Employment Duration and Match Quality over the Business Cycle*

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Abstract

This paper studies the cyclical behavior of employment duration. We estimate a proportional hazard model with competing risks, distinguishing different types of separations. A higher unemployment rate at the start of an employment relationship increases the probability of job-to-job transitions, while its effect on employment-to-unemployment transitions is close to zero. We find similar patterns when we distinguish the separations by different reasons and contrast quits and firings. We then build a simple job-ladder model to interpret our empirical results. The cyclical behavior of opportunities for job-to-job transitions plays an important role in the cyclical behavior of match quality.

Keywords: Business cycles, Match quality, Employment duration
JEL Classifications: E24, E32, J22, J63, J64.

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1 Introduction

In a frictional labor market, firms and workers may not always be able to find their best match. When a firm and a worker meet, they have to decide whether to form a match or keep looking for an alternative partner. If a match is not formed, a result can be "mismatch unemployment," that is, a co-existence of vacancy and unemployment because potential benefit from a match (the "match quality") is too low.[1] Even if a match is formed, the match quality may not be very high—the match may be formed just because it is too costly for both parties to keep looking for alternative partners. This type of "mismatch employment," caused by labor market frictions, is one of the important reasons for misallocation of productive resources in the macroeconomic context.[2]

When the quality of a match is not perfect, reallocating workers across firms can improve overall economic efficiency. Given that a frictional labor market often involves various externalities among market participants, there can be potential gains from government policies. Therefore, it is of interest to know how newly-formed match qualities can differ depending on various economic situations. From a macroeconomic viewpoint, since the degree of frictions in the labor market may vary over different phases of the business cycle, it is natural to ask whether a better-quality match is formed during booms than recessions. We approach this question by analyzing employment durations of workers.

The main idea behind our study is that a worker-firm match with a higher match quality would last longer. If a worker has a better match with a particular firm compared to another firm, it is more likely that he would feel better off working in the former firm, and thus he is less likely to leave that firm. From the firm's perspective, if a worker is a better match than another worker, it is less likely that the firm wants to fire that worker. Especially when a match is formed efficiently from the viewpoint of a worker-firm pair, a high match quality implies a high surplus, and it requires a large negative shock to break that match.

The advantage of our approach, compared to the alternative approach of directly measuring productivity and wages from matched employer-employee data, is that we can consider a broader concept of match quality that does not show up in output or wages, such as the attachment of a worker to a particular firm or the worker's geographical preferences.[3] Our approach is in the spirit of the revealed preferences theory—to the extent that what we eventually care about is aggregate *welfare*, rather than *output* itself, this is an advantage

[1]The issue of mismatch unemployment has received considerable attention recently, in the context of the Great Recession. See, for example, Şahin et al. (2014).

[2]There has been a substantial amount of recent research on misallocation of productive resources in the macroeconomic context, following Restuccia and Rogerson (2008) and Hsieh and Klenow (2009).

[3]Nosal and Rupert (2007) and Nunn (2013) emphasize the importance of considering non-wage characteristics in analyzing workers' job choices.

rather than a shortcoming.

At the general level, theoretical predictions about how the business cycle affect the newly-formed match quality is ambiguous. In the prototypical Mortensen and Pissarides (1994) model (modified so that the initial match quality is allowed to be stochastic), in which the match is formed efficiently from the viewpoint of the individual match, a high aggregate productivity in booms allows a relatively low-quality match to be formed. If this effect is strong, the average quality of new matches tends to be countercyclical. However, the result also depends on the cyclicality of the job arrival rate, and it is also affected by other elements such as the effectiveness of on-the-job search. When match formation/separation is not individually efficient, the disagreement between workers and firms may have conflicting cyclical effects. On the worker side, the unemployment rate is high during recessions, and jobseekers compete for a relatively small number of job openings. Thus the workers may be willing to accept a job that is not so desirable. On the firm side, labor market conditions are favorable for hiring firms during recessions, because there are a relatively small number of hiring firms. Thus the firm is able to wait until finding a worker with a high match quality. In addition, it is also possible to think about situations where the new match quality distribution itself varies cyclically.

In the following, we first empirically study the effects of aggregate labor market conditions on employment duration using data from the National Longitudinal Survey of Youth (NLSY) 1979 cohort. We use the Cox (1972) proportional hazard model for job separations. Our main innovation is that we estimate the effects of the unemployment rate separately for different types of job separations. We consider two different methods for dividing separations into different types. First, we consider the distinction between different transition types after the separation: job-to-job transitions (EE transitions) and separation into unemployment (EU transitions).[4] Second, we separate job spells by reasons for why the job ended; in particular, separations by quits or by firings. We find that a higher unemployment rate at the formation of the match has contrasting effects on subsequent EE and EU transitions. The distinction between quits and firings results in a similar contrasting outcome.

In order to interpret our empirical results, we build a simple job-ladder model to study the match quality over the business cycle. The model-generated data exhibits a similar pattern as the empirical results. It turns out that the cyclicality of the opportunities for EE transitions is essential in generating the observed pattern.

The pioneering work by Bowlus (1995) also studies the employment duration over the business cycle. We first replicate her study using our dataset. Our dataset includes a longer

[4]In our dataset, there is no distinction between unemployment and not in the labor force. We label all nonemployment as "unemployment" in this paper.

time period, and more importantly, we are able to include prime-aged workers. We show that Bowlus' (1995) result, which indicates that the unemployment rate at the start of the job has a negative effect on employment durations, is substantially weaker in our dataset which includes a longer time series. In macroeconomic literature, her result has been interpreted as evidence that matches formed during booms are of higher quality,[5] but in our dataset the result seems more nuanced. The main difference of our study from Bowlus (1995) is that we show that once we look at different types of job separations separately, we can draw a clearer conclusion on the effect of the business cycle on employment duration. Similarly to Bowlus (1995), a recent paper by Mustre-del-Rio (2014) also finds that a match formed during a boom lasts longer. His methodology is different from ours and he focuses on the contrast between the effect of the unemployment rate at the time of job separation versus the effect of the unemployment rate at the time of match formation. Finally, using a matched employer-employee data set, Kahn (2008) also finds that job spells are shorter when a match is formed during a recession. However, this relationship reverses after controlling for firm fixed effects.

There is an additional reason why it is important that we distinguish the types of job separations. In the estimation of Bowlus (1995) and Mustre-del-Rio (2014), the current unemployment rate is included as an independent variable. However, it is well known that different types of job separations can exhibit different cyclical properties. For example, the EE transition rate is known to be procyclical and the EU transition rate is countercyclical (similarly, the quit rate is procyclical and the firing rate is countercyclical), and thus the current unemployment rate has the opposite effect on employment duration and these opposing forces can cancel each other out. In our estimation, we can estimate both effects separately.

The distinction between EE and EU transitions results in strikingly contrasting outcomes: a high unemployment rate at the start of a match increases the probability that it ends with an EE transition but it has almost no (or slightly negative) effect on the probability that it ends with an EU transition. As is expected, an increase in the current unemployment rate reduces the probability that the job spell ends as an EE transition, but it increases the probability that it ends with an EU transition. We find a similar pattern when we make a distinction by causes—the result for quits is similar to the EE transition and the result for firings (and other reasons) is similar to the EU transition. This is as expected, because fired workers tend to move to nonemployment after separation, while those who quit tend

[5]For example, this is an implication of the models by Moscarini (2001) and Barlevy (2002). These models consider on-the-job search and share some features with our job-ladder model, although our model is substantially simpler. In Costain and Reiter (2008), this relationship between match quality and business cycles plays an important role in explaining labor market volatility.

to move on to new jobs.[6]

The contrasting effect on different types of separations calls for a theoretical interpretation. To this end, we build a quantitative job-ladder model that features both endogenous separation and on-the-job search. We estimate the model-generated data in the same way as we treat the NLSY data. There, EE transitions and EU transitions are both considered as separations. Theoretically, both types of separations tend to happen for a match with a low match quality. However, there are some important differences between different types of separations. The matches that endogenously end as EU transitions are at the bottom of the match quality distribution; that is, of very small match surplus. In contrast, it is possible that the matches that end in EE transitions have a decent match quality—workers quit because they find a job with even higher match quality. The responses of EU transitions are governed by variations in the creation of "very bottom" jobs over the cycle. The creation of very bottom jobs are mainly affected by the behavior of the reservation match quality for the unemployed. For EE transitions, the average level of match quality is more important, and thus the overall distribution matters. During recessions, the improvement of match quality is slow because there are fewer opportunities to move to a better job. This leads to a lower level of average match quality during recessions. This in turn implies that matches created by EE transitions during recessions are of lower quality than the ones created during booms, because they tend to originate from a lower-quality matches. This effect governs the cyclicality of new match quality through EE transitions.

In the next section, we describe the dataset. Section 3 describes the empirical methodology, in particular cause-specific and subhazard regressions. We present the estimation results in Section 4. Section 5 describes the theoretical framework and results. Section 6 concludes.

