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Discussion Paper

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NLS Discussion Papers

Evaluating Competing Theories of Worker Mobility

Henry S. Farber

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FINAL REPORT

EVALUATING COMPETING THEORIES OF WORKER MOBILITY

Henry S. Farber
National Bureau of Economic Research
1050 Massachusetts Avenue
Cambridge, MA 02138
(617) 868-3900
and
Department of Economics
Princeton University
Princeton, New Jersey 08544
(609) 258-4044
e-mail: farber@princeton.edu

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Objectives

In this study I use a sample of over fourteen thousand full-time jobs held by workers in the National Longitudinal Survey of Youth (NLSY) to examine mobility patterns and to evaluate theories of labor mobility (defined as change of employer). In particular, I investigate the following questions:

1) How important is heterogeneity in determining mobility rates for young workers?
2) Can heterogeneity in mobility rates be characterized as fixed differences across workers or as variable with workers changing types over time (either systematically or otherwise)?
3) How important is state dependence in mobility rates? In other words, does mobility vary importantly with how long a worker has held his or her job?
4) Does mobility decline systematically with how long a worker has held his or her job, or are there periods where likelihood of mobility increases?
5) What do the facts discovered about the nature of the relationships between mobility and both heterogeneity and state dependence tell us about what actually causes mobility? Specifically, how important is the accumulation of specific capital, how important is the the quality of particular matches between workers and firms, and how important is the underlying variation in the stability of workers?

Methods

The methods used in this study exploit two features of the NLSY that differentiate this study from earlier work and allow for the possibility of new insight:

1) The NLSY contains a more complete employment history than any other longitudinal survey of comparable length. Virtually all jobs since entry to the labor market are reported.
2) The NLSY allows precise determination of how long jobs are. The actual dates of the beginning and the end of all jobs are reported.

The first use of the complete employment history is to determine when workers initially make a substantial commitment to the labor force defined by me as three consecutive years working on full-time jobs for at least half of each year. A complete job history from this point forward for 3776 workers who made this commitment to the labor force between 1979 and 1985 covers 14160 full-time jobs and serves as the basis for the analysis. The precise information on duration is used to compute monthly probabilities (hazards) of jobs ending, and this yields findings not possible with lower frequency measures of mobility (annual or quarterly).

The first part of the analysis uses the complete employment histories and the monthly hazards of jobs ending to determine the importance of heterogeneity. This is accomplished using two statistical models. First, an ordered-probit analysis of the number of jobs held by workers in a given period of time since entry is estimated in order to examine how mobility varies with observable worker characteristics such as sex, race, age, and education. The ordered probit model is appropriate given the ordered-yet-discrete nature of the count of number of jobs held. Second, a discrete-time logit model of the monthly hazard of a job ending is estimated conditioning on the detailed history of mobility prior to the start of the job along with the observable characteristics of workers. This is done in order to examine how unmeasured differences in mobility rates are related to future mobility and whether the relationships are fixed over time.

The second part of the analysis uses the same discrete-time logit model of the monthly hazard of a job ending in order to investigate how the hazard varies with how long workers have held their jobs. It is particularly important that prior mobility is accounted for when carrying out this analysis in order to minimize the usual heterogeneity bias in estimating the role of duration in hazard models. The discrete-time logit model is an appropriate technique for this analysis because it allows for a completely flexible baseline hazard. The specification used allows each month early in the job to have a different baseline hazard rate.

Findings

There are five main findings. The first three relate to heterogeneity across workers in mobility rates. The last two are about state-dependence or how mobility rates vary with how long a worker has held his or her job.

1) Mobility in a new job is strongly positively related to the frequency of job change prior to the start of the job. There is substantial heterogeneity in mobility rates, and this persists throughout subsequent jobs.
2) Job change in the most recent year prior to the start of a new job is more strongly related than earlier job change to mobility on the new job. Thus, heterogeneity in mobility rates is not fixed over time, and workers seem to change, becoming fundamentally more or less mobile over time.
3) Females hold significantly fewer jobs than do males in a fixed period of time early in their careers. Thus, females who have committed to the

labor force exhibit less mobility than otherwise equivalent males. This result seems to be driven by a lower exit rate for females from the first job after entry. Potential links between the fact that the sex differential in wages rises with experience and the lower mobility of young females needs to be investigated further.

4) Mobility rates are very high early in jobs. One-third of jobs end within the first six months, and one-half are over within the first year. Mobility rates are much lower later in jobs. These findings demonstrate the importance of detailed analysis of mobility early in jobs, and they suggest the importance of accumulation of specific capital (in the form of both job-specific skills and job-specific information) on the job.

5) The monthly hazard of job ending is not monotonically decreasing in tenure as most earlier work using annual data has found, but it increases to a maximum at three months and declines thereafter. This finding is robust to controlling for worker heterogeneity, and it appears in jobs starting at any point after entry. This finding is consistent with a situation where workers and employers learn about the quality of the worker-firm match over the first several months on the job.

Conclusions

The findings suggest that heterogeneity is a very important determinant of mobility rates. However, this heterogeneity is not fixed over time, and this suggests that public policies designed to help young workers be more stable could have a real effect. Workers do change types. Important work remains to be done explicitly modeling the stochastic process underlying the heterogeneity and examining the extent to which there is systematic maturation of workers from less stable types into more stable types.

The finding that the hazard actually increases early in jobs before declining is consistent with models of heterogeneous match quality that cannot be observed *ex ante*. In this type of model, workers and employers learn over time whether the worker-job match is a good one. If the match is revealed to be good it persists. Otherwise it ends. The general decline in mobility rates after the first few months on the job is consistent with continued investment in specific capital on the job, but this investment occurs only after an initial period when it is determined that the employment match is likely to survive. To the extent that *ex ante* unknown match quality is an important cause of turnover early in jobs, public policies designed to provide better information *ex ante* to workers and employers about the quality of matches has the potential to reduce the very high mobility rates early in jobs.

The more general (and not new) finding is that half of all jobs end in the first year. This mandates a focus on the first year on the job in order to understand labor mobility. However, it also highlights a potential measurement problem in the NLSY: The measured low hazard early in jobs could result simply from under-reporting of very short jobs.

There are three comments on the design of the NLSY that would improve its usefulness for the purposes of the analysis of worker mobility. First, a special effort should be made to be sure that that the respondents report *all* jobs, regardless of their duration. Second, complete job information should be collected and reported on jobs of all durations. In the current survey, detailed information is collected only about jobs which last at least eight weeks. Since over twenty percent of jobs are over by the eighth week, important information is missed about a substantial fraction of jobs. Finally, wage data at more regular points would be very useful in the analysis of mobility. While the most recent waves of the NLSY have information on starting and ending wages on jobs along with wages at interview dates, data at monthly intervals in the first half-year would also be very useful.

In conclusion, the analysis in this study provides important new information on mobility patterns that are consistent with 1) important though variable worker differences in underlying mobility rates and 2) *ex ante* unobservable match quality that workers and firms learn about over a relatively short period during the first six months to one year on the job.

Section 1: Introduction

In this study I use a sample of over fourteen thousand full-time jobs held by workers in the National Longitudinal Survey of Youth (NLSY) to examine mobility patterns and to evaluate theories of labor mobility (defined as change of employer). In particular, I investigate the importance of both heterogeneity and state dependence in determining mobility rates for young workers. One question that has implications for the determinants of labor turnover is whether worker heterogeneity in mobility rates can be characterized as fixed differences across workers or as variable with workers changing types over time (either systematically or otherwise). Another important question is whether state dependence in mobility rates is such that the mobility rates decline monotonically with the time since the last job change (tenure).

The answers to these questions not only can help shed light on competing theories of labor mobility, but they can also help in the design and evaluation of public policies to help young workers have a stable employment history. For example, to the extent that heterogeneity is important in determining mobility rates and this heterogeneity is not fixed over time, there may be scope for training and supported-work programs to help workers become more stable. However, if worker types are fixed over time with little or no evidence of change, these sorts of programs may be less useful in reducing turnover.

Investigation of the role of state dependence in labor turnover can be equally informative. First, the relationship between mobility rates and tenure, by helping to distinguish "standard" specific-capital models (Becker, 1962; Oi, 1962; Mortensen, 1978) from models based on information about match quality (Jovanovic, 1979a), can provide information on the sorts of programs that would be most effective in promoting stable matches. Second, a clear understanding of how mobility rates vary with tenure is important in the evaluation of public policy in this area. For example, it may be that the effects of a one policy to reduce turnover might affect long-term survival probabilities of jobs while another policy might be most effective in reducing turnover early in jobs.

There are two features of the empirical analysis that differentiate it from earlier studies and allow for the possibility of new insight. First, the NLSY contains a more complete employment history than any other longitudinal survey of comparable length. This allows me to develop a virtually complete history of past mobility that can be used to control for heterogeneity across workers in underlying mobility rates. Worker heterogeneity is an important confounding factor when investigating the relationship between the hazard of a job ending and tenure, and very good measures of past mobility have the potential to limit the difficulties this poses.

The second new feature of the empirical analysis is that the NLSY allows precise determination (to the day!) of how long jobs are. While I aggregate job durations to the monthly level in most of my analysis, even that level is far finer than has been reliably used in the past.[1] The empirical importance of this is clear from figure 1 which contains the product-limit estimate of the monthly survivor function for the jobs in the NLSY sample I use in my analysis (described in detail in the next section). The exit rate is clearly very high early in jobs. About one-third of jobs are over within six months, and fully one-half of jobs are over by the end of the first year. Clearly, much of the important information about state

[1]See Brown and Light (1989) for an analysis of the difficulties in determining job durations in the Panel Study of Income Dynamics (PSID).

dependence in mobility unfolds very early on the job, and data on job durations that can be calibrated only annually or even quarterly is not likely to be very informative.

The next section contains both a detailed description of the data that lie at the heart of the analysis and a simple analysis of state-dependence in the raw data that shows a surprising regularity. In section 3, I present an analysis of heterogeneity in mobility rates that focuses on the relationship between prior mobility and mobility on the current job. Section 4 contains an analysis of state dependence in mobility rates that uses the information on prior mobility to control for heterogeneity. Section 5 concludes.

Section 2: The Data

The National Longitudinal Survey of Youth (NLSY) has a number of advantages for the analysis of turnover. First, by focusing on young workers, the NLSY allows us to use longitudinal information to determine relatively precisely when workers make their first long-term transition to the labor force. Second and as mentioned in the introduction, the detailed employment histories included in the NLSY allow me both to determine job durations with more than usual precision and to use previous mobility to account for heterogeneity in mobility rates.

This is not to say that the NLSY is perfect. There are at least two important drawbacks. First, information on wages is only collected for one (ambiguous) point in time at each interview until the most recent interview years. It would have been very useful to have additionally at least a starting wage and an ending wage for each job. In fact, the sparseness of the wage data precludes it use at this point. The second drawback is that detailed information on jobs is only collected for jobs that last more than eight weeks. There is information on the duration of the short jobs and on why these jobs ended, but there is no information on industry or occupation. Since what happens early in jobs is central to the analysis here, this means that industrial and occupational variation in mobility patterns cannot be examined. While this is a serious limitation, there is still much to be learned about mobility from these data.

Individuals in the NLSY were between the ages of fourteen and twenty-one on January 1, 1979. We eliminate from our analysis the 1280 workers in the military sample. The remaining sample is comprised of 11406 workers, including 6111 workers from a representative cross-section sample and 5295 individuals from a supplemental sample of under-represented minorities and economically disadvantaged workers. At the time I carried out my analysis, there were data available for the 1979 through 1988 interview years.

In order to focus on mobility from the time workers first make a primary commitment to the labor market, I limit our sample to individuals who make their first long-term transition from non-work to work during the sample period. I define a long term-transition to occur when an individual spends three consecutive years (i.e., intervals between interviews) primarily working after at least a year spent not primarily working. An individual is classified (by me) as primarily working if he/she worked in at least half of the weeks since the last interview and averaged at least thirty hours per week in the working weeks.[2] Only individuals aged 16 or older were asked the relevant questions on employment history. Thus, we could not classify the youngest cohorts (aged 14 and 15 in 1979) in the earliest years of the survey.

There are 2587 individuals whom we classify as primarily working at the first interview for which there is valid data to classify them. We dropped these individuals from the analysis because we could not determine whether the first observation for these workers was their first year primarily working. There were also 14 individuals who were classified as primarily working in all three years from 1975-1977 based on responses to retrospective questions asked in 1979. These individuals were also dropped from the sample because they had already made a long-term transition to the labor force by my definition. On this basis, the first year individuals could make their first long-term transition to the labor force was between the 1979 and 1980 interviews.

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[2]At the 1979 interview date, the last interview was assumed to be January 1, 1978.

Individuals were dropped from the sample if they were not classified as primarily working in three consecutive interviews. Because the data end in 1988, I cannot be sure that workers who enter after 1985 were primarily working for three years. On this basis, the last year individuals could make their first long-term transition to the labor force was between the 1985 and 1986 interviews. I dropped 4114 individuals who never made a long-term transition to the labor force by this definition as well as 468 individuals with missing data on key variables.

In order to focus on full-time jobs, I then dropped 5486 jobs which were never reported as full time (usual weekly hours greater than or equal to thirty). Two individuals had no jobs that qualified as full-time by my definition so that only 4225 individuals remained in the sample at this point. Next, I dropped 411 jobs where the worker was either self-employed or unpaid and 17 jobs that started before the worker was sixteen. This further reduced the sample of workers by 24. Finally, all 2070 jobs for 421 individuals whose first qualifying job started before 1979 or after 1985 were dropped from the sample.

The final sample consists of 14160 jobs for 3776 individuals who made their initial long-term transition to the labor force (by our definition) between 1979 and 1985. Table 1 summarizes the disposition of the original sample of 12686 individuals to yield the final sample of 3776.

My definition of a worker's initial long-term transition to the labor force is arbitrary. Redefining our criteria with regard to minimum weekly hours or minimum weeks worked had very little effect on the final sample size. Changing the three-year consecutive history requirement had a predictably larger effect on the final sample size. Some information is available to evaluate how sharply we have defined the transition into the labor force. Some workers were classified as primarily working for some years prior to their first long-term transition: 2870 were never classified as primarily working prior to their first long-term transition, but 582 were primarily working for one year, 280 for two years, and 44 for three or more years. Overall, our rule captures what seems to be a reasonably sharp transition from not working to working.

Table 2 contains sample average characteristics at the time of transition to primarily working (at the start of the first qualifying job). Most of these jobs (84.1 percent) end during the sample period. Average characteristics are also presented for the subset of jobs starting in each year since entry and for all 14160 jobs in the sample. For example, there are 2039 jobs (other than first jobs) that started in the year (year 1) that workers made their transition to primarily working and 2224 jobs that started in the next year (year 2). Only 12.3 percent of jobs starting in the first year are censored (last interview is held before the job ends) while 49.3 percent of jobs started in the seventh or later year are censored. This is due in large part to the fact that the jobs started in later years are closer to the last interview date. It could also be due to the fact that jobs started when workers are older and/or have more experience may be of longer duration. This will examined in more detail in the next section.

