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Declining Labor Turnover and Turbulence

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Abstract

The rate of job loss has been on a secular decline for the last four decades or longer. Changes in demographics or industry composition do not account for the trend. This paper seeks to identify possible sources of this decline using a simple labor matching model with two types of workers, experienced and inexperienced, where the former type faces a risk of skill loss during unemployment. When the skill loss occurs, the worker is required to restart his career and thus suffers a drop in his wage. I show that a higher risk of skill loss results in a lower job separation rate, because workers are willing to accept lower wages in exchange for keeping their jobs. Various other potential hypotheses are also examined in the model.

JEL Codes: E24, E32, J64
Keywords: job loss rate, search and matching, turbulence

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1 Introduction

It has been widely recognized in the macro/labor literature that various measures of labor market turnover have been on secular declining trends for the past several decades.[1] This paper focuses on the rate of job loss, more specifically, the transition probability from employment to unemployment (the EU rate) and shows that it has also been on a downward trend over the last four decades or longer. On the surface, this downward trend suggests, if literally interpreted, that the risk of job loss facing U.S. workers has gradually been falling over time. This interpretation, however, is at odds with anecdotal evidence that labor market conditions surrounding U.S. workers have been deteriorating. The following passage from a *New York Times* article summarizes this narrative:

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

Note that the above NYT piece was written in 1995 (long before the Great Recession), when the job loss rate was steadily falling. This passage also dovetails with a macroeconomic observation often referred to in a similar context that real wages have been stagnant for decades.[2]

I show empirically that neither changes in the demographic composition or the industry composition account for the declining trend of the EU rate.[3] Although the sample period of the main empirical analysis starts in 1976, as it utilizes the Current Population Survey (CPS) micro data, additional pieces of evidence suggest that the same trend spreads over a longer period starting in the 1940s. In addition to the trend in the EU rate, I also study the long-term trend in the job-finding probability from unemployment (the UE rate) and the occupation switching probability of the unemployed (OS rate), which is defined as the probability that a job loser switches to a different occupation upon finding a job. I find that the UE rate also exhibits a declining trend, but only in the last 15 years or so. I consider the OS rate as an empirical measure capturing the idea of "turbulence," proposed by

[1] For example, Davis (2008), Hyatt and Spletzer (2013), Davis and Haltiwanger (2014), Molloy et al. (2014), Molloy et al. (2016), and Kaplan and Schulhofer-Wohl (2017).

[2] The real average hourly earnings series available from the BLS establishment survey has not increased much since the late 1960s. The average level of this series over the last 10 years (2007-2016) is about the same as the average level in the 1970s.

[3] The trend level of the EU rate at the beginning of the sample period of the analysis (1976) is about 1.7 percent per month, while that at the end of the sample period (2016) is about 1.4 percent per month. This decline in the EU rate translates into roughly a 1 percentage point decline in the trend (steady-state) unemployment rate. See Section 2.2 for more explanations.

Ljungqvist and Sargent (1998). Kambourov and Manovskii (2008) suggest that the notion of turbulence can be linked to a rising occupational mobility. The idea is that human capital is largely occupation-specific (Kambourov and Manovskii (2009)) and thus the higher mobility is related to a higher risk of human capital loss. I follow their insight and construct the OS rate for the unemployed.[4] I show that it indeed has been on an increasing trend over the last four decades.

To study how changes in an economic environment interact with various labor market decisions, including job separation and creation decisions, I construct an equilibrium labor matching model with two types of workers, experienced and inexperienced. The former type is, on average, more productive than the latter; both types face the risk of endogenous match separation, but the former type faces an additional exogenous risk of downgrading his skills while searching for a new job. When hit by this shock, the worker is required to restart his career as an inexperienced worker and therefore tends to suffer a wage cut after reemployment.[5]

I use this model to explore various possibilities as potential causes of the empirical findings. The key experiment is to see how the model responds to a higher skill loss probability (i.e., a more turbulent environment). The model predicts that the separation rate falls in response to this change: a higher chance of skill loss makes the experienced workers reluctant to separate from their current jobs. In essence, these workers accept lower wages than before for the same level of productivity in exchange for keeping their jobs. It also implies that there is a larger mass of "low-quality" employment relationships that would have severed in the environment before the parameter change.[6]

Another interesting result is that the average size of wage loss is observed to be smaller in the environment with a higher skill loss probability (i.e., a more turbulent environment). This is because the lower wages of experienced workers imply that there is less room for their wages to fall. I discuss empirical evidence in the literature that is consistent with this prediction of the model.

The model also allows me to examine a wide range of other existing hypotheses in the

[4]Kambourov and Manovskii's measure of occupational mobility is based on the Panel Study of Income Dynamics (PSID) and does not explicitly consider occupation switching after unemployment. As will be clear later, the switching rate after an unemployment spell is more appropriate for the purposes of this paper.

[5]Using the data from the Survey of Income and Program Participation (SIPP), I show that workers with significant occupational tenure tend to suffer a large wage drop when they lose their job and end up in a different occupation upon reemployment.

[6]The intuition itself is not new and is stressed by Den Haan et al. (2005). Molloy et al. (2014), who empirically study the possible sources of the declines in inter-state migration rates, emphasize the possibility that outside options for workers have shifted in a way that make labor transitions less desirable. This general idea is consistent with the main hypothesis pursued in this paper.

literature.[7] I find that some of the hypotheses, such as an increase in hiring costs and a decline in match-quality uncertainty, can account for the trends in EU and UE rates, whereas some others, such as an increase in overhead, possibly due to more regulations and a decline in worker bargaining power, yield implications that are strongly at odds with the data. Furthermore, none of them account for the pattern in the occupation switching rate together with the trends in EU and UE rates.

The paper is organized as follows. The next section is devoted to establishing the empirical facts on the long-term trend in EU and UE transition rates and the OS rate. Section 3 lays out the structural model, which is calibrated in Section 4. Section 5 presents the comparative static exercises of various parameter changes and discusses economic intuitions behind the model predictions. Section 6 concludes the paper by discussing the limitation of this paper's approach and offering some structural interpretations of a higher skill loss probability.

2 Empirical Evidence

I study time series trends of the following three variables: the transition rate from employment to unemployment (the EU rate or the separation rate), the transition rate from unemployment to employment (the UE rate or the job-finding rate), and the occupation switching rate (the OS rate).[8] The last variable is defined as a fraction of occupation switchers within those who find a job after an unemployment spell.

2.1 Data

All series are constructed from the public-use micro data of the monthly CPS. I follow a standard procedure to match individuals across two monthly surveys.[9] After the matching, all records from all years are pooled. The linear probability model is then estimated for the EU rate, the UE rate, and the OS rate. The regression-based analysis allows me to easily and systematically control for changes in demographic and industry compositions over the sample period. The analysis here is not meant to provide any causal inference but to summarize the statistical relationships. The sample period is constrained by the availability of the monthly CPS data and thus starts in January 1976 and ends in December 2016.

[7]A paper by Molloy et al. (2016) provides fairly comprehensive empirical examinations of various hypotheses for the "declining fluidity" of the U.S. labor market.

[8]For brevity, I use the term "rate" instead of "probability" to refer to the three variables.

[9]See, for example, Shimer (2012) for a discussion of the CPS matching procedure. The data extraction and matching codes used for the current analysis are available upon request.

I use a gender dummy interacted with six age-group dummies (16-24, 25-34, 35-44, 45-54, 55-64, and 65+), marital status dummies (married, widowed/separated, and never married), 16 major industry codes, and month dummies.[10]

I consider two methods to gauge the long-term trend of each variable. First, I include year fixed effects in the regression and isolate the time effects, while fixing the values of the remaining regressors at their sample means. The time effects identified in this way also include business cycle variations. The second method is to capture a smooth trend using time polynomials in the regression. I use cubic polynomials for all variables. (I also consider second- and fourth-order polynomials and obtain similar results.) I extract the trend component after controlling for the observable characteristics of the worker. The point estimates and 95 percent confidence bands are reported.

For the EU rate, the underlying sample contains matched records that start with "employed" in the first month; the dependent variable takes 1 when an EU transition occurs and 0 otherwise. The sample for the UE rate consists of those who are unemployed in the first month; it takes 1 if the worker is employed in the second month and 0 otherwise.

The sample for the OS rate consists of those who make a UE transition between two adjacent months; it takes 1 when the occupation at the time of reemployment differs from the one reported as their previous occupation while being in the unemployment pool. The CPS collects occupation information on the last job the worker held before losing his job, allowing me to compute the OS rate among the unemployed. As in industry codes, the occupation classification system has changed several times during the sample period. Using the Census crosswalks, I create 13 major occupation codes that are consistent over time. This classification is again relatively coarse, but creating consistent codes necessarily requires aggregation of underlying three-digit codes into fairly broad categories such as those used in this paper.[11] Specifically, I ensure that employment shares of the 13 occupation categories are smooth when the new classification system is adopted. Moreover, within the sample for this analysis, the occupation information is collected through so-called independent coding, which tends to produce spurious occupation transitions, especially when finer codes are used. Using coarse titles helps mitigate this error.[12]

[10] Note that the Census industry classification system has gone through several changes during the sample period. I build up the 16 industry codes from three-digit level codes using the Census crosswalks available, for example, at IPUMS.org. The final classification is necessarily relatively coarse to ensure that there is no break within the industry (employment shares of these 16 industries are ensured to be smooth over time). The Stata code is available upon request. The CPS asks the unemployed the industry information for the most recent job held, and I use that information in the regressions for the UE rate and the OS rate.

[11] Before creating the major occupation titles, I standardize the three-digit codes from the different Census systems, following the procedure proposed by Meyer and Osborne (2005).

[12] See, for example, Moscarini and Thomsson (2007), on the effect of (in)dependent coding on occupational mobility. Dependent coding is known to reduce the erroneous transitions dramatically, but unfortunately in

I study the trend in the OS rate because the literature has shown that human capital is largely occupation specific (e.g., Kambourov and Manovskii (2008, 2009) and Poletaev and Robinson (2008)).[13] Therefore, switching occupation is likely to imply a loss of human capital, especially when a worker switches his occupation after an unemployment spell (rather than after a job-to-job transition, in which case occupation switching may reflect a step-up along the career ladder). Kambourov and Manovskii (2008) show that occupational mobility has been steadily increasing within their sample period (i.e., between the 1960s and late 1990s) and relate it to the notion of turbulence following Ljungqvist and Sargent (1998). But their occupational mobility measure is different from the one considered here because I focus on occupation switching with *an unemployment spell in between*. In Ljungqvist and Sargent (1998), the loss of human capital occurs when the worker enters the unemployment pool, and thus the OS rate considered in this paper appears to be more directly related to Ljungqvist and Sargent's notion of turbulence.[14]

