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DECLINING LABOR TURNOVER AND TURBULENCE

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Abstract

The purpose of this paper is to identify possible sources of the secular decline in the job separation rate over the past four decades. I use a simple labor matching model with two types of workers, experienced and inexperienced, where the former type faces a risk of skill loss during unemployment. When the skill loss occurs, the worker is required to restart his career and thus suffers a drop in his wage. I show that a higher risk of skill loss results in a lower separation rate. The key mechanism is that the experienced workers accept lower wages in exchange for keeping their jobs.

JEL codes: E24, J31, J64
Keywords: Separation Rate, Wage Loss, Turbulence

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1 Introduction

It has been widely recognized in the macro/labor literature that various measures of labor market turnover have been on a secular declining trend for the past several decades. One such measure of labor turnover is a transition rate from employment to unemployment. Figure 1 plots the annual averages of the monthly employment-to-unemployment transition rate between 1976 and 2014. During the first part of the sample, it averaged around 1.6 percent per month but came down to less than 1.2 percent right before the Great Recession. Although the Great Recession caused a sharp increase in the separation rate, it dropped to more or less the prerecession level in 2014. The secular downward trend, on the surface, appears to suggest that the risk of job loss facing U.S. workers has gradually been falling over time. This interpretation, however, is at odds with anecdotal evidence that labor market conditions surrounding U.S. workers have deteriorated in recent decades. The following quote from an article in the *New York Times* summarizes this narrative:

> As workers' job security has evaporated, so has their bargaining power — their ability to ask for more money, more vacation time, more health benefits. Across the nation, and across industries, employees perceive that they are more vulnerable to dismissal now than in the past (July 3, 1995).

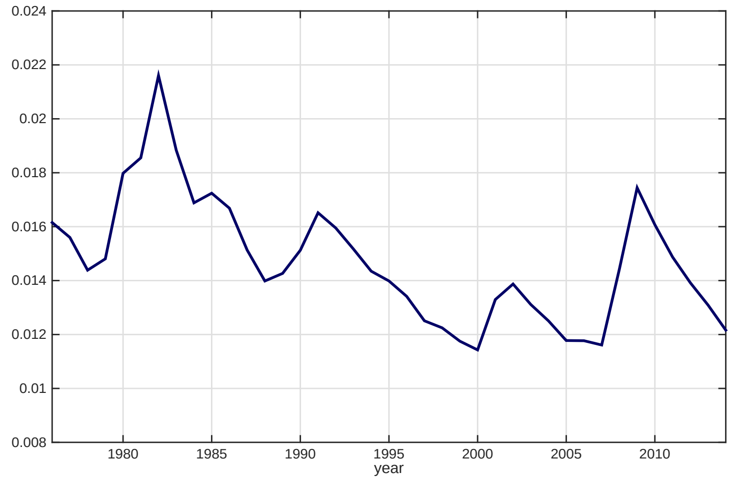
Note that this article was written in 1995, long before the Great Recession, when the separation rate was steadily falling. This quote also captures a macroeconomic observation often referred to in a similar context that real wages have been stagnant relative to labor productivity.

The purpose of this paper is to explore underlying sources of the phenomenon that separation rates have been on a downward trend, while anecdotal evidence points to heightened job insecurity, which I refer to as "turbulence," borrowing the term from Ljungqvist and Sargent (1998). Kambourov and Manovskii (2008) suggest that the notion of turbulence can be linked to a rising occupation mobility. The idea is that human capital is largely occupational specific (Kambourov and Manovskii (2009)), and thus higher mobility implies a higher risk of human capital loss. I follow their insight and construct a measure of how often a worker changes his/her occupation at a new job after experiencing an unemployment spell. I show that this occupation switching probability has indeed risen during the period between 1976 and 2014.[1]

To quantitatively study how a more turbulent economic environment interacts with various labor market decisions, including separation and job acceptance decisions, I construct an equilibrium labor matching model with heterogeneous workers. In the model, there are two types of workers whom I label "experienced" and "inexperienced"; the former type is more productive than the latter. Both types face the risk of endogenous match destruction. However, the experienced worker faces an additional risk of becoming inexperienced while

[1] Kambourov and Manovskii's measure of occupational mobility is based on the Panel Study of Income Dynamics (PSID) and thus does not explicitly consider occupation switching after unemployment. For the purpose of this paper, the occupation switching rate after job loss is more appropriate.

Figure 1: Separation Rate into Unemployment



Notes: Source, monthly CPS. Plotted are annual averages of the monthly transition rate from employment to unemployment. Data construction details are discussed in Section 2.

searching for a new job. When hit by this shock, the experienced worker needs to restart his career as an inexperienced worker and therefore tends to suffer a wage cut at a new job.

The key experiment in the model is to examine how the model responds to a higher skill loss probability. The observed increase in the occupation switching probability is used to discipline the size of this parameter change. The model predicts that the separation rate falls in response to this change. The reason is simple. A higher chance of skill loss makes the experienced workers reluctant to separate from their current jobs. In essence, these workers accept lower wages than before for the same level of productivity in exchange for keeping their jobs. It also implies that there is a larger mass of low-quality employment relationships that would have been severed in the environment before the parameter change.[2] Another interesting result is that the average size of wage loss is *observed to be smaller* in the environment with a higher skill loss probability (i.e., a more turbulent environment). This is because the lower wages of experienced workers imply that there is less room for their wages to decline.

I also consider two other plausible hypotheses using the model, namely, the effects of lower bargaining power of the worker and the smaller variance of the idiosyncratic shocks. The latter hypothesis is motivated by Davis et al. (2010), who empirically examine the smaller variance as an explanation for a downward trend in job flows and the unemployment inflow rate. I show that the lower bargaining power barely changes the separation rate and counterfactually implies a higher job finding rate. On the other hand, a lower variance of the idiosyncratic shock indeed generates lower separation rates as in the data. Davis et al.

[2]The intuition is not entirely new and is pointed out by den Haan et al. (2005). However, their analysis focuses on the robustness of the results by Ljungqvist and Sargent (1998), who explore the effects of the higher probability of skill loss on the job search behavior in the European welfare states.

(2010) appeal to the implication in the standard Mortensen and Pissarides (1994) model that a smaller idiosyncratic variance lowers the separation rate. The result here extends this implication to a search/matching framework with two types of workers. I conclude that the explanation based on turbulence is complementary to the one explored by Davis et al. (2010).

However, the turbulence story is attractive in that it reconciles lower separation rates with heightened job insecurity. It suggests that gauging job (in)security solely based on the level of labor turnover can be a misleading practice. It also sheds some light on the source of observed weak wage growth even during periods of healthy productivity growth.

There is a growing literature on the declines in labor market flows. Davis (2008) considers various measures of inflow rates into unemployment and concludes that the risk of job loss has decreased substantially. Davis and Haltiwanger (2014) consider more broadly job and worker flows and show that the U.S. labor market has become less fluid over the past two decades. They find that the declining trend is observed within narrowly defined groups by demographics and education. Drawing data from different sources, Hyatt and Spletzer (2013) also find large declines in labor flows between 1998 and 2010 and show that a declining share of short-term jobs accounts for the overall declines. Several papers also notice declines in internal migration rates within the U.S. (e.g., Molly et al. (2014) and Kaplan and Shulhofer-Wohl (2015)). In particular, Molly et al. (2014) show that changing demographic and socioeconomic factors do not account for the decline in migration rates. Their empirical result points to a mechanism similar to the one in this paper. That is, workers may be facing a less desirable set of outside options both across and within local labor markets, resulting in lower migration rates. Relative to these papers, this paper focuses on the transition rate into unemployment and uses a quantitatively calibrated equilibrium model as a tool to explore the underlying causes of the secular decline in labor turnover.[3]

The next section presents empirical facts on the long-term trend in transition rates between employment and unemployment and occupation switching probability (probability that unemployed workers land in an occupation different from the one prior to job loss). Section 3 lays out the search/matching model with heterogeneous workers. In Section 4, I discuss in detail the calibration of the model. Section 5 presents the main results of the paper. Section 6 concludes the paper by discussing a fruitful avenue for future research. The Appendix includes the quantitative results under alternative calibrations and additional pieces of empirical evidence that enhance the main story of this paper.

2 Empirical Evidence

This section puts together empirical evidence on the time-series trend in three variables during the period between 1976 and 2014: the transition probability from employment to

[3] A recent paper by Cairo and Cajner (2014) also studies the secular decline in labor turnover by using a model similar to the one in this paper. Their emphasis is on the changing composition of the labor force by age and education. Incorporating those features into the model would likely to enhance the channel emphasized in this paper.

unemployment (the separation rate), the transition probability from unemployment to employment (the job finding rate), and the occupation switching probability.[4] The last variable is measured as the fraction of workers who changed their occupation upon finding a job after an unemployment spell.

2.1 Data

All three series are measured within the same data source, the Current Population Survey (CPS). The CPS is the official household survey, conducted by the Bureau of Labor Statistics (BLS). While the purpose of the survey is to provide a cross-sectional snapshot of the aggregate U.S. labor market every month, it is possible to construct the flow data by matching individuals who are in the survey for two consecutive months.[5] By matching workers and tracking the labor market status between the two surveys in month $t-1$ and month t, one can compute transition rates across different labor market statuses. This paper focuses on the transitions between employment and unemployment. The sample period of the analysis is constrained by the availability of the monthly CPS micro data files and thus starts in January 1976. The sample period ends in December 2014.

After matching the individuals across two months, all records from all years are pooled. The linear probability model is then estimated for the separation rate, the job finding rate, and the occupation switching rate. The regression-based analysis allows me to easily and systematically control for changes in demographic compositions over the sample period. The analysis here is not meant to provide any causal inference but to summarize the statistical relationships.

For the separation rate, the underlying sample contains all matched records that start with employment in the first month. The dependent variable takes a value 1 when a transition from employment to unemployment (separation) occurs and 0 otherwise. It also includes year dummies, month dummies (to control for the seasonality), and demographic controls (gender dummy and age dummies that distinguish between young (16-24), middle-aged (25-54), and old (55-) workers). Using the estimated regression, we can simply turn on the year effects while fixing the values of the remaining regressors at their sample means. This allows me to isolate the time effect (which this paper is interested in) from the changes in the demographic composition and the seasonal effect. For the job finding rate, the sample contains all matched records that start with unemployment in the first month. The dependent variable takes a value 1 when a transition from unemployment to employment (i.e., job finding) occurs and 0 otherwise. The same explanatory variables as in the regression for the separation rate are used. Lastly, for the occupation switching probability, the sample contains all matched records that start with unemployment in the first month and end with employment in the second month (all "UE transitions"). The dependent variable takes a value 1 when a worker

[4]For brevity, I henceforth use the term transition (or switching) "rate" for the term transition (or switching) "probability."

[5]See Shimer (2012) and Fujita and Ramey (2006, 2009) for details of the measurement issues involved in constructing the flow measures from the CPS.

finds a job in an occupation different from the one prior to job loss.[6]

Measuring occupation changes after unemployment. While the CPS data on worker transitions across labor market statuses have been extensively used in the macro and labor economics literature, there are fewer attempts that measure the occupation switching rate after unemployment (those attempts include Jaimovich and Siu (2012) and Cortes et al. (2014)). In the CPS, all employed workers are asked their occupations. But the CPS also asks unemployed workers their occupations prior to the job loss. This information allows me to check if a worker (in the sample of UE transitions) changed his occupation after the unemployment spell. There are several measurement issues that need to be noted here. First, it is well known that the occupation coding is subject to classification error that tends to inflate the occupation switching rate. Unfortunately, there is no clear way of correcting this error.[7] However, there is no reason to believe that the extent of this measurement error has changed over time and the trend is affected by it. Second, the occupation classification system has changed over time. The analysis in this paper uses Meyer and Osborne's (2005) 3-digit occupation system, which is consistent over time. Third, the occupation switching rate depends on the level of aggregation of the occupation titles: the finer (coarser) the classification becomes, the higher (lower) the occupation switching rate is. Meyer and Osborne's 3-digit system includes a total of 371 titles. Because the classification error mentioned above is likely to be larger with finer occupation codes, I collapse the 3-digit system into the one with 79 titles and then into the one with 14 major titles. The results presented below are based on these two classification systems. In particular, the classification that distinguishes only the major titles is likely to be much less susceptible to the measurement problem. The specific titles are listed in Appendix G.

2.2 Trend in the Separation and Job Finding Rates

Figure 2 presents the time series of monthly transition rates between employment and unemployment. The blue solid lines are adjusted for demographics based on the regression discussed above. That is, each time series represents the predicted transition rate evaluated at the mean demographic characteristics over the entire sample period and only the year effects are extracted. The month dummies are also averaged out. The dashed lines are based on the regression without the demographic controls, and therefore the difference between the two lines can be thought of as the effect of the changing demographic composition.