Figure 2 contains empirical hazard functions for job ending at four frequencies using the sample of 14160 jobs from the NLSY. The upper-left panel contains the annual hazard function using 29387 annual observations on the 14160 jobs. This hazard is monotonically declining in tenure and shows the 0.5 hazard in the first year that was apparent from the survivor function in figure 1. The hazard falls to 0.3 by year 2, and it is less than 0.1 by year 8. The upper-right panel contains the quarterly hazard function using 93675 quarterly observations on the same jobs. This hazard is also monotonically declining. The decline is very sharp in the first year, with the hazard falling from greater than 0.2 in the first quarter to about 0.1 by the fourth quarter.

Both the annual and quarterly hazards are monotonically declining, and it is evidence on the hazards at roughly these frequencies that has driven the stylized fact that the probability of job change is monotonically declining with tenure. However, a different picture emerges when the hazard is computed at greater frequencies. The lower-left panel of figure 2 contains the monthly hazard function using 266449 monthly observations on the 14160 jobs. What is most striking about the hazard function in figure 2 is that the hazard is actually relatively low in the first month at 0.06, rising to a peak of almost 0.10 at three months and declining sharply thereafter before leveling off at less than 0.02. The high period-to-period volatility of the hazard function at the longer durations (> 48 months) is due to the relatively small number of observations on jobs that long, and it should not be taken seriously due to sampling error.

Given the new finding of an increasing hazard early in the job, the lower-right panel of figure 2 contains an even finer breakdown of the hazard early in jobs. This panel contains the weekly hazard function using 287882 weekly observations on the first 26 weeks on the 14160 jobs. This weekly hazard shows an increase from a low of less than 0.01 in the first week to a peak of about 0.025 in the third month. It is not surprising that the weekly hazard seems more variable week-to-week despite the large sample size given the low probability of separation in a given week. If anything, the weekly data show a more pronounced peak in the hazard with the ratio of the peak hazard to the first week's hazard being about 2.5 (.025/.01). The ratio of the peak monthly hazard to the first month's hazard is 1.57 (.0967/.0615).

In the analysis that follows, I use monthly data on the hazard of a job ending. This frequency seems an appropriate compromise between 1) the crudeness of annual or quarterly data which will miss important variation in the hazard and 2) the computational and expositional burden of weekly data. The basic data then become the 266,449 months observed for the 14,160 jobs in my sample. The maximum number of months observed for any single job is 121.

Table 3 contains tabulations of mean monthly rates of turnover by experience and by tenure. The breakdown by experience, measured in years since the first transition to primarily working, in the left-hand column shows a sharp decline in mobility with experience. Workers in their first year have a 6 percent monthly probability of job change while workers in their eighth year have only a 2.5 percent monthly probability of job change. Of course it is true that workers with more experience are also likely to have more tenure, and the right-hand column of table 3 shows a breakdown of the monthly hazard of job change.[3] This is a summary of the information in the monthly hazard plotted in figure 2, and it shows the peak in the hazard at 3 months followed by a decline in subsequent periods.

Given that investigation of the non-monotonicity of the hazard will be an important part of the the analysis in subsequent sections, it is worth investigating to the extent possible how likely it is that the lower observed hazard early in jobs is simply an artifact of under-reporting problems in the NLSY. In particular, if the NLSY is less likely to code information on short jobs or workers are more likely to fail to report very short jobs to the interviewer then the hazard earlier in jobs will be measured to be lower than it actually is.

It is interesting to ask how serious under-reporting of short jobs

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[3]Multivariate analyses in sections 3 and 4 will be used to determine the extent to which the hazard declines with experience after controlling for tenure.

would have to be in order to eliminate the lower measured failure rate in the first month. In the raw data graphed in figure 2 for the monthly hazard and tabulated in table 3, the failure rate is 6.2 percent in the first month and 9.7 percent in the peak (third) month. Assuming (unreasonably) that *all* jobs that fail in the third month are reported, there would have to be 557 additional jobs that failed in the first month but went unreported in our sample in order to equalize the hazards in these two periods. This compares with 871 reported jobs in our sample that failed in the first month.

Is 557 missed jobs an unreasonably large number? The NLSY survey instrument is designed to pick up all jobs held since the previous interview, though information on only a maximum of five jobs are reported on the public distribution of the data. It is unclear how these five are selected when more than five are reported, but the survey instrument asks about jobs in reverse chronological order with no reference to duration. The distribution does contain information on how many jobs each worker reported at each interview. For the 3776 individuals in my sample only 88 jobs after entry for 51 workers are reported but not coded in the public distribution, and some of these are likely to not qualify because they are part-time. Thus, omission of jobs in excess of five per worker per year cannot account for the problem.

If individuals simply forget short jobs, it is reasonable to expect that short jobs held immediately prior to the interview date would be more likely to be remembered and reported than short jobs held long before the interview date. Ignoring seasonality in job durations and assuming that the probability of a job starting is uniform over the year, one can investigate the distribution of short jobs as a function of time until the next interview.[4] There were 871 jobs in the sample that ended in the first month. Fully 113 of these jobs were started in the month prior to the interview. If we accept 113 as a full count of the very short jobs started in a given month then there ought to be 12·113 = 1356 very short jobs in my sample since there twelve months on average between interviews. Since I only observe 871, there is a shortfall of 485 one-month jobs. This is quite close to the 557 one-month jobs it would take to equalize the hazards for the first and third months.

The calculation in the preceding paragraph may be too extreme because it assumes that no jobs longer than one month went unreported. If I assume that there is under-reporting of jobs held two or fewer months, the conclusions are quite different. Of the 2036 jobs in the sample that ended in the first two months, 360 of these were started in the two months prior to the interview. If this is accepted as a full count of the very short jobs started within two months of the interview in my sample, then there ought to be 6·360 = 2160 jobs with completed duration less than two months. The shortfall here is only 124 = 2160 - 2036 jobs. This is less than twenty-five percent of the jobs required to equalize the hazards for the first and third months.

The indirect evidence is mixed regarding whether the finding of an increasing hazard in the first few months on the job is real or a statistical artifact. There is some possibility that part of it is due to under-reporting of short jobs, but there is no obvious way to get more direct evidence without a survey (like the Survey of Income and Program

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[4]In fact, the jobs in my sample are disproportionately likely to start in June and disproportionately likely to end in August. However, this does not account for the peak in the hazard since a multivariate analysis of the sort carried out in the next section that includes a complete set of dummy variables for calendar-months shows the same peak in the hazard.

Participation) that is conducted at more frequent intervals than one year. I will proceed assuming the increasing hazard found early in the job is a real phenomenon.

Section 3: How Important is Heterogeneity in Mobility?

In this section I abstract from variation in the probability of job change with tenure for a given worker (true duration dependence in the hazard) in order to focus on heterogeneity in mobility rates across workers. This is important for two reasons. First, the understanding the nature of heterogeneity in worker mobility is important in its own right. Second, consistent estimates of the role of state dependence in the probability of job change cannot be investigated without controlling for heterogeneity (e.g., Lancaster, 1979; Heckman and Singer, 1982). Thus, heterogeneity in mobility must be considered very carefully in order to evaluate even models of mobility that do not incorporate heterogeneity directly.

A. *Are the Data Consistent with a Pure Heterogeneity Model?*

It is easy do dismiss the possibility that labor turnover is strictly the result of fixed worker heterogeneity without any state dependence. Two pieces of evidence at odds with a pure-heterogeneity explanation for mobility have already been presented. First, the breakdown of mobility rates by experience, contained in table 3, shows that the probability of job change declines with experience. Heterogeneity implies that the probability of job change will be uncorrelated with experience. Second, the monthly hazard function, plotted in figure 2 and tabulated in table 3, rises to a peak after three months of tenure and declines subsequently. Heterogeneity implies that the hazard will decline monotonically with tenure.

A simple model suffices to demonstrate that heterogeneity in mobility rates implies no relationship between mobility rates and experience and a uniformly negative relationship between mobility rates and tenure. I assume that there are two types of workers, but the analysis generalizes straightforwardly to k types with an arbitrary distribution. The two types of workers are differentiated only by their turnover probabilities, λ_1 and λ_2. This sort of mover-stayer model was first used for the analysis of job mobility by Blumen, Kogen, and McCarthy (1955). Type 1 workers are relatively more mobile so that $\lambda_1 > \lambda_2$, and these turnover probabilities are fixed over time for each worker. The proportion of the population that is of type 1 is θ.

The overall turnover rate at any point in time is simply the θ weighted average of the individual turnover probabilities,

(3.1) $$P_1 = \theta\lambda_1 + (1-\theta)\lambda_2.$$

This implies that the average rate of job change does not vary with labor-market experience since the composition of the sample does not vary with experience. This property is clearly independent of the number of types, the distribution of the types (θ), or the turnover propensities of the types (the λ's).

The same model can be used to derive the result that pure heterogeneity implies that the hazard declines monotonically with tenure.[5] The simple intuition is that the sample of workers observed in the same job in multiple periods is disproportionately composed of low-turnover workers. The average mobility rate for workers these workers is lower. More formally, consider first $P_{1\cdot 0}$, the probability that a worker changes jobs in the second period conditional on not having changed jobs in the first period. This is

(3.2) $$P_{1\cdot 0} = \lambda_1 Pr[Type1 \mid C_1=0] + \lambda_2 Pr[Type2 \mid C_1=0]$$

where C_1 is a binary variable such that $C_1=0$ if the worker did not change

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[5]To be precise, the proof here of the proposition that pure heterogeneity implies that mobility declines monotonically with tenure is strictly valid only for the first jobs workers hold. However, the proposition holds generally, and the proof here illustrates the selection process that generates the result. I show later that the non-monotonicity of the hazard with illustrated in figure 2 for all jobs in my sample also holds for first jobs alone. See figure 4 and tables 15 and 16.

jobs in period one and $C_1=1$ if the worker did change jobs. The conditional probability that a worker who did not change jobs is type 1 is

(3.3) $$\Pr[\text{Type1} \mid C_1=0] = \frac{(1-\lambda_1)\theta}{(1-\lambda_1)\theta + (1-\lambda_2)(1-\theta)}$$

which is less than θ as long as $\lambda_1 > \lambda_2$ so that the sample of stayers is disproportionately composed of low-turnover workers. Substitution of equation 3.3 into equation 3.2 yields the probability of turnover in the second period for workers who did not change jobs. This is

(3.5) $$P_{1\cdot 0} = \lambda_1 \Pr[\text{Type1} \mid C_1=0] + \lambda_2 \Pr[\text{Type2} \mid C_1=0]$$

$$= \frac{\lambda_1(1-\lambda_1)\theta + \lambda_2(1-\lambda_2)(1-\theta)}{(1-\lambda_1)\theta + (1-\lambda_2)(1-\theta)}$$

which is less than both P_1 and $P_{1\cdot 1}$ as long as $\lambda_1 > \lambda_2$.

This generalizes easily to n periods of tenure where

(3.6) $$\Pr(\text{Change} \mid \text{no previous changes in n periods})$$

$$= \frac{\lambda_1(1-\lambda_1)^n\,\theta + \lambda_2(1-\lambda_2)^n(1-\theta)}{(1-\lambda_1)^n\theta + (1-\lambda_2)^n(1-\theta)},$$

and the derivative of this probability with respect to n is

(3.7) $$\partial\Pr(\text{Change} \mid \text{no previous changes in n periods})/\partial n$$

$$= \frac{\theta(\lambda_1-\lambda_2)(1-\theta)\delta\cdot\ln[\delta]}{(\theta\delta + (1-\theta))^2},$$

where

(3.8) $$\delta = \Big((1-\delta_1)/(1-\delta_2)\Big)^n .$$

This derivative never positive, and it is strictly negative for all but three special cases where there is no heterogeneity ($\lambda_1=\lambda_2$, $\theta=0$, or $\theta=1$). Thus, the probability of job change will decline monotonically with tenure in the presence of pure heterogeneity.

B. *The Relationship of Observable Worker Characteristics with Mobility*

Although the results presented so far suggest that other factors are also likely to be important, how important is heterogeneity in turnover rates? There are two manifestations of heterogeneity that I look for in the data. First, I examine the extent to which the number of earlier jobs a worker with a given amount of time since labor-market entry has held is related to observable characteristics of workers including age, education, race, sex, and the year of entry. This provides some evidence on the relationship between turnover rates and observable characteristics. Second, I examine the extent to which the hazard of a job ending is related to earlier mobility after controlling for observed characteristics. This provides some evidence on the relationship between turnover rates and unobserved characteristics.

Table 4 contains a breakdown of number of jobs held since entry by year since entry. There is considerable variation in this quantity. Naturally, it is the case that the number of previous jobs held is positively related to the number of years since entry. For this reason, separate analyses are carried out for each year of experience. The sample for each year of experience consists of those individuals in my sample who are observed in the sample at that point.

Table 5 contains the average number of previous jobs for different dimensions of the data separately for each experience level. The first dimension is sex. At all levels of experience, males have held more jobs than females suggesting that men change jobs with higher frequency than women.[6] On average, the 1878 men in the sample held 3.79 jobs while the 1898

[6]See Loprest (1991) for a detailed analysis of male-female differences in turnover rates in the NLSY and the relationship of turnover rates with male-female differences in wage growth.

women held 3.21 jobs.[7] The difference of 0.58 (s.e. = .063) is statistically different from zero at conventional levels. On average, the men did have 0.1 years more total experience than women, but this difference is not statistically significant (p-value = .154). The small difference in average experience cannot account for the difference in the number of jobs held.

There is only a a weak relationship between race and the number of jobs held. On average, the 2239 whites in the sample held 3.54 jobs while the 1537 nonwhites held 3.43 jobs. The difference of 0.11 (s.e. = .065) is only marginally statistically different from zero at conventional levels (p-value = .10). There is a sizable difference in the total experience of whites and nonwhites with nonwhites having 0.2 years less experience on average than whites. This difference is statistically significant (p-value = .003), and it can account for the small difference in number of jobs held. On balance there seems to be no difference in turnover rates by race.

Finally and with regard to education, the means in table 5 suggest that workers with sixteen or more years of education hold significantly fewer jobs than workers with twelve years education at every level of experience. The difference is small shortly after entry (less than 0.2 jobs in year two) but rises to about 0.5 jobs by year six. The differences are statistically signficant at conventional levels for all years through year nine.

In order to measure the relationship of mobility rates with observable characteristics in a multivariate context, separate ordered-probit models of the number of previous jobs were estimated at each level of experience. These models included controls for education (four categories), sex, race, age at entry, and dummy variables for the calendar year at entry. Ordered

[7] This count and the analogous counts of total jobs held include the current job, while the tabulations of previous jobs in the table do not include the current job.

probits were used because the number of jobs held is ordinal and takes on relatively few values so that standard linear regression techniques are not appropriate.[8] While there are up to 22 earlier jobs for a single worker, the distribution of observations with more than five earlier jobs is rather sparse, particularly at the low and middle experience levels. For this reason, the ordered probit analysis is carried out using seven categories for the dependent variable: six categories for zero through five earlier jobs and a single category for six or more earlier jobs. This is the breakdown used in table 4.

