JOB CHANGE PATTERNS AND THE WAGES OF YOUNG MEN

Audrey Light and Kathleen McGarry*

Abstract—This study uses data from the National Longitudinal Survey of Youth to distinguish empirically between mover–stayer, ''search good,'' and ''experience good'' models of job mobility. We estimate wage models in which the pattern of overall job mobility affects both the level and tenure slope of the log-wage path. After controlling for the correlation between mobility patterns and time-constant person- and job-specific unobservables, we find that workers who undergo persistent mobility have lower log-wage paths than less mobile workers. This finding is consistent with models in which job mobility is driven by time-varying unobservables, such as ''experience good'' models, where changes in perceived match quality cause turnover.

I. Introduction

DO YOUNG workers benefit from job mobility? A number of theoretical models have attempted to answer this question, leaving us with a range of predictions about which workers move, why workers move, and how mobility affects wages.[1] In this study we take a new approach to assessing empirically the relative importance of a number of competing theories. We exploit the fact that certain theoretical models make different predictions about intrapersonal mobility patterns that will be observed in the data and, more importantly, about the mechanisms by which those mobility patterns affect wages.

We focus on three models of job mobility. The oldest of the three is the mover–stayer model (Blumen et al. (1955)), which argues that underlying personal characteristics cause ''good'' (high-productivity) workers to avoid job turnover, and ''bad'' (low-productivity) workers to undergo persistent mobility. The model predicts that movers' mobility does not diminish over time, and that mobility is negatively related to wages only because it is correlated with the unobserved personal characteristics that determine productivity. Once the relationship between mobility and unobserved individual effects is taken into account, mobility should no longer be correlated with wages.

The second model we consider is the ''search good'' model of job matching (Burdett (1978), Jovanovic (1979b)) in which mobility reflects voluntary moves to more productive employment relationships. The model assumes the quality (productivity) of a match is known ex ante, making jobs ''search goods'' in the parlance of Nelson (1970). The search good matching model predicts that workers move to increasingly high-quality matches and that, as a result, mobility slows over time. Wages are affected by match quality, which is a time-invariant characteristic, but not by mobility per se—that is, mobility has no independent effect on wages after its relationship with time-invariant job-specific effects is taken into account.

The third model is the ''experience good'' model of job matching (Johnson (1978), Jovanovic (1979a)), so named (again using Nelson's terminology) because match quality is not known ex ante but is learned over time as the match is ''experienced'' and productivity-related information is revealed. In this model, job mobility occurs when a match proves to be worse than was initially believed. This leads to a downward adjustment of the wage, which in turn leads to a worker-initiated separation if the wage falls below the level available at another job. Although true match quality is time invariant, mobility is driven by time-*varying* perceptions of job quality. Hence mobility will be correlated with wages even after one controls for the relationship between wages and unobserved time-invariant individual and job effects. Moreover, the model allows for the possibility that an unlucky worker could experience a sequence of ''bad'' matches and, as a result, endure persistent (within-job) wage losses.

In an attempt to distinguish among these competing models of job mobility, we use data for a sample of young, white men from the National Longitudinal Survey of Youth (NLSY) to examine patterns of ''overall'' mobility, defined as the number of job separations experienced during the first eight years of the career. While the typical worker in our sample is seen changing jobs several times during the initial phase of his career (as Bartel (1980), Hall (1982), Topel and Ward (1992), and Farber (1994) also report) and moving to increasingly durable jobs, there is considerable interpersonal variation in mobility patterns. In particular, the mobility of some workers fails to decline over time, which is consistent with either mover–stayer or experience good matching models but not search good matching models.

We estimate a wage model that is standard in most respects, but allows both the level and tenure slope of the log-wage path to depend on the number of job separations undergone in the first eight years of the career. To control for the timing of overall mobility, we also hold constant the number of job separations incurred in the first two years of the career. We begin by estimating the wage model via ordinary least squares (OLS). Although the OLS assumptions are indefensible, the estimates reveal how ''overall'' mobility correlates with wages *before* we account for the relationship between mobility and unobserved individual and job characteristics. The OLS estimates reveal that mobility is negatively related to wages: workers who encounter several jobs of increasing duration begin their careers earning slightly less than immobile workers, and lose ground during the eight-year window. Workers whose mobility does not slow over time begin and end the

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* Ohio State University and University of California, Los Angeles, respectively.

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[1] In the models we consider, job mobility refers to ''voluntary'' changes of employers. That is, we ignore intrafirm changes in work activities as well as employer changes caused by layoffs and ''involuntary'' discharges.

eight-year window earning substantially less than their less mobile counterparts.[2]

After examining these ‘‘unconditional’’ patterns in the data, we introduce more elaborate error structures to contend with the fact that workers' job turnover rates are likely to be influenced by unobserved factors that we cannot control for directly. Our second error structure consists of time-invariant person-specific random effects plus white noise. In estimating the model with this more elaborate error structure, we account for any correlation between the person-specific random effects and the mobility-related regressors by using a modified version of the technique suggested by Hausman and Taylor (1981). The qualitative relationship between mobility and wages seen in the OLS model does not change and, in fact, is strengthened. Because mobility patterns are seen to be related to wages after individual effects are taken into account, we conclude (as have many others) that the mover–stayer model is not supported by the data.

We then extend the error structure further to include time-invariant job-specific random effects, and we again control for any correlation between the regressors and the random effects. With this error structure in place, the estimated relationship between overall mobility and wages is weakened considerably, but we continue to find that increases in overall mobility are negatively associated with wages. This result is inconsistent with a search good model of job mobility in which match quality is known ex ante, but is consistent with the notion that jobs are experience goods. Such models allow for the possibility that persistent mobility is (negatively) associated with wages after the effects of time-invariant individual and job characteristics have been removed. Of course, our finding is also consistent with any alternative model in which job mobility is correlated with time-varying components of the residual—for example, a model in which the returns to tenure are dependent on individual ability or match quality.

Although we focus our attention on the three mobility models detailed above, there are numerous other theories that pertain to voluntary job mobility. The human capital model (Becker (1962), Oi (1962)) highlights the inverse relationship between job mobility and investments in job-specific skills. While this model allows that job changes may be associated with substantial wage gains, it cannot predict a priori whether the between-job wage growth of job changers exceeds the within-job wage growth received by ‘‘stayers’’ as the return to their job-specific training. Models in which workers are assumed to post bonds, either to ensure productivity (Lazear (1979)) or for self-selection purposes (Salop and Salop (1976), Guasch and Weiss (1981)), also predict a negative correlation between within-job wage growth and between-job wage growth in a cross section. Lazear's (1986) raiding model predicts the opposite of the mover–stayer model by arguing that workers' wages are used by their employers' competitors as signals of their quality; in this model the best workers undergo the job turnover.[3] We do not directly assess the merits of these alternative theories, although we consider the human capital model in specifying our wage model and interpreting our results.