2 Data description

We use data from the NLSY 1979 cohort in this study. A total of 12,686 individuals born between 1957 and 1964 participated in this survey. These individuals were interviewed annually from 1979 through 1994 and biennially thereafter until the survey ended in 2012. The data set we use in this study covers all the survey years until 2010. The survey collects detailed information about each job a respondent holds or previously held. We use the Employer History Roster (Beta Version) for employment histories for all the individuals participating in the survey. This roster alleviates the more involved linking process across

[6] See Akerlof, Rose, and Yellen (1989) for a discussion.

different survey years.[7]

Our analysis is based on making a differentiation across job separations. There are two particular features of the data that we use to make such a distinction. First, the panel aspect of the data allows us to keep track of what happens after separating from the current employer, i.e., whether the worker becomes unemployed or finds another job immediately. Second, the data provides detailed information about the reason why a job spell ended. A detailed description of the reasons for job separations is available in Appendix B. In particular, we observe whether the job ended due to the worker's quit decision to take or look for another job or due to the firm's firing decision.

Using these two pieces of information, we make two classifications for job separations. In the first classification, we distinguish employment-to-employment transitions, EE, from transitions to unemployment, EU. When a worker loses his job, but is able to find a new job within one month, we call this separation an EE transition.[8] An exception is the case where the separation is due to an obvious layoff or firing. We check the reason for separation for each job spell, and if the reason is either "layoff, job eliminated" or "discharged or fired," we do not categorize that separation as an EE transition. The reason for this exception is that, by EE transition, we want to capture the behavior of a worker voluntarily moving to a new job—this is how the EE transition is modeled in Section 5. We call all separations that are not EE transitions EU transitions.

The second classification is based on the information about the reason why a job spell ended. We define three categories for the reasons of job separations: quits, firings, and other reasons. Our interest in quits partly comes from the intuition that, from a worker's perspective, job spells should be shorter for those jobs created during a recession because workers are willing to take a low match-quality job foreseeing that they will quit to take or look for a better job. Accordingly, it is natural to categorize quits due to reasons other than to take or look for another job into "other reasons." The firm-side incentives imply longer spells for jobs created during a recession, because these matches are expected to be high quality, and firms are less likely to fire these workers. Thus, the "firings" category includes discharges and layoffs. Termination of temporary and seasonal jobs are included in "other reasons" category, because these jobs are set for a fixed term regardless of match

[7]Obtaining some of the job characteristics, e.g., class of worker and union status, still requires linking across different survey years. We describe in detail the construction of our dataset in Appendix A.

[8]This is in line with the identification of EE transitions in the literature. Studies that use Monthly Current Population Survey, such as Fallick and Fleischman (2004), rely on survey responses that are one month apart from each other. Tjaden and Wellschmied (2014), who use the Survey of Income and Program Participation dataset, define job-to-job transitions as those transitions in which the worker works in two consecutive months without reporting unemployment in between (in addition to the ones identified from the occupational switch).

quality. Separations due to closings are also included in "other reasons" category since all jobs regardless of match quality are terminated with this type of job separation.[9]

Under each classification, our sample consists of multiple job spells for each individual. We measure the duration of a job spell in months. Some of the job spells are right-censored due to the finite horizon of the survey and loss of follow-up. We include the unemployment rate at the start of the job, u_0, to analyze the effect of aggregate labor market conditions when the job is created. We also include the current unemployment rate, u_t, as a time-varying regressor to capture on-going labor market conditions. We obtain data from the Bureau of Labor Statistics for the national unemployment rate. The time series is not seasonally adjusted so that it is consistent with the data from NLSY. The other explanatory variables include personal and job characteristics at the start of a job such as age, gender, race, education, and whether the job is protected by a union.

3 Estimation strategy

The Cox (1972) proportional hazard model is widely applied to duration data when time to a failure event is of interest. In the analysis of employment duration, the failure event of interest is job separation. In our analysis, there are multiple types ("causes") of job separations, and only the first of these causes for job separation, if any, is observed. In other words, each cause for job separation is a competing risk for the other causes. In this section, we start with a description of Cox's proportional hazard model when there is a single cause for the failure event. Then, we describe two alternative approaches proposed in the literature when there are competing risks: cause-specific hazard regressions and regression on a subhazard function.[10]

3.1 Cox Proportional Hazard Model

Let the hazard function for job separations be:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t}.$$

The hazard function is the instantaneous probability that a job separation occurs at time T conditional on surviving up to time t. Cox (1972) further imposes that the hazard function for job separations, conditional on a set of explanatory variables at time t, $X(t)$, takes the

[9] Inclusion of these type of job separations in the "firings" category does not change the conclusions.

[10] Both methods have their pros and cons—see, for example, Putter, Fiocco and Geskus (2006) for a general discussion.

following proportional form:

$$h(t|X(t)) = h_0(t)\exp(X(t)\beta), \tag{1}$$

where $X(t)$ are time-varying explanatory variables, β is a vector of parameters common across all job spells, and $h_0(t)$ is the baseline hazard. The baseline hazard is also common across all job spells, and its form is left unspecified. Cox (1972) describes a semi-parametric approach for obtaining estimates of the model parameters, $\hat{\beta}$, through the maximization of the following partial likelihood function:

$$\mathscr{L} = \prod_{i:C_i=1} \frac{h(t_i|X_i(t_i))}{\sum_{j:t_j \geq t_i} h(t_i|X_j(t_i))} = \prod_{i:C_i=1} \frac{\exp(X_i(t_i)\beta)}{\sum_{j:t_j \geq t_i} \exp(X_j(t_i)\beta)}, \tag{2}$$

where $C_i = 0$ if the job spell is right-censored. Note that right-censored job spells enter the partial likelihood function only through the denominator. Further, the baseline hazard can be recovered non-parametrically after obtaining $\hat{\beta}$ even though it cancels from the estimating equation. The proportionality assumption implies that the hazard functions are strictly parallel and inference is possible solely based on $\hat{\beta}$. Specifically, a positive (negative) value of $\hat{\beta}$ implies that the probability of job separation increases (decreases) with an increase in the value of the explanatory variable.

3.2 Cause-specific hazard functions

A standard application of the Cox proportional hazard model can be misleading when there are competing events. The proportional hazard model in equation (1) assumes that the explanatory variables affect the probability of job separation in the same way regardless of its cause. However, the model is misspecified under such a restriction if the effect of one of the explanatory variables is different for each cause-specific job separation. In this study, an EE transition and an EU transition (or a quit and a firing) are competing events for job separations, and the theory predicts that both the starting and current unemployment rate affect the probability of job separation due to these causes in opposite directions.

Taking this issue into account, here we define a separate hazard function for each cause-specific job separation. Formally, let k denote one of the K possible types of job separations. The hazard function for a job separation due to type k is:

$$h_k(t|X(t)) = h_{0,k}(t)\exp(X(t)\beta_k). \tag{3}$$

The specification in equation (3) is similar to the standard specification in equation (1) except that it is now separately defined for K different possible types for job separations. Both the baseline hazard functions and the parameters are allowed to differ across different types of job separations. The β_k's can be estimated separately for each cause-specific hazard function by maximizing the partial likelihood function in equation (2). However, the occurrence of a competing event is treated as right-censored in each of these estimations. While the estimation procedure with cause-specific hazard functions is the same as with the standard Cox proportional hazard model without competing risks, the interpretations of the parameter estimates are different. Because the distributions of time to a job separation for each cause-specific event are potentially dependent, the sign of the parameter estimates alone cannot determine the effect of a covariate on the duration of employment. When the hazard functions are estimated separately for each cause-specific job separation, the effect of a change in the variable of interest on a cause-specific job separation depends nonlinearly on baseline hazard functions and parameter estimates of the other cause-specific hazard functions.

To illustrate this point, let the baseline cumulative cause-specific hazard function be

$$H_k(t) = \int_0^t h_k(s)ds.$$

Then, the probability of surviving from any event at time t is

$$S(t) = \exp(-\sum_{k=1}^{K} H_k(t)).$$

The survival probability now depends on the baseline and parameter estimates not only from the hazard regression of the event of interest, but also from the hazard regressions of the other competing events. Further, the probability of failing from cause k before time t is:

$$I_k(t) = \int_0^t h_k(s)S(s)ds. \tag{4}$$

The probability in equation (4) is called the *cumulative incidence function*. The cumulative incidence function represents the probability that failure from cause k occurs before time t. Since this is an intuitively appealing object, below we measure the effect of a change in the starting and current unemployment rates on different types of separations by constructing cumulative incidence functions.

3.3 Regression on a subhazard function

As an alternative to cause-specific hazard regressions, Fine and Gray (1999) propose a methodology that allows inference on cumulative incidence functions solely based on estimates of β. They define a subhazard function for the competing risk k as follows:

$$\bar{h}_k(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T \geq t \cup (T \leq t \cap K \neq k))}{\Delta t}. \tag{5}$$

The subhazard function shows the instantaneous probability of a job ending due to reason k conditional on surviving up to time t *or* ending before time t due to a reason other than k. Similarly to Cox's proportional hazard model, Fine and Gray (1999) assume that the subhazard function takes the form:

$$\bar{h}_k(t|X(t)) = \bar{h}_{0,k} \exp(X(t)\beta_k). \tag{6}$$

The subhazard function in equation (6) can be estimated in a way that is analogous to equation (2). The only difference in the estimation procedure is in the treatment of the risk set. According to equation (5), job spells that have already ended due to another cause are still considered to be in the risk set for the competing risk k. Since these observations can potentially become right-censored and dropped from the risk set (but the censoring cannot be observed because job spells have already ended), Fine and Gray (1999) weight them using the Kaplan-Meier estimate of the survivor function for the censoring distribution.