2.2 Results

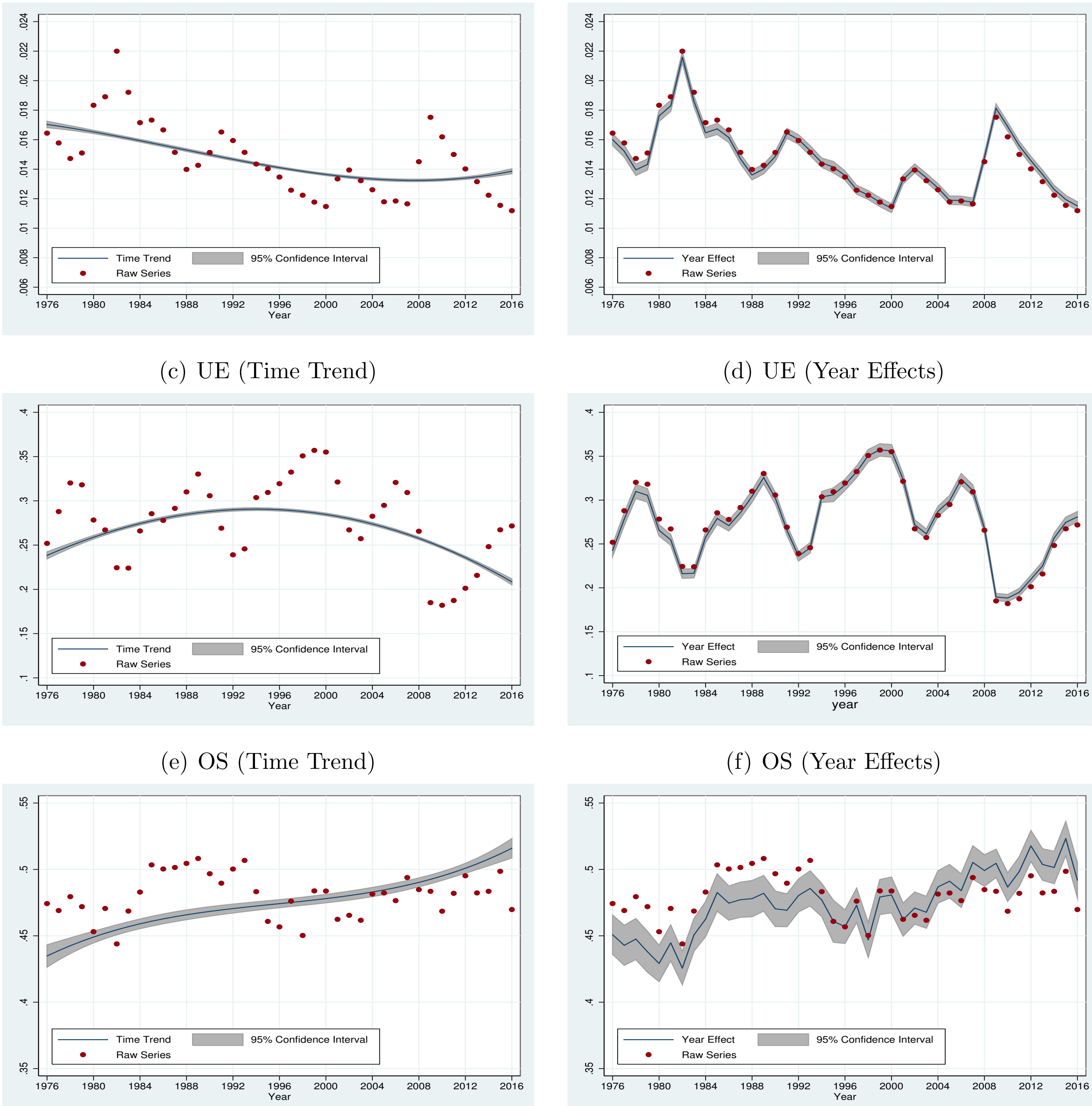
EU rate. Panels (a) and (b) in Figure 1 plot the polynomial time trend (left panel) and the year effects (right panel) together with unadjusted rates (dots). In the right panel, one can see the well-known strong countercyclicality of this series. The year effects after controlling for observables are not very different from the unadjusted measure. However, the adjusted measure tilts the unadjusted one counter-clockwise, which indicates that observable characteristics explain some portion of the decline in the EU rate. This is largely due to the aging of the labor force, since older workers tend to have greater attachment to their jobs. The polynomial trend, presented in the left panel, shows a gradual decline in the EU rate from around 1.7 percent per month in 1976 to around 1.3 percent per month in 2008. From that point on, it has increased somewhat to around 1.4 percent. The increase at the end of the sample is due to the spike in the EU rate during the Great Recession. To put the overall decline into perspective, consider the steady-state relationship between the two transition rates (EU and UE rates) and the unemployment rate: $u = \frac{EU}{EU+UE}$, which assumes the two-state worker transitions. This relationship implies that the decline in the EU rate from 1.7 percent to 1.4 percent, while holding the UE transition rate at the same level (say,

the CPS, occupations in two adjacent months when a worker makes a UE transition are coded independently.

[13] To be precise, there is some debate in the literature about the relative importance of occupational and industry-specific components of human capital. See Poletaev and Robinson (2008) and Sullivan (2010). I also look at the industry switching rate using the major industry titles and find that the trend in that series is very similar to the one in the OS rate.

[14] Jaimovich and Siu (2012) and Cortes et al. (2014) also construct a similar measure using the occupation information available for unemployed workers.

Figure 1: EU, UE, and OS Rates



(a) EU (Time Trend)

(b) EU (Year Effects)

(c) UE (Time Trend)

(d) UE (Year Effects)

(e) OS (Time Trend)

(f) OS (Year Effects)

Source: CPS micro data.

25 percent per month), leads the steady-state unemployment rate to fall by more than 1 percentage point.

Observe also that, while the Great Recession resulted in a large spike in the EU rate, its peak was significantly lower than the one in the early 1980s. This is quite surprising given the magnitude of the Great Recession itself.[15] Furthermore, although the polynomial trend in the final year of the sample is higher than its bottom level in 2008, the actual level in 2016 is at the lowest level in the entire sample. As I will discuss below, the current level is likely to be the lowest even over the entire post-WWII period.

In Appendix A.2, I estimate the same linear probability model separately for EU transition into quits and layoffs and find that the declines in the EU rate due to quits are particularly large.

UE rate. Panels (c) and (d) present the results for the UE rate. On the right panel, one can see the familiar procyclicality of the UE rate (see Shimer (2005, 2012)). Controlling for the changes in sample compositions makes little difference in its behavior. During the Great Recession, the UE rate fell dramatically, but, as of 2016, it almost returned to its pre-recession average.[16] The parametric time trend (left panel) shows a gradual increase until the mid-1990s, followed by a gradual decline.[17] Although the downward trend in the UE rate in the last 20 years is noticeable, the current level is not far from the level at the beginning of the sample period, because of the increase in the first half of the sample. This hump-shaped pattern makes the trend of the UE rate distinct from that of the EU rate. Again, in Appendix A.2, I present the results when the sample is split into job leavers (quits) and job losers (layoffs). The declining trend in the last 20 years is more noticeable for job leavers.

OS rate. Panels (e) and (f) present the results for the OS rate. Again, the dots in the figure represent the raw series; solid and dashed lines represent the regression-based results that control for observables.[18] First, observe in the right panel that controlling for observables makes a significant difference in this series. After controlling for the observables, one can see more clearly that this variable has been increasing over time. Relative to its 1976 level, the 2016 level is about 5 percentage points higher and this difference is statistically significant.

[15] To be more specific, real GDP fell 2.8 percent in 2009, whereas it had contracted 1.9 percent in 1982. Alan Greenspan famously characterized the Great Recession as a "once-in-a-century" financial crisis.

[16] The extracted year effects of the regression indicate that the average UE rate is 0.298 between 1976 and 2007, and it is 0.281 in 2016.

[17] Tasci (2012) points out that the "exit" rate from unemployment has been on a downward trend since 2000. His and my results are not inconsistent. First, the exit rate is conceptually different from the UE rate because the former does not distinguish between job finding and exiting the labor force. More important, a decline in the exit rate (see Figure 1 in his paper) became more apparent only before the Great Recession, and his sample period stops before its significant recovery in the past several years.

[18] The confidence bands for this variable are larger than those for the previous two variables because the number of observations is smaller for this variable. (The underlying sample includes only those who made UE transitions between adjacent months.)

Note also that this series does not show clear cyclical movements, in contrast to the other two variables. The parametric time trend shows a gradual upward trend over the entire sample, with some acceleration toward the end of the sample period. In Appendix A.2, I show that the OS rates for both job losers and job leavers are on similarly increasing trends.

As discussed earlier, I link the increasing trend in this series to a higher risk of (occupation-specific) human capital loss. In Appendix A.4, I examine the pattern of wage changes before and after an unemployment spell using the micro data from the SIPP and show that the pattern of wage changes strongly supports this interpretation. (This empirical observation from the SIPP is used to calibrate the model.)

2.3 Additional Evidence

In this section, I elaborate on the empirical evidence along three dimensions.

Male-only sample. One of the most well-documented labor market facts in the post-WWII era is a steady increase in female labor force participation, which continued until the late 1990s. This phenomenon exemplifies the increasing labor force attachment of female workers during this period. A greater attachment to a job (say, by taking a full-time salaried job instead of a part-time hourly paid job) implies a longer tenure and lower separation rate (see, for example, Abraham and Shimer (2002)). It is thus possible that a lower overall EU rate results from the greater female labor force attachment. Although the regression above controls for age, gender, and their interactions (among other variables), it does not allow for time-varying factors within each demographic group. The greater female labor force attachment can be considered one of the factors that are outside the quantitative model that I study below, and thus it is important to make sure that the declining trend in the overall EU rate is not driven by this force.

A simple way to deal with this concern is to focus on male workers only in the analysis. I repeat the same analysis using this sample. The results are presented in Figure A.1 in Appendix. The overall level of the EU rate is somewhat higher in this sample. However, the magnitude of the decline in this sample is proportionately (i.e., in terms of log difference) comparable to (or even slightly larger than) that in the full sample. In the full sample, its trend level dropped from 1.7 percent in 1976 to 1.4 percent in 2016, with a minimum level being around 1.3 percent in 2008; in the male-only sample, the initial level is higher at 1.9 percent, while the most recent level is around 1.5 percent, with its lowest level being around 1.4 percent in 2008. Thus I conclude that the greater female labor force attachment does not account for the trend in the overall EU rate.

Figure 2: Unemployment Insurance Initial Claims

(a) UI Initial Claim Rate and Time Trend

(b) UI Initial Claim Rate vs. Average Tax Rate

Sources: Unemployment insurance financial data handbook, CPS micro data. Weekly initial claims are aggregated into monthly levels and then divided by the CPS employment series.

Longer-run trend in job loss rates. The first data point of the above empirical analysis is constrained by the availability of the CPS micro data. A legitimate question is what the trend looks like before this sample period. This is especially important, because the so-called unemployment inflow rate, whose sample period extends to 1948, was somewhat lower before 1976. See, for example, Davis (2008) and Shimer (2012). This data is based on the number of unemployed workers who report unemployment durations of less than five weeks. The idea is that because these workers report their duration as being less than five weeks, these respondents must not be in the unemployment pool in the previous month and have just joined the unemployment pool. This series, normalized by employment, is sometimes used as an alternative measure of the separation rate.

I argue that the low-frequency trend of the job loss rate was unlikely to be increasing from a lower level into the sample period of my analysis and that the trend before my sample period was possibly even higher before the mid-1970s. One of the major problems of the inflow rate series, discussed in the previous paragraph, is that it does not distinguish between entrants from nonparticipation and separations from employment. This paper's focus is on the latter. It is known that the relative size of the former flow is equally large (compared with the latter flow) in the post-1976 sample period (where we can distinguish between these two flows) and is likely to be even larger and increasing before 1976, when baby boomers and women were entering the labor force. This suggests that the trend in the inflow rate between the late-1940s and the mid-1970s is strongly affected by increasing entry flows from nonparticipation.

I now present two additional pieces of evidence on the longer-run trend in the EU rate. First, I consider unemployment insurance (UI) initial claims, which go back to 1948. Panel

(a) of Figure 2 presents this series, normalized by the employment stock, together with its time trend and the 95-percent confidence intervals, which are computed from the regression of the initial claim series on cubic time polynomials.[19]

The confidence intervals are larger in this exercise since I can only use aggregate time series in this exercise. But the declining trend since the mid-1970s is apparent; more important, the trend extends back into the 1960s and 1950s, even though the downward trend is more noticeable after the 1970s. As noted in footnote 19, this series is not identical to the EU rate, mainly because not all unemployed workers file UI claims. However, over the period 1976-2016, the two series (solid red and dashed green lines in Panel (a)) share very similar cyclical and low-frequency (trend) behavior: the correlation coefficient between the two series is indeed very high at 0.94.[20]

A potential explanation for the declining trend, which applies especially to initial claims, but also to the EU rate in general, could be a stricter application (or an introduction) of the experience rating. Anderson and Meyer (2000) study such an episode in the mid-1980s when the state of Washington adopted the experience-rating system, thus effectively raising the payroll tax rate. They find that a higher tax rate lowered layoffs in Washington. However, I argue that it is unlikely that similar forces have been gradually driving down UI claims, or the rate of job loss in general, at the national level. Panel (b) of Figure 2 plots the average payroll tax rate together with UI initial claims.[21] While the average tax rate shows considerable variation over time, there is no evidence that it has been drifting higher over time. Instead, its trend is similar to that of the initial claim series. Observe also that the tax rate peaks one or two years after the initial claim series hits the peak due to a recession. This lagging behavior of the tax rate is not surprising because the experience-rating system makes the tax rate higher after the heavier usage of UI in a recession.