Before turning to our empirical analysis, it is worth noting the key difference between our approach and the empirical methods typically used to assess the relationship between mobility and wages. Among the many empirical studies in this area, those that focus on young workers include Bartel (1980), Borjas and Rosen (1980), Bartel and Borjas (1981), Mincer and Jovanovic (1981), Borjas (1984), Mincer (1986), Antel (1991), Loprest (1992), and Topel and Ward (1992). With few exceptions, these studies use first-difference estimators to assess the contemporaneous wage growth associated with a job change—for example, the size of the wage boost accompanying the typical transition or the within-job wage growth immediately preceding the transition.[4] This approach reveals whether mobility pays ‘‘on average,’’ but it does not consider the relationship between overall mobility patterns and wages, nor can it readily assess the estimators' sensitivity to the use of alternative error structures.

In the next section we describe the data and summarize the mobility patterns observed in our sample. In section III we detail the specification of each wage model and describe our estimation procedure. Section IV contains a discussion of the estimates, and section V contains concluding remarks.

II. Overview of Early-Career Mobility and Wage Growth

The data are from the NLSY, which began in 1979 with a sample of 12,686 men and women who were born between 1957 and 1964. Annual interviews of the respondents were conducted from 1979 to 1994, at which time the survey became biennial; our data are restricted to the 1979 through 1993 interviews. In selecting a sample for analysis, we confine our attention to white men, who account for 3790 (30%) of the original sample.[5]

We eliminate any male respondent from the sample if (1) we cannot accurately determine the date when he first leaves school or we cannot determine his schooling attainment at

[2] We make these inferences by computing predicted wages at various experience levels for workers who differ only in their overall mobility patterns.

[3] Omori (1990) develops a raiding model that predicts that good workers undergo *less* mobility than bad workers, in keeping with the mover–stayer model.

[4] Bartel's paper is an exception to the tendency to look at contemporaneous wage changes. Using the Coleman–Rossi Retrospective Life History Study, she estimates between-job, within-job, and total long differences over a roughly 15-year period. Models of wage levels, rather than period-to-period wage changes, appear in the Mincer/Jovanovic and Mincer studies.

[5] Our sample includes men from the nationally representative cross-section sample as well as from the supplemental sample of disadvantaged individuals and the military sample. After imposing the selection criteria described below, 78% of the individuals remaining in our sample originated from the cross section, 20% from the supplemental sample, and 2% from the military sample.

TABLE 1.—NUMBER OF SAMPLE DELETIONS BY REASON

Number of Respondents	Reason for Deletion
3790	White men in original NLSY sample
−34	1. School exit date and/or school attainment indeterminate
3756	
−61	2. School exit date precedes sixteenth birthday
3695	
−4	3. Stay in school throughout observation period
3691	
−1047	4. School exit date precedes January 1, 1978
2644	
−72	5. Observed for less than 8 years after school exit date
2572	
−280	6. No employment data during 8-year window
2292	Sample used for analysis

TABLE 2.—DISTRIBUTION OF NUMBER OF JOB SEPARATIONS DURING FIRST 2, 4, AND 8 YEARS OF CAREER

	2 Years		4 Years		8 Years	
Number of Job Separations	No. of Men	% of Sample	No. of Men	% of Sample	No. of Men	% of Sample
0	985	43.0	581	25.3	279	12.2
1	545	23.8	378	16.5	236	10.3
2	369	16.1	366	16.0	264	11.5
3	185	8.1	302	13.2	233	10.2
4	120	5.2	209	9.1	211	9.2
5	51	2.2	183	8.0	201	8.8
6	22	1.0	114	5.0	166	7.2
7	10	0.4	54	2.4	155	6.8
8	2	0.1	52	2.3	125	5.5
9	3	0.1	21	0.9	108	4.7
10+			32	1.4	314	13.7
All	2292	100.0	2292	100.0	2292	100.0
Mean	1.23		2.53		4.94	
S.D.	(1.49)		(2.45)		(4.09)	
Maximum	9		16		23	

that time, (2) his school exit date (defined as the start of the first nonenrollment spell lasting more than 12 months) precedes his sixteenth birthday, (3) he has not left school by the time he is last interviewed, (4) his school exit date precedes January 1, 1978, (5) he is not observed for at least eight years after the school exit date, or (6) he does not contribute valid employment data during the eight-year window. The deletions associated with each criterion are summarized in table 1.

Before imposing the first selection rule, we attempted to resolve all inconsistencies in reported schooling enrollment dates and completion levels in order to learn precisely when each respondent first leaves school. We base this determination on clean data because the school exit date is the point where we begin counting job changes and measuring work experience, and we wish to avoid having reporting errors in schooling attainment translate into measurement error in these key variables. Having done this, we find that 34 respondents report schooling information too inconsistently for us to determine reliably when their careers begin or how much schooling they received. We impose selection rules (2) and (4) because detailed information on employment activities is reported from January 1978 onward (although, generally, only for respondents age 16 or older), so we cannot construct accurate measures of overall mobility, work experience, and job tenure for individuals who start their careers prior to that date. This causes 1108 individuals to be deleted from the sample. Selection rule (5), which eliminates an additional 72 individuals, is imposed so that we can measure each respondent's overall mobility over a fixed period of time.[6]

After imposing these sample selection rules, we are left with 2292 white men who report 11,331 job separations during the first eight years of their careers. They encounter 13,109 jobs during those eight years, but a number of jobs remain in progress at the eight-year mark. This job separation count is obtained from the NLSY work history file, which reports starting dates and other characteristics for jobs held at the time of each annual interview, as well as for up to five jobs that began and ended since the last interview. The count includes any reported job whose starting date is no later than eight years after the respondent's first school exit, but excludes jobs that start and end before the school exit date.[7]

Table 2 shows the distribution of the number of job separations undergone by each person during the first two, four, and eight years of his career. The mean number of job separations in the first eight years is 4.9, with a standard deviation of 4.1. This, of course, understates the number of jobs actually held (but not necessarily separated from), the mean of which is 5.5 with a standard deviation of 3.9.[8] (These numbers are not reported in table 2.) As table 2 illustrates, 12% of individuals experience *no* job separations in the first eight years of their career (which necessarily means they hold one job because no one in the sample remains jobless), while another 10% separate from only one employer. At the other extreme, 14% separate from 10 or more employers; that is, they average well over one job separation per year for the entire eight-year period. While table 2 demonstrates that the typical worker in the sample is

[6] We choose an eight-year window because it causes relatively few respondents to be dropped, given that the nonattriters are typically long gone from school by 1993, while providing a suitably long time frame in which to observe job mobility.

[7] The NLSY elicits information on all jobs held, but limits the number to five in the public data release because only a handful of respondents report more than five jobs between any consecutive interviews. Hence we believe we have a complete count of all job separations. Information on wages, industry of employment and other characteristics is typically not collected for jobs lasting nine weeks or less. These very short jobs are included in our overall mobility count, but typically do not contribute a wage observation to the sample used for our wage analysis.