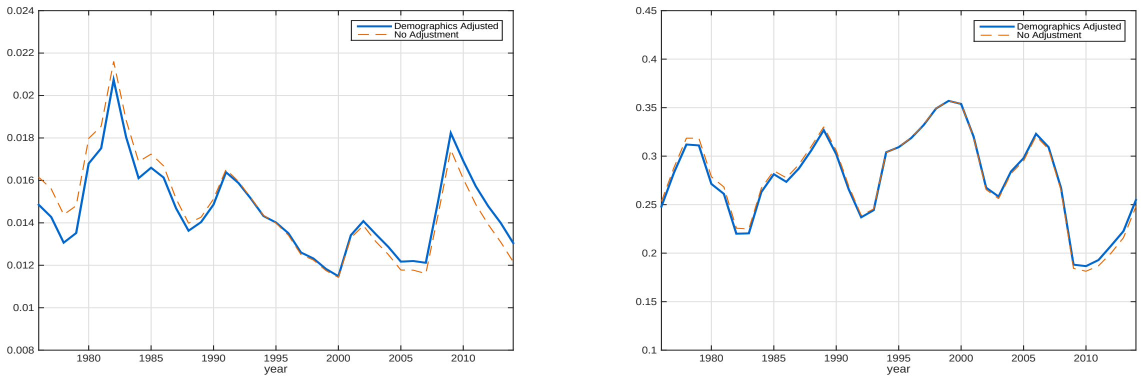
[6] Note that, within the sample of UE transitions, there are cases in which the worker's previous occupation is missing because the worker is an entrant to the labor force and those cases are excluded from the regression. However, including them in the regression and treating them as switchers increase the switching probability only slightly and do not materially change the trend.

[7] The major source of the error is the uncertainty in converting the respondents' description of their most important job activities into a specific occupation title. Moscarini and Thomsson (2007) show that the dependent coding technique adopted in the 1994 CPS redesign dramatically improved the measurement of the occupation switching rate. The dependent coding technique, however, is utilized only when the respondent is employed in both this and the previous months. Occupation coding in the cases considered in the current analysis remains independent.

Figure 2: Transition Rates Between Employment and Unemployment

(a) Separation Rate

(b) Job Finding Rate



Notes: Source, monthly CPS. Separation rate: transition probability from employment to unemployment; job finding rate: transition probability from unemployment to employment. Plotted are predicted transition probabilities based on the linear probability regression using CPS matched records. Each regression includes year dummies, month dummies, and demographic controls (gender and age). The unadjusted result is based on the same regression without the demographic controls.

Consider first the separation rate series without the demographic adjustment. While the separation rate has exhibited a significant increase in every recession in the sample period, its low frequency trend has been downward.[8] In particular, it stood around 1.6% per month right after the double-dip recession in the early 1980s, but it fell below 1.2% right before the Great Recession.[9] Not surprisingly, the Great Recession caused a sharp increase in the separation rate. More notable, however, are that (i) the peak in the separation rate during the Great Recession was significantly lower than the peak in the 80s and that (ii) it came down to the level (around 1.2% per month) close to the prerecession bottom in 2014. These facts are quite surprising given the magnitude of the Great Recession itself.

Fixing the demographic composition (blue solid line) tilts the time series counterclock wise. This is intuitive in that older workers tend to have lower separation rates and the U.S. labor force has been gradually aging over time. While the demographic adjustment can explain the significant portion of the decline in the aggregate separation rate, there remains an unexplained secular decline in the separation rate. If one compares the average levels over the first and last 15 years of the sample, the separation rate declined about 0.19 log points without the demographic adjustment and 0.11 log points with the adjustment between the two 15-year periods, which implies that the changes in the demographic composition account for 40% of the decline.

Panel (b) plots the job finding rate. One can see the familiar procyclicality of this series

[8] See, for example, Fujita and Ramey (2009) for the cyclicality of the separation rate.

[9] One may think that the 0.4 percentage point decline is small. Note, however, that the separation rate is expressed as a fraction of employment. Its effect on the unemployment rate is large. The relevant metric here is a log change: The log difference between 1.6% and 1.2% amounts to almost 0.30 log points.

(see Shimer (2005, 2012)). It is notable that it fell dramatically during the Great Recession and has not fully recovered yet to the prerecession level as of 2014. In contrast to the separation rate, the demographic adjustment makes little difference in the series. Regarding the trend, the job finding rate appears to be on a downward trend in the past 10 years or so. However, whether this represents indeed a trend or part of the cyclical movements due to a severe recession remains to be seen. The longer-run trend at least until 10 years or so ago is roughly flat.[10]

Note that the results here indicate that the downward trend in the unemployment rate since the early 80s, studied by Shimer (1998) is mainly due to the downward trend in the separation rate rather than the trend in the job finding rate.[11]

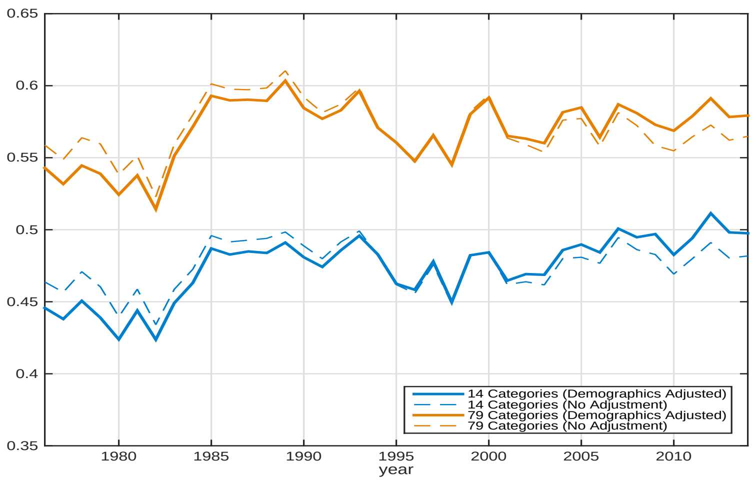
Other composition effects. There are other dimensions of the data that can possibly influence the trend in the separation rate. First, a changing industry composition is one of them. In particular, it is well known that the employment share of the manufacturing sector has been on a downward trend for a long time: If the manufacturing sector is characterized by a higher separation rate, then the declining employment share of the manufacturing sector lowers the observed separation rate. I can check whether this is indeed the case by calculating the separation rates by sector. It turns out that this hypothesis does not hold up empirically. Note that the separation rate from the manufacturing sector responds more sharply at the onset of the recession and comes down more quickly afterwards. However, there is no clear difference in the average levels of separation rates between the manufacturing and nonmanufacturing sectors. Moreover, separation rates within both sectors have been on a similar trend.

Another important compositional change in the labor force is the increase in the average educational attainment of the labor force (see, for example, Figure 13 in Shimer (1998)). It is true that more educated workers tend to have a lower separation rate and that educational attainment has increased in the long run. Thus, if one conducts the same analysis as above, by splitting the labor force based on educational attainment, one would find that the change in educational attainment has played a large role in the declining separation rate. As argued by Shimer (1998), such an analysis is misleading because changes in educational attainment cannot be taken as an exogenous force. Shimer develops a model in which employers care about workers relative educational attainment and endogenous educational choice is correlated with workers' unobserved ability. The model implies that the average abilities of both

[10] Tasci (2012) argues that the exit probability of unemployment has been on a downward trend since 2000. His claim and my interpretation of the data in panel (b) are not inconsistent. First, the exit probability is conceptually different from the job finding rate because the former does not distinguish between job finding and exiting the labor force. More important, a decline in the exit probability (see Figure 1 in his paper) became apparent only right before the Great Recession as shown in panel (b) above.

[11] Mukoyama and Şahin (2009) show that mean unemployment duration has become longer in the postwar period. The increase, however, is concentrated during the period prior to the 1980s. Since the 1980s, the mean duration itself has not shown an upward trend (as is consistent with a flat trend in the job finding rate shown in Figure 2). For this period, they emphasize the increase in the average duration *relative* to the unemployment rate, which had been drifting down until the end of their sample period. Thus, their result is consistent with panel (b) of Figure 2.

Figure 3: Occupation Switching Probability



Notes: Source, monthly CPS. Probability of changing occupation after unemployment. Plotted is the predicted probability based on the linear probability regression using the sample of records of UE transitions between two months. Each regression includes year dummies, month dummies, and demographic controls (gender and age). The unadjusted result is based on the same regression without demographic controls.

skilled workers (say, college graduates) and unskilled workers (say, high school graduates) decline as more workers go to college and that the unemployment rates of both groups increase, while aggregate unemployment is observed to be lower.[12] The quality of workers within each schooling category cannot be reasonably viewed as being constant over a long period of time. I followed this insight and thus made an adjustment only for age and gender.

2.3 Trend in Occupation Switching Rate After Unemployment

Figure 3 plots occupation switching rates, again, with and without demographic adjustments. As discussed above, I consider two occupation classifications. One can see that the demographic adjustments make relatively significant differences in both cases. The result indicates that older workers tend to have a lower switching probability and that aging of the labor force itself has had an effect of lowering the switching probability. Consider first the switching rates based on major (14) occupation categories (blue lines). In the late 1970s through the early 1980s, the switching rates averaged below 45%. Between the early 1980s and mid-1990s, the series exhibited a hump-shaped pattern, but, since the mid-1990s, it has been on a clear upward trend, reaching 50% in recent years. As noted above, using the occupation classification system with more titles raises the level of the series (orange lines),

[12]The aggregate unemployment rate can decline, given that the skilled group has a lower unemployment rate, because the shift of the composition toward the skilled group lowers the aggregate unemployment rate.

but the overall time-series pattern remains similar, although the upward trend becomes somewhat less clearcut. In Appendix F, I present the switching rates excluding workers on temporary layoffs. Those series show an even clearer upward trend.[13]

Why is the upward trend in the occupation switching rate important? As mentioned in the introduction, the literature has shown that human capital is largely occupation specific (e.g., Kambourov and Manovskii (2008, 2009)). Thus, this series carries some information about the risk of human capital loss. In Section 4, I examine the pattern of wage changes before and after unemployment and show that the analysis using wage information strongly supports this interpretation. The key quantitative experiment below examines the effects of the parameter change that matches the upward trend in the occupation switching rate on worker transition rates and other endogenous variables.

3 Model

The main theme of this paper is to link the declining separation rate with a more turbulent labor market environment. This section presents the labor matching model that incorporates the possibility that entering into the unemployment pool tends to cause a wage cut at the time of reemployment. Allowing for this possibility is important for this paper because it is a robust feature of the data that can be linked to the idea of labor market turbulence.[14] The basic structure of the model below is similar to the one by den Haan et al. (2005), which in turn is built on the model in den Haan et al. (2000).[15]

3.1 Environment

The economy is populated by a unit mass of risk-neutral workers and a potentially infinite mass of job positions. There are two types of workers: "experienced" and "inexperienced." When the job position is filled, the match produces output x_h and x_l, respectively, depending on its worker type. The productivity levels evolve according to the following process: When the match is first formed, experienced and inexperienced matches draw their productivities from $G_h(x_h)$ and $G_l(x_l)$, respectively, both of which are assumed to have support $[0, \infty)$. It is assumed that $G_h(.)$ (first order) stochastically dominates $G_l(.)$, namely, $G_h(x) < G_l(x)$ for any x and that production requires the fixed operating cost (i.e., overhead) per period κ. This parameter is introduced to facilitate the calibration of the model, as will be discussed later.

Existing matches face several possibilities at the start of each period. First, the inexperienced worker becomes experienced with probability μ, in which case the new productivity

[13] Excluding those on temporary layoffs from the calculation may be justified on the ground that most of those workers return to the same employer and stay in the same occupation as recently shown by Fujita and Moscarini (2013).

[14] There is ample empirical literature on earnings losses associated with a job loss. Early studies on this topic include Topel (1990), Jacobson et al. (1993), Ruhm (1991), and Stevens (1997).

[15] Other papers that explicitly incorporate wage losses include Pries (2004).

level is drawn from $G_h(.)$. Second, the experienced matches and inexperienced matches (that did not become experienced) face the possibility that their productivities switch to a new level. The switching of productivity occurs with probability γ. When it occurs, a new productivity level is drawn from either $G_h(.)$ or $G_l(.)$. Each match may be endogenously terminated when the new productivity level is too low. This match separation decision is described later. When the experienced workers are in the unemployment pool, they face an additional risk of becoming inexperienced. This occurs with probability δ every period.

Interpretation of the model environment. Note that becoming an "experienced" worker captures the idea that the worker accumulates human capital through working in a particular occupation. The accumulation of human capital is purely stochastic in this model and thus no explicit decision such as the one in the Ben-Porath framework is involved. The stochastic transition is convenient in that it dramatically simplifies the model, thus allowing me to focus on job separation and related decisions. It is also important to note that there is no explicit notion of occupation in the model. However, the "experience" in the model is *interpreted* as occupation specific. This interpretation is adopted because, as noted above, the empirical literature suggests that human capital is tied to occupation in the U.S. labor market.[16] It puts a discipline in taking the model to the data. In particular, the δ risk that an experienced worker faces while being unemployed is linked to the occupation switching rate. Furthermore, the calibration of the model utilizes the empirical fact about the wage cut that occurs when a worker with enough occupational tenure changes his occupation after unemployment. Inexperienced workers may also endogenously separate in the model without facing the risk of skill loss. The empirical counterpart of this case is also explicitly incorporated into the calibration of the model. See the discussion in Section 4.2.