The data in Panel (b) seem to be more in line with the idea that the causality is going from UI initial claims to the average tax rate. If instead a higher tax burden had been the reason for the downward trend in initial claims, we should have seen an increasing tax rate over time. However, that is not what we observe in the data. A formal statistical test

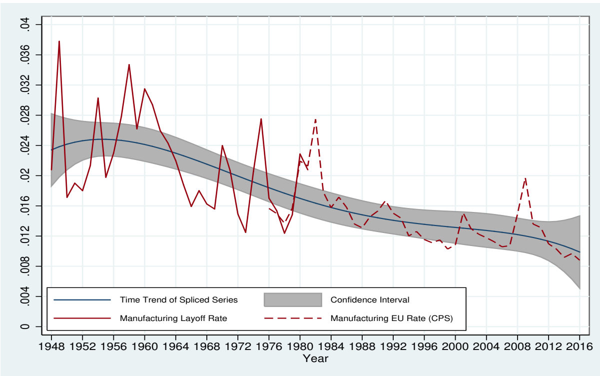
[19]Since this series counts the number of initial UI claimants, it is closely related to the rate of job losses. The number of UI claims is reported on a weekly basis and thus I multiply this series by 4.3 to obtain the monthly rate and then take an average over a year. The level of this series can be different from the level of the EU rate (although they are not far from each other) because (i) UI claims are reported on a weekly gross basis, whereas EU transitions are based on the point-in-time comparison of labor force status between two months and (ii) not all unemployed workers, as defined in the CPS, file UI claims.

[20]One can see from the two series that the initial claim series is "spikier" during recessions, which indicates that the take-up rate of UI is countercyclical.

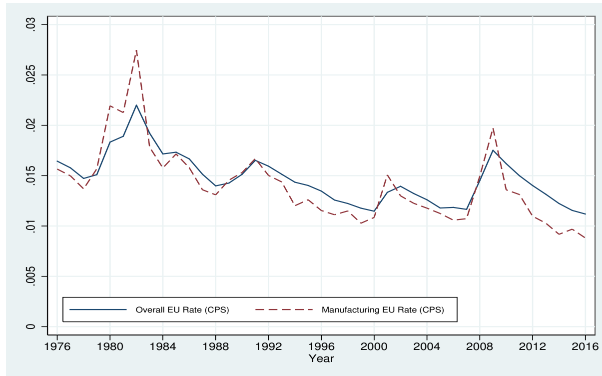
[21]The average tax rate is computed as total payroll taxes collected divided by total wage bills and is available at https://workforcesecurity.doleta.gov/unemploy/hb394.asp. (Unemployment Insurance Financial Data Handbook).

Figure 3: EU Rate in Manufacturing

(a) Trend in Manufacturing EU (Layoff) Rate



(b) Manufacturing vs. Overall EU Rates



Sources: NBER Macrohistory database; various issues of Survey of Current Business; CPS micro data

(Granger causality test) of the two series overwhelmingly suggests that the direction of the Granger causality goes from initial claims to the tax rate, but not the other way around.[22]

Another series that goes back further is the BLS's layoff-rate series in the manufacturing sector. This series was discontinued at the end of 1981 but allows me to study a longer-run trend of the job loss rate in that sector. An obvious limitation of this series is its coverage. However, the employment share of the manufacturing sector was higher in those years than it is now. More important, despite the sector's small employment share, its EU rate closely tracks that of the overall economy over my CPS sample period (1976-2016). Panel (b) of Figure 3 compares EU rates in the CPS for the overall economy and for the manufacturing sector. Although the countercyclical response of the manufacturing EU rate is more pronounced and the downward trend in that sector is even more noticeable, the two series are highly correlated overall at both business cycle and lower frequencies (the correlation coefficient between the two series is 0.93). This high correlation suggests that gauging the longer-run trend of the overall EU rate from the manufacturing data can be informative.

Panel (a) of Figure 3 plots the manufacturing layoff rate over 1948-1981 (solid red), the CPS manufacturing EU rate over 1976-2016 (dashed red), and the time trend based on the long-run series that is constructed by splicing the two series.[23]

[22]I estimate a bivariate VAR with a lag length of two years. The Granger-causality test overwhelmingly rejects the hypothesis that initial claims do not Granger-cause the tax rate, with the χ^2 statistic being larger than 100, while the test cannot reject the hypothesis that the tax rate does not cause initial claims with χ^2 statistic being less than 1 and the associated P-value being 0.6. The conclusion does not change at all when different lag lengths are used.

[23]To splice the two series, the manufacturing layoff rate is adjusted by a constant factor so that the average levels of the layoff rate and the EU rate over the overlapping sample period (1976-1981) are the

The downward trend in the manufacturing sector is even clearer and larger in its magnitude: The point estimate of the trend at the beginning of the sample is around 2.4 percent, whereas it drops to around 1 percent in 2016. Part of this large decline might be a sector-specific phenomenon, given that the long-run trend in initial UI claims was less dramatic. Nevertheless, it suggests that the downward trend in the EU rate in the CPS data since 1976 is likely to be only part of the longer-run trend.

Unemployment duration. As an alternative measure to the UE transition rate, one can look at average unemployment duration. Note that in the steady state of a two-state labor market where job-finding rate is independent of duration, mean unemployment duration corresponds simply to the reciprocal of the UE rate. These conditions are unlikely to hold in reality and thus mean duration may include additional information pertaining to this paper. There are a few measurement issues one needs to deal with before studying the trend of the mean duration. First, the reporting procedure of the duration data was changed at the time of the CPS redesign in 1994, which creates a break in mean duration. I correct this break, following the procedure suggested by Abraham and Shimer (2002), who propose using only the observations in the CPS incoming-rotation groups (first and fifth rotation groups).[24] Second, duration information prior to 1994 is top-coded at 99 weeks. To obtain the mean duration that is consistent over time, I impose this top-coding at 99 weeks in the post-redesign data.

Panel (a) of Figure 4 presents its time trend and year effects together with their confidence intervals. These results control for the worker's observable characteristics as before. The time trend of the mean duration has a U-shaped pattern. This shape itself is consistent with the inverted U-shaped pattern of the trend in the UE rate. However, the increasing trend in the mean duration over the last 15 years is more dramatic than can be accounted for by the decline in the UE transition rate. This difference is related to the well-documented dramatic increase in long-term unemployment (those with a duration longer than six months) in the aftermath of the Great Recession, which, in turn, resulted from a particularly large drop in the job-finding rates of the long-term unemployed.

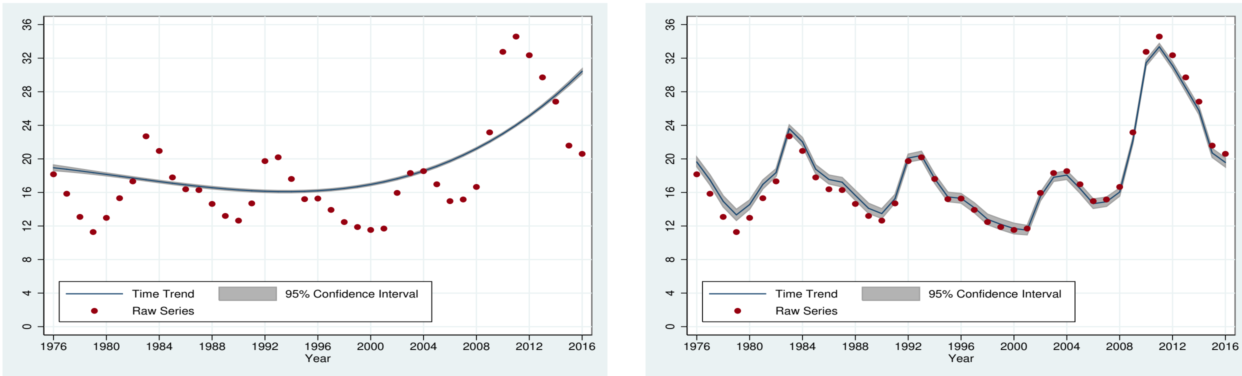
Note that the large increase in the share of long-term unemployment is arguably the result of the Great Recession. In this sense, the nature of the trend increase in the mean duration appears to be different from that of the longer-term trend decline in the EU rate.

same. I then splice the two series by taking the average of the two series for each year. The correlation coefficient between the two series over the overlapping period, albeit based on only six observations, is 0.97.

[24]The break is due to the introduction of the dependent coding of unemployment duration. Abraham and Shimer (2002) propose to use only those observations, because their duration information is collected in the same way before and after the redesign.

Figure 4: Mean Unemployment Duration

(a) Time Trend (b) Year Effects



Source: CPS micro data. First and fifth rotation groups only. Duration is top-coded at 99 weeks throughout the sample period.

Even though the time trend remains elevated at the end of the sample period, the point estimates show that the increase is largely reversed in the following five years, although its 2016 level remains high by historical standards. The mean duration in 2016 is about 20 weeks and thus 4.65 months, which translates into a monthly job-finding rate of 0.22 (= 1/4.65), which is not dramatically different from the level of the UE rate in 2016 (0.28; see Panel (d) of Figure 1).

Having studied the empirical behavior of EU and UE rates and the OS rate, I now write down a labor matching model with two types workers and examine various hypotheses for the underlying sources of their long-run trends.

3 Model

This section develops the model that incorporates the possibility that entering into the unemployment pool tends to cause a wage cut at the time of reemployment. Allowing for this possibility is important for this paper because it is a robust feature of the data that can be linked to the idea of labor market turbulence.[25] The basic structure of the model below is similar to the one by Den Haan et al. (2005).

[25]There is ample empirical literature on earnings losses associated with a job loss. See the paper by Davis and Von Wachter (2011) and references therein.

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." From here on, I label them h-type and l-type, respectively. The subscripts h and l indicate that the variable or the parameter applies to that particular type. When the job position is filled, the match produces output x_h and x_l, respectively. When the match is first formed, it draws its productivity either from $G_h(x_h)$ or $G_l(x_l)$, respectively, both of which are assumed to have support $[0, \infty)$. $G_h(.)$ (first order) stochastically dominates $G_l(.)$, namely, $G_h(x) < G_l(x)$ for any x. Production requires a fixed operating cost (i.e., overhead) κ per period.

Existing matches face several possibilities at the start of each period; (i) the l-type worker is upgraded to h-type with probability μ, in which case the new productivity level is drawn from $G_h(.)$. Second, both types face the possibility that their productivities switch to a new level. This switch occurs with probability γ. When it occurs, the new productivity level is drawn from $G_h(.)$ or $G_l(.)$. Each match may be endogenously terminated when the new productivity level is too low. The separation decision is described below. When h-type workers are in the unemployment pool, they face an additional risk of having their skills downgraded. This occurs with probability δ every period.

Interpretation of the model environment. Note that transitioning from l-type to h-type captures the idea that the worker accumulates human capital through working in a particular occupation. The accumulation of human capital is purely stochastic in the model and thus no explicit decision is involved. The stochastic transition is convenient in that it dramatically simplifies the model, thus allowing me to focus on job separation and related decisions. It is also important to note that there is no explicit notion of occupation in the model. However, the "experience" in the model is *interpreted* as occupation specific. This interpretation is adopted because, as noted above, the empirical literature suggests that human capital is tied to occupation in the U.S. labor market.[26] This interpretation matters when taking the model to the data. In particular, the δ risk is linked to the empirical OS rate studied above. Furthermore, the calibration of the model uses the empirical fact about the wage cut that occurs when a worker with significant occupational tenure changes his occupation after an unemployment spell. The l-type worker may also endogenously separate in the model without facing the risk of skill loss. The empirical counterpart of this case is also explicitly incorporated into the calibration.

