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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. First, I 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 his wage. I show that a higher skill depreciation risk results in a *lower* aggregate separation rate and *smaller* wage losses. 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 this prediction.

JEL codes: E24, J31, J64
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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 in 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 decline in wages. 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 wages. This structure parsimoniously captures the idea that human capital is occupation specific, as argued by Kambourov and Manovskii (2009).

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 their current job. This further implies that there is a larger mass of low-quality employment relationships that would have been severed in the environment before the parameter change. The wages of these workers are lower than before in exchange for maintaining the employment relationship. This intuition is not

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

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 the job search behavior in the European context. In contrast, this paper quantitatively evaluates the hypothesis in the calibrated model that incorporates various empirical regularities in 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 the size of wage losses. Note that the worker's reluctance to separate and thus the extent of the wage concession are largely concentrated among experienced workers. Given this, the size of the wage losses (which occur when a separation is unavoidable) is observed to be smaller in the new environment.

To examine the empirical plausibility of this prediction, I look at wage changes after an unemployment spell using the Survey of Income and Program Participation (SIPP). I first confirm that wages indeed tend to drop after an unemployment spell and that the incidence of wage losses is concentrated among occupation switchers. Both of these observations are consistent with the earlier empirical literature and the structure of the model. Further, I find that the size of the wage losses appear to be on a downward trend. A recent paper by Farber (2011) also computes earnings losses using the CPS's Displaced Workers Survey over the period between 1984 and 2010. His result shows no indication that average earnings losses have been increasing over time. In particular, the average earnings losses during the most recent recession, which is not covered by my SIPP sample, are not very different from those in 2004 and 1992. This is quite surprising, especially because of the severity of the recession in 2007-2009.

I examine two other plausible hypotheses using the model, namely, the effects of lower bargaining power of the worker and the smaller variance of the idiosyncratic shocks. The latter hypothesis is motivated by Davis et al. (2010), who empirically examine the smaller variance as an explanation for a downward trend in job flows and the unemployment inflow rate. I show that the lower bargaining power barely changes the separation rate and counterfactually implies a higher job finding rate. On the other hand, a lower variance of the idiosyncratic shock indeed generates lower separation rates as in the data. Davis et al. (2010) appeal to the implication in the standard Mortensen and Pissarides (1994) model that a smaller idiosyncratic variance lowers the separation rate. My result extends this implication to an extended search/matching framework with two types of workers. I conclude that the explanation based on turbulence is complimentary to the one explored by Davis et al. (2010).

The turbulence story is attractive in that it can reconcile the coexistence of the 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.

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 aging of the labor force. Section 3 lays out the model. In Section 4, I discuss the calibration of the model. Section 5 presents the main results of the paper. This section also includes the empirical findings based on 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.[2] 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.

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.[3] 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 (2012) points out, these measures are subject to time aggregation error. The 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

[2] 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.

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

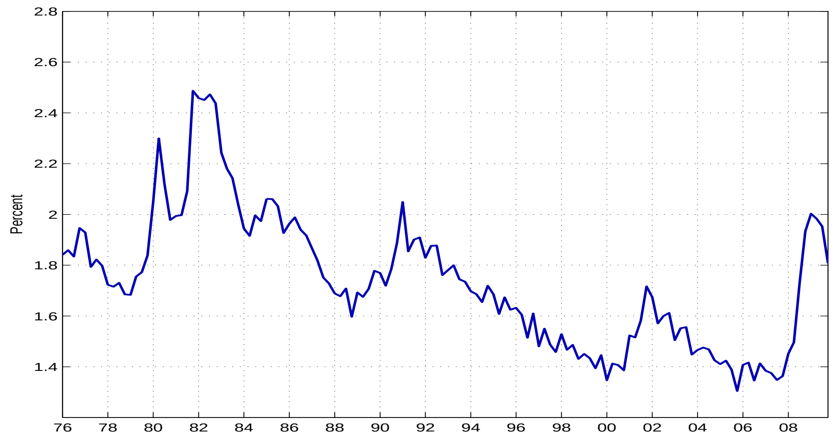

Figure 1: Aggregate Separation Rate into Unemployment

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.

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 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.

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 parentheses and is based on the monthly CPS Table A$-$1. Separation rates are adjusted for time aggregation error.

Assuming that the 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.

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

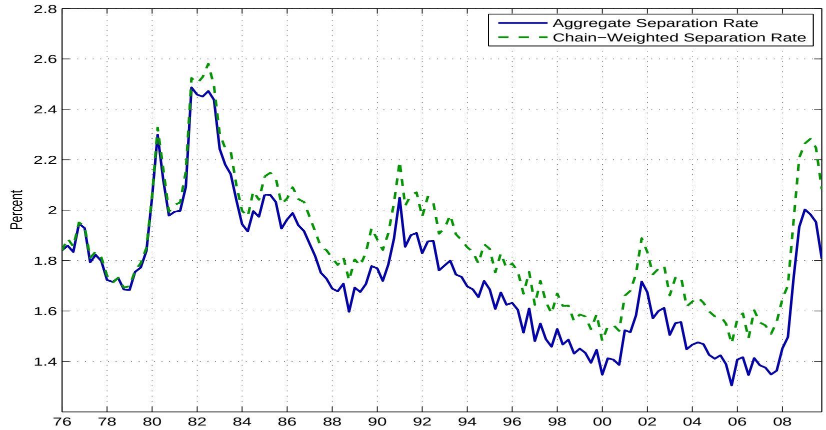

Figure 2: Chain-Weighted Separation Rate into Unemployment
Notes: See notes to Figure 1. The chain-weighted index is rescaled, such that it matches the average level of the actual separation rate in the first year of the sample.

rates for different demographic groups.[4]

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

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.

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

[4]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.

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.[5] 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.[6] 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 least at this point).[7] In the quantitative experiments below, I also examine whether each

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

[6] 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.

