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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 aggregate job separation rate over the last three decades. I first show that aging of the labor force alone cannot account for the entire decline. To explore other sources, I use a simple labor matching model with two types of workers, experienced and inexperienced, where the former type faces a risk of skill obsolescence during unemployment. When the skill depreciation occurs, the worker is required to restart his career and thus suffers a drop in earnings. I show that a higher skill depreciation risk results in a *lower* aggregate separation rate and a *smaller* earnings loss. The key mechanisms are that the experienced workers accept lower wages in exchange for keeping the job and that the reluctance to separate from the job produces a larger mass of low-quality matches. I also present empirical evidence consistent with these predictions.

JEL codes: E24, J31, J64
Keywords: Separation Rate, Earnings Losses, Turbulence

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1 Introduction

Labor market conditions surrounding American workers appear to have worsened in the recent decades even before the severe recession of 2007-09. An observation often referred to in this regard is that real wages have been stagnant even during the period of relatively healthy output growth. In contrast to this alarming view, academic studies have had difficulty finding clear evidence that the job security of American workers has worsened recently. Various papers in a special issue of the *Journal of Labor Economics* (1999) are devoted to this issue and the overall conclusion is that there is no clear evidence of increased job insecurity and instability.[1] A more recent paper by Davis (2008) looks at various measures of job separation rates and concludes that the risk of job loss has declined substantially.

The main purpose of this paper is to explain this puzzling observation that the job separation rate has been on a downward trend, while anecdotal evidence points to heightened job insecurity. This paper first verifies that the job separation rate, more specifically, the transition rate from employment to unemployment, has been indeed on a secular downward trend in the last three decades. One important issue is the extent to which aging of the labor force has contributed to this decline. Because older workers tend to have a higher labor force attachment, aging of the labor force artificially lowers the aggregate separation rate. By controlling for the demographic factor, I find that roughly one-half of the observed decline in the separation rate can be attributed to this effect. This means that the rest has to be explained by other factors.

I use a simple labor matching model with heterogeneous workers to explore other sources of the declining separation rate. The basic structure of the model is the same as the one developed by den Haan et al. (2005). This model is structured so that an unemployment spell is associated with a loss of earnings. In the model, there are two types of workers: "experienced" and "inexperienced." Both types of workers face the risk of endogenous match destruction. However, the experienced worker faces an additional risk of becoming inexperienced while searching for a new job. This skill obsolescence probability is specified exogenously as in Ljungqvist and Sargent (1998) and den Haan et al. (2005). When hit by this shock, the experienced worker needs to restart his career as an inexperienced worker and therefore tends to suffer a decline in earnings. This structure parsimoniously captures the idea that human capital is occupational or industry specific, as argued by Kambourov and Manovskii (2009) and Neal (1995).

The model is calibrated by matching various empirical moments on wages and worker flows. The key experiment based on the calibrated model is to look at how the model responds to a higher skill obsolescence probability, which I call turbulence, as proposed by Ljungqvist and Sargent (1998). The model predicts that the separation rate falls in response to this change. The reason is simple. A higher chance of skill obsolescence makes the experienced workers reluctant to separate from his current job. This further implies that there is a larger mass of low-quality employment relationships that would have been destroyed before the parameter change. Wages of these workers are lower than before in exchange for main-

[1]See, for example, Jaeger and Stevens (1999), Neumark et al. (1999) and Gottschalk and Moffitt (1999).

taining the employment relationship. This 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 obsolescence on job search behavior in the European context. In contrast, this paper quantitatively evaluates the hypothesis in the calibrated model that incorporates various empirical regularities of the U.S. labor market. I also consider other implications of the model. For example, one key prediction of the model is that a higher skill obsolescence parameter results in a *decline* in earnings losses. Note that workers' reluctance to separate and the associated wage cut are largely concentrated among experienced workers. Furthermore, a larger mass of low-quality matches (which would not have existed before the parameter change) also works to reduce the average wage of experienced workers. Given that these wage effects are concentrated among experienced workers, the magnitude of earnings losses is observed to be smaller in the new environment.

To examine the empirical plausibility of this prediction, I calculate changes in earnings and a fraction of workers who switch occupation or industry after an unemployment spell using the Survey of Income and Program Participation (SIPP) data over the period 1990 to 2006. I first confirm that earnings indeed tend to drop after an unemployment spell and that the incidence of earnings losses is often concentrated among occupation or industry switchers. Both of these observations are consistent with the earlier empirical literature and the structure of the model. I then show that average earnings losses among switchers are smaller and the fraction of switchers is higher later in the sample.[2]

I also examine two other plausible explanations using the model, namely, a lower bargaining power of the worker and the smaller variance of the idiosyncratic shocks. The latter is motivated by Davis et al. (2010), who identify the smaller variance as an explanation for a downward trend in job flows and the unemployment inflow rate. I find that the lower bargaining power of the worker implies higher separation rates for both types of workers and that it results in higher earnings losses and a lower switching probability. The lower variance of the idiosyncratic shock generates lower separation rates, although earnings losses are found to expand. I do not intend to advocate a more turbulent environment as a single source of the lower separation rate. I rather propose it as an attractive explanation complimentary to the one explored by Davis et al. (2010). The explanation of this paper is attractive in that it can reconcile the coexistence of lower separation rate and the downward wage pressure that we have seen even during boom years. It also tells that gauging job insecurity solely based on the level of labor turnover can lead to a misleading conclusion and thus policy prescriptions.

This paper is organized as follows. The next section presents empirical facts. After discussing the measurement issues on the separation rate, I show that the declining trend in the separation rate is not entirely accounted for by the aging of the labor force. Section 3

[2]Farber (2011) computes earnings losses of workers using the CPS's Displaced Workers Survey over the period between 1984 and 2010. While he does not distinguish between occupation (or industry) switchers and stayers, Farber's evidence is in line with the claim of this paper. For example, the size of earnings losses during the most recent recession, which is not covered by my SIPP sample, is not very different from those in 2004 and 1992. This is quite surprising given the severity of the most recent recession.

lays out the model. In Section 4, I calibrate the model as tightly as possible, incorporating as many empirical facts as possible. Section 5 presents the main results of the paper. This section also includes the empirical findings based on the SIPP. Section 6 concludes the paper.

2 Secular Decline in the Separation Rate

This section shows that the separation rate has been on a downward trend over the last 30 years even after accounting for the aging of the labor force. There are many ways to measure the extent of labor turnover. This paper focuses on the transition rate from employment into unemployment.[3] There are yet several different ways to measure this transition rate and the analysis in this paper uses one of them. As summarized by Davis (2008), other available measures, such as those based on short-term unemployment, share the same trend.[4]

2.1 Measurement

The separation rate is based on the Current Population Survey (CPS), 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 calculate the discrete-time separation rate as follows:

$$\hat{s}_t = \frac{eu_t}{e_{t-1}},$$

where eu_t is the number of workers whose labor market status was "employed" in month $t-1$ and "unemployed" in month t and e_{t-1} denotes the stock of employment in $t-1$. Similarly, the discrete-time transition rate from unemployment to employment (i.e., job finding rate) can be calculated as:

$$\hat{f}_t = \frac{ue_t}{u_{t-1}},$$

where ue_t is the number of workers whose labor market status was "unemployed" in month $t-1$ and "employed" in month t and u_t denotes the number of the unemployed in $t-1$. As Shimer (2007) points out, these measures are subject to time aggregation error. The error

[3]The main reason for focusing on the transition rate into unemployment is that it can be naturally linked to an empirical observation that workers tend to experience a decline in earnings relative to those prior to the job loss (e.g., Jacobson et al. (1993)). On the other hand, job-to-job transitions are typically associated with gains in earnings (Topel and Ward (1992)). Because this paper focuses on the effects of "turbulence" on labor turnover, flows into unemployment seem to be of first-order relevance.

[4]Davis et al. (2010) instead look at job flows and the inflow rate into unemployment and find the same secular decline. They argue that the decline is driven by smaller business volatility. I consider this hypothesis later in the paper.

[5]See Shimer (2007) and Fujita and Ramey (2006, 2009) for details of the measurement issues involved in constructing the flow measures from the CPS.

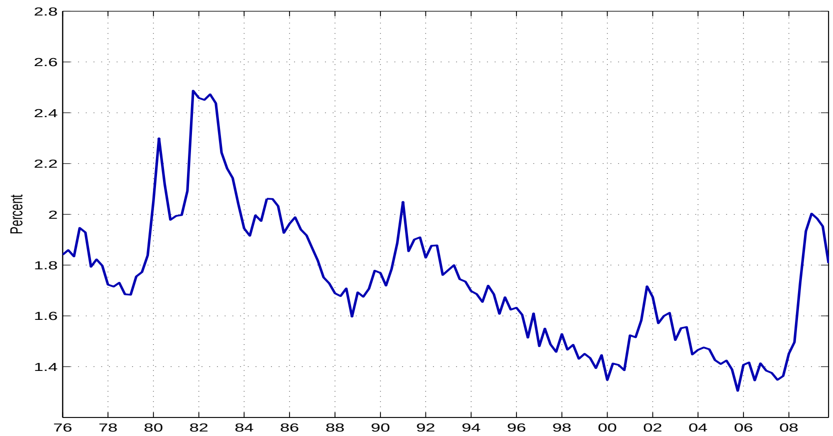

Figure 1: Aggregate Separation Rate into Unemployment

Notes: Based on the matched CPS data. The quarterly averages of the monthly separation rate over Jan. 1976 – Dec. 2009. Corrected for time aggregation error.

arises due to the fact that the CPS records workers' labor market status at one point in a month and thus misses the within-month spells. Under the assumption that the continuous-time flow hazard rates for transitions are constant within each month, one can calculate transition rates corrected for the time aggregation error as follows:

$$s_t \equiv -\log(1 - \hat{s}_t - \hat{f}_t)\frac{\hat{s}_t}{\hat{s}_t + \hat{f}_t}, \tag{1}$$

$$f_t \equiv -\log(1 - \hat{s}_t - \hat{f}_t)\frac{\hat{f}_t}{\hat{s}_t + \hat{f}_t}, \tag{2}$$

where s_t is the arrival rate of transitions to unemployment for a worker who is employed at any point in month t. Similarly, f_t is the arrival rate of transitions to employment for a worker who is unemployed at any point in month t. Throughout this paper, I use the terms "the separation rate" and "the job finding rate" for s_t and f_t, respectively. Note that each of these arrival rates is influenced by both observed discrete-time transition rates $\hat{s}_t$ and $\hat{f}_t$ as can be seen in Equation (1). For instance, a trend in $\hat{f}_t$ can influence the trend in the observed discrete-time separation rate s_t. It is therefore important to assess the trend movements based on the underlying hazard rates.

