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ESTIMATING THE DURATION DEPENDENCE OF OCCUPATIONAL SPELLS WITH UNOBSERVED HETEROGENEITY

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Estimating the Duration Dependence of Occupational Spells with Unobserved Heterogeneity*

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Abstract

I employ a mixed proportional hazard model to estimate the effect of occupational tenure on the probability of an occupational change, conditional on spell-level unobserved heterogeneity. The individual-level data come from the Panel Study of Income Dynamics and the Survey of Income and Program Participation. The data include information on occupational spells which began before the sample in order to allow for more precise estimates at high levels of tenure. I apply the method proposed by Wooldridge (2005) to solve the initial conditions problem. After accounting for the endogeneity of initial tenure, I find evidence of an increasing relationship between occupational tenure and the probability of an occupational change at higher tenure levels. This effect works through both pecuniary and non-pecuniary channels in PSID data but only through non-pecuniary channels in SIPP data.

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1 Introduction

The empirical pattern of occupational mobility recently has received increased attention from economists. This interest partly stems from evidence which suggests that human capital is more specific to occupations than it is to firms or to industries.[1] If human capital is largely occupation-specific, the pattern of occupational mobility has important implications for earnings at the microeconomic level and for productive capacity at the macroeconomic level. The apparent increase in the incidence of occupational mobility in recent years offers a second explanation for the increased interest in occupational mobility.[2]

Most of this increased interest in occupational mobility has been devoted to explaining and estimating the effects of occupational mobility on labor market outcomes. Less is known about the determinants of occupational mobility.[3] One determinant of occupational mobility that merits special attention is occupational tenure. Evidence of significant returns to occupational tenure point to a potential correlation between tenure and specific human capital accumulated in an occupational spell. A worker abandons this occupation-specific human capital in the event of an occupational change.[4] Consequently, the relationship between occupational tenure and

[1]Kambourov and Manovskii (2009) and Sullivan (2010b) determine how specific human capital is to firms, industries, and occupations. Both studies find returns to occupational tenure which exceed the returns to firm tenure and industry tenure. Pavan (2011) documents that the returns to career tenure exceed the returns to firm tenure, where careers are defined as occupation-industry pairs. However, Pavan (2011) concludes that search across firms is more important than search across careers as a source of wage growth.

[2]Kambourov and Manovskii (2008) document an increase in the rate of occupational mobility between 1969 and 1997. Similarly, Parrado, Caner and Wolff (2007) find that workers were more likely to change occupations between 1981 and 1993 than they were between 1969 and 1980. Lalé (2011) shows evidence of a corresponding increase in occupational mobility in France over the period 1982-2009 after accounting for demographic changes in labor force composition.

[3]Kambourov and Manovskii (2008), Moscarini and Vella (2008), and Parrado et al. (2007) conclude that younger workers and less educated workers are more likely to change occupations. Moscarini and Vella (2008) also find evidence that occupational mobility is declining in family attachments, though they argue that higher unemployment rates weaken the importance of individual characteristics in explaining occupational mobility. Kambourov and Manovskii (2008) also show that government employees are less likely to change occupations.

[4]A related literature including Gathmann and Schönberg (2010) and Poletaev and Robinson (2008) emphasizes a more nuanced view of occupation-specific human capital. This literature con-

occupational mobility is suggestive of how the empirical pattern of occupational mobility affects the stock of occupation-specific human capital.

The nature of the relationship between occupational tenure and occupational mobility is unclear from an *a priori* perspective. On one hand, workers might accumulate occupation-specific match quality improvements with tenure. The probability of finding a better occupational match and changing occupations would decrease with tenure as more of these improvements accumulate. On the other hand, workers might be less likely to change occupations at all tenure levels as a result of high initial occupational match quality. If no better alternative match arrives, these occupational matches will grow to exhibit a high level of occupational tenure. This tendency would also generate a negative correlation between occupational tenure and occupational mobility.

To separate these two effects, I estimate a mixed proportional hazard model of occupational spell duration. Workers are assumed to have unobservable, heterogeneous propensities to exit an occupation at each instant during an occupational spell. This unobserved effect is assumed to be time-invariant within an occupational spell. Thus, one interpretation of the unobserved effect is that it reflects initial occupational match quality. Given the distribution of this unobserved effect, it is possible to estimate consistently the baseline hazard function. Consequently, I estimate the probability of exiting an occupational spell at each level of tenure conditional on both the spell's survival until that level of tenure and spell-level unobserved heterogeneity. In other words, I assess the degree of duration dependence in the stochastic process determining occupational mobility.

Recent evidence suggests that both wages and non-wage characteristics of occupational matches are important determinants of the occupational choice and occu-

cludes that human capital is more specific to the tasks that a worker performs than it is to that worker's occupational affiliation per se. In that case, the amount of human capital that lies abandoned or unutilized after an occupational change depends on the similarity of the tasks performed in each occupation.

pational mobility decisions.[5] While much is known about how wages evolve with occupational tenure, we know less about how the non-wage characteristics of occupational matches evolve with tenure. To distinguish the impact of occupational tenure on occupational mobility through pecuniary and non-pecuniary channels, I estimate jointly a mixed proportional hazard model and a standard wage model.

I utilize data from the Panel Study of Income Dynamics (PSID) from 1981 to 1997 and the 1990 through 1993 panels of the Survey of Income and Program Participation (SIPP). After weighting, both of these samples are representative of the U.S. population. By contrast, models of occupational mobility typically use data from the National Longitudinal Survey of Youth (NLSY). Samples in these studies include only individuals who become attached to the labor force at some observable time in the survey. This results in a sample which is younger on average than a representative sample of the entire population. Evidence from Neal (1999) supports the claim that younger workers are likely to search more actively for an appropriate occupational match. Thus, we might expect a sample of younger workers to exhibit less average occupational tenure, leading to relatively imprecise estimates of hazard rates at high levels of tenure.

For this reason, I do not restrict the sample to include only individuals who join the labor force at some observable time. This decision introduces an interesting tension. On one hand, it likely leads to more precise estimates of how occupational tenure affects occupational mobility, especially for high levels of occupational tenure. On the other hand, it potentially introduces sample selection bias into estimates of the baseline hazard function. Intuitively, the set of occupational matches observed at the beginning of the sample is not a random sample of all occupational spells.

[5]Search models such as those described in Keane and Wolpin (1997) include non-wage characteristics of occupational matches as a means of matching aspects of the data. Sullivan (2010a) also finds that search over non-wage characteristics is an important determinant of the occupational mobility decision. Indeed, he shows that search over non-wage characteristics generates substantial heterogeneity in lifetime utility. Becker (2010) also concludes that non-wage characteristics are an important determinant of job mobility.

Rather, it is the set of occupational spells that have survived until the start of the sample. Occupational matches of better unobserved initial quality are less likely to end at any instant and thus are likely to survive longer. This generates a positive correlation between the first level of occupational tenure observed for the spell ("initial tenure") and spell-specific, unobserved, initial match quality. Without accounting for this correlation, the implied likelihood function will be misspecified and maximum likelihood estimation will not yield consistent estimates. However, it can be difficult to treat the endogeneity of initial tenure. This is known as "the initial conditions problem".

I account for the initial conditions problem following the methodology proposed by Wooldridge (2005). I specify the joint distribution of the observed mobility outcomes conditional on observable covariates, spell-level unobserved heterogeneity, and initial tenure. Wooldridge (2005) provides guidelines for specifying the distribution of the spell-level unobserved heterogeneity to account for the endogeneity of initial tenure. In the present context, I approximate the distribution of the unobserved effect conditional on initial tenure and a history of observable covariates. I then integrate out the unobserved effect to obtain consistent estimates of the baseline hazard function. Wooldridge (2005) argues that this estimation method is no worse than the most common alternative, which involves approximating a different conditional distribution. Moreover, the solution which Wooldridge (2005) proposes bears various practical advantages.

Estimates from PSID data suggest that the baseline hazard is roughly hump-shaped: increasing for lower levels of tenure and decreasing or non-increasing for higher levels of tenure.[6] This pattern emerges regardless of whether I estimate a

[6] All comparisons are significant at the 90 percent level. The estimates discussed here are based on responses from a sample of the population and may differ from the actual values because of sampling variability and other factors. As a result, apparent differences between the estimates for two or more groups may not be statistically significant. For information on sampling and nonsampling error see: http://www.census.gov/sipp/source.html.

proportional hazard model or a mixed proportional hazard model which treats initial tenure as exogenous. This suggests that workers at lower levels of occupational tenure are increasingly likely to change occupations as they accumulate tenure, although this trend reverses at higher levels of tenure. Estimates from SIPP data display the same qualitative pattern at higher levels of occupational tenure, though not at lower levels of tenure. However, a mixed proportional hazard model which treats the initial condition as endogenous reveals evidence of a negative bias caused by the initial conditions problem. After removing this bias, I find surprising evidence in both PSID data and SIPP data of a baseline hazard which is increasing at higher levels of occupational tenure. An increasing baseline hazard at higher levels of occupational tenure suggests that the accumulation of tenure does not create as strong a bond between workers and occupations as previously believed. This relationship between occupational tenure and occupational mobility at high levels of tenure seems to work through both pecuniary and non-pecuniary channels in PSID data but only through non-pecuniary channels in SIPP data.

The rest of the paper proceeds in the following fashion. Section 2 describes the data used. In Section 3, I discuss the econometric models used to estimate duration dependence. I present estimation results for these models in Section 4. In Section 5, I introduce a standard wage model and consider the effects of occupational tenure on occupational mobility through pecuniary and non-pecuniary channels. Section 6 concludes and lists future possibilities for research.

2 Data

My data come from two sources: the Panel Study of Income Dynamics and the Survey of Income and Program Participation. Both datasets exhibit two characteristics which make them well-suited for the current analysis. First, they offer detailed information about demographics, respondents' employment situation, and other characteristics. This allows me to control for a variety of covariates that have been linked to occupational mobility while estimating the relationship between occupational mobility and tenure. Second, they are representative of the entire U.S. population after weighting. By contrast, previous studies of occupational mobility generally have been estimated on a sample which is younger on average than the U.S. population at large. Consequently, the two data sets that I employ likely will yield more precise estimates of the occupational hazard function at higher levels of tenure.

2.1 Panel Study of Income Dynamics

I use data from the Panel Study of Income Dynamics (PSID) for the period 1981 to 1997. The PSID is relatively large and long. These are desirable characteristics for the present analysis because the relative infrequency at which many respondents change occupations poses an obstacle to obtaining precise estimates. A large and long sample is especially desirable given that I estimate a flexible function of occupational tenure conditional on spell-level unobserved heterogeneity.

I use data from household heads and their spouses only. I drop all yearly observations which have missing values for 3-digit occupational affiliation, occupational tenure, or hourly wage.[7] These sample selection criteria are relatively lenient in order to obtain as large a sample of occupational spells as possible. By contrast, similar studies drop subgroups that display special occupational mobility patterns. For instance, other studies drop workers over age 65 and part-time workers because these workers are likely to be more mobile than other workers. Instead, I include information from these respondents and control for membership in these groups when estimating the effects of occupational tenure on the probability of an occupational

[7] I consider 3-digit occupational affiliation to be missing if employed workers do not report their current 3-digit occupation or unemployed workers do not report their last 3-digit occupation. See the appendix for a description of how the occupational tenure and hourly wage data series were constructed.

change. Variation within these subgroups helps to identify the effect of occupational tenure on occupational mobility and the larger sample size allows for more precise estimates.[8]

The summary statistics for the sample that I use are listed in Table 1. The data contain 44,458 occupational spells from 21,449 individuals. This amounts to a weighted average of 2.31 occupational spells per person. Thus, Table 1 illustrates that there are a considerable number of completed occupational spells. Variation in the duration of these spells identifies the occupational hazard function.

Unfortunately, the PSID lacks direct information on the two variables which are most important for my empirical analysis: occupational changes and occupational tenure. Nevertheless, it is possible to impute this information by exploiting the length of this panel and annual information regarding respondents' current employment situations. By following respondents from year to year, I use information on occupational affiliation and position tenure to construct data series for occupational changes and occupational tenure.

In the absence of measurement error in occupational affiliation, a genuine occupational switch could be recorded when respondents report an occupation in one year which differs from the last reported occupation. However, Kambourov and Manovskii (2008) document that the occupational data in the PSID likely do suffer from measurement error. For instance, there are many reported occupational switches which do not correspond to any other observable labor market change. Kambourov and Manovskii (2008) estimate that approximately 50% of occupational changes implied by reported occupational affiliation result from measurement error instead of a genuine occupational change.[9]

[8]For similar reasons, I include workers who are non-white, Hispanic, female, self-employed, government-employed, or who have suffered unemployment spells. In addition, I choose not to restrict my sample by occupational affiliation or by region.

[9]Kambourov and Manovskii (2008) argue that much of the measurement error is due to misinterpretation by those responsible for translating reported task descriptions into occupational codes. This is consistent with experimental evidence presented in Mathiowetz (1992) and Mellow and Sider

In order to obtain more reliable data on occupational mobility, I follow a procedure proposed by Kambourov and Manovskii (2009). I consider an occupational switch as implied by reported occupational affiliation to be genuine if it is accompanied by an implied position change. In short, I identify a position change whenever the position tenure reported at the present survey time is inconsistent with the hypothesis that there was no position change, given tenure reported at the preceding survey time and the time elapsed between survey times. This procedure bears a strong similarity to "Partition T" as proposed by Brown and Light (1992). I list the details of this procedure in the appendix.

In the absence of measurement error in position tenure, occupational tenure could be constructed by summing tenure reported on each position held during an occupational spell. However, Brown and Light (1992) document that the tenure data in the PSID likely do suffer from substantial measurement error. For instance, many reports of position tenure in consecutive surveys are inconsistent with the calendar time elapsed between these surveys. Brown and Light (1992) recommend using internally consistent, corrected tenure responses when estimating wage-tenure profiles. For this reason, I use the procedure articulated by Kambourov and Manovskii (2009) to construct an internally consistent measure of position tenure.[10]

In order to obtain more reliable data on occupational tenure, I use this internally consistent measure of position tenure to follow a procedure proposed by Kambourov and Manovskii (2009). Occupational tenure is defined to coincide with position tenure when respondents enter the sample.[11] Subsequently, occupational tenure is defined

(1983). These studies both conclude that measurement error in occupational affiliation is most prevalent in less aggregated groups of occupations. This is potentially problematic for my analysis, as I consider mobility across 3-digit occupations. Indeed, Kambourov and Manovskii (2008) estimate that measurement error in occupational mobility is highest at the 3-digit level.

[10]See the appendix for more details on how I construct position tenure data.

[11]This decision introduces measurement error into the occupational tenure data for any respondents who held positions in the same occupation prior to the first observed position. This is potentially problematic for my analysis. Nevertheless, tenure in the first observed position is correlated with tenure in the first observed occupation. The direction and extent of the resulting bias depends on the shape of the baseline hazard function.

to coincide with position tenure when there is a genuine occupational change. When there is no reported occupational change, occupational tenure increments by one each year that the respondent remains in the sample.

I construct occupational tenure under two extreme assumptions regarding how occupation-specific human capital depreciates between occupational spells. Suppose that a carpenter decided to become a salesman, only to return to his occupation as a carpenter after several years. Under the Full Depreciation assumption, all occupation-specific human capital accumulated in an occupational spell is assumed to be lost when that spell ends. To reflect this, the carpenter's tenure is initialized at 0 upon returning to his previous occupation, regardless of the duration of his interim spell as a salesman. Under the No Depreciation assumption, all occupation-specific human capital accumulated in an occupational spell is assumed to persist when that spell ends. To reflect this, the carpenter's tenure continues to accumulate upon returning to carpentry as if he had never changed occupations, regardless of the duration of his interim spell as a salesman. Table 1 shows that 6.9% of all occupational spells in the PSID represent a return to an occupation which was sampled earlier in the panel, and that average occupational tenure according to the Full Depreciation assumption and the No Depreciation assumption is 3.160 years and 3.301 years, respectively.

2.2 Survey of Income and Program Participation

I use data from the 1990 through 1993 panels of the Survey of Income and Program Participation (SIPP), covering October 1989 through December 1995. These four overlapping panels of the SIPP result in a sample of more individuals than the PSID. Moreover, SIPP data include the characteristics of up to two jobs that each individual may have held in the previous four months. By contrast, PSID data include the characteristics of only one job that each individual may have held in the previous twelve months. To the extent that individuals work in different occupations simultaneously or over short durations, the SIPP will result in a sample of more occupational spells than the PSID.

While it may cover a larger sample of individuals and occupational spells at a point in time, the SIPP spans a shorter time series than the PSID; each panel followed the same individuals for up to 32 months before the 1992 panel and for up to 36 months thereafter. This is potentially problematic given the relative infrequency at which many respondents change occupations. If occupational changes occur stochastically in each month, a sample window which spans fewer months likely will yield fewer occupational spells per individual. Any resulting sample size concerns might be especially acute at higher levels of tenure if individuals are less likely to exit occupations as they accumulate tenure. Consequently, the relatively short panel offered by the SIPP might feasibly undermine efforts to obtain more precise estimates of the relationship between occupational tenure and occupational mobility at higher levels of tenure.

My sample selection criteria for the SIPP analysis differ from the criteria for the PSID analysis in three ways. First, I do not restrict the sample to household heads and their spouses only. The SIPP collects labor force information about all household members rather than only household heads and their spouses as the PSID does. Second, I do not use the occupational spells of business owners. To the extent that owners and non-owners differ in their relative propensities to change occupations along the tenure profile, we would expect the results of the SIPP and PSID analyses to differ. Finally, I drop all occupational spells of individuals who ever work two jobs in the same occupation during the same four month wave. Occupation-specific human capital may accumulate differentially during these reference periods. Alternatively, information about the unobserved occupation-specific match quality may arrive differentially during these reference periods. As in the PSID analysis, I drop all yearly observations which have missing values for 3-digit occupational affiliation, occupational tenure, or hourly wage.[12]

The summary statistics for the sample that I use are listed in Table 2. The data contain 92,736 occupational spells from 68,929 individuals. This amounts to a weighted average of 1.34 occupational spells per person. Thus, Table 2 illustrates that the shorter panel counteracts the larger sample size and sample frequency of the SIPP, resulting in fewer observed occupational spells per person. Nevertheless, there are a considerable number of completed occupational spells. Variation in the duration of these spells identifies the occupational hazard function.

I impute information on occupational mobility following a procedure which strongly resembles the corresponding imputation procedure for the PSID analysis. The potential sources of measurement error in occupational affiliation enumerated by Kambourov and Manovskii (2008) are not entirely survey-specific. Indeed, the SIPP also includes many reported occupational switches which do not correspond to any other observable labor market change. In order to obtain more reliable data on occupational mobility, I consider an occupational switch as implied by reported occupational affiliation to be genuine if it is accompanied by an implied employer change.

I employ a more direct approach to identify employer changes in the SIPP than is feasible for position changes in the PSID analysis. The SIPP offers unique employer identifiers for up to two jobs which a respondent held during the reference period. These employer identifiers were intended to be consistent over time. In the absence of measurement error in these variables, a comparison of identifiers across reference periods would indicate an employer change. However, these identifiers were not always consistent over time in practice. Stinson (2003) details the extent and potential

[12]I consider 3-digit occupational affiliation to be missing if employed individuals do not report a 3-digit occupation for the entirety of their spell with an employer. If an individual did not report a 3-digit occupation during a particular reference period but did report one earlier or later on the same employer spell, I impute occupational affiliation to match that report. Similarly, I consider 3-digit occupational affiliation to be missing if unemployed workers do not report their last 3-digit occupation. See the appendix for a description of how the occupational tenure and hourly wage data series were constructed.

sources of this measurement error, and constructs revised job identifiers which are more consistent over time. I compare these revised identifiers over time to obtain an indicator of an employer change. Specifically, I record an employer change in any wave when a respondent's revised job identifier does not match either of that respondent's revised job identifiers from the previous wave.