[8] Topel and Ward (1992), who analyze a sample from the longitudinal employer–employee data, find that the average worker holds 6.1 jobs by the time he has eight years of potential experience. The similarity of the two means is somewhat surprising given that Topel and Ward count only full-time jobs held after the 18th birthday. Because of those restrictions on their sample, we would expect them to understate early-career mobility by a small amount.

quite mobile, it also reveals these young men to be extremely heterogeneous in the amount of early-career job turnover they experience.

Our data on job separations also indicate that job mobility typically slows over time, as Topel and Ward (1992) and others have found. Roughly 28% of the sample undergoes no job mobility during the second four years, and 47% undergoes at most one job separation during that time. However, a comparison of the three distributions shown in table 2 reveals a pronounced rightward shift in the right tails as we move from two to four to eight years, which suggests that a subset of individuals undergoes a large number of job changes during the latter half of the eight-year window. In fact, 22% of the sample increases their cumulative number of job separations more than threefold during the second four years of their career. Clearly, young men are heterogeneous in the timing of their early-career job mobility as well as in their overall mobility levels.

In table 2 and throughout our analysis we examine the total number of job separations rather than the number of voluntary job separations. We do this for a number of reasons. First, it is not clear how to distinguish between voluntary and involuntary job separations. The NLSY codes a large number of reported reasons for each job exit, ranging from ''plant closed'' to ''found better job'' to ''spouse changed job.'' If we were to define involuntary separations as those corresponding to discharges and layoffs and voluntary separations as everything else, then 67% of all job separations for which reasons are reported would be classified as voluntary. Furthermore, the ratio of voluntary to total job separations incurred in the first eight years of the career would be 0.7 or greater for 63% of the sample, including those with no separations of any type. However, the voluntary separations would include those caused by illness and family obligations as well as those occurring when the respondent found a better job or was unhappy with his pay. Second, the reason for job exit is either missing or coded as ''other'' for 26% of all job separations. We must either eliminate these jobs or arbitrarily assign them to the voluntary or involuntary category. Third, if we replace our measures of total job separations with measures of *voluntary* job separations (defined as all separations other than those corresponding to discharges and layoffs), our inferences about the effects of job mobility on wage paths are qualitatively unchanged. In the wage functions described in sections III and IV this substitution causes the coefficients for the job mobility measures to be 3% to 8% larger in absolute value, but it has no effect on our conclusions about the relationship between mobility, wage levels, and wage growth.

We now examine the average duration of each job in order to learn whether job duration (and presumably job quality) increases with each successive transition. In table 3 we report mean job durations after breaking the sample down by the total number of job separations and the particular job number. The first column of table 3 shows that among the 279 individuals holding only one job in the first eight years of their careers, the mean job duration is 8.7 years and the median duration is 8.9 years.[9] The typical individual who changes jobs once moves from a job that lasts 2.0 years to one that lasts 6.4 years, while workers who make several transitions tend to hold a string of jobs lasting one year or less before finally moving into a more durable employment situation. Looking down any column of table 3, we find a fairly consistent pattern of increasing mean durations and an even more pronounced pattern of increasing medians, although transitions to shorter jobs do occur among workers who undergo numerous job separations. The ''majority'' evidence that workers tend to move into increasingly durable jobs is consistent with the predictions of search good matching models (e.g., Burdett (1978) and Jovanovic (1979b)). However, it should be noted that experience good matching models (Johnson (1978) and Jovanovic (1979a)) allow for the possibility of a decline in job duration from one job to the next because workers are unable to determine ex ante the quality of a new job match and could, therefore, inadvertantly move to a lower quality match.

In table 4 we provide preliminary evidence of the relationship between job mobility and wage levels and growth by examining initial wages and ''final'' wages for workers with different levels of overall mobility.[10] The top row of table 4 shows that the average starting hourly wage for workers who never change jobs is \$6.44. Reading across the top row, we see a steady decline in average starting wages as future job turnover increases. The next row of table 4 shows a similar decline in ''final'' wages, which refers to the wage reported when each worker has roughly eight years of potential experience. The mean hourly wage is \$10.72 among workers who remain with their first employer, and it declines steadily to a low of \$7.09 among workers who have separated from 10 or more jobs. When we compute sample means of the percent change in the wage, however, the monotonic decline in career ''success'' is no longer observed. Workers who change jobs 1 or 2 times average 92% wage growth during the first eight years of their career, which is significantly more than the 61% to 79% wage growth received by all other workers. In summary, table 4 reveals that immobile workers receive the highest wages, but that workers who undergo a moderate amount of job mobility appear to catch up to them during the eight-year interval. These patterns are masked in studies that focus on the wage growth of the typical worker.[11]

[9] The uncensored (true) duration is used if the job ends before the individual is last interviewed, even if it ends when he has more than eight years of potential experience. In all other cases, job durations are censored at the point where the jobs are last observed.

[10] Throughout the analysis, our wage measure is the average hourly wage computed from reported data on earnings and hours and weeks worked.

[11] For example, the study by Topel and Ward (1992), which provides some of the most recent and comprehensive evidence on the relationship between job mobility and wages, indicates that the average change in quarterly earnings associated with a job change during the first 10 years of the career is 11.4%. Because this is much larger than the average within-job change in quarterly earnings that they estimate, it is taken as