[7] 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

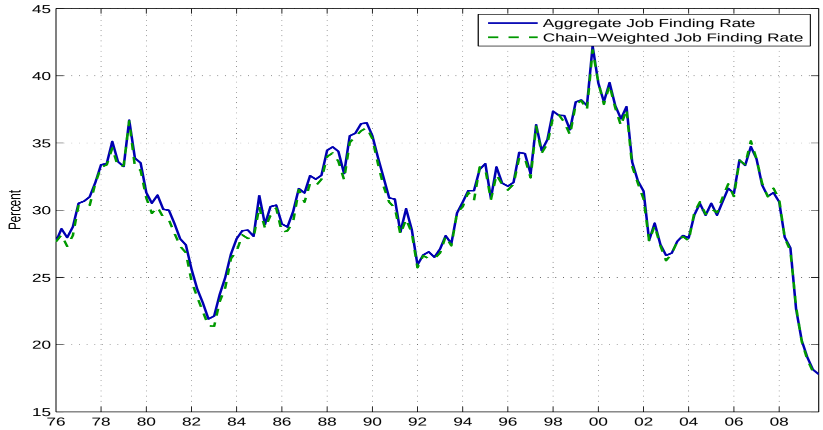

Figure 3: Aggregate Job Finding Rate

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.

experiment delivers the implication for the job finding rate that is consistent with the data in Figure 3.

3 Model

The main theme of this paper is to link the declining separation rate with a more turbulent labor market environment. This section presents the labor matching model that incorporates the possibility that entering into the unemployment pool can result in wage losses. Allowing for the possibility of wage 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).[8]

3.1 Environment

The economy is populated by a unit mass of risk-neutral workers and a potentially infinite mass of job positions. There are two types of workers: "experienced" and "inexperienced." When the job position is filled, the match produces output x_h and x_l, respectively, depending on its worker type. The productivity levels evolve according to the following process: When the match is first formed, experienced and inexperienced matches draw their productivities from $G_h(x_h)$ and $G_l(x_l)$, respectively, both of which are assumed to have support $[0, \infty)$. It is

in the average duration *relative* to the unemployment rate.

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

also assumed that $G_h(.)$ (first order) stochastically dominates $G_l(.)$, namely, $G_h(x) < G_l(x)$ for any x. It is also assumed that production requires the fixed operating cost (i.e., overhead) per period κ. This parameter is introduced to facilitate the calibration process, as will be discussed later. Existing matches face several possibilities at the start of each period. First, the inexperienced worker becomes experienced with probability μ, in which case the new productivity level is drawn from $G_h(.)$. Second, the experienced matches and inexperienced matches (that did not become experienced) face the possibility that their productivities switch to a new level. The switching of productivity occurs with probability γ. When it occurs, a new productivity level is drawn from either $G_h(.)$ or $G_l(.)$. Each match may be endogenously terminated when the new productivity level is too low. This match separation decision is described later. When the experienced workers are in the unemployment pool, they face an additional risk of becoming inexperienced. This occurs with probability δ every period.

3.2 Labor Market Matching

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

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

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

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

The vacant job is paired randomly with the experienced or inexperienced worker with probability $p_h q(\theta)$ and $(1 - p_h)q(\theta)$, respectively, where $p_h \equiv \frac{u_h}{u}$. As in the standard search/-matching model, posting a job opening entails a flow vacancy posting cost c.[9]

3.3 Continuation Values

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

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

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

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

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).[10]

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 $W_l(x_l)$ is the value of the inexperienced employed worker before the match rejection (or acceptance) decision is made, which is further written as:

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

Upon meeting a potential employer, the worker faces several possibilities. First, with probability δ, he may become inexperienced at the start of the next period. After the meeting takes place, the idiosyncratic productivity is drawn. There is a chance that productivity is too low to start production, in which case the potential employment relationship is rejected. The worker then starts the next period as an unemployed worker. This decision is expressed in Equations (5) and (7). Lastly, if the worker fails to meet a potential employer, he stays unemployed and faces the risk of skill loss at the start of the next period.

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

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

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

where $w_l(x_l)$ is the current-period wage payment to the inexperienced worker. At the start of the period, he becomes experienced with probability μ, in which case new productivity is drawn from $G_h(.)$ and the match separation decision as an experienced worker is made, based on the new productivity level. If he continues to be an inexperienced worker, new productivity is drawn with probability γ from $G_l(.)$, and the separation decision as an inexperienced worker is made based on it. The separation decisions are again characterized by Equations (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 skill loss. Note also that I adopt the timing assumption that upgrading to becoming experienced does not occur in the first period of the match formation.

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

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

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 $J_l^c(x_l)$ is written as:

$$J_l^c(x_l) = x_l - \kappa - w_l(x_l) + \beta\Bigg[\mu\int_0^\infty J_h(x_h')dG_h(x_h') + (1-\mu)\Bigg((1-\gamma)J_l^c(x_l) + \gamma\int_0^\infty J_l(x_l')dG_l(x_l')\Bigg)\Bigg], \tag{12}$$

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:

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

The interpretation of Equation (12) is straightforward.

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

$$\frac{c}{\beta q(\theta)} = \left[(1-\delta)p_h \int_0^\infty J_h(x_h')dG_h(x_h') + \left[1-(1-\delta)p_h\right]\int_0^\infty J_l(x_l')dG_l(x_l')\right]. \tag{13}$$

The marginal return from the match (RHS of (13)) depends on whether the worker is experienced or inexperienced. The composition of the matching market thus influences the vacancy posting. As in the values of unemployed workers, (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.[11]

3.4 Separation Decision and Wages

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

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

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

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

The optimal value of the match surplus is determined by:

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

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

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

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

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

[11]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).

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

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

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

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

3.5 Labor Market Flows and Stocks

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

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

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

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 the other terms in the square brackets on the left-hand side. The right-hand side consists of flows out of $e_h(x_h)$ due to match separation and switching of productivity to a level higher than x_h. Solving Equation (19) for the distribution results in:

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

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. 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 represents the inexperienced employed workers whose matches are terminated after becoming experienced. The right-hand side includes the outflows associated with downgrading to inexperienced workers and the hiring of experienced workers.

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

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

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:

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

I also normalize 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 for all labor market stocks.