One of the advantages of the estimation strategy proposed by Fine and Gray (1999) is that inference can now be made solely based on $\hat{\beta}$, because the subhazard function is directly linked to the cumulative incidence function. Note that the baseline cumulative incidence function and subhazard function for the competing risk k are related as follows:

$$I_k(t) = 1 - \exp\left(-\int_0^t \bar{h}_k(s) ds\right).$$

The estimates of β have a similar interpretation to the standard Cox proportional hazard model. A positive (negative) value of $\hat{\beta}_k$ implies that increasing the value of the explanatory variable increases (decreases) the probability of job separation due to cause k.

4 Results

4.1 Sample restrictions

Following Bowlus (1995), we restrict the dataset to include only private sector employment. Jobs that start before the individual completes all schooling or is younger than 16 years old are dropped from the sample. Further, jobs with missing information and those lasting less than a month are not included in the sample. Unlike Bowlus (1995), we include females in our sample. Bowlus (1995) restricts the sample to only males on the grounds that females are likely to quit for reasons other than poor match quality, such as marriage, pregnancy, and childcare. We do not make such a restriction on our sample, because it is likely that distinctions among job separations can control for these differences.

The original dataset consists of multiple job spells for each individual. If there is an individual-specific unobserved component, the job spells for the same individual are potentially correlated and the estimates of β are biased. To address the concerns about unobserved heterogeneity, we follow Bowlus (1995) and randomly select one spell per individual. Bowlus (1995) argues that such a restriction on the sample (under certain restrictions on the distribution of unobserved heterogeneity) produces unbiased estimates of β.[11] However, the estimates for the baseline hazard functions are still biased, because longer spells are now overrepresented in the sample. Since cumulative incidence functions are constructed from the estimates of the baseline hazard functions, they are also potentially biased. While the bias in cumulative incidence function calculations is problematic for inference from the cause-specific hazard regressions, this is not a concern for the subhazard regressions because inference is possible solely based on the estimates of β.

4.2 Preliminary estimation

As a preliminary step, we first repeat Bowlus's (1995) analysis. First, we run her estimation with the same time period as hers (from 1979 to 1988). For comparability, we exclude females from our sample in this section along with other restrictions in the previous section. Also only in this section, we use the weekly employment status instead of monthly. In the subsequent sections, we use monthly employment status so that it can be directly comparable to the model in Section 5.

Table 1 presents the estimation results. The first column is from Table 1 in Bowlus (1995), and the second column is from our sample which covers the same time period as hers.

[11] See pp. 340-341 of Bowlus (1995) for detailed discussions. She argues that even when the unobservables do not have the correct distribution, inference is still possible and when a variable has a significant impact on the hazard rate, this indicates that the variable's impact is real and not due to the misspecification bias.

Variable	Bowlus Sample	Our sample (Short Panel)	Our sample (Long Panel)
u_0	.050*	.052**	.007
	(.023)	(.016)	(.014)
u_t	−.460*	−.321*	.389***
	(.183)	(.126)	(.098)
u_t^2	.028*	.018*	−.025***
	(.011)	(.008)	(.006)
HS	−.260**	−.170***	−.107*
	(.066)	(.045)	(.045)
COL	−.521***	−.790***	−.545***
	(.106)	(.080)	(.067)
AGE	−.152	−.027	.262***
	(.112)	(.085)	(.026)
SQAGE	−.003	.001	−.005***
	(.003)	(.002)	(.001)
NWHITE	.090	.069	.171***
	(.068)	(.039)	(.035)
UNION	−.174*	−.481***	−.360***
	(.076)	(.048)	(.043)
Occurrence:	1392	2873	3456
# of observations:	2135	4330	4073
# of right-censored:	743	1457	617

Table 1: Replication of Bowlus (1995). The first column is taken from Bowlus (1995, Table 1). The second and third columns are the replication of her results with our samples from 1979 to 1988 and from 1979 to 2010, respectively. UNION=1 if the job is covered under a union contract or collective bargaining agreement; NWHITE=1 if the respondent is black or hispanic; SQAGE=age squared; HS=1 if the respondent is a high school graduate, and COL=1 if he completed 16 or more years of education. Standard errors are given in parentheses. * indicates significant at 5%, ** indicates significant at 1%, and *** indicates significant at 0.1%.

Despite the retrospective corrections of the samples and randomness in selecting spells, our result is qualitatively very similar to hers. In particular, u_0 has a significantly positive effect on separation probability, indicating that the match quality is higher for the jobs that are created in booms.

Next, we extend the sample period to the same as the current analysis (from 1979 to 2010) and repeat the analysis. We maintain the same sample restrictions as Bowlus (1995). The third column in Table 1 presents the estimation results from the longer panel. Now the effect of u_0 becomes statistically insignificant. The difference is likely due to the age of samples—Bowlus' (1995) samples consist of very young workers, whose labor market experiences are very different from older workers. To the extent that we are interested in the behavior of typical worker-firm match, our samples are more representative of the entire economy than hers. Below, in our main analysis, we show that the effect of u_0 is more transparent once we take different types of separations into account.

4.3 EE and EU transitions

In this section, we treat movement to another job and transition to non-employed status as competing risks. Table 2 presents our main estimation results. The first two columns show the estimation results from the cause-specific hazard regressions for EE transitions and EU transitions. The last two columns show the results from the subhazard resgressions. The coefficients of interest are those for the unemployment rate at the start of the job spell, u_0, and the current unemployment rate, u_t, for EE transitions and EU transitions.

The effects of the explanatory variables can be directly inferred from the estimates of the subhazard regressions. The effect of u_0 is positive and statistically significant for EE transitions. The positive sign implies that a high unemployment rate at the start of a job spell increases the probability that the worker moves from his current job to another job. In contrast, for the job separations that results in EU transitions, the sign of the coefficient for u_0 is negative, which implies that a high unemployment rate at the start of a job reduces the probability that the worker experiences EU transition in the future.

In the aggregate data, the cyclical behavior of the EE and EU flow rates are qualitatively different. While the EE flow rate is strongly procyclical, the EU flow rate is strongly countercyclical. This macro-level observation suggests that they also respond to u_t in opposite directions. The negative coefficient for u_t from the subhazard regression for EE transitions indicates that the probability that a job spell ends with an EE transition is lower during recessions. In contrast, the coefficient estimate from the subhazard regression for the EU transitions is positive and statistically significant. The positive coefficient implies that the

	Cause-Specific Hazard		Subhazard	
Variable	EE	EU	EE	EU
u_0	.043**	−.029	.134***	−.050**
	(.015)	(.015)	(.020)	(.018)
u_t	−.035*	.096***	−.188***	.086***
	(.016)	(.014)	(.023)	(.019)
HS	.042	−.255***	.186**	−.236***
	(.055)	(.046)	(.055)	(.045)
COL	−.066	−1.080***	.419***	−.948***
	(.067)	(.078)	(.066)	(.076)
AGE	.388***	.105***	.263***	−.040
	(.028)	(.022)	(.025)	(.021)
SQAGE	−.007***	−.002***	−.005***	.000
	(.000)	(.000)	(.000)	(.000)
NWHITE	−.008	.272***	−.116**	.283***
	(.038)	(.036)	(.038)	(.035)
GEN	−.191***	.247***	−.287***	.309***
	(.037)	(.035)	(.036)	(.035)
UNION	−.501***	−.366***	−.226***	−.105*
	(.050)	(.046)	(.048)	(.043)
Occurrence:	3111	3276	3111	3276
# of observations: 7551				
# of right-censored observations: 1164				

Table 2: Estimation results for hazard functions under EE and EU classifications. UNION=1 if the job is covered under a union contract or collective bargaining agreement; GEN=1 if the respondent is female; NWHITE=1 if the respondent is black or hispanic; SQAGE=age squared; HS=1 if the respondent is a high school graduate, and COL=1 if he completed 16 or more years of education. Standard errors are given in parentheses. * indicates significant at 5%, ** indicates significant at 1%, and *** indicates significant at 0.1%

probability that a job spell ends with an EU transition is higher during a recession. Both of these estimates are consistent with the cyclical behavior of EE and EU flows.

The results for the effect of u_t are crucial for isolating the effect of u_0, as the duration of a job spell is affected by the current cyclical fluctuations. Both Bowlus (1995) and Mustre-del-Rio (2014) include the unemployment rate as an explanatory variable for hazard regressions. However, the model suffers from misspecification bias if u_t has opposite effects on the decisions of workers and firms. In both of these papers, the coefficient estimate for u_t is statistically insignificant when it is added linearly to the model. Bowlus (1995) further adds the squared value of u_t to the right-hand side variables, and the estimates for the explanatory variables involving u_t are significant in her results. By distinguishing job separations according to their causes, we separately identify the effects of current cyclical fluctuations on the duration of a job spell ended with EE transitions and EU transitions. The opposite signs for different causes support the discussion about the effect of u_t raised in Bowlus (1995).[12]

While the estimates from the subhazard regressions provide a direct inference on the effects of u_0 and u_t on EE transitions and EU transitions, using these estimates to make inferences about the overall duration of employment can be misleading. The subhazard functions for different reasons of job separations are estimated separately, and the probability of job separation can potentially exceed one when the value of one of the explanatory variables is changed.