Figure 1 presents the quarterly average of the monthly separation rate between 1976 and 2009. While its countercyclicality is clear, the focus of this paper is on the secular downward trend. The most pronounced downward trend can be observed between the early 1980s through the mid-2000s. Also observe that even though it has sharply increased in the recent severe recession, its peak level during the recession is significantly lower than the peak in the early 1980s. The peak level in the most recent recession is actually comparable to that during the recession in the early 1990s, which is considered quite shallow. The mean level

Table 1: Separation Rate and Employment Share by Age and Gender

		Male			Female		
		16 − 24	25 − 54	55−	16 − 24	25 − 54	55−
1980 − 1989	s_t	4.79	1.91	0.99	3.23	1.37	0.82
		(10.11)	(37.89)	(8.04)	(9.17)	(29.24)	(5.55)
1990 − 1999	s_t	4.18	1.59	0.99	2.99	1.19	0.82
		(8.07)	(39.15)	(6.87)	(7.31)	(33.19)	(5.40)
2000 − 2009	s_t	3.75	1.54	1.01	2.66	1.13	0.88
		(7.20)	(37.52)	(8.68)	(6.74)	(32.33)	(7.53)

Notes: Both separation rates and employment shares are expressed as %. The employment share of each demographic group is in parenthesis and is based on the monthly CPS Table A−1. Separation rates are adjusted for time aggregation error.

during the 1980s (1980−1989) is 2.0%, whereas in the 2000s (2000−2009) the mean level has come down to 1.5%. To see how large this change is, note first that the steady-state unemployment rate is related to the two transition rates by $\frac{s_t}{s_t+f_t}$ in the two-state model. Assuming that job finding rate from the unemployment pool is 27%, which is the mean level in the 1980s, the 0.5-percentage-point decline in the separation rate would bring the steady-state unemployment rate down from 6.7% to 5.3%. This is arguably substantial.

2.2 The Effect of Aging of the Labor Force

One of the important changes that has occurred in the last three decades is the aging of the labor force. The change in the composition of the labor force causes the observed aggregate separation rate to decline, because older workers tend to have stronger labor force attachment. Shimer (1998) makes the point that the aging of the labor force lowers the level of the unemployment rate for the same reason. Here I look at labor force attachment through separation rates of different demographic groups.

Table 1 presents separation rates and employment shares of the six demographic groups for each decade since the 1980s. First, consider the average separation rates in the 1980s. The first row of the table shows that there are relatively large differences in the separation rates across different demographic groups. Young workers (16-24 years old), whether male or female, have much higher separation rates compared to the other groups (see for example Blanchard and Diamond (1990) and Fujita and Ramey (2006) for more details about this observation). As can be seen from Table 1, the employment share of young workers has declined from roughly 10% in the 1980s to 7% in the 2000s, thus lowering the aggregate separation rate solely through the composition effect. While the share of prime-age male workers has not changed between the 1980s and 2000s, the share of prime-age female workers has increased roughly 3 percentage points. The separation rates within these two groups have experienced substantial declines over the three decades. As for the old workers (55 or older), their employment share has increased, as these workers stay longer in the labor force, contributing to the decline in the observed aggregate separation rate.

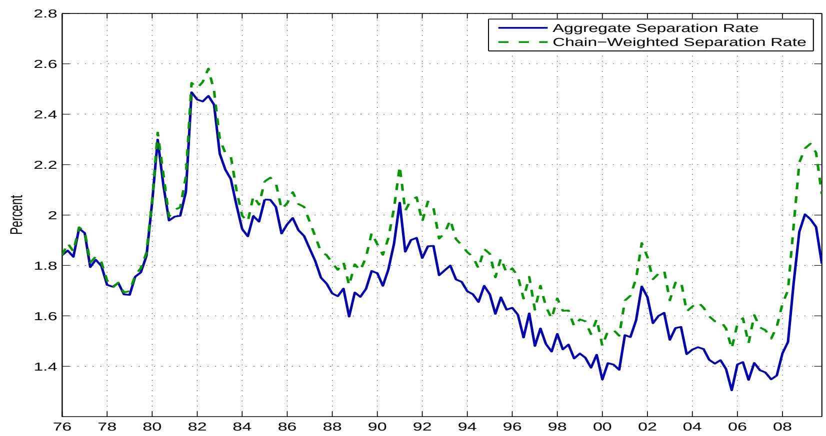

Figure 2: Chain-Weighted Separation Rate into Unemployment

Notes: See notes to Figure 1. The chain-weighted index is rescaled, such that it matches the average level of the actual separation rate in the first year of the sample.

To quantify the effects of the aging of the labor force, I construct the chain-weighted index of the separation rate s_t^c. Shimer (1998) applies the same methodology to the unemployment rates for different demographic groups.[6]

$$s_t^c = \Pi_{j=1}^t \left(\frac{\sum_{i=1}^6 \omega_{ij} s_{ij+1}}{\sum_{i=1}^6 \omega_{ij} s_{ij}} \right) \text{ for } j = 1, \cdots, T. \tag{3}$$

where ω_{ij} and s_{ij} refer, respectively, to the employment share and the separation rate of the demographic group i, and T is the total number of observations. Since this measure is an index, it is rescaled such that it matches the average level of the actual separation rate in the first year. Figure 2 plots the chain-weighted separation rate (dashed green line) along with the actual series (solid navy line) already shown in the previous figure. The figure shows that the two series start to diverge from each other in the mid-1980s, and the difference looks substantial in recent years. Of course, correcting the changes in the demographic composition makes the separation rate higher than the actual one and the decline in the trend thus becomes less steep. The mean level in the 1980s is roughly the same as before at 2.1%, while that in the 2000s is now 1.7%. I can therefore conclude that roughly one-half of the decline in the separation rate in the last 30 years can be accounted for by the aging of the labor force. This is a large contribution but calls for further explanations for the remaining part of the decline.

[6]A similar but simpler method would be to calculate the fixed employment-weight separation rate. The chain-weighted index avoids the problem of the fixed-weight method that the result can be sensitive to the selection of the base period.

Other composition effects. There are other dimensions of the data that can possibly influence the trend in the separation rates. First, 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.[7] However, there is no clear difference in the average levels of separation rates between manufacturing and non-manufacturing sectors. Moreover, separation rates within both sectors have been trending down.

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. However, 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 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.[8] In a nutshell, 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 sex.

Trend in the job finding rate. This paper focuses on the secular trend in the separation rate. But it is also interesting to see if there is a similar trend in the job finding rate f_t which is plotted in Figure 3. As can be seen from the figure, there is no discernible trend in the series and the adjustment for the demographic factor makes a little difference. In other words, over the last three decades, the job finding rate has been fluctuating around roughly the same level. Davis et al. (2010) also reach the same conclusion based on the unemployment outflow rate. In the last few years, the job finding rate plummeted to the lowest level ever seen. However, this large decline at the end of the sample is due to the severe recession that started at the end of 2007 and thus cannot be viewed as a secular downward trend (at

[7] Davis et al. (1996) point out the same pattern in job flows.

[8] 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.

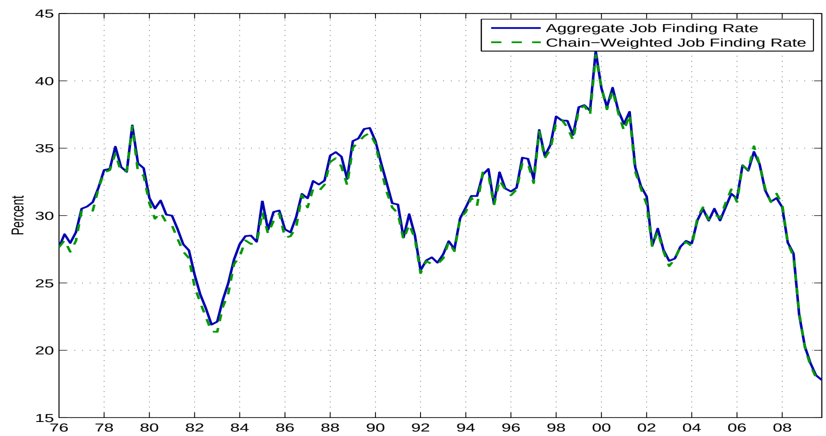

Figure 3: Aggregate Job Finding Rate

Notes: Based on the matched CPS data. The quarterly averages of the monthly separation rate over Jan. 1976 – Dec. 2009. Corrected for time aggregation error.

least at this point).[9] In the quantitative experiments below, I also examine whether each experiment delivers the implication for the job finding rate that is consistent with the data in Figure 3.