I impute information on occupational tenure following a procedure which strongly resembles the corresponding imputation procedure for the PSID analysis. The employer tenure variables that I use for this procedure come from two sources. First, the Employment History Topical Module offers the starting month and year of a respondent's main job during the four month reference period. This topical module was administered in the second wave before the 1992 panel, and in the first wave thereafter. Thus, this source enables me to compute employer tenure for many jobs that were in progress when the sample window began. Second, the core data offer the starting day and month for each of a respondent's two main jobs that may have begun during the four wave reference period. I apply the procedure suggested by Kambourov and Manovskii (2009) to data from these two sources in order to construct an internally consistent measure of employer tenure.[13] I then define occupational tenure to coincide with employer tenure either when respondents enter the occupation or when they enter the sample for job spells that were ongoing at the start of the sample.[14] When there is no reported occupational change, occupational tenure increments by one each year that the respondent remains in the sample.

Table 2 presents average occupational tenure. Average spell duration under the Full Depreciation assumption is 79.735 months or 6.645 years. Note that for the SIPP analysis I assume only full depreciation of occupation-specific human capital when an

[13]See the appendix for more details on how I construct employer tenure data.

[14]This decision introduces measurement error into the occupational tenure data for any respondents who held positions in the same occupation prior to the first observed position. The Employment History Topical Module to the SIPP offers a direct measure of occupational tenure as a more accurate alternative. I choose not to employ this more direct measure for the purpose of comparison with the PSID.

occupational spell ends. Given the short sample window of the SIPP, occupational tenure is likely to vary little between the Full Depreciation assumption and the No Depreciation assumption.

3 Econometric Model of Duration Dependence

Duration models are a natural approach for an examination of the relationship between occupational tenure and the probability of an occupational change. An occupational change at time t marks the end of an occupational spell that has necessarily survived until time t. Consequently, it is desirable to estimate a hazard model of occupational exit at time t conditional on the spell's survival until t.

A second desirable characteristic of duration models is that they allow for consistent estimation of the relationship between occupational tenure and mobility conditional on explanatory covariates. Kambourov and Manovskii (2008), Moscarini and Vella (2008), and Parrado et al. (2007) show evidence that individual characteristics such as age and education are linked to occupational mobility. Moscarini and Vella (2008) document that occupational mobility is related to family commitments. Moscarini and Vella (2008) also argue that the effect of individual characteristics on occupational mobility is diminished during poor macroeconomic times. It is important to control for such heterogeneity when estimating the relationship between occupational tenure and the probability of an occupational change. For example, if older workers are less likely to change occupations at every level of occupational tenure, these workers are also more likely to accumulate high levels of occupational tenure. This would generate a negative relationship between occupational tenure and the probability of an occupational change. A model that does not control for this observable source of heterogeneity would confound the effects of occupational tenure on mobility with the effects of age on mobility.

A third desirable characteristic of duration models is that they allow for consistent estimation of the relationship between occupational tenure and mobility conditional on spell-level unobserved heterogeneity. Pavan (2010) and Sullivan (2010a) show evidence that unobserved occupational match quality impacts occupational mobility. It is important to control for such heterogeneity when estimating the relationship between occupational tenure and the probability of an occupational change. For example, any estimated relationship may be due to aggregation across individuals with heterogeneous, unobservable propensities to change occupations at any level of tenure. Individuals who initially have a particularly poor occupation-specific match are more likely to change occupations at any level of tenure. Thus, the population for which I observe high levels of tenure would exhibit disproportionately high unobserved initial match quality. This would generate a negative relationship between occupational tenure and the probability of an occupational change, even if occupational matches do not improve with tenure. A model that does not control for this unobservable source of heterogeneity would confound the effects of occupational tenure on mobility with the effects of unobserved initial match quality on mobility.

When estimating mixed proportional hazard models, we typically assume that the first observed level of tenure is exogenous. However, this assumption holds only if a genuinely new process is observed at the start of the sample. Heckman (1981) shows that if the initial conditions are not exogenous, treating them as if they were exogenous leads to inconsistent parameter estimates. The endogeneity of initial tenure can be framed as a sample selection problem. Rather than observing a random sample of occupational spells, we observe a random sample of occupational spells conditional on the spell being in progress at the beginning of the sample. Regardless of when they began, spells of particularly good unobserved initial quality are more likely to survive until the start of the sample. Furthermore, this sample selection problem is expected to deteriorate with tenure; the worst remaining matches are the most likely to exit at every level of tenure. The resulting correlation between initial tenure and the unobserved effect is likely to generate a negative bias in the estimated effect of tenure on the probability of an occupational change. A model that does not control for this correlation would confound the effects of occupational tenure on mobility with the effects of unobserved initial match quality on mobility.

3.1 Proportional Hazard Model

In order to estimate the relationship between occupational tenure and the probability of an occupational change, I begin by positing a proportional hazard model. This model does not distinguish between the effects of occupational tenure on mobility and the effects of spell-level unobserved heterogeneity on mobility. In subsequent sections, I decompose the baseline hazard rate to examine how occupational mobility varies with tenure due to spell-level unobserved heterogeneity. I also examine how occupational mobility varies with occupational tenure through pecuniary and non-pecuniary channels. Consider the following proportional hazard model:

$$\lambda(\tau_{ijt}; X_i) = \exp\{b(\tau_{ijt})'\gamma + x'_{ijt}\beta\}. \tag{1}$$

In equation (1), $\lambda(\tau_{ijt}; X_i)$ represents the instantaneous probability that person i exits occupation j at time t and tenure τ_{ijt}, given the spell's survival until τ_{ijt} and the full history of explanatory covariates X_i.

The product $b(\tau_{ijt})'\gamma$ expresses the baseline hazard as a piecewise-linear function of tenure τ_{ijt} with six nodes given by n_1, n_2,...,n_6.[15] Thus, γ is my parameter vector of

[15]I select the piecewise-linear approximation of the baseline hazard function with nodes $n_1 = 1$, $n_2 = 2$, $n_3 = 3$, $n_4 = 4$, $n_5 = 9$, and $n_6 = 17$ according to the method recommended by Lillard and Panis (2003).

interest. $b(\tau_{ijt})$ is assumed to be a vector with seven elements, given by the following:

$$b(\tau) = \begin{bmatrix} \min(\tau, n_1) \\ \max(0, \min(\tau - n_1, n_2 - n_1)) \\ \max(0, \min(\tau - n_2, n_3 - n_2)) \\ \max(0, \min(\tau - n_3, n_4 - n_3)) \\ \max(0, \min(\tau - n_4, n_5 - n_4)) \\ \max(0, \min(\tau - n_5, n_6 - n_5)) \\ \max(0, \tau - n_6) \end{bmatrix}.$$

The full history of explanatory covariates is contained in the set X_i. Given T observations for person i, X_i is a set of T vectors of regressors $\{x_{ijt}\}_{t=1}^{T}$. Thus, the explanatory covariates in this model are time-varying.[16] Note that the model specified by equation (1) imposes the assumption that the hazard function depends only on x_{ijt} and not on the entire history of explanatory covariates in X_i.[17] These covariates affect the hazard function proportionately.

Each element of X_i contains a variety of controls which attempt to capture the mobility patterns of the various subgroups that I choose to include. For instance, each x_{ijt} includes a male indicator, weeks unemployed, government worker indicator, self-employed indicator, part-time worker indicator, a cubic in age, regional fixed effects, and 1-digit occupation fixed effects. Additionally, each element of X_i contains a variety of demographics which have been linked to occupational mobility in previous studies. Specifically, each x_{ijt} includes a cubic in education and a married indicator.

[16]Time-varying covariates pose important practical problems for duration models, as described in Wooldridge (2002) and Cameron and Trivedi (2005). However, both studies show that it is possible to derive a log-likelihood which allows for consistent estimation if the covariates are assumed to be constant within a number of time intervals. This assumption is natural given that the PSID and the SIPP collect information on respondents at discrete intervals. This assumption is more likely to hold in SIPP data, since observations occur every month or every four months rather than every year. Thus, the explanatory covariates in x_{ijt} are assumed to be constant between sample observations.

[17]This assumption is not particularly strong, as x_{ijt} may include lagged values of explanatory covariates.

Based on the evidence presented by Moscarini and Vella (2008), I also include a cubic in education, a married indicator, and a cubic in age each interacted with county unemployment rate.[18] Finally, I include a union member indicator in each x_{ijt} because Kambourov and Manovskii (2008) suggest that changes in unionization may explain the recent change in occupational mobility. In some cases, these explanatory variables have missing values.[19] When this is the case, I impute a value of zero. Alternatively, I could drop these observations. I choose not to do so in order to obtain more precise estimates of the relationship between occupational tenure and occupational mobility.

One advantage of the model specified in equation (1) is that it takes a flexible approach to approximating the baseline hazard function. This allows me to assess more accurately how the empirical relationship between occupational tenure and the probability of an occupational change varies over the occupational tenure profile. In this way, the present model of the baseline hazard function improves upon the baseline hazard functions which are implied by recent models of occupational mobility which impose more structure.

The hazard function that I propose in equation (1) can be used to construct the probability that a transition occurs between any two points in time. The probability that person i exits occupational spell j in survey time t between tenure levels $\tau_{ij,t-1}$ and τ_{ijt} conditional on survival until survey time $t-1$ is given by:

$$\Pr\left(y_{ijt}=1|y_{ij,t-1}=0, X_i, \{\tau_{ijk}\}_{k=t-1}^{t}\right) = 1-\exp\left[-\int_{\tau_{ij,t-1}}^{\tau_{ijt}} \lambda(s;X_i)ds\right].$$

Here, y_{ijt} is a binary variable which takes the value one if the spell is considered complete at any instant between survey time t and survey time $t+1$. This conditional

[18] I drop the self-employed indicator, the cubic in age, and the interaction between the unemployment rate and the cubic in age from the SIPP analysis. Models which include these regressors are not well-identified.

[19] In PSID data, this is true for county unemployment rate, education, age, region, weeks unemployed, and part-time worker. In SIPP and Local Area Unemployment Statistics data, this is true for education, weeks unemployed, gender, union status, and government worker status.

probability can be used to construct the probability that a spell survives through time T, given X_i. This product is the following survivor function:

$$S\left(T; X_i, \{\tau_{ijk}\}_{k=0}^{T}\right) = \prod_{t=1}^{T} \exp\left[-\int_{\tau_{ij,t-1}}^{\tau_{ijt}} \lambda(s; X_i) ds\right]. \tag{2}$$

The survivor function can be used to construct the partial likelihood contribution for each occupational spell.[20] Specifically, the contribution to the partial likelihood of individual i in occupational spell j is given by the following equation. Here, d_{ij} is an indicator variable which takes the value one if spell j is right-censored at time t^c and the value zero if it is observed to end between time t^l and time t^u:

$$\begin{aligned} L_{ij} = & \left[S\left(t^c; X_i, \{\tau_{ijk}\}_{k=0}^{t^c}\right)\right]^{d_{ij}} \times \\ & \left[S\left(t^l; X_i, \{\tau_{ijk}\}_{k=0}^{t^l}\right) - S\left(t^u; X_i, \{\tau_{ijk}\}_{k=0}^{t^u}\right)\right]^{1-d_{ij}}. \end{aligned} \tag{3}$$

After taking the product of these partial likelihood contributions, I estimate γ and β via maximum likelihood.

3.2 Mixed Proportional Hazard Model

Next, I consider a mixed proportional hazard model in order to avoid confounding the effects of occupational tenure with the effects of spell-level unobserved heterogeneity. At every level of tenure, the difference between the estimated baseline hazard functions associated with a proportional hazard model and a mixed proportional hazard model represents the effect of unobserved heterogeneity. I introduce unobserved

[20] I use the partial likelihood function for estimation because I am only modeling the distribution of y_{ijt} conditional on $y_{ij,t-1}$, X_i, τ_{ijt}, and $\tau_{ij,t-1}$. If I modeled the joint distribution of $(y_{ij1}, \ldots, y_{ijt})$ given X_i and τ_{ij0} instead, then I would use the full conditional likelihood function for estimation. However, if the density of spell duration is dynamically complete, the partial likelihood is equivalent to the full conditional likelihood. See Wooldridge (2002) for details.

heterogeneity to the hazard function in the following fashion:

$$\lambda(\tau_{ijt}; X_i, \nu_{ij}) = \nu_{ij} \exp\{b(\tau_{ijt})'\gamma + x'_{ijt}\beta\}. \tag{4}$$

The spell-level unobserved effect ν_{ij} captures the effect of all unobserved heterogeneity which is constant within spells, such as unobserved initial match quality. I assume that ν_{ij} is distributed with cdf $H(\nu)$. I assume that ν_{ij} is independent of the covariates X_i, the censoring process, and the initial condition y_{ij0}.[21] If this assumption holds, the parameter vectors γ and β may be estimated consistently by integrating the unobserved effect out of the partial likelihood contribution. For now, I assume that the cdf $H(\nu)$ is such that the log of ν_{ij} is distributed normally with mean 0 and variance σ_a^2.

I use the hazard function proposed in equation (4) to construct the probability of an occupational change at survey time t between tenure levels $\tau_{ij,t-1}$ and τ_{ijt} conditional on survival until survey time $t-1$ and the unobserved effect ν_{ij}:

$$\Pr\left(y_{ijt} = 1 | y_{ij,t-1} = 0, X_i, \{\tau_{ijk}\}_{k=t-1}^{t}, \nu_{ij}\right) = 1 - \exp\left[-\int_{\tau_{ij,t-1}}^{\tau_{ijt}} \lambda(s; X_i, \nu_{ij}) ds\right]. \tag{5}$$

These conditional probabilities allow me to construct the probability that a spell survives through time T, given X_i and the unobserved effect ν_{ij}. This product is the survivor function conditional on the unobserved effect, which is:

$$S\left(T; X_i, \{\tau_{ijk}\}_{k=0}^{T}, \nu_{ij}\right) = \prod_{t=1}^{T} \exp\left[-\int_{\tau_{ij,t-1}}^{\tau_{ijt}} \lambda(s; X_i, \nu_{ij}) ds\right]. \tag{6}$$

The survivor function in equation (6) can be used to construct the partial likelihood contribution for person i in occupational spell j. In order to compute the value

[21] The assumption that ν_{ij} and y_{ij0} are independent embeds the assumption that ν_{ij} and initial tenure τ_{ij0} are independent.

of the partial likelihood contribution, I integrate out ν_{ij} over its assumed distribution:

$$L_{ij} = \int_0^{\infty} \left[S\left(t^c; X_i, \{\tau_{ijk}\}_{k=0}^{t^c}, \nu\right)\right]^{d_{ij}} \times \\ \left[S\left(t^l; X_i, \{\tau_{ijk}\}_{k=0}^{t^l}, \nu\right) - S\left(t^u; X_i, \{\tau_{ijk}\}_{k=0}^{t^u}, \nu\right)\right]^{1-d_{ij}} dH(\nu). \quad (7)$$

3.3 Initial Conditions

If the spell-level unobserved effect ν_{ij} is independent of the initial condition $y_{ij0} = 0$, then the partial likelihood contribution given by equation (7) allows for consistent estimation of γ. Often, this assumption is invalid in dynamic models with serially correlated unobserved heterogeneity. Heckman (1981) shows that estimated parameters of models that do not account for the correlation between the unobserved effect and the initial condition can exhibit substantial bias. However, it can be difficult to treat the endogeneity of the initial condition. This is known as the "initial conditions problem".

As equation (5) suggests, I interpret mixed proportional hazard models as dynamic models with unobserved heterogeneity. Equations (5) and (6) imply that the probability of survival through survey time T is given by the product:

$$S\left(T; X_i, \{\tau_{ijk}\}_{k=0}^{T}, \nu_{ij}\right) = \prod_{t=1}^{T} \Pr\left(y_{ijt} = 1 | y_{ij,t-1} = 0, X_i, \{\tau_{ijk}\}_{k=t-1}^{t}, \nu_{ij}\right).$$

This allows me to construct the joint density of the outcomes $y_{ij1}, y_{ij2}, \ldots, y_{ijT}$ conditional on $y_{ij0}, X_i, \{\tau_{ijk}\}_{k=0}^{T}$, and ν_{ij}. If the initial condition is exogenous, it is possible to obtain consistent estimates of γ despite the presence of the serially correlated unobserved effect ν_{ij}. For spells that begin at some observable time in the sample, y_{ij0} is necessarily exogenous. These spells have yet to begin when person i is first interviewed, so they cannot have been complete prior to that time (*i.e.* $y_{ij0} = 0$). This initial condition holds for all spells that begin during the sample, independent of

ν_{ij}. However, the initial condition is unlikely to be exogenous for occupational spells which are already in progress at the start of the sample. These spells likely survived until person i is first interviewed due to their spell-level unobserved heterogeneity.[22] If I do not account for this relationship between ν_{ij} and y_{ij0}, the likelihood function will be misspecified and the resulting estimates will be inconsistent.

Typically, attempts to estimate the effect of tenure on career mobility escape the initial conditions problem through sample selection.[23] These analyses only use information from individuals who become attached to the labor market initially during the survey. This convention ensures that all spells represent the beginning of a genuinely new process in the terminology of Heckman (1981). Consequently, the initial condition is exogenous.

Most individuals initially join the labor force at a young age. Given the length of most available panels, this conventional sample selection criterion yields a sample which is younger than a representative sample of the labor force, on average. Younger individuals are more likely to search actively for occupational match improvements.[24] As a result, average occupational tenure in this sample is expected to be smaller than it would be in a representative sample of the entire population. This could lead to relatively imprecise estimates of the relationship between occupational tenure and the probability of an occupational change at high levels of tenure.

To obtain more precise estimates, I use information on occupational spells which were in progress at the beginning of the sample. I address the initial conditions problem using the methodology proposed by Wooldridge (2005). He advocates specifying

[22]Note that my sample includes only occupational spells for which $y_{ij0} = 0$. The PSID does not include any information on the duration of occupational spells that ended before the sample window. While the Employment History Topical Module to the SIPP does include information on occupational spells that ended before the sample window, it lacks information about time-varying covariates during this previous spell.

[23]See Pavan (2011) for one example.

[24]See Neal (1999) for evidence that younger workers are more mobile across careers than older workers. See Topel and Ward (1992) for evidence that job mobility is an important source of wage growth for young workers.

a distribution which approximates the true distribution of the unobserved effect conditional on the initial condition y_{ij0} and the full history of explanatory covariates X_i. The conditional mean of this assumed distribution summarizes the relationship between the initial condition and the spell-level unobserved effect. He also proposes two general guidelines for specifying this conditional distribution. First, we should specify a flexible distribution in order to improve the accuracy of the approximation. Second, we should specify a distribution which enables straightforward estimation using standard software. He then proceeds to show that this model of the relationship between y_{ij0} and ν_{ij} allows for consistent estimation of the parameters of the density of outcomes $y_{ij1}, \ldots, y_{ijT}$ conditional on the initial condition y_{ij0} and X_i.