3.6 Steady-State Equilibrium

The steady-state equilibrium is defined by $(\theta, \underline{x}_h, \underline{x}_l, p_h)$ that satisfy (i) the job creation condition (13), (ii) the two job separation conditions, embedded in (16), and (iii) the stock-flow balance condition, which expresses the composition of the matching market p_h as a function of the other three endogenous variables:

$$p_h = \frac{f(\theta)(1-s_l)}{(1-\delta)f(\theta)(1-s_l) + \delta\big(1 + \frac{1-\mu}{\mu}\gamma s_l\big)}. \tag{29}$$

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

4 Calibration

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

4.1 Parameters Set Exogenously

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

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

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

Next, the discount factor is set to 0.99. This value may be considered low for a monthly model. One can view this low discount factor as reflecting the possibility that matches break up for reasons other than the separation into unemployment (such as retirement, death, etc.).[12] The parameter κ is set to 0.35. A natural interpretation of this parameter is a cost of capital or some other overhead costs. This value implies that roughly 30% of output goes into this cost on average.[13] The upgrading probability to the experienced worker μ is set to 1/36. This value implies that it takes 3 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 a normalization because I can adjust the average wage premium, which

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

[13]The mean of the idiosyncratic distribution for the inexperienced matches is normalized to one. As discussed in the next subsection, the average productivity advantage of the experienced matches amounts to 17%.

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

Symbol	Description	Value Assigned
π	Bargaining power of the worker	0.5
α	Elasticity of the matching function w.r.t unemployment	0.5
$\overline{m}$	Scale parameter of the matching function	0.615
β	Discount factor	0.99
γ	Arrival rate of the idiosyncratic shocks	0.167
Δ	Mean productivity premium of the experienced match	0.170
σ_x	Standard deviation of productivity shocks	0.240
μ	Probability of upgrading to become experienced	0.028
δ	Probability of downgrading to become inexperienced	0.19
b_h	Outside flow value for experienced worker	0.911
b_l	Outside flow value for inexperienced worker	0.670
κ	Fixed operating cost	0.350

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, implying the mean renewal frequency of 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, 1/3. The entire model is recalibrated at the new value of γ. The assigned parameter values and the results under the alternative calibration are presented in the Appendix B.

4.2 Parameters Set Internally

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

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

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

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

Remember that $f(\theta)$ represents the meeting probability for the worker. The terms in the square brackets in Equation (30) take into account the fact that the matching probability is influenced by the composition of the unemployment pool p_h 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, it has been fluctuating around this value over time. Equation (31) represents the

[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.

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.

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 the model does not necessarily correspond to a worker with long (short) firm tenure because the experienced worker can be newly hired if he escapes the skill loss in the unemployment pool. However, the aforementioned empirical observation is useful to pin down the relative levels of s_l and s_h. To see this, first note that employment for each type at tenure τ can be expressed as:

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

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

$$\begin{aligned} e_h(0) &= (1-s_h)(1-\delta)f(\theta)u_h, \\ e_l(0) &= (1-s_l)f(\theta)u_l. \end{aligned}$$

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

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

Observe that when $s_l > s_h$, $s(\tau)$ is decreasing in τ. The aggregate separation rate goes down over time as the composition of the employment pool shifts toward experienced workers who have a lower separation rate. In the context of the model, calibrating the model so as to achieve $s_l > s_h$ is the only way to match the empirical observation that the separation rate declines with firm tenure. Specifically, Anderson and Meyer (1994) report that the separation rate of those with a firm tenure of 16 quarters is one-fourth that of those with a firm tenure of less than one quarter. Therefore, I use the following condition:[15]

$$\frac{s(46) + s(47) + s(48)}{s(1) + s(2) + s(3)} = 0.25. \tag{32}$$

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

[15] Anderson and Meyer's result is based on the total job separation rate, which includes job-to-job transitions. Since the present model does not allow for direct job-to-job transitions, Equation (32) matches only the relative level of separation rates.

hired as an inexperienced worker. As mentioned before, the model is structured so that it can parsimoniously capture the occupational specificity of human capital. It is therefore natural to associate this statistic in the model with the fraction of workers who switch their occupation after an unemployment spell. I construct the empirical measure from SIPP. In subsection 5.2, I show that this statistic is 35-40% in the SIPP data. In the model, the corresponding measure can be calculated by:

$$1-\frac{f(\theta)(1-\delta)(1-s_h)}{1-(1-\delta)(1-f(\theta)+f(\theta)s_h)}, \tag{33}$$

where the second term gives the probability that the unemployed worker finds a job as an experienced worker and the term $(1-\delta)(1-f(\theta)+f(\theta)s_h)$ in the denominator corresponds to the probability that the unemployed worker stays in the unemployment pool as an experienced worker. 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 distributed with mean $\overline{x}_h$ and $\overline{x}_l$, respectively, and the common standard deviation of σ_x. I adopt a normalization that $\ln \overline{x}_l = 0$ and then 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 becomes inexperienced from experienced to be -0.10:

$$\widehat{w}_l - \widehat{w}_h = -0.10. \tag{34}$$

Recall that the model is structured to capture the empirical regularity that an unemployment spell is often followed by a lower wage at the subsequent job. In the model, this empirical regularity is replicated by the risk that the experienced unemployed worker is employed only as an inexperienced worker. Using the SIPP data, I calculate log 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 they are 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 wage losses amount to roughly 10%. This empirical finding is consistent with the results in the earlier literature that human capital is tied specifically to a worker's occupation (e.g., Kambourov and Manovskii (2009) and Poletaev and Robinson (2008)). The equivalent interpretation of Equation (34) is that an experienced worker enjoys a 10% wage gain on average. Kambourov and Manovskii (2009) estimate Mincer-style regressions using the PSID and their estimates on the returns to occupation tenure are broadly in line with this targeted number (see Table 2 in their paper).