Table 6 contains estimates of ordered probit models of the number of previous jobs as a function of fixed observable worker characteristics. A separate model is estimated for each experience level from one through six years. The results are fairly consistent across experience levels, with females showing less mobility (having fewer previous jobs) than males at every experience level. After the first year, nonwhites show significantly less mobility than whites though the difference by race is much smaller than the sex difference. The findings in these two dimensions are consistent with the univariate mean differences in table 5. However, the ordered-probit results with regard to education differ somewhat from the univariate means in table 5. The multivariate analysis yields the result that workers with less than twelve years education have significantly lower mobility (fewer previous jobs) at most experience levels than workers with exactly twelve years education. Workers with thirteen to fifteen years education have mobility rates that are indistinguishable from workers with twelve years education. Workers with at least sixteen years education have significantly fewer previous jobs in the first year than do workers with twelve years

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[8]See Maddala (1983) for a discussion of the ordered probit technique.

education, but after the first year the difference, while estimated to be negative, is not significant at conventional levels.

Age at entry has a different relationship with prior mobility depending on the experience level. In the first year, workers who were older when they entered have had significantly more prior mobility. However, by the time workers attain five years experience, workers who were older upon entry have had significantly less prior mobility. Note that these results are found after controlling for education so that older workers are those workers who took longer to enter the labor force perhaps because they took longer to complete a given course of schooling.

Finally, calendar year of entry seems to be related to mobility with entrants in later years showing less mobility than earlier entrants other things equal. This is true at every experience level.

A likelihood-ratio test statistic is presented for each probit model. This statistic refers to a test of a constrained model with only the six ordered-probit thresholds against the unconstrained model presented in table 6. The constrained model can be rejected at conventional levels in every case. This suggests that the observable characteristics of workers are significantly related to mobility and that there is significant heterogeneity across workers in mobility rates.

The last column of table 6 contains estimates of a pooled model that includes all observations on years one through six. This model also includes a set of five dummy variables (not shown) for experience level in order to account for the natural phenomenon that workers with more experience will have had more prior jobs on average. While the pooled model is not strictly appropriate because workers (and jobs) are included multiple times (up to a maximum of six), it does give a rough summary of the overall relationships of worker characteristics with prior mobility. However, a likelihood-ratio test of this constrained model against the unconstrained model implicit in the first six columns of the table resoundingly rejects the constrained model.[9]

C. *The Relationship of the Hazard Rate with Prior Mobility*

One way to investigate the relationship of the hazard rate to prior mobility is to examine turnover probabilities conditional on previous turnover in the context of the simple two-type model used above. As was discussed in section 3A, turnover probabilities differ by turnover history because the sub-population with any particular turnover history is not distributed as type 1 with probability θ and type 2 with probability $1-\theta$.

I already derived $P_{1\cdot 0}$, the probability that a worker changes jobs in the second period conditional on not having changed jobs in the first period, in equation 3.5. The analogous quantity, $P_{1\cdot 1}$, is the probability that a worker changes jobs in the second period conditional on having changed jobs in the first period. This is

$$P_{1\cdot 1} = \lambda_1 \Pr[\text{Type1} \mid C_1=1] + \lambda_2 \Pr[\text{Type2} \mid C_1=1] \tag{3.9}$$

Applying Bayes's rule yields the result that

$$P_{1\cdot 1} = \frac{\lambda_1^2\theta + \lambda_2^2(1-\theta)}{\lambda_1\theta + \lambda_2(1-\theta)}\,. \tag{3.10}$$

It is straightforward to show that $P_{1\cdot 1}$ must be greater than both P_1 and $P_{1\cdot 0}$. The intuition is the same as that used earlier: the sub-population that changed jobs last period is composed of a higher fraction of workers with high turnover probabilities (type 1) than either the entire population or the sub-population that did not change jobs last period. A worker with a history of prior turnover has a higher probability of turnover than a worker

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[9]The unconstrained log-likelihood is -32280.5. The likelihood-ratio test statistic is 2365.6 with 52 degrees of freedom. The constrained model is rejected at any reasonable level of significance.

without such a history.

Figure 3 contains separate plots for each year of experience of the hazard of job ending by number of previous jobs. This figure shows that the hazard increases with the number of previous jobs at all experience levels.[10] It also shows the general decline in the hazard with experience.

It is straightforward to show that all that matters for the probabilities of turnover conditional on previous turnover history in a pure heterogeneity model is the number of prior periods with job changes (c) and the number of prior periods without job changes (n-c). The order in which prior turnover took place is irrelevant. The general formula is[11]

(3.11) Pr(Change | c previous changes in n periods) =

$$= \frac{\lambda_1^{c+1}(1-\lambda_1)^{n-c}\theta + \lambda_2^{c+1}(1-\lambda_2)^{n-c}(1-\theta)}{\lambda_1^{c}(1-\lambda_1)^{n-c}\theta + \lambda_2^{c}(1-\lambda_2)^{n-c}(1-\theta)}.$$

Clearly, c and n-c are sufficient statistics for the sample information on heterogeneity. This sufficiency is what underlies Chamberlain's (1984) fixed-effect logit model that incorporates heterogeneity of this sort. It also underlies efforts by Mincer and Jovanovic (1981) and others to control for heterogeneity by including the number of previous jobs as a control variable in mobility models.

The relationship in equation 3.11 provides an additional prediction of the pure heterogeneity model: if prior mobility history in the form of c and

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[10] The relationship is not monotonic in the first year and the ninth year because of the small number of workers in the first year who have had more than two previous jobs and the relatively small total sample size in the ninth year. The plot for the tenth year is not contained in figure 3 because it is not very informative due to the very small number of observations. See table 4 for a detailed breakdown.

[11] Equation 3.6 is the special case of this relationship where there have been no previous changes in n periods (c=0).

n-c is appropriately controlled for, there will be no partial correlation of mobility with tenure. Only when prior mobility and experience are not controlled for appropriately will a negative negative relationship between current mobility and tenure be found.[12]

I now turn to an analysis of hazard rates that controls explicitly for prior mobility along with experience and observable characteristics. Table 7 contains estimates of a logit model of the monthly probability of job ending. In order to focus on the role of worker characteristics and prior mobility, separate logit models are estimated and presented for jobs by years since entry at the start of the job. The first column of table 8 contrains estimates of a logit model with all monthly observations on the first job workers hold. The second column of the table contains estimates of a logit model with all monthly observations on jobs (after the first job) that started in the first year in the labor market, the third column contains estimates of a logit model with all monthly observations on all jobs that started in the second year in the labor market, and so on. All models include measures of:

1) sex,
2) marital status (measured at the start of the job),
3) the interaction of sex and marital status,
4) race,
5) age at the start of the job,
6) education,
7) months of nonemployment immediately prior to the start of the job,

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[12]In the model worked out in section 3A, tenure and experience are indistinguishable so that there is no prior history.

8) prior mobility history measured by a set of variables for prior jobs started in each year (12 month interval) preceding the start of the current job,

9) tenure (measured by six monthly dummies for the first half year, one semi-annual dummy for the second half of the first year, and up to four annual variables for years two through five),

10) dummy variables for each calendar year, and

11) a dummy variable for residence in an urban area.

Table 7 contains the estimates of the parameters only on the first eight sets of variables (the demographic characteristics other than urban residence, months of nonemployment, and prior mobility history). The tenure effects (duration dependence in the hazard) are presented in table 15 and discussed in the next section.

The first column of table 7 contains the estimates of the turnover model for the first job workers hold after entry. Of course, there is no prior history in this job. Of the 3776 individuals in the sample, 633 hold only one job for the entire period they are observed. The hazard of the first job ending is significantly related to the set of demographic characteristics (p-value <1.e-5).[13] The major differences across groups are that women and nonwhites are less likely to leave their first job than men or whites. Because the probability of mobility in any month is small, the coefficient estimate in the logit model is approximately the average proportional marginal effect of the relevant variable on the probability of

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[13]This and later p-values related to restricted models are derived from likelihood ratio tests computed from estimates of the restricted model and the unrestricted estimates contained in table 7.

job change.[14] Thus, women have about a twenty percent lower probability than men of leaving their first job while nonwhites have about a ten percent lower probability than whites of leaving their first job. There seems to be no systematic relationship between mobility on the first job and age at start, marital status, or education.

The specification used in table 7 constrains the effect of the demographic variables to be the same throughout the job. It may be that particular demographic characteristics are more important early in a job than later or vice-versa. In order to examine this possibility, I reestimated the mobility function separately for the first six months on the job and for all months after the first six months.[15] These estimates are in the first columns of tables 8 and 9 respectively. It is of course true that all first jobs are represented in the hazard for the first six months in table 8 while only those first jobs that last more than six months are represented in the hazard for later months in table 9. To the extent that heterogeneity is important, the estimates in table 9 are based on a sample of workers who have demonstrated that they are less mobile while the estimates in table 8 are based on the full sample. The relationships I find between the hazard later in the job and the demographic variables will be driven in part by this selection mechanism.

The estimates for the first six months, contained in the first column

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[14]To be precise, the proportional effect is computed by multiplying the relevant parameter by one minus the average probability of job change. Since the probability of mobility in any month is small (<.1), this is well approximated by the coefficient itself.

[15]I also split the jobs at three months and twelve months. The substantive results on early-late contrasts are not affected by the precise split, and I use the six-month split as a convenient rule. Fully 38 percent of first jobs (1448 of 3776) end in the first six months.

of table 8, are somewhat different than those for later in the job, contained in the first column of table 9. Women have about a one-third lower monthly probability of mobility in the first six months of the first job, while there seems to be no significant difference by sex after the first six months for those jobs that survive. There is an approximately ten percent difference by race that seems to persist throughout the job. The least educated workers (<12 years education) have a fifteen percent lower probability of mobility early in their first job than do workers with exactly 12 years education. This does not persist after six months. On the other hand, while there is no significant difference in mobility early in jobs for college graduates relative to workers with 12 years education, college graduates on jobs that last more than six months have significantly lower mobility after six months.

The remaining columns in tables 7 through 9 contain estimates of the same basic specification of mobility functions for jobs starting in the first through sixth years after entry. The jobs starting in the first year exclude the first jobs held after entry. Each of the samples of jobs starting sometime after entry are subject to systematic selection in that a previous job has to end in order for a new job to start in one of these periods. Since the probability of job ending is correlated with observable characteristics of workers to the extent that heterogeneity is important, the results must be interpreted with this selection process in mind.

There are some interesting contrasts between the hazard on first jobs and hazards on jobs starting later. There is no significant male-female differential in mobility rates after the first job while the white-nonwhite differential persists for jobs starting through year two. More educated workers generally have less mobility from jobs after the first job than do less educated workers. The contrasts between these estimates and the estimates for the first job may be partly driven by the facts that there is sample selection in who starts a job in a given year and that there are controls for prior mobility. Reestimation of the model without the prior mobility variables (not presented here) yields results roughly similar to those in the tables.

The stratification of the sample by year-of-start is very useful in controlling appropriately for the relationship between current mobility and prior mobility. In the remainder of this section, I investigate the extent to which current mobility is related both to prior mobility and to worker demographics. I leave for the next section an examination of the shape of the hazard (how the probability of a job ending is related to tenure) when prior mobility is controlled for.

Two sets of measures in the mobility functions (for jobs other than the first) are meant to control for prior history. First I include a measure of the length of any spell of nonemployment immediately prior to the start of the job.[16] This is rounded to the nearest month. By this measure, there is no nonemployment spell prior to 58 percent of the jobs (not counting first jobs), and there is a one month gap prior to 14 percent of the jobs. Only seven percent of jobs are preceded by a gap of more than six months. Second, I include as measures of the prior mobility history a set of variables for the number of prior jobs started in each year (12 month interval or fraction thereof) preceding the start of the current job. For jobs starting in the first year, there is only one such variable; for jobs starting in the second year, there are two such variables; and so on. Table 10 contains the frequency distributions of the set of prior mobility variables.

The estimates in table 7 show that mobility is positively related to

[16] I also investigated models that used the accumulated time not employed since entry. Nothing interesting was revealed using this variable.

the employment gap only on jobs starting five or six years after entry. One month of nonemployment is related to an increase in subsequent mobility of about five percent.

Prior mobility is found to be a very important indicator of mobility from the current job. For example, in the jobs that start in the first year, each prior job is related to a ten percent increase in the subsequent probability of mobility. In later years, mobility in the year immediately prior to the start of the job is related to an even larger increase in mobility from the subsequent job. This is on the order of twenty percent.

Given an average monthly mobility rate of about five percent in the first year on a job, one job change in the immediately preceding year raises the mobility rate to six percent. This has a substantial effect on the survival probability. As a crude approximation, if the monthly mobility rate is five percent, the one-year survival probability is 0.54. Contrast this with a six percent monthly mobility rate where the one-year survival probability is 0.48.

An important question to ask is if the timing of earlier job changes matters holding the total number of earlier job changes fixed. If workers change over time (perhaps maturing) one would expect that the more recent mobility history is more important than the part of the history that is further removed from the current job. The simple model of "fixed" heterogeneity outlined above implies that the coefficients on lagged mobility in each year will all be equal.

The estimates in table 7 provide mixed evidence on this point. The jobs starting in years two through six all have multiple years of prior history, and I test the hypothesis that within each column (the set of jobs starting at a particular year of experience) the coefficients on lagged mobility are equal. Inspection of the estimates in table 7 shows 1) that prior mobility is a very important determinant of current mobility and 2) that in every category the largest coefficient is on prior mobility in the most recent year. This suggests that more recent history is the most important, and this is supported by formal statistical tests.

The first panel in Table 11 contains the maximized log-likelihood values for three specifications of prior mobility in the logit model of monthly mobility. Model #1 is the unconstrained model, presented in table 7, where the number of job changes in each year prior to the start of the current job is entered separately. Model #2 constrains the prior mobility to enter through a single variable measuring the total number of jobs held prior to the start of the current job. Model #3 is an intermediate specification where prior mobility is measured by two variables: 1) the total number of previous jobs and 2) the number of job changes in the year immediately prior to the start of the current job. This model allows job changes in the most recent year prior to the job to have a differential relationship with mobility than job changes in earlier years, but it constrains the relationship to be the same for all earlier years.

The first panel of table 11 also contains results of likelihood-ratio tests of models #2 and #3 versus the unconstrained model #1. The fully constrained model #3 can be rejected only for jobs starting in year 3. In all other years, there is not a significant difference in the relationship of prior mobility with the probability of current mobility by when the prior mobility occurred. The intermediate model #3 is never rejected against the unconstrained model.

The second panel of table 11 contains estimates and the results of statistical tests of constrained model #3 against the intermediate model #2. These results show two things. First, mobility on the current job is strongly and significantly related to mobility in earlier years. Second, there is a marginally statistically significant difference in the relationships for mobility in the most recent prior year and for mobility in earlier years. Recent mobility seems to have a marginally stronger positive relationship with current mobility than earlier mobility.

It is interesting to know whether prior mobility has the same relationship with current mobility throughout the job. For example, it may be that a history of much prior mobility implies a higher probability of job change early in jobs but no difference later. In order to investigate this, I once again split the employment spells at six months, separately analyzing mobility in the first six months and mobility after six months (on jobs that last that long). Tables 12 and 13 contain the results of statistical tests for the subsamples analogous to the tests in table 11.

The results in table 12 suggest that the relationship between mobility early in a job and prior mobility does depend significantly on the timing of earlier mobility. Constrained model #2 can be rejected against the unconstrained model #1 except for jobs starting in year 6. However, intermediate model #3 cannot be rejected against the unconstrained model #1. Taken together, the results suggest that mobility in the year immediately prior to the start of a job bears a special relationship with mobility early in the job. The analysis in the bottom panel of table 12 tests this directly, and it indicates that mobility in the year immediately prior to the start of the job has a significantly larger effect on mobility than does mobility earlier in workers' careers.