Heckman (1981) proposes an alternative approach. Rather than modeling the distribution of ν_{ij} conditional on y_{ij0} and X_i, Heckman (1981) suggests modeling the distribution of y_{ij0} conditional on ν_{ij} and X_i. This allows for consistent estimation of the parameters of the density of $y_{ij0}, y_{ij1}, \ldots, y_{ijT}$ conditional on X_i and ν_{ij}. Wooldridge (2005) argues that both methodologies are similarly flawed approximations which rely on a distributional assumption. Moreover, neither approximation has a clear economic interpretation in the context of a reduced form analysis. Consequently, I follow the Wooldridge (2005) approach for ease of computation. The Heckman (1981) approach would have required joint estimation with bivariate normally distributed unobserved effects to explain the mobility outcomes.

Given that the log hazard model in equation (4) is linear in the unobserved effect, I apply the methodology proposed by Wooldridge (2005) by assuming that the conditional distribution of ν_{ij} takes the form:

$$\ln \nu_{ij} | y_{ij0}, \tau_{ij0}, X_i \sim N\left(\tau_{ij0}\alpha_1 + X_i'\alpha_2, \sigma_a^2\right).$$

Here, τ_{ij0} is the initial level of occupational tenure. The magnitude of the correlation between the binary variable y_{ij0} and ν_{ij} depends on τ_{ij0}, which reflects how the sample selection problem worsens with tenure. I assume that the conditional mean of the spell-level unobserved effect depends upon the full history of explanatory covariates that are relevant for the occupational mobility decision, X_i. Specifically, this assumption implies that ν_{ij} depends on $x_{ij1}, \ldots, x_{ijT}$ rather than only one vector x_{ijt} for some survey time t during spell j.

Given the conditional distribution of the unobserved effect, I decompose the logarithm of ν_{ij} in the following manner, where $a_{ij} \sim N(0, \sigma_a^2)$:

$$\ln \nu_{ij} = \tau_{ij0}\alpha_1 + X_i'\alpha_2 + a_{ij}.$$

According to this assumption, ν_{ij} is independent across occupational spells conditional on the full history of observable covariates in X_i. However, ν_{ij} would not be independent across occupational spells within respondents in a model that does not condition on X_i. This dependence stems from the assumption that the conditional mean of the distribution of ν_{ij} depends on X_i, which does not vary across spells within individuals.

The log of the hazard given in equation (4) can be expressed as follows to embed the assumed density of ν_{ij} conditional on y_{ij0}, τ_{ij0}, and X_i:

$$\ln \lambda(\tau_{ijt}; X_i, a_{ij}) = b(\tau_{ijt})'\gamma + x_{ijt}'\beta + \tau_{ij0}\alpha_1 + X_i'\alpha_2 + a_{ij}. \tag{8}$$

Depending upon the contents of X_i, the computational burden of estimating this model may be comparable to the computational burden of estimating the log hazard in equation (4). Estimation is straightforward with the aid of standard mixed proportional hazard software. A second advantage of the approach described by Wooldridge (2005) is that the assumed conditional distribution of ν_{ij} is fairly flexible. Consequently, this assumed distribution may provide a good approximation to the true conditional distribution of ν_{ij}. If this is not the case, the resulting estimates of γ will be inconsistent. Even if it is possible to estimate γ consistently, it may not be possible to identify the relationship between some explanatory covariates and the probability of an occupational change. Specifically, it is not possible to identify separately the direct effects of time-constant covariates in X_i (*i.e.* the β parameters) and the indirect effects (*i.e.* the α parameters). While not ideal, this is not particularly problematic for the present analysis; I am more interested in estimating duration dependence than I am the effects of the explanatory covariates on the hazard function.

Wooldridge (2005) shows for the general case how to derive the likelihood contribution implied by the assumed conditional density of the unobserved effect. He also describes for the general case conditions under which this likelihood contribution yields consistent parameter estimates of the joint density of $y_{ij1}, \ldots, y_{ijt}$ given y_{ij0} and X_i. In the present context, the hazard function can be used to construct the probability that a spell survives through time T, given y_{ij0}, ν_{ij}, and X_i:

$$S\left(T; X_i, \{\tau_{ijk}\}_{k=0}^{T}, a_{ij}\right) = \prod_{t=1}^{T} \exp\left[-\int_{\tau_{ij,t-1}}^{\tau_{ijt}} \lambda(s; X_i, a_{ij})ds\right]. \tag{9}$$

Equation (9) gives the survivor function conditional on the unobserved effect. In order to compute the value of the partial likelihood conditional on unobserved heterogeneity, I integrate out the stochastic component of ν_{ij}. Specifically, the contribution to the partial likelihood of individual i in occupational spell j is given by the following equation:

$$\begin{aligned} L_{ij} = \int_0^\infty & \left[S\left(t^c; X_i, \{\tau_{ijk}\}_{k=0}^{t^c}, a\right)\right]^{d_{ij}} \times \\ & \left[S\left(t^l; X_i, \{\tau_{ijk}\}_{k=0}^{t^l}, a\right) - S\left(t^u; X_i, \{\tau_{ijk}\}_{k=0}^{t^u}, a\right)\right]^{1-d_{ij}} \frac{1}{\sigma_a}\phi\left(\frac{a}{\sigma_a}\right) da. \end{aligned} \tag{10}$$

This partial likelihood contribution is the joint density of $(y_{ij1}, \ldots, y_{ijT})$ conditional on $(y_{ij0}, \{\tau_{ijk}\}_{k=0}^{T}, X_i)$ for those spells characterized by a non-zero correlation between the unobserved effect and the initial condition. Specifically, all spells in progress at the beginning of the sample are associated with a likelihood contribution of the form in equation (10).

By contrast, occupational spells that begin during the survey are assumed to have initial conditions which are uncorrelated with the unobserved effect. In the terminology of Heckman (1981), I assume that I observe the start of a genuinely new stochastic process generating observed spell duration. In this case, the level of initial tenure is exogenous. Consequently, these spells have a partial likelihood contribution given by equation (7). For these spells, the true parameter values α_1 and α_2 are both zero by assumption. This implies that ν_{ij} has conditional mean 0 and that ν_{ij} is identically a_{ij}. After taking the product of these partial likelihood contributions, I estimate the parameters of the hazard function via maximum likelihood.

The similarities between these two types of partial likelihood contributions might lead us to question the need to pursue the approach recommended by Wooldridge (2005). Despite these similarities, the likelihood contribution in equation (10) results from a conceptually different model and yields consistent estimates under different circumstances than does the one in equation (7). Specifically, the claim that standard estimation software can estimate γ consistently does not imply that a_{ij} is uncorrelated with $b(\tau_{ijt})$. Rather, consistent estimation requires that a_{ij} be independent of τ_{ij0}. Furthermore, the claim that standard estimation software can estimate β consistently for the time-varying covariates does not imply that ν_{ij} is uncorrelated with X_i. In fact, the mean of the distribution of ν_{ij} is determined in part by X_i. This dependence approximates any correlation between spell-level unobserved heterogeneity and the observable covariates. Consistent estimation of β for time-varying covariates requires that only the stochastic component of ν_{ij} (a_{ij}) be independent of X_i.

4 Results

I now present the results of the model posited in section 3 estimated on PSID data and SIPP data. Section 4.1 discusses the estimates of the proportional hazard model specified in section 3.1. Section 4.2 elaborates on the estimates of the mixed proportional hazard model from section 3.2 that treats the initial condition as exogenous. Finally, section 4.3 reports the estimates of the mixed proportional hazard model from section 3.3 that treats the initial condition as endogenous.

4.1 Proportional Hazard Model

The estimates of γ from the proportional hazard model described in section 3.1 are presented in Tables 3 and 4 based on PSID data and SIPP data, respectively. Recall that the vector γ contains the main parameter estimates of interest for this study, as $b(\tau_{ijt})'\gamma$ represents an approximation to the baseline hazard function. Column (1) of Table 3 includes the results of a model with occupational tenure calculated using the Full Depreciation assumption. Figure 1 depicts the baseline hazard implied by these estimates. Column (2) of Table 3 reports the results of a model with occupational tenure calculated using the No Depreciation assumption. Figure 2 illustrates the baseline hazard implied by these estimates. Figure 3 depicts the baseline hazard implied by the estimates in Table 4 with occupational tenure calculated using the Full Depreciation assumption.

Under both assumptions for occupational tenure, I find evidence in PSID data that the baseline hazard increases at lower levels of tenure, then decreases or remains flat at higher levels of tenure.[25] Workers become more likely to change occupations as they accumulate tenure during the first year of a new occupational spell. Workers become less likely to change occupations as they accumulate tenure after spending three years

[25]To the extent that there is measurement error in occupational tenure for spells already in progress at the start of the sample, these estimates suggest that the estimated baseline hazard model is biased downwards.

in the occupation. The rate of decline in the probability of an occupational change is relatively high at first, then slows as workers accumulate tenure in the occupation. Indeed, the region of the estimated baseline hazard above 17 years of tenure is the only piece of the function that has a slope which is statistically insignificant from 0 at standard confidence levels. However, I expected to find only one peak in the estimated baseline hazard function. It is unclear why workers would be less likely to exit occupations with tenure between one and two years of tenure and why this tendency would reverse between two and three years of tenure.

Table 4 reveals two salient qualitative differences between the results from the PSID and the SIPP. First, the estimates of the baseline hazard model on SIPP data do not display the same increasing likelihood of occupational exit over the first year in a new occupational spell. Rather, beginning from the first month in a new spell, workers appear to become less likely to change occupations as they accumulate tenure. Second, this decreasing trend appears to continue until workers become increasingly likely to exit the occupation as they accumulate tenure after 17 years in an occupational spell. These differences may stem from differences in the specifications used for the PSID and SIPP analyses.

These results are as expected. Some workers may learn quickly that their occupational match is unsatisfactory. More workers are likely to learn this as more information arrives. If workers exit the occupation after learning that their occupational match is unsatisfactory, this would yield the increasing baseline hazard function early in occupational spells that we observe in PSID data. After workers with relatively poor occupational matches exit, workers with relatively strong occupational matches would remain. Thus, workers that remain in their occupational spells for longer periods would be less likely to leave their matches at all levels of occupational tenure. While some workers may learn slowly that their occupational match is unsatisfactory, this outcome is less likely as workers accumulate more tenure. Consequently, workers would become less likely to exit an occupation as they accumulate tenure at high levels. This behavior would generate the non-increasing baseline hazard function late in occupational spells that we observe in both PSID data and SIPP data.

The estimates of the β parameters are generally consistent with the findings of the occupational mobility literature. These estimates are presented in Tables A.1 and A.2 for the PSID and the SIPP, respectively. Kambourov and Manovskii (2008) and Parrado et al. (2007) document that older workers and better educated workers are less likely to change occupations. Kambourov and Manovskii (2008) also finds that government workers are less likely to change occupations. Finally, Moscarini and Vella (2008) find evidence that more educated workers and workers with family commitments are less likely to change occupations. However, they also document that the effects of these individual characteristics are diminished during hard macroeconomic times. With one exception, I find evidence in the PSID which is consistent with all of these findings. The only inconsistency I find is that older workers' tendency to change occupations less often appears to be amplified during poor macroeconomic times. Similarly, the results of the SIPP analysis are generally consistent with previous literature. The only inconsistencies I find are that married workers' and more educated workers' tendency to change occupations less often appears to be amplified during poor macroeconomic times. By contrast, Moscarini and Vella (2008) find that poor macroeconomic times dampen these tendencies. These conclusions result from estimating a model with 1-digit occupation fixed effects. This suggests that variation in observables explains some differences in occupational mobility, even after removing the effects of unobserved heterogeneity within 1-digit occupation.

4.2 Mixed Proportional Hazard Model Assuming an Exogenous Initial Condition

The estimates of γ from the mixed proportional hazard model described in section 3.2 are presented in Tables 5 and 6 for the PSID and the SIPP, respectively.[26] This model assumes that the initial condition is exogenous. Column (1) of Table 5 contains the results of a model with occupational tenure calculated using the Full Depreciation assumption. Figure 4 shows the baseline hazard implied by these estimates. Column (2) contains the results of a model with occupational tenure calculated using the No Depreciation assumption.[27] Figure 5 illustrates the baseline hazard implied by these estimates. Figure 6 depicts the baseline hazard implied by the estimates in Table 6 with occupational tenure computed according to the Full Depreciation assumption.

Several conclusions emerge upon comparing the estimates from the PSID in Tables 5 and 3. First, introducing spell-level unobserved heterogeneity to the proportional hazard model does not seem to have a qualitative effect on the estimated shape of the baseline hazard function. Under both assumptions for occupational tenure, I find that the baseline hazard increases at lower levels of tenure, then decreases at higher levels of tenure. Similarly, a comparison of estimates from SIPP data in Tables 6 and 4 reveals little qualitative impact on the estimated shape of the baseline hazard function. The only qualitative difference is that the positive slope of the baseline hazard after 17 years of tenure in the proportional hazard model no longer differs statistically from 0 at standard confidence levels in the mixed proportional hazard model. For both PSID data and SIPP data, the effects of the key explanatory covariates on occupational mobility are similarly consistent with the evidence presented in Kambourov and Manovskii (2008), Parrado et al. (2007), and Moscarini and Vella

[26] Gauss-Hermite Quadrature with 12 support points was used to approximate the normal integral.

[27] Unobserved heterogeneity ν_{ij} is assumed to differ across a respondent's spells in the same occupation. For instance, suppose that a carpenter decided to become a salesman, only to return to his occupation as a carpenter after several years. In this case, the two spells as a carpenter are assumed to have a different unobserved effect.

(2008). The estimates of these coefficients are presented in Table A.3 and A.4 for PSID and SIPP data, respectively.

Second, introducing spell-level unobserved heterogeneity does seem to have a quantitative effect on the estimated shape of the baseline hazard function. The PSID analysis illustrates that estimates of γ from the proportional hazard model seem to be biased in the direction of negative duration dependence at low levels of occupational tenure. While this bias appears to be present in SIPP data between 0 and 1 years of tenure, between 1 and 2 years of tenure the estimates of the proportional hazard model seem to be biased in the direction of positive duration dependence. Tables 5 and 6 also show that the estimate of σ_a is strongly statistically significant under both tenure assumptions. This suggests that there is some relevant form of heterogeneity across occupational spells which is not captured by either X_i or $b(\tau_{ijt})$. Since X_i includes 1-digit occupation fixed effects, unobserved heterogeneity across occupational spells in the same 1-digit occupation appears to explain some differences in occupational mobility behavior.

4.3 Mixed Proportional Hazard Model Assuming an Endogenous Initial Condition

The estimates of the mixed proportional hazard model described in section 3.3 are presented in columns (1) and (3) of Table 7 and column (1) of Table 8 for the PSID and the SIPP, respectively.[28] This model accounts for the endogeneity of the initial condition by specifying the conditional density of the unobserved effect given y_{ij0} and X_i. Column (1) of Table 7 includes the results of a model with occupational tenure calculated using the Full Depreciation assumption. Figure 7 depicts the baseline hazard implied by these estimates. Column (3) of Table 7 includes the results of a

[28]Gauss-Hermite Quadrature with 12 support points was used to approximate the normal integral.

model with occupational tenure calculated using the No Depreciation assumption.[29] Figure 8 shows the baseline hazard implied by these estimates. Figure 9 illustrates the baseline hazard implied by the estimates in column (1) of Table 8 with occupational tenure computed under the Full Depreciation assumption.

Accounting for the endogeneity of the initial condition does seem to have a qualitative impact on the shape of the baseline hazard. As column (1) of Table 7 illustrates, the baseline hazard function no longer appears to decrease at higher levels of occupational tenure. I find that the estimated baseline hazard function is now flat between 3 and 4 years of occupational tenure and upward sloping thereafter.[30] Similarly, the estimates in column (3) of Table 7 suggest that the baseline hazard function slopes upwards above 4 years of occupational tenure under the No Depreciation assumption. The results of the SIPP analysis in Table 8 lead to a similar inference, with the baseline hazard function now strictly increasing after 2 years of occupational tenure.

This poses a stark contrast to the estimates of γ that I present in Tables 3 and 5 for the PSID. Those estimates suggest that the baseline hazard is flat or decreasing at higher levels of tenure. Regardless of how I compute occupational tenure, the estimates of γ at higher levels of tenure in Table 7 exceed the corresponding estimates in Tables 3 and 5. A comparison of Figures 4 and 7 (or Figures 5 and 8) emphasizes how striking these differences are. This contrast is also apparent for the SIPP. Table 4 presents a baseline hazard function which does seem to be increasing above 17 years of tenure in the proportional hazard model. Nevertheless, no other segments of the baseline hazard function seem to be increasing in either the proportional hazard model or the mixed proportional hazard model assuming exogenous initial conditions.

[29] The stochastic component a_{ij} of the unobserved effect is assumed to differ across a respondent's spells in the same occupation. For instance, suppose that a carpenter decided to become a salesman, only to return to his occupation as a carpenter after several years. In this case, the two spells as a carpenter are assumed to have a different stochastic component of the unobserved effect.

[30] To the extent that there is measurement error in occupational tenure for spells already in progress at the start of the sample, these estimates suggest that the estimated baseline hazard model is biased upwards.

It appears that the initial conditions problem introduces a negative bias in estimates of the effect of occupational tenure on the probability of an occupational change at higher levels of tenure. The negative and statistically significant estimated coefficient on initial tenure in the conditional mean of the distribution of spell-level unobserved heterogeneity supports this conclusion. This result is expected, since individuals with higher initial occupational tenure are likely to have occupational matches of better unobserved quality.

This evidence of an increasing baseline hazard function at high levels of tenure is surprising. To the extent that occupational tenure serves as a proxy for occupation-specific human capital accumulation, occupational tenure accumulation should decrease the probability of an occupational change. The probability of finding a better alternative match is expected to decrease with occupational tenure as more occupational match improvements accumulate. If the baseline hazard function is increasing at higher levels of tenure, this suggests that the bond between workers and occupations begins to weaken at higher levels of tenure.

5 Wages and Non-Wage Determinants of Mobility

The estimates presented in section 4 come from a model which does not condition on wage outcomes. Consequently, the estimates of γ presented in columns (1) and (3) of Table 7 and column (1) of Table 8 reflect the effects of occupational tenure on the probability of an occupational change through both pecuniary and non-pecuniary channels. However, the literature on occupational mobility has established that both wages and non-wage characteristics of occupational matches play an important role in the occupational mobility decision.

The evidence suggests that the accumulation of occupational tenure increases wages, though at a decreasing rate.[31] If occupation-specific human capital depreciates,

[31] See Kambourov and Manovskii (2009), Pavan (2011), and Sullivan (2010b).

we may observe a wage decrease at high levels of occupational tenure.[32] The evidence also suggests that workers are less likely to change occupations at higher current wages.[33] This implies that the effect of occupational tenure on occupational mobility through its effect on wages should be convex and potentially u-shaped. Workers initially would be less likely to leave the occupation as they accumulate wage gains with tenure. They eventually would become increasingly likely to change occupations with tenure if wages fall at high tenure levels.

Considerably less is known about how the non-wage characteristics of occupational matches vary over the tenure profile. To improve our understanding of how occupational tenure impacts occupational mobility through non-pecuniary channels, I estimate a version of the mixed proportional hazard model given by equation (8) which conditions on log wages. These estimation results are presented in columns (2) and (4) of Table 7 and column (2) of Table 8 for PSID and SIPP data, respectively. Column (2) of both tables contains the results of a model with occupational tenure calculated using the Full Depreciation assumption. Column (4) of Table 7 contains the results of a model with occupational tenure calculated using the No Depreciation assumption.