3 Model

This main theme of this paper is to link the declining separation rate with a more turbulent labor market environment. This section presents the labor search/matching model that incorporates the possibility that going into the unemployment pool can result in earnings losses. Allowing for the possibility of earnings losses 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 proposed by Ljungqvist and Sargent (1998). 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).[10]

3.1 Environment

The economy is populated by a unit mass of risk-neutral workers and a fixed mass $\bar{n}$ of job positions. The latter assumption is further discussed later. There are two types of

[9]Mukoyama and Şahin (2009) show that the 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. For this period, they emphasize the increase in the average duration *relative* to the unemployment rate.

[10]Other papers that explicitly incorporates earnings losses include Pries (2004).

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 be supported on an interval $[0, \infty)$. It is also assumed that $G_h(.)$ (first order) stochastically dominates $G_l(.)$, namely, $G_h(x) < G_l(x)$ for any x. 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 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 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. This match separation decision is described later. When the experienced workers are in the unemployment pool, they face an additional risk that they become inexperienced. This occurs with probability δ every period.

3.2 Labor Market Matching and Vacancy Posting

The frictions of reallocating workers across 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 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 is written as:

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

The vacant job is paired randomly with the experienced or inexperienced worker with probability $p_h q(\theta)$ and $(1 - ph)q(\theta)$, respectively, where $p_h \equiv \frac{u_h}{u}$.

There are two assumptions regarding the job opening and hiring process, which differs from the standard search/matching model. First, I assume that there is no flow cost for posting a vacancy. Second, as mentioned above, the economy is populated by a fixed mass of jobs $\bar{n}$. In a standard model, the presence of the flow cost and the free entry ensure that the value of a vacant job is driven down to zero in equilibrium. Instead, in this paper, the value of a vacant job is ensured to be non-negative given that there is no cost of posting a vacancy and that the available number of jobs in the economy is fixed. As will be stated formally later, the equilibrium of the economy is achieved by the condition that the total number of jobs stays constant at $\bar{n}$. The reason for adopting this specification instead of the standard one is to make sure that the value of a vacant job is non-negative, so that changes in the value of vacating the job would have a feedback impact on the wage determination and separation decision in the Nash bargaining framework.

An alternative way to ensure a non-negative value for a vacant job is to assume there is some entry cost, for example, as in Fujita and Ramey (2007). Extending the present model in this direction is straightforward. However, it makes the model messier in terms of its notation and calibration, with no apparent benefits of gaining additional economic insights for the question posed for this paper. Thus I decided to adopt the specification just described.

3.3 Continuation Values

I now 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 in this period. The continuation value of this worker, $W_h^c(x_h)$, can be expressed as:

$$W_h^c(x_h) = w_h(x_h) + \beta\left[(1-\gamma)W_h^c(x_h) + \gamma\int_0^\infty W_h(x_h')dG_h(x_h')\right], \tag{4}$$

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

$$W_h(x_h) = \max\left[W_h^c(x_h), U_h\right], \tag{5}$$

where U_h is the value of being unemployed as an experienced worker. Equation (5) characterizes the optimal continuation/separation decision of the experienced worker. The first term in the square brackets in Equation (4) 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 (5).[11]

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

$$\begin{aligned} U_h = b_h + \beta\Bigg[& f(\theta)\left(\delta\int_0^\infty W_l(x_l')dG_l(x_l') + (1-\delta)\int_0^\infty W_h(x_h')dG_h(x_h')\right) \\ & + \Big(1-f(\theta)\Big)\Big(\delta U_l + (1-\delta)U_h\Big)\Bigg], \end{aligned} \tag{6}$$

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 is the value of the inexperienced employed

[11]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:

$$W_l(x_l) = \max\Big[W_l^c(x_l), U_l\Big]. \tag{7}$$

Upon meeting with the potential employer with a job opening, 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 (5) and (7). Note also that since newly formed meetings and preexisting matches whose productivity is switched face the identical situation, the rejection (acceptance) decision and match separation decision are identical in the model. Lastly, if the worker fails to meet with a potential employer, he stays unemployed and faces the risk of skill loss at the start of the next period.

Next, consider the continuation values of the inexperienced workers. Let $W_l(x_l)$ be the value of the inexperienced employed worker who has decided to continue the match in this period. It is expressed as:

$$\begin{aligned} W_l^c(x_y) = w_l(x_l) + \beta\Bigg[\mu\int_0^\infty W_h(x_h')dG_h(x_h') + (1-\mu)\Bigg((1-\gamma)W_l^c(x_l) \\ + \gamma\int_0^\infty W_l(x_l')dG_l(x_l')\Bigg)\Bigg], \end{aligned} \tag{8}$$

where $w_l(x_l)$ is the current-period wage payment to the inexperience 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 characterized by Equations (5) and (7).

The value of the inexperienced unemployed worker is written as:

$$U_l = b_l + \beta\Bigg[f(\theta)\int_0^\infty W_l(x_l')dG_l(x_l') + \Big(1-f(\theta)\Big)U_l\Bigg], \tag{9}$$

where b_l is the flow value of being an inexperienced unemployed worker. The interpretation is similar to Equation (6) except that the inexperienced worker faces no risk of further downgrading of his skill. 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 embodies the following value:

$$J_h^c(x_h) = x_h - w_h(x_h) + \beta\Bigg[(1-\gamma)J_h^c(x_h) + \gamma\int_0^\infty J_h(x_h')dG_h(x_h')\Bigg], \tag{10}$$

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:

$$J_h(x_h) = \max\Big[J_h^c(x_h), V\Big]. \tag{11}$$

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 is written as:

$$\begin{aligned} J_l^c(x_l) = x_l - w_l(x_l) + \beta\Bigg[\mu\int_0^\infty J_h(x'_h)dG_h(x'_h) + (1-\mu)\Bigg((1-\gamma)J_l^c(x_l) \\ + \gamma\int_0^\infty J_l(x'_l)dG_l(x'_l)\Bigg)\Bigg], \end{aligned} \tag{12}$$

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:

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

Again the interpretation of Equation (12) is straightforward. The main difference from Equation (10) is that Equation (12) takes into account the probability μ that the inexperienced worker becomes experienced.

Lastly, the value of a vacant job is characterized by:

$$V = \beta\Bigg[q(\theta)\Bigg((1-\delta)p_h\int_0^\infty J_h(x'_h)dG_h(x'_h) + (\delta p_h + p_l)\int_0^\infty J_l(x'_l)dG_l(x'_l)\Bigg) + \Big(1-q(\theta)\Big)V\Bigg]. \tag{13}$$

When the meeting occurs with probability $q(\theta)$, the worker can be experienced or inexperienced. The composition of the matching market thus influences the meeting probabilities. As in the values of unemployed workers, (6) and (9), 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.[12]

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 the match enjoys the surplus of

$$S_i^c(x_i) \quad = \quad J_i^c(x_i) + W_i^c(x_i) - U_i - V \text{ for } i \in \{h, l\}. \tag{14}$$

[12]Note also that, at the beginning of the next period, the experienced worker becomes inexperienced with probability δ. This possibility is incorporated in Equation (13).

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

$$\begin{aligned} \pi S_i^c(x_i) &= W_i^c(x_i) - U_i, \\ (1-\pi)S_i^c(x_i) &= J_i^c(x_i) - V. \end{aligned} \tag{15}$$

The optimal value of the match surplus is determined by:

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

Observe that $J_i^c(x_i) + W_i^c(x_i)$ (and thus $S_i^c(x_i)$) is increasing in x_i. Thus 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:

$$S_i^c(\underline{x}_i) = 0. \tag{16}$$

The separation rates 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 $\pi[J_i^c(x_i) - V] = (1-\pi)[W_i^c(x_i) - U_i]$:

$$w_h = \pi x_h + (1-\beta)(1-\pi)U_h - (1-\beta)\pi V, \tag{17}$$

$$w_l = \pi x_l + (1-\beta)(1-\pi)U_l - (1-\beta)\pi V - \beta\mu(U_h - U_l). \tag{18}$$

These expressions highlight how outside values as well as current-period productivity influence the flow wages. Wages of both types are increasing in their own outside option value and decreasing in the vacancy value.

3.5 Labor Market Flows and Stocks

In this subsection, I present steady-state stock-flow balance equations. Let me start with the steady-state distributions of experienced and inexperienced workers. Let $e_h(x_h)$ and $e_l(x_l)$ be the CDF 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 $e_h(x_h)$:

$$\big(G_h(x_h) - s_h\big)\big[\mu e_l + f(\theta)(1-\delta)u_h + \gamma(e_h - e_h(x_h))\big] = \gamma(1 - G_h(x_h) + s_h)e_h(x_h), \tag{19}$$

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 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 (19) for the distribution results in:

$$e_h(x_h) = \frac{(G_h(x_h) - s_h)[\mu e_l + f(\theta)(1-\delta)u_h + \gamma e_h]}{\gamma} \text{ for } x_h \in [\underline{x}_h, \infty), \tag{20}$$

which further implies:

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

The left-hand side of Equation (21) 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:

$$\begin{aligned}(G_l(x_l) - s_l)\big[f(\theta)(\delta u_h + u_l) + (1-\mu)\gamma(e_l - e_l(x_l))\big] \\ = \big[\mu + (1-\mu)\gamma(1 - G_l(x_l) + s_l)\big]e_l(x_l),\end{aligned} \tag{22}$$

where the left-hand side gives inflows and the right-hand side outflows. The interpretation of Equation (22) is similar to that of Equation (19) with minor differences. First, the right-hand side of Equation (22) takes into account the possibility that inexperienced workers become experienced. Second, on the left-hand side, the first term in the square brackets includes unemployed workers who are downgraded to inexperienced (δu_h).