Table 13 contains the same analysis of mobility for later in the job (after the sixth month). The results here are very different from what was found early in the job. The constrained model #2 can be rejected against the unconstrained model #1 only for jobs starting in year 2, and the intermediate model #3 cannot be rejected against the unconstrained model #1 in for any set of jobs. The analysis in the bottom panel of table 13 shows that mobility later in a job has a significant relationship with prior mobility but that there is no special relationship with mobility in the first year prior to the start of the job. Three of the five estimated coefficients on mobility in the most recent year are actually negative.[17]

Overall, the analysis of the relationship of current mobility with prior mobility in tables 11 through 13 provides a clear message that workers who have changed jobs relatively frequently have a higher probability of mobility on their current job. An example serves to illustrate this. Consider a worker in the base group (white, male, not married, 12 years education, not living in an urban area, no prior spell of nonemployment) who is 23 years old. Suppose he starts a job in year 4 and but has not changed jobs in the last year. The six-month and one-year survival probabilities of this job depend on the number of prior jobs. Simple calculation using the estimates of the intermediate model #3 in tables 12 and 13 yields the survival probabilities contained in the top panel of table 14. These show the large effect that prior mobility has on the survival probabilities. Workers with no prior jobs have a one-year survival probability of 0.6 while those with six prior jobs have a one-year survival probability of only 0.4.

I noted from tables 12 and 13 that the relationship of mobility with prior mobility is not uniform throughout the job. The mobility history in the year immediately prior to the start of a job is relatively more important early in the current job than later (for jobs that survive the early stages). An extension of the example serves to illustrate this. Consider a worker in

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[17]Of course, the net effect of recent mobility is not estimated to be negative because the net effect is the sum of the coefficient on the total number of prior jobs and the coefficient on the the number of jobs in the most recent year.

the base group who starts a job in year 4 and has had four prior jobs (the median number for this type of worker). The six-month and one-year survival probabilities of this job depends on the temporal distribution of the four prior jobs. The second panel in table 14 contains the calculations of these survival probabilities using the estimates of the intermediate model #3 in tables 12 and 13. These show the large effect that the distribution of prior jobs has on the probability that a job lasts the first six months or the first full year. If the four jobs were all in the last year, the job has a probability of less than 30 percent of lasting the first full year while if all prior jobs were earlier in the worker's career, the job has a probability of almost 50 percent of lasting the first full year. All of this difference is due to differences in the probability of the job lasting the first six months.

D. *Overview of the Role of Heterogeneity*

I presented clear evidence that heterogeneity alone cannot account for the mobility patterns seen the data. First, mobility declines with labor market experience while a pure heterogeneity model suggests that they would be uncorrelated. Additionally, mobility does not decline monotonically with tenure. The hazard rises to a peak at three months after which it declines. However, I did find that heterogeneity plays a strong role in mobility. Mobility is significantly related to certain observable characteristics of workers including, most prominently, sex and race. Females and nonwhites have held fewer jobs since entry at any point in the first six years in the labor force.

The most important evidence for the role of heterogeneity in turnover rates is that mobility on the current job is strongly related to prior mobility. Workers who have changed jobs frequently in the past are more likely to change jobs in the future. However, this heterogeneity does not seem to be fixed over the long periods. While it is true that even mobility several years prior to the start of a job is related to turnover probabilities, the relationship is strongest for mobility that occurs in the year prior to the start of a job. Workers who have been relatively mobile in the recent past have higher turnover rates early in a new job than do workers with the same amount of total mobility who moved in the more distant past.

This last finding suggests a model where a worker's type evolve slowly over time, either as a random walk or as systematic change.[18] In this sort of model, the most recent mobility history would be more closely related to current mobility than to the more distant history. However, it is not really possible to determine whether pattern I found reflects changes over time in workers' underlying propensities to move or in the types of jobs they hold. Of course, these are not independent, and it is unfortunate that the NLSY does not have the information on industry and occupation in very short jobs that would be an important part of the investigation of the role of types of jobs. Nonetheless, the results can rule out a model where the only form of heterogeneity comes from fixed worker types because that would suggest that all parts of the mobility history was equally informative about current mobility.

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[18]For example, Osterman (1980) presents an analysis of the youth labor market with a focus on the maturation of workers as they get older.

Section 4: How Mobility Varies with Tenure: The Shape of the Hazard

In the previous section I examined the evidence on inter-firm mobility with regard to the predictions of a pure heterogeneity model of turnover, and I concluded that while heterogeneity in mobility is important, there are clearly other factors that determine mobility. One factor that is likely to be important in determining mobility is the accumulation of firm-specific capital of various types, and the central evidence on this comes from investigation of the variation in mobility rates with tenure.

A. *Some Further Empirical Results*

Figure 4 contains separate plots of the empirical monthly hazard function for the first 48 months on jobs starting in each of the first five years since entry. This is a disaggregation of the overall empirical hazard in figure 2, and it shows the same basic pattern as figure 2. For each subset of jobs, the hazard first rises to a peak at about three months then declines steadily. Table 15 contains the estimates of the set of tenure dummy variables for the logit mobility model whose coefficients on worker characteristics and heterogeneity are presented in table 7. The base level of tenure is more than five years, and the coefficients can be interpreted as the approximate proportional difference in mobility rates between the indicated tenure group and otherwise equivalent workers with more than five years tenure. These are estimates of the shape of the hazard after controlling for heterogeneity using observable worker characteristics and prior mobility.

The results in table 15 reinforce the general impression from the raw empirical hazards in figure 4. Even after controlling for heterogeneity through worker characteristics and and prior mobility, the hazard first rises to a peak at about three months and subsequently declines. The proportional difference between the hazard at the peak and the hazard in the first month is computed approximately as the difference in the relevant coefficients. On the first job this difference is 0.71 suggesting that jobs are over 2/3 again as likely to end in month three than in month 1. For the subsets of jobs starting in years 1, 2, and 3, the differences are 0.41, 0.46, and 0.65 respectively. For jobs starting in later years, the difference is less precisely estimated but of the same general magnitude.

Table 16 presents the results on the shape of the hazard for the model of mobility estimated using only the first six months on the job.[19] The base tenure group here has six months of tenure, and the coefficients can be interpreted as the approximate proportional difference in mobility rates between the indicated tenure group and otherwise equivalent workers with six months tenure. Recall that I found that the relationship of current mobility with prior mobility was different early in the job relative to late in the job, and it is possible that constraining the effect to be the same could yield misleading estimates of the shape of the hazard. However, the estimates in table 16 yield approximately the same results as the estimates in table 15. The hazard peaks at about three months before declining. The proportional differences between the hazard at the peak and the hazard in the first month are very close to what was computed from table 15: 0.72 for first jobs, 0.46 for other jobs starting in the first year, 0.41 for jobs starting in the second year, and 0.67 for jobs starting in the third year.

For completeness, table 17 contains estimates of the shape of the hazard for the logit model of mobility estimated using only observations

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[19]The coefficients on worker characteristics and heterogeneity for this model are contained in table 8.

after the first six months on the job.[20] The base tenure level is more than five years. Of course, this does not yield estimates of the shape of the hazard early in the job, but it does verify that the hazard is declining after the first six months.

The task of a theoretical framework will be to account not only for the general decline of the hazard but also for the peak early in the hazard.

B. *A Pure Specific Capital Model*

The defining characteristic of specific capital is that it is the result of an investment that makes a particular match more valuable and that is not useful in any other match. Turnover of the sort analyzed here simply destroys the value of this capital. Efficiency implies that the gains from the match will be shared in such a way as to reduce the probability of turnover. Since the gains from the match increase with the length of the match as more is invested in specific capital, it is expected that turnover will decrease with tenure due to the accumulation of specific capital. Models developed by Becker (1962) and Oi (1962) are among the early efforts to incorporate specific capital into our understanding of wages and turnover.[21] Mortensen (1978) and Jovanovic (1979b) present a theoretical analysis of specific capital accumulation and turnover where optimal investment, search, and turnover behavior are derived. Parsons (1986)

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[20]The coefficients on worker characteristics and heterogeneity for this model are presented in table 9.

[21]Work by Mincer and Jovanovic (1981) argues that apportioning earnings growth into components correlated with general labor-market experience and with employer-specific tenure can provide evidence on the relative importance of general versus specific human capital. Topel (1991) and Lang (1988) argue persuasively that one has to be extremely careful about apportioning earnings growth into components due to experience and tenure due to the fact that turnover is endogenous.

presents a recent survey of the literature on specific capital and turnover.

Consider the following <u>very</u> simple statistical model of the relationships between the probability of job change and labor-market experience and firm-specific tenure in the presence of investment in firm-specific human capital. All workers and jobs are assumed to be identical, and workers have an *ex ante* turnover probability of P_1 that perhaps comes from firm-specific demand shocks. Firms and workers invest in specific capital at some optimal rate, and the rate of compensation is adjusted so that the probability of turnover the next period for a worker who does not change jobs is reduced to some value $P_{1 \cdot 0} < P_1$. The $1 \cdot 0$ notation refers to this period's probability of turnover (event 1) conditional on last period's event (stay with employer, event 0). Similarly, the probability of turnover after two periods for a worker who does not change jobs is reduced by further investment in specific capital to some value $P_{1 \cdot 00} < P_{1 \cdot 0} < P_1$. If the worker does change jobs after the first period, he starts from fresh with a new employer, and investment in specific capital starts again. Thus, the probability of turnover is unchanged at $P_{1 \cdot 1} = P_1$. Repeated turnover does not change the probability of turnover so that $P_{1 \cdot 11} = P_{1 \cdot 1} = P_1$. Only the length of the most recent job affects the turnover probability. Thus, the relative turnover probabilities for the complete set of two year employment histories are:

(4.1) $$P_{1 \cdot 1} = P_{1 \cdot 10} = P_{1 \cdot 11} = P_1 > P_{1 \cdot 0} = P_{1 \cdot 01} > P_{1 \cdot 00}.$$

Clearly, a pure specific human capital model without any heterogeneity implies that mobility will decline monotonically with tenure.[22]

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[22]Mobility will also decline with labor-market experience simply due to the fact that workers cannot accumulate tenure without accumulating experience. However, once tenure is controlled for, the probability of turnover will not be correlated with labor-market experience.

The heterogeneity in mobility rates that I found is likely to have important effects on the accumulation of specific capital. If firms can observe who the stable (type 2) workers are then they will invest more in these workers, and any heterogeneity in the likelihood that a worker will remain with the firm will be reinforced through variation in investment in specific capital (Jovanovic, 1979b). Even if firms cannot observe who the type 2 workers are but they learn this over time, there will be more investment in specific capital for workers who are revealed to be more likely to be type 2. Thus, the turnover probability of stable workers will be further reduced in a way that is correlated with tenure, and mobility will be negatively related to tenure even after controlling for previous mobility.

This specific capital model implies that mobility rates decline monotonically with tenure, and it does not support the initial increase in the hazard found in the empirical analysis. I now examine whether heterogeneity in job and/or match quality can account for this finding.

C. *Ex Ante Observable Job and Match Heterogeneity*

Suppose now that all workers are identical but that jobs and/or matches are heterogeneous and that there is no specific human capital of the usual sort. Jobs may be heterogeneous in the sense that there are jobs which have lower turnover rates than others, perhaps because some firms pay higher wages than others precisely to reduce turnover. This is implied by some efficiency wage theories (Katz, 1986). Matches may be heterogeneous in the sense that some worker-firm matches may be more productive than others. Efficiency implies that the gains from such matches will be shared (at least in part in the form of higher wages) in a way that lowers turnover rates.

Consider a very simple model with two types of jobs or matches. The notation here is very similar to the case of individual heterogeneity with two types of workers, but the empirical implications are quite different. The match types are differentiated by their exogenous turnover probabilities, λ_1 and λ_2. Type 1 matches are relatively less stable so that $\lambda_1 > \lambda_2$, and these turnover probabilities are fixed over time for each match. I will make a pair of assumptions for the present in order to simplify the analysis. First, it is assumed that the type of match is known by both the worker and the firm from the start (match quality is an inspection good). Second, it is assumed that the probability that a worker draws a type 1 match is fixed at θ and that this probability does not change over time as workers are sorted into good matches.

In this model, the probability that a worker changes jobs in the first period is

(4.2) $$P_1 = \theta\lambda_1 + (1-\theta)\lambda_2$$

because the fraction θ of the sample is in type 1 matches and the fraction $1-\theta$ of the sample is in type 2 matches. The workers who change jobs in the first period draw new matches of types 1 and 2, again with probability θ and $1-\theta$ respectively. Since the $1-\theta$ workers who were in good matches the first period only change jobs with probability λ_2, the fraction of workers who are in bad matches in the second period is

(4.3) $$\theta_2 = (1-\lambda_1)\theta + \lambda_1\theta^2 + \lambda_2(1-\theta)\theta.$$

The first term represents the fraction of workers in bad first period matches who do not change jobs. The second term represents the fraction of workers in bad first period matches who change jobs and wind up in a bad match again. The final term represents the fraction of workers in good first-period matches who change jobs and wind up in a bad match. Equation 10 can be rewritten as

(4.4) $$\theta_2 = \theta[1 - (1-\theta)(\lambda_1-\lambda_2)] < \theta.$$

Thus, the turnover rate in the second period, which is

(4.5) $$P_2 = \theta_2\lambda_1 + (1-\theta_2)\lambda_2,$$

is lower than the initial turnover rate, and the first empirical implication is that turnover rates fall with experience as the sample is progressively sorted into better matches.[23]

What I have outlined here is a simple Markov transition process between type 1 and type 2 jobs. This process does not govern the probability of job change, only the probability of change of job *type*. It is straightforward to derive the steady state fraction of bad matches, $(\lambda_2\theta/[\lambda_2\theta+\lambda_1(1-\theta)])$, and the steady state turnover rate, $(\lambda_1\lambda_2/[\lambda_2\theta+\lambda_1(1-\theta)])$. It is also straightforward to show that average match quality is improving over time and that turnover rates are falling.

What of the relationship between mobility rates and tenure? A worker observed to have a large amount of tenure is more likely to be in a type 2 match. Thus, mobility rates will fall with tenure. The general formula for the turnover probability of a worker with T years of tenure is

(4.6) $$\Pr(\text{Change} \mid \text{tenure} = T) = \frac{\lambda_1(1-\lambda_1)^T\theta + \lambda_2(1-\lambda_2)^T(1-\theta)}{(1-\lambda_1)^T\theta + (1-\lambda_2)^T(1-\theta)}.$$

Thus, pure match quality considerations suggest that mobility rates depend only on tenure and not on experience or turnover prior to the current job. Tenure is a sufficient statistic for the probability of job change. This is in marked contrast to the pure heterogeneity model where past mobility history (number of job changes and number of years of experience) is a sufficient statistic for the probability of job change.

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[23]Note that the progressive sorting of the sample over time into better jobs and/or matches is what underlies the decline in mobility with experience in the search model developed by Burdett (1978). This has also been emphasized by Topel (1986) and Topel and Ward (1988).

The introduction of endogenous investment in specific capital again reinforces these results. More will be invested in specific capital where match quality is known to be high. The decline in turnover rates with tenure will be reinforced by investment in specific capital, and current tenure is remains a sufficient statistic for the likelihood of mobility.