3.2 Labor Market Matching

The frictions of reallocating workers across productive matches are captured by the aggregate CRS matching function $m(u, v)$, where u is the total number of unemployed workers and v is the number of vacancies posted. Standard regularity conditions apply to this function. Unemployed workers consist of the two types of workers, denoted respectively, by u_h (experienced) and u_l (inexperienced). The meeting probability for each unemployed worker $f(\theta)$ is written as:

$$f(\theta) = \frac{m}{u},$$

where θ is the tightness of the matching market, which is the ratio of vacancies to the total number of unemployed ($\frac{v}{u}$) and $u \equiv u_h + u_l$. The meeting probability for the vacant job $q(\theta)$ is written as:

$$q(\theta) = \frac{m}{v}.$$

[16] Because the model itself is silent about the nature of human capital, one can take a different stand on the nature. For example, it is logically possible to assume that human capital is tied to a certain industry (as in Neal (1995)) or a firm.

The vacant job is paired randomly with the experienced or inexperienced worker with probability $p_h q(\theta)$ and $(1-p_h)q(\theta)$, respectively, where $p_h \equiv \frac{u_h}{u}$. As in the standard search/-matching model, posting a job opening entails a flow vacancy posting cost c.[17]

3.3 Continuation Values

I write down the recursive evolution of the value of each labor market status. Consider first the situation facing the experienced worker. Let W_h^c be the value of the experienced employed worker who has decided to stay in the match this period. The continuation value of this worker, $W_h^c(x_h)$, can be expressed as:

$$W_h^c(x_h) = w_h(x_h) + \beta\left[(1-\gamma)W_h^c(x_h) + \gamma\int_0^\infty W_h(x_h')dG_h(x_h')\right], \tag{1}$$

where $w_h(x_h)$ is the current-period wage payment for the experienced worker, β is the discount factor, and x_h' is the productivity draw of the experienced match in the next period. $W_h(x_h)$ represents the value of the worker before the separation decision is made, which in turn is written as:

$$W_h(x_h) = \max\left[W_h^c(x_h), U_h\right], \tag{2}$$

where U_h is the value of being unemployed as an experienced worker. Equation (2) characterizes the optimal continuation/separation decision of the experienced worker. The first term in the square brackets in Equation (1) is the continuation value of the worker in the next period if productivity of the match stays the same. The second term represents the value when the productivity switch occurs. As mentioned before, when the worker is in the unemployment pool, he faces the risk of becoming inexperienced. It is assumed that in the period when he becomes unemployed, he is not subject to this risk. This assumption is embedded in Equation (2).[18]

The value of the experienced unemployed worker U_h can be expressed as:

$$\begin{aligned} U_h = b_h + \beta\Bigg[f(\theta)\bigg(\delta\int_0^\infty W_l(x_l')dG_l(x_l') + (1-\delta)\int_0^\infty W_h(x_h')dG_h(x_h')\bigg) \\ + \Big(1-f(\theta)\Big)\Big(\delta U_l + (1-\delta)U_h\Big)\Bigg], \end{aligned} \tag{3}$$

where b_h is the flow value of being unemployed as an experienced worker, U_l is the value of the inexperienced unemployed worker, and $W_l(x_l)$ is the value of the inexperienced employed

[17] I also considered an alternative specification in which creating a new job position entails a one-time job creation cost as in Fujita and Ramey (2007). However, I find that this alternative specification yields similar results.

[18] This is simply a timing assumption and has no material implications for the results.

worker before the match rejection (or acceptance) decision is made, which is further written as:

$$W_l(x_l) = \max\Big[W_l^c(x_l), U_l\Big]. \tag{4}$$

Upon meeting a potential employer, the worker faces several possibilities. First, with probability δ, he may become inexperienced at the start of the next period. After the meeting takes place, the idiosyncratic productivity is drawn. There is a chance that productivity is too low to start production, in which case the potential employment relationship is rejected. The worker then starts the next period as an unemployed worker. This decision is expressed in Equations (2) and (4). Lastly, if the worker fails to meet a potential employer, he stays unemployed and faces the risk of skill loss at the start of the next period.

Next, $W_l^c(x_y)$ is expressed as:

$$\begin{aligned} W_l^c(x_y) = w_l(x_l) + \beta\Bigg[\mu\int_0^\infty W_h(x_h')dG_h(x_h') + (1-\mu)\Bigg((1-\gamma)W_l^c(x_l) \\ + \gamma\int_0^\infty W_l(x_l')dG_l(x_l')\Bigg)\Bigg], \end{aligned} \tag{5}$$

where $w_l(x_l)$ is the current-period wage payment to the inexperienced worker. At the start of the period, he becomes experienced with probability μ, in which case new productivity is drawn from $G_h(.)$ and the match separation decision as an experienced worker is made, based on the new productivity level. If he continues to be an inexperienced worker, new productivity is drawn with probability γ from $G_l(.)$, and the separation decision as an inexperienced worker is made based on it. The separation decisions are again characterized by Equations (2) and (4).

The value of the inexperienced unemployed worker is written as:

$$U_l = b_l + \beta\Bigg[f(\theta)\int_0^\infty W_l(x_l')dG_l(x_l') + \Big(1-f(\theta)\Big)U_l\Bigg], \tag{6}$$

where b_l is the flow value of being an inexperienced unemployed worker. The interpretation is similar to Equation (3) except that the inexperienced worker faces no risk of skill loss. Note also that I adopt the timing assumption that upgrading to becoming experienced does not occur in the first period of the match formation.

The job position filled with an experienced worker, denoted by $J_h^c(x_h)$, embodies the following value:

$$J_h^c(x_h) = x_h - \kappa - w_h(x_h) + \beta\Bigg[(1-\gamma)J_h^c(x_h) + \gamma\int_0^\infty J_h(x_h')dG_h(x_h')\Bigg], \tag{7}$$

where $J_h(x_h')$ is the value of the job position going into the next period before the separation decision is made. Let V be the value of the unfilled position. The match dissolution decision is then written as:

$$J_h(x_h) = \max\Big[J_h^c(x_h), V\Big]. \tag{8}$$

Given the productivity level x_h, the firm chooses whether to continue the relationship comparing the value of the continuation and the value of posting a vacancy.

Similarly, the value of the job position filled with an inexperienced worker $J_l^c(x_l)$ is written as:

$$
\begin{aligned}
J_l^c(x_l) = x_l - \kappa - w_l(x_l) + \beta \Bigg[\mu \int_0^\infty J_h(x_h') dG_h(x_h') \\
+ (1-\mu)\left((1-\gamma) J_l^c(x_l) + \gamma \int_0^\infty J_l(x_l') dG_l(x_l') \right) \Bigg],
\end{aligned} \tag{9}
$$

where $J_l(x_l')$ is the value of the job with an inexperienced worker going into the next period before the separation decision is made and is characterized by:

$$
J_l(x_l) = \max \left[J_l^c(x_l), V \right].
$$

The interpretation of Equation (9) is straightforward.

Lastly, free entry into the matching market ensures that the value of a vacant job is zero and thus the following "job creation condition" holds:

$$
\frac{c}{\beta q(\theta)} = \left[(1-\delta) p_h \int_0^\infty J_h(x_h') dG_h(x_h') + \left[1 - (1-\delta)p_h\right] \int_0^\infty J_l(x_l') dG_l(x_l') \right]. \tag{10}
$$

The marginal return from the match (RHS of (10)) depends on whether the worker is experienced or inexperienced. The composition of the matching market thus influences the vacancy posting. As in the values of unemployed workers, (3) and (6), production may not start when idiosyncratic productivity drawn from either $G_h(.)$ or $G_l(.)$ is too low, in which case the meeting is dissolved before production begins.[19]

3.4 Separation Decision and Wages

I assume that the separation decision and wage determination are based on Nash bargaining, as in Mortensen and Pissarides (1994). When the employment relationship decides to produce in the current period, each type of match enjoys the surplus of:

$$
S_i^c(x_i) \quad = \quad J_i^c(x_i) + W_i^c(x_i) - U_i \text{ for } i \in \{h, l\}. \tag{11}
$$

The worker takes a constant fraction, denoted as π, of the total surplus, and the firm takes the rest $1-\pi$. Thus,

$$
\begin{aligned}
\pi S_i^c(x_i) &= W_i^c(x_i) - U_i, \\
(1-\pi) S_i^c(x_i) &= J_i^c(x_i).
\end{aligned} \tag{12}
$$

[19]Note also that, at the beginning of the next period, the experienced worker becomes inexperienced with probability δ. This possibility is incorporated in Equation (10).

The optimal value of the match surplus is determined by:

$$S_i(x_i) = \max\Big[S_i^c(x_i), 0\Big].$$

Since $J_i^c(x_i) + W_i^c(x_i)$ is increasing in x_i, there exists a cutoff productivity $\underline{x}_i$ below (above) which both sides optimally choose to sever (continue) the employment relationship. The separation margins, $\underline{x}_h$ and $\underline{x}_l$, are determined by:

$$S_i^c(\underline{x}_i) = 0. \tag{13}$$

The separation rates (conditional on receiving the shock) for the experienced and inexperienced types, s_h and s_l, are respectively written as:

$$s_h \equiv G(\underline{x}_h) \text{ and } s_l \equiv G(\underline{x}_l).$$

Wages. There are several different ways to obtain wage functions. I drive the following expressions by plugging $W_i^c(x_i)$ and $J_i^c(x_i)$ into $\pi J_i^c(x_i) = (1-\pi)[W_i^c(x_i) - U_i]$:

$$w_h(x_h) = \pi(x_h - \kappa) + (1-\pi)(1-\beta)U_h, \tag{14}$$
$$w_l(x_l) = \pi(x_l - \kappa) + (1-\pi)\big[(1-\beta)U_l - \beta\mu(U_h - U_l)\big]. \tag{15}$$

These expressions imply that, at the same idiosyncratic productivity level, say x, $w_h(x) > w_l(x)$ if $U_h - U_l > 0$. This last condition holds in the quantitative exercises below because (i) the calibration procedure below sets b_h higher than b_l, and (ii) the distribution of idiosyncratic productivity for x_h stochastically dominates that one for x_l, as mentioned above.

3.5 Labor Market Flows and Stocks

In this subsection, I present steady-state stock-flow balance equations. I start with the steady-state distributions of experienced and inexperienced workers. Let $e_h(x_h)$ and $e_l(x_l)$ be the CDFs of the experienced and inexperienced workers, respectively. First, note that $e(x_i) = 0$ for $x_i < \underline{x}_i$ for $i = \{h, l\}$. The stocks of employed workers are, respectively, written as $e_h = \lim_{x_h \to \infty} e_h(x_h)$ and $e_l = \lim_{x_l \to \infty} e_l(x_l)$. Note that solving the model itself does not require obtaining the employment distributions, but these distributions are important objects for my quantitative analysis.

To calculate the steady-state CDF for the experienced employed workers, I equate flows into and out of $e_h(x_h)$:

$$\big(G_h(x_h) - s_h\big)\big[\mu e_l + f(\theta)(1-\delta)u_h + \gamma(e_h - e_h(x_h))\big] = \gamma(1 - G_h(x_h) + s_h)e_h(x_h), \tag{16}$$

where the left-hand side gives flows into $e_h(x_h)$ and the right-hand side gives flows out of $e_h(x_h)$. Consider the term μe_l on the left-hand side. This term corresponds to the measure of workers who have become experienced. Among these workers, those who receive idiosyncratic productivity that lies between x_h and $\underline{x}_h$ flow into $e_h(x_h)$. Similar interpretations are applied to the other terms in the square brackets on the left-hand side. The right-hand side consists of flows out of $e_h(x_h)$ due to match separation and switching of productivity to a level higher than x_h. Solving Equation (16) for the distribution results in:

$$e_h(x_h) = \frac{(G_h(x_h) - s_h)[\mu e_l + f(\theta)(1-\delta)u_h + \gamma e_h]}{\gamma} \text{ for } x_h \in [\underline{x}_h, \infty), \tag{17}$$

which further implies:

$$\gamma s_h e_h = (1 - s_h)[\mu e_l + f(\theta)(1-\delta)u_h]. \tag{18}$$

The left-hand side of Equation (18) gives total flows out of the pool of experienced workers, while the right-hand side gives total flows into the pool.

Similarly, equating flows into and out of $e_l(x_l)$ results in the steady-state CDF for the inexperienced employed workers as follows:

$$\begin{aligned}(G_l(x_l) - s_l)\big[f(\theta)(\delta u_h + u_l) + (1-\mu)\gamma(e_l - e_l(x_l))\big] \\ = \big[\mu + (1-\mu)\gamma(1 - G_l(x_l) + s_l)\big]e_l(x_l),\end{aligned} \tag{19}$$

where the left-hand side gives inflows and the right-hand side outflows. The interpretation of Equation (19) is similar to that of Equation (16), with minor differences. Equation (19) can be solved for the distribution as follows:

$$e_l(x_l) = \frac{(G_l(x_l) - s_l)[f(\theta)(\delta u_h + u_l) + (1-\mu)\gamma e_l]}{\mu + (1-\mu)\gamma}, \tag{20}$$

which further implies:

$$\big[\mu + (1-\mu)\gamma s_l\big]e_l = (1 - s_l)f(\theta)(\delta u_h + u_l). \tag{21}$$

Consider next the steady-state stock-flow relationship of the experienced unemployed workers. Setting inflows and outflows to be equal gives:

$$\gamma s_h e_h + \mu s_h e_l = \big[\delta + f(\theta)(1-\delta)(1-s_h)\big]u_h. \tag{22}$$

The two terms on the left-hand side are inflows associated with separations from two pools of employment due to the endogenous match termination. The second term represents the inexperienced employed workers whose matches are terminated after becoming experienced. The right-hand side includes the outflows associated with downgrading to inexperienced workers and the hiring of experienced workers.