Equation (22) can be solved for the distribution as follows.

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

which further implies:

$$\big[\mu + (1-\mu)\gamma s_l\big]e_l = (1 - s_l)f(\theta)(\delta u_h + u_l). \tag{24}$$

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

$$\gamma s_h e_h + \mu s_h e_l = \big[\delta + f(\theta)(1-\delta)(1-s_h)\big]u_h. \tag{25}$$

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 gives 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 hires of experienced workers.

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

$$(1-\mu)\gamma s_l e_l + \big[1-(1-s_l)f(\theta)\big]\delta u_h = (1-s_l)f(\theta)u_l, \tag{26}$$

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, i.e.,

$$\mu e_l = \delta u_h. \tag{27}$$

The left-hand side represents those who become experienced and the right-hand side represents the experienced unemployed workers becoming inexperienced. I also normalized the population of the economy to unity:

$$e_l + e_h + u_l + u_h = 1. \tag{28}$$

Out of Equations (21), (24), (25), (26) and (27), only three of them are linearly independent for given θ, s_h and s_l. Adding Equation (28) as a normalizing equation would allow me to solve all labor market stocks.[13]

3.6 Steady-State Equilibrium

The steady-state equilibrium of the model is defined by e_h, e_l, u_h, u_l, θ, $\underline{x}_h$, and $\underline{x}_l$ such that (i) the four flow-stock balance equations are satisfied, (ii) the two job separation conditions hold, and (iii) the supply condition for jobs holds. Some of the derivations are presented in Appendix A. The idea is as follows. The separation condition $S_i(\underline{x}_i) =$ can be solved for each separation margin, given all other endogenous variables. The job supply condition, which is written as:

$$(u_l + u_h)\theta + e_h + e_l = \bar{n} \tag{29}$$

then can be used to solve for the market tightness θ, given the labor market stocks. Recall that, in the model of Mortensen and Pissarides (1994), the steady-state equilibrium is characterized by one job separation margin and the labor market tightness. Apart from the obvious fact that there are two separation margins to be solved, the present model requires that all labor market stocks and separation margins be solved simultaneously. Also, Equation (29) replaces the free entry condition imposed in the standard model.

[13]Note that the stock-flow balance conditions of workers also imply that flows into and out of the vacancy pool are also equated.

Table 2: Model Parameters and Assigned Values in the Benchmark Calibration

Symbol	Description	Value Assigned
π	Bargaining power of the worker	0.720
α	Elasticity of the matching function w.r.t unemployment	0.720
$\overline{m}$	Scale parameter of the matching function	0.546
β	Discount factor	0.975
γ	Arrival rate of the idiosyncratic shocks	0.167
Δ	Mean productivity premium of the experienced match	0.270
σ_x	Standard deviation of productivity shocks	0.410
μ	Probability of upgrading to become experienced	0.017
δ	Probability of downgrading to become inexperienced	0.270
b_h	Outside flow value for experienced worker	0.910
b_l	Outside flow value for inexperienced worker	0.303
$\bar{n}$	Total number of jobs in the economy	0.966

4 Calibration

There are 12 parameters in the model. The parameters and their assigned values are summarized in Table 2. Four parameters are set exogenously and the remaining eight parameters are determined so that the model can match eight selected statistics. One period in the model is associated with one month in the real world.

4.1 Parameters Set Exogenously

The four parameters, π, α, γ, and μ are determined without actually solving the model. First, the bargaining power of the worker π and the elasticity of the matching function α are both set to 0.72, as in Shimer (2005). The matching function is assumed to take the following Cobb-Douglas form:

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

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

The upgrading probability to the experienced worker μ is set to 1/60. This value implies that it takes 5 years on average for an inexperienced worker to become an experienced worker conditional on the worker being employed throughout. This value should be viewed as normalization because I can adjust the average wage premium, which is determined later, depending on how fast the worker becomes experienced. The arrival rate of the idiosyncratic shock γ is chosen to be 1/6 in this benchmark calibration. The productivity level of each employment relationship is, on average, renewed every six months. Since I cannot provide a clear empirical guidance on the value of this parameter, I also consider an alternative value for this parameter (1/4). The entire model is recalibrated at this new value of γ. The assigned parameter values and the results under this alternative calibration are presented in the Appendix B.

4.2 Parameters Set Internally

To determine the remaining eight parameters, I impose the following eight conditions on the model. Note that the moments I match below correspond to the values in the "initial" steady state.

First, the following three conditions that match the aggregate job finding rate, the aggregate separation rate, and the vacancy rate, respectively, are imposed:

$$\Big[\Big(\delta(1-s_l)+(1-\delta)(1-s_h)\Big)p_h+(1-s_l)p_l\Big]f(\theta)=0.30, \tag{30}$$

$$\frac{\gamma s_h e_h+\big[\mu s_h+(1-\mu)\gamma s_l\big]e_l}{e_h+e_l}=0.02, \tag{31}$$

$$\frac{v}{e_h+e_l+v}=0.03. \tag{32}$$

Remember that $f(\theta)$ represents the meeting probability for the worker. The terms in the square brackets in Equations (30) take into account the fact that the matching probability is influenced by the composition of the unemployment pool, p_h and p_l, as well as the rejection rates, s_h and s_l.[14] The aggregate job finding rate is targeted at 30% per month. As presented in Figure 3, the aggregate transition rate has been fluctuating around 30% over time. Equation (31) represents the aggregate separation rate as a weighted average of the separation rates for the experienced and inexperienced workers. As shown earlier in Figure 2, the aggregate separation rate fluctuates roughly around 2% in the early part of the sample. Thus I calibrate the model to match this level in the initial steady state. Lastly, Equation (32) sets the target value for the vacancy rate. The left-hand side of Equation (32) corresponds to the definition of the vacancy rate in the BLS's Job Openings and Labor Turnover Survey (JOLTS). The mean level of the vacancy rate in the JOLTS data is roughly around 3%.[15]

Next, I use a well-known observation that the separation rate declines sharply with firm tenure (Anderson and Meyer (1994)). Remember that the experienced (inexperienced) worker in this paper does not necessarily correspond to a worker with long (short) firm tenure because the experienced worker can be newly hired if he escapes the risk of skill downgrading in the unemployment pool. Note, however, that the aforementioned empirical observation is useful to pin down the relative levels of s_l and s_h. To be consistent with the empirical observation, first note that I can write the separation-rate-tenure profile in the model as follows.

$$\begin{aligned} e_h(\tau) &= (1-\gamma s_h)e_h(\tau-1)+(1-s_h)\mu e_l(\tau-1), \\ e_l(\tau) &= (1-\gamma s_l)(1-\mu)e_l(\tau-1), \end{aligned}$$

[14] 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.

[15] The JOLTS data cover only the most recent 10 years. To be consistent with other parts of the calibration, it is more appropriate to use the vacancy rate in the 1980s. Unfortunately, consistent data for the vacancy rate are not available. However, the quantitative results below are not sensitive to the targeted value of the vacancy rate.

where $e_i(\tau)$ is the number of type-i employed workers at tenure τ (measured in months). Note that the initial conditions of these recursions are

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

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 that $s_l > s_h$ holds is the only way to achieve 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:[16]

$$\frac{s(46) + s(47) + s(48)}{s(1) + s(2) + s(3)} = 0.25. \tag{33}$$

Next, one of the key ingredients of the model is that the experienced worker may be hired as an inexperienced worker. 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. As mentioned before, the model is structured so that it can parsimoniously capture the occupational (or industry) specificity of human capital. It is therefore natural to associate this statistic in the model with the fraction of workers who switch their occupation (or industry) after an unemployment spell. I construct the empirical measure from the Survey of Income and Program Participation (SIPP). As described in the subsection 5.2 and Appendix C, I use the SIPP's major occupation (or industry) classification, which includes 23 occupations (or 21 industries).[17] In subsection 5.2, I show that this statistic is 45-50% in the early part of the sample of the SIPP data. Thus, the initial steady state is calibrated to achieve the following condition:

$$1 - \frac{f(\theta)(1 - \delta)(1 - s_h)}{1 - (1 - \delta)(1 - f(\theta) + f(\theta)s_h)} \approx 0.50. \tag{34}$$

[16] Anderson and Meyer's result is based on the total job separation rate, which includes job-to-job transitions. Since the model in this paper does not allow for direct job-to-job transitions, Equation (33) matches only the relative level of separation rates.

[17] This somewhat coarse classification is chosen so that the data can provide a clearer identification about the link between earnings losses and occupation (or industry) switch. Note also that the fraction of switchers is not insensitive to the classification. However, the size of earnings losses, which is calibrated below, is consistently associated with the occupation switch between 23 occupations.

where the second term on the left-hand side 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. This condition is most useful to identify the skill depreciation rate δ.