The implications of this simple match quality model are identical to those of a pure specific capital model. In fact, Mincer and Jovanovic (1981) consider match quality to be a form of specific capital. This is consistent with the view that anything having value within the firm but not having value (or having less value) outside is specific capital.[24] But it also implies that the *ex ante* observable match job/match heterogeneity model cannot support the positive relationship between tenure and mobility early in jobs.

C. *Ex Ante Unobservable Job and Match Heterogeneity*

A richer version of the match quality model does yield different implications from the standard specific human capital model and can imply an initial increase in the hazard with tenure followed by a decline. This model starts with the assumption that the type of match is not known *ex ante* by either the worker or the firm but that the firm and the worker get noisy signals over time about the quality of the match (perhaps by observing output). Thus, match quality is an experience good. Maintain the assumption that the probability that a worker draws a type 1 match is fixed at θ and that this probability does not change over time as workers are sorted into good matches. Further assume that it is costly to change jobs and that

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[24]Flinn (1986) develops a model of turnover based on match heterogeneity. He draws out the implications for wage dynamics, and estimates a wage determination model in order to test this model. He finds that the wage dynamics are quite consistent with his matching model, but he does not estimate a model of turnover.

workers are infinitely lived.[25] This is essentially the model worked out by Jovanovic (1979a) who assumes that workers are paid their expected output each period. Output, which is assumed to be a noisy signal of match quality, is observed every period, and the worker and firm use this information to update their beliefs about the quality of the match.

Jovanovic (1979a) derives a reservation match quality such that workers will decide to sample a new match if the posterior distribution on the current match has mean less than the reservation match quality. The reservation match quality is inversely related to the variance of the posterior distribution because there is option value for workers in sampling further from a job with large up-side potential. Jovanovic uses a normal learning model (DeGroot, 1970) which has the reasonable property that the variance of the posterior distribution falls with the arrival of new information. Since a new signal arrives each period on the job, this suggests that the reservation match quality increases with tenure.

Since job change is costly and the variance is high early in jobs, workers will be relatively unlikely to change jobs early because there is still much option value. Even a job about which the first piece of information is negative may be worth keeping in order to get more information on match quality. Note that having a positive cost to job change early in jobs is required for this result. If job change was costless, as soon as the posterior mean fell below the initial prior expected value the worker would change jobs because jobs are freely available at the initial prior value. Using this framework, Jovanovic (1979a) concludes that the hazard of a job ending will first be quite low as workers and firms learn about the match

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[25] The latter assumption is surely no problem in the sample of young workers in the NLSY.

quality and then will fall as matches revealed to be bad end and the continuing matches are disproportionately of high quality.

Thus, a matching model where match quality is an experience good and job change is costly will generate a hazard that initially increases with tenure and then declines, as I find in the data here. It is difficult to find another class of model that has the single-peaked hazard predicted by this version of the matching model.

D. *An Indirect Test of Matching vs. "Standard" Specific Capital*

A less direct test of matching models (of either type) can be derived from the recognition that specific capital that derives from the quality of the match is a different sort of specific capital than, say, knowledge of a production process that is derived over a relatively long period of time. The test requires some *a priori* assumptions regarding the relative rates of of accumulation of match capital and other specific capital. Two assumptions that seem reasonable are that 1) most learning about match quality occurs soon after the start of a job (very likely within one year) and 2) specific capital in the form of task specific knowledge is accumulated more gradually over a longer period of time. To the extent that these restrictions are accepted it becomes possible to distinguish between these two variations of the "general" specific-capital model.

While it is true that these restrictions are arbitrary, I find the opposite set of assumptions, that learning about match quality occurs slowly over time and that most investment in specific capital occurs relatively quickly, to be less plausible. This is because learning that a match is high quality is likely to cause more investment in specific capital. Firms and workers will be unwilling to invest very much until they have some information that a match is a good one. This is not to deny either that there are important specific investments made at the time of hiring (e.g., basic training and orientation) or that learning about match quality can occur later in the job (e.g., learning about unsuitability for a higher position). However, with these caveats, it seems reasonable to interpret the evidence in the context of a model where learning about match quality occurs early while investment in specific capital occurs on a more continuous basis.

The tremendous amount of turnover found early in a job may be due to individual heterogeneity or it may be due to match heterogeneity. Controlling for heterogeneity using prior mobility, the estimates in tables 15 and 16 show very high turnover rates in the first year on jobs. The turnover rates decline relatively slowly after the first year on the job (tables 15 and 17). This is the expected pattern where learning about match quality is important.

Section 5: Concluding Remarks

The analysis of inter-firm worker mobility here shows the importance of both heterogeneity and state dependence. The most basic finding with regard to heterogeneity is that the probability of exit from the current job is strongly related to the frequency of job change prior to the start of the job. This relationship is quite strong, and it persists throughout the current job. Workers with a history of frequent job change are more likely to leave their current job within the first six months, but even if they survive the first six months, they are also more likely to leave at some later point.

A more subtle but equally important finding is that, while all previous job change is related to the probability of exit from the current job, job change in the most recent year prior to the start of the job bears a significantly stronger relationship with mobility on the current job. In particular, the hazard of the current job ending in the first six months is higher where there has been mobility in the year immediately prior to the start of the current job. This suggests that while workers vary substantially in their underlying mobility, these differences in mobility are not fixed over time. Important work remains to be done in examining the *movements* individual workers' propensities to move.

The most striking difference in turnover rates by observable characteristics is between males and females. Females hold significantly fewer jobs than do males in a fixed period of time early in their careers. Thus, females who have committed to the labor force exhibit less mobility than otherwise equivalent males. This result seems to be driven by a lower exit rate for females early in the first job after entry, and it runs contrary to results using earlier data from the National Longitudinal Surveys of Young Men and Young Women which show higher turnover rates for women (Blau and Kahn, 1981). Recent work by Topel and Ward (1988) and Loprest (1991) which examines links between wage growth and job change for young workers suggests important directions for further work using more detailed job characteristics.

With regard to state dependence, the key finding is that the monthly hazard of job ending is not monotonically decreasing in tenure as most earlier work using annual data has found. The hazard increases to a maximum at three months and declines thereafter. The finding of an initially increasing hazard followed by a monotonic decline is new evidence consistent with a model of heterogeneous match quality that cannot be observed *ex ante*. More work, using data on both wage dynamics and mobility, remains to be done in evaluating the importance of the role played by matching and in determining where (which jobs and sectors) matching most important.

To the extent that learning about match quality is an important cause of turnover early in jobs, policies designed to give workers and firms realistic previews of how good a match is likely to be have the potential to reduce mobility. For example, recent theoretical work by Montgomery (1988) and empirical work by Staiger (1990) using the NLSY focuses on the role of referrals as a means of finding a job in this context.[26] While the theoretical results suggest that there should be less mobility from jobs found through personal contacts (where there is likely to be better information about match quality), Staiger's empirical results do not support this view.

A more general (and not new) finding is that half of all jobs end in the first year. This mandates a focus on the first year on the job in order

[26]Earlier work by Rees and Schultz (1970) and Granovetter (1974) also addresses the role of referrals and information about match quality.

to understand labor mobility, and it highlights the importance of using data at a greater frequency than one year. Indeed, if I used data on job durations at a lower frequency, the hazard would appear to be monotonically declining throughout. However, it also highlights a potential measurement problem in the NLSY: If very short jobs are under-reported, the measured low hazard early in jobs could simply be a statistical artifact of this under-reporting.

There are three comments on the design of the NLSY that would improve its usefulness for the purposes of the analysis of worker mobility. First, a special effort should be made to be sure that that the respondents report *all* jobs, regardless of their duration. Second, complete job information should be collected and reported on jobs of all durations. In the current survey, detailed information is collected only about jobs which last at least eight weeks. Since over twenty percent of jobs are over by the eighth week, important information is missed about a substantial fraction of jobs. This precluded me from investigating industrial and occupational differences in mobility. Finally, wage data at more regular points would be very useful in the analysis of mobility. While the most recent waves of the NLSY have information on starting and ending wages on jobs along with wages at interview dates, data at monthly intervals in the first year would also be very useful.

In conclusion, the analysis in this study provides important new information on mobility patterns that are consistent with 1) important though variable worker differences in underlying mobility rates and with *ex ante* unobservable match quality that workers and firms learn about over a relatively short period during the first six months to one year on the job.

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Table 1

Disposition of Sample

Initial Sample:	12686 Individuals
Deletions:	
Military subsample	1280
Primarily working in first year	2601
Without 3 years primarily working	4114
Missing data on key variables	468
Never held full-time job	2
Always self-employed or unpaid	22
Had full-time job before age 16	2
First qualified job before 1979 or after 1985	421
Total Deletions:	8910 Individuals
Final Sample:	3776 Individuals

Note: See Section 2 of text for details.

Table 2

Summary Statistics for Jobs
NLSY
(Means and Standard Deviations)

At Time of Start of Job

by Years Since Entry at Start of Job, for First Job, and for All Jobs

Year of Start (since entry)	N	age	Education	female	non-white	censor	duration in months (not censored)	censoring time in months (censored)	Number of Prev Jobs
First Job	3776	20.6 (2.34)	12.7 (2.17)	.503	.407	.159	17.5 (19.9)	69.5 (23.0)	---
1	2039	21.0 (2.28)	12.6 (2.12)	.424	.408	.123	14.4 (17.0)	59.4 (23.8)	1.30 (.586)
2	2224	21.8 (2.31)	12.8 (2.17)	.441	.391	.164	14.1 (15.2)	50.6 (22.6)	2.04 (1.14)
3	1641	22.7 (2.32)	12.8 (2.18)	.449	.389	.204	12.7 (13.3)	34.6 (21.9)	2.92 (1.62)
4	1412	23.5 (2.26)	12.7 (2.08)	.448	.382	.270	10.4 (10.6)	25.2 (20.0)	3.70 (2.19)
5	1112	24.2 (2.13)	12.7 (2.12)	.418	.401	.296	9.37 (9.48)	20.1 (16.6)	4.12 (2.38)
6	845	25.0 (2.00)	12.6 (2.14)	.406	.388	.369	9.60 (9.07)	17.6 (14.7)	4.81 (2.91)
>=7	1111	26.2 (1.98)	12.7 (2.19)	.410	.386	.493	7.53 (6.90)	11.9 (9.46)	5.66 (3.47)
All Jobs	14160	22.3 (2.87)	12.7 (2.15)	.450	.397	.220	13.7 (15.9)	36.8 (28.9)	2.27 (2.50)

Notes: The numbers in parentheses are standard deviations. The Female, Nonwhite, and Censored variables are dummy variables. The sample consists of jobs started after transition to primarily working that were ever full time (>30 hours per week). The sample in year 1 row consists of jobs other than the first job started within one year of labor market entry. See Section 2 of text for details of sample selection criteria.

Table 3

Monthly Probability of Job Change by Experience and by Tenure

Experience	Monthly Mobility Rate	Number of Job-Months	Tenure	Monthly Mobility Rate	Number of Job-Months
Year 1	.0639	43720	Month 1	.0615	14160
Year 2	.0416	46405	Month 2	.0883	13198
Year 3	.0389	45891	Month 3	.0967	11937
Year 4	.0393	40592	Month 4	.0823	10690
Year 5	.0368	32569	Month 5	.0636	9746
Year 6	.0348	24131	Month 6	.0606	9064
Year 7	.0300	16907	Quarter 3	.0456	23991
Year 8	.0251	10422	Quarter 4	.0369	20632
Year 9	.0235	4856	Year 2	.0329	59417
year 10	.0167	956	Year 3	.0250	37307
			Year 4	.0219	23589
			Year 5	.0192	14661
			≥Year 6	.0145	18057
Total	.0414	266449		.0414	266449

Note: Based on the sample of 14160 jobs for 3776 individuals summarized in table 2 and described in the text.

Table 4

Frequency Distribution

Number of Previous Jobs by Years of Experience

Years Experience	Workers	Distribution of Number of Previous Jobs 0	1	2	3	4	5	>=6	Total
1	3776	.168	.667	.134	.0252	.0053	.0003	.0003	1.0
2	3751	.166	.372	.280	.125	.0413	.0101	.0064	1.0
3	3706	.165	.281	.252	.151	.0882	.0359	.0259	1.0
4	3578	.161	.243	.224	.155	.0984	.0598	.0590	1.0
5	3089	.146	.211	.210	.154	.110	.0715	.0978	1.0
6	2447	.137	.192	.188	.150	.116	.0793	.138	1.0
7	1804	.133	.171	.181	.142	.119	.0898	.164	1.0
8	1273	.123	.167	.170	.143	.113	.101	.185	1.0
9	796	.111	.157	.177	.138	.108	.0842	.225	1.0
10	339	.0796	.153	.171	.136	.118	.0649	.277	1.0
All	24559	.152	.311	.209	.127	.0800	.0480	.0723	1.0

Note: The sample consists of annual observations on the 3776 workers in the sample. There is one observation for each year since entry that each worker is observed in the sample.

Table 5

Average Number of Previous Jobs by Selected Worker Characteristics by Year of Experience

(standard deviation of mean in parentheses)

Years Experience	N	Average Number of Previous Jobs: Sex: Male	Female	Race: White	Nonwhite	Years of Education: <12	12	13-15	≥16
1	3776	1.10 (.016)	.970 (.015)	1.04 (.014)	1.02 (.018)	1.02 (.036)	1.06 (.017)	1.03 (.024)	.997 (.021)
2	3751	1.70 (.028)	1.42 (.025)	1.59 (.024)	1.52 (.030)	1.63 (.062)	1.61 (.029)	1.60 (.039)	1.48 (.036)
3	3706	2.16 (.038)	1.73 (.033)	1.99 (.033)	1.88 (.039)	2.10 (.088)	2.00 (.038)	1.91 (.052)	1.78 (.046)
4	3578	2.54 (.048)	1.99 (.040)	2.34 (.042)	2.15 (.047)	2.49 (.111)	2.34 (.047)	2.23 (.065)	2.02 (.056)
5	3089	2.93 (.059)	2.29 (.050)	2.68 (.052)	2.50 (.060)	2.84 (.138)	2.71 (.059)	2.58 (.083)	2.29 (.068)
6	2447	3.27 (.074)	2.56 (.065)	3.01 (.065)	2.79 (.077)	3.07 (.176)	3.05 (.075)	2.95 (.103)	2.54 (.085)
7	1804	3.55 (.096)	2.83 (.084)	3.29 (.083)	3.06 (.102)	3.37 (.224)	3.30 (.096)	3.24 (.134)	2.78 (.111)
8	1273	3.87 (.129)	2.97 (.102)	3.47 (.106)	3.37 (.136)	3.64 (.291)	3.50 (.123)	3.55 (.179)	2.96 (.141)
9	796	4.15 (.177)	3.18 (.135)	3.68 (.140)	3.60 (.185)	3.57 (.372)	3.74 (.165)	3.88 (.245)	3.14 (.291)
10	339	4.53 (.266)	3.44 (.216)	4.02 (.210)	3.93 (.308)	4.34 (.599)	3.94 (.249)	4.13 (.392)	3.65 (.287)
All	24559	2.49 (.021)	1.97 (.017)	2.29 (.018)	2.13 (.020)	2.370 (.046)	2.31 (.021)	2.22 (.029)	1.96 (.023)

Note: The sample consists of annual observations on the 3776 workers in the sample. There is one observation for each year since entry that each worker is observed in the sample.