Evidence from both the PSID and the SIPP indicates that introducing log-wages to the model has no qualitative impact on the salient features of the estimated baseline hazard function, regardless of how occupational tenure is computed. The baseline hazard function only appears to be affected between 0 and 1 years of tenure for SIPP data and between 1 and 2 years of tenure for PSID data when occupational tenure is computed under the Full Depreciation assumption. In both datasets, I still observe that the baseline hazard function is increasing at higher levels of occupational

[32]Standard human capital accumulation models such as the one proposed in Ben-Porath (1967) suggest that workers at high levels of tenure should allow their human capital to depreciate. In doing so, they devote their time to reaping the rewards of past investments as opposed to building human capital which will bear relatively little fruit before retirement.

[33]See Pavan (2011) and Parrado et al. (2007).

tenure. These results suggest that the non-wage characteristics of a job do change over the occupational tenure profile. Indeed, the effect of occupational tenure on the probability of an occupational change through non-pecuniary channels is positive at high levels of tenure.

5.1 Econometric Model of Wages

If the estimated baseline hazard function displays the same general pattern regardless of whether the model controls for wages, how does occupational tenure affect occupational mobility through wages? To understand this aspect of the relationship between occupational tenure and occupational mobility, I jointly estimate a wage regression and the mixed proportional hazard model given by equation (8). If occupational tenure is a good proxy for occupation-specific human capital, I would expect to find positive and decreasing returns to occupational tenure. The results in Tables 7 and 8, together with previous estimates, point to a negative estimated correlation between wages and the log-hazard. In the presence of positive returns to tenure, this would generate a negative relationship between occupational tenure and occupational mobility through wages. This negative relationship should weaken with tenure to reflect the decreasing returns to occupational tenure.

I posit the following relationship between log-wages w_{ijt} and occupational tenure:

$$w_{ijt} = b^w(\tau_{ijt})'\delta + z'_{ijt}\eta + c_{ij} + \varepsilon_{ijt}. \tag{11}$$

In equation (11), z_{ijt} contains explanatory covariates for individual i in occupational spell j at time t. Note that this imposes the assumption that wages at survey time t only depend on regressors in z_{ijt} and not on the entire history of explanatory covariates. The full history of explanatory covariates is contained in the set Z_i. Given T observations for person i, Z_i is a set of T vectors of regressors $\{z_{ijt}\}_{t=1}^{T}$. The full regressor set z_{ijt} is listed in the notes of Tables 9 and 10 for ease of exposition.

$b^w(\tau_{ijt})$ is assumed to be a vector with six elements, given by the following:

$$b^w(\tau) = \begin{bmatrix} \min(\tau, n_1^w) \\ \max(0, \min(\tau - n_1^w, n_2^w - n_1^w)) \\ \max(0, \min(\tau - n_2^w, n_3^w - n_2^w)) \\ \max(0, \min(\tau - n_3^w, n_4^w - n_3^w)) \\ \max(0, \min(\tau - n_4^w, n_5^w - n_4^w)) \\ \max(0, \tau - n_5^w) \end{bmatrix}.$$

The product $b^w(\tau_{ijt})'\delta$ summarizes the returns to occupational tenure as a piecewise-linear function of tenure τ_{ijt} with five nodes given by n_1^w, n_2^w,...,n_5^w.[34] Thus, δ is a second parameter vector of interest.

The stochastic term ε_{ijt} is assumed to be normally distributed with mean 0 and variance σ_ε^2. The distributional assumption on ε_{ijt} allows me to find the density of wages given observables and the unobserved effect c_{ij}:

$$g(w_{ijt}|y_{ij,t-1} = 0, Z_i, \tau_{ijt}, c_{ij}) = \frac{1}{\sigma_\varepsilon}\phi\left(\frac{w_{ijt} - b^w(\tau_{ijt})'\delta - z_{ijt}'\eta - c_{ij}}{\sigma_\varepsilon}\right).$$

The spell-level unobserved effect c_{ij} captures all spell-level unobserved heterogeneity, such as unobserved, initial occupation-specific ability. In order to compute the value of the partial likelihood conditional on unobserved heterogeneity I integrate out c_{ij}.[35] I assume that c_{ij} is jointly distributed with the stochastic component of ν_{ij} from the mixed proportional hazard model. This accounts for non-random survival of

[34] I select the piecewise-linear approximation of the returns to occupational tenure with nodes $n_1^w = 1$, $n_2^w = 2$, $n_3^w = 7$, $n_4^w = 20$, and $n_5^w = 34$ according to the method proposed by Lillard and Panis (2003).

[35] In general, there are less computationally intensive ways of removing the unobserved effect in linear models. However, I choose to integrate out the unobserved effect given the need to estimate this linear model jointly with a non-linear model.

occupational spells due to high unobserved, initial occupation-specific ability.[36] The cdf associated with this joint distribution is $H(a,c)$. I assume that a_{ij} and c_{ij} are bivariate normally distributed with mean 0 and covariance matrix:

$$\Sigma = \begin{bmatrix} \sigma_a^2 & \sigma_{ac} \\ \sigma_{ac} & \sigma_c^2 \end{bmatrix}.$$

Consider person i who earns wages w_{ijt} in occupational spell j, which is first observed at time t_0 and last observed at time T. This person's partial likelihood contribution during occupational spell j takes the general form:[37]

$$\prod_{t=t_0}^{T} f(y_{ijt}|y_{ij,t-1}, X_i, \{\tau_{ijk}\}_{k=t-1}^{t}) g(w_{ijt}|y_{ij,t-1}, Z_i, \tau_{ijt}). \tag{12}$$

This spell may end either because j is censored at time t^c or because j is observed to end during the time window from t^l to t^u. This person's partial likelihood contribution during occupational spell j takes the specific form:

$$L_i = \begin{cases} \iint S(t^c; a) \prod_{t=t_0}^{T} g(w_{ijt}|y_{ij,t-1}, Z_i, \tau_{ijt}, c) h(a,c)\ da\ dc & \text{if } d_{ij} = 1 \\ \iint \left[S(t^l; a) - S(t^u; a)\right] \prod_{t=t_0}^{T} g(w_{ijt}|y_{ij,t-1}, Z_i, \tau_{ijt}, c) h(a,c)\ da\ dc & \text{if } d_{ij} = 0 \end{cases}. \tag{13}$$

The joint density h represents the bivariate normal density of c_{ij} and a_{ij}. Given the partial likelihood contribution above, the parameters of the joint conditional density

[36]One convenient feature of joint estimation is that it accounts for the endogeneity of tenure in the wage model. Matches of high unobserved quality are likely to earn higher wages and they are likely to survive to high levels of occupational tenure. This leads to a positive bias in OLS estimates of the returns to occupational tenure. The most common way to account for this is to use an IV estimator such as the one proposed by Altonji and Shakotko (1987). This is the approach taken by Kambourov and Manovskii (2009) and Sullivan (2010b). I choose to pursue joint estimation instead because this allows me to estimate the effect of occupational tenure on occupational mobility through both pecuniary and non-pecuniary channels.

[37]Since log-wages are included in the conditioning set of the mixed proportional hazard model, equation (12) results from Bayes' Law. This statement assumes that the conditional density of occupational spell durations is dynamically complete.

may be estimated consistently via maximum likelihood.[38]

5.2 Identification

Before proceeding to estimate the models, it is important to discuss how each model is identified. In order to identify the parameters of the conditional density of wages, X_i must contain some determinant of occupational mobility which is excluded from Z_i. Similarly, in order to identify the parameters of the conditional density of occupational spell duration, Z_i must contain some determinant of wages which is excluded from X_i. It is difficult to find such exclusion restrictions because occupational mobility and wages share many of the same determinants.

To identify the parameters of the log-wage regression, Neal (1995) proposes the general strategy of including in X_i variables that are related to search costs, but that are not related to wage offers conditional on observable characteristics. To that end, I include in X_i a married indicator interacted with local unemployment rate.[39] Moscarini and Vella (2008) show evidence that married workers have a tendency to switch occupations less often than non-married workers, although this tendency is weaker in poor macroeconomic times. They argue that married workers may be less likely to change occupations because an occupational change that entails a loss of occupation-specific human capital may lead to wage losses initially. Similarly, if occupational matches are experience goods, then an occupational switch may impose

[38]Gauss-Hermite Quadrature with 12 support points is used to approximate the normal integral over the stochastic component of the unobserved effect in the mixed proportional hazard model, a_i. The unobserved effects in the wage regression, c_{ij} and ε_{ijt}, are not approximated via Gauss-Hermite Quadrature. Instead, the estimation package that I use obtains an expression analytically for the partial likelihood contribution of a continuous model.

[39]The local labor market is defined as the county for the PSID analysis and the state for the SIPP analysis. PSID data include the county unemployment rate for each individual. On the other hand, SIPP does not offer county unemployment rate for each individual, nor does it include county of residence on the public use file. However, SIPP does include state of residence on the public use file. I merge SIPP data with state-level unemployment rates from the Local Area Unemployment Statistics. Where SIPP data group together small states, I compute the local unemployment rate for this group as the unweighted average of the state-level unemployment rate for each state in the group.

a welfare cost on risk averse workers and their families. In stronger macroeconomic times, married workers might be reluctant to impose such a cost on family. However, the low arrival rate of job offers during weaker macroeconomic times may be enough to outweigh this reluctance.

Estimating separately the wage model given by equation (11) shows no evidence from the SIPP of a growing or shrinking wage gap between married workers and unmarried workers during poor macroeconomic times. The estimated coefficient on the interaction between marital status and the state unemployment rate is .000 (t-statistic .102). This result suggests that the inclusion of a married indicator interacted with local unemployment rate in X_i identifies the parameters of the wage regression.

To identify the parameters of the conditional density of occupational spell duration, I include racial and ethnic group indicators in Z_i. This decision stems from the results presented in Parrado et al. (2007). They find no evidence of a significant tendency for white men to be more or less mobile across occupations than non-white men. For this reason, I assume that race and ethnicity are not significant determinants of occupational mobility.

Estimating separate the wage model given by equation (11) shows evidence that the racial and ethnic indicators are significant determinants of wages. White, non-Hispanic workers appear to have a 4.75% wage premium (t-statistic 7.78), while black, non-Hispanic workers do not appear to earn significantly larger or smaller wages (t-statistic 0.395). These results suggest that the inclusion of racial and ethnic indicators in Z_i identifies the parameters of the mixed proportional hazard function.

5.3 Results

Table 9 provides the estimates of the model with partial likelihood contribution given by equation (13) on PSID data. Columns (1) and (2) present the estimates of a model with occupational tenure calculated using the Full Depreciation and No Depreciation assumptions, respectively. Table 10 lists the estimates of the model on SIPP data with occupational tenure calculated using the Full Depreciation assumption. Panel A contains estimates of the mixed proportional hazard model. Panel B offers estimates of the wage model.

As in columns Tables 7 and 8, the baseline hazard function appears to be increasing at high levels of tenure when estimated on PSID data and SIPP data, respectively. Figures 10 and 11 illustrate this relationship in PSID data for the Full Depreciation and No Depreciation assumptions, respectively. Figure 14 illustrates this relationship in SIPP data. This is expected, as the estimates of γ result from mixed proportional hazard models which differ only in the structure of the stochastic component of the unobserved effect, a_{ij}. The estimated coefficients of the piecewise-linear function of occupational tenure in the wage regression are also as expected.

Panel B of Table 9 shows evidence from the PSID that the returns to occupational tenure are positive and statistically significant over the first seven years in an occupation. The estimated returns to tenure level off after this period. Finally, the returns to tenure are negative later in a career. For the Full Depreciation assumption, the returns to tenure are negative between 20 and 34 years of occupational tenure. I can reject at the 90% confidence level the null hypothesis that the slope of this part of the wage-tenure profile is 0. For the No Depreciation assumption, the returns to tenure are negative beyond 34 years of occupational tenure. I can reject at the 95% confidence level the null hypothesis that the slope of this part of the wage-tenure profile is 0. Figures 12 and 13 illustrate this relationship for the Full Depreciation and No Depreciation assumptions, respectively.

Panel B of Table 10 shows evidence from the SIPP that the returns to occupational tenure are positive and statistically significant over the first 34 years in an occupation. The estimated returns to tenure level off after this period. I cannot reject at the 90% confidence level the null hypothesis that the slope of this part of the wage-tenure profile is 0. Figure 15 illustrates this relationship.

Also as expected, panel A of Table 9 reports a negative and statistically significant estimated coefficient on log-wages in the mixed proportional hazard model. This result, paired with the statistically significant returns to occupational tenure, suggests that occupational tenure affects occupational mobility at least in part through its effect on wages. The accumulation of tenure appears to be rewarded by wage gains at first, followed by weaker or negative returns to tenure later in careers. As workers earn more by accumulating occupational tenure earlier in careers, they appear to become less likely to change occupations. To the extent that the returns to occupational tenure become negative later in careers, workers seem to become more likely to change occupations as they accumulate tenure. The increasing estimated baseline hazard function later in careers suggests that occupational tenure also affects occupational mobility if wages remain unchanged. The eventually decreasing returns to tenure in PSID data indicate that the relationship between occupational tenure and occupational mobility at high levels of tenure reflects both pecuniary and non-pecuniary considerations. By contrast, there do not appear to be decreasing returns to tenure at any tenure level in SIPP data. Consequently, the impact of occupational tenure on occupational mobility through non-pecuniary channels appears to counteract the impact through pecuniary channels below 34 years of tenure. Above 34 years of tenure, the relationship between occupational tenure and occupational mobility seems to reflect only non-pecuniary considerations.

Results from the PSID point to a positive correlation (ρ) between the unobserved effect c_{ij} in the wage model and the stochastic component a_{ij} of the unobserved effect in the mixed proportional hazard model. This suggests that workers who earn higher wages as a result of their unobserved occupation-specific ability are more likely to change occupations due to the non-pecuniary characteristics of their occupational match. In other words, workers earning higher wages in their current occupation than workers with the same observable characteristics appear to be less attached to their occupations for unobserved, non-pecuniary reasons. On the other hand, results from the SIPP point to a negative correlation between c_{ij} and a_{ij}. This suggests that workers who earn higher wages as a result of their unobserved occupation-specific ability are less likely to change occupations due to the non-pecuniary characteristics of their occupational match.

The implied relationship between spell-level unobserved heterogeneity and the probability of an occupational change is ambiguous in PSID data. On one hand, workers who have high spell-level unobserved ability (c_{ij}) are rewarded with higher wages and consequently are less likely to change occupations. On the other hand, these same workers are more likely to leave their occupations for non-pecuniary reasons due to their initial unobserved match quality (a_{ij}). We can use the estimates presented in Table 9 and 10 to assess which of these effects dominates. PSID estimates suggest that workers who are one standard deviation above the mean of the distribution of c_{ij} have a log hazard function which is 0.337 higher on average than workers who are at the mean of the distribution of c_{ij}.[40] This result is puzzling. I expected to find that workers who earn higher wages due to their unobserved ability are less likely to leave occupations. On the other hand, the implied relationship between spell-level unobserved heterogeneity and the probability of an occupational change is negative in SIPP data.

6 Conclusion

In this paper, I estimate the relationship between occupational tenure and the probability of an occupational change conditional on spell-level unobserved heterogeneity.

[40] A one standard deviation increase in c_{ij} increases log wages by 0.805 on average. Given the estimated coefficient on log wages in Panel A of Table 9, this decreases the log hazard function by 0.088. The conditional mean of a_{ij} given $c_{ij} = 0.805$ is computed as $\mu_{a|c=0.805} = \rho\sigma_a = 0.203 \times 2.094$. This implies that on average, a one standard deviation increase in c_{ij} increases the log hazard function by 0.425 via its effect on the conditional distribution of a_{ij}.

I use data from the Panel Study of Income Dynamics for the period 1981-1997 and the 1990 through 1993 panels of the Survey of Income and Program Participation. Analyses that estimate models of occupational mobility typically disregard information provided by individuals who did not begin their labor force attachment during the survey. Instead, I choose to exploit information from these individuals. This allows me to obtain more precise estimates of how the effect of occupational tenure on occupational mobility varies with tenure. I account for the resulting initial conditions problem following the method proposed in Wooldridge (2005). Specifically, I model the conditional density of spell-level unobserved heterogeneity given observables and the initial level of tenure.

I find evidence that the initial conditions problem introduces a negative bias in estimated duration dependence. After removing this bias, I estimate that the baseline hazard function is increasing at high levels of tenure. This relationship between occupational tenure and occupational mobility appears to reflect both pecuniary and non-pecuniary considerations in PSID data but only non-pecuniary considerations in SIPP data. This underscores the importance of obtaining more precise estimates of the effect of occupational tenure on occupational mobility at high levels of tenure.

Much work remains to be done in order to understand the relationship between occupational tenure and occupational mobility. For example, it would be desirable to estimate a more structural model of mobility than the one considered here. This would allow for a better explanation of why the effect of non-pecuniary considerations on the occupational mobility decision varies over the tenure profile. Second, one might ask how important it is to include information on occupational spells of respondents who begin their attachment to the labor force at some unobserved time. This would serve as a test of how well the method proposed in Wooldridge (2005) solves the initial conditions problem. Third, one might allow for the pattern of mobility over the tenure profile to vary with an occupation's relative proximity to other occupations, perhaps using measures of task intensities. This would enable an investigation of whether the estimated increasing baseline hazard function at higher tenure levels characterizes all occupations, or whether it mainly characterizes occupations which employ tasks in relatively similar intensities to their neighboring occupations. Finally, extending the SIPP analysis detailed here to the forthcoming SIPP-EHC may reduce the impact of seam bias relative to the SIPP analysis. SIPP-EHC will include detailed information on the starting and ending weeks of up to seven jobs held during the twelve month reference period. The four month reference period of SIPP implies more seams relative to SIPP-EHC, perhaps resulting in more spurious occupational changes.

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7 Figures and Tables

Table 1: Sample Characteristics — PSID

	Mean	S.D.	Min	Max
Spells per person	2.310	2.044	1	13
Spell duration (years) – Full Depreciation	3.160	—	0	58.270
Spell duration (years) – No Depreciation	3.301	—	0	58.270
Return spell?	0.069	0.227	0	1
Wage ($)	13.48	109.04	0.00	34807.23
Age (years)	37.898	11.666	16	94
Education (years)	12.482	2.630	0	17
Married?	0.700	0.458	0	1
White, non-Hispanic?	0.503	0.500	0	1
Black non-Hispanic?	0.253	0.435	0	1
Person-year observations	154,377			
Spells	44,458			
Individuals	21,449			

Source: 1981-1997 Panel Study of Income Dynamics
Note: Under the assumption of full depreciation, occupation-specific human capital is assumed to depreciate fully when an occupational spell ends. As such, if a worker leaves one occupation for an alternate occupation only to return later, that worker's tenure is initialized at 0 upon returning to the original occupation. Under the assumption of no depreciation, occupation-specific human capital is assumed to remain undepreciated when an occupational spell ends. As such, if a worker leaves one occupation for an alternate occupation only to return later, that worker's tenure continues to accumulate as if there were no interruption. All occupational spells are defined at the 3-digit level using the 1970 Census occupational classification system. See the Appendix for details of how I construct data on occupational changes and occupational tenure. Wages are listed in year 2000 dollars.