TABLE 3.—DURATION OF EACH JOB HELD DURING FIRST 8 YEARS OF CAREER

Job Number	Number of Job Separations in 8 Years 0	1	2	3	4	5	6	7	8	9
1										
Mean	8.65	2.00	1.08	1.11	0.88	0.88	0.77	0.84	0.62	0.58
(S.D.)	(3.52)	(2.08)	(1.42)	(1.37)	(1.06)	(1.11)	(0.97)	(1.08)	(1.08)	(0.73)
[Median]	[8.94]	[1.05]	[0.46]	[0.48]	[0.48]	[0.44]	[0.38]	[0.44]	[0.25]	[0.33]
2										
Mean		6.40	1.68	1.05	1.06	0.82	0.68	0.74	0.57	0.59
(S.D.)		(2.87)	(1.69)	(1.18)	(1.33)	(0.96)	(0.83)	(0.91)	(0.76)	(0.72)
[Median]		[6.48]	[1.02]	[0.57]	[0.48]	[0.48]	[0.31]	[0.42]	[0.31]	[0.33]
3										
Mean			6.07	1.57	1.00	1.06	0.99	0.95	0.87	0.61
(S.D.)			(3.11)	(1.56)	(1.07)	(1.20)	(1.13)	(1.18)	(1.11)	(0.73)
[Median]			[5.69]	[1.00]	[0.59]	[0.62]	[0.50]	[0.44]	[0.44]	[0.33]
4										
Mean				5.01	1.46	1.01	0.89	0.94	0.81	0.83
(S.D.)				(2.96)	(1.51)	(1.09)	(0.98)	(1.08)	(1.04)	(1.12)
[Median]				[4.52]	[0.81]	[0.61]	[0.55]	[0.50]	[0.40]	[0.42]
5										
Mean					4.77	1.21	0.83	1.01	0.90	0.91
(S.D.)					(2.98)	(1.25)	(0.94)	(1.20)	(1.05)	(1.01)
[Median]					[4.28]	[0.88]	[0.51]	[0.58]	[0.46]	[0.49]
6										
Mean						4.69	1.14	0.96	0.95	0.94
(S.D.)						(2.95)	(1.20)	(1.06)	(1.11)	(1.13)
[Median]						[4.48]	[0.73]	[0.56]	[0.47]	[0.50]
7										
Mean							4.25	1.18	0.88	0.89
(S.D.)							(2.69)	(1.23)	(0.94)	(0.98)
[Median]							[3.52]	[0.71]	[0.50]	[0.53]
8										
Mean								3.46	0.93	0.88
(S.D.)								(2.43)	(0.91)	(0.96)
[Median]								[3.06]	[0.63]	[0.56]
9										
Mean									3.83	0.85
(S.D.)									(2.45)	(0.97)
[Median]									[3.45]	[0.49]
10										
Mean										3.40
(S.D.)										(2.63)
[Median]										[3.00]

III. Model Specification and Estimation Issues

In this section we describe the alternative wage equations that we estimate. The most general specification—and one that nests the remaining models—can be written as

$$\ln W_{ijt} = \alpha + \beta_1 Z_{ijt} + \beta_2 \Gamma_{ijt} + \phi_{ij} + \alpha_i + \nu_{ijt} \quad (1)$$

where $\ln W_{ijt}$ represents the CPI-deflated average hourly wage for individual i on job j at time t, and Z represents a standard set of regressors that are often included in ''human capital'' earnings functions. Among the Z's are work experience X accumulated between the start of the career and time t and job tenure T, which is the portion of X acquired subsequent to beginning job j; X^2 and T^2 are also included in the model. We define X by summing, on a week-by-week basis, the usual number of hours worked on all jobs from the career starting date (the first time the individual leaves school for more than one year) to the time the wage is

TABLE 4.—WAGE CHANGES DURING FIRST 8 YEARS OF CAREER

Variable	Number of Job Separations in 8 Years 0	1–2	3–4	5–6	7–9	10–23
Initial wage	6.44	5.37	5.22	4.97	4.92	4.81
	(2.82)	(2.60)	(2.28)	(2.31)	(2.59)	(2.18)
Final wage	10.72	9.37	8.43	7.79	7.14	7.09
	(6.03)	(5.39)	(5.25)	(4.13)	(4.69)	(5.86)
(Percent change in wage)/100	0.76	0.92	0.78	0.79	0.61	0.76
	(1.00)	(1.26)	(1.20)	(1.17)	(1.18)	(1.58)

Notes: Initial and final wages are earned ''close to'' 0 and 8 years of potential experience (at 0–1 and 7.5–8.5 years of potential experience). We omit 922 (40%) of the 2292 men in our sample from these calculations because they do not report two wages satisfying these criteria. Wages are CPI-deflated average hourly values expressed in 1982 dollars. Standard deviations are in parentheses.

evidence that mobility pays. We find that the average annual change in hourly wages associated with a job change is 12.3%, which compares closely to the Topel and Ward estimate. However, this figure hides a great deal of heterogeneity: workers who change jobs only once in eight years receive an average wage boost of 9% when they do so, workers who separate 3 or 4 jobs receive an average boost of 15%, and workers who leave 7 to 9 jobs receive an average boost of only 4%.

reported to have been earned. This variable is divided by 2080 to convert it to full-time, full-year equivalents. Tenure is defined similarly, but the starting point is the starting date for the job denoted by j. Z also includes dummy variables indicating the highest grade of school completed (0–11, 12, 16, or 17+, with 13–15 the omitted group), whether the respondent is enrolled in school at time t, his marital status and health status, whether he works part time or for the government, his union status, whether he resides in a city or in the South, and his industry of employment. To control for economywide wage fluctuations, we also include the quarterly seasonally adjusted local unemployment rate for 20–24-year-old males, and the average hourly wage earned by private-sector nonfarm workers in the United States during the year in which the wage was reported. Although Z is subscripted by i, j, and t in equation (1), some of its components (e.g., schooling, marital status, and unemployment rate) are independent of j.

The vector Γ contains the mobility-related variables that are unique to our study. Γ includes controls for the number of job separations experienced in the first two years of the career ($TJ2$) and the total number of separations incurred in eight years ($TJ8$). Our objective in including both $TJ2$ and $TJ8$ is to control for "very early" mobility ($TJ2$) in addition to "overall" mobility ($TJ8$). We also include interactions between $TJ2$ and $TJ8$ and the linear and quadratic tenure terms, thus allowing investment in job-specific human capital to differ by mobility. We exclude interactions between mobility levels and other explanatory variables (most notably X and X^2) because they prove to have no additional explanatory power. Summary statistics for each regressor in Z and Γ appear in the appendix.

In equation (1) we specify the residual to be $\phi_{ij} + \alpha_i + \nu_{ijt}$, where ϕ_{ij} captures the effects of unobserved time-invariant job characteristics, α_i captures the effects of unobserved time-invariant individual characteristics, and ν_{ijt} includes all other unobservables. We maintain the (testable) assumption that ν_{ijt} is white noise. Given this assumption, the error structure in equation (1) nests both the mover–stayer model and the search good matching model.[12] Each component of the residual is assumed to be independently distributed with zero mean and variance equal to σ^2_ϕ, σ^2_α, and σ^2_ν, respectively.

In estimating equation (1), we use a variant of the instrumental-variables generalized least-squares (IV/GLS) procedure proposed by Hausman and Taylor (1981).[13] The instrumental-variables procedure is necessitated by the fact that ϕ_{ij} and α_i are likely to be correlated with a number of regressors, including experience, tenure, and the number of total job separations because both mobility and employment continuity are undoubtedly determined in part by individual and job-specific characteristics that we are unable to observe. We treat each regressor in Γ as endogenous, along with experience and tenure (and their squared terms), and the dummy variables indicating schooling levels, school enrollment status, and part-time work. We could treat additional regressors in Z as endogenous, but our estimated coefficients for the variables of interest are not sensitive to whether we do so.[14]

Generalizing Hausman and Taylor, the deviations from within-job (rather than within-person) means of each time-varying regressor (whether endogenous or exogenous) are used as instrumental variables, along with the within-job means of each exogenous regressor. All regressors except $TJ2$, $TJ8$, and the dummy variables indicating government employment, union status, residence in a city, residence in the South, and industry are time varying within jobs (see table 5). The deviations are valid instruments because they are uncorrelated with the error terms by construction.[15] We also use three additional instrumental variables. One is constructed by tracking the counties in which the respondent resides during the first two and eight years of his career and computing the average percent urbanized for those counties. We also calculate the average number of weeks per year each respondent's wife spends working during the first two and eight years of his career (using zero weeks if the respondent is unmarried in a particular year) and the number of children each respondent has during the two- and eight-year windows.[16]

As noted at the outset of this section, equation (1) nests the other models that we estimate. Two of the alternative models specify the same relationship between log wages and observables as equation (1), but assume different error structures. One assumes the error structure is $\alpha_i + \nu_{ijt}$, which is consistent with the mover–stayer model. The other assumes that all unobserved factors are time-varying random variables that are orthogonal to the regressors, that is, the error structure consists only of ν_{ijt}. This error structure appears to be indefensible, but by examining the relationship

[12] The error structure in equation (1) is identical to the one used by Altonji and Shakotko (1987).