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

3.2 Labor Market Matching

The frictions of worker reallocation across jobs 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 and u_l. The meeting probability for each job seeker is written as $f(\theta) = \frac{m}{u}$, where θ is the ratio between the number of vacant positions and the total number of the unemployed ($\frac{v}{u}$) and $u \equiv u_h + u_l$. The meeting probability for a vacant job $q(\theta)$ is written as $q(\theta) = \frac{m}{v}$. The vacant job is paired randomly with the h-type or the l-type 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. Section A.5 in Appendix presents the model where there are two separate matching markets for the different types workers and show that the quantitative results are very similar in that environment.

3.3 Continuation Values

Workers. Let W_h be the value of the h-type employed worker, written as:

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

where $w_h(x_h)$ is the current-period wage, β is the discount factor, x_h' is output of this match in the next period, and U_h is the value of the h-type unemployed worker. The max operator in (1) characterizes the optimal continuation/separation decision. The first term in the square brackets is the continuation value of the worker in the next period if productivity stays the same. The second term represents the value when productivity switches. As mentioned before, when the worker is in the unemployment pool, he faces the risk of the skill downgrading. In the period when he becomes unemployed, he is not subject to this risk.[27]

The value of the h-type unemployed worker is:

$$\begin{aligned} U_h = b_h + \beta\Big[& f(\theta)\Big(\delta \int_0^\infty \max[W_l(x_l'), U_l] dG_l(x_l') + (1-\delta) \int_0^\infty \max[W_h(x_h'), U_h] dG_h(x_h')\Big) \\ &+ \big(1 - f(\theta)\big)\big(\delta U_l + (1-\delta)U_h\big)\Big], \end{aligned} \tag{2}$$

where b_h is the flow outside value for the worker, U_l is the value of the l-type unemployed worker, and W_l is the value of the l-type employed worker. Again, the two max operators characterize the optimal continuation/separation decisions. Upon meeting a potential

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

employer, this worker faces several possibilities. First, with probability δ, his skill may be downgraded at the start of the next period. After the meeting takes place, productivity is drawn. It may be too low and thus the match may be rejected. The worker then starts the next period as jobless. If the worker fails to meet a potential employer, he remains jobless and faces the risk of skill loss at the start of the next period.

The value of the l-type employed worker is:

$$\begin{aligned} W_l(x_l) = w_l(x_l) + \beta\Big[\mu \int_0^\infty \max[W_h(x_h'), U_h] dG_h(x_h') \\ + (1-\mu)\Big\{(1-\gamma)W_l(x_l) + \gamma \int_0^\infty \max[W_l(x_l'), U_l] dG_l(x_l')\Big\}\Big]. \end{aligned} \tag{3}$$

At the start of the period, he becomes the h-type with probability μ, in which case new productivity is drawn and the match separation decision as the h-type is made. If he continues to be l-type, new productivity is drawn with probability γ from G_l, and the separation decision is made.

The value of the l-type unemployed worker is:

$$U_l = b_l + \beta\Big[f(\theta)\int_0^\infty \max[W_l(x_l'), U_l] dG_l(x_l') + \big(1 - f(\theta)\big)U_l\Big], \tag{4}$$

where b_l is the flow outside value for the l-type unemployed worker. The interpretation is similar to Equation (2) except that the l-type worker faces no risk of skill loss. Note also the timing assumption that upgrading to the h-type does not occur in the first period of the match formation.

Jobs. The job position filled with the h-type worker embodies the following value:

$$J_h(x_h) = x_h - \kappa - w_h(x_h) + \beta\Big[(1-\gamma)J_h(x_h) + \gamma \int_0^\infty \max[J_h(x_h'), V] dG_h(x_h')\Big], \tag{5}$$

where V is the value of the unfilled position and the max operator characterizes the match destruction decision. The interpretation is straightforward. Similarly, the value of the position filled with the l-type worker is:

$$\begin{aligned} J_l(x_l) = x_l - \kappa - w_l(x_l) + \beta\Big[\mu \int_0^\infty \max[J_h(x_h'), V] dG_h(x_h') \\ + (1-\mu)\big\{((1-\gamma)J_l(x_l) + \gamma \int_0^\infty \max[J_l(x_l'), V] dG_l(x_l')\big\}\Big]. \end{aligned} \tag{6}$$

Lastly, free entry into the matching market drives the value of the vacant job to zero and thus the following "job creation condition" holds:

$$\frac{c}{\beta q(\theta)} = \left[(1-\delta)p_h \int_0^\infty J_h(x_h') dG_h(x_h') + \big[1 - (1-\delta)p_h\big] \int_0^\infty J_l(x_l') dG_l(x_l')\right]. \tag{7}$$

The return from forming a match (RHS of (7)) depends on which type of worker fills the position. The composition of the matching market thus influences the vacancy posting decision.[28]

3.4 Separation Decision and Wages

The separation decision and wage determination are assumed to be based on Nash bargaining, as in Mortensen and Pissarides (1994). When the employment relationship continues, each match type enjoys the surplus:

$$S_i(x_i) = J_i(x_i) + W_i(x_i) - U_i \text{ for } i \in \{h, l\}. \tag{8}$$

The worker takes a constant fraction, denoted as π, of the total surplus and the firm takes the rest $1-\pi$. Given this rule, the worker and the firm agree on the separation/continuation decision. Since $J_i(x_i) + W_i(x_i)$ is increasing in x_i, there exists a cutoff productivity $\underline{x}_i$ below (above) which both sides choose to sever (continue) the employment relationship; at $\underline{x}_i$,

$$S_i(\underline{x}_i) = 0. \tag{9}$$

The separation rates (conditional on receiving the shock) for the h- and l-type workers are written as as $s_h \equiv G(\underline{x}_h)$ and $s_l \equiv G(\underline{x}_l)$, respectively. Using the expressions for $W_i(x_i)$ and $J_i(x_i)$ in $\pi J_i(x_i) = (1-\pi)[W_i(x_i) - U_i]$, one can obtain the following wage functions:

$$w_h(x_h) = \pi(x_h - \kappa) + (1-\pi)(1-\beta)U_h, \tag{10}$$

$$w_l(x_l) = \pi(x_l - \kappa) + (1-\pi)\big[(1-\beta)U_l - \beta\mu(U_h - U_l)\big]. \tag{11}$$

Wages of h-type workers tend to be higher than those of l-type workers, mainly because of the stochastic dominance of $G_h(x_h)$ over $G_l(x_l)$. In the quantitative exercises below, the value of b_h is set to be higher than the value of b_l (see the discussion in Section 4.2), which also contributes to raising the wages of h-type workers.

3.5 Labor Market Flows and Stocks

Let $e_h(x_h)$ and $e_l(x_l)$ be the CDFs of the h- and l-type workers, respectively. 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 they are used in the quantitative

[28] Note that (7) assumes that $J_h(x_h) > 0$ and $J_l(x_l) > 0$ for any x_h and x_l, respectively. Note also that, at the beginning of the next period, the h-type worker is downgraded to the l-type with probability δ.

analysis. In particular, I calculate the average wage of each type by integrating (10) and (11) with respect to the respective employment distributions.

By equating flows into and out of $e_h(x_h)$, one can obtain the steady-state CDF for the h-type employed:

$$\big(G_h(x_h) - s_h\big)\big[\mu e_l + f(\theta)(1-\delta)u_h + \gamma(e_h - e_h(x_h))\big] = \gamma(1 - G_h(x_h) + s_h)e_h(x_h), \quad (12)$$

where the LHS gives flows into $e_h(x_h)$ and the RHS gives flows out of $e_h(x_h)$. Consider the term μe_l on the LHS. This term corresponds to the measure of workers that are upgraded to the h-type. Among them, workers 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 LHS. The RHS consists of flows out of $e_h(x_h)$ due to match separations and the change in productivity to a level higher than x_h. (12) implies

$$\gamma s_h e_h = (1 - s_h)[\mu e_l + f(\theta)(1-\delta)u_h]. \quad (13)$$

The LHS of (13) gives total flows out of the pool of h-type workers, while the RHS gives total flows into the pool.

Similarly, equating flows into and out of $e_l(x_l)$, one obtains the steady-state CDF for the l-type employed:

$$(G_l(x_l) - s_l)\big[f(\theta)(\delta u_h + u_l) + (1-\mu)\gamma(e_l - e_l(x_l))\big] = \big[\mu + (1-\mu)\gamma(1 - G_l(x_l) + s_l)\big]e_l(x_l), \quad (14)$$

where the LHS gives inflows and the RHS outflows. The interpretation of (14) is similar to that of (12), with only minor differences. (14) implies:

$$\big[\mu + (1-\mu)\gamma s_l\big]e_l = (1 - s_l)f(\theta)(\delta u_h + u_l). \quad (15)$$

Consider next the steady-state stock-flow relationship of the h-type unemployed. Setting inflows and outflows equal to each other gives:

$$\gamma s_h e_h + \mu s_h e_l = \big[\delta + f(\theta)(1-\delta)(1 - s_h)\big]u_h. \quad (16)$$

The two terms on the LHS are inflows associated with separations from two pools of employment. The second term represents the l-type employed workers whose matches are terminated after becoming the h-type. The RHS includes the outflows associated with downgrading to the l-type and the hiring of h-type workers.

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

$$(1-\mu)\gamma s_l e_l + \big[1 - (1 - s_l)f(\theta)\big]\delta u_h = (1 - s_l)f(\theta)u_l, \quad (17)$$

where again the LHS gives inflows and the RHS gives outflows. The first term on the LHS gives the separation flow from l-type employment. The second term gives the number of workers who flow from the h-type unemployment pool. Among those who are downgraded from u_h to u_l (i.e., δu_h), those who are employed as l-type workers (i.e., $(1-s_l)f(\theta)$) would avoid flowing into this pool. The RHS represents the hiring flow from the l-type unemployment pool.

The stock-flow relationships presented so far imply that the flows between h-type and l-type workers are equal to each other:

$$\mu e_l = \delta u_h. \tag{18}$$

Out of (13), (15), (16), (17), and (18), three of them are linearly independent for given values of θ, s_h, and s_l. Adding $e_l + e_h + u_l + u_h = 1$ as a normalizing equation allows 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 (7), (ii) the two job separation conditions (9) 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:

$$p_h = \frac{f(\theta)(1-s_l)}{(1-\delta)f(\theta)(1-s_l) + \delta\big(1 + \frac{1-\mu}{\mu}\gamma s_l\big)}. \tag{19}$$

Appendix A.3 presents the system of equations used to solve for the four endogenous variables.

4 Calibration

There are 13 parameters in the model. The parameters and their assigned values are summarized in Table 1. Six parameters are set exogenously and the remaining seven are determined internally. One period in the model is assumed to be one month.

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. The matching function is assumed to be Cobb-Douglas $m(u,v) = \overline{m}u^{\alpha}v^{1-\alpha}$ where $\overline{m}$

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

Symbol	Description	Value Assigned
π	Bargaining power of the worker	0.5
α	Elasticity of the matching function w.r.t. unemployment	0.5
$\overline{m}$	Scale parameter of the matching function	0.5692
β	Discount factor	0.995
γ	Arrival rate of the idiosyncratic shocks	0.167
Δ	Mean productivity premium of h-type match	0.28
σ_x	Standard deviation of productivity shocks	0.53
μ	Probability of upgrading to the h-type	0.0417
δ	Probability of downgrading from the l-type	0.214
b_h	Outside option value for the h-type worker	1.0397
b_l	Outside option value for the l-type worker	0.7631
κ	Fixed operating cost	0.350
c	Vacancy posting cost	1.3489

is a scale parameter determined below. The discount factor is set to 0.995. The parameter κ is set to 0.35, which implies that roughly 30 percent of output goes into this cost on average. The upgrading probability μ is set to 1/24, implying that transitions to an h-type worker takes two years on average, conditional on the worker being employed throughout. The arrival rate of the shock γ is chosen to be 1/6 in the benchmark calibration, implying a mean renewal frequency of six months. The model properties are robust with respect to alternative values of μ and γ. The robustness of the results is discussed in Section 5.3.