Table 2: Sample Characteristics — SIPP

	Mean	S.D.	Min	Max
Spells per person	1.342	0.762	1	10
Spell duration (years) – Full Depreciation	6.645	7.921	0	48.208
Wage ($)	14.69	13.19	0	3,995.52
Age (years)	41.085	10.982	13	85
Education (years)	13.215	2.788	0	18
Married?	0.750	0.433	0	1
White, non-Hispanic?	0.795	0.404	0	1
Black non-Hispanic?	0.092	0.289	0	1
Person-month observations	1,870,755			
Spells	92,736			
Individuals	68,929			

Source: 1990-1993 panels of the Survey of Income and Program Participation
Note: Under the assumption of full depreciation, occupation-specific human capital is assumed to depreciate fully when an occupational spell ends. As such, if a worker leaves one occupation for an alternate occupation only to return later, that worker's tenure is initialized at 0 upon returning to the original occupation. All occupational spells are defined at the 3-digit level using the 1980 and 1990 Census occupational classification system for the 1990-1991 panels and the 1992-1993 panels, respectively. See the Appendix for details of how I construct data on occupational changes and occupational tenure. Wages are listed in year 2000 dollars.

Table 3: Maximum Likelihood Estimates of Proportional Hazard Model — PSID Data

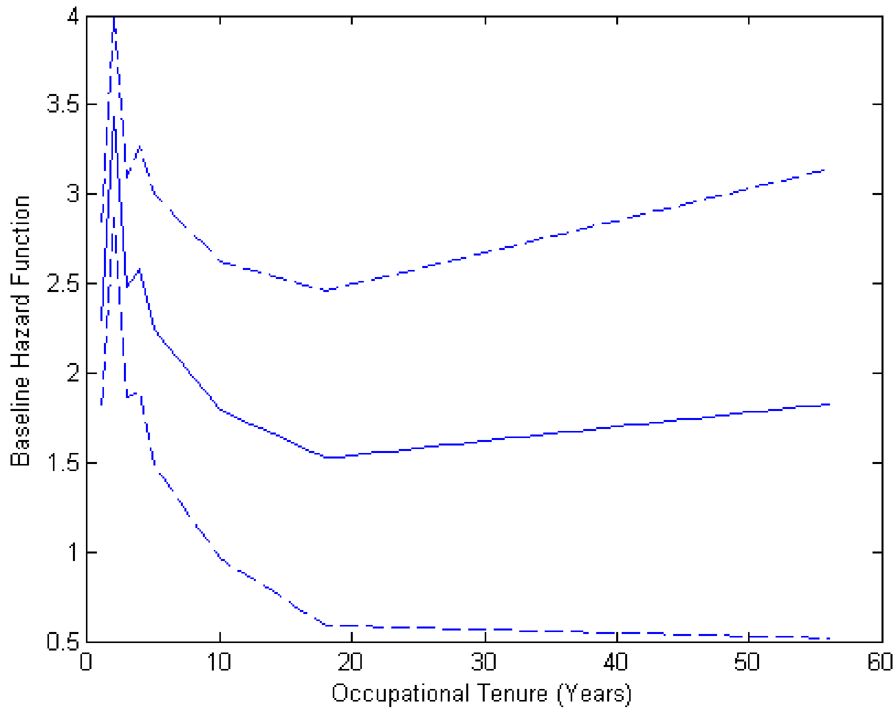
	(1)	(2)
0-1 years tenure	1.132***	1.094***
	(.028)	(.029)
1-2 years tenure	-0.947***	-0.933***
	(.033)	(.033)
2-3 years tenure	0.104**	0.114***
	(.043)	(.043)
3-4 years tenure	-0.339***	-0.364***
	(.042)	(.041)
4-9 years tenure	-0.090***	-0.084***
	(.009)	(.009)
9-17 years tenure	-0.034***	-0.043***
	(.008)	(.008)
17+ years tenure	0.008	-0.004
	(.006)	(.006)
$-\ln L$	77,246.430	77,124.843

Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses. The baseline hazard is assumed to be piecewise-linear, with 1-digit occupation-specific intercepts. I choose the baseline hazard function according to the strategy suggested by Lillard and Panis (2003). The values at which the approximated baseline hazard is evaluated within a spell are determined by the depreciation assumption. Column (1) assumes full specific-capital depreciation between two spells in the same occupation. Column (2) assumes no specific-capital depreciation between two spells in the same occupation. Additional regressors are a linear time trend, a male indicator, a cubic in education, a married indicator, county unemployment rate, weeks unemployed in the survey year, union member indicator, government worker indicator, self-employed indicator, part-time worker indicator, a cubic in age, and region indicators. The regressor set also includes interactions of county unemployment rate with the married indicator, the cubic in education, and the cubic in age. The estimates presented in column (2) result from a model which also includes in the regressor set occupational tenure in the previous 6 occupations and an indicator variable which takes value one if the current spell is a return to an occupation which was previously sampled. All occupational spells are defined at the 3-digit level using the 1970 Census occupational classification system. See the Appendix for details of how data on occupational changes were derived.

Table 4: Maximum Likelihood Estimates of Proportional Hazard Model — SIPP Data

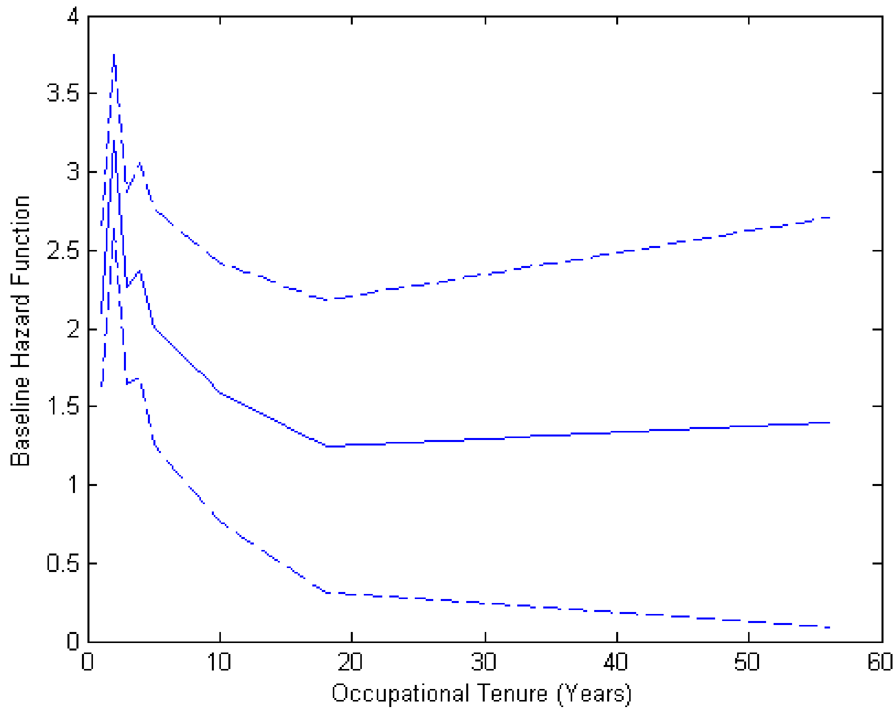
	(1)
0-12 months (0-1 years) tenure	-.056***
	(.002)
12-24 months (1-2 years) tenure	-.062***
	(.003)
24-36 months (2-3 years) tenure	-.011**
	(.005)
36-48 months (3-4 years) tenure	-.008*
	(.004)
48-108 months (4-9 years) tenure	-.008***
	(.001)
108-204 months (9-17 years) tenure	-.003***
	(.001)
204+ months (17+ years) tenure	.001*
	(.000)
$-\ln L$	113,746.521

Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses. The baseline hazard is assumed to be piecewise-linear, with 1-digit occupation-specific intercepts. I choose the baseline hazard function according to the strategy suggested by Lillard and Panis (2003). The values at which the approximated baseline hazard is evaluated within a spell are determined by the depreciation assumption. Column (1) assumes full specific-capital depreciation between two spells in the same occupation. Additional regressors are a male indicator, a cubic in education, a married indicator, weeks unemployed in the reference month, union member indicator, government worker indicator, part-time worker indicator, and region indicators. The regressor set also includes interactions of state unemployment rate with the married indicator and the cubic in education. All occupational spells are defined at the 3-digit level using the 1980 and 1990 Census occupational classification system for the 1990-1991 panels and the 1992-1993 panels, respectively. See the Appendix for details of how data on occupational changes were derived.

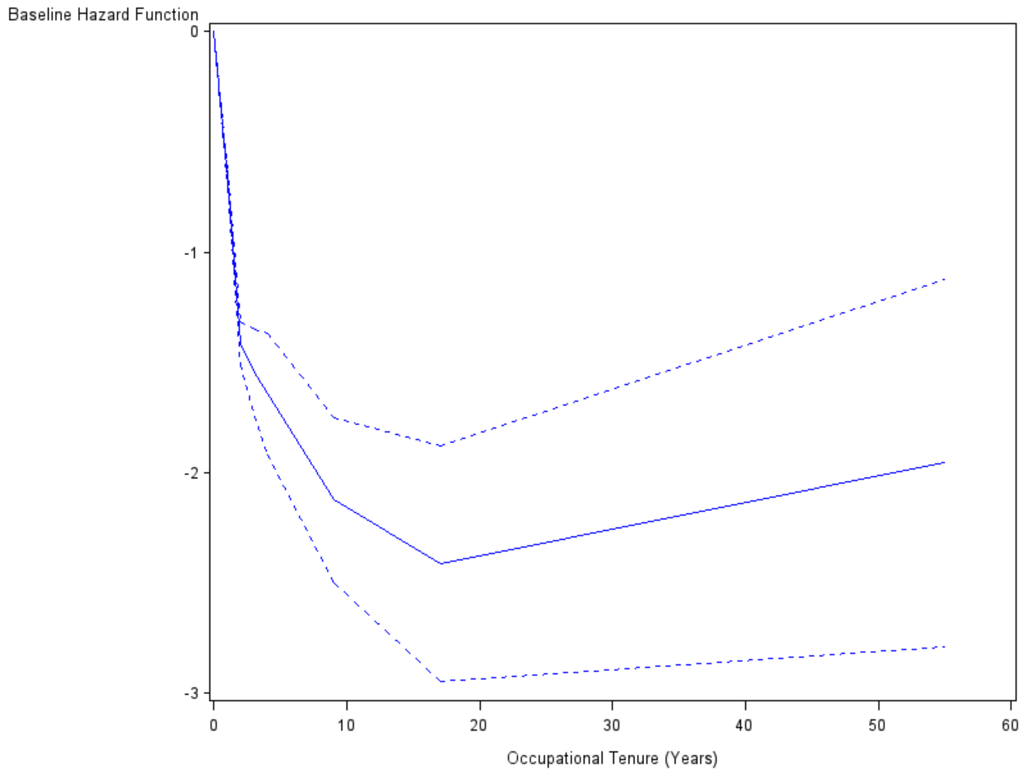


Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics

Figure 1: This figure plots the baseline hazard function of a proportional hazard model. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the Full Depreciation assumption. See column (1) of Table 3 for details regarding the specification.



Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics
Figure 2: This figure plots the baseline hazard function of a proportional hazard model. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the No Depreciation assumption. See column (2) of Table 3 for details regarding the specification.



Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics

Figure 3: This figure plots the baseline hazard function of a proportional hazard model. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the Full Depreciation assumption. See Table 4 for details regarding the specification.

Table 5: ML Estimates of Mixed Proportional Hazard Model Assuming Exogenous Initial Conditions — PSID Data

	(1)	(2)
0-1 years tenure	1.957***	1.681***
	(.084)	(.064)
1-2 years tenure	-0.649***	-0.719***
	(.042)	(.038)
2-3 years tenure	0.174***	0.162***
	(.047)	(.045)
3-4 years tenure	-0.251***	-0.315***
	(.046)	(.043)
4-9 years tenure	-0.075***	-0.072***
	(.011)	(.010)
9-17 years tenure	-0.050***	-0.055***
	(.009)	(.009)
17+ years tenure	0.001	-0.002
	(.007)	(.007)
σ_a	1.126***	0.917***
	(.058)	(.047)
$-\ln L$	76,865.742	76,838.689

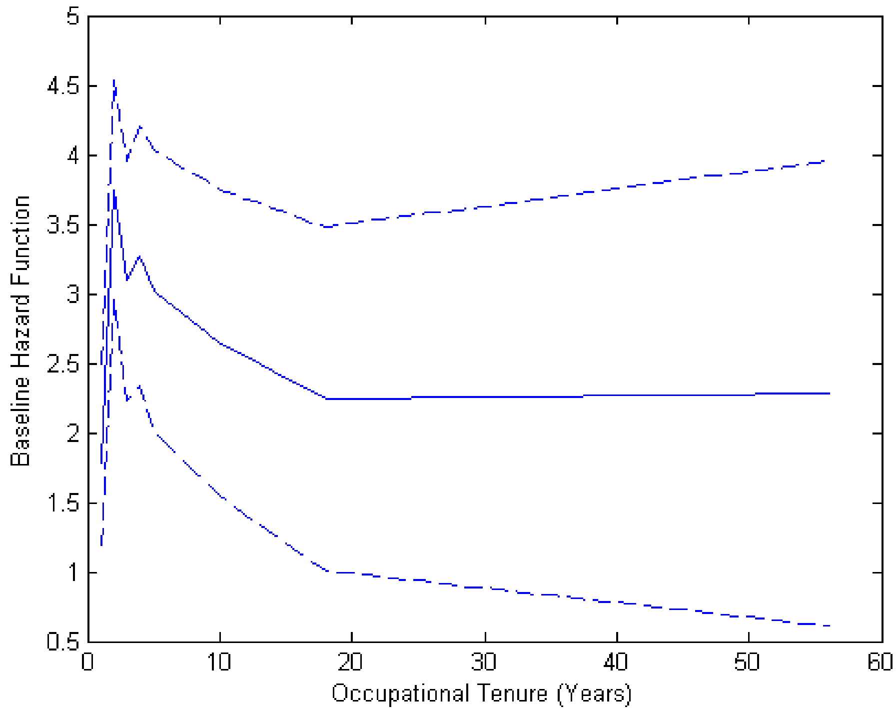
Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics

Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses. The estimates presented in this table result from a mixed proportional hazard model which accounts for spell-level unobserved heterogeneity ν_{ij}. I assume that the log of this unobserved effect is normally distributed with mean 0 and variance σ_a^2. The baseline hazard is assumed to be piecewise-linear, with 1-digit occupation-specific intercepts. I choose the baseline hazard function according to the strategy suggested by Lillard and Panis (2003). The values at which the approximated baseline hazard is evaluated within a spell are determined by the depreciation assumption. Column (1) assumes full specific-capital depreciation between two spells in the same occupation. Column (2) assumes no specific-capital depreciation between two spells in the same occupation. Additional regressors are a linear time trend, a male indicator, a cubic in education, a married indicator, county unemployment rate, weeks unemployed in the survey year, union member indicator, government worker indicator, self-employed indicator, part-time worker indicator, a cubic in age, and region indicators. The regressor set also includes interactions of county unemployment rate with the married indicator, the cubic in education, and the cubic in age. The estimates presented in column (2) result from a model which also includes in the regressor set occupational tenure in the previous 6 occupations and an indicator variable which takes value one if the current spell is a return to an occupation which was previously sampled. All occupational spells are defined at the 3-digit level using the 1970 Census occupational classification system. See the Appendix for details of how data on occupational changes were derived.

Table 6: ML Estimates of Mixed Proportional Hazard Model Assuming Exogenous Initial Conditions — SIPP Data

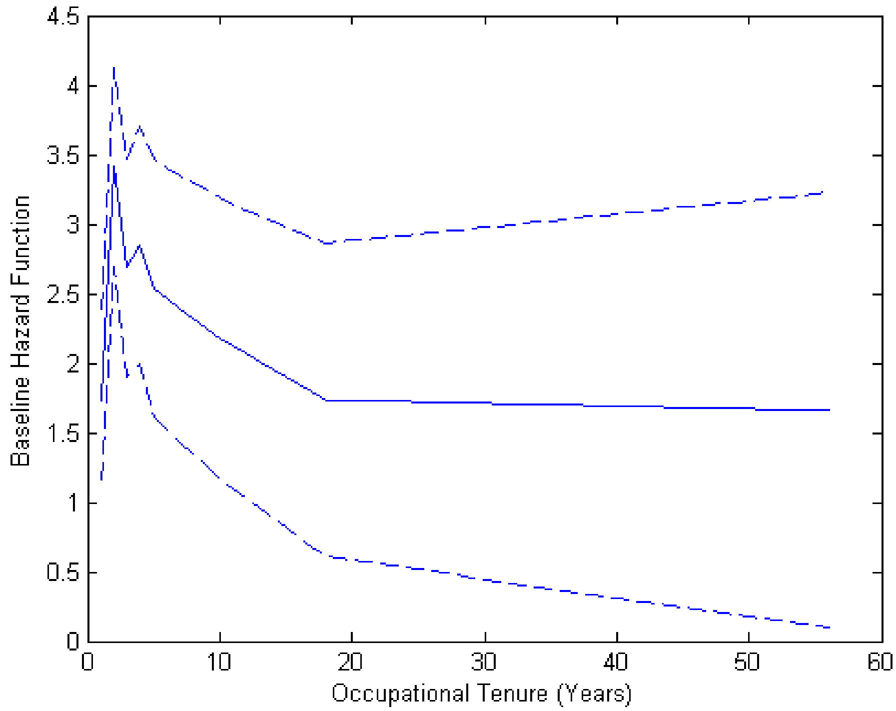
	(1)
0-12 months (0-1 years) tenure	-.016***
	(.003)
12-24 months (1-2 years) tenure	-.075***
	(.004)
24-36 months (2-3 years) tenure	-.015***
	(.005)
36-48 months (3-4 years) tenure	-.013***
	(.005)
48-108 months (4-9 years) tenure	-.009***
	(.001)
108-204 months (9-17 years) tenure	-.003***
	(.001)
204+ months (17+ years) tenure	.001
	(.000)
σ_a	.786***
	(.020)
$-\ln L$	113,409.413

Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses. The estimates presented in this table result from a mixed proportional hazard model which accounts for spell-level unobserved heterogeneity ν_{ij}. I assume that the log of this unobserved effect is normally distributed with mean 0 and variance σ_a^2. The baseline hazard is assumed to be piecewise-linear, with 1-digit occupation-specific intercepts. I choose the baseline hazard function according to the strategy suggested by Lillard and Panis (2003). The values at which the approximated baseline hazard is evaluated within a spell are determined by the depreciation assumption. Column (1) assumes full specific-capital depreciation between two spells in the same occupation. Additional regressors are a male indicator, a cubic in education, a married indicator, weeks unemployed in the reference month, union member indicator, government worker indicator, part-time worker indicator, and region indicators. The regressor set also includes interactions of state unemployment rate with the married indicator and the cubic in education. All occupational spells are defined at the 3-digit level using the 1980 and 1990 Census occupational classification system for the 1990-1991 panels and the 1992-1993 panels, respectively. See the Appendix for details of how data on occupational changes were derived.