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

Statistic	Equation	Target	Model
Aggregate job finding rate	(30)	0.300	0.293
Aggregate separation rate	(31)	0.020	0.020
Tenure effect on separation	(32)	0.250	0.321
Switching probability	(33)	0.35−0.40	0.377
Wage losses for experienced worker	(34)	−0.100	−0.100
Wage variance within experienced matches	(35)	≈ 0.016	0.022
Wage variance within inexperienced matches	(35)	≈ 0.016	0.014

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

$$\sigma^2_{\hat{w}_i} = \int_{\underline{x}_i}^{\infty} [\ln w_i(x_i)]^2 d\hat{e}_i(x_i) - \widehat{w}_i^2 \text{ for } i = \{l, h\}. \tag{35}$$

The only reason that wages vary within each type in the model is due to the match-specific idiosyncratic shock. It is important to use the empirical measure that is consistent with this interpretation. Hagedorn and Manovskii (2010) provide such evidence. They estimate that the wage variance due to the differences of match quality is 0.016. I target the two wage variance measures in the model to be around this point estimate.[16]

In summary, the six equations (30) through (35) are used to pin down the following six parameters: δ, Δ, σ_x, b_h, b_l, and $\overline{m}$. As mentioned above, the identification of δ, Δ, and σ_x can be directly associated with Equations (33), (34), and (35), respectively. The parameter $\overline{m}$ is useful to hit the condition for the job finding rate (30) because it can directly influence the level of the meeting probability $f(\theta)$. The outside option parameters b_h and b_l are useful for satisfying the conditions for the aggregate separation rate (31) and the tenure effect (32). Intuitively, each of these two parameters directly influences the separation rate of the corresponding type. Thus, the two parameters together can be used to control the aggregate separation rate as well as the separation-rate-tenure profile summarized by Equation (32).

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 Exercises

The main quantitative experiment entails raising the skill obsolescence probability δ. After presenting how the model reacts to the change, I present some empirical evidence that can

[16]In the model, the wage variances of the two types of workers differ from each other, even though the variance of the productivity shock is assumed to be the same, given that wage functions are different.

Table 4: Other Statistics in the Benchmark Calibration

γs_h	0.013	$f(\theta)$	0.420	e_h	0.794	u_h	0.021
γs_l	0.064	$q(\theta)$	0.900	e_l	0.141	u_l	0.044
p_h	0.317	θ	0.467				

be useful to test the implications. I then consider two other parameter changes and try to 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 0.19 to 0.22. The changes in the key endogenous variables are presented in Table 5. First, the separation rate goes down from 2% to 1.6%.[17] A simple intuitive reason is that the experienced workers become reluctant to separate when there is a higher chance of skill obsolescence. Recall the measurement of the aggregate separation rate (see (31)). The main driver of the lower aggregate separation rate is the lower s_h in that equation. The separation rate of the inexperienced workers, on the other hand, is hardly affected. The share of the experienced workers e_h therefore increases. Because the separation rate of the inexperienced workers is calibrated to be higher than that of the experienced workers, the changes in the composition also work to lower the aggregate separation rate.

The job finding rate declines but only slightly (see (30)). First, note that the market tightness θ decreases slightly ($0.467 \rightarrow 0.458$), and thus the meeting probability $f(\theta)$ also declines ($0.420 \rightarrow 0.416$). Note that the decline in the separation rate lowers steady-state unemployment. However, vacancies decline more, resulting in the decline in the ratio of the two variables. Lower job openings reflect the decline in p_h (the share of the experienced workers in the unemployment pool), which, in turn, results from the direct effect of faster skill obsolescence as well as lower separation flows of experienced workers. The lower p_h represents deterioration of the "quality" of the unemployment pool, thus discouraging new job openings.[18]

The last column of the top panel shows that the switching probability increases from 37.7% to 41.8%. Clearly, the increase in δ directly contributes to the increase in the observed switching probability. As indicated by (33), 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 finding a job as an experienced worker and thus raises the probability of the switch (although the impact is small given that the decline in the meeting probability is also small, as discussed above). This effect adds to the direct impact

[17]Given that there is no direct empirical measure of the parameter δ, the new value of δ is chosen to roughly match the level of the separation rate in the recent years. I therefore cannot claim that the model quantitatively matches the size of the decline in the separation rate. However, the model does predict the decline in the separation rate qualitatively, and I consider other dimensions to assess the quantitative performance of the model.

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

Table 5: Effects of Increased Turbulence

	Job Finding Rate	Separation Rate	Unemployment Rate	Vacancy Rate	Switching Probability
Benchmark	0.293	0.020	0.065	0.031	0.377
$\delta = 0.22$	0.288	0.016	0.052	0.024	0.418

	$\mathbb{E}$(Wage)		Wage	Var(Wage)	
	Experienced	Inexperienced	Change	Experienced	Inexperienced
Benchmark	0.881	0.793	−0.101	0.022	0.014
$\delta = 0.22$	0.874	0.794	−0.088	0.024	0.014

from the higher δ. Second, this statistic is increasing in s_h. Remember that s_h declines as discussed above, thus having the effect of counteracting the previous two effects. 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 is hardly affected as in the case of the separation rate. The third column presents the average of wage changes of those who switch from experienced to inexperienced after an unemployment spell.[19] Given that the average wage of the experienced workers decreases, while that of the inexperienced worker stays roughly the same, the average wage losses due to the switch go down (from 0.101 log points to 0.088 log points).

To see the mechanism more closely, Figure 4 plots the employment CDFs and wage functions. Let me first discuss the solid lines, which represent the economy prior to the parameter change. In this economy, the employment distribution starts at 0.84 for the experienced workers and 0.93 for the inexperienced workers, which correspond to the cutoff productivities for the respective types. The vertical lines in panel (b) correspond to those cutoff productivity levels. First, note that these graphs indicate that experienced workers actually have lower cutoff productivity. Remember that the calibration sets the mean productivity level of the experienced matches higher by 17%. However, one can see that there is a range of idiosyncratic productivity levels at which an inexperienced worker separates while the experienced worker stays in the match. For the experienced workers in this range of productivities, the choice is whether to wait for their wage to increase as an experienced worker or to separate. While the latter choice gives them the opportunity to find a better

[19] 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. See also footnote 22.