4.2 Parameters Set Internally

I assume that productivities x_l and x_h are log-normally distributed with mean $\overline{x}_h$ and $\overline{x}_l$, respectively, and a common standard deviation of σ_x. I adopt a normalization that $\ln \overline{x}_l = 0$ and then set a value for $\Delta \equiv \ln \overline{x}_h - \ln \overline{x}_l$. After this reparameterization, seven parameters remain to be determined ($\bar{m}$, δ, Δ, σ_x, b_h, b_l, and c). The values of these parameters are determined so that the model matches the following seven conditions as closely as possible (minimizing the sum of absolute log differences).

First, the following two conditions match the aggregate EU and UE rates:

$$\frac{\gamma s_h e_h + \left[\mu s_h + (1-\mu)\gamma s_l\right] e_l}{e_h + e_l} = 0.017, \tag{20}$$

$$\left[\big(\delta(1-s_l) + (1-\delta)(1-s_h)\big)p_h + (1-s_l)(1-p_h)\right] f(\theta) = 0.27. \tag{21}$$

(20) gives the aggregate separation rate as a weighted average of the separation rates for the

Table 2: Targeted Value vs. Model's Steady-State Value

Statistic	Equation	Target	Model
Aggregate separation rate	(20)	0.017	0.0174
Aggregate job-finding rate	(21)	0.27	0.2673
Switching probability	(22)	0.45	0.4493
Average wage losses for h-type	–	-0.13	-0.1277
Replacement ratio (h-type)	–	0.016	0.8246
Replacement ratio (l-type)	–	0.016	0.7374

two types of workers. The UE rate (21) is affected not only by the meeting probability $f(\theta)$ but also by the match rejection rates (s_h and s_l) and the composition of the unemployment pool p_h. One can see from Figure 1 that the two target values correspond to the empirical trend values early in the sample.

The key ingredient of the model is that the h-type worker faces a risk of being hired only as an l-type worker after going through an unemployment spell. Given the skill loss probability δ, the fraction of workers who were initially unemployed as h-type workers and later hired as l-type workers, denoted by ω, is written as:

$$\omega = 1 - \frac{f(\theta)(1-\delta)(1-s_h)}{1-(1-\delta)(1-f(\theta)+f(\theta)s_h)}. \tag{22}$$

The calibration links this probability with the OS rate presented Figure 1.[29] The value of ω is targeted to be 0.45 in the initial steady state, and this condition is most useful in identifying the value of δ.

The average wage loss due to the δ shock is simply the average wage difference of the two types of workers. One can compute average wages of the two types of workers by integrating the wage functions (10) and (11) with respect to the employment distributions of each type, (12) and (14), respectively. I target the average log wage difference between l-type and h-type workers at -0.13, meaning that downgrading from h-type to l-type results in an average wage loss of about 13 percent. In the model, it also corresponds to the average wage premium of h-type workers over l-type workers. This condition is most useful for the identification of the productivity premium Δ. I obtain the empirical value for the wage loss, using the micro data from the SIPP. Unlike the CPS, SIPP is a panel that keeps track of workers over several years, allowing me to observe wages of individual workers before and after an unemployment spell. It also includes information about occupational tenure, which also

[29] One issue here is that the empirical measure of the OS rate is not conditioned on the worker's experience because there is no occupation tenure information in the CPS. Thus, the implicit assumption here is that these data are not sensitive to this conditioning. See also the discussion in the last paragraph of this section.

Table 3: Other Statistics in the Benchmark Calibration

γs_h	0.0122	$f(\theta)$	0.36	e_h	0.8264	u_h	0.0219
γs_l	0.055	$q(\theta)$	0.9	e_l	0.1124	u_l	0.0393
p_h	0.3577	θ	0.4				

allows me to compute the wage loss when a worker with experience in a certain occupation switches to a different occupation after an unemployment spell. Details of this empirical exercise are presented in Appendix A.4. Importantly, the results are highly consistent with the idea that human capital is occupation-specific: the incidence of wage loss is concentrated among workers who have lost a job after accumulating significant experience in a particular occupation and switched to a different occupation upon finding a job; in contrast, occupation stayers and switchers with little prior occupational experience suffer only very small wage losses that are mostly statistically insignificant.

Next, I target the flow values of unemployment b_h and b_l to be 70 percent of the average wages within each type. The replacement ratio of 70 percent is often used in the calibration exercise in the search and matching literature. Obviously, the two conditions directly restrict the values of b_h and b_l, conditional on the values of all other parameters.

Lastly, I assign the vacancy posting cost c to achieve the steady-state meeting rate for the firm $q(\theta)$ at 0.9, as used, for example, by Fujita and Ramey (2007). Note, however, that the choice of a particular target value of q is inconsequential for the model equilibrium because I can set the value of c, such that $c/q(\theta)$ the LHS of the free-entry condition (7) remains the same.

Table 2 shows that the model can match the targeted statistics fairly well, although it is not possible to match the targets perfectly. Other statistics that are not directly targeted are presented in Table 3. 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 2.[30]

Let me close this section by clarifying an issue about the mapping between the empirical OS rate and ω in the model. In calibrating the model, I associate the empirical measure with the probability, ω, that the h-type worker switches to the l-type worker after an unemployment spell, and then use the empirical evidence on wage loss to calibrate the value of Δ. However, the empirical OS rate itself carries no information about the "distance" between

[30] The calibrated model replicates an important and robust labor-market fact that the separation rate falls steeply with firm tenure. 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. In the calibrated model, this ratio is 0.34, which is somewhat higher than one-fourth but not far from it.

two occupations and therefore I could choose different values for Δ and μ without changing the mapping between the OS rate and ω in the model.[31] I address this arbitrariness by examining the robustness of the quantitative results with respect to a different pair of values for Δ and μ (while keeping the same target for ω). (See Section 5.3.)[32]

5 Model Implications

This section studies the effects of the various parameter changes. I first discuss in detail the main hypothesis for this paper, namely, a higher value of the turbulence parameter δ, and then consider various other hypotheses discussed in the literature. All results are summarized in Table 4.

5.1 Higher Skill Loss Probability

In this first experiment, I raise the value of δ from 0.215 to 0.245, which results in ω from 0.45 to 0.49, thus mimicking roughly the increase in the OS rate over the last four decades. A higher δ causes the EU rate to drop from 1.7 percent to 1.3 percent. A simple intuition is that h-type workers become more reluctant to separate when there is a higher chance of skill loss. The overall EU rate falls mainly because of a lower EU rate among h-type workers; the EU rate of the l-type workers is hardly affected. The composition of employment shifts toward h-type. Because of $s_l > s_h$ in the initial steady state, this shift in composition also lowers the overall EU rate. The UE rate declines but only slightly. Market tightness θ decreases slightly ($0.40 \to 0.39$), thus lowering the meeting probability $f(\theta)$. The lower θ reflects the decline in p_h (the share of h-type workers in the unemployment pool), which, in turn, results from the direct effect of higher δ as well as the lower EU flow of h-type workers. The lower p_h represents a deterioration in the "quality" of the unemployment pool and thus discourages job creation.[33] These effects, however, are quantitatively relatively small. Raising δ increases ω to the level close to the date as intended. While a higher δ directly contributes to this increase, there are several other factors affecting this statistic (see (22)). First, this statistic is decreasing in $f(\theta)$: A lower meeting rate translates into a lower probability of finding a job as an h-type worker and thus raises the probability of the switch (although this effect is

[31] Note that the values of Δ and μ need to be chosen together because the value of μ determines the average time it takes for the skill upgrading, and the value of Δ controls the wage premium of the h-type over the l-type.

[32] One can view that the issue discussed here is related to the assumptions that there are only two levels of human capital and that the evolution between them is purely stochastic. A more complete but ambitious setup would be to model human capital investment explicitly together with a more sophisticated process for the erosion of human capital off the job.

[33] In the calibrated economy, matching with an h-type worker yields a higher return for the firm.

quantitatively small, as discussed above). Second, this statistic is increasing in s_h. Recall that s_h declines as discussed above, thus having an effect of lowering ω. In the current context, the lower level of s_h represents the endogenous response that there are meetings that would have been rejected in the initial steady state but now are accepted because the worker is urged to take the job as an h-type worker even when the offered wage is relatively low. The first two effects dominate this effect. The same mechanism that generated the lower EU rate for h-type workers lowers their average wage: they are willing to accept lower wages that they would have rejected in the initial steady state. The average wage of l-type workers increases slightly. The average wage loss for the h-type due to the switch *decreases*: the model implies that the economy with a higher δ is associated with a *smaller* wage loss.

Figure 5 plots the employment CDFs and wage functions as functions of productivities. The solid (dashed) lines represent the economy prior to (after) the parameter change. These functions start at respective cutoff productivities.[34] One can see the decline in the cutoff productivity for the h-type worker. Panel (a) shows the change in the composition of the workforce toward the h-type. In panel (b), the wage function for the h-type shifts down slightly, meaning that they receive lower wages for a given level of productivity in the new steady state, making the wage difference between the two types at a given level of productivity smaller. From the wage functions (10) and (11), one can see that the wage difference at the same x is proportional to $U_h - U_l$. Because U_h declines by more as a direct effect of higher δ, the wage difference gets smaller.

But a more important effect on the difference in average wages is that there is a larger mass of "low-quality" h-type matches that would have severed in the economy prior to the parameter change, which is a direct implication of the lower separation rate of this group. This composition effect lowers the average wage of the h-type workers. The increase in "low-quality" h-type matches as well as the downward shift of the wage function contributes to reducing the size of the wage loss when they do go through an unemployment spell.

The result that the wage loss gets smaller with a higher value of δ is natural, given the mechanism in the model. Farber (2017) presents some supporting evidence of this result using the CPS's Displaced Workers Survey (DWS) over 1984-2010. He presents the time series of average (weekly) earning losses of full-time displaced workers. The striking feature of the time series (see the dashed-dotted line in Figure 13 of the paper) is that the peak of

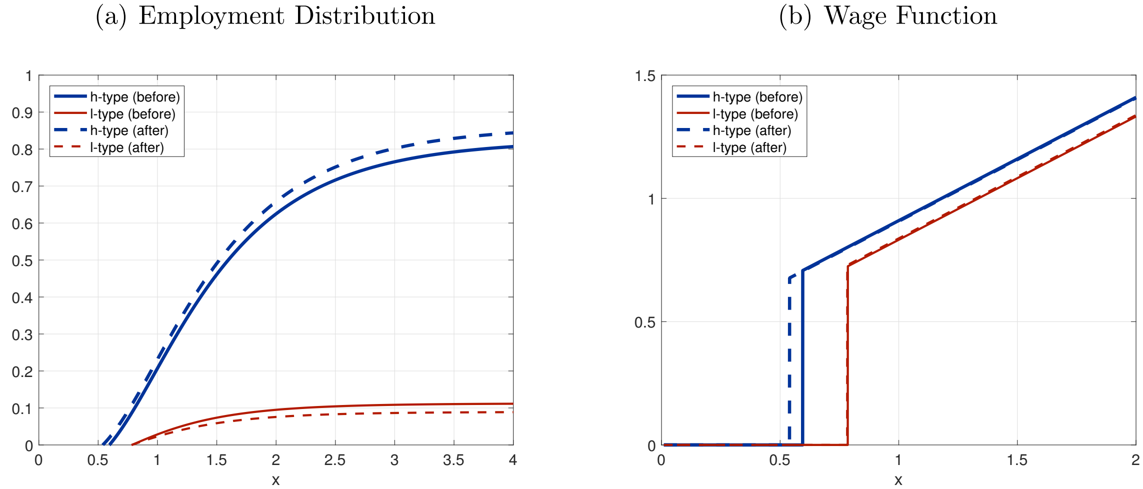
[34]Notice that these graphs indicate that h-types actually have a lower cutoff productivity, even though their mean productivity level is much higher than that of l-types, implying that there is a range of productivity levels at which an l-type worker separates, while an h-type worker stays in the match. The h-type workers in this range of productivities decide whether to wait for their wages to increase as h-type workers or to separate. While the latter choice gives them the opportunity to find a better match, it also includes the possibility of skill loss. The worker opts for the first choice. The l-type workers face no risk of downgrading their skills and thus are more likely to separate to look for a better match.