[13] The advantage of assuming the components ϕ_{ij} and α_i to be random effects and using GLS is that it yields more efficient estimators than a fixed-effect (within-person/within-job) procedure. Moreover, GLS enables us to estimate the effects of variables for which there is no within-person or within-job variation—most notably, the variables indicating each worker's overall mobility pattern.

[14] Adding the dummy variables indicating marital status, health status, government employment, union status, and residence in a city and in the South to the list of endogenous variables has a statistically insignificant effect on the coefficients for the variables of primary interest, namely, $TJ2$ and $TJ8$, and their interactions with tenure.

[15] This statement is correct only if ν_{ijt} is white noise—an assumption that is inconsistent with the experience good matching model, as we have already noted. In the experience good model, the error structure should be written as $\phi_{ijt} + \alpha_i + \eta_{ijt}$, which is equivalent to $\bar{\phi}_{ij} + \alpha_i + (\tilde{\phi}_{ijt} + \eta_{ijt})$, where $\tilde{\phi}_{ijt} = \phi_{ijt} - \bar{\phi}_{ij}$. Our estimation procedure treats $\nu_{ijt} = \tilde{\phi}_{ijt} + \eta_{ijt}$ as white noise. If ν_{ijt} is not white noise, then we will obtain biased and inconsistent parameter estimates for all regressors that are correlated with ν_{ijt}. Most notably, we will obtain biased (nonzero) coefficients for $TJ8$.

[16] A test of the overidentification restrictions related to these "extra" instrumental variables fails to reject the hypothesis that the model is correctly specified using conventional significance levels. We include the extra instruments because they improve the R^2 in the first-stage regressions. However, the estimated coefficients for the key variables ($TJ2$, $TJ8$, and their interactions with tenure) are not sensitive to whether the additional instrumental variables are used.

TABLE 5.—ESTIMATES OF ALTERNATIVE WAGE MODELS

	OLS				IV/GLS				IV/GLS			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Intercept	−1.117	0.313	−1.174	0.314	−0.044	0.012	0.075	0.026	−0.016	0.007	−0.024	0.007
Separations in 2 years												
$TJ2$†[a]			0.010	0.003			0.008	0.026			−0.001	0.009
$TJ2 \cdot T$†[c]			0.002	0.002			0.006	0.002			0.002	0.003
$TJ2 \cdot T^2/10$†[c]			−0.005	0.002			−0.006	0.002			−0.005	0.003
Separations in 8 years												
$TJ8$†[a]			−0.009	0.001			−0.029	0.008			−0.013	0.004
$TJ8 \cdot T$†[c]			−0.001	0.001			−0.001	0.001			−0.002	0.001
$TJ8 \cdot T^2/10$†[c]			0.002	0.001			0.002	0.001			0.004	0.001
Years of work experience												
X†[c]	0.050	0.003	0.055	0.003	0.051	0.002	0.052	0.002	0.042	0.004	0.049	0.004
$X^2/10$†[c]	−0.017	0.002	−0.019	0.002	−0.017	0.002	−0.017	0.002	−0.013	0.002	−0.018	0.002
Years of job tenure T†[c]	0.054	0.003	0.048	0.004	0.040	0.003	0.035	0.004	0.031	0.004	0.026	0.005
$T^2/10$†[c]	−0.025	0.003	−0.022	0.003	−0.019	0.002	−0.017	0.003	−0.014	0.003	−0.010	0.004
1 if years of school is												
<12†[c]	−0.191	0.008	−0.182	0.008	−0.157	0.031	−0.113	0.032	−0.146	0.028	−0.116	0.028
12†[c]	−0.140	0.007	−0.139	0.007	−0.079	0.016	−0.077	0.016	−0.089	0.019	−0.082	0.019
16†[c]	0.208	0.010	0.202	0.010	0.176	0.021	0.162	0.021	0.178	0.025	0.182	0.025
>17†[c]	0.228	0.010	0.225	0.010	0.183	0.017	0.175	0.017	0.205	0.024	0.187	0.023
1 if in school†[c]	−0.111	0.010	−0.108	0.010	−0.101	0.010	−0.102	0.010	−0.101	0.014	−0.075	0.014
1 if married[c]	0.083	0.006	0.078	0.006	0.064	0.007	0.056	0.008	0.059	0.009	0.060	0.009
1 if divorced[c]	0.043	0.010	0.044	0.010	0.029	0.012	0.025	0.012	0.028	0.013	0.033	0.014
1 if health problems[c]	−0.099	0.014	−0.094	0.014	−0.039	0.014	−0.034	0.014	−0.028	0.014	−0.026	0.014
1 if works <35 h/week†[c]	−0.071	0.007	−0.066	0.007	−0.033	0.007	−0.032	0.007	−0.019	0.011	−0.014	0.011
1 if government job[b]	−0.141	0.015	−0.142	0.015	−0.052	0.016	−0.052	0.016	−0.062	0.020	−0.064	0.020
1 if union job[b]	0.199	0.008	0.199	0.008	0.181	0.009	0.180	0.009	0.170	0.011	0.170	0.011
1 if lives in city[b]	0.114	0.006	0.116	0.006	0.071	0.008	0.071	0.008	0.069	0.009	0.073	0.009
1 if lives in South[b]	−0.019	0.006	−0.019	0.006	−0.013	0.010	−0.015	0.010	−0.017	0.011	−0.017	0.011
Unemployment rate[c]	−0.002	0.001	−0.002	0.001	−0.006	0.001	−0.006	0.001	−0.007	0.001	−0.007	0.001
Log of wage index[c]	1.283	0.151	1.327	0.151	0.835	0.018	0.751	0.025	0.791	0.012	0.820	0.014
Error structure	ν_{ijt}		$\alpha_i + \nu_{ijt}$		$\phi_{ij} + \alpha_i + \nu_{ijt}$							
σ^2_ϕ	—		—		—		—		0.0760		0.0760	
σ^2_α	—		—		0.0589		0.0585		0.0531		0.0528	
σ^2_ν	0.1965		0.1954		0.1403		0.1402		0.0689		0.0689	

Notes: σ^2_ϕ, σ^2_α, and σ^2_ν are estimated variances of the job, individual, and transitory components of the residual, respectively. Each specification also includes eight dummy variables indicating industry of employment. The sample size for each model is 30,307.