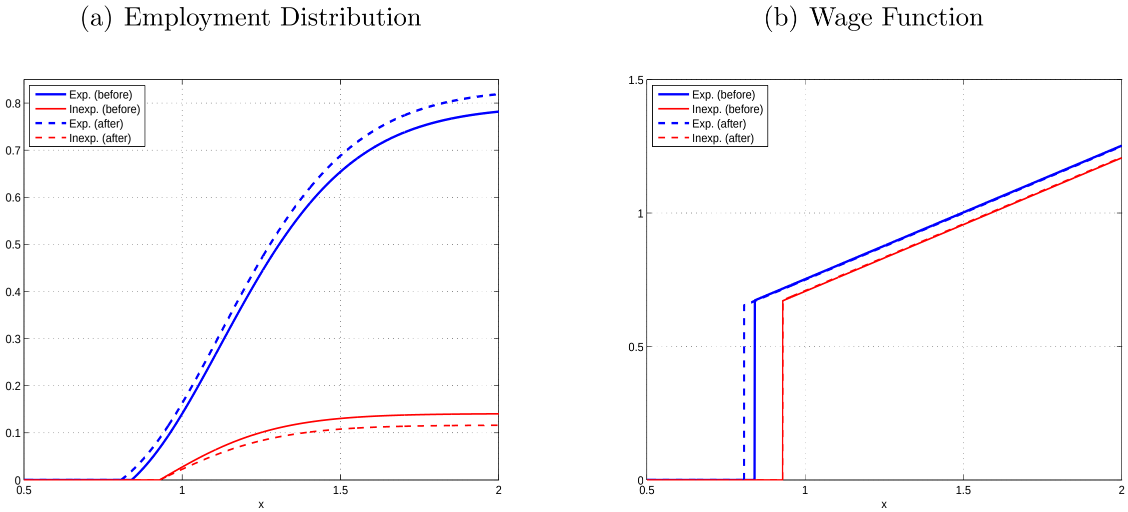

Figure 4: Effects of a Higher Turbulence Parameter

Notes: Panel (a) plots CDFs of the 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 lines correspond to cutoff productivities.

match as an experienced worker, it also includes the possibility of becoming inexperienced. The worker opts for the first choice. On the other hand, the inexperienced workers face no risk of further downgrading of their skills and thus are more likely to separate to look for a better match.

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

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. In panel (b), the wage function for the experienced type shifts downward somewhat (although it is difficult to see it in the graph), meaning that workers receive lower wages for a given level of productivity in the new steady state. Given this, 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:

$$w_h(x) - w_l(x) = \Big[(1-\beta)(1-\pi) + \beta\mu\Big](U_h - U_l). \tag{36}$$

Because U_h declines by more as a direct effect of higher δ, this difference gets smaller. But more important, there is a larger 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 lowers the average wage of

Table 6: Coverage of SIPP Panels

Panel	Number of Waves	Number of Months Covered	First Reference Month
1990	8	32	Oct. 1989
1991	8	32	Oct. 1990
1992	9	36	Oct. 1991
1993	9	36	Oct. 1992
1996	12	48	Dec. 1995
2001	9	36	Oct. 2000
2004	12	48	Oct. 2003

Notes: Each wave (interview) covers the previous four-month period.

the experienced workers. The increase in low-quality experienced matches as well as the downward shift of the wage function contributes to reducing the size of the wage losses of the experienced workers when they do go through an unemployment spell.

5.2 Empirical Evidence on Wage Losses and Occupation Switch

The previous subsection has shown that the higher turbulence parameter results in the lower separation rate, as observed in the data. There are, however, two other important implications. That is, the model predicts 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 SIPP data. 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 2004). The coverage of each panel is presented in Table 6. Importantly, workers report their labor market status (employed, unemployed, not in the labor force), which is defined consistently with the CPS.[20] Relative to the CPS, an obvious advantage is that the SIPP is a panel, in which workers report their wages whenever they are employed, while in the CPS, wages are reported only when workers are in the outgoing rotation group.

Among all labor market experiences contained in each panel, I choose the events in which a worker moves from one job to a new job with an unemployment spell in between. Using the collection of these employment-unemployment-employment (EUE) spells, I calculate changes in real hourly wages before and after an unemployment spell. The nominal hourly wage reported in the survey is deflated by the CPI. Recall that the model is structured so that it can parsimoniously capture the occupational specificity of human capital. In light of the model, I calculate wage changes of occupation switchers and occupation stayers. I also

[20] Fujita et al. (2007) show that the CPS-based measures of worker transition rates between unemployment and employment and the corresponding SIPP-based measures are similar in terms of their trend behavior as well as their cyclical behavior.

calculate the share of occupation switchs out of total spells, which can be compared with the switching probability shown in (33).

Only the workers who are 25 years or older are included in my sample. Younger workers are excluded because their EUE spells are likely to be influenced by considerations outside the model. For example, switching their occupation may simply represent job hopping before settling into a specific occupation. Thus, their unemployment spells are less likely to be associated with the loss of human capital. All statistics below are calculated for each of the 7 panels using the panel weights, which make each panel nationally representative. As shown in Figure 6, SIPP is a short panel. Selecting EUE spells from a short panel such as SIPP results in a bias in the sample selection due to the right censoring of the panel. In particular, the EUE spells that occur toward the end of the panel are necessarily biased toward the ones with short unemployment duration. In other words, many of the potential EUE spells are truncated because the panel ends before the worker finds a new job. To the extent that unemployment duration is correlated with the propensity to switch occupation and thus the size of wage losses, the right censoring causes biases in these two statistics. To avoid this problem, I include only the spells in which employment-to-unemployment separations occurred the first two years (6 waves) of each panel.[21] Lastly, the switching of occupation is based on 79 occupation categories. Different SIPP panels rely on the different census occupation classification systems. But the 79 occupation categories are created by relying on Meyer and Osborne (2005) who propose the detailed occupation titles that are consistent over time. More details are discussed in Appendix C.

To control for the changes in the composition across the panels, I run the regression in which the log real wage change is regressed on panel dummies, occupation switch dummy, age, gender, education, and the aggregate unemployment rate at the time of the transition into unemployment. Including worker characteristics (age, gender, and education) are useful to control for the correlation of those variables with the wage change that are not explicitly incorporated into the model. The aggregate unemployment rate is included to control for the differences in the aggregate condition. Table 7 presents the predicted wage changes from the regression for each panel. The first row presents the predicted wage change including both occupation switchers and stayers. The second and third rows calculate the predicted wage changes for the switchers and stayers, respectively. Note that these numbers are calculated by turning on the panel dummy only in the regression, while holding the composition of the sample constant across the panels. These numbers show that an unemployment spell is followed by a decline in wages and the wage losses are mainly associated with switching to a different occupation. Observe that workers tend to experience wage losses even when they stay in the same occupation, although they are often statistically insignificant. In the model, the wages of those who are rehired within the same type on average stay the same as before, and thus the model is unable to replicate this observation.[22] But again, the main

[21] This ensures that even in the shortest two panels (1990 and 1991), unemployment duration before finding a new job can last at least 8 months. One may think that this is still not enough for dealing with the right censoring problem. However, it is well known that a vast majority of job finding occurs within a few months.