Next, the mean productivity levels between the experienced and inexperienced workers and the standard deviation of the idiosyncratic productivities are determined by using the information on wages. First, it is assumed that x_l and x_h are log-normally distribution 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 choose a value for $\Delta \equiv \ln \overline{x}_h - \ln \overline{x}_l$. Using the wage functions, (17) and (18), and the employment distributions (20) and (23) for the two types of workers, I can calculate average log wages of the two types of workers as follows:

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

where $\hat{e}_i(x_i)$ is a normalized CDF of employment of type-i worker, defined by $e_i(x_i)/e_i$. I target the decline in log wage when a worker moves to inexperienced from experienced to be -0.15:

$$\widehat{w}_l - \widehat{w}_h = -0.15. \tag{35}$$

Recall that the model is structured to capture the empirical regularity that an unemployment spell is often followed by lower earnings in the subsequent job. In the model, this empirical regularity is replicated by the risk that experienced job seekers are employed only as inexperienced workers. Using the SIPP data, I calculate wage differences of the same individuals before and after an unemployment spell (details are discussed in subsection 5.2). I find that the unemployment experience is indeed associated with wage losses and is largely accounted for by those who switch their occupation. In the early part of the sample, to which the initial steady state of the model is calibrated, the average loss amounts to roughly 15% (see Table 6, which will be discussed more later). This empirical finding is consistent with the idea that human capital is tied specifically to a worker's occupation as suggested, for example, by Kambourov and Manovskii (2009) and Poletaev and Robinson (2008). Another interpretation is that when the worker moves up the ladder by becoming experienced, his wage goes up roughly by 15% on average. Kambourov and Manovskii (2009) estimate Mincer-style regressions using the PSID and find that 5 years of 2-digit (1-digit) occupational tenure are associated with an 11% (8%) to 17% (16%) wage increase, depending on the estimation method.[18] Therefore, the moment condition (35) is in broad agreement with the estimates in the literature that are based on different data sets and methodologies.

To identify σ_x, I refer to the literature on residual wage inequality (i.e., wage dispersion

[18]The numbers here are taken from Table 2 of their paper.

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

Statistic	Equation	Target	Model
Aggregate job finding rate	(30)	0.300	0.301
Aggregate separation rate	(31)	0.020	0.020
Vacancy rate	(32)	0.030	0.030
Tenure effect on separation	(33)	0.250	0.275
Switching probability	(34)	0.45−0.50	0.471
Earnings losses for experienced worker	(35)	−0.150	−0.147
Wage variance within experienced matches	(36)	0.1−0.2	0.165
Wage variance within inexperienced matches	(36)	0.1−0.2	0.105
Replacement ratio for the experienced worker	(37)	0.750	0.780

within various groups).[19]

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

Lemieux (2006) calculates the residual wage variance over time using the CPS-MORG (Merged Outgoing Rotation Groups) data between 1973 and 2003. The main purpose of Lemieux (2006) is to examine the time-series trend in the residual wage variance. Visually inspecting the graph in the paper suggests that targeting the residual wage variance between 0.15 and 0.20 is a reasonable calibration for the steady state. That is,

$$0.15 < \sigma^2_{\hat{w}_i} < 0.20 \text{ for } i = \{l, h\}. \tag{36}$$

Last, I impose a restriction that the average replacement ratio for the experienced worker is 0.75:

$$\frac{(1-\delta)b_h + \delta b_l}{\overline{w}_h} = 0.75 \tag{37}$$

where $\overline{w}_h$ is the mean wage of the experienced workers, calculated by $\overline{w}_h = \int_{\underline{x}_i}^{\infty} w_i(x_i) d\hat{e}_i(x_i)$. The numerator takes into account the possibility of the skill depreciation. The chosen value is arbitrary, but it seems that this value is considered reasonable in the labor matching/search literature.

In summary, the eight equations (30) through (37) are used to pin down, δ, Δ, σ_x, b_h, b_l, β, $\bar{n}$, and $\overline{m}$. As mentioned above, the identification of δ, Δ and σ_x can be directly associated with Equations (34), (35), and (36), respectively. However, it is less obvious which of the remaining parameters is useful to achieve which condition. I can schematically describe the moment matching process as follows. First, the total number of jobs $\bar{n}$ is directly linked to

[19]The wage variance of the two types of workers differs from each other even though the variance of the productivity shock is assumed to be the same, given that wage functions are different. As described below, the calibration attempts to make the two variance measures in the model to be as close as possible to the targeted value.

Table 4: Other Statistics in the Benchmark Calibration

γs_h	0.009	$f(\theta)$	0.440	e_h	0.738	u_h	0.012
γs_l	0.060	$q(\theta)$	0.950	e_l	0.200	u_l	0.050
p_h	0.197	θ	0.463				

the condition for the vacancy rate (32). Next, $\overline{m}$ can be assigned to match the condition for the job finding rate (30) because it can directly influence the level of the meeting probability $f(\theta)$. The two outside option parameters b_h and b_l can be assigned to achieve the conditions for the separation-tenure profile (33) and the replacement ratio (37)). Last, one can think of controlling the overall level of the separation rate (31) by changing the discount factor β. Lowering the discount factor has an effect that the employment relationship puts more emphasis on the current productivity level. A decline in current-period productivity is thus more likely to result in separation.

Table 3 shows that the model can match the targeted statistics reasonably 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 Experiments

The main quantitative experiment entails raising the skill obsolescence probability δ. After presenting how the model reacts to the change, I present a few more pieces of empirical evidence that can be useful to test the implications. I then consider other parameter changes and distinguish them from the turbulence story.

5.1 Higher Probability of Skill Obsolescence

In this comparative static, I raise the probability of skill obsolescence from 0.27 to 0.30. The changes in key endogenous variables are presented in Table 5. First, the separation rate goes down from 2% to 1.7%. A simple intuitive reason is that experienced workers become reluctant to separate when there is a higher chance of skill obsolescence. Recall the measurement of the aggregate separation rate in Equation (31). The main driver of the lower aggregate separation rate is the lower s_h in that equation. On the other hand, the separation rate of the inexperienced workers increases slightly, which will be discussed shortly. It follows that the share of experienced workers (e_h) increases. Because the separation rate of the inexperienced workers is 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 slightly. Again, see Equation (30). First, note that the market tightness θ and thus the meeting probability $f(\theta)$ decline. The reason for the lower tightness is that the number of filled jobs (i.e., employment) increases mainly due to the lower separation rate for the experienced workers and thus the number of vacant jobs necessarily

Table 5: Effects of Increased Turbulence

	Job Finding Rate	Separation Rate	Unemployment Rate	Vacancy Rate	Switching Probability
Benchmark	0.301	0.020	0.063	0.030	0.471
$\delta = 0.30$	0.282	0.017	0.056	0.023	0.514

	$\mathbb{E}$(Wage)		Wage Change	Var(Wage)	
	Experienced	Inexperienced		Experienced	Inexperienced
Benchmark	0.959	0.804	−0.147	0.165	0.105
$\delta = 0.30$	0.918	0.782	−0.124	0.187	0.110

declines, resulting in a lower $f(\theta)$ and a higher $q(\theta)$.[20] The composition of the unemployment pool shifts towards the inexperienced workers (i.e., lower p_h), which further reduces the job finding rate because the job rejection rate is higher for these workers.

As I mentioned above, the separation rate of the inexperienced worker increases slightly. This comes from a higher value of posting a vacancy, which in turn results from a higher $q(\theta)$. In equilibrium, there are fewer job openings in the economy and thus the resulting higher meeting probability for the firm raises the value of a vacant position. For the inexperienced worker whose outside option is not directly affected by the higher turbulence parameter, the higher vacancy value implies the higher separation rate.

The last column of the top panel shows that the switching probability increases from 47.1% to 51.4%. Clearly, the increase in δ directly contributes to the increase in the observed switching probability. However, note that the increase is larger than the increase in δ itself. As indicated by Equation (34), there are several factors affecting this statistic other than δ. First, this statistic is decreasing in $f(\theta)$: a lower meeting probability translates into a lower probability of actually finding a job as an experienced worker and thus raises the probability of the switch. This effect adds to the direct impact from the higher δ. Second, observe that it is increasing in s_h. Remember that s_h declines as discussed above, thus having the effect of counteracting the previous two effects. Note that in the present context, s_h should be interpreted as the job rejection rate. The lower 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 the 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 also declines, but the size of the decline is smaller. The third column presents the average of wage changes

[20] The number of unemployed workers also decline. However, the decline in vacancies is larger and thus the market tightness falls.

of those who switch from experienced to inexperienced.[21] Given that the average wage of the experienced workers decreases more than that of the inexperienced workers, the average wage losses due to the switch goes down (from 0.15 log points to 0.12 log points).

To see the mechanism more closely, Figure 4 plots the employment CDFs and wage functions for the two types of workers. Let me first discuss the solid lines, which represent the economy prior to the parameter change. In this economy, the employment distribution starts at around 0.7 for the experienced workers and 0.85 for the inexperienced workers, which correspond to the cutoff idiosyncratic productivities for the respective types. The vertical lines in panel (b) correspond to the 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 roughy 27% higher. 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 wage 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 skill 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 them a stronger bargaining position (relative to the inexperienced workers).

Let me now turn to the changes in the distributions and wage functions in response to the higher turbulence parameter. 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. We can make several observations in panel (b). First, the wage functions for both types shift downward, meaning that workers receive lower wages for a given level of productivity in the new steady state. However, the shift is larger for the experienced workers. In other words, the difference between wages of the two types of workers at a given level of productivity shrinks. From the wage functions (17) and (18), one can see that the wage difference at x is written as:

$$w_h(x) - w_l(x) = \Big[(1-\beta)(1-\pi) + \beta\mu\Big](U_h - U_l). \tag{38}$$

Because U_h declines by more as a direct effect of higher δ, this difference gets smaller. Another important effect can be seen in panel (b). That is, there is a lager mass of low-quality experienced matches that would have been severed before the parameter change. This is simply a direct implication of the lower separation rate of this group. This composition effect itself lowers the average wage of the experienced workers. In summary, the decline in the wage difference between the two groups in Table 5 results from two sources: (i) the

[21] The switch is the only source of the wage loss in the model. When workers move to a different employer within each type, there is neither wage loss nor gain on average.