Table 4: Effects of Various Parameter Changes

		EU	UE	u	θ	p_h	$\bar{w}_h$	$\bar{w}_h$	Wage loss	ω	s_l	s_h
(1)	benchmark	0.017	0.267	0.061	0.358	0.400	1.202	1.054	-0.123	0.449	0.330	0.073
(2)	Higher δ	0.013	0.263	0.047	0.326	0.391	1.175	1.040	-0.115	0.490	0.328	0.051
(3)	Lower κ	0.013	0.325	0.038	0.435	0.514	1.274	1.098	-0.138	0.414	0.280	0.057
(4)	Higher c	0.013	0.261	0.047	0.364	0.355	1.177	1.021	-0.133	0.459	0.303	0.054
(5)	Higher τ	0.013	0.267	0.046	0.349	0.406	1.176	1.016	-0.136	0.442	0.343	0.052
(6)	Lower (b_h, b_l)	0.013	0.315	0.039	0.420	0.494	1.179	1.011	-0.142	0.419	0.291	0.057
(7)	Lower b_h	0.013	0.270	0.046	0.353	0.410	1.176	1.048	-0.109	0.441	0.340	0.053
(8)	Lower σ_x	0.013	0.267	0.046	0.365	0.378	1.155	0.995	-0.138	0.451	0.312	0.054
(9)	Lower π	0.013	0.484	0.026	0.526	1.149	1.181	1.029	-0.129	0.322	0.311	0.059

Notes: EU rate: see (20), UE rate: see (21), u: unemployment rate, θ: market tightness, p_h: see (19), $\bar{w}_h$ ($\bar{w}_l$): average wage of h-type (l-type) workers, Wage loss: average log wage difference between l-type and h-type workers, ω: see (22), s_h (s_l): job rejection rate (or separation rate conditional on receiving a shock) for h-type (l-type) workers. Parameter changes: (2) $\delta = 0.214 \to 0.245$, (3) $\kappa = 0.35 \to 0.256$, (4) $c = 1.406 \to 1.575$ (5) $\tau = 0 \to 0.035$, (6) $(b_h, b_l) = (1.014, 0.761) \to (0.912, 0.685)$, (7) $b_h = 1.014 \to 0.761.$, (8) $\sigma_x = 0.55 \to 0.513$, (9) $\pi = 0.5 \to 0.283$.

Figure 5: Effects of a Higher Skill Loss Probability



Notes: Panel (a): CDFs of h-type and l-type workers along idiosyncratic productivity levels. Solid and dashed lines, respectively, represent the distributions before and after the parameter change. Panel (b): Wage functions for the two types of workers. The vertical lines correspond to the cutoff productivities.

the average loss associated with the Great Recession is quite small and clearly smaller than those associated with the previous two recessions that were much shallower and shorter than the Great Recession. While the sample of his analysis is limited to those in the DWS and his analysis does not distinguish between occupation stayers and switchers, his results are overall consistent with the model's prediction.

Note that in the model, the smaller average wage loss for h-type workers is the same thing as a smaller average wage premium for h-type workers. In this context, Jeong et al. (2015) provide empirical evidence consistent with the prediction of the model. They show that the return to experience has been falling steadily since the mid-1980s, while the supply of experienced labor has been increasing. Although their model and thus the economic mechanism are different from the ones considered in this paper, their (model-free) empirical evidence also provides some empirical support for the paper.

5.2 Other Potential Explanations

I now study the effects of the other parameter changes. A useful reference for this purpose is a paper by Molloy et al. (2016). They provide fairly comprehensive examinations of various hypotheses in accounting for the "declining fluidity" of the U.S. labor market. I map some of their empirical considerations to the changes in the model parameters and assess their plausibilities using the model. A challenge, however, is that it is difficult to obtain empirically tight estimates for the magnitude of those parameter changes. Thus, instead of attempting to estimate the magnitude of each parameter change, I set the value of each parameter to the level that allows me to replicate the decline in the EU rate over the last four decades. I then assess how plausible each hypothesis is by looking at responses of other endogenous variables. These experiments are qualitative in nature, but still informative about which parameter change is more plausible than others.

Hiring costs, overhead, and training costs. Molloy et al. (2016) point out that hiring has become more "formal." One way to map this into a model parameter is to think of it as an increased hiring cost, which is further translated into a higher vacancy posting cost (c). Another related story is increased regulations, such as occupational licensing, discussed more extensively by Davis and Haltiwanger (2014). The increased regulations can be mapped into a higher value of c as in the previous case, but can also manifest as a higher overhead κ (if, for example, regulations take the form of a fixed operating cost of businesses). Molloy et al. (2016) further discuss the idea put forth by Caiŕo and Cajner (forthcoming) and Caiŕo (2013) that job-related training requirements have increased over time. This possibility can be easily incorporated into the model above by assuming that there is an additional training cost (which I call τ) while the worker is l-type. I set this cost τ in the initial steady state to zero and a positive value in the new steady state. The only modification to accommodate this change is to introduce another term $-\tau$ on the RHS of (6). The term $x_l - \kappa$ in the wage function for the l-type worker (11) is also replaced by $x_l - \kappa - \tau$.

A higher vacancy posting cost lowers market tightness as expected. The resulting lower meeting rate f implies that the separation rates for both types of workers, conditional on receiving the shock (s_h and s_l), drop since finding a different employer takes more time in the event they decide to separate. Average wages of both workers drop (by roughly equal proportions), keeping the average wage loss roughly the same. The switching rate increases slightly, because of the lower meeting rate f. But as discussed with respect to the main hypothesis, the lower job rejection rate s_h offsets part of this effect, because the h-type worker is now willing to accept an offer that he would have rejected before, knowing that the meeting rate is lower than before.[35]

Regarding the effect of κ, it turns out that κ needs to have *fallen* over time in order for it to be a key explanation for the lower EU rate. When production becomes more costly (a higher κ), say, due to more regulations, the match quality needs to be higher than before,

[35]Note that the lower matching efficiency parameter $\bar{m}$ has the exact same effects on all endogenous variables except for the effect on θ, because the LHS of (7) is log-linear in c and $\bar{m}$.

implying a higher rate of separation. A lower κ also stimulates job creation, thus raising market tightness and the higher overall UE rate. A higher meeting rate raises wages for both types of workers and also allows h-type workers to escape the δ shock.

Introduction of the training cost lowers the overall EU rate through a mechanism similar to the higher value of δ: it makes the h-type workers reluctant to separate while accepting lower wages, because, in the event of job loss and being reemployed as only an l-type worker, upgrading to the h-type again requires training expenses. The training expenses, under the current Nash bargaining setup, translate into lower wages for l-types, thus implying larger wage losses. The separation rate for l-types increases, because it is more costly to maintain the l-type match (the same logic as in the case of a higher κ). The effects on the UE rate and the occupation-switching rate are small.

None of these three explanations explain simultaneously the long-run behavior of the EU rate, UE rate, OS rate, and wage loss (or experience premium) as well as the δ shock does. Molloy et al. (2016) are also skeptical about these three explanations.

Lower replacement ratios. As discussed above, the effect of a higher value of δ works through the change in the outside option for the worker. In a similar spirit, we can consider the possibility that the values of b_h and b_l have fallen over time. Specifically, the values of the two parameters are lowered by the same proportion to the point where they generate the EU rate at 1.3 percent. Lower replacement ratios imply larger surplus values, lowering separation rates for both types of workers. However, it not only affects separation decisions, but it also strongly influences the job creation margin. It implies significantly higher market tightness and thus the UE rate, which is clearly counterfactual. This hypothesis does not explain the higher OS rate, either. A related possibility is to lower the value of b_h, while maintaining the level of b_l. This parameter change works even more similarly to the higher value of δ. The UE rate does not increase as much as in the previous case: the effect of a larger surplus exists but becomes quantitatively smaller, because this parameter change shifts the unemployment pool to the l-type, which lowers the firm's expected profits from creating more jobs. However, it lacks the mechanism that accounts for a higher switching rate.

A more important issue with these two stories is that the empirical evidence suggests that the flow outside option values have increased over time. Chodorow-Reich and Karabarbounis (2016) present a time series of the real value of benefits per unemployed persons since the 1960s that include both UI and non-UI (Figure 1 in their paper). It is clear from the figure that both of these components have been rising since the mid-1980s. Over the same period, real wages have grown very little (see also footnote 2) and thus unemployment benefits have increased much more than real wages.

Lower uncertainty about match-specific productivities. Molloy et al. (2016) also entertain the idea that uncertainty about worker-employer match quality has decreased over time. Within the model, this can be studied through the effect of a lower value of σ_x. Relatedly, Davis et al. (2010) show that business volatility has fallen over time. They link this empirical finding to the same parameter change in an off-the-shelf Mortensen and Pissarides (1994) model and show that it indeed has the effect of lowering the separation rate. In the current model, it also works as a mechanism to reduce labor turnover. However, this does not simultaneously account for the increases in the OS rate. Moreover, implications for wages are not necessarily consistent with the data.

Lower worker bargaining power. It may be plausible a priori to assume that worker bargaining power has fallen over time, as the passage at the beginning of the paper indicated. It turns out that in order for the model to generate a decline in the EU rate comparable to the data through this channel, worker bargaining power must have fallen quite dramatically ($0.5 \to 0.28$). Moreover, its implications for other variables are counterfactual. A higher share of surplus going to the firm implies that the firm posts more job openings and thus raises the meeting rate f quite drastically, to 0.61 (from 0.36). The UE rate also increases significantly to 0.48. The dramatically higher f also implies a much lower OS rate. Neither of these results is consistent with the data. Despite a much higher f, separation rates for both types of workers fall. A higher f has the effect of raising the separation rate, since it allows workers to find jobs more quickly. However, gains from moving to a new job are much lower now (because of lower worker bargaining power), thereby reducing separation rates.[36]

Recap. None of these alternative explanations account for the empirical pattern of the EU rate, UE rate, OS rate, and wage loss (or wage premium) as well as the explanations based on the δ shock. Of course, it is possible and even likely that various forces are at work simultaneously driving the long-run behavior of the data. However, at least through the lens of the fairly standard model, some of the explanations appear implausible: more regulations, if operating through higher overhead (κ), are likely to raise the observed EU rate or more generally labor turnover; in order for the changes in flow outside values (b_h and b_l) to be an important reason for the lower EU rate, those values must have fallen over

[36]One can think of an extreme situation where worker bargaining power is zero, and thus the wage is equal to the outside option value (independent of match-specific productivity). In this situation, the worker gains nothing by switching to a different employer, even if new match-specific productivity is expected to be much higher than with the current firm.

time; but the empirical evidence suggests the opposite pattern; lowering the value of worker bargaining power also counterfactually implies a large increase in the UE rate. Remaining ones, namely, increases in hiring and/or training costs and lower uncertainty about match-specific productivity, are all useful explanations of some of the facts, but again, do not explain simultaneously the patterns in the OS rate and the wage loss as well as the main hypothesis of the paper.

5.3 Robustness Checks

Robustness with respect to γ and μ. 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, and the upgrading probability μ is also set arbitrarily to 1/24. As robustness checks, two alternative calibrations, where the values of γ and μ are set to 1/3 and 1/36, respectively, are therefore studied. As discussed before, checking the robustness with respect to μ is especially important, given the lack of the "distance" information in the OS rate. Under each of these two cases, the entire model is recalibrated following the same procedure as in the baseline calibration. Note for the case with $\mu = 0.36$ that, since it now takes on average three years for the skill upgrading, the calibration takes a different target value for the average wage loss, which is -0.16 instead of -0.13 as presented in the second row of Table A.1) in Appendix. This directly influences the value of Δ in this alternative calibration. I repeat the same experiments under these two alternative calibrations. The results are very similar to those under the baseline calibration and therefore omitted.

Model with two matching markets. In the model, it is assumed that there is a single matching market where both types look for jobs and the firms meet with the different types of workers randomly. But it might also be plausible to assume that firms create two different types of jobs, h-type and l-type jobs. In this case, the job creation condition holds for each job type. The modification of the model is straightforward and presented in Appendix A.5. I calibrate this model such that, in the initial steady state, allocation of the economy is identical to one in the baseline model.[37] To examine the effects of various parameter changes, I follow the same procedure as in the baseline model. The results in this modified model are very similar to those in the baseline model. Calibrated parameter values and all the results are presented in Appendix A.5.