Similarly, the steady-state stock-flow relationship of inexperienced unemployed workers can be written as:

$$(1-\mu)\gamma s_l e_l + \big[1 - (1-s_l)f(\theta)\big]\delta u_h = (1 - s_l)f(\theta)u_l, \tag{23}$$

where again the left-hand side gives inflows and the right-hand side gives outflows. The first term on the left-hand side gives the separation flow from the pool of inexperienced employed workers. The second term gives the number of workers who flow from the pool of experienced unemployed workers. Among those who are downgraded from u_h to u_l, given by δu_h, those who are employed as inexperienced workers, given by $(1 - s_l)f(\theta)$, would avoid flowing into this pool. The right-hand side represents the hiring flow from the pool of inexperienced unemployed workers.

The stock-flow relationships presented so far imply that the flows between experienced and inexperienced workers are equal:

$$\mu e_l = \delta u_h. \tag{24}$$

I also normalize the population of the economy to unity:

$$e_l + e_h + u_l + u_h = 1. \tag{25}$$

Out of Equations (18), (21), (22), (23), and (24), only three of them are linearly independent for given values of θ, s_h, and s_l. Adding Equation (25) as a normalizing equation would allow me to solve for all labor market stocks.

3.6 Steady-State Equilibrium

The steady-state equilibrium is defined by $(\theta, \underline{x}_h, \underline{x}_l, p_h)$ that satisfy (i) the job creation condition (10), (ii) the two job separation conditions, embedded in (13), and (iii) the stock-flow balance condition, which expresses the composition of the matching market p_h as a function of the other three endogenous variables:

$$p_h = \frac{f(\theta)(1 - s_l)}{(1 - \delta)f(\theta)(1 - s_l) + \delta\big(1 + \frac{1-\mu}{\mu}\gamma s_l\big)}. \tag{26}$$

Appendix B explicitly presents the system of equations used to solve for the four endogenous variables.

4 Calibration

There are 12 parameters in the model. The parameters and their assigned values are summarized in Table 1. Six parameters are set exogenously and the remaining six are determined so that the model can match six selected statistics. One period in the model is associated with one month in the real world.

4.1 Parameters Set Exogenously

The parameter values for π, α, β, κ, γ, and μ are set without solving the model. First, the bargaining power of the worker π and the elasticity of the matching function α are both set to 0.5, as is often the case in the literature. The matching function is assumed to take the following Cobb-Douglas form:

$$m(u, v) = \overline{m}u^{\alpha}v^{1-\alpha},$$

Table 1: Model Parameters and Assigned Values in the Benchmark Calibration

Symbol	Description	Value Assigned
π	Bargaining power of the worker	0.5
α	Elasticity of the matching function w.r.t. unemployment	0.5
$\overline{m}$	Scale parameter of the matching function	0.569
β	Discount factor	0.99
γ	Arrival rate of the idiosyncratic shocks	0.167
Δ	Mean productivity premium of the experienced match	0.18
σ_x	Standard deviation of productivity shocks	0.22
μ	Probability of upgrading to become experienced	0.042
δ	Probability of downgrading to become inexperienced	0.215
b_h	Outside flow value for experienced worker	0.963
b_l	Outside flow value for inexperienced worker	0.710
κ	Fixed operating cost	0.350

where $\overline{m}$ is a scale parameter of the function that is to be determined in the next section.

Next, the discount factor is set to 0.99. This value may be considered low for a monthly model. One can view this low discount factor as reflecting the possibility that matches break up for reasons other than the separation into unemployment (such as retirement, death, etc.).[20] The parameter κ is set to 0.35. A natural interpretation of this parameter is a cost of capital or some other overhead costs. This value implies that roughly 30% of output goes into this cost on average.[21] The upgrading probability to the experienced worker μ is set to 1/24. This value implies that it takes 2 years on average for an inexperienced worker to become an experienced worker conditional on the worker being employed throughout. Note that there is a link between the value of μ and the productivity premium γ. The value of γ is determined later by matching the empirical evidence on the wage premium of the experienced worker. Thus, a different choice for μ implies a different value for γ as well: A lower value of μ $-$ thus it takes longer to become experienced $-$ implies a higher value of γ, making the heterogeneity between the two types of workers in the model starker. I will discuss later in Appendix C how the predictions of the model are affected when an alternative value for μ (i.e., 1/36) is used.

The arrival rate of the idiosyncratic shock γ is chosen to be 1/6 in the benchmark calibration, implying the mean renewal frequency of six months. Since I cannot provide clear empirical guidance on the value of this parameter, I also consider an alternative value for this parameter, 1/3. The results are presented in Appendix C.

[20]This low discount factor makes it easier to achieve some of the moment conditions below, although this parameter itself is not used to match those moments.

[21]The mean of the idiosyncratic distribution for the inexperienced matches is normalized to one. As discussed in the next section, the average productivity advantage of the experienced matches amounts to 18%.

4.2 Parameters Set Internally

To determine the remaining six parameters, I impose the following six moment conditions on the steady state of the model. The parameter values are set by minimizing the distance between the target values and the values in the model. Note that the moments I match below correspond to the values in the "initial" steady state.

Aggregate separation and job finding rates. First, the following two conditions that match the aggregate job finding rate and the aggregate separation rate, respectively, are imposed:

$$\frac{\gamma s_h e_h + \left[\mu s_h + (1-\mu)\gamma s_l\right] e_l}{e_h + e_l} = 0.017, \tag{27}$$

$$\left[\Big(\delta(1-s_l) + (1-\delta)(1-s_h)\Big)p_h + (1-s_l)(1-p_h)\right] f(\theta) = 0.27. \tag{28}$$

Remember that $f(\theta)$ represents the meeting probability for the worker. Equation (27) represents the aggregate separation rate as a weighted average of the separation rates for the experienced and inexperienced workers. The terms in the square brackets in Equation (28) take into account the fact that the matching probability is affected by the composition of the unemployment pool p_h as well as the rejection rates s_h and s_l.[22] The separation and job finding rates are targeted at 1.7% and 27% per month, respectively. As can be seen in Figure 2, the two transition rates fluctuated around these values early in the sample. I therefore calibrate the model to match these levels in the initial steady state.

Separation rates and firm tenure. Next, I use a well-known observation that the separation rate declines sharply with firm tenure (e.g., Anderson and Meyer (1994)). Remember that the experienced (inexperienced) worker in the model does not necessarily correspond to a worker with long (short) *firm* tenure. An experienced worker can be reemployed as an experienced worker, escaping the skill loss while searching for a new job. As discussed in Section 3.1, one can think of this situation as a worker with significant occupational experience finding a job in a similar position at a different firm. However, the empirical relationship between firm tenure and separation rates is useful to pin down the relative levels of s_l and s_h. To see this, first note that employment for each type at tenure τ can be expressed as:

$$e_h(\tau) = (1-\gamma s_h)e_h(\tau-1) + (1-s_h)\mu e_l(\tau-1),$$
$$e_l(\tau) = (1-\gamma s_l)(1-\mu)e_l(\tau-1),$$

where $e_i(\tau)$ is the number of type-i employed workers at tenure τ (measured in months). The initial conditions of these difference equations are:

$$e_h(0) = (1-s_h)(1-\delta)f(\theta)u_h,$$
$$e_l(0) = (1-s_l)f(\theta)u_l.$$

[22] The term $\delta(1-s_l)p_h$ in this equation represents the fraction of the unemployed workers who have become inexperienced and survived job rejection that occurs at rate s_l.

The aggregate separation rate $s(\tau)$ at tenure τ can then be calculated as:

$$s(\tau) = \frac{s_h[\gamma e_h(\tau-1) + \mu e_l(\tau-1)] + \gamma s_l(1-\mu)e_l(\tau-1)}{e_h(\tau-1) + e_l(\tau-1)}.$$

Observe that when $s_l > s_h$, $s(\tau)$ is decreasing in τ. The aggregate separation rate goes down over time as the composition of the employment pool shifts toward experienced workers who have a lower separation rate. In the context of the model, calibrating the model so as to achieve $s_l > s_h$ is the only way to match the empirical observation that the separation rate declines with firm tenure. Specifically, Anderson and Meyer (1994) report that the separation rate of those with a firm tenure of 16 quarters is one-fourth that of those with a firm tenure of less than one-quarter. Therefore, I use the following condition:[23]

$$\frac{s(46) + s(47) + s(48)}{s(1) + s(2) + s(3)} = 0.25. \tag{29}$$

Skill loss and occupation switching rate. The key ingredient of the model is that the experienced worker faces a risk of being hired only as an inexperienced worker after going through an unemployment spell. Recall that an experienced unemployed worker becomes an inexperienced worker with probability δ every period. Given this probability, I can calculate the fraction of workers who were initially unemployed as an experienced worker and later hired as an inexperienced worker, which I call ω, as follows:

$$\omega = 1 - \frac{f(\theta)(1-\delta)(1-s_h)}{1-(1-\delta)(1-f(\theta)+f(\theta)s_h)}, \tag{30}$$

where the second term gives the probability that the unemployed worker finds a job as an experienced worker and the term $(1-\delta)(1-f(\theta)+f(\theta)s_h)$ in the denominator corresponds to the probability that the unemployed worker stays in the unemployment pool as an experienced worker. Remember that the risk captured by δ is interpreted as the possibility that a worker with significant experience in a certain occupation is reemployed only at a different occupation for which his prior experience is not useful. Thus, Equation (30) can be linked to the occupation switching rate presented in Figure 3.[24] Equation (30) is most useful to identify the value of δ.

Remember that in Figure 3 I considered two occupation switching rates that are based on two different classification systems. While the two series share a similar trend over time, it is necessary to determine the level of the switching rate to which the model is calibrated. Given that using the finer occupation classification is likely to inflate the switching rate, I target the level based on the major occupation titles: The model is calibrated to deliver

[23] Anderson and Meyer's result is based on the total job separation rate, which includes job-to-job transitions. Since the present model does not allow for direct job-to-job transitions, Equation (29) matches only the relative level of separation rates.

[24] One issue here is that the empirical measure of the occupation switching rate is not conditioned on the worker's experience because there is no occupation tenure information in the CPS. Thus, the implicit assumption here is that these data are not sensitive to this conditioning.

0.45 as the occupation switching rate, which corresponds to its level in the early part of the sample.

Wage loss after unemployment. The average wage loss due to the δ shock is simply the average wage difference of the two types of workers. Using wage functions (14) and (15) and the employment distributions (17) and (20) for the two types of workers, one can calculate average log wages of the two types of workers as follows:

$$\widehat{w}_i \equiv \int_{\underline{x}_i}^{\infty} \ln w_i(x_i) d\hat{e}_i(x_i) \text{ for } i = \{l, h\},$$

where $\hat{e}_i(x_i)$ is a normalized CDF of employment of type-i worker, defined by $e_i(x_i)/e_i$. It is assumed that idiosyncratic productivities x_l and x_h are log-normally distributed with mean $\overline{x}_h$ and $\overline{x}_l$, respectively, and the common standard deviation of σ_x. I adopt a normalization that $\ln \overline{x}_l = 0$ and then set a value for $\Delta \equiv \ln \overline{x}_h - \ln \overline{x}_l$. This variable is calibrated by using the information on wages. More specifically, I compute wage changes of those who switched occupations after an unemployment spell, using the Survey of Income and Program Participation (SIPP). Unlike the CPS, SIPP is a panel data set that keeps track of workers over several years, allowing one to observe the wages of individual workers before and after unemployment. First, I gather a sample of *EU...UE* events (where each letter represents a worker's monthly labor market status, with E being employment and U being unemployment) from which I calculate the difference in wages before and after an unemployment spell. Importantly, SIPP includes a question on the worker's occupational tenure, starting in the 1996 panel. This variable allows me to observe wage changes when an (previously) "experienced" worker is reemployed in a different occupation.[25] See Appendix D for more details on the data construction.

I run a regression in which a log real wage difference between the two jobs (log real wage associated with the first E minus log real wage associated with the second E after an unemployment spell) is regressed on demographic controls (age and gender), unemployment duration, and the interaction terms between the occupation switch dummy and "experience" dummy. The latter variable takes a value 1 when a worker has occupation tenure of longer than some cutoff and 0 otherwise. Recall that, in the model, it takes on average two years to become an experienced worker, and thus the cutoff of two years is consistent with the model calibration. I also consider the cutoff of three years. Note that the unemployment duration variable is included in the regression to control for the features of the data that are not present in the model.[26]

Table 2 presents the regression result. The three columns, respectively, give the marginal effects of cases in which (i) occupational tenure was shorter than 2 years, and the worker

[25] I would like to thank Jose Mustre-del-Rio of the Kansas City Fed for technical assistance on the occupation tenure variable in the SIPP.