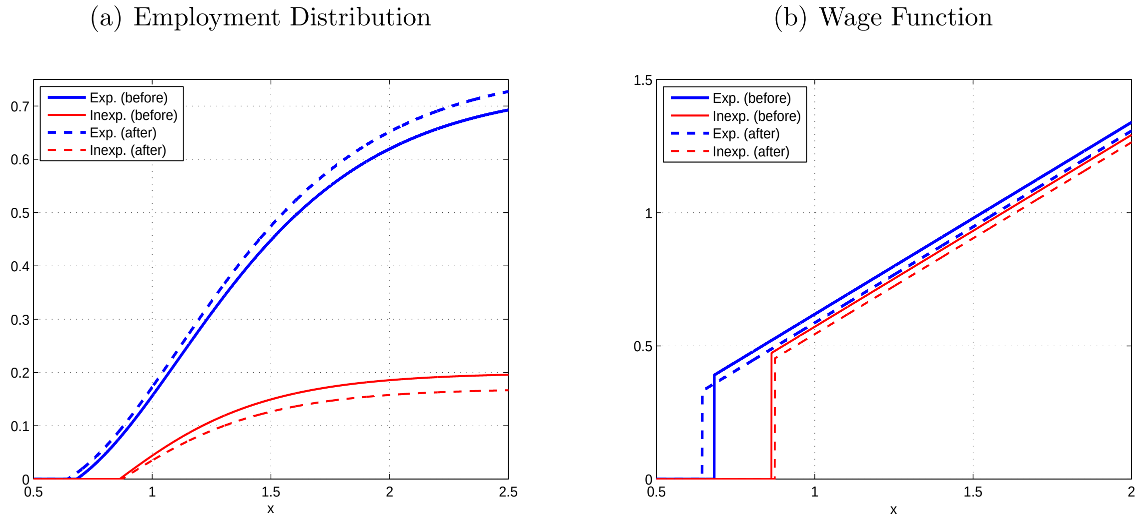

Figure 4: Effects of a Higher Turbulence Parameter

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 wages for the two types of workers as a function of idiosyncratic productivity. The vertical line corresponds to cutoff productivity.

decline in the wage difference at a given productivity level and (ii) the increase in low-quality experienced matches.

5.2 Empirical Support for Model Implications

I have shown that the higher turbulence parameter results in the lower separation rate, as observed in the data. However, the quantitive experiment above has also revealed a few other interesting implications. In particular, the model has predicted that wage losses associated with unemployment experience shrink and that the fraction of workers switching from experienced to inexperienced increases.

In this subsection, I examine whether these predictions are broadly supported by the observed data, using the Survey of Income and Program Participation (SIPP). Let me first discuss the data set and how I construct the statistics presented below. The SIPP is a panel that keeps track of labor market experience of a nationally representative sample of workers. I use the most recent 7 panels (1990, 1991, 1992, 1993, 1996, 2001, and 2007) that are readily available. Each of the panels traces workers over a roughly three-year period (except for the 1996 panel, which lasted longer).[22] Importantly, workers report their labor market status

[22] The previous literature on earnings losses, pioneered by Ruhm (1991) and Jacobson et al. (1993), has mostly focused on the experience of displaced workers, where displacement is often defined by job losses due to a business closing. Because my interest is in the aggregate labor market, selecting the sample based on displacement is not appealing. Further, these studies sometimes rely on annual data (e.g., Farber (2005)).

(employed, unemployed, not in the labor force), which is defined consistently with the CPS.[23] Relative to the CPS, an obvious advantage is that the SIPP is a panel where workers report their earnings whenever they are employed, while in the CPS, earnings are reported only when workers are in the outgoing rotation group.

Among all labor market experiences contained in the panels, I choose the events in which a worker moves from one job to a new job with an unemployment spell in between. Only workers older than 25 are included in my sample. Younger workers are excluded because I would like to minimize the effects of schooling choice on my results. I calculate log differences in real earnings before and after an unemployment spell. The nominal earnings reported in the survey are deflated by the CPI. All statistics below are calculated for each of the 7 panels using the panel weights. I collect events that start with employment and end with employment at a different job with an unemployment spell in between. I impose a few more sample selection criteria. First, I impose the restriction that an employment spell before and after unemployment has to be be longer than 3 months. Second, the top and bottom 1% of the distribution of the earnings difference is also excluded from the sample. These two restrictions are used to smooth out extreme variations in the original data. Lastly, I also exclude those who return to the same firm after an unemployment spell, since the model above is not intended to capture this case, although including these cases does not change the result.[24]

After applying these sample selection criteria, I compare real earnings before and after an unemployment spell. Recall that the model is structured so that it can parsimoniously capture the occupational and/or industry specificity of human capital, as emphasized by Kambourov and Manovskii (2009) and Neal (1995), respectively. In light of the model, I calculate earnings losses depending on whether the worker switched to a different occupation or industry. The fraction of the occupation or industry switch out of total spells is also calculated. The calculations are based on 23 occupations and 21 industries. Appendix C presents the list of occupations and industries used.

Table 6 presents the results of these calculations.[25] The second-from-the-last row of the table reports the average of the changes in real earnings, pooling all cases. Not surprisingly, the average change in earnings is negative, confirming the observation in the earlier literature that job loss tends to be associated with a decline in earnings. The top part of the table presents the results when the observations are separated, depending on whether the worker changed his/her occupation. The middle part of the table uses industry to split the data. Observe that in most of the cases, switching to a different occupation or industry results in

Given that separation and job finding occur quickly, it is important for me to use the data set that allows me to keep track of workers at least at monthly frequency.

[23]In Fujita et al. (2007), we show that the CPS-based measure of the employment-to-unemployment separation rate and the SIPP-based measure are similar in their trend as well as their cyclical behavior.

[24]Here I use monthly earnings for my analysis. I have also calculated the same analysis using hourly wage. The average wage losses are somewhat smaller than the average earnings losses. However, the time-series pattern of the statistics based on hourly wage is similar to that based on monthly earnings.

[25]Note that because the results are based on the changes in earnings of the same individuals, any (linear) heterogeneities, whether unobserved or observed, are differenced out.

Table 6: Average Earnings Change after an Unemployment Spell

	SIPP Panel						
	1990	1991	1992	1993	1996	2001	2004
	Occupation						
Switch	−0.172	−0.117	−0.163	−0.054	0.016	−0.097	−0.097
Frac. of Switch	(0.437)	(0.510)	(0.540)	(0.494)	(0.523)	(0.560)	(0.550)
Stay	−0.113	−0.021	−0.035	−0.032	−0.050	−0.003	−0.029
	Industry						
Switch	−0.179	−0.118	−0.135	−0.050	−0.004	−0.101	−0.068
Frac. of Switch	(0.442)	(0.475)	(0.514)	(0.470)	(0.531)	(0.568)	(0.554)
Stay	−0.096	−0.001	−0.055	−0.035	−0.029	0.015	−0.070
All	−0.141	−0.073	−0.103	−0.044	−0.014	−0.057	−0.069
# of Spells	1,046	672	1,036	929	2,113	1,346	1,401

Notes: The earnings change is expressed as a log difference in real monthly earnings before and after an unemployment spell. See Appendix C for the list of occupation and industry classifications and for the periods covered by each panel.

larger declines in earnings on average. However, the fact that workers experience a decline in earnings even when they stay in the same occupation or industry suggests that the loss of specific human capital is not the entire story behind overall earnings losses. The model above implies that the earnings of those who are rehired as experienced, on average, stay the same as before and thus is unable to replicate this observation.[26]

One can see that the average earnings losses calculated in first three panels are considerably larger than those in the subsequent four panels. The aggregate labor market conditions differ across these seven panels and the earlier literature suggests that the size of earnings losses is larger during recessionary periods (e.g., Jacobson et al. (1993) and Weinberg (2001)). One plausible comparison may be between the first two panels (1990 and 1991) and the 2001 panel. The economic conditions during these panels are characterized by a short recession followed by the so-called jobless recovery.[27] As can be seen in the table, average earnings losses in the earlier two panels are considerably larger than those in the 2001 panel. Another noticeable change over time is that the fraction of the occupation and industry switch appears to have risen in more recent panels. While the results in Table 6 alone would not provide the definitive confirmation of the model, the overall pattern is consistent with the key predictions of the model.

A recent paper by Farber (2011) computes earnings losses of workers using the CPS's

[26] Separation occurs because current-period productivity of the match and thus wage is too low to sustain the match. When the worker is reemployed as an experienced worker, the match quality necessarily improves. However, since the productivity that induced the separation is memoryless, wage before and after the unemployment spell stays the same on average within the experienced matches.

[27] The recession in the early 1990s officially started in July 1990 and ended in March 1991. The 1990 and 1991 panels follow workers between October 1989 and August 1992 and between October 1990 and August 1993, respectively. The 2001 recession officially started in March 2001 and ended in November 2001. Workers in the 2001 panel are followed over the period between October 2000 and December 2003.