Table 6
Ordered Probit Analysis of Number of Previous Jobs

Variable	Year of Experience 1	2	3	4	5	6	Pooled
Female	-.232	-.264	-.290	-.295	-.297	-.312	-.277
	(.0378)	(.0348)	(.0346)	(.0352)	(.0379)	(.0428)	(.0149)
Nonwhite	-.0469	-.0741	-.0870	-.105	-.0938)	-.111	-.0858
	(.0389)	(.0359)	(.0357)	(.0362)	(.0391)	(.0441)	(.0153)
Entry Age	.0287	.00986	-.00578	-.0150	-.0229	-.0316	-.00663
	(.0106)	(.00987)	(.00985)	(.0101)	(.0112)	(.0130)	(.00429)
Education							
<12 yrs	-.136	-.0727	-.0509	-.0712	-.100	-.194	-.111
	(.0595)	(.0550)	(.0548)	(.0557)	(.0597)	(.0676)	(.0235)
13-15 yrs	-.0441	-.0698	-.0271	-.0260	-.0253	.0148	-.0301
	(.0487)	(.0450)	(.0448)	(.0455)	(.0493)	(.0553)	(.0193)
>=16 yrs	-.124	-.0995	-.0831	-.0862	-.0728	-.0417	-.0772
	(.0562)	(.0519)	(.0517)	(.0524)	(.0578)	(.0678)	(.0224)
Entry Year							
1980	-.0469	-.109	-.111	-.0846	-.0939	-.159	-.105
	(.0646)	(.0594)	(.0591)	(.0599)	(.0618)	(.0645)	(.0248)
1981	-.151	-.196	-.165	-.117	-.105	-.166	-.150
	(.0658)	(.0602)	(.0597)	(.0606)	(.0629)	(.0652)	(.0251)
1982	-.186	-.192	-.106	-.0807	-.107	-.196	-.146
	(.0669)	(.0616)	(.0611)	(.0620)	(.0644)	(.0674)	(.0257)
1983	-.171	-.183	-.115	-.126	-.167	-.261	-.175
	(.0692)	(.0637)	(.0634)	(.0643)	(.0667)	(.0735)	(.0268)
1984	-.267	-.217	-.198	-.243	-.283	---	-.240
	(.0741)	(.0683)	(.0681)	(.0692)	(.0759)		(.0303)
1985	-.582	-.527	-.510	-.588	---	---	-.507
	(.101)	(.0945)	(.0942)	(.0985)			(.0456)
N	3776	3751	3706	3578	3089	2447	20347
Log L	-3599.2	-5544.7	-6293.7	-6451.3	-5763.3	-4628.3	-33463.3
χ^2 stat.	80.2	105.0	130.2	160.0	112.0	100.0	633.2
χ^2 D.F.	12	12	12	12	11	10	12

Note: The numbers in parentheses are asymptotic standard errors. The base group consists of white male workers with twelve years education who entered the labor market in 1979. Each model includes as parameters a set of six threshold values separating the seven ordered categories for number of previous jobs (0, 1, 2, 3, 4, 5, >=6). The pooled model includes a complete set of dummy variables for experience level. The χ^2 statistic is for a likelihood ratio test of the relevant model against a constrained model with only the six ordered-probit thresholds. The constrained specification for the pooled model additionally includes the set of dummy variables for experience level.

Table 7
Logit Analysis of Monthly Turnover Rates
Selected Coefficients on Prior Mobility and Worker Characteristics

Variable	First Job	Year of Experience at Start of Job 1	2	3	4	5	6
Constant	-3.79 (.223)	-3.42 (.332)	-3.89 (.330)	-3.84 (.446)	-4.13 (.518)	-3.86 (.580)	-3.58 (.727)
Female	-.202 (.0401)	-.0373 (.0562)	-.0189 (.0550)	-.0567 (.0695)	-.139 (.0813)	-.0169 (.0967)	-.0190 (.121)
Married (at start)	.0352 (.0858)	.121 (.0921)	-.0579 (.0838)	-.127 (.0900)	-.208 (.0978)	-.161 (.107)	.0348 (.125)
Female* Married	-.122 (.108)	-.326 (.133)	-.0079 (.119)	.142 (.130)	.251 (.145)	.110 (.161)	-.0653 (.192)
Nonwhite	-.101 (.0387)	-.0930 (.0524)	-.121 (.0515)	-.0130 (.0616)	-.0244 (.0707)	-.0232 (.0806)	-.0236 (.0988)
Age (at start)	-.00106 (.0114)	-.0228 (.0161)	-.0239 (.0149)	-.0346 (.0175)	-.00865 (.0197)	-.0113 (.0235)	-.0264 (.0285)
Education							
<12 yrs	-.0865 (.0513)	.0978 (.0673)	.262 (.0705)	.254 (.0844)	.131 (.0979)	.115 (.110)	-.0603 (.135)
13-15 yrs	-.0189 (.0489)	-.0766 (.0683)	-.0329 (.0642)	.0678 (.0764)	-.0504 (.0856)	-.118 (.0990)	-.129 (.123)
>=16 yrs	-.104 (.0649)	-.207 (.0881)	-.209 (.0780)	-.233 (.0967)	-.240 (.114)	-.195 (.138)	-.0799 (.167)
Nonemploy Spell prior	---	.00988 (.00987)	-.0184 (.00828)	-.0123 (.0165)	.00481 (.0141)	.0429 (.0129)	.0541 (.0130)
Prior Jobs 1 year prior	---	.106 (.0419)	.207 (.0273)	.249 (.0308)	.186 (.0327)	.152 (.0434)	.215 (.0573)
2 years prior	---	---	.137 (.0419)	.111 (.0317)	.101 (.0338)	.0975 (.0414)	.144 (.0543)
3 years prior	---	---	---	.0997 (.0495)	.0974 (.0361)	.0416 (.0413)	.0715 (.0493)
4 years prior	---	---	---	---	.184 (.0533)	.121 (.0434)	.109 (.0513)
5 years prior	---	---	---	---	---	.0640 (.0636)	.130 (.0487)
6 years prior	---	---	---	---	---	---	.0721 (.0746)

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Table 7
(continued)

Logit Analysis of Monthly Turnover Rates
Selected Coefficients on Prior Mobility and Worker Characteristics

	First Job	Year of Experience at Start of Job 1	2	3	4	5	6
Monthly Obs	97112	40629	44722	28085	20317	13963	10619
Jobs	3776	2039	2224	1641	1412	1112	845
Individuals	3776	1541	1612	1237	1057	861	681
Ending Rate	.0327	.0441	.0416	.0465	.0507	.0561	.0502
Log L	-13235.8	-6980.0	-7423.2	-5090.8	-3898.9	-2915.8	-2030.3
χ^2 stat.	1500.8	711.6	618.0	389.1	351.7	201.2	167.6
χ^2 D.F.	29	31	31	31	30	29	29

Note: The numbers in parentheses are asymptotic standard errors. All models also include up to eleven categorical variables for tenure (six monthly variables for the first half year, one semiannual variable for the second half of the first year, and up to four annual variables for the next four years), dummy variables for each calendar year, and a dummy variable for residence in an urban area. The base group consists of unmarried white male workers with twelve years education in 1979 and who live outside an urban area. The model for jobs that start in the first year excludes the first job held by each worker. The χ^2 statistic is for a likelihood ratio test of the relevant model against a constrained model with only a constant. The tenure coefficients are contained in table 15, and they are discussed in section 4.

Table 8
Logit Analysis of Monthly Turnover Rates
Selected Coefficients on Prior Mobility and Worker Characteristics
First Six Months on Job

Variable	First Job	Year of Experience at Start of Job 1	2	3	4	5	6
Constant	-2.34 (.355)	-1.96 (.476)	-1.84 (.479)	-1.91 (.584)	-1.63 (.661)	-2.19 (.775)	-2.36 (.994)
Female	-.359 (.0610)	-.0860 (.0829)	-.0920 (.0852)	-.0980 (.106)	-.0418 (.116)	-.0412 (.130)	-.0738 (.167)
Married (at start)	.119 (.121)	.132 (.129)	.153 (.126)	-.0908 (.134)	-.128 (.139)	-.216 (.148)	-.0428 (.176)
Female* Married	-.262 (.162)	-.290 (.195)	.0729 (.194)	-.0916 (.207)	.0565 (.208)	.00289 (.227)	-.222 (.284)
Nonwhite	-.116 (.0592)	-.00035 (.0760)	.0219 (.0794)	-.116 (.0949)	-.0325 (.101)	-.0300 (.111)	.0293 (.143)
Age (at start)	-.00224 (.0177)	-.0237 (.0232)	-.0404 (.0228)	-.0529 (.0265)	-.0523 (.0288)	-.0318 (.0323)	-.0392 (.0403)
Education							
<12 yrs	-.164 (.0789)	.137 (.0956)	.321 (.100)	.377 (.120)	.184 (.133)	.153 (.147)	-.186 (.193)
13-15 yrs	-.0135 (.0741)	.00479 (.0983)	-.119 (.102)	.134 (.115)	.0695 (.123)	-.174 (.137)	-.0933 (.174)
>=16 yrs	-.0655 (.0966)	-.233 (.133)	.262 (.127)	-.274 (.157)	-.172 (.169)	-.0873 (.192)	-.0955 (.242)
Nonemploy Spell prior	---	-.00011 (.0148)	-.0623 (.0154)	-.0475 (.0274)	.00215 (.0208)	.0524 (.0170)	.0634 (.0171)
Prior Jobs							
1 year prior	---	.103 (.0595)	.247 (.0383)	.269 (.0434)	.266 (.0450)	.251 (.0581)	.272 (.0761)
2 years prior	---	---	.0614 (.0615)	.0878 (.0461)	.0705 (.0464)	.0816 (.0570)	.0563 (.0743)
3 years prior	---	---	---	.168 (.0700)	.0559 (.0504)	-.0689 (.0584)	.162 (.0653)
4 years prior	---	---	---	---	.210 (.0719)	.0881 (.0571)	.0653 (.0687)
5 years prior	---	---	---	---	---	.174 (.0843)	.157 (.0657)
6 years prior	---	---	---	---	---	---	.0113 (.102)

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Table 8
(continued)

Logit Analysis of Monthly Turnover Rates
Selected Coefficients on Prior Mobility and Worker Characteristics
First Six Months on Job

	First Job	Year of Experience at Start of Job 1	2	3	4	5	6
Monthly Obs	18404	9729	11067	8306	6842	5262	4038
Jobs	3776	2039	2224	1641	1412	1112	845
Individuals	3776	1541	1612	1237	1057	861	681
Ending Rate	.0787	.0893	.0733	.0693	.0761	.0796	.0664
Log L	-4956.0	-2887.3	-2808.5	-2014.5	-1770.0	-1430.5	-943.3
χ^2 stat.	229.3	74.7	183.1	156.4	144.5	63.1	85.2
χ^2 D.F.	23	25	25	25	25	25	25

Note: The numbers in parentheses are asymptotic standard errors. All models also include five monthly dummy variables for tenure, dummy variables for each calendar year, and a dummy variable for residence in an urban area. The base group consists of unmarried white male workers with twelve years education in 1979 and who live outside an urban area. The model for jobs that start in the first year excludes the first job held by each worker. The χ^2 statistic is for a likelihood ratio test of the relevant model against a constrained model with only a constant. The tenure coefficients are contained in table 16, and they are discussed in section 4.

Table 9
Logit Analysis of Monthly Turnover Rates
Selected Coefficients on Prior Mobility and Worker Characteristics
After First Six Months on Job

Variable	First Job	Year of Experience at Start of Job 1	2	3	4	5	6
Constant	-4.288 (.379)	-2.34 (.641)	-4.29 (.649)	-4.22 (.536)	-5.89 (1.19)	-3.58 (.955)	-4.11 (1.21)
Female	-.0764 (.0536)	.00586 (.0767)	-.106 (.0727)	-.0272 (.0924)	-.215 (.115)	-.113 (.146)	.0127 (.178)
Married (at start)	-.0342 (.123)	.116 (.132)	.0195 (.113)	-.118 (.123)	-.250 (.139)	-.136 (.157)	.105 (.179)
Female* Married	-.0197 (.148)	-.358 (.183)	.0135 (.154)	.239 (.170)	.373 (.202)	.264 (.229)	.0508 (.268)
Nonwhite	-.0945 (.0514)	-.178 (.0726)	-.188 (.0684)	.0711 (.0814)	-.0707 (.0999)	-.0321 (.120)	-.0943 (.139)
Age (at start)	.00489 (.0150)	-.0185 (.0226)	-.0110 (.0199)	-.0131 (.0237)	-.0309 (.0275)	.00492 (.0350)	-.00969 (.0411)
Education <12 yrs	-.0105 (.0674)	.0667 (.0955)	.173 (.101)	.111 (.121)	.0652 (.147)	.0379 (.169)	.0974 (.191)
13-15 yrs	-.0449 (.0652)	-.151 (.0954)	-.0316 (.0832)	.0127 (.103)	-.0679 (.121)	-.0659 (.145)	-.187 (.177)
>=16 yrs	-.247 (.0886)	-.208 (.119)	-.184 (.0998)	-.239 (.124)	-.334 (.156)	-.293 (.202)	-.0649 (.233)
Nonemploy Spell prior	---	.0177 (.0133)	.00286 (.00988)	.0124 (.0209)	.00598 (.0192)	.0293 (.0200)	.0411 (.0203)
Prior Jobs 1 year prior	---	.104 (.0594)	.164 (.0395)	.214 (.0445)	.0843 (.0507)	.0309 (.0672)	.139 (.0882)
2 years prior	---	---	.205 (.0577)	.128 (.0441)	.130 (.0499)	.111 (.0616)	.255 (.0829)
3 years prior	---	---	---	.0224 (.0711)	.141 (.0523)	.164 (.0596)	-.0316 (.0778)
4 years prior	---	---	---	---	.145 (.0797)	.166 (.0684)	.153 (.0796)
5 years prior	---	---	---	---	---	-.0567 (.100)	.0955 (.0743)
6 years prior	---	---	---	---	---	---	.144 (.112)

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Table 9
(continued)

Logit Analysis of Monthly Turnover Rates
Selected Coefficients on Prior Mobility and Worker Characteristics
After First Six Months on Job

	First Job	Year of Experience at Start of Job 1	2	3	4	5	6
Monthly Obs	78708	30900	33655	19794	13475	8701	6581
Jobs	2328	1171	1413	1046	820	606	483
Individuals	2328	1143	1339	1007	780	591	462
Ending Rate	.0220	.0298	.0311	.0369	.0377	.0418	.0403
Log L	-8254.7	-4082.7	-4587.9	-3060.5	-2117.7	-1468.7	-1078.7
χ^2 stat.	106.0	119.9	158.8	131.7	98.3	85.9	64.2
χ^2 D.F.	23	25	25	25	24	23	23

Note: The numbers in parentheses are asymptotic standard errors. All models also include up to 5 dummy variables for tenure (one semiannual variable for the second half of the first year, and up to four annual variables for the next four years), dummy variables for each calendar year, and a dummy variable for residence in an urban area. The base group consists of unmarried white male workers with twelve years education in 1979 and who live outside an urban area. The model for jobs that start in the first year excludes the first job held by each worker. The χ^2 statistic is for a likelihood ratio test of the relevant model against a constrained model with only a constant. The tenure coefficients are contained in table 17, and they are discussed in section 4.