[26] The model implies a positive correlation between the size of the wage loss and unemployment duration. However, this correlation exists only because, as unemployment duration gets longer, the probability that the worker is hit by the δ shock rises. Thus, once the occupation switching probability is controlled in the regression, unemployment duration has no explanatory power for the wage loss in the model.

Table 2: Wage Difference Before and After Unemployment

Occ. Tenure → Occ. Switch →	< Cutoff Yes	≥ Cutoff No	≥ Cutoff Yes	Unemp. Duration	R^2	Sample Size
Cutoff = 2 yrs	-0.015 (0.033)	-0.017 (0.019)	-0.130^{**} (0.025)	-0.013^{**} (0.002)	0.032	6,271
Cutoff = 3yrs	-0.032 (0.026)	-0.035^{*} (0.017)	-0.160^{**} (0.025)	-0.013^{**} (0.002)	0.034	6,271

Notes: Source, 1996, 2001, 2004, and 2008 SIPP Panels. Demographic controls (age and gender) are also included in the regression. ** (*) indicates statistical significance at 1 (5)% level. Occupation switch dummy is based on major (14) occupation categories plotted in Figure 3. Results using the detailed (79) categories are very similar.

switched to a different occupation after unemployment; (ii) tenure was longer than 2 years, but the worker did not switch to a different occupation; and (iii) tenure was longer than 2 years and the worker changed his occupation. The coefficients give the effect of each of the three cases relative to the base case in which the worker had a short occupational tenure and stayed in the same occupation. The top portion of Table 2 presents the regression result that uses the cutoff of two years. The unconditional mean in the base case is -0.001, which is practically zero. Note that the results in the first two columns indicate that either short tenure or switching occupation (without the other) does not lead to a statistically significant wage loss. The most striking result is given in the third column: When a worker with longer occupation tenure changes his occupation after unemployment, it leads to a large and statistically significant decline (roughly 13%) in real wage. The calibration of the model takes this number as the target:[27]

$$\Delta\hat{w} \equiv \widehat{w}_l - \widehat{w}_h = -0.13. \tag{31}$$

Note that in the context of the model, the case (ii) corresponds to the situation in the model in which an experienced worker who lost his job was able to find a job as an experienced worker (avoiding the δ shock). The case (iii) is obviously associated with the situation in which an experienced worker loses his skill and is reemployed only as an inexperienced worker. The remaining two cases (the base case and the case (i)) correspond to the inexperienced worker's transitions between employment and unemployment in the model. In this case, as in the empirical result, wages before and after an unemployment spell are on average the same. As explained before, there is no explicit notion of occupations in the model. However, the model is structured to capture parsimoniously the empirical pattern in Table 2 by way of featuring two types of workers labeled as "experienced" and "inexperienced" workers.

The fourth column indicates that unemployment duration itself has a statistically significant negative impact on wage changes. In the model, the only reason for a positive correlation between unemployment duration and the size of the wage loss is that longer duration implies a higher chance of being hit by the skill loss shock. In this sense, the model is

[27] As mentioned earlier, the occupation tenure variable is not available before the 1996 panel. Thus, I simply take the result in Table 2 as the cross-sectional evidence for the calibration of the initial steady state.

Table 3: Targeted Value vs. Model's Steady-State Value

Statistic	Equation	Target	Model
Aggregate separation rate	(27)	0.017	0.017
Aggregate job finding rate	(28)	0.27	0.27
Tenure effect on separation	(29)	0.25	0.34
Switching probability	(30)	0.45	0.45
Wage losses for experienced worker	(31)	−0.13	−0.13
Wage variance within experienced matches	(32)	0.016	0.019
Wage variance within inexperienced matches	(32)	0.016	0.013

not able to capture the empirical result that duration has an independent negative impact on wage changes.

The bottom part of Table 2 presents the results when an alternative cutoff (three years) for the "experienced" worker is used. Relative to the previous result, the wage loss for those who changed occupations after accumulating more than three years of experience in the same occupation, not surprisingly, increases. One difference is that the wage loss of the experienced workers who did not change occupations becomes statistically significant. However, overall results remain the same.[28]

Conditional on all other parameter values and moment conditions, Equation (31) allows me to choose the productivity premium at $\Delta = 0.18$.

Wage variance. Next, to identify σ_x, I refer to the literature on wage variance. In the model, variance of log wages for each group can be calculated by:

$$\sigma^2_{\hat{w}_i} = \int_{\underline{x}_i}^{\infty} [\ln w_i(x_i)]^2 d\hat{e}_i(x_i) - \hat{w}_i^2 \text{ for } i = \{l, h\}. \tag{32}$$

The only reason that wages vary within each type in the model is due to the match-specific idiosyncratic shock. It is important to use the empirical measure that is consistent with this interpretation. Hagedorn and Manovskii (2010) provide such evidence. They estimate that the wage variance due to the differences in match quality is 0.016. I target the two wage variance measures in the model to be around this point estimate.

In summary, the six equations (28) through (32) are used to pin down the following six parameters: δ, Δ, σ_x, b_h, b_l, and $\overline{m}$. As mentioned above, the identification of δ, Δ, and σ_x can be directly associated with Equations (30), (31), and (32), respectively. The parameter $\overline{m}$ is useful to hit the condition for the job finding rate (28) because it can directly influence the level of the meeting probability $f(\theta)$. The outside option parameters b_h and b_l are useful to satisfy the conditions for the aggregate separation rate (27) and the tenure effect

[28] Note that the result in Table 2 uses the major occupation categories to construct occupation switching. However, when the classification system with detailed (79) occupation titles are used, I obtain very similar results.

Table 4: Other Statistics in the Benchmark Calibration

γs_h	0.009	$f(\theta)$	0.360	e_h	0.826	u_h	0.022
γs_l	0.055	$q(\theta)$	0.900	e_l	0.113	u_l	0.040
p_h	0.357	θ	0.400				

(29). Intuitively, each of these two parameters directly influences the separation rate of the corresponding type. Thus, the two parameters together can be used to control the aggregate separation rate as well as the separation-rate-tenure profile summarized by Equation (29).

Table 3 shows that the model can match the targeted statistics fairly well. Other statistics that are not directly targeted are presented in Table 4. The focus of the quantitative experiments below is to analyze how the model responds to various parameter changes, relative to the initial steady state characterized by the moments in Table 3.

5 Quantitative Exercises

The main quantitative experiment entails raising the skill loss probability δ. I then consider two other parameter changes and try to distinguish them from the main story.

5.1 Higher Skill Loss Probability

In this comparative static, I raise the probability of skill loss δ from 0.215 to 0.25. Remember that the value of δ in the initial steady state was chosen to match the empirical value of the occupation switching rate, which averaged around 0.45 early in the sample (see Figure 3). The value in the new steady state, 0.25, is chosen such that the occupation switching rate increases to 0.5, which roughly corresponds to the empirical value in recent years. The idea of this experiment is to see quantitatively how the model economy (particularly, the separation rate) responds to this exogenous parameter change. The changes in the key endogenous variables are presented in Table 5. First, the separation rate drops from 1.7% to 1.3%. A simple intuitive reason is that the experienced workers become reluctant to separate when there is a higher chance of skill loss. Recall the measurement of the aggregate separation rate (see (27)). The main driver of the lower aggregate separation rate is lower s_h in that equation. The separation rate of the inexperienced workers, on the other hand, is hardly affected. The share of the experienced workers e_h therefore increases. Because the separation rate of the inexperienced workers is calibrated to be higher than that of the experienced workers, the changes in the composition also work to lower the aggregate separation rate.

The job finding rate declines but only slightly. First, note that market tightness θ decreases slightly ($0.40 \to 0.39$), and hence the meeting probability $f(\theta)$ also drops. Note that the decline in the separation rate lowers the steady-state unemployment rate. However, vacancies decline by more, resulting in the decline in market tightness. Lower job creation (vacancy posting) reflects the decline in p_h (the share of the experienced workers in the

Table 5: Effects of Increased Turbulence

	Job Finding Rate	Separation Rate	Unemployment Rate	Market Tightness	Switching Rate
Benchmark	0.270	0.017	0.065	0.40	0.45
$\delta = 0.25$	0.262	0.013	0.052	0.39	0.50

	Average Wage		Wage Change	Var(Wage)	
	Experienced	Inexperienced	($\Delta\hat{w}$)	Experienced	Inexperienced
Benchmark	0.886	0.774	−0.130	0.019	0.013
$\delta = 0.25$	0.879	0.778	−0.118	0.020	0.013

unemployment pool), which, in turn, results from the direct effect of higher δ as well as lower separation flows of the experienced workers. The lower p_h represents deterioration of the "quality" of the unemployment pool and thus discourages new job creation.[29] Note, however, again that these effects are quantitatively relatively small.

Next, as presented in the last column of the top panel of Table 5, changing δ from the value in the benchmark calibration (0.215) to a new value 0.25 raises the switching rate to 0.5 as intended. While the increase in δ directly contributes to the increase in the observed switching rate, it is important to note that there are several other factors affecting this statistic, as indicated by (30). First, this statistic is decreasing in $f(\theta)$: A lower meeting probability translates into a lower probability of finding a job as an experienced worker and thus raises the probability of the switch (although the impact is small given that the decline in the meeting probability is also small, as discussed above). This effect adds to the direct impact from the higher δ. Second, this statistic is increasing in s_h. Remember that s_h declines as discussed above, thus having the effect of counteracting the previous two effects. In the present context, s_h should be interpreted as the job rejection rate. That is, the lower value of s_h represents the endogenous response that there are meetings that would have been rejected in the initial steady state but now are accepted because the worker is urged to take the job as an experienced worker even when the offered wage is relatively low. The first two effects dominate this last effect.

The first two columns of the lower panel show how average wages of the two types of workers change as a result of the higher turbulence parameter. The same mechanism that generated the lower separation rate for the experienced workers lowers their average wage: the experienced workers are willing to accept lower wages that they would have rejected in the initial steady state. The average wage of the inexperienced workers increases slightly. The third column presents the average wage loss of those who switch from experienced to inexperienced after an unemployment spell. The average wage loss due to the switch decreases (from 0.13 log points to 0.118 log points). This result is interesting in that the model implies that a more turbulent environment is associated with a smaller wage loss.[30]

[29] In the calibrated economy, matching with an experienced worker yields a higher surplus for the firm.

[30] Note that $\Delta\hat{w}$ in Table 5 corresponds to the average wage loss when an experienced worker is hit by the δ shock. When workers move to a different employer within each type after unemployment, there is neither

(a) Employment Distribution

(b) Wage Function

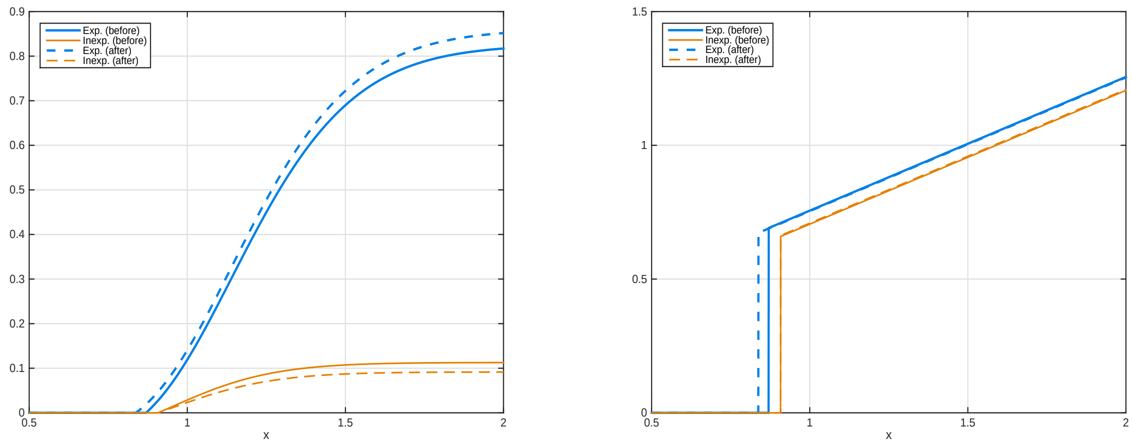


Figure 4: Effects of a Higher Skill Loss Probability

Notes: Panel (a) plots CDFs of experienced and inexperienced workers across idiosyncratic productivity levels. Solid and dashed lines, respectively, represent the distributions before and after the parameter change. Panel (b) plots wage functions for the two types of workers. The vertical lines correspond to cutoff productivities.