[22] Separation occurs because current-period productivity of the match and thus wages are too low to sustain the match. When the worker is reemployed as an experienced worker, the match quality necessarily

Table 7: Predicted Wage Changes and Occupation Switch Rates after Unemployment

	SIPP Panel						
	1990	1991	1992	1993	1996	2001	2004
Overall	−0.057	−0.055	−0.061	−0.044	−0.015	−0.024	−0.032
	(0.013)	(0.012)	(0.013)	(0.012)	(0.024)	(0.024)	(0.025)
Switch	−0.107	−0.105	−0.112	−0.094	−0.065	−0.075	−0.083
	(0.016)	(0.015)	(0.016)	(0.015)	(0.025)	(0.025)	(0.025)
No Switch	−0.022	−0.020	−0.026	−0.009	0.020	0.011	0.003
	(0.013)	(0.012)	(0.013)	(0.012)	(0.025)	(0.025)	(0.025)
Switch Rate	0.389	0.410	0.407	0.425	0.382	0.419	0.387
	(0.016)	(0.014)	(0.014)	(0.013)	(0.026)	(0.027)	(0.026)

Notes: The wage change is expressed as a log difference in real hourly wages before and after an unemployment spell. Numbers in parentheses are robust standard errors. First rows: average log wage change of all cases; second rows: average log wage change with a change in occupation; third rows: average log wage change with no change in occupation; fourth rows: fraction of occupation switches. Total number of EUE spells: 14,311. Calculations for each panel are based on the spells in which an employment-to-unemployment transition occurs in the first two years of the panel. Wage change regression includes panel dummies, occupation switch dummy, age, gender, education, and aggregate unemployment rate. Occupation switch regression includes the same variables except for the occupation dummy. See the text for more details.

source of wage losses is switching of occupations.

One can see that the average wage losses for occupation switchers appear to be on the downward trend. Note that the earlier literature suggests that the size of wage losses is larger during recessionary periods (e.g., Jacobson et al. (1993) and Weinberg (2001)). However, this business cycle effect is controlled by having the unemployment rate in the regression. Nevertheless, one plausible comparison could 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.[23] In the first two panels, the predicted wage loss for switchers are about 10.5%, whereas it is 7.5% in the 2001 panel. while the standard errors around these estimates suggest that they are not statistically significant, the differences in the point estimates appear fairly large.

I also estimate a logit regression to characterize the occupation switching rate. This regression includes the same set of control variables (except for the occupation dummy, since it is now a dependent variable). Again, I calculate the predicted switching probabilities for each panel by turning on each panel dummy only, again ensuring that the composition is held constant over time. Recall that the model predicts that the switch rates are on the upward

improves. However, since the productivity that induced the separation is memoryless, wages before and after the unemployment spell stay the same on average within each type.

[23]The recession in the early 1990s officially started in July 1990 and ended in March 1991. The results for the 1990 and 1991 panels include separations that occurred between October 1989 and September 1992. The 2001 recession officially started in March 2001 and ended in November 2001. The results for the 2001 panel are based on separations that occurred between October 2000 and September 2002.

Table 8: Effects of Various Parameter Changes

	Job Finding Rate	Separation Rate	Unemployment Rate	Vacancy Rate	Switching Probability
Benchmark	0.293	0.020	0.065	0.031	0.377
$\pi = 0.4$	0.376	0.020	0.050	0.038	0.325
$\sigma_x = 0.225$	0.299	0.016	0.050	0.024	0.373

	$\mathbb{E}$(Wage)		Wage Change	Var(Wage)	
	Experienced	Inexperienced		Experienced	Inexperienced
Benchmark	0.881	0.793	-0.101	0.022	0.014
$\pi = 0.4$	0.876	0.787	-0.103	0.015	0.009
$\sigma_x = 0.225$	0.870	0.779	-0.105	0.021	0.013

trend. The last row presents the switching rates by panel. Unfortunately, switching rates do not show a clear trend, and thus it does not appear to be consistent with the prediction of the model. Subsection 5.4 will discuss the possible reason for this inconsistency.

A recent paper by 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 switchers and stayers, Farber provides a valuable piece of evidence on the time-series trend of earnings losses. While his results do 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.[24] 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 SIPP. It is also important to remember that real wages have been stagnant even while the unemployment rate was drifting down in the last two to three decades. This macro-level evidence is consistent with the implication of the model.

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 compiled in Table 8. Specifically, the following parameter changes are considered. First, the worker's bargaining power parameter is reduced from 0.5 to 0.4. This parameter change seems to be a plausible experiment to consider. The straightforward implication of this experiment is a decline in wages and is 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.

[24] The most recent SIPP panel (2008 panel) covers the period during and after the Great Recession. However, the survey is still ongoing, and final results have not been released yet.

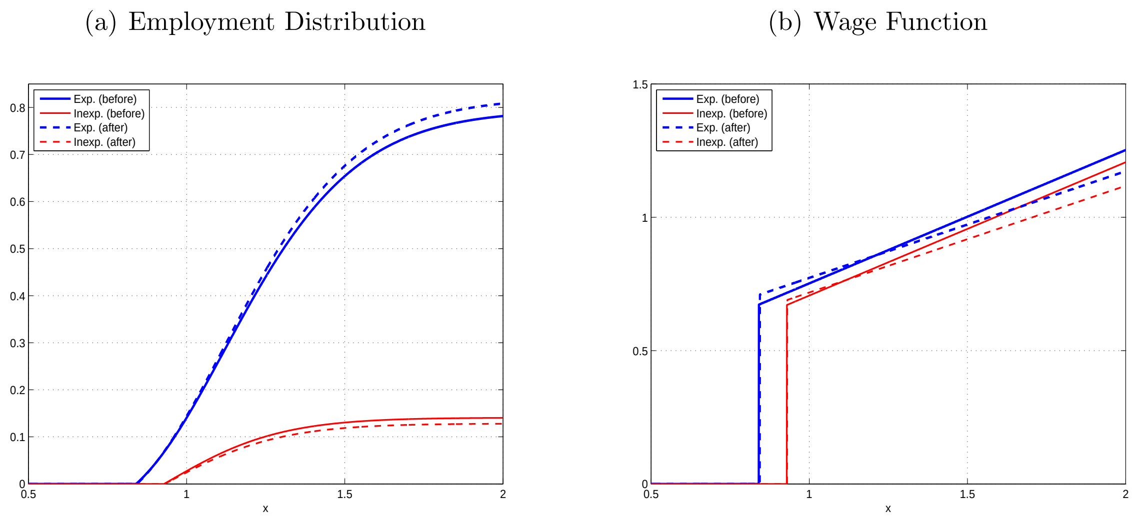

Figure 5: Effects of Lower Bargaining Power of the Worker

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.