Table 10

Frequency Distribution

Number of Previous Jobs Started
in Each Year Prior to the Start of the Current Job
(row percentages)

Year Prior to Start of Job	Distribution of Number of Previous Jobs 0	1	2	3	4	5	6	7	Total
1	4367 (42.1)	4170 (40.2)	1375 (13.2)	349 (3.36)	96 (0.92)	20 (0.19)	6 (0.06)	1 (0.01)	10384 (100%)
2	2993 (35.9)	3808 (45.6)	1122 (13.4)	307 (3.68)	84 (1.01)	29 (0.35)	2 (0.02)	0 (0.0)	8345 (100%)
3	2251 (36.8)	2704 (44.2)	862 (13.4)	232 (3.79)	51 (0.83)	16 (0.26)	5 (0.08)	0 (0.0)	6121 (100%)
4	1551 (34.6)	2097 (46.8)	612 (13.7)	170 (3.79)	35 (0.78)	9 (0.20)	4 (0.09)	2 (0.04)	4480 (100%)
5	1003 (32.7)	1459 (47.6)	459 (15.0)	118 (3.85)	17 (0.55)	10 (0.32)	2 (0.06)	0 (0.0)	3068 (100%)
6	579 (29.6)	1029 (52.6)	244 (12.5)	79 (4.04)	17 (0.87)	7 (0.36)	1 (0.05)	0 (0.0)	1956 (100%)
All	12744 (37.1)	15267 (44.4)	4674 (13.6)	1255 (3.65)	300 (0.87)	91 (0.26)	20 (0.06)	3 (0.01)	34354 (100%)

Note: The sample consists of observations on prior mobility for the 10384 jobs after the first job for the 3776 workers in the sample.

Table 11
Analysis of Equality of Prior Mobility Effects
All Periods

Equality of Coefficients of Lagged Mobility Variables
Likelihood-Ratio Tests

Year of Experience	Model #1 Log L	Model #2 Log L	Model #3 Log L	LR test #2 v. #1 DF	LR test #2 v. #1 p-value	LR test #3 v. #1 DF	LR test #3 v. #1 p-value
2	-7423.2	-7424.1	-7423.2	1	.180	0	---
3	-5090.8	-5096.5	-5090.8	2	.0033	1	.888
4	-3898.9	-3901.5	-3900.0	3	.158	2	.333
5	-2915.8	-2917.5	-2916.7	4	.493	3	.615
6	-2030.3	-2032.2	-2031.0	5	.579	4	.791
All	-21359.0	-21371.8	-21351.7	15	.0424	10	.156

Model #1 - unconstrained specification in table 7
Model #2 - constrained with single prior mobility variable (total prior jobs)
Model #3 - constrained with two prior mobility variables (total prior jobs and number of job changes in most recent year)

Note: The "All" row is computed as the sum of the specific-year rows.

Difference in Coefficient of First Prior Year Mobility

Year of Experience	Coeff. of Total # Prior Jobs	Coeff. of # Jobs in 1 year prior	p-value (#3 v. #2)
2	.137 (.0419)	.0692 (.0522)	.185
3	.107 (.0251)	.142 (.0417)	.00068
4	.113 (.0209)	.0755 (.0431)	.0802
5	.0829 (.0186)	.0662 (.0514)	.198
6	.108 (.0192)	.106 (.0652)	.105

Note: The numbers in parentheses are asymptotic standard errors. The coefficient estimates are from a logit model with a specification identical to those used in table 7 with the exception that the set of prior history variables is replaced by two variables: 1) the total number of prior jobs and 2) the number of job changes in the most recent prior year. This is model #3 above. The p-value is for a test of the hypothesis that the coefficient of the number of jobs in the most recent year is zero (model #3 v. model #2).

Table 12
Analysis of Equality of Prior Mobility Effects
First Six Months

Equality of Coefficients of Lagged Mobility Variables
Likelihood-Ratio Tests

Year of Experience	Model #1 Log L	Model #2 Log L	Model #3 Log L	LR test #2 v. #1 DF	LR test #2 v. #1 p-value	LR test #3 v. #1 DF	LR test #3 v. #1 p-value
2	-2808.5	-2811.6	-2808.5	1	.0128	0	---
3	-2014.5	-2018.2	-2014.9	2	.0247	1	.371
4	-1770.0	-1776.2	-1771.6	3	.00613	2	.202
5	-1430.5	-1437.8	-1433.8	4	.00561	3	.0858
6	-943.3	-946.3	-944.6	5	.306	4	.627
All	-8966.8	-8990.1	-8973.4	15	.587	10	.156

Model #1 - unconstrained specification in table 8
Model #2 - constrained with single prior mobility variable (total prior jobs)
Model #3 - constrained with two prior mobility variables (total prior jobs and number of job changes in most recent year)

Note: The "All" row is computed as the sum of the specific-year rows.

Difference in Coefficient of First Prior Year Mobility

Year of Experience	Coeff. of Total # Prior Jobs	Coeff. of # Jobs in 1 year prior	p-value (#3 v. #2)
2	.0614 (.0615)	.186 (.0761)	.0148
3	.114 (.0358)	.153 (.0595)	.0101
4	.0892 (.0285)	.181 (.0599)	.00250
5	.0510 (.0254)	.196 (.0679)	.00388
6	.100 (.0250)	.162 (.0860)	.0594

Note: The numbers in parentheses are asymptotic standard errors. The coefficient estimates are from a logit model with a specification identical to those used in table 8 with the exception that the set of prior history variables is replaced by two variables: 1) the total number of prior jobs and 2) the number of job changes in the most recent prior year. This is model #3 above. The p-value is for a test of the hypothesis that the coefficient of the number of jobs in the most recent year is zero (model #3 v. model #2).

Table 13
Analysis of Equality of Prior Mobility Effects
After First Six Months

Equality of Coefficients of Lagged Mobility Variables
Likelihood-Ratio Tests

Year of Experience	Model #1 Log L	Model #2 Log L	Model #3 Log L	LR test #2 v. #1 DF	LR test #2 v. #1 p-value	LR test #3 v. #1 DF	LR test #3 v. #1 p-value
2	-4587.9	-4588.1	-4587.9	1	.527	0	---
3	-3060.5	-3063.3	-3061.2	2	.0608	1	.237
4	-2117.7	-2118.0	-2117.7	3	.896	2	.995
5	-1468.7	-1471.7	-1470.8	4	.199	3	.241
6	-1078.7	-1082.1	-1082.0	5	.236	4	.159
All	-12313.5	-12352.3	-12319.6	15	.196	10	.272

Model #1 - unconstrained specification in table 9
Model #2 - constrained with single prior mobility variable (total prior jobs)
Model #3 - constrained with two prior mobility variables (total prior jobs and number of job changes in most recent year)

Note: The "All" row is computed as the sum of the specific-year rows.

Difference in Coefficient of First Prior Year Mobility

Year of Experience	Coeff. of Total # Prior Jobs	Coeff of # Jobs in 1 year prior	p-value (#3 v. #2)
2	.205 (.0578)	-.0408 (.0727)	.575
3	.0956 (.0355)	.122 (.0594)	.0400
4	.137 (.0307)	-.0524 (.0645)	.416
5	.125 (.0279)	-.104 (.0805)	.1964
6	.119 (.0305)	.0320 (.100)	.748

Note: The numbers in parentheses are asymptotic standard errors. The coefficient estimates are from a logit model with a specification identical to those used in table 9 with the exception that the set of prior history variables is replaced by two variables: 1) the total number of prior jobs and 2) the number of job changes in the most recent prior year. This is model #3 above. The p-value is for a test of the hypothesis that the coefficient of the number of jobs in the most recent year is zero (model #3 v. model #2).

Table 14
Illustration of One Year Survival Probabilities

by Number of Prior Jobs

Jobs Since Entry	Prob Survive 6 months	Prob Survive 2nd 6 months (conditional)	Prob Survive one year
0	.675	.896	.603
1	.652	.878	.573
2	.627	.861	.540
3	.602	.843	.507
4	.575	.823	.473
5	.548	.800	.438
6	.519	.775	.402

Note: These probabilities were calculated using monthly mobility rates predicted by the estimates of intermediate model #3 summarized in tables 12 and 13. The probabilities refer to a base group worker (white, male, not married, 12 years education, not living in an urban area, no prior spell of nonemployment) who is 23 years old and who starts a job in year 4. None of the prior jobs are in the most recent year. The six-month survival probability is computed as the product of one minus the hazard at each of the first six months. The conditional probability of survival for the second six months is computed as the product for the second six months of one minus the monthly hazard. The one-year survival probability is computed as the product of the two six-month survival probabilities.

by Distribution of Prior Jobs

Jobs in Most Recent Year	Prob Survive 6 months	Prob Survive 2nd 6 months (conditional)	Prob Survive one year
0	.575	.823	.473
1	.518	.831	.431
2	.459	.838	.385
3	.398	.846	.337
4	.336	.853	.287

Note: These probabilities were calculated using monthly mobility rates predicted by the estimates of intermediate model #3 summarized in tables 12 and 13. The probabilities refer to a base group worker (white, male, not married, 12 years education, not living in an urban area, no prior spell of nonemployment) who is 23 years old and who starts a job in year 4 with four previous jobs. The six-month survival probability is computed as the product of one minus the hazard at each of the first six months. The conditional probability of survival for the second six months is computed as the product of one minus the hazard for the second six months. The one-year survival probability is computed as the product of the two six-month survival probabilities.

Table 15

Logit Analysis of Monthly Turnover Rates
Coefficients on Tenure

Tenure	First Job	Year of Experience 1	2	3	4	5	6
Month 1	1.45 (.127)	1.60 (.190)	1.39 (.204)	1.10 (.330)	1.20 (.337)	1.19 (.276)	.460 (.336)
Month 2	1.83 (.122)	1.99 (.186)	1.85 (.198)	1.45 (.300)	1.90 (.329)	1.39 (.274)	1.11 (.322)
Month 3	2.16 (.120)	2.01 (.189)	1.78 (.200)	1.75 (.297)	1.71 (.333)	1.53 (.274)	.792 (.334)
Month 4	1.85 (.125)	2.00 (.189)	1.74 (.203)	1.56 (.301)	1.33 (.341)	1.25 (.283)	1.17 (.326)
Month 5	1.30 (.137)	1.66 (.198)	1.57 (.207)	1.42 (.305)	1.62 (.337)	1.37 (.284)	.507 (.354)
Month 6	1.27 (.139)	1.49 (.204)	1.40 (.213)	1.55 (.304)	1.54 (.341)	1.30 (.289)	.779 (.346)
Months 7-12	.650 (.116)	1.02 (.179)	1.14 (.188)	1.23 (.286)	1.22 (.321)	.973 (.259)	.636 (.307)
Year 2	.563 (.109)	.895 (.172)	.891 (.183)	.923 (.284)	.966 (.320)	.778 (.259)	.356 (.308)
Year 3	.406 (.109)	.481 (.177)	.670 (.187)	.604 (.293)	.843 (.330)	.342 (.286)	-.114 (.342)
Year 4	.354 (.110)	.448 (.177)	.435 (.199)	.488 (.306)	.409 (.367)	---	---
Year 5	.183 (.121)	.510 (.195)	.174 (.227)	.387 (.341)	---	---	---

Note: The numbers in parentheses are asymptotic standard errors. All models also include dummy variables for each calendar year, a dummy variable for residence in an urban area, and the controls for worker characteristics and prior mobility in table 7. The base group consists of unmarried white male workers with twelve years education in 1979 who live outside an urban area and who have been on the job more than the maximum tenure level in the relevant column. The model for jobs that start in the first year excludes the first job held by each worker. The χ^2 statistic is for a likelihood ratio test of the relevant model against a constrained model with only a constant. The worker characteristic and prior mobility coefficients are contained in table 7 along with the summary statistics for the estimations. The results are discussed in section 3.

Table 16

Logit Analysis of Monthly Turnover Rates
Coefficients on Tenure

First Six Months on Job

Tenure	First Job	Year of Experience 1	2	3	4	5	6
Month 1	.142 (.114)	.120 (.144)	-.0360 (.145)	-.481 (.164)	-.363 (.177)	-.110 (.190)	-.336 (.246)
Month 2	.526 (.109)	.505 (.139)	.435 (.137)	-.129 (.155)	.353 (.161)	.0966 (.187)	.322 (.226)
Month 3	.865 (.107)	.526 (.141)	.371 (.140)	.188 (.149)	.159 (.169)	.240 (.187)	.00740 (.242)
Month 4	.564 (.113)	.513 (.143)	.332 (.144)	-.00320 (.158)	-.210 (.186)	-.0383 (.201)	.392 (.232)
Month 5	.028 (.127)	.168 (.155)	.170 (.151)	-.138 (.166)	.0841 (.179)	.0737 (.201)	-.269 (.271)

Note: The numbers in parentheses are asymptotic standard errors. All models also include dummy variables for each calendar year, a dummy variable for residence in an urban area, and the controls for worker characteristics and prior mobility in table 8. The base group consists of unmarried white male workers with twelve years education in 1979 who live outside an urban area and who have been on the job for six months. The model for jobs that start in the first year excludes the first job held by each worker. The χ^2 statistic is for a likelihood ratio test of the relevant model against a constrained model with only a constant. The worker characteristic and prior mobility coefficients are contained in table 8 along with the summary statistics for the estimations. The results are discussed in section 3.

Table 17

Logit Analysis of Monthly Turnover Rates
Coefficients on Tenure

After First Six Months on Job

Tenure	First Job	Year of Experience 1	2	3	4	5	6
Months 7-12	.751 (.121)	1.00 (.185)	1.12 (.192)	1.19 (.291)	1.23 (.328)	.910 (.267)	.591 (.319)
Year 2	.639 (.113)	.890 (.177)	.878 (.186)	.894 (.288)	.978 (.325)	.770 (.263)	.318 (.315)
Year 3	.458 (.111)	.481 (.180)	.666 (.189)	.585 (.295)	.853 (.333)	.377 (.287)	-.136 (.344)
Year 4	.385 (.111)	.442 (.186)	.431 (.200)	.495 (.307)	.417 (.368)	---	---
Year 5	.198 (.121)	.496 (.196)	.173 (.227)	.394 (.341)	---	---	---

Note: The numbers in parentheses are asymptotic standard errors. All models also include dummy variables for each calendar year, a dummy variable for residence in an urban area, and the controls for worker characteristics and prior mobility in table 9. The base group consists of unmarried white male workers with twelve years education in 1979 who live outside an urban area and who have been on the job more than the maximum tenure level in the relevant column. The model for jobs that start in the first year excludes the first job held by each worker. The χ^2 statistic is for a likelihood ratio test of the relevant model against a constrained model with only a constant. The worker characteristic and prior mobility coefficients are contained in table 9 along with the summary statistics for the estimations. The results are discussed in section 3.