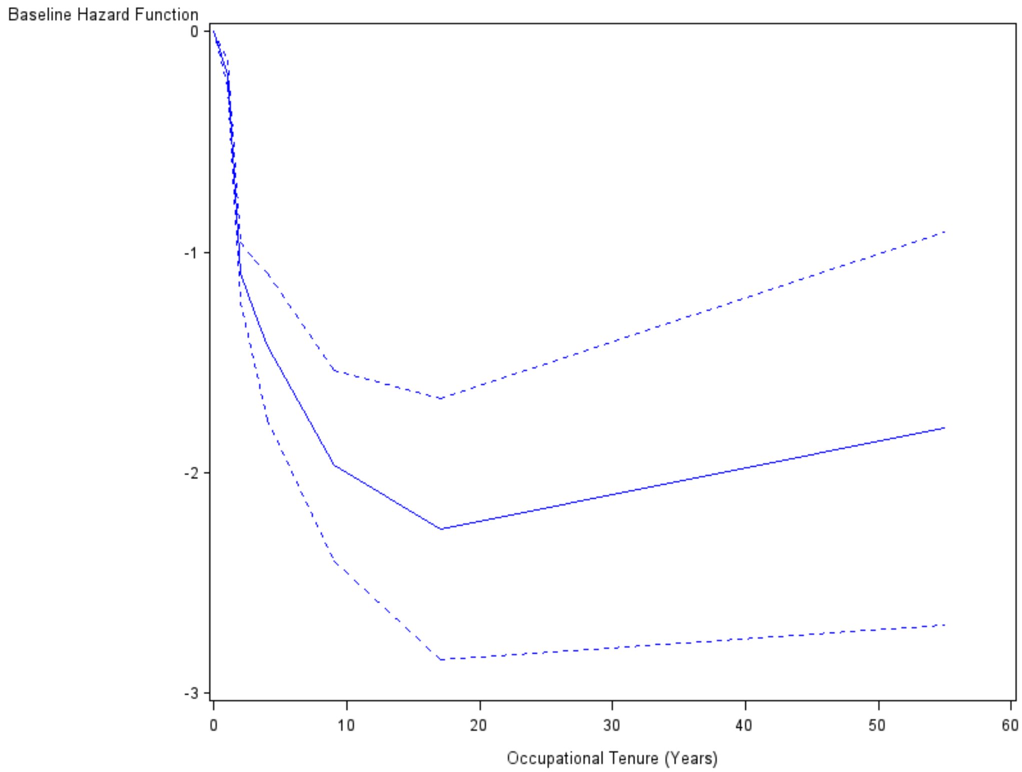


Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics

Figure 4: This figure plots the baseline hazard function of a mixed proportional hazard model. Initial tenure is assumed to be exogenous. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the Full Depreciation assumption. See column (1) of Table 5 for details regarding the specification.



Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics
Figure 5: This figure plots the baseline hazard function of a mixed proportional hazard model. Initial tenure is assumed to be exogenous. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the No Depreciation assumption. See column (2) of Table 5 for details regarding the specification.



Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics

Figure 6: This figure plots the baseline hazard function of a mixed proportional hazard model. Initial tenure is assumed to be exogenous. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the Full Depreciation assumption. See column (1) of Table 6 for details regarding the specification.

Table 7: ML Estimates of Mixed Proportional Hazard Model Assuming Endogenous Initial Conditions — PSID Data

	(1)	(2)	(3)	(4)
0-1 years tenure	3.596***	3.530***	2.801***	2.795***
	(.276)	(.159)	(.128)	(.125)
1-2 years tenure	-0.104	-0.124**	-0.323***	-0.323***
	(.088)	(.058)	(.053)	(.052)
2-3 years tenure	0.470***	0.458***	0.380***	0.379***
	(.068)	(.056)	(.051)	(.051)
3-4 years tenure	0.037	0.029	-0.107**	-0.105**
	(.063)	(.053)	(.049)	(.049)
4-9 years tenure	0.130***	0.122***	0.078***	0.077***
	(.030)	(.020)	(.015)	(.015)
9-17 years tenure	0.152***	0.147***	0.095***	0.094***
	(.030)	(.015)	(.014)	(.014)
17+ years tenure	0.207***	0.202***	0.154***	0.152***
	(.023)	(.017)	(.013)	(.013)
Initial tenure	-0.262***	-0.255***	-0.191***	-0.191***
	(.031)	(.018)	(.015)	(.014)
ln Wage	—	-0.059***	—	-0.055***
		(.006)		(.005)
σ_a	2.175***	2.145***	1.678***	1.681***
	(.167)	(.092)	(.078)	(.075)
$-\ln L$	76,063.554	76,008.207	76,183.152	76,125.774

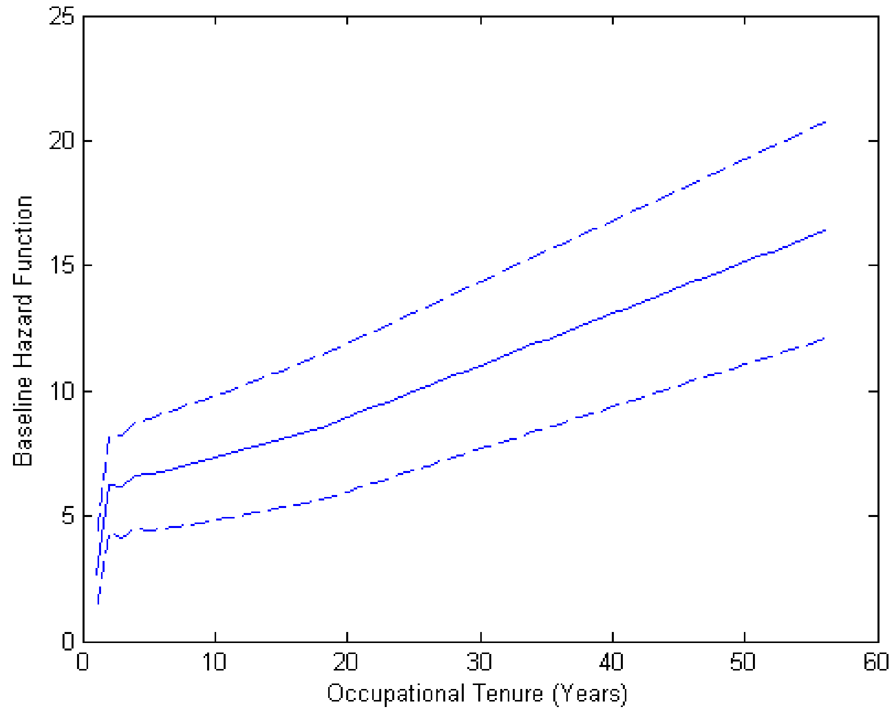
Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses. The estimates presented in this table result from a mixed proportional hazard model which accounts for spell-level unobserved heterogeneity ν_{ij}. I assume that the log of this unobserved effect is normally distributed with mean $\alpha_1\tau_{ij0} + \alpha_2 X_i$ and variance σ_a^2. The baseline hazard is assumed to be piecewise-linear, with 1-digit occupation-specific intercepts. The values at which the approximated baseline hazard is evaluated within a spell are determined by the depreciation assumption. Columns (1) and (2) assume full specific-capital depreciation between two spells in the same occupation. Columns (3) and (4) assume no specific-capital depreciation between two spells in the same occupation. Additional regressors are a linear time trend, a male indicator, a cubic in education, a married indicator, county unemployment rate, weeks unemployed in the survey year, union member indicator, government worker indicator, self-employed indicator, part-time worker indicator, a cubic in age, and region indicators. The regressor set also includes interactions of county unemployment rate with the married indicator, the cubic in education, and the cubic in age. Initial tenure and a history of all time-variant covariates were only included as regressors for those occupational spells with non-zero initial tenure. The estimates presented in columns (3) and (4) result from a model which also includes in the regressor set occupational tenure in the previous 6 occupations and an indicator variable which takes value one if the current spell is a return to an occupation which was previously sampled. The estimates presented in columns (2) and (4) result from a model which also includes in the regressor set log-wages. All occupational spells are defined at the 3-digit level using the 1970 Census occupational classification system. See the Appendix for details of how data on occupational changes were derived.

Table 8: ML Estimates of Mixed Proportional Hazard Model Assuming Endogenous Initial Conditions — SIPP Data

	(1)	(2)
0-12 months (0-1 years) tenure	.022***	-.002
	(.004)	(.004)
12-24 months (1-2 years) tenure	-.024***	-.025***
	(.004)	(.004)
24-36 months (2-3 years) tenure	.214***	.203***
	(.006)	(.006)
36-48 months (3-4 years) tenure	.205***	.184***
	(.007)	(.006)
48-108 months (4-9 years) tenure	.168***	.148***
	(.003)	(.003)
108-204 months (9-17 years) tenure	.174***	.155***
	(.003)	(.003)
204+ months (17+ years) tenure	.177***	.157***
	(.003)	(.003)
Initial tenure	-.176***	-.157***
	(.003)	(.003)
ln Wage	—	-.188***
		(.008)
σ_a	1.136***	.922***
	(.027)	(.028)
$-\ln L$	101,068.529	100,761.693

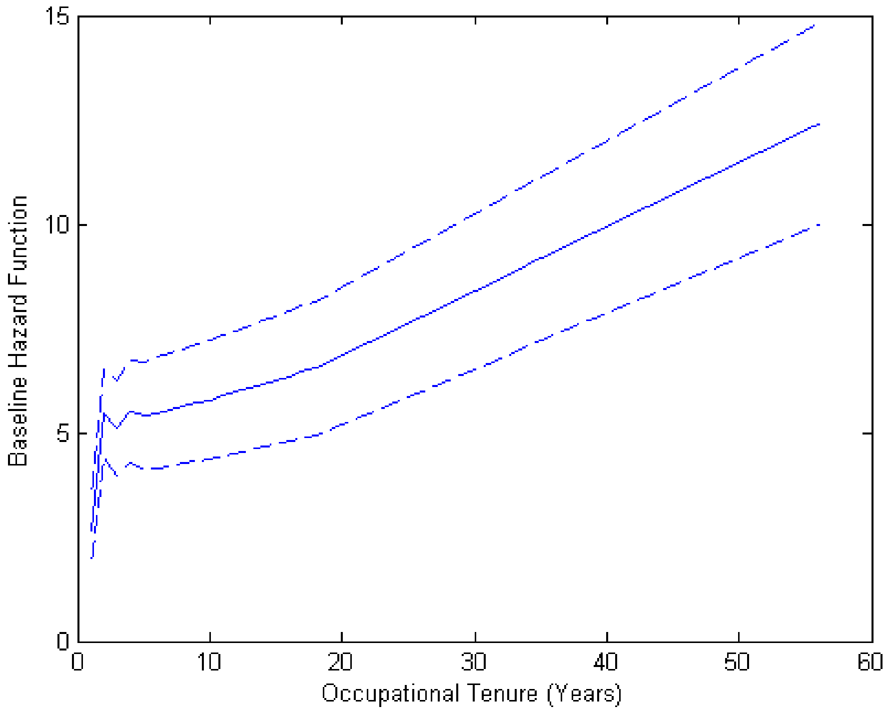
Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics

Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses. The estimates presented in this table result from a mixed proportional hazard model which accounts for spell-level unobserved heterogeneity ν_{ij}. I assume that the log of this unobserved effect is normally distributed with mean $\alpha_1 \tau_{ij0} + \alpha_2 X_i$ and variance σ_a^2. The baseline hazard is assumed to be piecewise-linear, with 1-digit occupation-specific intercepts. The values at which the approximated baseline hazard is evaluated within a spell are determined by the depreciation assumption. Columns (1) and (2) assume full specific-capital depreciation between two spells in the same occupation. Additional regressors are a male indicator, a cubic in education, a married indicator, weeks unemployed in the reference month, union member indicator, government worker indicator, part-time worker indicator, and region indicators. The regressor set also includes interactions of state unemployment rate with the married indicator and the cubic in education. Initial tenure and a history of all time-variant covariates throughout the spell were only included as regressors for those occupational spells with non-zero initial tenure. The estimates presented in columns (2) result from a model which also includes in the regressor set log-wages. All occupational spells are defined at the 3-digit level using the 1980 and 1990 Census occupational classification system for the 1990-1991 panels and the 1992-1993 panels, respectively. See the Appendix for details of how data on occupational changes were derived.



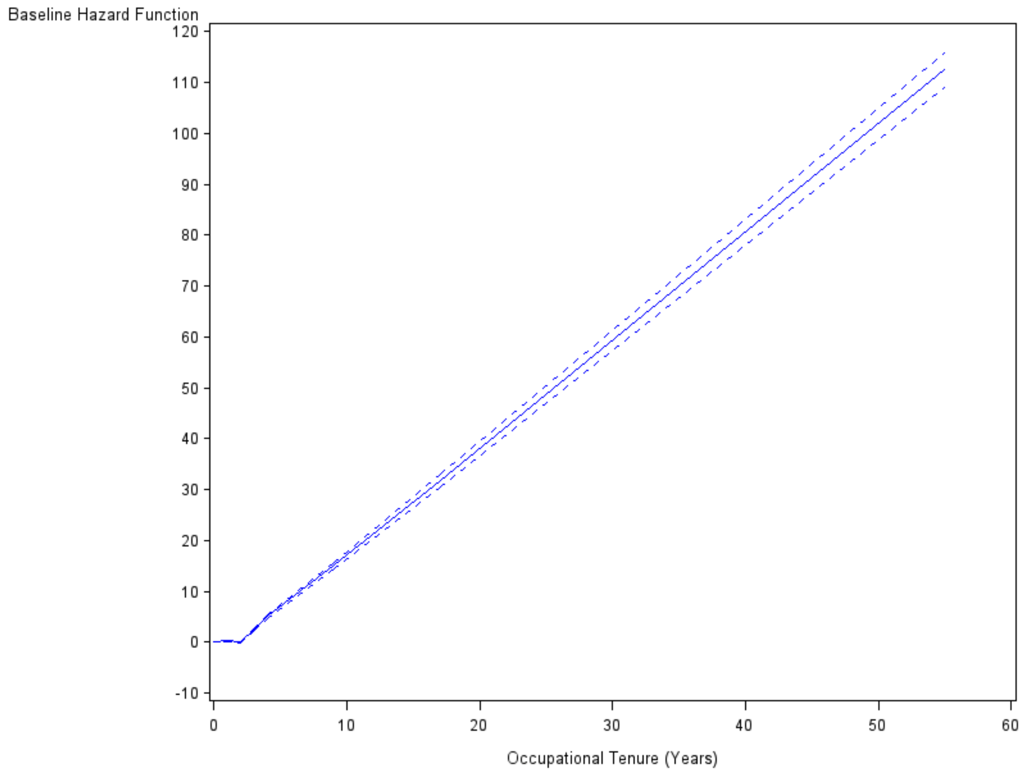
Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics

Figure 7: This figure plots the baseline hazard function of a mixed proportional hazard model. Initial tenure is assumed to be endogenous. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the Full Depreciation assumption. See column (1) of Table 7 for details regarding the specification of the hazard function and the conditional distribution of ν_{ij}.



Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics

Figure 8: This figure plots the baseline hazard function of a mixed proportional hazard model. Initial tenure is assumed to be endogenous. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the No Depreciation assumption. See column (3) of Table 7 for details regarding the specification of the hazard function and the conditional distribution of ν_{ij}.



Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics

Figure 9: This figure plots the baseline hazard function of a mixed proportional hazard model. Initial tenure is assumed to be endogenous. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the Full Depreciation assumption. See column (1) of Table 8 for details regarding the specification of the hazard function and the conditional distribution of ν_{ij}.

Table 9: Joint Estimates of Mixed Proportional Hazard Model Assuming Endogenous Initial Conditions and a Wage Model — PSID Data

	(1)	(2)
Panel A: Mixed Proportional Hazard Model		
0-1 years tenure	3.426***	2.703***
	(.150)	(.136)
1-2 years tenure	-0.165***	-0.355***
	(.057)	(.053)
2-3 years tenure	0.433***	0.363***
	(.054)	(.052)
3-4 years tenure	0.013	-0.122**
	(.053)	(.049)
4-9 years tenure	0.112***	0.070***
	(.018)	(.016)
9-17 years tenure	0.137***	0.083***
	(.014)	(.014)
17+ years tenure	0.195***	0.146***
	(.015)	(.014)
Initial tenure	-0.243***	-0.178***
	(.016)	(.015)
ln Wage	-0.109***	-0.106***
	(.007)	(.006)
σ_a	2.094***	1.640***
	(.086)	(.082)

Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses. The estimates presented in this table result from the joint estimation of a mixed proportional hazard model and a wage model. Panel (A) presents the estimates from the mixed proportional hazard model which accounts for spell-level unobserved heterogeneity ν_{ij}. I assume that the log of the unobserved effect can be decomposed as $\ln \nu_{ij} = \alpha_1 \tau_{ij0} + \alpha_2 X_i + a_{ij}$. The wage model is assumed to include a spell-level random effect, c_{ij}. The stochastic component of ν_{ij} and c_{ij} are assumed to be bivariate normally distributed, with correlation ρ. The baseline hazard is assumed to be piecewise-linear, with 1-digit occupation-specific intercepts. The values at which the approximated baseline hazard is evaluated within a spell are determined by the depreciation assumption. Column (1) assumes full specific-capital depreciation between two spells in the same occupation. Column (2) assumes no specific-capital depreciation between two spells in the same occupation. Additional regressors are a linear time trend, a male indicator, a cubic in education, a married indicator, county unemployment rate, weeks unemployed in the survey year, union member indicator, government worker indicator, self-employed indicator, part-time worker indicator, a cubic in age, log-wages, and region indicators. The regressor set also includes interactions of county unemployment rate with the married indicator, the cubic in education, and the cubic in age. Initial tenure and a history of all time-variant covariates were only included as regressors for those occupational spells with non-zero initial tenure. The estimates presented in column (2) result from a model which also includes in the regressor set occupational tenure in the previous 6 occupations and an indicator variable which takes value one if the current spell is a return to an occupation which was previously sampled. Wages are listed in year 2000 dollars.

Table 9: Joint Estimates of Mixed Proportional Hazard Model Assuming Endogenous Initial Conditions and a Wage Model — PSID Data

	(1)	(2)
Panel B: Wage Model		
0-1 years tenure	0.119***	0.125***
	(.021)	(.022)
1-2 years tenure	0.037**	0.037**
	(.015)	(.015)
2-7 years tenure	0.014***	0.019***
	(.004)	(.004)
7-20 years tenure	-0.002	-0.004
	(.003)	(.003)
20-34 years tenure	-0.012*	-0.008
	(.007)	(.007)
34+ years tenure	-0.026	-0.032**
	(.016)	(.015)
σ_c	0.805***	0.805***
	(.010)	(.010)
ρ	0.203***	0.233***
	(.012)	(.015)
$-\ln L$	419,644.095	419,727.793

Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses. The estimates presented in this table result from the joint estimation of a mixed proportional hazard model and a wage model. Panel (B) presents the estimates from the wage model, which is assumed to include a spell-level random effect c_{ij}. The stochastic component of ν_{ij} and c_{ij} are assumed to be bivariate normally distributed with correlation ρ. Column (1) assumes full specific-capital depreciation between two spells in the same occupation. Column (2) assumes no specific-capital depreciation between two spells in the same occupation. Regressors for the wage model include a piecewise-linear function of occupational tenure, with 1-digit occupation-specific intercepts. I choose the function of occupational tenure according to the strategy posited by Lillard and Panis (2003). The values at which the wage-tenure profile is evaluated within a spell are determined by the depreciation assumption. Additional regressors include a linear time trend, education, a male indicator, a white non-Hispanic indicator, a black non-Hispanic indicator, number of children, region dummies, weeks unemployed, a part-time worker indicator, county unemployment rate, SMSA, a married indicator, a union member indicator, a government worker indicator, and a self-employed indicator, an unemployed indicator, and a quadratic in age. The regressor set also includes interactions of county unemployment rate with education and the quadratic in age. The estimates presented in column (2) result from a model which also includes in the regressor set occupational tenure in the previous 6 occupations and an indicator variable which takes value one if the current spell is a return to an occupation which was previously sampled. Wages are listed in year 2000 dollars. All occupational spells are defined at the 3-digit level using the 1970 Census occupational classification system. See the Appendix for details of how data on occupational changes were derived.