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

5.3.1 Lower Bargaining Power

In Table 8, one can observe that the aggregate separation rate is insensitive to this parameter change, although both s_h and s_l (i.e., each type's separation rate conditional on receiving the shock) increase slightly. This can be seen in panel (b) of Figure 5 where the vertical part of the dashed lines slightly shifts to the right. The insensitivity of the separation rate is intuitive given that the separation decision is jointly optimal in the model, and thus how to split the surplus should not have a first-order effect on the separation decisions. The largest impact of the lower bargaining power of the worker is on the job finding rate, which increases from 29% to 38%. This is because the higher share of surplus that goes to the firm directly raises the values of the jobs, $J_h^c(x_h)$ and $J_c^l(x_l)$, thereby encouraging vacancy postings. The increase in the job finding rate indirectly influences the separation rate (raising s_h and s_l as mentioned above), but this effect is small.

The switching probability declines because a higher job meeting probability makes it

(a) Employment Distribution (b) Wage Function

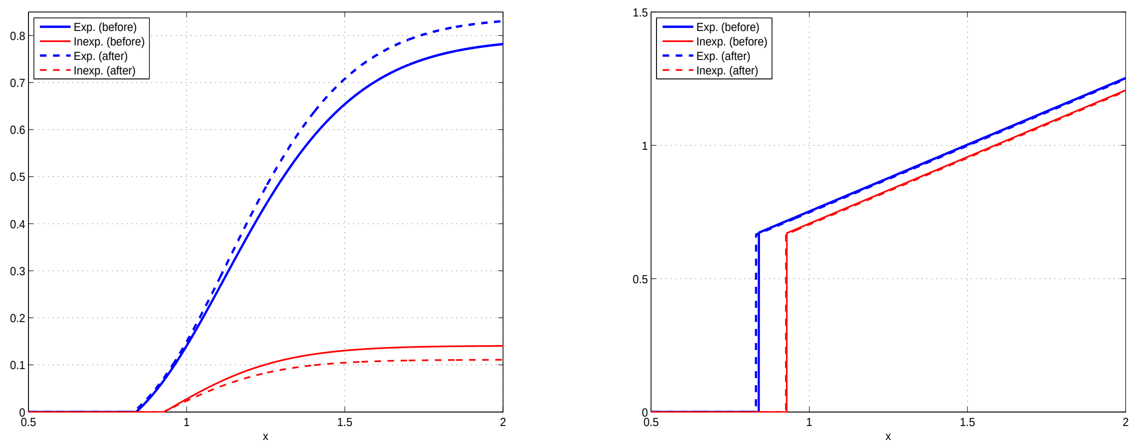

Figure 6: Effects of Smaller Idiosyncratic Variance

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.

easier for the experienced worker to find a new job within the same type. This effect causes the composition of employment to shift toward the experienced workers (as indicated by panel (a) of Figure 5). Wages of both types of workers decline as a direct consequence of the lower bargaining power. Panel (b) of Figure 5 shows the flattening of the wage functions and the flattening further implies lower wage variances.

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

5.3.2 Lower Variance of the Idiosyncratic Shock

Next, consider the parameter change from $\sigma_x = 0.24$ to 0.225. The size of this parameter change is chosen so that it matches the magnitude of the decline in the separation rate observed in the data, after confirming that the separation rate indeed declines in the extended version of the matching model. Recall that I used a similar procedure for the experiment of a higher δ. Note that, in contrast to the case of the higher turbulence parameter, the separation rates for both types decline in this case. Behind the lower separation rates are the two competing effects that apply to both types of workers. First, given that the productivity distribution is truncated below the cutoff value, the smaller variance reduces the upside potential of the match, reducing the expected surplus. Second, a lower variance directly reduces the possibility that productivity falls below a certain level, which reduces the separation rate. This direct effect dominates the first (indirect) effect and thus the separation rate falls on net.

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

5.4 Robustness and Discussion

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 ($\gamma = 1/3$). 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.

The quantitative results suggest that the faster skill depreciation and the lower idiosyncratic variance are both appealing explanations of the decline in the separation rate. However, the two stories give rise to different implications on wage losses and the switching rate: The higher turbulence parameter implies smaller wage losses and higher switching probability, while the smaller idiosyncratic variance results in roughly constant switching probability and increases in the size of wage losses (although the increase is not very large in the quantitative experiments).

The SIPP data seem to suggest that the size of wage losses has shrunk, or at least has not increased in recent years. This is consistent with the turbulence story. However, the higher occupation switching probability implied by the model is not consistent with the data. Recall that the higher switching probability comes through the direct effect of higher δ. However, recall also that there was a competing effect against this direct effect. That is, the higher δ results in the lower job rejection rate. Intuitively, because of the higher skill obsolescence risk, the experienced worker is willing to accept a new job offer with a lower wage. Specifically, the job rejection rate for the experienced worker declines from 7.6% to 5.5% as a result of the higher δ in the benchmark calibration.[25] It is possible that this effect is larger in reality. As discussed in Subsection 4.2, the existing empirical evidence suggests that breakup rates of new hires are much higher than those of established employment relationships. My calibration replicated this evidence only by way of experienced workers being hired as inexperienced workers whose separation rate is calibrated to be higher. A more flexible specification where new hires, regardless of their types, face higher job reject rates, could help mitigate the effect of the higher δ on the switching rate.

[25]Note that these numbers correspond to s_h in the two steady states. The separation rate of the existing match is γs_h. Conditional on receiving the shock, the rejection decision and the separation decision are the same in the model.