To evaluate the overall behavior of employment durations, we use the coefficient estimates from the cause-specific hazard regressions. Note that the estimates of the coefficients from the cause-specific regressions alone are not informative about the effects of u_0 and u_t, although the signs agree with the estimates from the subhazard regressions. Therefore, we obtain the cumulative incidence functions for each job separation category using the coefficient and baseline hazard estimates from the cause-specific hazard regressions. By construction, the probability of job separation is less than one at any point in time.

Figure 1 shows the cumulative incidence functions for each cause-specific job separations. The cumulative incidence functions are drawn for a 29 year-old high-school graduate white male whose job is not protected by a union. The unemployment rate is set equal to the average value of the unemployment rate for the survey years, 6.15%, and it is assumed to be equal to this value for all of the time periods from the start of the job. The plots for both termination types are stacked so that the differences show the probability of observing

[12] Bowlus' (1995) motivation for including the current unemployment rate non-linearly in her analysis is to capture the countercyclicality of firings. Because we make a distinction across job spells according to transition type and reason, we do not need to maintain this non-linearity assumption. Hence, we drop u_t^2 from our analysis.

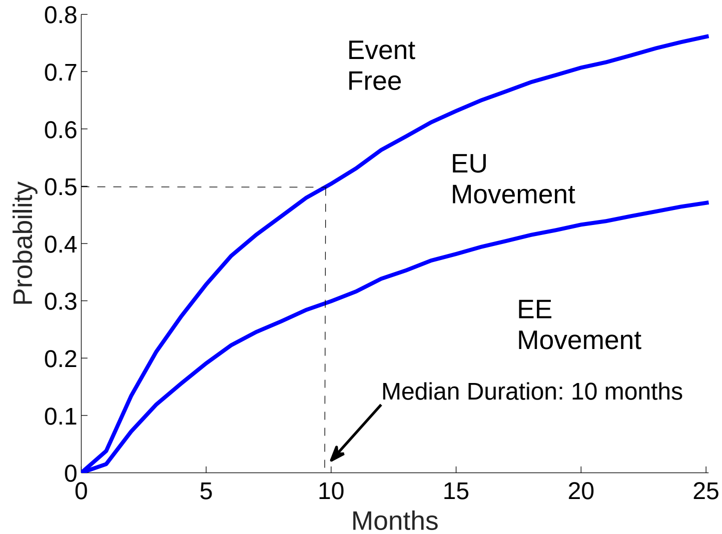

Figure 1: Cumulative incidence functions for quits, firings, and other reasons. The cumulative incidence functions are stacked so that the distance between two curves represents the probabilities of the different events.

the corresponding cause-specific job separation before time t. At any time t, the difference between the sum of cumulative incidence functions and one represents the survival probability. From the survival probability, we can calculate that the median duration of a job is 10 months.

Figure 2 shows the effects of a change in u_0 on the cumulative incidence functions for EE transitions and EU transitions. In each plot, the solid curve shows the cumulative incidence functions when u_0 is equal to its sample mean for the period under study, 6.15%. The dashed and dotted curves correspond to the cumulative incidence functions when u_0 is one standard deviation, 1.71 percentage points, above or below its sample mean. The current unemployment rate is still kept at its average value for all of the remaining time periods. It can be seen that the quantitative magnitude of the effect of u_0 on the EE transition probability is significantly larger than the effect on the EU transition probability.

Similar results hold for the effects of u_t. Figure 3 shows the change in the cumulative incidence functions for cause-specific job separations after a change in u_t. In each plot, the solid curves show the cumulative incidence functions when u_t is equal to its sample mean. The dashed and dotted curves correspond to the cumulative incidence functions when u_t is permanently one standard deviation above or below its sample mean for all the periods after the job spell has started.

Comparing Figures 2 and 3, the effect of u_0 on the probability of EE movements is of quantitatively comparable order to the effect of u_t. The effect of aggregate economic

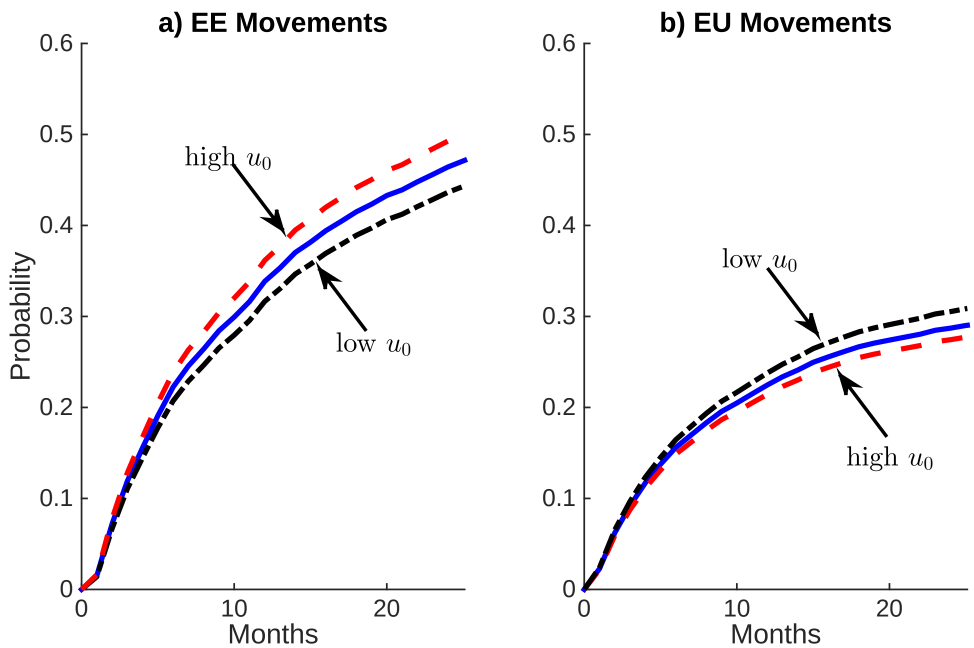

Figure 2: Changes in cumulative incidence functions in response to a change in u_0.

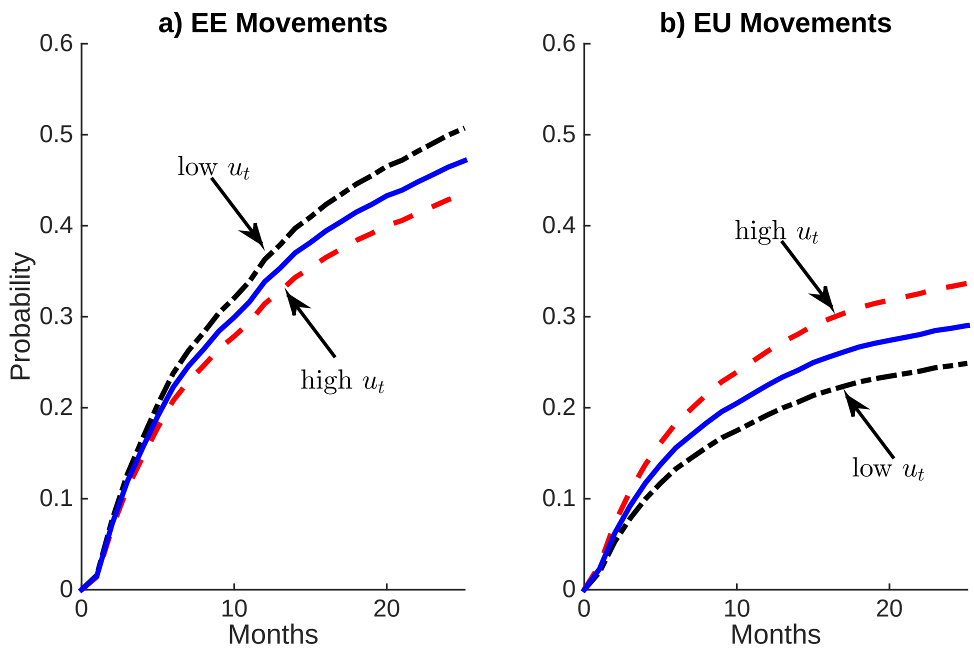

Figure 3: Changes in cumulative incidence functions in response to a change in u_t.

conditions (here represented by u_t) on worker flows is well documented and extensively studied. These figures show that the effect of u_0 on worker flows is also quantitatively important.

4.4 Quits, firings, and other reasons

In this section, we distinguish job spells based on the reasons for job separation. The first three columns show the estimation results from the cause-specific hazard regressions for job separations due to quits, firings, and other reasons, respectively. The last three columns show the results from the subhazard regressions.

Table 3 paints a very similar picture as Table 2, with quits corresponding to EE transitions and firings (and other reasons) corresponding to EU transitions. The unemployment rate upon match has a positive effect on quits and small negative effect on firings. The current unemployment rate has a negative effect on quits and a positive effect on firings and other reasons. Again, these effects of u_t can easily be understood by the procyclical aggregate quit rate and countercyclical aggregate firing rate.