To see the mechanism more closely, Figure 4 plots the employment CDFs and wage functions. The solid lines represent the economy prior to the parameter change. In this economy, the employment distribution starts at 0.87 for the experienced workers and 0.91 for the inexperienced workers, which correspond to the cutoff productivities for the respective types. The vertical lines in panel (b) correspond to those cutoff productivity levels. First, note that these graphs indicate that experienced workers actually have lower cutoff productivity. Remember that the calibration sets the mean productivity level of the experienced matches higher by 18%. However, one can see that there is a range of idiosyncratic productivity levels at which an inexperienced worker separates while the experienced worker stays in the match. For the experienced workers in this range of productivities, the choice is whether to wait for their wages to increase as an experienced worker or to separate. While the latter choice gives them the opportunity to find a better match as an experienced worker, it also includes the possibility of becoming inexperienced. The worker opts for the first choice. On the other hand, the inexperienced workers face no risk of further downgrading of their skills and thus are more likely to separate to look for a better match.

Panel (b) shows that at a given level of match productivity, the experienced worker receives a higher wage. This is because the experienced worker has a higher outside value (U_h) than the inexperienced worker, thus giving him a stronger bargaining position. There

wage loss nor gain on average. Thus, one can calculate the average wage loss of *all workers* by $\omega p_h \Delta\hat{w}$. The higher δ results in a smaller average wage loss, because p_h and $\Delta\hat{w}$ fall, although the occupation switching rate (ω) increases.

are two reasons for this result. First, the flow value of being unemployed is calibrated to be higher. (Remember that b_h and b_l are calibrated as part of the moment matching exercise discussed in the previous section.)[31] Secondly, expected productivity of the experienced unemployed worker is higher than that of the inexperienced unemployed worker and this is embodied in the value of U_h.

Let me now discuss how the parameter change affects the employment distributions and wage functions. Both panels show the decline in the separation margin for the experienced worker. Panel (a) illustrates the change in the composition of the workforce toward the experienced workers. In panel (b), the wage function for the experienced type shifts downward slightly somewhat (although it is difficult to see it in the graph), meaning that workers receive lower wages for a given level of productivity in the new steady state, making the difference in wages of the two types of workers at a given level of productivity smaller. From the wage functions (14) and (15), one can see that the wage difference at x is written as:

$$w_h(x) - w_l(x) = \Big[(1-\beta)(1-\pi) + \beta\mu\Big](U_h - U_l). \tag{33}$$

Because U_h declines by more as a direct effect of higher δ, this difference gets smaller. The more important effect of the parameter change is that there is a larger mass of low-quality experienced matches that would have been severed in the economy prior to the parameter change. This is simply a direct implication of the lower separation rate of this group. This composition effect lowers the average wage of the experienced workers. The increase in low-quality experienced matches as well as the downward shift of the wage function contributes to reducing the size of the wage loss of the experienced workers when they do go through an unemployment spell.

Empirical evidence on the trend in wage loss. The result that wage loss gets smaller with a higher δ is natural given the mechanism in the model. Unfortunately, the results presented in Table 2 do not provide the evidence on the trend in the size of wage loss. However, a paper by Farber (2011) presents the average wage loss of workers using the CPS's Displaced Workers Survey during the period between 1984 and 2010. While he does not distinguish between occupation switchers and stayers, Farber provides a valuable piece of evidence on the time-series trend of the size of wage loss. Although his results do not show a clear downward trend, what is more surprising is the fact that they do not exhibit any upward trend over the past two decades. In particular, the average size of the loss during the most recent recession is not very different from that in 2004 and 1992. This is quite surprising given the severity of the recession. I therefore view the results by Farber (2011) as being largely in line with the quantitative implication of the model.

[31] $b_h > b_l$ is mostly driven by the moment condition (29). More specifically, a lower separation rate for the experienced worker implies the higher outside option value.

Table 6: Effects of Various Parameter Changes

	Job Finding Rate	Separation Rate	Unemployment Rate	Market Tightness	Switching Rate
Benchmark	0.270	0.017	0.065	0.40	0.45
$\pi = 0.4$	0.341	0.017	0.050	0.64	0.39
$\sigma_x = 0.20$	0.274	0.012	0.042	0.39	0.45

	Average Wage		Wage Change	Var(Wage)	
	Experienced	Inexperienced	($\Delta\hat{w}$)	Experienced	Inexperienced
Benchmark	0.886	0.774	−0.130	0.019	0.013
$\pi = 0.4$	0.881	0.772	−0.130	0.012	0.008
$\sigma_x = 0.20$	0.874	0.760	−0.136	0.017	0.011

5.2 Other Parameter Changes

Next, I consider the effects of two other parameter changes and examine whether the responses of the model to those parameter changes are in line with the empirical evidence. All results are compiled in Table 6. The following specific parameter changes are considered. First, the worker's bargaining power parameter is reduced from 0.5 to 0.4. This parameter change seems to be a plausible experiment to consider. The underlying idea is consistent with the decline in the labor share (see Elsby et al. (2013) and Neiman and Brent (2013)). I will discuss whether it is consistent with the other empirical evidence such as the decline in the separation rate.

Second, I lower the variance of the idiosyncratic productivity shocks. This change is motivated by Davis et al. (2010), who also look at the downward trend in job flows as well as unemployment inflows. Davis et al. (2010) argue that the smaller variance of idiosyncratic shocks may be one of the key sources generating the downward trend. They empirically show that the dispersion of firm-level employment growth rates is declining over the same period and appeal to the implication of the standard matching model with endogenous separation (Mortensen and Pissarides (1994)) that a smaller variance of the idiosyncratic shock results in a lower separation rate.

5.2.1 Lower Bargaining Power

In Table 6, one can see that the aggregate separation rate is insensitive to this parameter change, although both s_h and s_l (i.e., each type's separation rate conditional on receiving the shock) increase slightly. This can be seen in panel (b) of Figure 5 where the vertical part of the dashed lines slightly shifts to the right. The insensitivity of the separation rate is intuitive given that the separation decision is jointly efficient in the model and thus how to split the surplus should not have a first-order effect on the separation decisions. The largest impact of the lower bargaining power of the worker is on the job finding rate, which increases from 29% to 38%. This is because the higher share of surplus that goes to the firm directly

(a) Employment Distribution (b) Wage Function

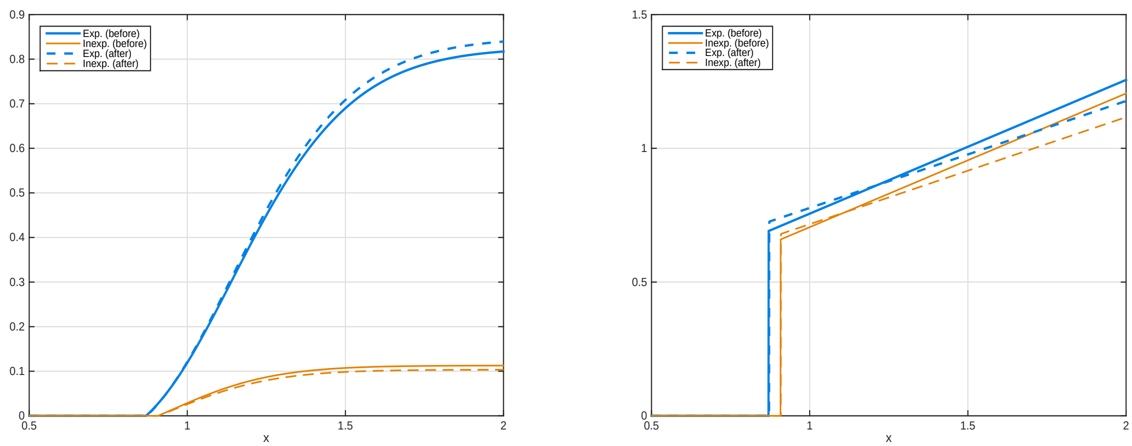


Figure 5: Effects of Lower Bargaining Power of the Worker

Notes: The solid lines represent the employment distributions and wage functions before the parameter change. The dashed lines represent those after the change. See notes to Figure 4.

raises the values of the jobs, $J_h^c(x_h)$ and $J_c^l(x_l)$, thereby encouraging vacancy postings. The increase in the job finding rate indirectly influences the separation rate (raising s_h and s_l as mentioned above), but this effect is small.

The switching rate declines because a higher job meeting probability makes it easier for the experienced worker to find a new job within the same type. This effect causes the composition of employment to shift toward the experienced workers (as indicated by panel (a) of Figure 5). Wages of both types of workers decline as a direct consequence of the lower bargaining power. Panel (b) of Figure 5 shows the flattening of the wage functions, which further implies lower wage variances.

Given these results, I conclude that lower bargaining power of the worker by itself is not an appealing explanation for the decline in the separation rate. It also implies a higher job finding rate and lower switching rate, both of which we do not observe in the data.

As mentioned above, the underlying idea behind the lower bargaining power of workers is consistent with the long-run decline in the labor share. The result here does not necessarily imply that the long-run declines in the labor share and the separation rate are unrelated phenomena. It only suggests that the exogenous change in the bargaining power itself (which can directly result in the lower labor share) does not appear to be an attractive explanation for the lower separation rate. In fact, the turbulence story is at least qualitatively consistent with the lower labor share as an endogenous outcome because it implies experienced workers are willing to accept lower wages for a given level of productivity.[32]

[32]Of course, the model does not feature physical capital, and thus it is unreasonable to interpret the results quantitatively as an explanation for the lower labor share.

(a) Employment Distribution (b) Wage Function

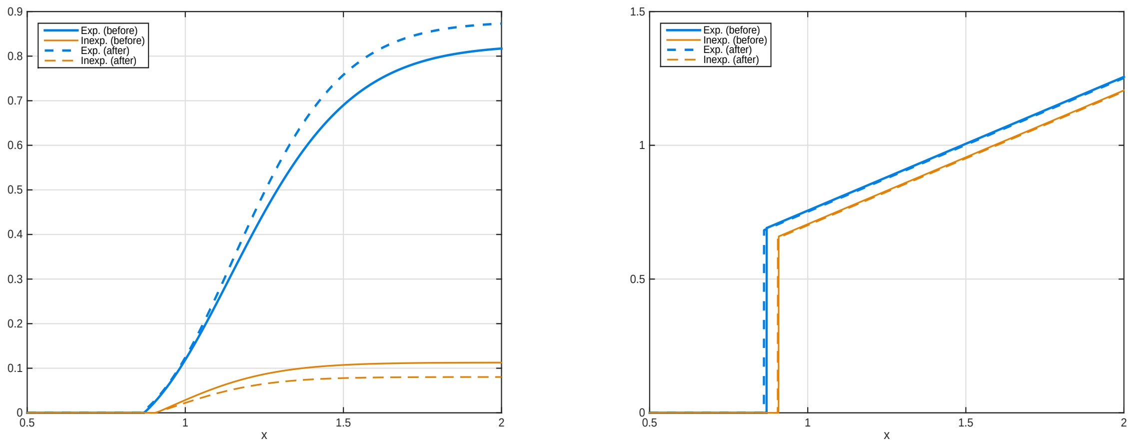


Figure 6: Effects of Smaller Idiosyncratic Variance

Notes: The solid lines represent the employment distributions and wage functions before the parameter change. The dashed lines represent those after the change. See notes to Figure 4.

5.2.2 Lower Variance of the Idiosyncratic Shock

Next, consider the parameter change from $\sigma_x = 0.215$ to 0.20. In Davis et al. (2010) and Davis et al. (2006), the authors show that various measures of business volatility have declined in a similar proportion as the change considered here.[33] Note that, in contrast to the case of the higher turbulence parameter, the separation rates for both types decline in this case. Behind the lower separation rates are the two competing effects that apply to both types of workers. First, given that the productivity distribution is truncated below the cutoff value, the smaller variance reduces the upside potential of the match, reducing the expected surplus. Second, a lower variance directly reduces the possibility that productivity falls below a certain level, which reduces the separation rate. This direct effect dominates the first (indirect) effect, and thus the separation rate falls on net.

The job meeting probability $f(\theta)$ declines slightly because the lower variance limits the upside potential of match productivity. But because job rejection rates decline for both types, the job finding rate actually increases somewhat relative to the benchmark case. Average wages of both types decline, although the decline for the inexperienced workers is somewhat larger and thus the size of the wage loss on average expands. Lastly, wage variances of both types drop as a direct consequence of the parameter change. In contrast to the case of the increased turbulence parameter, the switching probability is hardly affected, given that δ, which directly affects this statistic, remains constant in the present experiment.

The result above indicates that the story put forth shown by Davis et al. (2010) can be

[33] See, for example, Figure 3 in Davis et al. (2010), which presents two such measures. Both series in the figure show a decline of somewhat less than 10 percent between the early part and last part of the sample.

an important force in generating a lower job separation rate and thus is complementary to the main story in this paper. The strength of the turbulence story is the fact that it can coherently account for the lower separation rate, the higher occupation switching rate, and weaker wage growth within one framework.

5.3 Robustness

Recall that, in the benchmark calibration, some of the parameters are ex ante fixed. In particular, I picked the arrival rate of the idiosyncratic shock with no reference to the data. The upgrading probability is also set arbitrary to 1/24. In Appendix C, I consider the calibrations with an alternative value for the arrival rate ($\gamma = 1/3$) and the upgrading probability ($\mu = 1/36$). The entire model is recalibrated following the same procedure described in Section 4.2. The results are largely intact relative to those under the benchmark calibrations.