[37] There are two market tightness measures in the modified model, but the model is calibrated such that market tightness is the same between the two markets in the initial steady state. This can be easily achieved by selecting the two vacancy posting costs accordingly. All other parameter values remain the same as in the baseline model.

6 Discussion and Conclusion

This paper has argued that a more turbulent environment can be an important source of declining labor turnover. The main mechanism in the model is that workers face a higher risk of skill loss and thus accept a lower wage in exchange for job security. I also examined various other possibilities within the model and showed that none of a priori seemingly plausible stories such as more regulations and lower worker bargaining power simultaneously generate the long-run patterns of data.

An important limitation of the paper is the reduced-form nature of the turbulence parameter δ. A legitimate question is, "What does the 'turbulence' parameter represent?" As noted before, Ljungqvist and Sargent (1998) introduced this modeling device without explicitly specifying its deeper causes in their model. They mention restructuring from manufacturing to the service industry, the adoption of new information technologies, and international competition as major sources of turbulence.[38] Friedman (2007) and Greenspan (2008) include ample anecdotal evidence in line with this interpretation. For example, Greenspan (2008) writes:

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

A more structural model of turbulence can be found in the job polarization literature (see, for example, Acemoglu and Autor (2011), Autor and Dorn (2013), and references therein). An important phenomenon emphasized in the literature is the secular decline in demand for middle-skilled workers. This literature also identifies similar factors as mentioned above as contributing to the phenomenon (see, for example, Autor (2010)).[39] With respect to this interpretation of the δ shock, there are features of the model that merit further discussions. In the model, h-type workers are subject to the δ shock only when they are jobless. Within this environment, the workers and firms respond endogenously to the change and the equilibrium outcome entails lower separation rates (and thus higher employment and lower unemployment) and lower wages. However, one may suppose that underlying

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

[39]There are many ways in which such underlying forces manifest in firms' employment decisions. For example, Deming and Kahn (forthcoming) discuss the changes in skill requirements for new hires. From an already-employed worker's perspective, the changes in skill requirements would mean fewer outside options and thus is likely to work in a way similar to the higher value of δ.

forces, such as technological advances that replace middle-skilled jobs or result in offshoring of those jobs, would increase rates of job loss *regardless of* workers' willingness to accept lower wages.[40] This line of thinking, however, makes it even more challenging to explain the declining trend of the EU rate (since it presumes the presence of an unobserved upward trend in the exogenous job destruction rate). The model studied in this paper is a model of worker flows and thus is not suitable to studying the changing "job" composition. Jaimovich and Siu (2012) develop a parsimonious search/matching model with job heterogeneities where the job-switching decision is endogenous, although their research interest is different. A further extension in this direction is a fruitful avenue for future research.

Relatedly, the reduced-form nature of the δ shock poses a challenge in that it is difficult to use the model to predict the future course of the separation rate. In the model, the parameter is linked to the OS rate in the data. However, as discussed earlier, the mapping is admittedly arbitrary. In the model, a further increase in this parameter implies an even lower separation rate, but this cannot be true globally. A more structural modeling of this parameter is therefore requisite to forecast long-run trends in the job separation rate.

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[40]Molloy et al. (2016) in fact find that declines in labor turnover are smaller in states with larger initial shares of workers in routine occupations.

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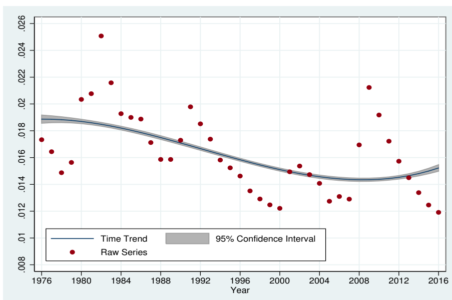
A Appendix

A.1 Trends in the Male-Only Sample

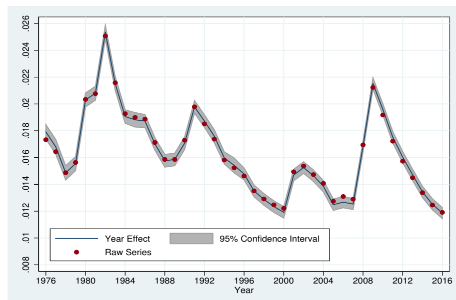
Figure A.1 shows the results within the sample of male workers. The trend line in the EU rate fell from 1.9 percent in the beginning of the sample to 1.5 percent at the end after reaching the bottom (1.4 percent) in 2008. The magnitude of the decline (log difference) is somewhat larger in this sample than in the full sample. The trend in the UE rate is also similar to the one in the overall sample. The overall level of the OS rate is a few percentage points higher in this sample, but the trend is roughly parallel to the full-sample trend.

Figure A.1: EU, UE, and OS Rates, Male Only

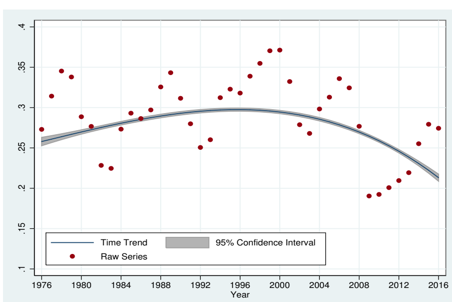
(a) EU (Time Trend)



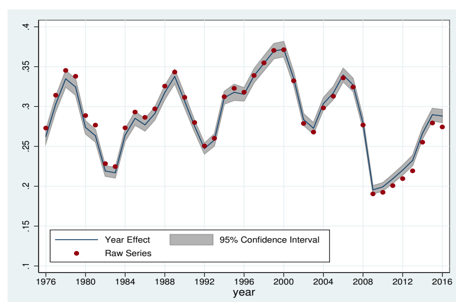
(b) EU (Year Effect)



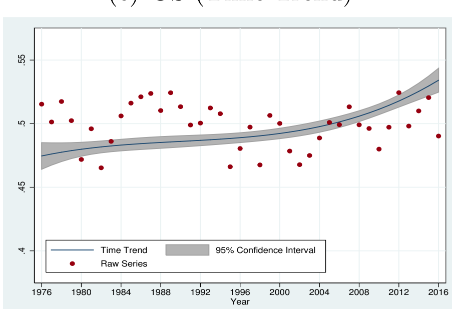
(c) UE (Time Trend)



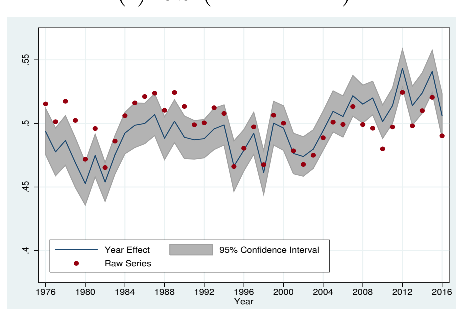
(d) UE (Year Effect)



(e) OS (Time Trend)



(f) OS (Year Effect)

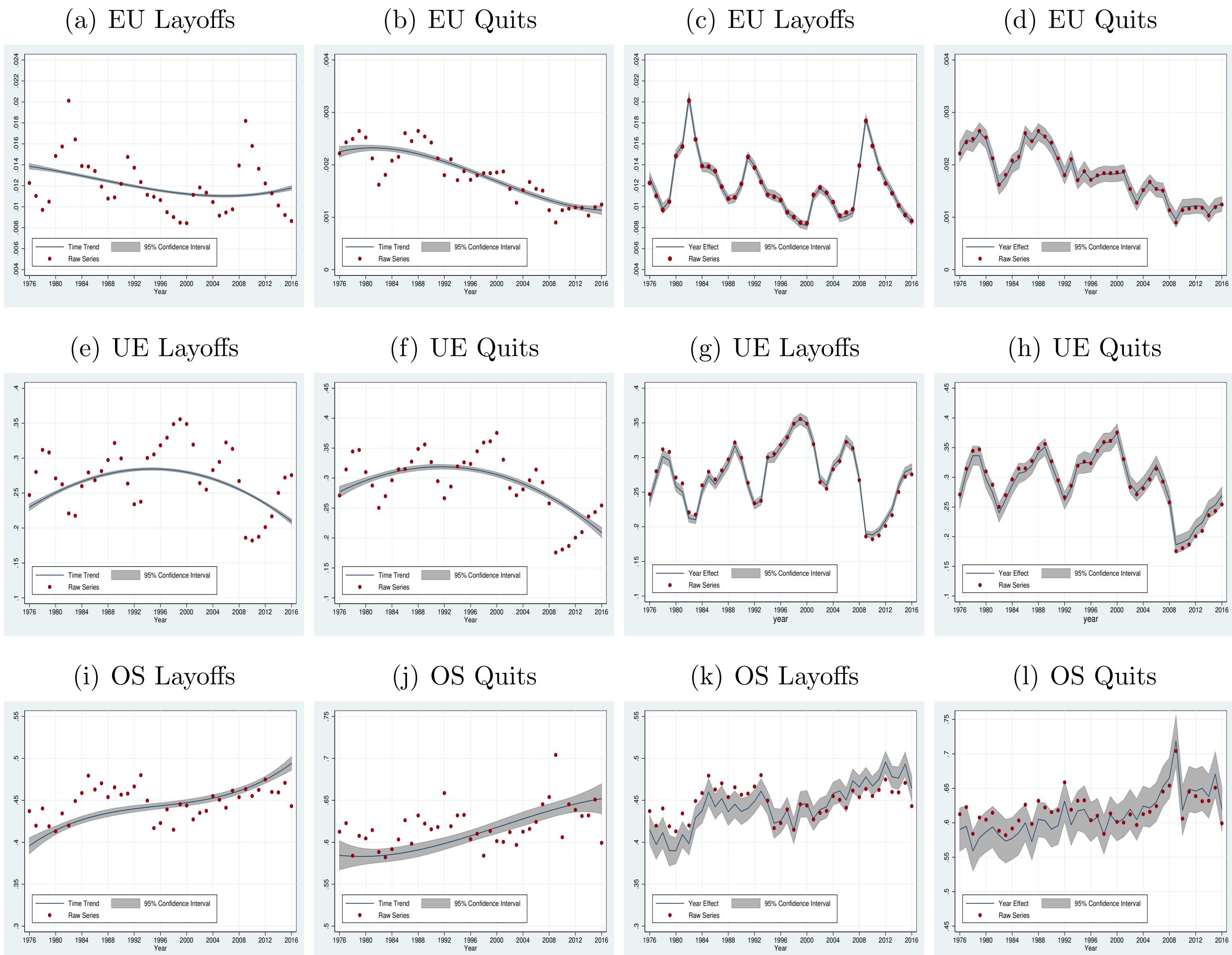


Source: CPS micro data

A.2 Trends by Reason for Unemployment

Here I repeat the same empirical analysis by splitting the sample into two groups, layoffs and quits. This analysis provides one validation of the mechanism emphasized in this paper. In particular, the interpretation of the model exercises is more intuitively applicable to job leavers, although there is no conceptual distinction in the model between quits and layoffs given that all separations occur as a jointly efficient outcome.

Figure A.2: EU, UE, and OS Rates by Reason for Unemployment



(a) EU Layoffs (b) EU Quits (c) EU Layoffs (d) EU Quits

(e) UE Layoffs (f) UE Quits (g) UE Layoffs (h) UE Quits

(i) OS Layoffs (j) OS Quits (k) OS Layoffs (l) OS Quits

Source: CPS micro data.

The CPS asks all unemployed workers the reason for their unemployment, and one of the categories is quit. I split the full sample into job leavers and layoffs (which include both permanent job losers and temporary layoffs).[A.1]

[A.1]For EU rates, I take all employed workers and separately estimate the linear probability model of layoffs

The first row of Figure A.2 presents the results for EU rates. Note first that EU transitions due to quits are a small share of overall EU transitions (the full sample average is around 0.15 percent per month). However, the downward trend is particularly striking; the downward trend in the EU rate due to layoffs is smaller but still noticeable. In the second row, one can see that UE rates for both groups exhibit a similar hump-shaped pattern, but the downward trend for separations due to quits is more pronounced. OS rates for both job leavers and job losers exhibit similar upward trends.