Figures 4, 5, and 6 correspond to Figures 1, 2, and 3 in the previous subsection. The results are very similar, with quits corresponding to EE transitions and firing (and other reasons) corresponding to EU transitions. In the following model analysis, we focus solely on the EE-and-EU distinction, mainly because of the difficulty in defining quits and firings at a theoretical level. However, given these direct associations, we believe that the quits-and-firings distinction can also be interpreted similarly.[13]

5 Model

In this section, we analyze a simple job-ladder model in order to interpret our empirical findings in a more formal setting.[14] Our model focuses on a worker's decision of whether to accept a job with a given match quality. Firms' decisions are not modeled explicitly—one interpretation is that firms' decisions are implicit in the distribution of offered match quality

[13]One alternative interpretation of the difference in results between quits and firings is the different motivations for workers and firms. For matches where workers' decisions are important in the match formation/separation, workers tend to take low-quality jobs in recessions and they tend to quit into another job in future. For matches where firms' decisions are important, the match quality improves during recessions because the firms can wait longer until a good match comes along, and they are less likely to end up with firings in the future. This interpretation is not explicitly considered in the model in the next section—we leave it to future research to investigate this (and other potential) interpretation further.

[14]Given that the fit of the model to the empirical results turns out to be very good, another possible interpretation of this paper's exercise is that we are estimating the job-ladder model with indirect inference (Smith (1993) and Gouriéroux and Monfort (1996)), using the Cox model as the auxiliary model.

	Cause-Specific Hazard			Subhazard		
Variable	Quits	Firings	Other	Quits	Firings	Other
u_0	.182***	−.065**	−.175***	.396***	−.123***	−.272***
	(.017)	(.023)	(.019)	(.021)	(.032)	(.024)
u_t	−.131***	.161***	.135***	−.423***	.179***	.174***
	(.019)	(.021)	(.017)	(.025)	(.031)	(.023)
HS	.023	−.250***	−.173**	.149*	−.185**	−.097
	(.060)	(.069)	(.055)	(.061)	(.069)	(.055)
COL	−.083	−1.316***	−.707***	.382***	−1.028***	−.454***
	(.074)	(.131)	(.082)	(.074)	(.129)	(.079)
AGE	.646***	.089**	.070**	.541***	−.060	−.065**
	(.040)	(.035)	(.024)	(.048)	(.034)	(.023)
SQAGE	−.012***	−.002***	−.002***	−.010***	.001	.001
	(.001)	(.001)	(.001)	(.001)	(.001)	(.000)
NWHITE	.084**	.286***	.114**	.017	.236***	.053
	(.042)	(.055)	(.042)	(.042)	(.054)	(.042)
GEN	−.083**	−.252***	.313***	−.130***	−.294***	.341***
	(.041)	(.056)	(.041)	(.040)	(.055)	(.041)
UNION	−.510***	−.156**	−.520***	−.241***	.179**	−.255***
	(.056)	(.064)	(.056)	(.054)	(.062)	(.053)
Occurrence:	2536	1398	2453	2536	1398	2453
# of observations: 7551						
# of right-censored observations: 1164						

Table 3: Estimation results for hazard functions under quits, firing, and other reasons classifications. UNION=1 if the job is covered under a union contract or collective bargaining agreement; NWHITE=1 if the respondent is black or hispanic; SQAGE=age squared; HS=1 if the respondent is a high school graduate, and COL=1 if he completed 16 or more years of education. Standard errors are given in parentheses. * indicates significant at 5%, ** indicates significant at 1%, and *** indicates significant at 0.1%

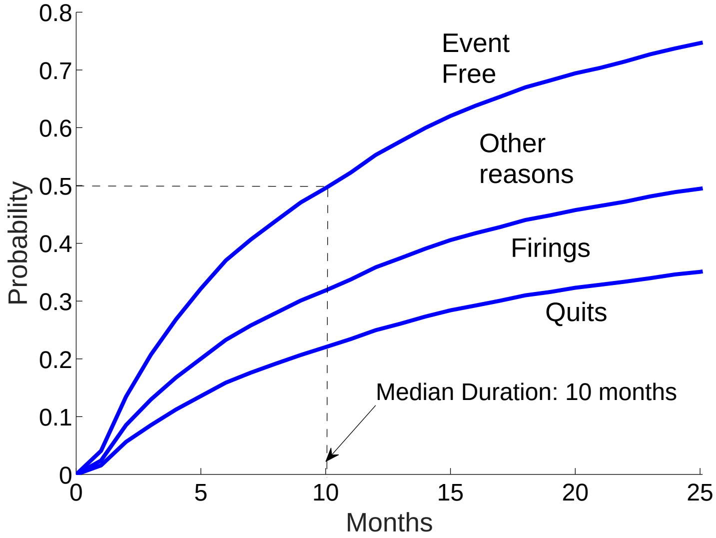

Figure 4: Cumulative incidence functions for quits, firings, and other reasons. The cumulative incidence functions are stacked so that the distance between two curves represents the probabilities of the different events.

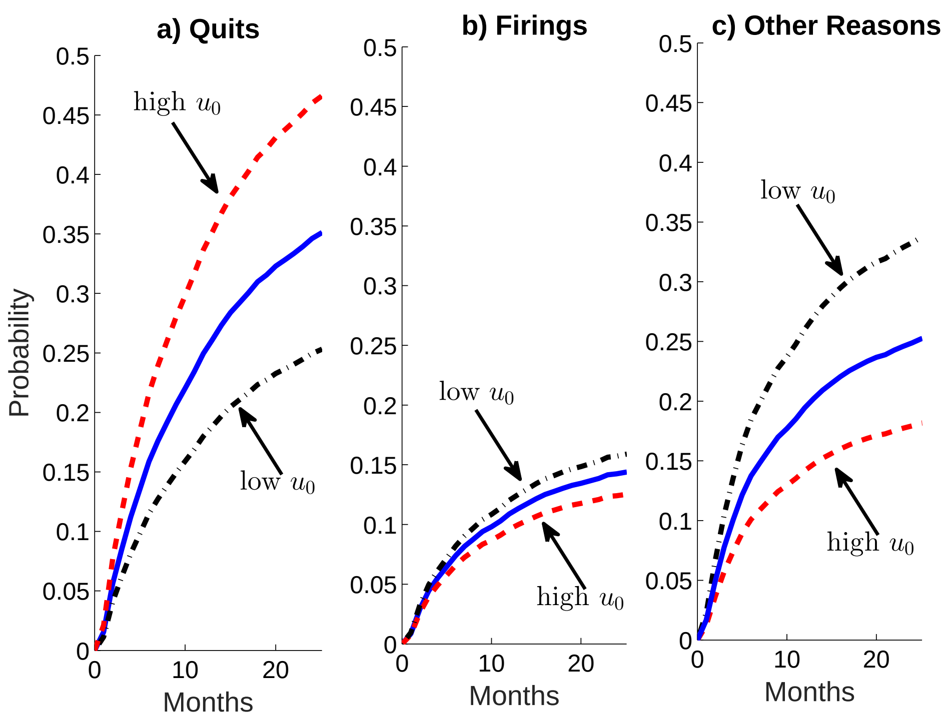

Figure 5: Changes in cumulative incidence functions in response to a change in u_0.

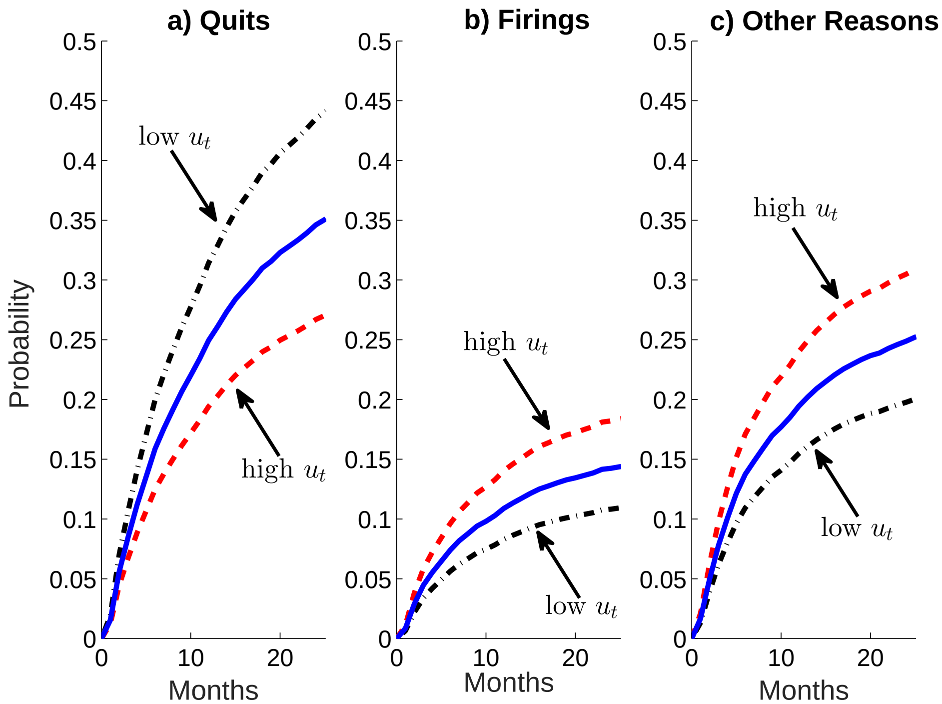

Figure 6: Changes in cumulative incidence functions in response to a change in u_t.