[a] Regressor is time-invariant within and across jobs for a given individual.

[b] Regressor can change value across jobs, but not within jobs; industry dummies are in this category.

[c] Regressor can change value within and across jobs.

† Denotes endogenous regressors in the IV/GLS models. See section III for a description of the instrumental variables.

between Γ and log wages *without* controlling for the correlation between Γ and unobserved individual and job effects, we can learn something about the relative importance of the mobility models discussed in section I. The model where the error term is assumed to consist of ν_{ijt} only is estimated via OLS. When the error structure is specified as $\alpha_i + \nu_{ijt}$, we use the IV/GLS estimator described above. However, the instruments consist of deviations from *individual* means of the time-varying regressors and *individual* means of the exogenous regressors, as well as the three additional instrumental variables described in the preceding paragraph. All regressors except $TJ2$ and $TJ8$ change values over time (although not necessarily within job) and can be used as instruments in deviations-from-the-mean form.

In addition, we reestimate the three models just described after eliminating Γ from the set of regressors. These three models serve as benchmarks so we can see how the inclusion of the mobility-related regressors Γ affects the coefficients for the tenure and experience terms.

IV. Estimates

Table 5 presents estimates for the six wage models described in the preceding section. Columns (1) and (2) show OLS estimates for two specifications that differ only in whether controls for overall mobility are included. Columns (3) and (4) show IV/GLS estimates for the same two specifications as columns (1) and (2), but now the error term is expanded to include time-invariant individual effects, and the correlation between those random effects and the endogenous regressors is taken into account. IV/GLS estimates for a similar pair of models appear in columns (5) and (6), but now time-invariant job effects are added to the error term. The column (6) estimates correspond to the model described by equation (1).

In interpreting the estimates in table 5, we begin by comparing columns (1), (3), and (5). These columns correspond to a "standard" wage model (no overall mobility measures are included) and differ only in their error structure and endogeneity assumptions. What is noteworthy about the three sets of estimates is that the effect of tenure decreases as we move from column (1) to (3) to (5). The column (1) estimates imply that five years of tenure raise wages 20.8%, whereas the column (3) and (5) estimates imply a 15.0% and 12.0% wage increase, respectively. It appears that the column (1) tenure coefficients are biased upward relative to column (3) by virtue of the positive correlation between tenure and individual effects α_i. Similarly, the column (3) estimates are biased upward relative to column (5) because tenure and job effects ϕ_{ij} are positively correlated. These results confirm what other researchers have found and what mover–stayer and matching models predict: jobs held by good (high α_i) workers and good (high ϕ_{ij}) jobs last and, therefore, are associated with high levels of tenure.

Next we turn to the estimates in columns (2), (4), and (6) of table 5, where measures of overall mobility are included among the regressors. Following up on the point made in the preceding paragraph, we note that the addition of $TJ2$ and $TJ8$ to the models (along with their interactions with tenure) does little to change the estimated tenure parameters. For workers who undergo no job mobility in eight years ($TJ2 = TJ8 = 0$), the implied return to five years of tenure is 18.5%, 13.2%, and 10.2% in columns (2), (4), and (6), respectively. Each of these numbers is only slightly smaller than the return to tenure implied by the corresponding model in which $TJ2$ and $TJ8$ are omitted.

While the addition of overall mobility measures does little to change the tenure parameters, these regressors do play a significant role in explaining log wages. In column (2), where we do not contend with the relationship between the overall mobility measures and unobserved heterogeneity, the coefficient for $TJ2$ is 0.010 and the coefficient for $TJ8$ is -0.009. Both coefficients are statistically different than zero at a 1% significance level. These parameters are small in absolute value, however, and imply that mobility occurring in the first two years of the career does little to affect wages. Using the sum of the two parameters, we find that an individual who undergoes 10 job separations in the first two years of his career (an implausibly high rate of mobility, which, in fact, is not seen in our sample) earns only 1% higher wages when he first begins a job than does an individual who stays with his initial employer for at least eight years. Job changes undertaken in the next six years lower the log-wage path—a worker who separates from 10 employers during this period earns 9% less than an individual who remains immobile, holding tenure constant at zero. The mobility–tenure interaction terms are generally small, but they serve to widen the predicted wage gap between movers and stayers for two reasons: mobile workers have less tenure than stayers, and they receive a lower return to their tenure, as the human capital model predicts. According to these estimates, early-career mobility does little to "help" but can do a significant amount to "hurt" wages.

As discussed in section I, many theories of job mobility would attribute the negative relationship between overall mobility and wages seen in column (2) to unobserved factors. Specifically, the mover–stayer model attributes the relationship to the effects of time-invariant individual characteristics that drive mobility and affect wages. The jobs-as-search-goods matching model attributes it to the effects of time-invariant job characteristics—the *only* reason workers change jobs is that a higher quality match has been found, where match quality is a known time-constant characteristic that influences wages. In the jobs-as-experience-goods model, the unobserved factor that affects both mobility and wages is *perceived* match quality, which is a time-varying effect. Thus of these three models, only the experience good model is consistent with overall mobility having an effect on wages after its correlation with time-invariant individual and job effects is taken into account.

We control for the relationship between the mobility-related regressors and time-invariant individual effects in column (4) of table 5 and control for both individual effects and time-invariant job effects in column (6). The coefficient for $TJ2$ falls only slightly from 0.010 in column (2) to 0.008 in column (4), and the 0.008 is not statistically different from zero at conventional significance levels. The coefficient for $TJ8$ increases in absolute value from -0.009 in column (2) to -0.029 in column (4), and the column (4) parameter is estimated very precisely. When time-invariant job effects are added to the model in column (6), the coefficient for $TJ2$ remains around zero (-0.001, with a standard error of 0.009) while the coefficient for $TJ8$ moves toward zero but remains a statistically significant -0.013. Using the same "test case" considered earlier, the column (4) estimates imply that an individual who changes jobs 10 times in two years earns 21% less than his immobile counterpart, whereas an individual who changes jobs 10 times after the two-year mark but before the eight-year mark earns 29% less than an immobile worker. Mobility also lowers wages in the column (6) model, but by less than the column (4) model—the corresponding wage losses are 14% and 13%.