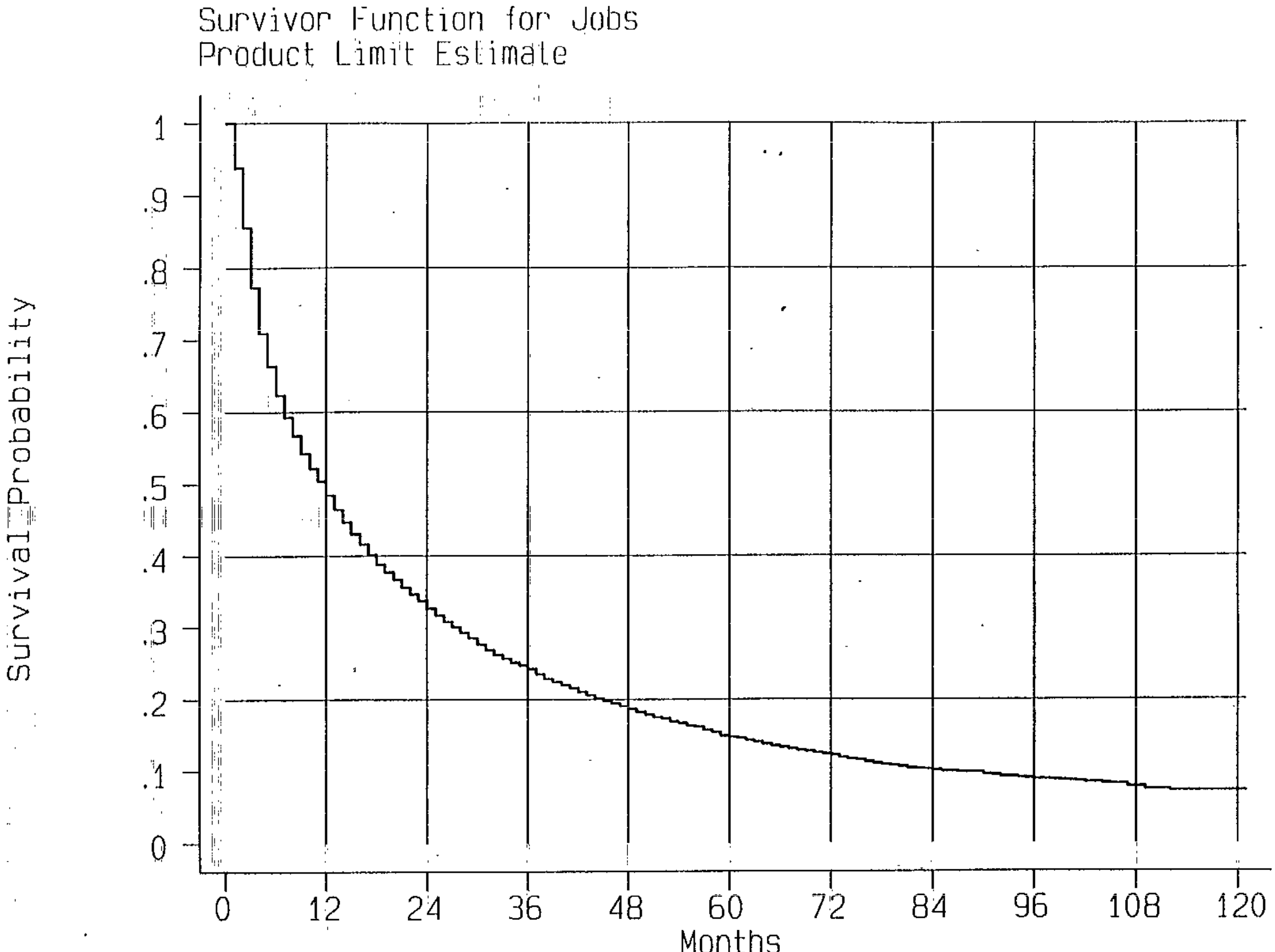
Survivor Function for Jobs
Product Limit Estimate
Survival Probability
1
.9
.8
.7
.6
.5
.4
.3
.2
.1
0
0
12
24
36
48
60
72
84
96
108
120
Months

Figure 1

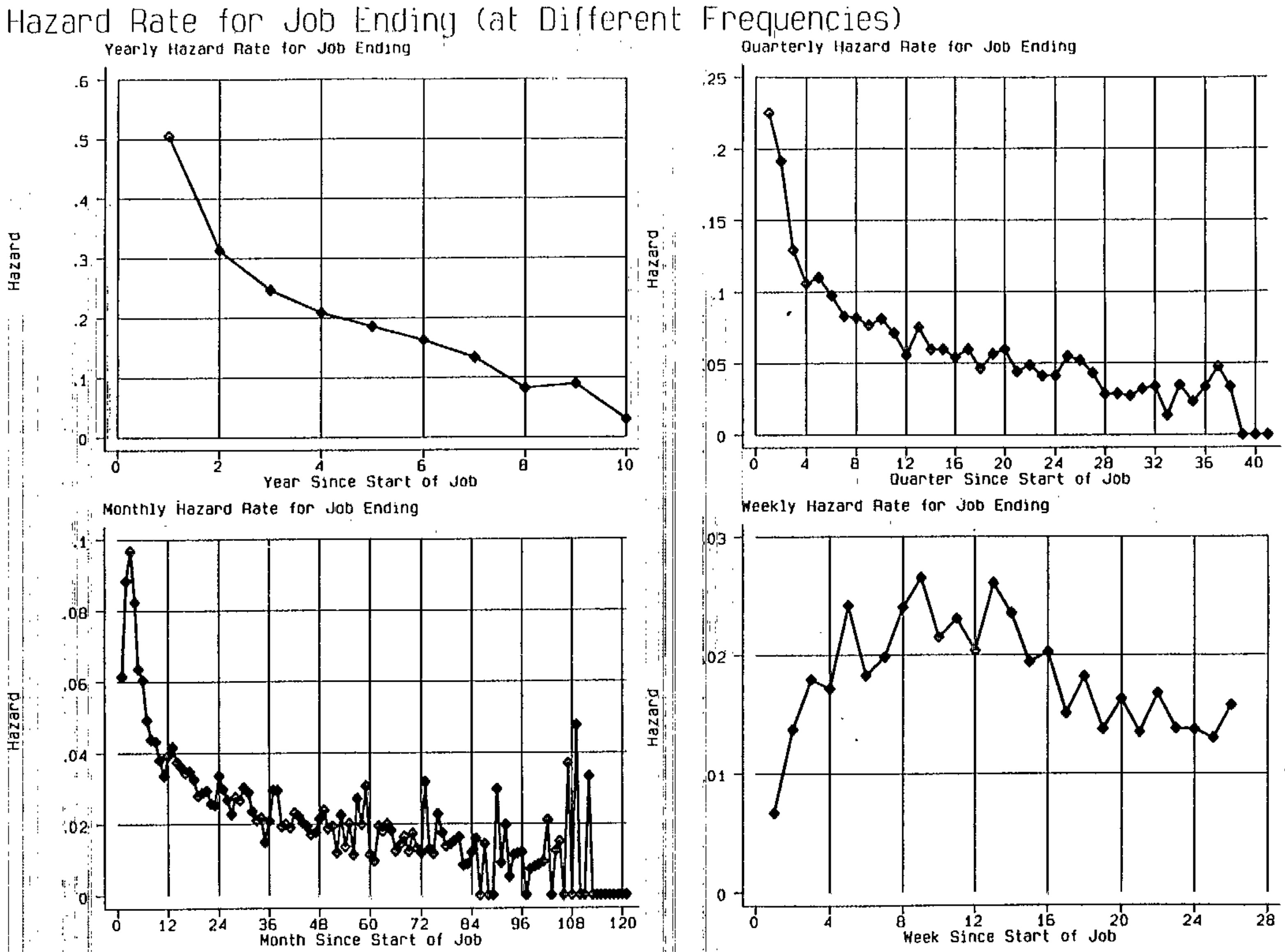
Hazard Rate for Job Ending (at Different Frequencies)
Yearly Hazard Rate for Job Ending
Hazard
Year Since Start of Job
Quarterly Hazard Rate for Job Ending
Quarter Since Start of Job
Monthly Hazard Rate for Job Ending
Month Since Start of Job
Weekly Hazard Rate for Job Ending
Week Since Start of Job

Figure 2

Hazard Rate by Number of Previous Jobs
For Each Year of Experience

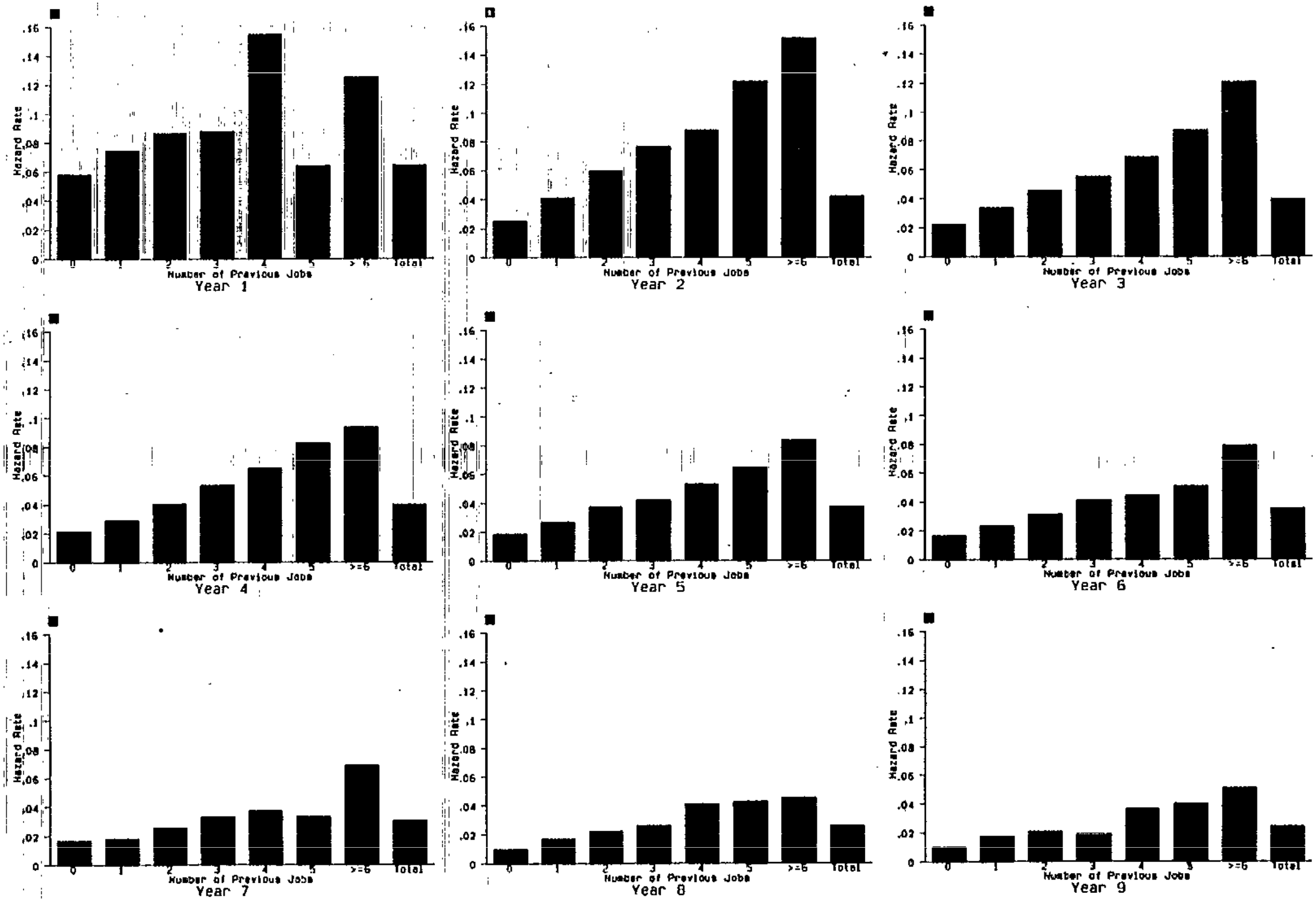

Figure 3

Monthly Hazard Rate for Job Ending
by Year of Prior Experience

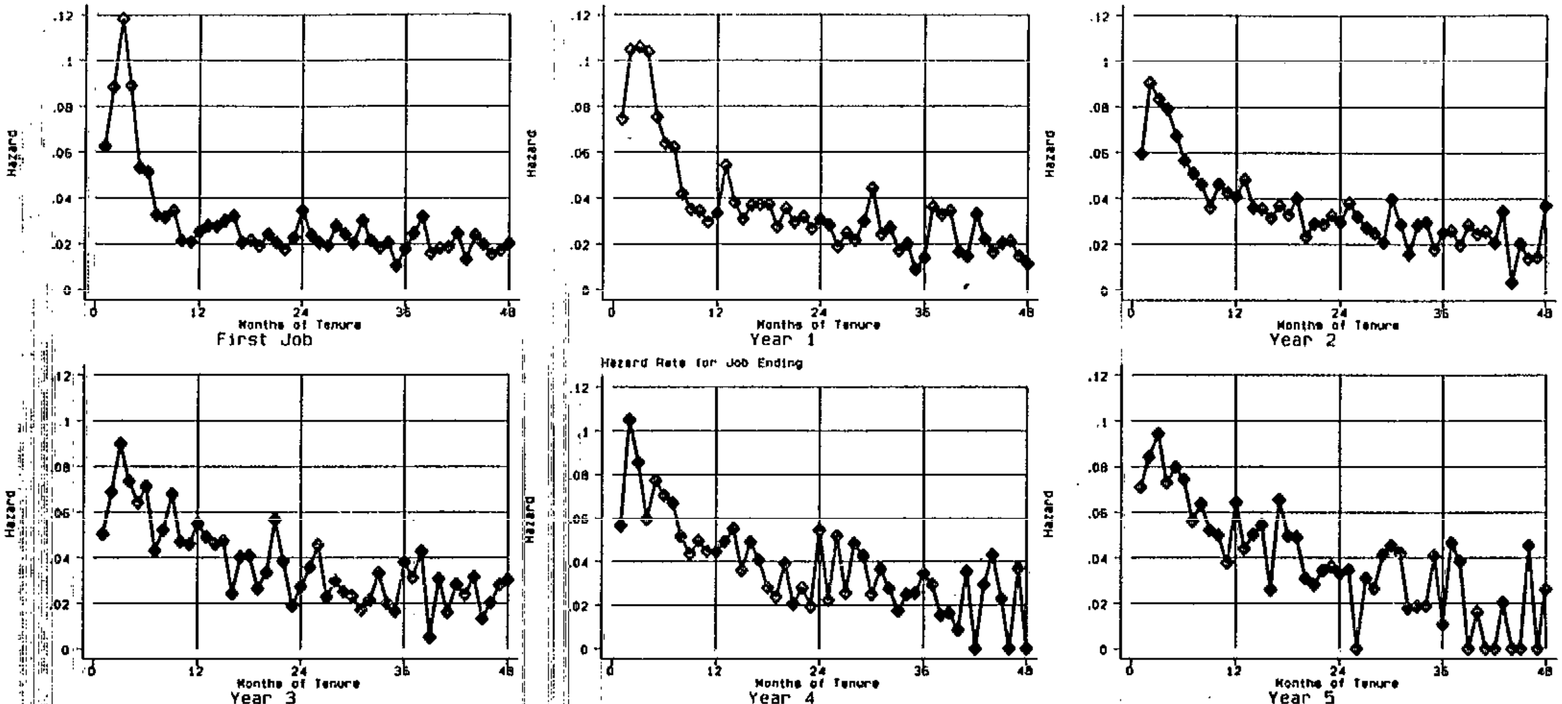

Figure 4