(the distribution is assumed to be the same over time) and labor market frictions. Another interpretation is that the match formation/separation decision is efficient so that workers' decisions and firms' decisions agree with each other.

As is mentioned in the previous section, there can be interpretations that are not captured in this simple model. This model should therefore be viewed as a first step, and although it is indeed quite surprising that this model can quantitatively capture the above empirical patterns quite well, it does not rule out alternative (possibly more complex) interpretations.

5.1 Setup

The model setup is the standard job-ladder model.[15] An infinitely-lived worker is either employed or unemployed. We assume that his utility is linear and he consumes what he receives each period. An employed worker receives a wage of zx. The component z is the aggregate productivity and x is the match quality. z follows a Markov process according to $F(z'|z)$, where $'$ (prime) represents the next period. We assume that x is constant for a given job. At the beginning of the following period, an employed worker can receive two different shocks. First, he may receive a job offer from another employer. The probability of this

[15]Moscarini and Postel-Vinay (2014) use a similar model in their analysis of the Great Recession.

shock is $\lambda_e(z') \in [0,1]$. Note that this probability is a function of the next period aggregate state z'. The match quality of this new job is randomly drawn from a distribution that is constant over time, $G(x)$. After seeing the match quality, the worker chooses whether to stay in the same job, move to the new job, or move to unemployment. The second shock is a separation shock with probability $\delta(z') \in [0,1]$ which forces him to move to unemployment. We assume that $\lambda_e(z') + \delta(z') \leq 1$ for all z'.

An employed worker's Bellman equation can be written as

$$\begin{aligned} W(x,z) =& zx + \beta E_{x',z'}[\lambda_e(z') \max\{W(x',z'), W(x,z'), U(z')\} \\ & + (1-\lambda_e(z') - \delta(z')) \max\{W(x,z'), U(z')\} + \delta(z')U(z')]. \end{aligned}$$

Here, $W(x,z)$ is the value function of an employed worker, $U(z)$ is the value function of an unemployed worker, and β is the discount factor. The operator $E_{x',z'}[\cdot]$ takes the expected value with regard to x' and z'.

An unemployed worker receives a job offer with probability $\lambda_u(z') \in [0,1]$. While unemployed, he receives a flow value of b, which can be interpreted as the combination of unemployment insurance benefit, home production, and the value of leisure. After observing the match quality of the offer, he chooses whether to take that job. An unemployed worker's Bellman equation is therefore

$$U(z) = b + \beta E_{x',z'}\left[\lambda_u(z') \max\{W(x',z'), U(z')\} + (1-\lambda_u(z'))U(z')\right].$$

5.2 Calibration

One period is set as one month. The discount factor is set at $\beta = 0.99^{\frac{1}{3}}$, as in Gertler and Trigari (2009). Following Hall and Milgrom (2008), we choose b so that it is 71% of the average wage. $F(z'|z)$ approximates an AR(1) process:

$$\log(z_{t+1}) = \rho_z \log(z_t) + \epsilon_t,$$

where $\epsilon_t \sim N(0, \sigma_z^2)$. We set $\rho_z = 0.95^{\frac{1}{3}}$, again following Gertler and Trigari (2009). For σ_z, we target the cyclicality of the wages of new hires. This is because it is commonly considered that existing workers' wages tend to be sticky, and here what affects the match formation is the wages at the time of contact between the worker and the firm. Shimer (2005b) estimates the standard deviation of labor productivity to be 2 percent quarterly, after HP-filtering with parameter 10^5. In Pissarides (2009), the elasticity of job changers' wages with respect to labor productivity is estimated to be 1.70. Haefke et al. (2013) estimates this elasticity to be 1.31 for new hires from non-employment and 2.02 for job changers, although the standard errors are large (Table 8). This provides the target of the quarterly standard deviation of wages for new matches to be from 2.6 percent to 4.0 percent. We set σ_z to be 0.01, which gives us 3.1 percent value for this target.

The logarithm of the match quality shock is normally distributed with its mean normalized to zero, $\log(x) \sim N(0, \sigma_x^2)$. The dispersion in x directly affects the gains from switching to another employer. Tjaden and Wellschmied (2014) estimate the average wage gain upon job-to-job transition to be 3.3%, and we target this value. This gives us $\sigma_x = 0.035$.

The labor market frictions, $\lambda_u(z)$, $\lambda_e(z)$, and $\sigma(z)$, are calibrated using labor market flows. First, we assume that $\lambda_e(z)$ is proportional to $\lambda_u(z)$; $\lambda_e(z) = \alpha\lambda_u(z)$.[16] We set $\alpha = 0.27$ to target an average job-to-job flow rate of 1.4% per month, again taken from Tjaden and Wellschmied (2014).

We assume that $\lambda_u(z)$ and $\delta(z)$ take the following form:

$$\lambda_u(z) = \bar{\lambda}_u + \phi_\lambda \log(z),$$

and

$$\delta(z) = \bar{\delta} - \phi_\delta \log(z).$$

The average values, $\bar{\lambda}_u$ and $\bar{\delta}$, are set so that the model replicates the gross flow rate for unemployment to employment and employment to unemployment. Krusell et al. (2015) calculate these values (with adjustments for measurement errors) as 0.235 and 0.014 per month, using the Current Population Survey dataset.[17] The parameter values are $\bar{\lambda}_u = 0.242$ and $\bar{\delta} = 0.014$. The parameters governing the fluctuations, ϕ_λ and ϕ_δ, are set so that the fluctuations of the corresponding flow rates in the model mimics the behavior of the data. Krusell et al. (2015) calculate the standard deviation of (quarterly averaged, logged, and HP-filtered with parameter 1,600) these flows as 0.085 and 0.085. We obtain $\phi_\lambda = 1.10$ and $\phi_\delta = 0.063$. Table 4 summarizes the calibration.

5.3 Results

The model implies the steady-state value of unemployment at 5.6%. The standard deviation of employment and the unemployment rate are 0.009 and 0.136. The corresponding empirical

[16] Shimer (2005a), Moscarini and Postel-Vinay (2014), and Mukoyama (2014) employ a similar assumption. This property comes out naturally from a search and matching model where employed and unemployed workers compete for the same set of vacancies, but they differ in the efficiency of search.

[17] The time span that Krusell et al. (2015) analyze is from 1978 to 2009, which is almost identical to our data period.

Parameter	Description	Target/Source	Value
β	Discount Factor	Gertler and Trigari (2009)	$0.99^{\frac{1}{3}}$
b	Value of unemployment	Hall and Milgrom (2008)	0.735
ρ_z	Persistence of aggregate shocks	Gertler and Trigari (2009)	$0.95^{\frac{1}{3}}$
σ_z	Dispersion of aggregate shocks	cyclicality of new hire's wages	0.01
σ_x	Dispersion of match quality	Tjaden and Wellschmied (2014)	0.035
α	$\lambda_e(z)$ relative to $\lambda_u(z)$	Tjaden and Wellschmied (2014)	0.27
$\bar{\lambda}_u$	Average value of λ_u	Krusell et al. (2015)	0.242
$\bar{\delta}$	Average value of δ	Krusell et al. (2015)	0.014
ϕ_λ	Fluctuation parameter of λ_u	Krusell et al. (2015)	1.10
ϕ_δ	Fluctuation parameter of δ	Krusell et al. (2015)	0.063

Table 4: Calibration

	Cause-Specific Hazard		**Subhazard**	
Variable	EE	EU	EE	EU
u_0	.051***	$-$.005*	.074***	$-$.085***
	(.002)	(.002)	(.003)	(.003)
u_t	$-$.084***	.090***	$-$.141***	.161***
	(.002)	(.002)	(.003)	(.003)
Occurrence:	95741	93014	95741	93014
# of observations: 188755				

Table 5: Regression results from model generated data. Standard errors are given in parentheses. * indicates significant at 5%, ** indicates significant at 1%, and *** indicates significant at 0.1%

values are 0.010 and 0.113 in the data (Krusell et al. 2015).[18] As in the data, the flow rate for job-to-job transition and UE flow are procyclical and EU flow rate is countercyclical (the corresponding correlation coefficients with the unemployment rate are -0.686, -0.876, and 0.821). Thus the model represents the aggregate cyclical movement of the labor market very well.

Now we turn to the micro-level behavior of employment duration. Table 5 presents the results from running the same estimation as Section 4 on model-generated data. The model predictions are largely consistent with the empirical result.

[18] For all summary statistics below, the variables are quarterly averaged, logged, and HP-filtered with parameter 1,600.