Table 7: Effects of Various Parameter Changes

	Job Finding Rate	Separation Rate	Unemployment Rate	Vacancy Rate	Switching Probability
Benchmark	0.301	0.020	0.063	0.030	0.471
$\pi = 0.6$	0.299	0.023	0.073	0.039	0.463
$\sigma_x = 0.39$	0.289	0.017	0.056	0.023	0.479

	$\mathbb{E}$(Wage)		Wage	Var(Wage)	
	Experienced	Inexperienced	Change	Experienced	Inexperienced
Benchmark	0.959	0.804	−0.147	0.165	0.105
$\pi = 0.6$	0.852	0.709	−0.158	0.142	0.092
$\sigma_x = 0.39$	0.908	0.753	−0.157	0.169	0.104

Displaced Workers Survey over the period between 1984 and 2010. While he does not distinguish between occupation (or industry) switchers and stayers, Farber provides a valuable piece of evidence on the time-series trend of earnings losses. One thing that is interesting is that there is no discernible trend in the time series plot even among these displaced workers. While it does not show a clear downward trend, what is more surprising is the fact that it does not exhibit any upward trend over the last two decades. In particular, the size of earnings losses during the most recent recession is not very different from that in 2004 and 1992. This is quite surprising given the severe nature of the most recent recession. I therefore view the results by Farber (2011) as being largely in line with my earlier findings from the SIPP. Furthermore, at an aggregate level, it is well documented that real wages have been stagnant even while the unemployment rate has been drifting down in the last two to three decades. The macro-level evidence is consistent with the implication of the model.[28]

5.3 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 put together in Table 7. Specifically, the following parameter changes are considered. First, the worker's bargaining power parameter is reduced from 0.72 to 0.6. This parameter change seems to be a plausible experiment to consider. The straightforward implication of this experiment is a decline in wages and thus consistent with the observed stagnant aggregate real wage. 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

[28]Another potentially useful piece of evidence would be the time-series trend on the return to occupational/industry-specific human capital based on the Mincer-style wage regression. However, I have not been able to find the existing research that is informative on this dimension.

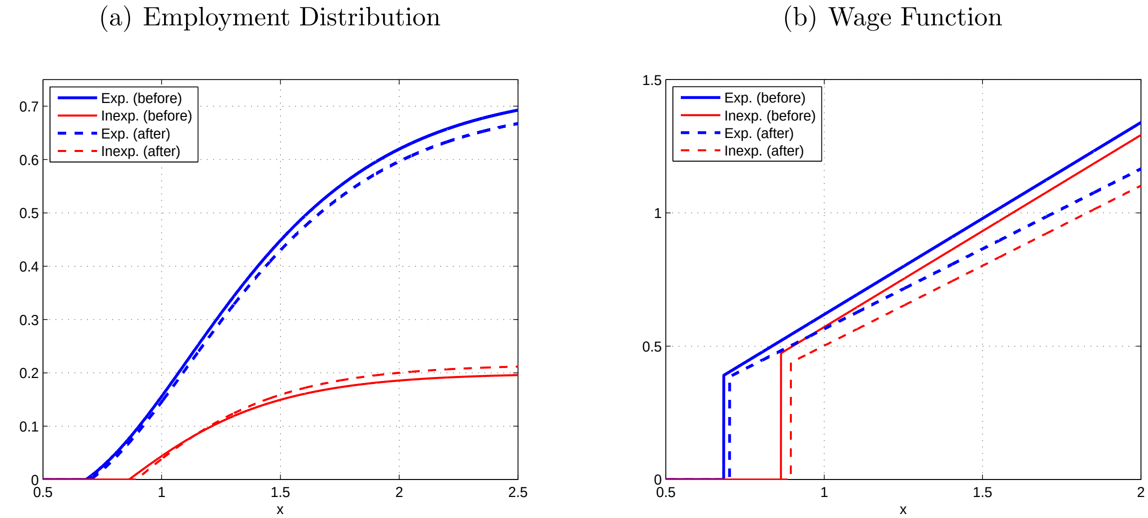

Figure 5: Effects of Lower Bargaining Power of the Worker

Notes: 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.

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. Therefore, this is another important case to consider. σ_x is lowered from 0.31 to 0.29.

5.3.1 Lower Bargaining Power

In Table 7, one can observe that the aggregate separation rate goes up from 2% to 2.3% in response to lower worker bargaining power. This increase results from the rise in the separation rates for both types of workers, as can be seen in the wage functions plotted in panel (b) of Figure 5. The first direct effect of shifting the surplus to the firm (holding endogenous variables constant) can be understood by thinking about how the sum of the outside option values ($U_h + V$ or $U_l + V$) is influenced by the parameter change.[29] When the bargaining power of the worker declines, the value of unemployment declines while the value of a vacant job increases. How the sum of the two outside values responds depends on the relative values of the meeting probabilities $f(\theta)$ and $q(\theta)$. Under a reasonable calibration where $q(\theta) > f(\theta)$ holds, the increase in V is larger because the surplus from actually producing output materializes more quickly.[30] Next note that the decline in the value of

[29]The value of the match ($J_h + W_h$ or $J_l + W_l$) is not directly affected by how the surplus is split.

[30]As presented in Table 4, the condition $q(\theta) > f(\theta)$ is satisfied. It is well known empirically that vacancy duration is much shorter than unemployment duration. See, for example, the evidence discussed in Ramey

unemployment is larger for experienced workers, because future surplus from having an employment relationship is larger for them. This means that the effect of the increase in the vacancy value, which is to raise the separation rate, is somewhat mitigated for the experienced worker. In sum, the increase in the separation rate is larger for the inexperienced workers.

Other results follow from these predictions of the separation rates. First, the increase in the separation rate implies that employment (unemployment) declines (increases). The number of vacant positions then rises given the fixed supply of jobs. The increase in vacancies is larger than that in unemployment and thus market tightness increases, raising $f(\theta)$ and lowering $q(\theta)$. The aggregate job finding rate declines slightly even with the higher $f(\theta)$ because the job rejection rate for both types of workers increases. The effect on the switching probability is negative. As mentioned above, this variable is a decreasing function of $f(\theta)$ and an increasing function of s_h: the effect of higher $f(\theta)$ is the dominating factor for the lower switching probability here.

As can be seen in panel (b) of Figure 5, the wage functions become flatter as a direct consequence of the lower bargaining power. The average wages for both types of workers decline as a result of the flatter wage functions. The result for the average wage losses indicates that the wages of inexperienced workers decline by more on average. Recall that the separation rate for the inexperienced workers increases by more and that the value of unemployment declines by more for them. Both of these factors make the average wage losses (when the switch occurs) smaller. However, as can be seen from Equation (38), there is also an effect that a higher π raises the wage difference given that $U_h - U_l > 0$ holds. This last factor dominates the first two effects. Lastly, a smaller bargaining power of the workers has a significant impact on the wage variance: The wage variance of both types of workers shrinks because of the flatter wage functions (i.e., a lager portion of wages is accounted for by the outside option values, which do not depend on current-period productivity).

5.3.2 Lower Variance of the Idiosyncratic Shock

Next, lower variance of the idiosyncratic shocks results in a decline in the aggregate separation rate to 1.70%. The size of the decline in the variance is chosen to match the decline in the aggregate separation rate that is roughly comparable to the decline in the observed data. The fact that the lower variance results in the decline in the separation rate is consistent with the implication in the standard Mortensen-Pissarides model, as explored by Davis et al. (2010). 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 sepa-

(2008).

ration rate falls on net. Lower separation rates imply higher employment and therefore fewer job openings. This further implies lower market tightness. The job finding rate declines as a result of the lower meeting probability even though job rejection rates fall.

The average wages of both types of workers decline. At a given productivity level, wages of both types decline because the outside option values for workers, U_h and U_l, fall while the outside option value for firms V increases. Note that a smaller variance lowers expected surplus from having a match as noted above. This effect lowers all of these three values. However, a lower $f(\theta)$ and a higher $q(\theta)$ differentially influence the worker's and firm's outside values: a lower $f(\theta)$ pushes down U_h and U_l further, while a higher $q(\theta)$ increases the value of vacancies. In fact, the value of vacancies increases on net. These mechanisms bring down wages of both types of workers at a given productivity level. The decline in the average wage is larger for the inexperienced worker. Recall that the average wage is affected by the average quality of the matches as well. The decline in the separation rate for both types of workers implies that the average quality of matches deteriorates for both types. This effect is larger for the inexperienced workers and therefore the decline in the average wage is larger for the inexperienced workers.[31]

5.4 Summary and Robustness

Given the results so far, the last two parameter changes are not as attractive a story to account for the empirical evidence. The lower bargaining power of the worker implies higher separation rates for both types of workers. Furthermore, it also results in higher average wage losses and a lower switching probability, both of which do not appear to be consistent with the evidence. The lower variance of the idiosyncratic shock generates lower separation rates. However, average wage losses are found to be larger. Of course, I cannot exclude the possibility that a combination of different parameter changes is behind the observed empirical evidence.[32] However, the increase turbulence appears to be a quite powerful explanation since it matches all three pieces of evidence: (i) lower separation rate, (ii) smaller earnings losses, and (iii) higher switching probability.

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. In Appendix B, I consider the calibration with an alternative value for the arrival rate. The entire model is recalibrated following the same procedure described in subsection 4.2. The results are largely intact relative to those under the benchmark calibration. Among the three parameter changes, there are a few cases in which the direction of the response of some endogenous variables is reversed. However, none of these changes overturn the results regarding the three statistics I highlighted above.

[31]This last effect is larger for the inexperienced workers mainly because the calibration requires that the steady-state separation rate is much higher for the inexperienced matches. The higher steady-state separation rate implies that the small change in the equilibrium separation rate has a larger impact on the average quality of the matches because there is more mass right above the separation margin.