6 Discussion and Conclusion

This paper has argued that a more turbulent environment can be an important source of declining labor turnover. The main mechanism in the model is that workers face a higher risk of skill loss and thus accept a lower wage in exchange for keeping the job. What does the "turbulence" parameter represent? As noted before, Ljungqvist and Sargent (1998) introduced this modeling device without explicitly specifying its deeper causes in their model. They, however, mention restructuring from manufacturing to the service industry, the adoption of new information technologies, and the international competition as major sources of turbulence.[34] Friedman (2007) and Greenspan (2008) include ample anecdotal evidence in line with this interpretation. For example, Greenspan (2008) writes:

> ⋯ fear of outsourcing of service trades not previously subject to international competition has added to job insecurity. That insecurity, fostered by global competition, was new for many middle-income Americans, who increasingly became willing to forgo pay raises for job-tenure guarantees.

A more structural model of turbulence can be found in the job polarization literature (see, for example, Acemoglu and Autor (2011), Autor and Dorn (2013), and references therein). An important phenomenon emphasized in the literature is the disappearance of routine jobs driven by the "routine-biased technical change." Interestingly, a paper by Jaimovich and Siu (2012) constructs the occupation switching rate that is similar to the series in Figure 3 but focuses on the cases in which workers were previously employed in routine jobs. This series also displays a strong upward trend. One can loosely relate the routine-biased technical change to a higher value of the turbulence parameter in the model. However, the model

[34] While Ljungqvist and Sargent's focus is how the increased economic turbulence interacts with workers' job search decision in the European welfare states, the same changes in the economic environment themselves apply to the U.S. economy as well.

presented in this paper does not feature *job* heterogeneity and thus is not suitable for analyzing the changing job composition in the economy as emphasized in the job polarization literature. Jaimovich and Siu (2012) develop a parsimonious search/matching model with job heterogeneities where the job switching decision is endogenous. Their interest is in a link between job polarization and jobless recoveries. But a further extension in this direction is a fruitful avenue for our deeper understanding of the U.S. labor market.

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Appendix

A Longer Run Trend in Job Loss Rates

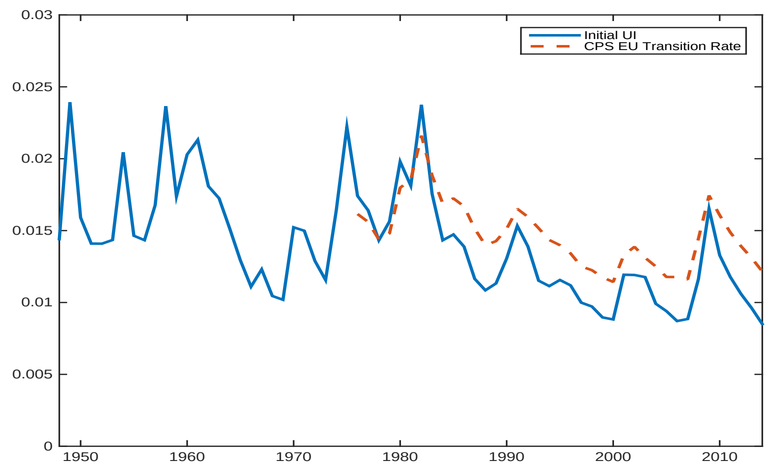
The sample period of the empirical analysis in Section 2 is retrained by the availability of the CPS micro data. However, the evidence we can gather suggests that the trend in the probability of job loss prior to 1976 is roughly flat. One measure sometimes used in place of the employment-to-unemployment transition rate is the unemployment inflow rate based on the short-term unemployment series (duration of less than 5 weeks). This series has an advantage of going back to 1948. However, using this series to gauge the trend in the separation rate is problematic, because it is strongly affected by the trend in entrants (flow from nonparticipation to unemployment). In particular, flows of young workers into the labor force associated with the baby boom produce a strong upward trend through the 1970s, which is followed by a steady downward trend.[35]

To gauge the trend in the rate of job loss over a longer run period, one can use the data on initial unemployment insurance (UI) claims. This series counts the number of new UI claimants each week and goes back to 1948. Figure A.1 plots the number of initial UI claims normalized by employment and compares it with the CPS employment-to-unemployment transition rate. The level of initial UI claims is adjusted by a constant factor such that its average level during the first 10 years of the overlapping sample period (1976-1985) matches that of the CPS separation rate.[36] One can notice a few differences between the two series. First, initial UI claims are more cyclically sensitive (more precisely, spikier). This makes sense because the take-up rate of UI is countercyclical, thereby exaggerating the countercyclicality of the underlying job loss rate. Second, initial UI claims appear to have a somewhat stronger downward trend. One likely explanation is the institutional change in the UI system concerning the experience rating, which took place in the mid-1980s. The stricter application of the experience rating is likely to cause a permanent drop in initial UI claims and the time-series behavior of the series appears to support this interpretation: In

[35] Comparing the magnitude of the secular declines in the inflow rate and the employment-to-unemployment transition rate between 1980s and 2014, one can see that the decline in the inflow rate is significantly larger because it also reflects the slower entry from nonparticipation.

[36] Initial UI claims are collected at the weekly frequency, and even after the series is aggregated into monthly series, the levels of the two series do not match up for two reasons. The first is that not everybody files UI when unemployed. Second, the CPS transition rate is based on the point-in-time comparison of the monthly labor force statues.

Figure A.1: UI Initial Claims and Employment-to-Unemployment Transition Rate



Notes: Sources, Department of Labor; monthly CPS. The level of initial claims is adjusted by a constant factor such that the average level over the first 10 years of the overlapping sample period (1976-1985) matches that of the CPS employment-to-unemployment transition rate.

the mid-1980s, the initial claims series dropped more than the CPS separation rate, and the two series have moved more or less parallel since then.

A more important observation pertaining to the longer run trend in the job loss rate is the fact that that the trend in initial UI claims prior to the mid 1970s is roughly flat. Although it fell significantly toward the end of the long expansion in the 1960s, the long-run trend over the first 30 years of the data is roughly flat. The average level of initial UI claims over the first 30 years of the sample period is very similar to the level that I used as the initial steady-state level of the separation rate in the quantitative exercise.

B Steady-State Equilibrium

I solve for the steady-state equilibrium of the model as follows. To simplify the notation, the next-period expected surplus value is defined as follows:

$$\mathbb{E}S_i^c(x_i') \equiv \int_{\underline{x}_i}^{\infty} S_i^c(x_i')dG_i(x_i') \text{ for } i = \{h, i\}. \tag{34}$$

I can derive the evolution of surplus for the experienced match by plugging (1), (3), and (7) into (11):

$$\begin{aligned} S_h^c(x_h) = x_h - \kappa - b_h + \beta\Big[&(1-\gamma)S_h^c(x_h) + \gamma\mathbb{E}S_h^c(x_h') - f(\theta)\pi\Big(\delta\mathbb{E}S_l^c(x_l') + (1-\delta)\mathbb{E}S_h^c(x_h')\Big) \\ &+ \delta(U_h - U_l)\Big]. \end{aligned} \tag{35}$$

Similarly, by using (5), (6), and (9) in (11), the surplus for the inexperienced match can be written as:

$$S_l^c(x_l) = x_l - \kappa - b_l + \beta\Big[(1-\mu)\Big((1-\gamma)S_l^c(x_l) + \gamma\mathbb{E}S_l^c(x_l')\Big) + \mu\mathbb{E}S_h^c(x_h') - f(\theta)\pi\mathbb{E}S_l^c(x_l') \\ + \mu(U_h - U_l)\Big]. \tag{36}$$

Evaluating (35) and (36) at $\underline{x}_h$ and $\underline{x}_l$, respectively, results in

$$\underline{x}_h - \kappa - b_h + \beta\Big[\gamma\mathbb{E}S_h^c(x_h') - f(\theta)\pi\Big(\delta\mathbb{E}S_l^c(x_l') + (1-\delta)\mathbb{E}S_h^c(x_h')\Big) + \delta(U_h - U_l)\Big] = 0, \tag{37}$$

$$\underline{x}_l - \kappa - b_l + \beta\Big[(1-\mu)\gamma\mathbb{E}S_l^c(x_l') + \mu\mathbb{E}S_h^c(x_h') - f(\theta)\pi\mathbb{E}S_l^c(x_l') + \mu(U_h - U_l)\Big] = 0. \tag{38}$$

Furthermore, the difference between U_h and U_l can also be expressed as a function of match surpluses as follows:

$$U_h - U_l = \frac{b_h - b_l + \beta(1-\delta)f(\theta)\pi\Big(\mathbb{E}S_h^c(x_h') - \mathbb{E}S_l^c(x_l')\Big)}{1-\beta(1-\delta)}. \tag{39}$$

Subtracting (37) and (38), respectively, from (35) and (36) results in:

$$S_h^c(x_h) = \frac{x_h - \underline{x}_h}{1-\beta(1-\gamma)} \text{ and } S_l^c(x_l) = \frac{x_l - \underline{x}_l}{1-\beta(1-\mu)(1-\gamma)}. \tag{40}$$

Using (39) and (40) in (37) and (38) gives the job separation conditions that solve for $\underline{x}_h$ and $\underline{x}_l$ for a given market tightness θ. The free entry condition (10) can also be rewritten as:

$$\frac{c}{\beta q(\theta)} = (1-\pi)\Big[(1-\delta)p_h\mathbb{E}S_h^c(x_h') + \big[1-(1-\delta)p_h\big]\mathbb{E}S_l^c(x_l')\Big]. \tag{41}$$

Lastly, the stock-flow balance equations imply:

$$p_h = \frac{f(\theta)(1-G(\underline{x}_l))}{(1-\delta)f(\theta)(1-G(\underline{x}_l)) + \delta\big(1+\frac{1-\mu}{\mu}\gamma G(\underline{x}_l)\big)}. \tag{42}$$

The steady-state equilibrium is defined by θ, $\underline{x}_l$, $\underline{x}_h$, and p_h that solve (37), (38), (41), and (42). I solve the nonlinear system numerically, and all integrals associated with the truncated log-normal distributions are calculated by Simpson's rule.

C Results Under Alternative Calibrations

In the comparative static exercises in the main text, I chose the arrival rate of the idiosyncratic shock γ at 1/6 and the probability of becoming experienced μ at 1/24. In this section, I present the results using alternative values for these two parameters. Table A.1 presents the case with $\gamma = 1/9$ and Table A.2 presents the case with $\mu = 1/36$. In both cases, the

Table A.1: Effects of Parameter Changes: Alternative Calibration $\gamma = 1/9$

	Job Finding Rate	Separation Rate	Unemployment Rate	Market Tightness	Switching Rate
Initial SS	0.270	0.017	0.060	0.54	0.45
$\sigma_x = 0.21$	0.259	0.014	0.052	0.50	0.50
$\pi = 0.4$	0.353	0.017	0.047	0.88	0.39
$\sigma = 0.21$	0.278	0.012	0.042	0.53	0.44

	Average Wage		Wage Change	Var(Wage)	
	Experienced	Inexperienced	$(\Delta\hat{w})$	Experienced	Inexperienced
Initial SS	0.994	0.867	−0.130	0.018	0.009
$\delta = 0.3$	0.987	0.871	−0.119	0.019	0.009
$\pi = 0.4$	0.989	0.868	−0.127	0.012	0.006
$\delta = 0.21$	0.978	0.847	−0.137	0.016	0.008

Notes: Parameter values used to calibrate the initial steady state are as follows: $\pi = 0.5$, $\alpha = 0.5$, $\bar{m} = 0.659$, $\beta = 0.99$, $\gamma = 1/9$, $\Delta = 0.258$, $\sigma_x = 0.23$, $\mu = 0.042$, $\delta = 0.261$, $b_h = 0.862$, $b_l = 0.790$, and $\kappa = 0.35$. See Table 1 for a description of each parameter.

Table A.2: Effects of Parameter Changes: Alternative Calibration $\mu = 1/36$

	Job Finding Rate	Separation Rate	Unemployment Rate	Vacancy Rate	Switching Rate
Initial SS	0.270	0.017	0.060	0.40	0.45
$\delta = 0.256$	0.267	0.010	0.036	0.40	0.50
$\pi = 0.4$	0.343	0.017	0.046	0.63	0.40
$\sigma_x = 0.20$	0.277	0.011	0.039	0.40	0.45

	Average Wage		Wage Change	Var(Wage)	
	Experienced	Inexperienced	$(\Delta\hat{w})$	Experienced	Inexperienced
Initial SS	0.896	0.760	−0.160	0.019	0.013
$\delta = 0.256$	0.886	0.765	−0.141	0.021	0.013
$\pi = 0.4$	0.891	0.756	−0.162	0.012	0.009
$\sigma_x = 0.20$	0.883	0.746	−0.166	0.017	0.011

Notes: Parameter values used to calibrate the initial steady state are as follows: $\pi = 0.5$, $\alpha = 0.5$, $\bar{m} = 0.57$, $\beta = 0.99$, $\gamma = 1/6$, $\Delta = 0.19$, $\sigma_x = 0.22$, $\mu = 0.028$, $\delta = 0.217$, $b_h = 1.30$, $b_l = 0.69$, and $\kappa = 0.35$. See Table 1 for a description of each parameter.

entire model is re-calibrated by using the same moment conditions as in the benchmark calibration. Note, however, that in the latter case, it takes three years (instead of two years) on average to become experienced. This requires changing the moment condition for the wage loss, Equation (31). As shown in Table 2, when the cutoff for "experienced" is changed to three years, the size of the wage loss, not surprisingly, increases. The calibration with the case of $\mu = 1/36$ uses 0.16 for the average wage loss of the experienced worker. As in the exercises under the benchmark calibration, three experiments are considered. In the case of the increase in δ, the size of the change is chosen, again, by matching the occupation switching rate at 0.5 in the new steady state. The worker bargaining power is lowered from 0.5 to 0.4. Regarding the effect of the smaller variance of the idiosyncratic shock, it is lowered by about 10% from the level in the initial steady state. See notes to each table for the specific parameter values.