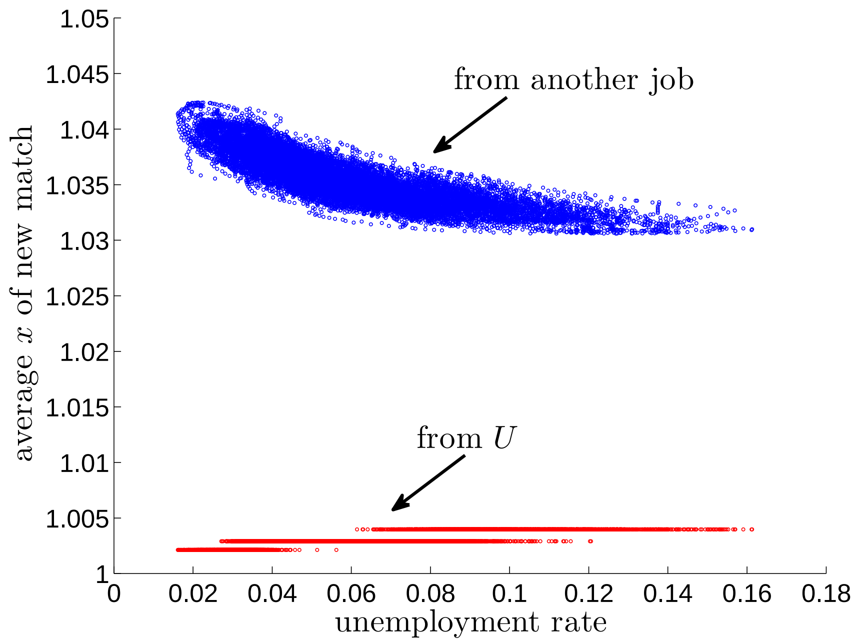

Figure 7: Average value of new x at each period, plotted against the unemployment rate

5.3.1 Intuitions

Interpreting the coefficients for u_t is straightforward. Largely because of the movements in $\lambda_e(z)$ and $\delta(z)$, the EE flow rate is procyclical and the EU flow rate is countercyclical. Interpreting the coefficients on u_0 requires more information, as it is a reflection of the quality of matches formed in the past.

The key to understanding these coefficients is what type of matches are created at each point in time. Figure 7 plots the simulated average match quality for new workers, calculated separately for the matches formed by EE transitions ("from another job") and the matches formed by UE transitions ("from U"). The average match quality is plotted against the unemployment rate. One can see striking differences in these two series. First, the average quality of matches formed by EE transitions is higher than that of matches formed by UE transitions. This is natural because EE transitions are more selective. Second, they exhibit a different relationship with the unemployment rate. Let us consider them one by one.

For the UE transition, because the distribution of new x is constant over the business cycle, the average quality in Figure 7 reflects the reservation match quality. The reservation match quality, in relation to the aggregate state z, is plotted in Figure 8.[19]

There are two properties that are notable in Figure 8. First, the reservation match quality

[19]The discreteness of the graph in Figure 8 comes from the grid points we use. This is also reflected in the outcome for UE transitions in Figure 7.

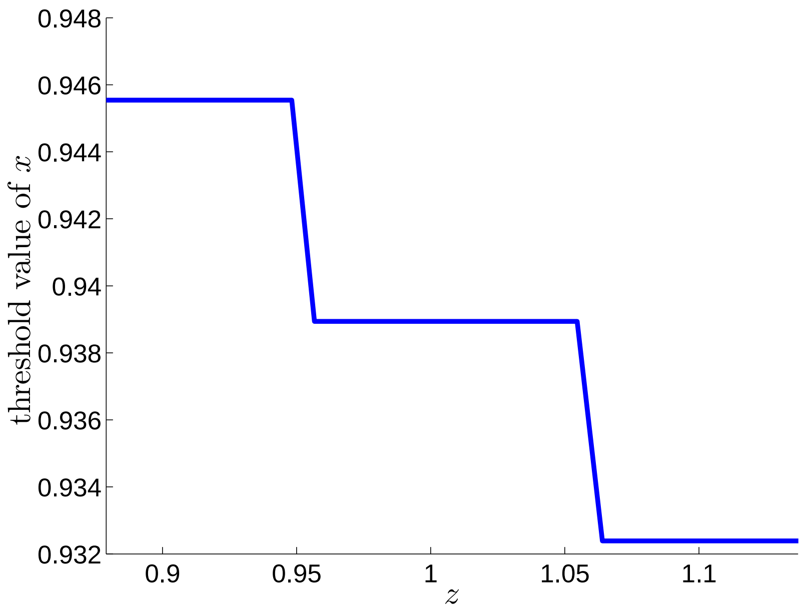

Figure 8: Reservation match quality for each z

is decreasing in z. This means that more of the "very bottom quality" jobs are created in booms, and they are destroyed when a recession arrives. This is reflected in the (small but) negative entry of u_0's influence on EU flow, although the mapping between the average match quality and the coefficient is not exact.[20] The jobs that are created in booms are more likely to be separated into unemployment. Second, the slope is very small, compared to the fluctuations in z. This is because there are multiple effects offsetting each other. First and the most obvious effect is that when z is high, zx can be high even if x is low, so that even a low x can be accepted. Second, because $\lambda_u(z)$ is increasing in z, there are more chances of obtaining another draw in booms, and this makes the worker more choosy during booms. This raises the reservation match quality in booms—the exact opposite of the first effect. The third effect is that because $\lambda_e(z)$ is increasing in z, the worker is willing to take a low-x match, thinking that there will soon be another chance on the job. This offsets (a part of) the second motive of waiting in booms.

The fact that the profile in Figure 8 is close to flat implies that these effects almost exactly offset each other. This is reflected in the small size in the coefficient of u_0 for EU

[20]Another reason for the negative coefficient on u_0 here is that u_t does not adjust immediately to the change in z. For example, when z decreases very rapidly, u_t does not increase immediately and thus the term with u_t under-predicts the increase in the EU flow rate. A part of increase in the EU flow rate is thus attributed to the fact that the recent unemployment rate was low, and to the extent that u_0 is a reflection of the recent unemployment rate, this effect can generate a negative coefficient on u_0.

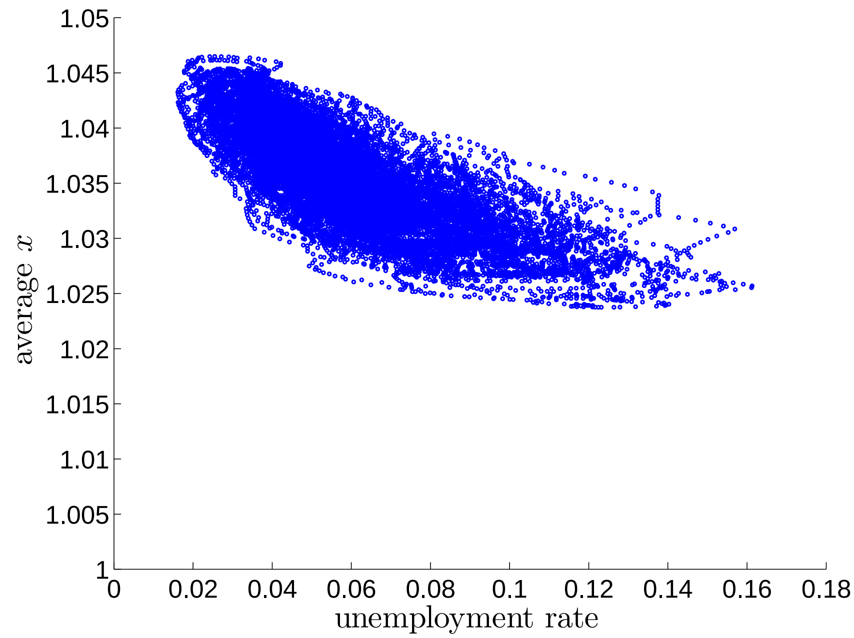

Figure 9: Average value of x, plotted against the unemployment rate

transitions in the cause-specific hazard regression (although, once again, the mapping is not exact because of the competing risks structure). It is almost statistically insignificant despite generating a very large sample. We believe that this is in fact a favorable property of the model, considering that the corresponding coefficient in Table 2 is insignificant.

It is relatively straightforward to understand the relationship between the unemployment rate and the average new match quality for EE transitions in Figure 7. In booms, the average match quality for existing matches is already good, because of the frequent opportunity for job-to-job transitions (this can be seen from Figure 9 which plots the average match quality for all matches). Thus the new match formed by a job-to-job transition in a boom should have a higher match quality compared to the match formed in a recession. The pattern in Figure 7 for EE transitions is reflected in the coefficient on u_0 for EE in Table 5. Because the average x of jobs created in recessions by job-to-job transitions are worse, these jobs will have more opportunity to experience EE transitions in future.

In sum, the model provides theoretical intuitions for our empirical results in earlier sections. It is substantially easier to interpret the outcome by inspecting the mechanism in the model than directly speculating what is in behind the regression coefficients from the data, since we can directly observe the match quality in the model.