[32]In particular, the smaller idiosyncratic variance advocated by Davis et al. (2010) is an important explanation for lower labor turnover that is complementary to this paper's explanation.

6 Conclusion

This paper has argued that a more turbulent environment can be one of the important sources of the declining separation rate. The key idea is that workers fear of losing their skills accept wage concession in exchange for job security. The model's explanation is consistent with the widely recognized fact that real wage have been stagnant even during the period when unemployment has been on a downward trend (at least until the most recent recession). The findings of this paper highlight the fact that gauging job insecurity solely based on the level of labor turnover can be a misleading exercise.

In the paper, I have treated the skill obsolescence probability as given. What does this parameter represent? The plausible interpretations include the possibility of jobs being outsourced overseas or permanently destroyed due to technological changes. When the parameter is interpreted in this way, it is not difficult to find anecdotal evidence that supports the explanation explored in this paper. Friedman (2007) and Greenspan (2008) include many relevant examples. For instance, Greenspan (2008) writes that "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." Deepening our understanding of the underlying structural sources is an important future research topic.

A Solving for the 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:

$$\mathbb{E}S_i^c(x_i') \equiv \int_{\underline{x}_i}^{\infty} S_i^c(x_i')dG_i(x_i') \text{ for } i = \{h, i\}. \tag{39}$$

I can derive the evolution of surplus for the experienced match by plugging Equations (4), (6), and (10) into Equation (14):

$$\begin{aligned} S_h^c(x_h) = x_h - b_h + \beta\Big[&(1-\gamma)S_h^c(x_h) + \gamma\mathbb{E}S_h^c(x_i') - f(\theta)\pi\Big(\delta\mathbb{E}S_l^c(x_i') + (1-\delta)\mathbb{E}S_h^c(x_i')\Big) \\ &- q(\theta)(1-\pi)\Big((p_l + \delta p_h)\mathbb{E}S_l^c(x_i') + (1-\delta)p_h\mathbb{E}S_h^c(x_i')\Big) + \delta(U_h - U_l)\Big]. \end{aligned} \tag{40}$$

Similarly, by using Equations (8), (9), and (12) in Equation (14), the surplus for the inexperienced match can be written as:

$$\begin{aligned} S_l^c(x_l) = x_l - b_l + \beta\Big[&(1-\mu)\Big((1-\gamma)S_l^c(x_l) + \gamma\mathbb{E}S_l^c(x_i')\Big) + \mu\mathbb{E}S_h^c(x_i') - f(\theta)\pi\mathbb{E}S_l^c(x_i') \\ &- q(\theta)(1-\pi)\Big((p_l + \delta p_h)\mathbb{E}S_l^c(x_i') + (1-\delta)p_h\mathbb{E}S_h^c(x_i')\Big) + \mu(U_h - U_l)\Big]. \end{aligned} \tag{41}$$

Evaluating (40) and (41) at $\underline{x}_h$ and $\underline{x}_l$, respectively, results in

$$\begin{aligned} \underline{x}_h - b_h + \beta\Big[&\gamma\mathbb{E}S_h^c(x_i') - f(\theta)\pi\Big(\delta\mathbb{E}S_l^c(x_i') + (1-\delta)\mathbb{E}S_h^c(x_i')\Big) \\ &- q(\theta)(1-\pi)\Big((p_l + \delta p_h)\mathbb{E}S_l^c(x_i') + (1-\delta)p_h\mathbb{E}S_h^c(x_i')\Big) + \delta(U_h - U_l)\Big] = 0, \\ \underline{x}_l - b_l + \beta\Big[&(1-\mu)\gamma\mathbb{E}S_l^c(x_i') + \mu\mathbb{E}S_h^c(x_i') - f(\theta)\pi\mathbb{E}S_l^c(x_i') \\ &- q(\theta)(1-\pi)\Big((p_l + \delta p_h)\mathbb{E}S_l^c(x_i') + (1-\delta)p_h\mathbb{E}S_h^c(x_i')\Big) + \mu(U_h - U_l)\Big] = 0. \end{aligned}$$

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

$$U_h - U_l = \frac{b_h - b_l + \beta(1-\delta)f(\theta)\pi\Big(\mathbb{E}S_h^c(x_i') - \mathbb{E}S_l^c(x_i')\Big)}{1 - \beta(1-\delta)}. \tag{42}$$

By evaluating Equations (40) and (41) at $\underline{x}_h$ and $\underline{x}_l$, respectively and subtracting each expression from itself, one can obtain:

$$S_h^c(x_h) = \frac{x_h - \underline{x}_h}{1 - \beta(1-\gamma)} \text{ and } S_l^c(x_l) = \frac{x_l - \underline{x}_l}{1 - \beta(1-\mu)(1-\gamma)}. \tag{43}$$

After substituting out $U_h - U_l$ from Equations (40) and (41) using (42), expressions in (43) can be plugged back into Equations (40) and (41). The resulting expressions can be

Table 8: Effects of Various Parameter Changes: Alternative Calibration

	Job Finding Rate	Separation Rate	Unemployment Rate	Vacancy Rate	Switching Probability
Initial SS	0.301	0.020	0.063	0.027	0.477
$\delta = 0.27$	0.288	0.018	0.058	0.023	0.508
$\pi = 0.6$	0.306	0.024	0.073	0.039	0.466
$\sigma_x = 0.41$	0.291	0.018	0.057	0.022	0.485
	$\mathbb{E}$(Wage)		Wage	Var(Wage)	
	Experienced	Inexperienced	Change	Experienced	Inexperienced
Initial SS	0.989	0.834	−0.150	0.164	0.118
$\delta = 0.27$	0.965	0.821	−0.136	0.176	0.121
$\pi = 0.6$	0.907	0.762	−0.157	0.132	0.097
$\sigma_x = 0.41$	0.954	0.798	−0.157	0.161	0.114

Notes: Parameter values used to calibrate the initial steady state are as follows: $\pi = 0.720$, $\beta = 0.955$, $\sigma_x = 0.430$, $b_h = 0.87$, $\alpha = 0.720$, $\gamma = 0.167$, $\mu = 0.017$, $b_l = 0.41$, $\overline{m} = 0.484$, $\Delta = 0.230$, $\delta = 0.250$, and $\bar{n} = 0.964$. See Table 2 for a description of each parameter.

evaluated at two separation margins, resulting in the two nonlinear equations in $\underline{x}_h, \underline{x}_l, \theta$ and p_h. Next, three of the four stock-flow balance equations (21), (24), (25), and (26) as well as the equation for normalizing the population mass (28) need to be satisfied. Lastly, the job supply condition $(u_l + u_h)\theta + e_h + e_l = \bar{n}$ is imposed. The nonlinear equation system that consists of these seven equations can be numerically solved for the seven endogenous variables: $\underline{x}_h, \underline{x}_l$, θ, e_h, e_l, u_h, and u_l.

B Results Under An Alternative Calibration

In the comparative statics conducted in the main text, I fixed the arrival rate of the idiosyncratic shock at 1/6. I set it to an alternative value of 1/4 here and show that the results are largely intact. Recall that there were four exogenously chosen parameters, including the arrival rate γ. The other three parameters are kept at the same values as before. The remaining 8 parameters are re-calibrated again by matching the same 8 moment conditions. Changing the arrival rate of the shock induces a few noticeable differences in the parameter values in achieving the same moment conditions.[33] In particular, when the shock arrival is more frequent, the implied discount factor needs to be lowered to achieve the same moment conditions. Specifically, more frequent arrival raises the chance of reversal of the bad draw today and makes it more difficult to achieve the same targeted separation rates for a given level of the replacement ratio. Accordingly, the discount factor needs to be lowered, so that the worker puts more weight on the current-period productivity level.[34]

[33] See notes to Table 8 for the parameter values.

[34] As an extreme example, suppose that productivity follows an i.i.d process. Even when today's draw happens to be very low, it is expected to go back to the mean level in the next period.

Table 8 presents the results of the same comparative statics as I did under the benchmark calibration. The results are largely intact, relative to those under the benchmark calibration. There are a few cases in which the direction of the response is reversed. However, none of these changes overturn the overall conclusion under the benchmark calibration. Quantitatively, the responses of the endogenous variables are of similar magnitude.

C Occupation and Industry Classification in the SIPP

When determining whether a worker switched his/her occupation or industry in the SIPP, the following classification is used.

Occupation Classification: Management; Business and Financial Operations; Computer and Mathematical; Architecture and Engineering; Life, Physical and Social Sciences; Community and Social Services; Legal; Education, Training and Library; Arts, Design, Entertainment, Sports and Media; Healthcare Practitioners and Technical; Healthcare Support; Protective Service; Food Preparation and Serving Related; Building and Grounds Cleaning and Maintenance; Personal Care and Services; Sales; Office and Administrative Support; Farming, Fishing and Forestry; Construction and Extraction; Installation, Maintenance and Repair; Production; Transportation and Material Moving; Military Specific.

Industry Classification: Agriculture; Mining and Oil & Gas Extraction; Utilities; Construction; Manufacturing; Wholesale Trade; Retail Trade; Transportation and Warehousing; Information; Finance and Insurance; Real Estate, Rental and Leasing; Professional, Scientific and Technical Services; Management of Companies and Enterprises; Administrative, Support, Waste Management and Remediation Services; Educational Services; Health Care and Social Assistance; Arts, Entertainment and Recreation; Accommodation and Food Services; Other Services; Public Administration; Military.

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