6 Conclusion

This paper has argued that a more turbulent environment can be one of the sources of the declining separation rate. The key idea is that workers who fear losing their skills will accept wage concession in exchange for job security. The model's explanation is consistent with the widely recognized fact that real wages have been stagnant even during the period when unemployment has been on a downward trend (at least until the most recent recession). I also show that the explanation based on the smaller idiosyncratic variance, which is empirically explored by Davis et al. (2010), holds in the extended version of the matching model that incorporates wage losses and thus is another attractive explanation.

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 rapid technological advances. 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 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:

$$\mathbb{E}S_i^c(x_i') \equiv \int_{\underline{x}_i}^{\infty} S_i^c(x_i')dG_i(x_i') \text{ for } i = \{h, i\}. \tag{37}$$

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

$$\begin{aligned} S_h^c(x_h) = x_h - \kappa - b_h + \beta\Big[&(1-\gamma)S_h^c(x_h) + \gamma\mathbb{E}S_h^c(x_h') - f(\theta)\pi\Big(\delta\mathbb{E}S_l^c(x_l') + (1-\delta)\mathbb{E}S_h^c(x_h')\Big) \\ &+ \delta(U_h - U_l)\Big]. \end{aligned} \tag{38}$$

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

$$\begin{aligned} S_l^c(x_l) = x_l - \kappa - b_l + \beta\Big[&(1-\mu)\Big((1-\gamma)S_l^c(x_l) + \gamma\mathbb{E}S_l^c(x_l')\Big) + \mu\mathbb{E}S_h^c(x_h') - f(\theta)\pi\mathbb{E}S_l^c(x_l') \\ &+ \mu(U_h - U_l)\Big]. \end{aligned} \tag{39}$$

Evaluating (38) and (39) at $\underline{x}_h$ and $\underline{x}_l$, respectively, results in

$$\underline{x}_h - \kappa - b_h + \beta\Big[\gamma\mathbb{E}S_h^c(x_h') - f(\theta)\pi\Big(\delta\mathbb{E}S_l^c(x_l') + (1-\delta)\mathbb{E}S_h^c(x_h')\Big) + \delta(U_h - U_l)\Big] = 0, \quad (40)$$

$$\underline{x}_l - \kappa - b_l + \beta\Big[(1-\mu)\gamma\mathbb{E}S_l^c(x_l') + \mu\mathbb{E}S_h^c(x_h') - f(\theta)\pi\mathbb{E}S_l^c(x_l') + \mu(U_h - U_l)\Big] = 0. \quad (41)$$

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

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

Subtracting (40) and (41), respectively, from (38) and (39) results in:

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

Using (42) and (43) in (40) and (41) gives the job separation conditions that solve for $\underline{x}_h$ and $\underline{x}_l$ for a given market tightness θ. The free entry condition (13) can also be rewritten as:

$$\frac{c}{\beta q(\theta)} = (1-\pi)\Big[(1-\delta)p_h\mathbb{E}S_h^c(x_h') + \big[1-(1-\delta)p_h\big]\mathbb{E}S_l^c(x_l')\Big]. \quad (44)$$

Lastly, the stock-flow balance equations imply:

$$p_h = \frac{f(\theta)(1-G(\underline{x}_l))}{(1-\delta)f(\theta)(1-G(\underline{x}_l)) + \delta\big(1 + \frac{1-\mu}{\mu}\gamma G(\underline{x}_l)\big)}. \quad (45)$$

The steady-state equilibrium is defined by θ, $\underline{x}_l$, $\underline{x}_h$, and p_h that solve (40), (41), (44), and (45). I solve the nonlinear system numerically, and all integrals associated with the truncated log-normal distributions are calculated by Simpson's rule.

B Results Under 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 1/3 here. Recall that there are six exogenously chosen parameters, including the arrival rate γ. The other five parameters are kept at the same values as before. The remaining six parameters are re-calibrated again by matching the same six moment conditions. The results are summarized in Table 9; see notes to that table for the specific parameter values used.

The results largely stay the same: an increase in the turbulence parameter as well as a decline in the idiosyncratic variance both yield plausible results in terms of the effects on the separation rates. The differences between these two experiments again lie in the implications on the size of wage losses and the switching probability.

Table 9: Effects of Various Parameter Changes: Alternative Calibration $\gamma = 1/3$

	Job Finding Rate	Separation Rate	Unemployment Rate	Vacancy Rate	Switching Probability
Initial SS	0.305	0.020	0.062	0.029	0.371
$\delta = 0.18$	0.306	0.017	0.051	0.024	0.385
$\pi = 0.4$	0.385	0.019	0.047	0.033	0.321
$\sigma_x = 0.21$	0.307	0.016	0.049	0.022	0.371

	$\mathbb{E}$(Wage)		Wage	Var(Wage)	
	Experienced	Inexperienced	Change	Experienced	Inexperienced
Initial SS	0.797	0.723	−0.094	0.022	0.017
$\delta = 0.18$	0.795	0.724	−0.089	0.022	0.016
$\pi = 0.4$	0.794	0.719	−0.098	0.014	0.011
$\sigma_x = 0.21$	0.793	0.717	−0.096	0.020	0.015

Notes: Parameter values used to calibrate the initial steady state are as follows: $\pi = 0.5$, $\alpha = 0.5$, $\bar{m} = 0.537$, $\beta = 0.99$, $\gamma = 1/3$, $\Delta = 0.11$, $\sigma_x = 0.22$, $\mu = 0.028$, $\delta = 0.17$, $b_h = 0.963$, $b_l = 0.657$, and $\kappa = 0.35$. See Table 2 for a description of each parameter.

C Construction of Occupation Categories

When determining whether a worker switched his/her occupation in SIPP, I use 79 occupation categories. SIPP relies on the census classification system for occupation coding. As the census classification system has changed over time, the occupation classification in SIPP also has changed. Specifically, the 1990 and 1991 SIPP panels rely on the census 1980 classification system; the 1992, 1993, 1996, and 2001 panels rely on the census 1990 classification system; and the 2004 panel relies on the census 2000 classification system. I first convert the original SIPP occupation codes into the standardized codes proposed by Meyer and Osborne (2005) that are consistent over time. The original census classification systems include more than 500 occupation titles. The procedure by Meyer and Osborne (2005) reduces the titles to 371. I further aggregate these titles to obtain these 79 occupation titles. The occupation switching rate in the text is based on this 79 occupation categories. The actual titles and the detailed aggregation procedure are available upon request.

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