Overall, the results under these two calibrations remain similar to the ones under the benchmark calibration. A higher turbulence parameter and a decline in the idiosyncratic variance both yield lower separation rates. The differences between these two experiments again lie in the implications on the size of the wage loss and the switching rate. One noticeable result in the case of $\mu = 1/36$ is that the increase in the value of δ leads to a larger decline in the separation rate: It declines 0.7 percentage point in this calibration, while it fell 0.4 percentage point in the benchmark calibration. The reason is that, in this alternative calibration, being experienced gives the worker a larger wage premium (0.16 instead of 0.13), and thus, the effect of the higher risk of losing the skill becomes larger.

D Computing Wage Loss After Unemployment

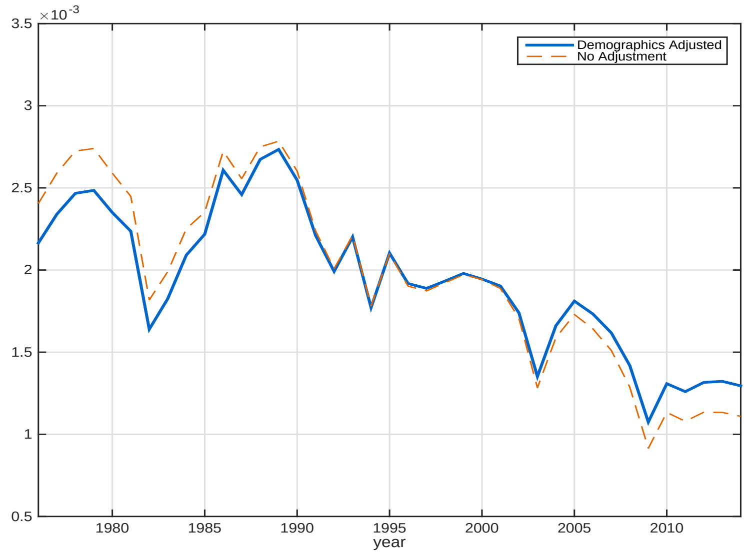
Table 2 presented the regression result showing that a worker suffers a significant wage cut when the worker who previously accumulated experience in a certain occupation switches to a different occupation after an unemployment spell. This calculation requires panel data so that one can keep track of the worker's labor market experience. Using the data from SIPP, I collect events that start with employment followed by unemployment and end with employment, namely, $EU...UE$ spells.[37] The SIPP survey has been conducted roughly every three to four years since 1983, and each SIPP panel follows the same individuals over three to four years with an exception of the 2008 panel, which lasted five years. For my analysis, I use the data from the 1996, 2001, 2004, and 2008 panels. The occupational tenure variable (eocctim1) is available only after 1996. The SIPP data allow me to collect the information on wages before and after an unemployment spell, unemployment duration, and workers' demographic characteristics, occupation, and occupation tenure.[38] The question on occupation tenure is asked only in the first interview, but with this information, one can extend the tenure information. Note also that I construct the same two occupation classifications (major and detailed classifications) that are constant over time and are used in the CPS analysis. See Appendix G for the complete list of occupations.

I pool all $EU...UE$ spells from the four panels. Several sample selection criteria are imposed. First, I focus on individuals with nonzero longitudinal weights. These weights are meant to be used for longitudinal analysis. Focusing on these individuals in the analysis minimizes the effect of attrition. Second, the spells in which the transition from E to U that occurs in the last year of each panel are excluded from the analysis. These cases are necessarily skewed toward the cases with short unemployment duration because the entire

[37] The monthly labor market status is determined from the status in the second week in each month so that it is roughly consistent with the timing used in the CPS.

[38] Nominal hourly wage is converted into real wage using the PCE deflator.

Figure A.2: Transition Rate into Unemployment: Job Leavers



Notes: Source, monthly CPS. See notes to Figure 2.

$EU...UE$ events occur within a year.[39] Third, I consider only the individual's first $EU...UE$ events within the panel. In other words, if an individual experiences two or more such events within the panel, the worker is not part of the sample. Fujita and Moscarini (2013) provide detailed analysis on the various measurement issues on the SIPP, such as the consistency of the definitions of the labor market status between the CPS and the SIPP. That paper also provides the overall description of the SIPP data.

E Quit Rate into Unemployment

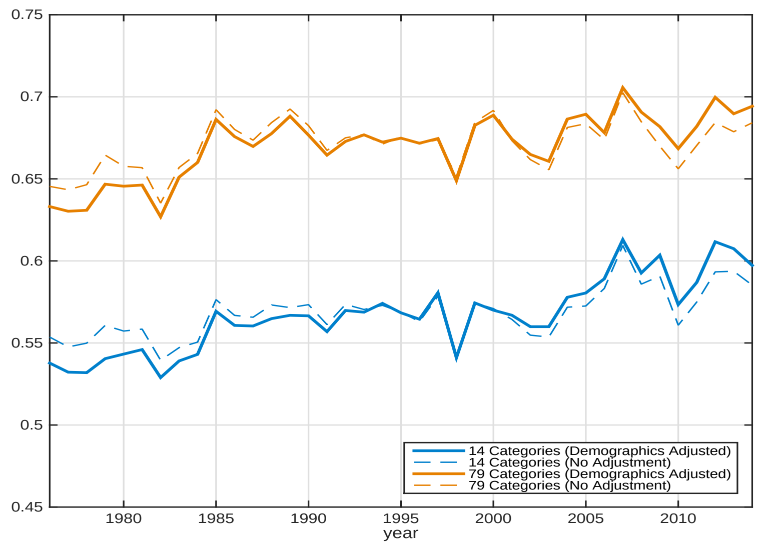
The separation rate presented in Figure 2 includes all transitions into unemployment. However, one may think that the economic mechanism emphasized in this paper applies more directly to the case of job leavers, because the underlying reason for a lower separation probability is a higher chance of skill loss, making the worker reluctant to separate in a new environment.[40] Remember that the overall transition rate in Figure 2 is constructed by taking all workers who transit from "employed" in month t to "unemployed" in month $t+1$. Within this group, one can consider only those who are reported to be a job leaver.

Figure A.2 plots the quit rate into unemployment. Not surprisingly, the size of this flow is relatively small: the transition rate averages around 0.1 to 0.2 percent per month; it is

[39] Including these cases does not materially change the regression results, however.

[40] It is important to note, however, that in the model developed in Section 3, there is no conceptual distinction between quits and layoffs because all separations occur as a jointly efficient outcome. Thus, the data on the quit rate into unemployment are simply additional pieces of evidence that strenghen the economic story emphasized in this paper.

Figure A.3: Trend in Occupation Switching Rate: Permanently Separated Workers



Notes: Source, monthly CPS. Permanently separated workers are job losers not on temporary layoffs and job leavers.

at most 20 percent of all separation flows. However, what is more interesting is a clear downward trend. Note also that while the demographic adjustment makes the downward trend less steep, the large downward trend still remains even after the adjustment. The mean level in in the first 10 years of the sample is 0.22 percent and it fell to 0.14 percent in the last 10 years of the sample. This empirical observation is consistent with the turbulence story, supplementing the analysis in the main text.[41]

F Occupation Switching Rate: Permanently Separated Workers

In Figure 3, occupation switching rates are computed for all unemployed workers (except for entrants, who do not report their previous occupation). It is interesting to see if the upward trend in the occupation switching rate in the earlier figure applies even after excluding those on temporary layoffs. This exclusion is motivated by a recent finding by Fujita and Moscarini (2013), who show that most of the workers on temporary layoffs return to the same employer after a short spell of unemployment and remain in the same occupation. Figure A.3 presents occupation switching rates, focusing on those permanently separated workers. The levels of switching rates are higher than those presented in the earlier figures, implying that these workers indeed face a higher chance of switching to a different occupation. One can clearly

[41]The recent literature has also noted a striking downward trend in the job-to-job transition rate (the majority of which is likely to be quits) constructed from the CPS. For example, Hyatt and Spletzer (2013) show that the job-to-job transition rate constructed by Fallick and Fleischman (2004) fell more than 50% during the period between 1998 and 2010.

see that both series show a clear upward trend. In fact, the upward trend is even clearer once we focus on permanently separated workers.

G Construction of Occupation Categories

The occupation classification used in this paper is based on the standard occupation titles proposed by Meyer and Osborne (2005), which are in turn based on the 1990 census occupation definitions. The Meyer-Osborne classification system is intended to be consistent over time and includes a total of 371 occupation titles. I further reduce the number of titles to 79 and then 14. In the main text of this paper, the classification with 79 titles is called "detailed" categories and the one with 14 titles "major" categories. Note that the same classification system is applied to both CPS- and SIPP-based analyses. Table A.3 presents the mapping from Meyer and Osborne codes (middle column) into the 79 and 14 titles.

Table A.3: Occupation Classifications

Detailed titles	M/O Codes	Major titles
Executive, administrative, and managerial	3-22	Executive, administrative, and managerial
Management related	23-37	
Architects	43	Professional
Engineers	44-59	
Math and computer scientists	64-68	
Natural scientists	69-83	
Health diagnosing	84-89	
Nurses, pharmacists, and dietitians	95-97	
Therapists	98-106	
Teachers (postsecondary)	113-154	
Teachers (excl. postsecondary) and vocational counselors	155-159	
Librarians, archivists, and curators	164-165	
Social scientists and urban planners	166-173	
Social, recreation, and religious workers	174-176	
Lawyers and judges	178-179	
Writers, artists, entertainers, and athletes	183-200	
Health technologists and technicians	203-208	Technicians and related support
Engineering and related technicians	213-218	
Science technicians	223-225	
Technicians (excl. health engineering and science)	226-235	
Sales supervisors and proprietors	243	Sales
Finance service sales	253-256	
Sales engineers	258	
Sales persons n.e.c., clerks, cashiers, promoters, and models	274-283	
Office supervisors	303	Administrative support
Computer and peripheral equipment operators	308	
Secretaries, stenographers, and typists	313-315	
Information clerks	313-323	
Records processing (excl. financial)	326-336	
Financial records processing	337-344	
Duplicating, mail, and other office machine operators	345-357	
Telephone and telecom operators	348-349	
Mail and message distributors	354-357	
Material recording, scheduling, and distributing clerks	359-373	
Adjusters and investigators	375-378	
Miscellaneous administrative support	379-389	
Private household occupations	405-407	Private household services
Supervisors of guards	415	Protective service
Firefighting, prevention, and inspections	417	
Police, detective, private investigators, and other law enforcement	418-423	
Guards, watchmen, and other protective service	424-427	
Food preparation and service occupations	433-444	Other services
Health service	445-447	
Cleaning and building service (excl. household services)	448-455	
Personal service occupations	456-469	
Farm operators and managers	473-476	Farming, forestry, and fishing
Farm occupations (excl. managerial)	479-484	
Related agricultural occupations	485-489	
Timber, logging, and forestry workers	496	
Fishers, hunters, and kindred	498	
Supervisors of mechanics and repairers	503	Precision production, craft, and repair
Vehicle and mobile equipment mechanics and repairers	505-519	
Electrical and electronic equipment repairers	523-534	
Miscellaneous mechanics and repairers	535-549	
Supervisors of construction work	558	
Other construction occupations	563-599	
Extractive occupations	613-617	
Production supervisors or foremen	628	
Metal precision	634-653	
Wood precision	657-659	
Textile, apparel, and furnishing precision	666-674	
Optical and other craft precision	675-684	
Food production	686-688	
Adjusters and calibrators	693	
Plant and system operators	694-699	
Fabricating machine operators	703-717	Machine operators, assemblers, and inspectors
Metal and plastic processing machine operators	719-724	
Woodworking machine operators	726-733	
Printing machine operators	734-736	
Textile, apparel, and furnishing machine operators	738-749	
Machine operators, assorted materials	753-779	
Fabricators, assemblers, and hand working occupations	783-789	
Production checkers, inspectors, and graders/sorters	796-799	
Motor vehicle operators	803-813	Transportation and material moving
Transportation occupations (excl. motor vehicles)	823-859	
Helpers, construction	865	Handlers, equipment cleaners, helpers, and laborers
Helpers, construction and extractive occupations	866-874	
Freight, stock, and material handlers	875-889	
Military	905	Military