Table 10: Joint Estimates of Mixed Proportional Hazard Model Assuming Endogenous Initial Conditions and a Wage Model — SIPP Data

	(1)
Panel A: Mixed Proportional Hazard Model	
0-12 months (0-1 years) tenure	-.001
	(.004)
12-24 months (1-2 years) tenure	-.025***
	(.004)
24-36 months (2-3 years) tenure	.203***
	(.006)
36-48 months (3-4 years) tenure	.185***
	(.006)
48-108 months (4-9 years) tenure	.149***
	(.003)
108-204 months (9-17 years) tenure	.155***
	(.003)
204+ months (17+ years) tenure	.158***
	(.003)
Initial tenure	-.157***
	(.003)
ln Wage	-.184***
	(.008)
σ_a	.929***
	(.028)

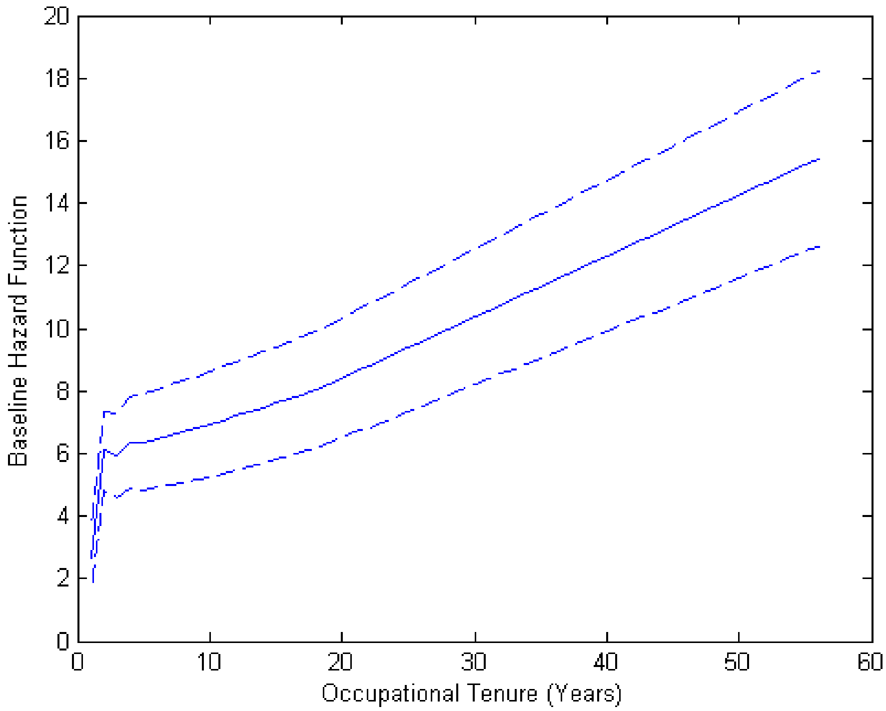
Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses. The estimates presented in this table result from the joint estimation of a mixed proportional hazard model and a wage model. Panel (A) presents the estimates from the mixed proportional hazard model which accounts for spell-level unobserved heterogeneity ν_{ij}. I assume that the log of the unobserved effect can be decomposed as $\ln \nu_{ij} = \alpha_1 \tau_{ij0} + \alpha_2 X_i + a_{ij}$. The wage model is assumed to include a spell-level random effect, c_{ij}. The stochastic component of ν_{ij} and c_{ij} are assumed to be bivariate normally distributed, with correlation ρ. The baseline hazard is assumed to be piecewise-linear, with 1-digit occupation-specific intercepts. The values at which the approximated baseline hazard is evaluated within a spell are determined by the depreciation assumption. Column (1) assumes full specific-capital depreciation between two spells in the same occupation. Additional regressors are a male indicator, a cubic in education, a married indicator, weeks unemployed in the reference month, union member indicator, government worker indicator, part-time worker indicator, and region dummies. The regressor set also includes interactions of state unemployment rate with the married indicator and the cubic in education. Initial tenure and a history of all time-variant covariates throughout the spell were only included as regressors for those occupational spells with non-zero initial tenure. Wages are listed in year 2000 dollars.

Table 10: Joint Estimates of Mixed Proportional Hazard Model Assuming Endogenous Initial Conditions and a Wage Model — SIPP Data

	(1)
Panel B: Wage Model	
0-12 months (0-1 years) tenure	.007***
	(.000)
12-24 months (1-2 years) tenure	.003***
	(.000)
24-84 months (2-7 years) tenure	.002***
	(.000)
84-240 months (7-20 years) tenure	.001***
	(.000)
240-408 months (20-34 years) tenure	.001***
	(.000)
408+ months (34+ years) tenure	.000
	(.000)
σ_c	.482***
	(.003)
ρ	-.019*
	(.010)
$-\ln L$	583,093.121

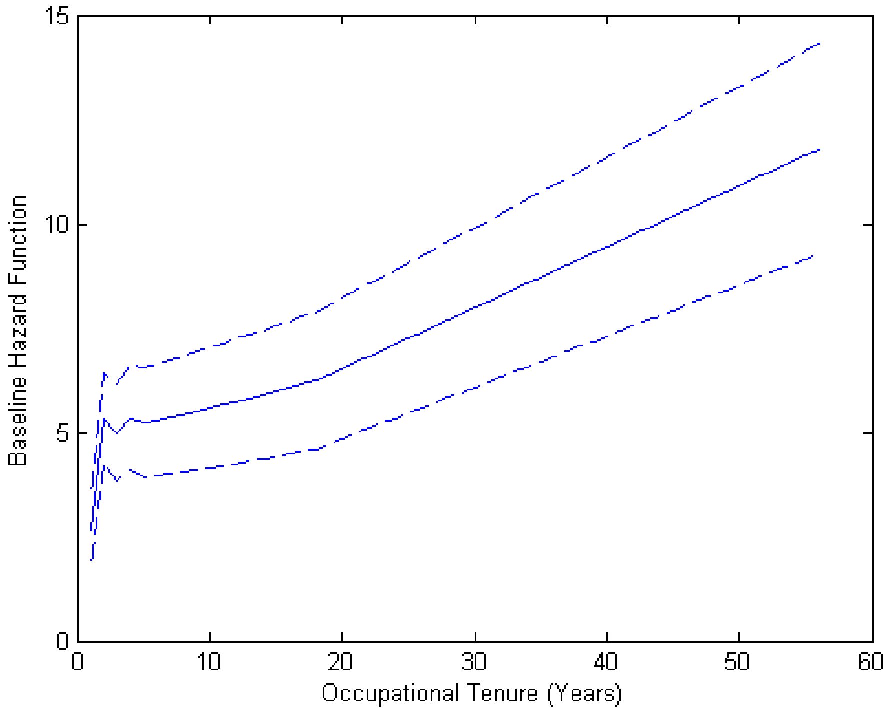
Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics

Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses. The estimates presented in this table result from the joint estimation of a mixed proportional hazard model and a wage model. Panel (B) presents the estimates from the wage model, which is assumed to include a spell-level random effect c_{ij}. The stochastic component of ν_{ij} and c_{ij} are assumed to be bivariate normally distributed with correlation ρ. Column (1) assumes full specific-capital depreciation between two spells in the same occupation. Regressors for the wage model include a piecewise-linear function of occupational tenure, with 1-digit occupation-specific intercepts. I choose the function of occupational tenure according to the strategy posited by Lillard and Panis (2003). The values at which the wage-tenure profile is evaluated within a spell are determined by the depreciation assumption. Additional regressors include education, a male indicator, a white non-Hispanic indicator, a black non-Hispanic indicator, number of children, region dummies, weeks unemployed, a part-time worker indicator, state unemployment rate, SMSA, a married indicator, a union member indicator, a government worker indicator, an unemployed indicator, and a quadratic in age. The regressor set also includes interactions of state unemployment rate with education and the quadratic in age. Wages are listed in year 2000 dollars. All occupational spells are defined at the 3-digit level using the 1980 and 1990 Census occupational classification system for the 1990-1991 panels and the 1992-1993 panels, respectively. See the Appendix for details of how data on occupational changes were derived.



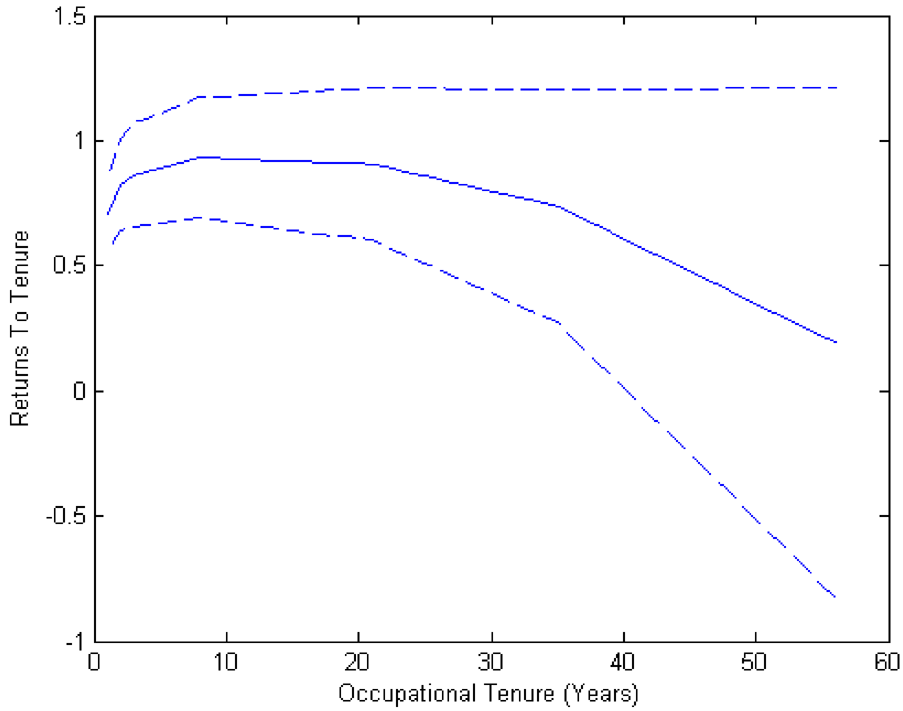
Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics

Figure 10: This figure plots the baseline hazard function of a mixed proportional hazard model which conditions on log wages. Initial tenure is assumed to be endogenous. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the Full Depreciation assumption. See column (1), Panel A of Table 9 for details regarding the specification of the hazard function and the conditional distribution of ν_{ij}.

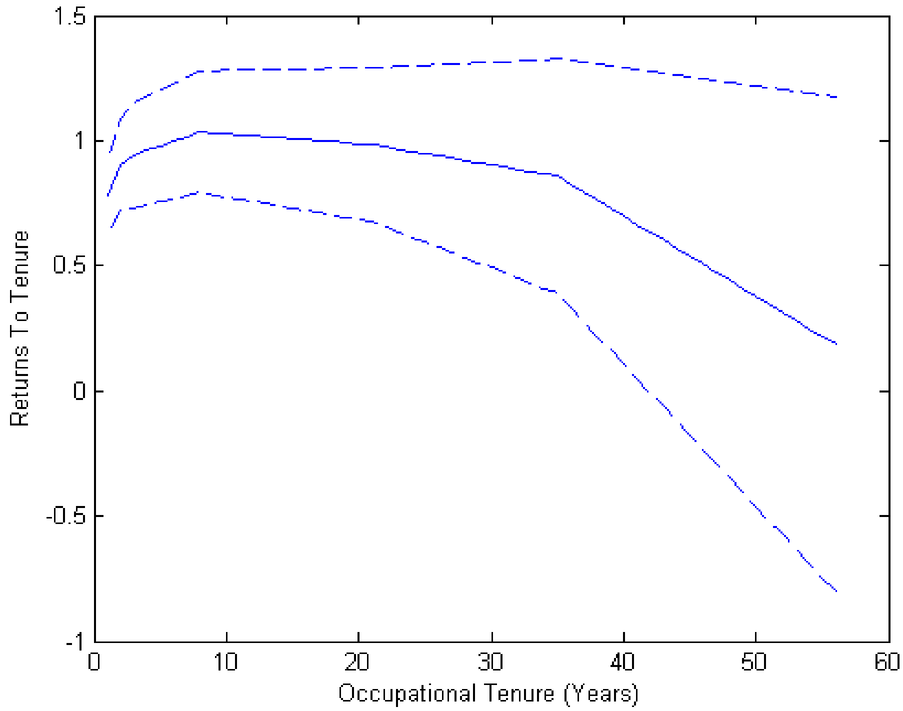


Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics

Figure 11: This figure plots the baseline hazard function of a mixed proportional hazard model which conditions on log wages. Initial tenure is assumed to be endogenous. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the No Depreciation assumption. See column (2), Panel A of Table 9 for details regarding the specification of the hazard function and the conditional distribution of ν_{ij}.

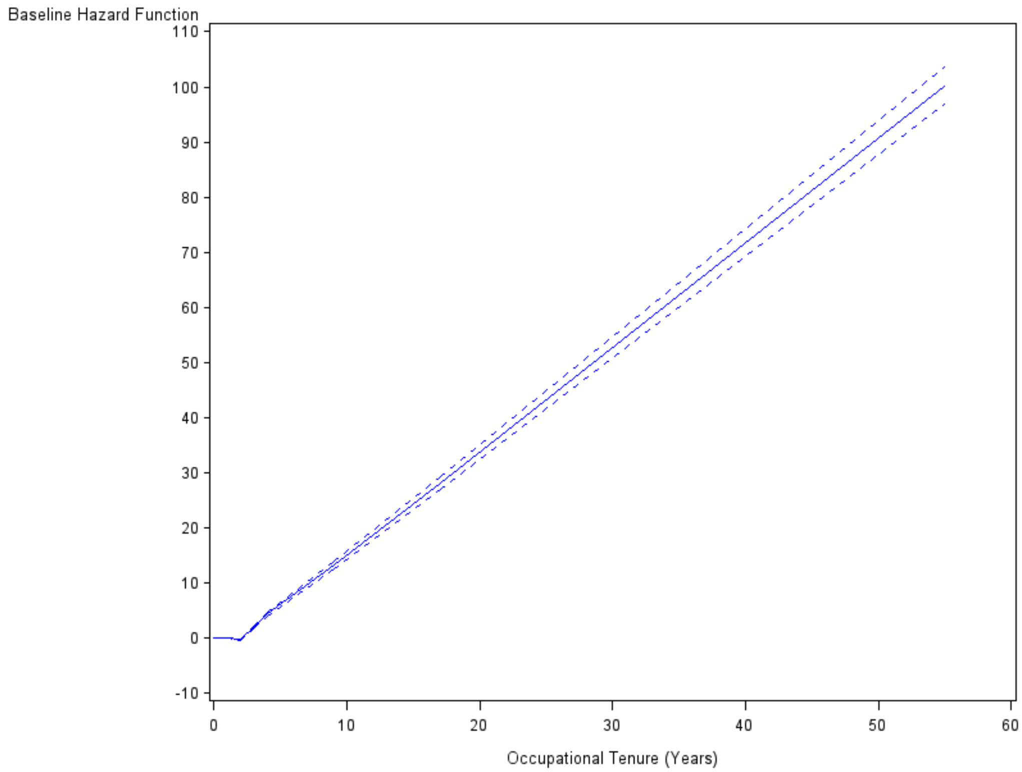


Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics
Figure 12: This figure plots the returns to occupational tenure from a wage regression which is estimated jointly with a mixed proportional hazard model. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the Full Depreciation assumption. See column (1), Panel B of Table 9 for details regarding the specification of the wage regression.



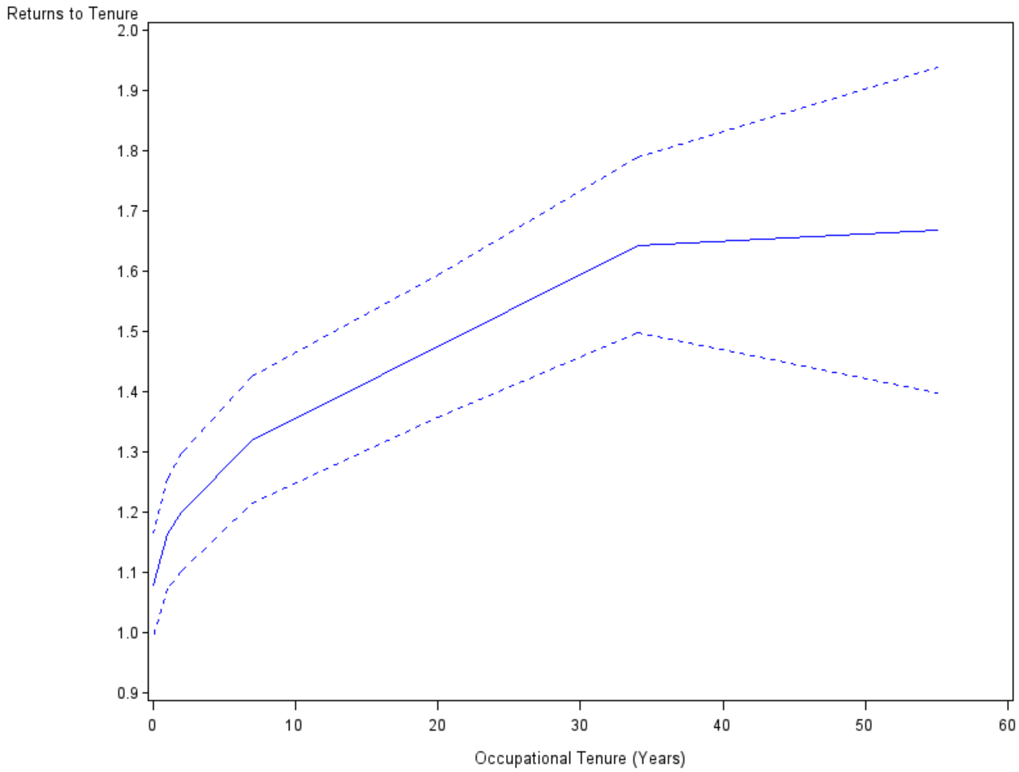
Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics

Figure 13: This figure plots the returns to occupational tenure from a wage regression which is estimated jointly with a mixed proportional hazard model. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the No Depreciation assumption. See column (2), Panel B of Table 9 for details regarding the specification of the wage regression.



Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics

Figure 14: This figure plots the baseline hazard function of a mixed proportional hazard model which conditions on log wages. Initial tenure is assumed to be endogenous. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the Full Depreciation assumption. See column (1), Panel A of Table 10 for details regarding the specification of the hazard function and the conditional distribution of ν_{ij}.



Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics

Figure 15: This figure plots the returns to occupational tenure from a wage regression which is estimated jointly with a mixed proportional hazard model. Dotted lines indicate bounds of the 90% confidence interval. Tenure is computed according to the Full Depreciation assumption. See column (1), Panel B of Table 9 for details regarding the specification of the wage regression.