Finally, going back to the original question of whether a better quality match is created during booms or recessions, we provide two answers. First, because the offered match quality

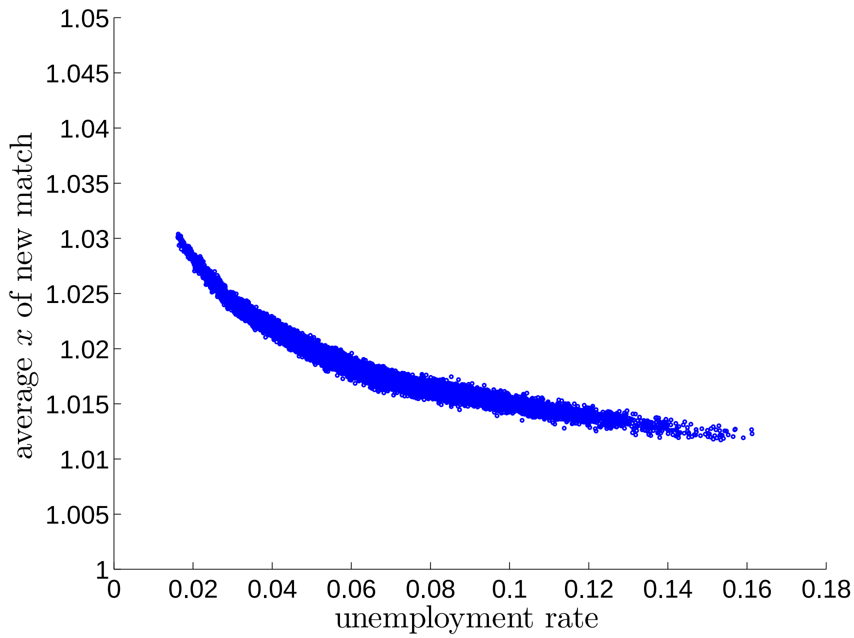

Figure 10: Average value of x for newly formed match, plotted against the unemployment rate

distributions in the job-ladder model is acyclical and it is still capable of generating the regression coefficients that are empirically relevant, we can conclude that the cyclicality of offered match quality distribution is not necessary in explaining the pattern of employment duration. This is important because one possible explanation of Bowlus' (1995) result is a technology shock that is cohort-specific.[21] Second, the change in job-to-job transition rate is an essential driver of the quality distribution of new matches over the business cycle. Figure 10 plots the overall average quality of new matches, and it is clearly procyclical. In this sense, Bowlus' (1995) takeaway that the quality of new matches is procyclical survives, despite the fact that the coefficient on u_0 for her Cox (1972) regression in our extended samples is not statistically different from zero (in Table 1). We reach this conclusion from an entirely different route from Bowlus (1995). Our approach is to distinguish different types of separations and to build a model that matches the data properties in order to directly observe the match quality of newly-formed matches.

[21] See, for example, Costain and Reiter (2008).

6 Conclusion

In this paper, we empirically examined the effects of labor market conditions on the duration of employment. Using data from NLSY 1979 cohort, we estimated a proportional hazard model under the assumption that different causes of job separations are competing risks. Making a distinction between different types of separations is the main contribution of this paper, because it allowed us to test separately for *both* of these opposing forces rather than estimating their *net* effect on the duration of employment.

Two functions, the cause-specific hazard function and the subhazard function, have been widely used in the literature to estimate hazard models when there are competing risks. We applied both of these in this paper and they produced results that are consistent with each other. We found that an increase in the unemployment rate at the start of an employment relation increases the probability that a separation with job-to-job transition occurs, but it reduces the probability that it ends with the worker moving into unemployment.

The distinction based on reasons for the separation, which divides the separations into quits, firings, and other reasons, yielded a similar result. This was as expected because the majority of quits result in job-to-job transitions and fired workers tend to transit into unemployment.

There can be several different interpretations for the different patterns of job-to-job transitions and transitions into unemployment (or quits and firings) in relation to the aggregate condition at the time of match formation. In order to examine the mechanism formally, we built a simple job-ladder model and calibrated it to match the U.S. data. The model outcome is largely consistent with the empirical results.

The model allowed us to interpret the results in the empirical part more directly in the context of match quality. The model outcome shows that the average quality of new matches is procyclical. It also clarifies that job-to-job transitions play an important role in analyzing the time-series of the average quality of new matches. Our result suggests that when studying the issues of "mismatch" in the labor market, it is essential to take job-to-job transitions into account.[22]

[22]Barlevy (2002) and Mukoyama (2014) emphasize the consequences of this "mismatch employment" on aggregate productivity.

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Appendix

A Details of Data Construction and Summary Statistics

We use the Employer History Roster (Beta version) provided by NLYS 1979. This roster contains information about each of the up to 57 jobs every individual holds. We retrieved the job start and end dates, employment status, and reason for job separations directly from this roster. Class of worker and union status are spread out on a roster created separately for each survey year. We created these variables by linking the rosters for each survey year. We removed observations with inconsistent information. We use the job start and end dates to calculate the duration of the job spells and the information on employment status to determine censored observations.

Starting from 1980, each survey asks respondents about their school enrollment for each month from the date of the last interview until the date of the current interview. We use this information in all survey years to determine the last month a respondent was enrolled in school. For those who did not attend school after 1980, we use the information in the first survey in 1979 about the last date a respondent attended school. If the year of last school enrollment is missing, we drop this individual from our sample. If only the month of last school enrollment is missing, we insert May as the graduation month, which is the modal month in our sample. For duration analysis, we drop job spells that start before all schooling is completed.

To determine EE and EU transitions for a job spell, we compare the stop date of that job spell with the start date of other job spells. If there is less than a month of difference and the job did not end with a firing, we label this job as EE. There are some cases where a respondent holds multiple jobs. For these cases, if the respondent already has another job at the time the job ended, we labeled it as EE. All the other job spells are labeled as EU.

When creating the sample for the shorter panel, we restrict our dataset to the jobs that start before the year 1988. This restriction reduces the maximum number of jobs that an individual holds to 32. For the jobs that started before 1988, but ended after 1988, we change the job ending date to the interview date in 1988 for that individual. We also label these job spells as censored. Similarly, when we determine the date for last school enrollment, we restrict our dataset to survey years until 1988. This process overwrites some of the jobs with missing ending dates and the last school enrollment dates for respondents, which causes a difference between the sample sizes of shorter and longer panels. Table 6 shows summary statistics from our short and long panel samples after imposing the restriction above.

Variable	Explanation	Mean (Short Panel)	Mean (Long Panel)
u_0	Unemployment rate at the start of the job	7.400	7.002
AGE	Age of the respondent at the start of the job	22.606	25.231
HS	=1 if obtained high school diploma or equivalent	0.659	0.703
COL	=1 if completed 16 years of schooling	0.120	0.145
NWHITE	=1 if black or Hispanic	0.407	0.389
UNION	=1 if covered by union	0.218	0.184
GENDER	=1 if female	0.000	0.461
# of Observations:		4330	7551
# of right-censored:		1457	1164
Median duration:		61 weeks	12 months

Table 6: Description and Means for Our Samples. Short panel uses survey years until 1988 and long panel uses survey years until 2010.

B List of Job Separation Reasons

Employer History Roster (Beta version) in NLSY 1979 provides the following reasons for job separations. We categorize these reasons as [Q]-quit, [F]-firing, and [O]-other reasons.

1. Layoff, job eliminated [F]
2. Company, office or workplace closed [O]
3. End of temporary or seasonal job [O]
4. Discharged or fired [F]
5. Government program ended [O]
6. Quit for pregnancy, childbirth or adoption of a child [O]
7. Quit to look for another job [Q]
8. Quit to take another job [Q]
9. Other (SPECIFY) [O]
10. Quit because of ill health, disability, or medical problems [O]

11. Moved to another geographic area [O]
12. Quit to spend time with or take care of children, spouse, parents, or other family members [O]
13. Quit because didn't like job, boss, coworkers, pay or benefits [O]
14. Quit to attend school or training [O]
15. Went to jail, prison, had legal problems [O]
16. Transportation problems [O]
17. Retired [O]
18. No desirable assignments available [O]
19. Job assigned through a temp agency or a contract firm became permanent [O]
20. Dissatisfied with job matching service [O]
21. Project completed or job ended [O]
22. Business failed or bankruptcy [O]
23. Sold business to another person or firm [O]
24. Business temporarily inactive [O]
25. Closed business down or dissolved partnership [O]

The last four reasons are related to self-employment jobs. Because we restrict our sample to private sector employment only, our sample does not include any job spell that ends due to one of these reasons.

Of our interest is how well quitsmatch with EE transitions. Table 7 shows the cross tabulation of these job separation categories from our sample with the longer panel. About three-fourths of quits turn out to be an EE transition.

C Computational Details of the Model

The Bellman equations are computed on discretized grids. We put 31 grid points in $\log(z)$ dimension and 51 grid points on $\log(x)$ dimension. The upper and lower bounds of the $\log(z)$ grid are set at plus and minus three standard deviations of the unconditional distribution

	Transition Type		
Reason	EE	EU	Total
Quits	1894	642	2536
Firings	0	1398	1398
Other reasons	1217	1236	2453
Total	3111	3276	6387

Table 7: Cross tabulation of job separations by transition type and reason from our longer panel sample.

of $\log(z)$. The upper and lower bounds of the $\log(x)$ grid are set at plus and minus five standard deviations of the $\log(x)$ draw. The stochastic processes are approximated with Markov chains using Tauchen's (1986) method.

The value functions are computed by the standard value function iteration. Once the value functions and the policy function is computed, we simulate the model and generate samples. The samples are treated in the same way as the NLSY samples, and used for estimation. In the benchmark case, we simulate 200,000 people for 20,000 periods each. For each observation, we randomly select one employment spell per person from the first 200 spells.

Additional References for Appendix

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