A.3 Computing the Steady-State Equilibrium

I solve for the steady-state equilibrium of the model as follows. To simplify the notation, let me define the expected surplus as $\mathbb{E}S_i(x_i') \equiv \int_{\underline{x}_i}^{\infty} S_i(x_i')dG_i(x_i')$ for $i = \{h, i\}$. The evolution of the surplus for the h-type match is written as:

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

Evaluating (A.1) at $\underline{x}_h$ and subtracting that from (A.1), one obtains $S_h(x_h) = \frac{x_h - \underline{x}_h}{1-\beta(1-\gamma)}$. Similar algebras for the l-type match yield $S_l(x_l) = \frac{x_l - \underline{x}_l}{1-\beta(1-\mu)(1-\gamma)}$. Note also that the difference between U_h and U_l can also be expressed as

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

The separation conditions

$$S(\underline{x}_h) = 0 \text{ and } S(\underline{x}_l) = 0 \tag{A.2}$$

can be expressed as a function of $\underline{x}_h$, $\underline{x}_l$, and θ. The free-entry condition (7) can also be rewritten as:

$$\frac{c}{\beta q(\theta)} = (1-\pi)\Big[(1-\delta)p_h\mathbb{E}S_h(x_h') + \big\{1-(1-\delta)p_h\big\}\mathbb{E}S_l(x_l')\Big]. \tag{A.3}$$

Lastly, the stock-flow balance equations imply:

$$p_h = \frac{f(\theta)(1-G(\underline{x}_l))}{(1-\delta)f(\theta)(1-G(\underline{x}_l)) + \delta\big(1 + \frac{1-\mu}{\mu}\gamma G(\underline{x}_l)\big)}. \tag{A.4}$$

into unemployment and quits into unemployment. Thus, the sum of the two probabilities corresponds to the overall EU rate presented in the main text. For UE rates, the sample includes either job leavers or job losers (layoffs), and thus the overall UE rate is a weighted average of the two series. Similarly for the OS rate, the sample includes either job leavers who made UE transitions or job losers who made UE transitions.

The steady-state equilibrium is defined by θ, $\underline{x}_l$, $\underline{x}_h$, and p_h that solve (A.2), (A.3), and (A.4). I solve the nonlinear system numerically, and all integrals associated with the truncated log-normal distributions are calculated by Simpson's rule (as the distributions are truncated by the cutoff productivities).

A.4 Computing Wage Loss After Unemployment

In calibrating, I compute wage changes of those who switched occupations after an unemployment spell, using the information available from the SIPP. Unlike the CPS, SIPP is a panel, which allows me to observe the wages of individual workers before and after an unemployment spell. First, I gather a sample of $EU...UE$ spells (where each letter represents a worker's monthly labor market status, with E being employment and U being unemployment).[A.2]

I collect the information on nominal hourly wages, deflated by the PCE price index, that are associated with employment at the beginning and the end of the $EU...UE$ spell, unemployment duration, and workers' demographic characteristics, occupations before and after unemployment, and occupation tenure prior to the job loss. The question on occupation tenure is asked only in the first interview, but with this information, one can extend the tenure information.[A.3] Note also that I construct the same major occupation classifications used in the CPS analysis. The occupational tenure variable allows me to gauge the effect of occupational experience on wage changes.

Several sample selection criteria are imposed. First, I focus on individuals with nonzero longitudinal weights. These weights are meant to be used for longitudinal analysis. Focusing on these individuals in the analysis minimizes the effect of attrition. Second, the spells in which a transition from E to U that occurs in the last year of each panel are excluded from the analysis. These cases are necessarily skewed toward the cases with short unemployment duration because the entire $EU...UE$ event occurs within a year.[A.4] Third, I consider only the individual's first $EU...UE$ event within the panel. In other words, if an individual experiences two or more such events within the panel, the worker is not part of the sample. Fujita and Moscarini (2017) provide detailed analysis on the various measurement issues in the SIPP, such as the consistency of the definitions of the labor market status between the CPS and the SIPP. That paper also provides the overall description of the SIPP data.

I run a regression in which a log real wage difference between the two jobs is regressed on

[A.2] The monthly labor market status is determined from the status in the second week in each month so that it is roughly consistent with the timing used in the CPS.

[A.3] I would like to thank Jose Mustre-del-Rio of the Kansas City Fed for assistance on the occupation tenure variable in the SIPP.

[A.4] Including these cases does not materially change the regression results, however.

Table A.1: Wage Difference Before and After Unemployment

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

Notes: Source, 1996, 2001, 2004, and 2008 SIPP Panels. Demographic controls (age and gender) are also included in the regression. ** (*) indicates statistical significance at 1 (5)% level.

demographic controls (age and gender), unemployment duration, and the interaction terms between the occupation switch dummy and the "experience" dummy. The latter variable takes a value of 1 when a worker has an occupation tenure of longer than some cutoff and 0 otherwise. Recall that, in the model, it takes on average two years to become an "experienced" worker, and thus a cutoff of two years is in line with the model calibration. I also consider the cutoff of three years. Note that the unemployment duration variable is included in the regression to control for the features of the data that are not present in the model.

Table A.1 presents the regression result. The three columns, respectively, give the marginal effects of cases in which (i) occupational tenure was shorter than the cutoff and the worker switched to a different occupation after unemployment; (ii) tenure was longer than the cutoff, but the worker stayed in the same occupation; and (iii) tenure was longer than two years and the worker changed the occupation. The coefficients give the effect of each of the three cases relative to the base case in which the worker had a short occupation tenure and stayed in the same occupation. The top portion of Table A.1 presents the regression result that uses the cutoff of two years. The unconditional mean in the base case is −0.001, which is practically zero. Note that the results in the first two columns indicate that neither a short tenure nor switching occupations before accumulating experience leads to a statistically significant wage loss. The most striking result is given in the third column: When a worker with a longer occupation tenure changes his occupation after unemployment, it leads to a large and statistically significant decline (roughly 13 percent) in real wages. The calibration of the model takes this number as the target.[A.5]

Note that in the context of the model, the case (ii) corresponds to the situation in the model in which an h-type worker who lost his job avoids the δ shock. The case (iii)

[A.5] As mentioned earlier, the occupation tenure variable is not available before the 1996 panel. Thus, I simply take the result in Table A.1 as the cross-sectional evidence for the calibration of the initial steady state.

is obviously associated with the situation in which an h-type worker loses his skill and is reemployed as only an l-type worker. The remaining two cases (the base case and the case (i)) correspond to the l-type worker's transitions between employment and unemployment in the model. In this case, as in the empirical result, wages before and after an unemployment spell are on average the same. As emphasized in the main text, there is no explicit notion of occupations in the model. However, the model is structured to capture parsimoniously the empirical pattern in Table A.1 by way of featuring two types of workers labeled as the h-type (experienced) and the l-type (inexperienced) workers.

The fourth column indicates that unemployment duration itself has a statistically significant negative impact on wage changes. In the model, the only reason for a positive correlation between unemployment duration and the size of the wage loss is that longer duration implies a higher chance of being hit by the δ shock. In this sense, the model is not able to capture the empirical result that duration has an independent negative impact on wage changes.

The bottom part of Table A.1 presents the results when an alternative cutoff (three years) for the experienced worker is used. Relative to the previous result, the wage loss increases for those who changed occupations after accumulating more than three years of experience in the same occupation. One difference is that the wage loss of the experienced workers who did not change occupations becomes statistically significant. However, overall results remain similar.

A.5 Model with Two Types of Jobs

The baseline model assumes that there are two types of workers, but there is only one ex-ante identical job type. In this section, I present a simple modification of the model where there are two types of jobs and each type can hire workers of the same type. This modification implies that there are two separate matching markets for each type of job and workers participate in the matching market for their type while looking for a job. Let $f_i(\theta_i)$ and $q_i(\theta_i)$ be worker and firm meeting rates, respectively, in the i-type matching market. Value functions (1) through (6) remain the same after replacing $f(\theta)$ with either $f_h(\theta_h)$ or $f_l(\theta_l)$ accordingly. The single free-entry condition is replaced by the following two free-entry conditions:

$$\frac{c_h}{\beta q_h(\theta_h)} = (1-\pi)(1-\delta)\int_{\underline{x}_h}^{\infty} S_h(x'_h)dG_h(x'_h),$$
$$\frac{c_l}{\beta q_l(\theta_l)} = (1-\pi)\int_{\underline{x}_l}^{\infty} S_l(x'_l)dG_l(x'_l),$$

where I allow for different vacancy posting costs in the two markets (c_h and c_l). The same separation condition $S_i(\underline{x}_i) = 0$ applies to each match type. Laws of motion of labor market stocks also remain the same, except that $f(\theta)$ is replaced by either $f_h(\theta_h)$ or $f_l(\theta_l)$ accordingly.

I calibrate the initial steady state of this modified version of the model, such that all endogenous variables take the same values as those in the baseline model. This can be easily done by setting $f_l = f_h = 0.36$ and $q_l = q_h = 0.9$, where 0.36 and 0.9 are, respectively, the initial steady state values of f and q in the baseline model. I can choose c_h and c_l to achieve these conditions, while keeping all other parameters at the same values as before.[A.6] To see the effects of the parameter changes, I follow the same procedures as those used for the baseline model: I first raise δ to a value that matches the increase in the OS rate.[A.7] This change results in a decline in the EU rate of roughly the same magnitude as in the baseline model. For the remaining parameters, I set the values to the levels that generate the same decline in the EU rate. For the increases in the hiring costs c_h and c_l, I raise them by the same proportion.

All results and associated parameter changes are summarized in Table A.2. One can see that the numbers in the first row take exactly the same values as before and the results of all comparative statics are very similar to those in the baseline model with a single matching market.

[A.6] There are two matching efficiency terms in the two CRS matching functions, and they are set equal to each other and to the value used for the calibration of the baseline model.

[A.7] Of course, the value of δ to achieve this does not need to be the same as in the baseline model. It is indeed only slightly different from it.

Table A.2: Effects of Various Parameter Changes (Two Separate Matching Markets)

		EU	UE	u	p_h	θ_l	θ_h	$\bar{w}_h$	$\bar{w}_h$	Wage loss	ω	s_l	s_h
(1)	benchmark	0.017	0.267	0.061	0.358	0.400	0.400	1.202	1.054	−0.123	0.449	0.330	0.073
(2)	Higher δ	0.013	0.264	0.047	0.319	0.403	0.397	1.188	1.062	−0.106	0.496	0.332	0.052
(3)	Lower κ	0.013	0.296	0.042	0.403	0.435	0.452	1.247	1.088	−0.127	0.434	0.295	0.056
(4)	Higher c_h, c_l	0.013	0.261	0.047	0.365	0.357	0.356	1.189	1.039	−0.126	0.458	0.304	0.054
(5)	Higher τ	0.013	0.272	0.045	0.353	0.441	0.393	1.189	1.025	−0.138	0.432	0.335	0.053
(6)	Lower b_h, b_l	0.013	0.294	0.042	0.398	0.435	0.446	1.191	1.035	−0.130	0.434	0.299	0.056
(7)	Lower b_h	0.013	0.274	0.045	0.357	0.440	0.397	1.189	1.061	−0.108	0.433	0.332	0.054
(8)	Lower σ_x	0.013	0.268	0.046	0.366	0.389	0.370	1.169	1.012	−0.135	0.448	0.308	0.055
(9)	Lower π	0.013	0.378	0.033	0.458	0.721	0.720	1.184	1.032	−0.128	0.374	0.308	0.057

Notes: See notes to Table 4. Parameter changes: (2) $\delta = 0.214 \to 0.252$, (3) $\kappa = 0.35 \to 0.294$, (4) $(c_h, c_l) = (1.96, 0.980) \to (2.178, 1.088)$ (5) $\tau = 0 \to 0.038$, (6) $(b_h, b_l) = (1.014, 0.761) \to (0.948, 0.711)$, (7) $b_h = 1.014 \to 0.852.$, (8) $\sigma_x = 0.55 \to 0.517$, (9) $\pi = 0.5 \to 0.355$.