8 Appendices

A.1 Identifying position switches — Panel Study of Income Dynamics

I use the following criteria to identify position switches according to"Partition T" as proposed by Brown and Light (1992). A position switch is identified:

1. if the reported length of employment on the present position is smaller than the time elapsed since the previous interview;

2. if the reported length of employment on the current position is less than 10 months and the time elapsed since the last interview is not known;

3. if the reported length of employment on the current position is between 10 and 15 months, the reported length of position employment in the previous year is higher than 5 months, and the time elapsed since the last interview is not known;

4. if the reported length of employment on the current position is between 15 and 21 months, the reported length of position employment in the previous year is higher than 11 months, and the time elapsed since the last interview is not known;

5. if the reported length of employment on the current position is between 10 and 15 months, and the respondent is a new entrant into the sample; or

6. if the reported length of employment on the current position is between 10 and 15 months, is longer than the time elapsed since the last interview, and no position switch could be identified in the previous year due to missing data on position tenure in that year.

In addition to the criteria of "Partition T", I use the following criteria to identify genuine position switches. A position switch is identified:

1. if the respondent is currently employed and reports a change in employment status from the previous survey (from unemployed or not in the labor force to employed); or

2. if survey respondents left the sample or did not report an occupation for one or more years:

   (a) the reported length of employment in the current position minus the number of months missed (12 times the number of annual observations missed) is less than 10 months and the time elapsed since the last interview is not known.

   (b) the reported length of employment in the current position minus the number of months missed (12 times the number of annual observations missed) is between 10 and 15 months, the reported length of position employment before leaving the sample is higher than 5 months, and the time elapsed since the last interview is not known.

   (c) the reported length of employment in the current position minus the number of months missed (12 times the number of annual observations missed) is between 15 and 21 months, the reported length of position employment before leaving the sample is higher than 11 months, and the time elapsed since the last interview is not known.

   (d) the reported length of employment in the current position minus the number of months missed (12 times the number of annual observations missed) is between 10 and 15 months, is longer than the time elapsed since the last interview, and no position switch could be identified before leaving the sample due to missing data on position tenure in that year.

A.2 Constructing occupational switches

A reported occupational switch occurs in the Panel Study of Income Dynamics when the current report of 3-digit occupation differs from the immediately succeeding report of 3-digit occupation. A reported occupational switch occurs in the Survey of Income and Program Participation when at least one of the current reports of 3-digit occupation differs from both of the reports of 3-digit occupation in the immediately succeeding wave. A reported occupational switch is considered to be genuine when the reported switch coincides with a position switch or an employer switch for the PSID and SIPP analyses, respectively. When a respondent reports an occupational switch that is not genuine, I assign 3-digit occupational affiliation as if no new occupation had been reported.

A.3 Constructing position and employer tenure

A.3.1 Panel Study of Income Dynamics

Once position switches are identified, I construct position tenure variables as follows. A respondent's position tenure is assumed to be given by reported position tenure when a respondent enters or re-enters the sample. I also assume that a respondent's position tenure is given by reported position tenure in the first year of a new position, as implied by "Partition T". If there is no reported position tenure in any of these cases, position tenure is assumed to be missing for that observation. When position tenure is first observed after such an instance, I assume that position tenure is then given by the reported level of tenure. In all other years, position tenure increments by one year if the individual works more than 800 hours during that year. If the respondent works less than 800 hours during that year, position tenure remains unchanged from the previous observation.

A.3.2 Survey of Income and Program Participation

Once employer switches are identified, I construct employer tenure variables as follows. A respondent's employer tenure is assumed to be implied by the job's reported starting day and month in the first month with a new employer.[41] If I recorded an employer change but there is no information on the starting day and ending day for the job, I assume that the job began on the first day of the reference period. I define employer tenure under a second circumstance during the first month of the wave when the Employment History Topical Module was administered. Specifically, for jobs with reported starting months and years in the Employment History Topical Module, employer tenure is assumed to be implied by the job's reported starting month and year. I assume that the job began at the end of the reported month. If the reported month is imputed and the reported year is not imputed, I assume that the job began at the earlier of the last day of the reported year and the first day of the reference period. In all other months, employer tenure increments from the initial level set in either of these two circumstances. In all months after employer tenure is first defined, employer tenure increments by either one month or the fraction of the month that passed before the job ended. I also define employer tenure for months when a job did not end before the Employment History Topical Module in the 1990 and 1991 panels. Employer tenure in these months decrements by either one month or the fraction of the month that passed after the job began.

A.4 Constructing occupational tenure

A.4.1 Panel Study of Income Dynamics

Once occupational switches and position tenure are identified, I construct occupational tenure variables as follows. For both the Full Depreciation and the No De-

[41] For jobs that started and ended in the same month, a respondent's employer tenure is assumed to be implied by the job's reported starting day and ending day.

preciation assumption, a respondent's occupational tenure is assumed to be given by position tenure when a respondent enters the sample. If there is no position tenure in this case, I assume that occupational tenure is missing for that observation. When position tenure is first observed after such an instance, I assume that occupational tenure is then given by the position tenure. At the beginning of the sample, the No Depreciation assumption imposes that occupational tenure is zero for all occupations other than the one first observed.

Under the Full Depreciation assumption, a respondent's occupational tenure is assumed to be given by position tenure in the first year after a genuine occupational change. If there is no position tenure in this case, occupational tenure is assumed to be missing for that observation. When position tenure is first observed after such an instance, I assume that occupational tenure is then given by the position tenure. In all other years, occupational tenure increments by one year if the respondent did not report an occupational change and the respondent did not leave the sample. If the respondent reports an occupational change which is not genuine, occupational tenure remains unchanged from the previous value. Under the Full Depreciation assumption, only the first occupational spell ever observed has non-zero initial tenure.

Under the No Depreciation assumption, a respondent's occupational tenure in the first year after a genuine occupational change is assumed to be given by position tenure plus any tenure accumulated in that occupation earlier in the sample. If there is no position tenure in any of these cases, I assume that occupational tenure is given by previously accumulated tenure for that observation. When position tenure is first observed after such an instance, occupational tenure is then assumed to be given by the position tenure plus the previously accumulated tenure in that occupation. In all other years, occupational tenure increments by one year if the respondent does not report an occupational change and the respondent does not leave the sample. If the respondent reports an occupational change which is not genuine, occupational tenure remains unchanged from the previous observation. Occupational tenure for all occupations other than the reported occupation is assumed to take the same value as in the immediately preceding observation. Under the No Depreciation assumption, the first occupational spell ever observed has a non-zero initial tenure. The only other occupational spells that have non-zero initial tenure represent returns to a previously sampled occupation.

A.4.2 Survey of Income and Program Participation

Once occupational switches and employer tenure are identified, I construct occupational tenure as follows. I begin by initializing occupational tenure under two circumstances. First, during the wave when the Employment History Topical Module was administered, a respondent's occupational tenure is assumed to be given by employer tenure in the first month of the wave if the topical module indicates that the job was already ongoing. If only the starting month of the job was imputed from the Employment History Topical Module, and if the starting year of the job from the topical module coincides with the current year, I assume that the job began on the first day of the reference period. Second, a respondent's occupational tenure is assumed to be given by employer tenure in the first year after a genuine occupational change.

In all months after occupational tenure is first defined under either of these circumstances, occupational tenure increments if the respondent did not report an occupational change. The amount by which occupational tenure increments is either one month or the fraction of the month that passed before the occupational spell ended according to the reported ending day on that job. I also define occupational tenure for months when a job did not end before the Employment History Topical Module in the 1990 and 1991 panels. Employer tenure in these months decrements by either one or the fraction of the month that passed after the occupational spell began according to the reported starting day on that job. On the other hand, if the respondent reports an occupational change which is not genuine, occupational tenure remains unchanged from the previous value. Under the Full Depreciation assumption, only the occupational spell observed by the Employment History Topical Module has non-zero initial tenure. I do not consider the No Depreciation assumption for the SIPP analysis.

A.5 Constructing outcomes for the hazard model

There are two types of variables that summarize the outcome of a hazard model. These are necessary in order to construct the partial likelihood contribution of any occupational spell. First, I must determine whether the spell was right-censored. Second, I must determine an end date to the spell.

Spells are right-censored if I do not observe an end to the spell. This occurs only for spells that are in progress either at the end of the sample or when we last observe respondents who exit the sample prematurely. All other spells are assumed to be uncensored, as they end within some observable window of time. For right-censored spells, the spell's end date is the last tenure level at which the spell was observed. The outcome of an uncensored spell is a time window during which the ending date feasibly could have occurred. This time window is defined by lower bound, t^l, and an upper bound, t^u.

A.5.1 Panel Study of Income Dynamics

For an uncensored spell, the PSID does not contain information on the precise end date of an occupational spell. Rather, I observe the spell to end within some time window. The lower time bound of this time window is defined as the last tenure level at which the spell was observed to be in progress. Intuitively, t^u is the latest time at which the spell could have ended. The precise definition of t^u depends on the information that is available. In general, the upper time bound t^u is defined as t^l plus the time elapsed until the start of the next observed occupation.

This computation requires two pieces of information in addition to t^l: time elapsed until the survey date when the spell is observed to have ended and tenure in the new occupation when it is first observed to be in progress. If neither of these pieces of information is missing, t^u is defined as t^l plus time elapsed between survey dates minus tenure in the new occupation when it is first observed to be in progress. If occupational tenure is missing for the first observation of the new occupation, I impute a lower bound of 0 for this measure of occupational tenure. I then use this lower bound on occupational tenure in the new occupation to compute t^u. If time elapsed between surveys is missing, I impute an upper bound on the time elapsed between surveys. If information is missing on the survey date at which the spell is last observed to be in progress, I impute the upper bound on time elapsed between surveys as if the survey were conducted at the start of the year. If information is missing on the survey date at which the spell is first observed to have ended, I impute the upper bound on time elapsed between surveys as if the survey were conducted at the end of the year. Thus, given the information that is available on survey dates, I use this upper bound on the time elapsed between surveys to compute t^u.

A.5.2 Survey of Income and Program Participation

For many uncensored spells, the SIPP contains information on the precise end date of the employer and occupational spell. When the SIPP contains no information on the precise end date of an uncensored spell, I assume that the employer and occupational spell ended on the last day of the reference period. The lower time bound for an uncensored spell is defined as the last tenure level at which the spell was observed to be in progress, assuming that the job ended at the start of the last day. The precise definition of the upper bound for this uncensored spell depends on the information available regarding that spell's starting date. This upper bound thus incorporates uncertainty about when the spell began. It is defined broadly as the last tenure level at which the spell was observed to be in progress plus a time window during which the spell could have been in progress before it was observed to be in progress with certainty.

For some occupational spells, we observe only a precise starting day and month. In this case, we observe a time window of one day during which the spell could have been in progress before it was observed to be in progress with certainty. For other occupational spell, we observe only a starting month and year from the Employment History Topical Module. In this case, we observe a time window of one month during which the spell could have been in progress before it was observed to be in progress with certainty. For still other occupational spells, we observe both a precise starting day and month from the SIPP core data and a starting month and year from the Employment History Topical Module. These two reported starting times do not always coincide. In this case, we observe a time window stretching the distance between these disparate reports during which the spell could have been in progress before it was observed to be in progress with certainty. For a final set of occupational spells, we observe neither a precise starting day and month from the SIPP core data nor a starting month and year from the Employment History Topical Module. In this case, I assume a time window of four months during which the spell could have been in progress before it was observed to be in progress with certainty.

A.6 Constructing wages

Wages in the PSID are assumed to be given by reported hourly wages or hourly salary at the current job. If the respondent reports earning tips or commission, wages are assumed to be given by reported hourly wages or hourly salary plus hourly tips or hourly commission. If no hourly wage or hourly salary is reported, I impute an hourly wage as reported labor income during the survey year divided by hours worked in the survey year. Wages in the SIPP are assumed to be given by reported monthly earnings on a particular job divided by usual hours worked in that month. If two occupational spells are ongoing simultaneously, I include in regressions only reported monthly earnings on the relevant job. Each report aggregates wages, salary, tips, and commission. Recall bias is likely to be smaller in the SIPP relative to the PSID as a result of the shorter reference period and an emphasis on the use of records. Wages are expressed in year 2000 dollars. I adjust for inflation using the PCE deflator.

A.7 Constructing education

The PSID does not ask all survey respondents about their level of education in each survey year. Education is asked of sample entrants and of every respondent in 1985. Consequently, a respondent's education is assumed to be time-invariant at the largest level ever observed. To that end, I assume that education is given by the level reported in 1985. If no level of education is reported in 1985, I assume that education is given by the level reported at sample entry. If no level of education is reported in 1985 or at sample entry, I assume that education is given by the first level of education reported after 1985. If no level of education is reported in 1985, at sample entry, or after 1985, I assume that education is given by the first level of education ever reported. By contrast, the SIPP asks all survey respondents about completed education in each wave.

A.8 Appendix Tables

Appendix Table A.1: ML Estimates of Proportional Hazard Model – Explanatory Covariates – PSID Data

	(1)	(2)
Constant	2.296***	2.099***
	(.314)	(.312)
Linear time trend	-0.032***	-0.028***
	(.002)	(.002)
Male	0.067**	0.073***
	(.015)	(.014)
Education	-0.224***	-0.206***
	(.045)	(.045)
Education^2	0.025***	0.023***
	(.005)	(.005)
Education^3	-0.001***	-0.001***
	(.000)	(.000)
Married	-0.179***	-0.182***
	(.020)	(.020)
County Unemployment Rate	-0.013	-0.010
	(.057)	(.056)
Weeks Unemployed	0.023***	0.023***
	(.001)	(.001)
Union Member	-0.433**	-0.431***
	(.026)	(.026)
Government Worker	-0.446***	-0.449***
	(.022)	(.022)
Self-employed	-0.495***	-0.488***
	(.030)	(.030)
Part-time worker	0.271***	0.272***
	(.016)	(.016)
Age	-0.205***	-0.196***
	(.022)	(.022)
Age^2	0.004***	0.004***
	(.001)	(.001)
Age^3	-0.000***	-0.000***
	(.000)	(.000)
County Unemployment$\times$Married	0.012***	0.013***
	(.003)	(.003)

Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses.

Appendix Table A.1: ML Estimates of Proportional Hazard Model – Explanatory Covariates – PSID Data (continued)

	(1)	(2)
County Unemployment×Education	0.018*	0.017*
	(.010)	(.010)
County Unemployment×Education^2	-0.001	-0.001
	(.001)	(.001)
County Unemployment×Education^3	0.000	0.000
	(.000)	(.000)
County Unemployment×Age	-0.007*	-0.007*
	(.004)	(.004)
County Unemployment×Age^2	0.000*	0.000*
	(.001)	(.000)
County Unemployment×Age^3	-0.000	-0.000*
	(.000)	(.000)
Return Spell	—	-0.017
		(.024)
Last Occupation Tenure	—	-0.026***
		(.003)
2nd to Last Occupation Tenure	—	0.011***
		(.004)
3rd to Last Occupation Tenure	—	0.029***
		(.005)
4th to Last Occupation Tenure	—	0.036***
		(.008)
5th to Last Occupation Tenure	—	0.062***
		(.016)
6th to Last occupation Tenure	—	0.002
		(.024)

Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses.

Appendix Table A.2: ML Estimates of Proportional Hazard Model – Explanatory Covariates – SIPP Data

	(1)
Male	-.262***
	(.016)
Education	-.513***
	(.063)
Education^2	.044***
	(.009)
Education^3	-.001***
	(.000)
Married	-.218***
	(.054)
Weeks Unemployed	.173***
	(.006)
Union Member	-.421***
	(.024)
Government Worker	-.327***
	(.025)
Part-time worker	.509***
	(.016)
State Unemployment$\times$Married	-.038***
	(.008)
State Unemployment$\times$Education	-.023***
	(.009)
State Unemployment$\times$Education^2	.003**
	(.001)
State Unemployment$\times$Education^3	-.000**
	(.000)

Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics

Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses.

Appendix Table A.3: ML Estimates of Mixed Proportional Hazard Model – Explanatory Covariates – PSID Data

	(1)	(2)
Constant	1.788***	1.727***
	(.396)	(.373)
Linear time trend	-0.020***	-0.019***
	(.003)	(.002)
Male	0.091**	0.090***
	(.021)	(.019)
Education	-0.268***	-0.238***
	(.061)	(.057)
Education^2	0.031***	0.027***
	(.007)	(.006)
Education^3	-0.001***	-0.001***
	(.000)	(.000)
Married	-0.230***	-0.216
	(.027)	(.025)
County Unemployment Rate	0.047	0.037
	(.071)	(.067)
Weeks Unemployed	0.033***	0.031***
	(.001)	(.001)
Union Member	-0.612**	-0.560***
	(.037)	(.034)
Government Worker	-0.637***	-0.589***
	(.034)	(.030)
Self-employed	-0.670***	-0.613***
	(.042)	(.037)
Part-time worker	0.336***	0.318***
	(.021)	(.019)
Age	-0.230***	-0.213***
	(.029)	(.027)
Age^2	0.005***	0.004***
	(.001)	(.001)
Age^3	-0.000***	-0.000***
	(.000)	(.000)
County Unemployment×Married	0.015***	0.015***
	(.004)	(.004)

Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses.

Appendix Table A.3: ML Estimates of Mixed Proportional Hazard Model – Explanatory Covariates – PSID Data (continued)

	(1)	(2)
County Unemployment×Education	0.021*	0.015*
	(.012)	(.011)
County Unemployment×Education^2	-0.002	-0.002
	(.001)	(.001)
County Unemployment×Education^3	0.000	0.000
	(.000)	(.000)
County Unemployment×Age	-0.012***	-0.007***
	(.004)	(.004)
County Unemployment×Age^2	0.000**	0.000**
	(.000)	(.000)
County Unemployment×Age^3	-0.000**	-0.000**
	(.000)	(.000)
Return Spell	—	-0.355***
		(.044)
Last Occupation Tenure	—	-0.028***
		(.003)
2nd to Last Occupation Tenure	—	0.011**
		(.005)
3rd to Last Occupation Tenure	—	0.031***
		(.007)
4th to Last Occupation Tenure	—	0.039***
		(.010)
5th to Last Occupation Tenure	—	0.078***
		(.021)
6th to Last occupation Tenure	—	-0.004
		(.031)

Source: Author's calculation from 1981-1997 Panel Study of Income Dynamics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses.

Appendix Table A.4: ML Estimates of Mixed Proportional Hazard Model – Explanatory Covariates – SIPP Data

	(1)
Male	-.226***
	(.017)
Education	-.614***
	(.069)
Education^2	.054***
	(.010)
Education^3	-.001***
	(.000)
Married	-.299***
	(.058)
Weeks Unemployed	.193***
	(.006)
Union Member	-.421***
	(.026)
Government Worker	-.348***
	(.027)
Part-time worker	.681***
	(.019)
State Unemployment$\times$Married	-.029***
	(.008)
State Unemployment$\times$Education	-.025**
	(.010)
State Unemployment$\times$Education^2	.003**
	(.001)
State Unemployment$\times$Education^3	-.000**
	(.000)

Source: Author's calculation from 1990-1993 panels of the Survey of Income and Program Participation and the Local Area Unemployment Statistics
Note: * denotes significant at 10 percent confidence level, ** denotes significant at 5 percent confidence level, *** denotes significant at 1 percent confidence level. Robust standard errors are listed in parentheses.