The finding that overall mobility continues to be associated negatively with wages after we account for its correlation with time-invariant individual and job effects suggests that the error structure is misspecified and there are time-varying components of the error term that are correlated with the regressors. This interpretation is consistent with the notion that jobs are experience goods, for the experience good model holds that mobility is driven by factors that are job specific but time *varying.* If this model accurately reflects the matching process taking place in the labor market (even partially), then the nonzero mobility coefficients in column (6) of table 5 simply reflect this correlation. Of course, the estimates in column (6) are consistent with any model in which mobility has no independent effect on wages but is correlated with factors that we have not controlled for. For example, one could argue that our measure of unemployment and the wage index do not adequately control for fluctuations in labor market conditions. Assuming changes in market conditions are correlated

TABLE 6.—PREDICTED LOG WAGE BY EXPERIENCE LEVEL AND MOBILITY PATTERN

	Years of Experience					
	0	2	4	6	8	8–0
Specification 2						
1 job (8 years)	1.353 (0.012)	1.543 (0.009)	1.699 (0.010)	1.822 (0.011)	1.912 (0.012)	0.559
6 jobs (0.5 + 0.5 + 0.5 + 0.5 + 2 + 4)	1.338 (0.012)	1.463 (0.009)	1.611 (0.009)	1.683 (0.009)	1.800 (0.011)	0.462
6 jobs (4 + 2 + 0.5 + 0.5 + 0.5 + 0.5)	1.309 (0.011)	1.490 (0.009)	1.644 (0.010)	1.648 (0.009)	1.647 (0.010)	0.338
10 jobs (0.8 year each)	1.293 (0.011)	1.411 (0.008)	1.513 (0.008)	1.570 (0.008)	1.642 (0.009)	0.349
Specification 4						
1 job (8 years)	1.419 (0.028)	1.578 (0.028)	1.710 (0.029)	1.814 (0.030)	1.890 (0.031)	0.471
6 jobs (0.5 + 0.5 + 0.5 + 0.5 + 2 + 4)	1.297 (0.058)	1.417 (0.058)	1.561 (0.058)	1.630 (0.058)	1.749 (0.058)	0.452
6 jobs (4 + 2 + 0.5 + 0.5 + 0.5 + 0.5)	1.273 (0.057)	1.424 (0.058)	1.556 (0.058)	1.575 (0.059)	1.588 (0.059)	0.315
10 jobs (0.8 year each)	1.172 (0.061)	1.283 (0.061)	1.379 (0.062)	1.434 (0.062)	1.502 (0.062)	0.330
Specification 6						
1 job (8 years)	1.450 (0.023)	1.588 (0.022)	1.703 (0.023)	1.795 (0.025)	1.864 (0.026)	0.414
6 jobs (0.5 + 0.5 + 0.5 + 0.5 + 2 + 4)	1.381 (0.022)	1.483 (0.022)	1.593 (0.023)	1.654 (0.023)	1.743 (0.026)	0.362
6 jobs (4 + 2 + 0.5 + 0.5 + 0.5 + 0.5)	1.384 (0.021)	1.511 (0.020)	1.633 (0.023)	1.649 (0.021)	1.667 (0.022)	0.283
10 jobs (0.8 year each)	1.328 (0.020)	1.425 (0.018)	1.507 (0.019)	1.562 (0.020)	1.615 (0.021)	0.287

Notes: Predictions are based on the estimates shown in columns (2), (4), and (6) of table 5. Standard errors are in parentheses.

with both wages and voluntary mobility, we would expect to find nonzero coefficients for $TJ2$ and/or $TJ8$. We do not rule out alternative explanations for our finding, but given the difficulties inherent in distinguishing among alternative job matching models, we believe our results are striking.

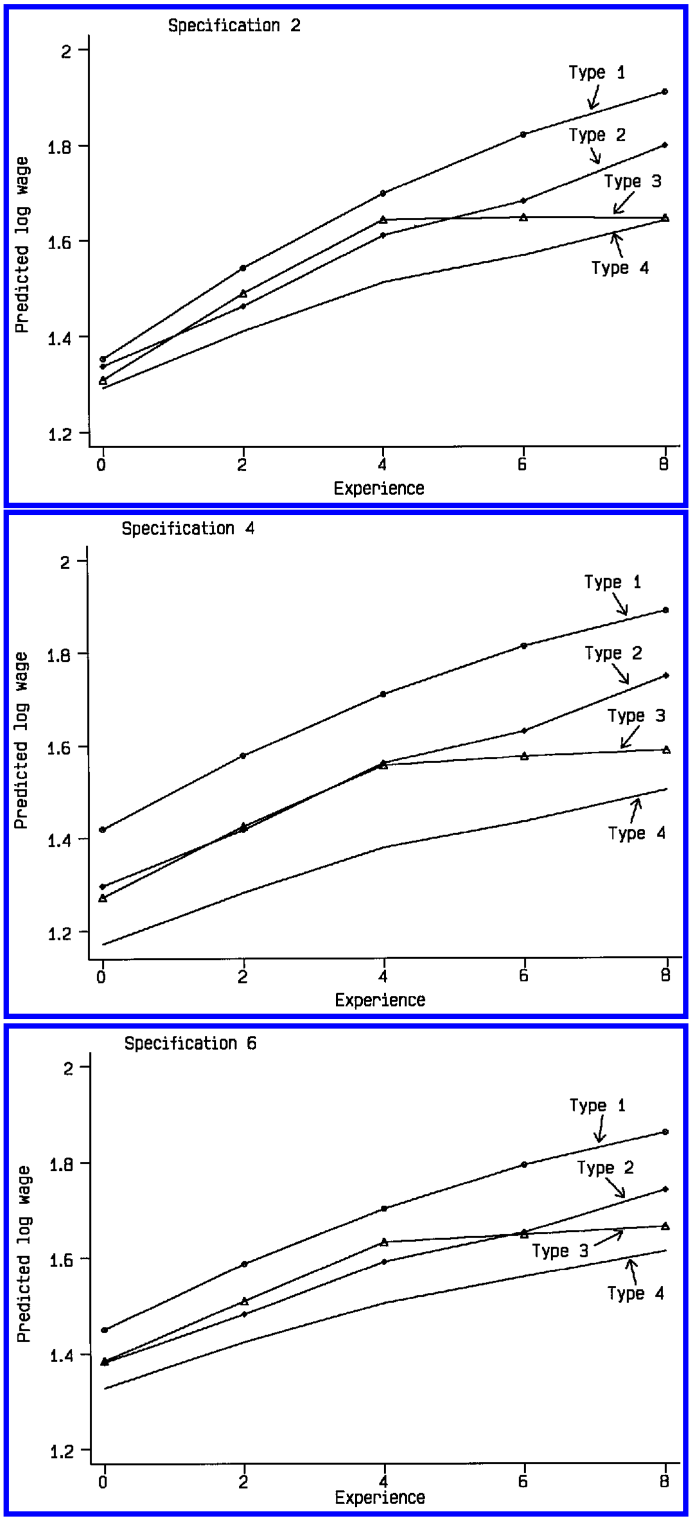
At the level of pure data description, we believe it is also interesting to see that immobile workers fare better than their mobile counterparts regardless of how we control for observed and unobserved heterogeneity. Indeed, the patterns seen here are robust to substantial changes in the regressors beyond what is reported in table 6. For example, replacing the wage index with year dummies, adding higher order terms in tenure and experience, interacting experience with the schooling dummies, and adding ability test scores and family background measures does not alter our general results. However, workers with different mobility patterns also tend to differ in their levels of job tenure, so it is difficult to determine the exact relationship between mobility patterns and wages from the estimates in table 5.

