since $1-p=P(C=1|S) \geq 1-q=P(C=1|M))$. Thus $d>0$ as was to be shown. □

This section clearly shows that heterogeneity of wage growth rates among jobs makes it more likely that stayers earn more than movers. As a result, the size of within-job wage

growth may be less relevant than the heterogeneity of such wage growth rates. Despite the mechanical framework adopted here, the key point of these analytics is to show that mobility effects on wages may be generated without appealing any sort of individual fixed effect.[23] Although it is beyond the scope of this paper, perhaps a more realistic equilibrium model of mobility and wages, where the optimization of both workers and firms are explicitly considered, can generate results consistent with our findings about the net effects of mobility on wages and turnover.

5. Conclusion

A possible extension to this work is to explicitly model the differential effects of prior mobility across more and less experienced workers. It is reasonable to suppose that workers search for goodmatches in the early part of their careers (job search process), and then, subsequent to finding a good match, workers invest in firm specific human capital. This sequencing of search and investment processes can be derived from ideas already present in the literature. For example, the basic intuition in Jovanovic (1979b) is that good matches create incentives to invest in firm specific human capital because good matches are more durable. Since good matches take time to find, young workers are more likely to be involved in search, while older workers (consequent to finding a good match) are more likely to be involved in firm specific investments. A similar idea can be found in Antel (1986), where he argues that specific training and search represent mutually exclusive human capital investments because specific skills cannot be transferred between jobs and because search and training are costly; as a consequence, "at a given time, workers will choose between more training specific to their current job or opt for further search leading to some more remunerative employment" (Antel, 1986, p. 477). It seems more likely that young workers will opt to search and that older workers will opt to invest in job specific training. These ideas could be extended to study the optimal life cycle sequence of search and specific investments with ramifications for differential effects of prior mobility on wages and turnover of older and young workers.

We also conjecture that stayers will tend to earn more than movers over time. In the limit where the current wage of stayers (presumably due to wage growth) is higher than the best outside offer (assuming a distribution with an upper bound), it is easy to understand why stayers would earn more than movers irrespective of the specifics of the outside wage offer distributions. Such a result would further support the findings of differential impact of prior mobility on wages and turnover of older and younger workers.

Finally, it is important to ask whether the results for the uniform distribution hold for other distributions. The empirical results imply that this is so for the "real" wage offer distribution. But of course we do not know what that distribution is: recorded wage data are not from the underlying wage offer distribution; they are conditional distributions from it.

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[23] Note that heterogeneity of wage growth rates is not a fixed individual effect. In the current formulation it can be viewed as a parameter specific to each worker-firm pair. For a more detailed discussion see Munasinghe (2001).

Acknowledgements

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