To describe more accurately the ''overall'' effect of job mobility on wages, we plot in figure 1 predicted log-wage paths implied by the column (2), (4), and (6) estimates of table 5 for workers with four different mobility patterns. The first type of worker we consider is someone who works for the same employer for the first eight years of his career ($TJ2 = 0$, $TJ8 = 0$). The second worker has six jobs (five job separations) during this period of time, which is close to the average amount of mobility seen in our sample: each of his first four jobs last six months, while his fifth jobs lasts two years and his final jobs last four years ($TJ2 = 3$, $TJ8 = 5$). The third worker also holds six jobs, but follows a very different mobility pattern—he holds a four-year job followed by a two-year job followed by four jobs lasting six months each ($TJ2 = 0$, $TJ8 = 5$). The fourth worker holds 10 jobs, each lasting eight-tenths of a year ($TJ2 = 2$, $TJ8 = 9$). Note that the type 2 mobility pattern is consistent with a search good job matching model where the worker moves to progressively better job matches. The type 3 and type 4 patterns are inconsistent with such a model, but can be justified by either a mover–stayer or an experience good matching model.

In computing the predicted wages, we assume that each individual works continuously for the first eight years of his career, has completed 12 years of school (and does not reenroll), is unmarried and childless, works full time in nonunion jobs, lives in a nonsouthern city, and begins his career in 1980.[17] We compute each worker's predicted wage at zero, two, four, six, and eight years of experience.

[17] Men with different job mobility patterns differ significantly in a number of observable dimensions, including schooling attainment and work continuity. If we control for this heterogeneity, the predicted wage paths discussed below differ even more dramatically across mobility patterns, but we ignore these differences in order to isolate the effects of mobility on wage paths

FIGURE 1.—PREDICTED LOG WAGES BY EXPERIENCE LEVEL AND MOBILITY PATTERN.



Based on predictions presented in table 6. Type 1 workers hold one job that lasts eight years. Type 2 workers hold four jobs lasting 0.5 year, each followed by one two-year job and one four-year job. Type 3 workers hold one four-year job followed by one two-year job followed by four jobs lasting 0.5 year each. Type 4 workers hold 10 jobs lasting 0.8 year each.

The predicted log-wage path corresponding to the column (2) (OLS) estimates in table 5 appears in figure 1a, the column (4) predictions are plotted in figure 1b, and the column (6) predictions appear in figure 1c. All three sets of predictions and the associated standard errors are also presented in table 6. The plot corresponding to the OLS estimates reveals that at every point in their career, the type 1 (immobile) workers earn more than the workers who move to increasingly durable jobs, who in turn earn more than the type 4 workers who change jobs approximately every 10 months. The wage gap among these workers is very small at the start of the career, but grows over time as the gap in their tenure levels grows. In fact, it is the tenure effects that cause the type 3 workers to overtake but then fall well behind the type 2 workers, for type 3 workers lose tenure as they move to increasingly less durable jobs.

What is remarkable about our results is that the patterns seen in figure 1a continue to exist after we control for the effects of time-invariant job and individual effects. The plots in figures 1b and 1c actually show more wage dispersion at the start of the career than does the OLS-based plot because, as seen in table 5, the coefficient for *TJ*8 becomes more negative as we enrich the error structure.

V. Conclusions

Most of what is known about the relationship between early-career job mobility and earnings comes from first-differenced wage models that estimate the average wage boost associated with a job change. We have taken a different approach by examining the association between wage paths and "overall mobility," defined as the number of job separations undergone in the eight years following school exit. Estimates from wage models that control for overall mobility reveal that job mobility is associated negatively with wage levels. By computing predicted log-wage paths for four workers who differ only in their mobility patterns, we have found that immobile workers (those who stay with their initial employers for at least eight years) earn the highest wages, whereas workers whose mobility fails to move them into increasingly durable employment relationships earn the lowest wages. In the middle are individuals whose mobility patterns conform to search good job matching models in which workers locate increasingly high-quality and, therefore, long-term jobs as they age.

The negative relationship between overall job mobility and wages is found in a simple wage model estimated via OLS, but also in models that account for the correlation between mobility and unobserved time-invariant personal and job characteristics. This is a particularly noteworthy finding because it is contrary to the predictions of two well-known models of job mobility. The mover–stayer model predicts that the negative relationship between job mobility and wages should disappear after time-invariant individual factors are taken into account. Models in which jobs are search goods and workers move to increasingly high-paying (and long-lasting) jobs predict that the negative relationship should vanish after we control for unobserved time-invariant job effects. According to these models, controlling for these unobservables is equivalent to controlling for match quality.

The finding that overall mobility is associated negatively with wages net of its association with unobserved time-invariant individual and job characteristics is consistent with any model in which mobility is driven by other unobservables—namely, those that vary over time. We note that experience goods job matching models fall into this category, for in such models wages and job mobility are determined by *perceived* match quality. Such perceptions are unknown to the analyst and, therefore, are represented in wage models as job-specific time-varying components of the error term. Our analysis has not proven the validity of experience goods models, but has provided evidence that is consistent with such models.

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APPENDIX

TABLE A.1.—MEANS AND STANDARD DEVIATIONS OF VARIABLES USED IN WAGE MODELS

	Mean	S.D.
ln(wage) (dependent variable)	1.808	0.527
Separations in 2 years $TJ2$	1.430	1.609
$TJ2 \cdot T$	2.275	4.879
$TJ2 \cdot T^2/10$	10.142	40.604
Separations in 8 years $TJ8$	5.942	4.454
$TJ8 \cdot T$	8.665	12.863
$TJ8 \cdot T^2/10$	34.392	98.257
Years of work experience X	5.496	4.021
$X^2/10$	46.373	57.693
Years of job tenure T	2.146	2.659
$T^2/10$	11.672	28.403
1 if years of school is		
<12	0.174	0.379
12	0.378	0.485
16	0.107	0.310
>16	0.099	0.299
1 if in school	0.074	0.262
1 if married	0.401	0.490
1 if divorced	0.077	0.267
1 if has health problems	0.033	0.179
1 if works <35 h/week	0.164	0.370
1 if government job	0.055	0.229
1 if union job	0.115	0.319
1 if lives in city	0.710	0.454
1 if lives in South	0.303	0.460
Unemployment rate	11.398	2.353
Log of wage index	2.026	0.026

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