Abstract

During economic downturns, labor markets are characterized not only by a higher unemployment rate and by lower transitions from unemployment to employment, but also by a reduction in the transitions from job to job. In this paper I propose a new mechanism to explain the reduction in job-to-job flows. I argue that when workers start a new job, the risk of separation is initially higher. Therefore, in a recession, workers are more reluctant to leave their existing jobs because they know that if they end up separating early from their new jobs, they would face longer unemployment spells. Using data from the Survey of Income and Program Participation (SIPP), I show that hazard rates of separation are initially high after a job-to-job transition. I then extend the job ladder model of Burdett and Mortensen (1998) to introduce the risk of early match dissolution and capture the mechanism described above. I estimate the model using U.S. data and find that workers’ reluctance to move generates a drop in the transition rate of 10 percentage points in a recession of the size of the Great Recession. Moreover, this mechanism generates a decrease in productivity of about 1 percent.

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1 Introduction

Recessions are times of deteriorating labor market conditions. Besides the spike in unemployment, recessions also bring about a dramatic slow-down in the flow of workers that move across different employers. For example, data from the Current Population Survey (CPS) reveal that the Employer-to-Employer transition rate decreased by about 46% during the Great Recession of 2007-2009. Employer-to-Employer flows are an important source of labor reallocation across firms: on average, they represent more than one third of total monthly hiring, and they are almost twice as large as total hiring of workers coming from unemployment. Foster, Haltiwanger, and Krizan (2000) show that the process of reallocation of labor and capital across establishments explains about one half of the total TFP growth in U.S. manufacturing during 1977-1987. Therefore, the decrease in job-to-job flows has important effects on aggregate productivity because it slows down the process of reallocation of workers across firms.

In this paper, I explore a mechanism that can contribute to explaining the reduction in job-to-job transition rates observed during recessions. This mechanism is based on workers’ unwillingness to move on-the-job. A worker may be more reluctant to start a new job with a different employer during a recession compared to normal times, since it can be risky for workers to “experiment” with new careers when the labor market is in turmoil. The match with a new employer can turn out to be poor and end up in a separation, and this outcome can be particularly costly during times of high unemployment, such as recessions, when it is more difficult to find a new job.

In order to provide empirical evidence for this mechanism, I document that the choice of making a job-to-job transition is indeed ex ante risky. By using worker-level data from the Survey of Income and Program Participation (SIPP), I estimate the hazard rates of separation for jobs originating after job-to-job transitions. Such hazard rates are particularly high in the first twelve months after the formation of a new match, and then they sharply decline. Moreover, these hazard rates are very similar to those obtained by considering new jobs of workers who come from unemployment. This previously undocumented empirical fact indicates the presence of a sizable risk of separation following job-to-job transitions.

In light of this new evidence, I introduce the risk of early match dissolution in the job-ladder model of Burdett and Mortensen (1998). In this model, a decrease in the job-finding rate of employed and unemployed workers during a recession causes a decline in job-to-job transitions because workers have fewer chances to move to other firms. Introducing a risk of early match dissolution generates an amplification mechanism based
on a labor supply channel: when job-finding rates are low, an employed worker is less likely to accept offers from poaching firms, and this effect magnifies the decline in workers’ transitions. I estimate the model through Simulated Method of Moments (SMM) and find that workers’ reluctance to move is indeed quantitatively important, as it can generate a drop in the job-to-job transition rate of 10% in a recession of the Great Recession’s size. Accordingly, this mechanism has important effects on aggregate productivity, as it inhibits the reallocation of workers from low to high productivity firms.

In the canonical model of Burdett and Mortensen (1998), firms with different productivity compete with each other in attracting workers, who can search both while unemployed and on-the-job. Firms post wage offers knowing that a higher wage increases the probability of hiring new workers and retaining existing ones, but it decreases the profit per worker. In equilibrium, employers with higher productivity offer a higher wage and have a larger workforce; at the same time, workers move from less productive to more productive firms, attracted by the wage differentials. Due to the presence of exogenous job destruction and search frictions, the steady state equilibrium is characterized by a process of reallocation of workers between employment and unemployment, and across firms of different productivities. In this framework, a worker who is offered a wage slightly higher than the wage paid by the current firm will always move to the new firm.

I introduce ex ante risk into this framework by letting match quality depend on the outcome of a match-specific stochastic shock. A bad realization of this shock results in the dissolution of the match right after its formation, and in this case, the worker becomes unemployed. As a consequence, in equilibrium, employed workers are no longer willing to accept all offers higher than the current wage, but only offers that are higher than a given endogenous reservation wage. Intuitively, workers who move to a new firm need a wage that is sufficiently high to compensate them for the risk of unemployment, in case the new match is not successful. The reservation wage for the employed is affected by business cycle conditions, in particular by the job-finding rate: when it is harder for unemployed workers to find a job, as during a recession, the reservation wage of employed workers increases, hence they become more reluctant to quit, and the job-to-job transition rate declines.

I measure the quantitative importance of this mechanism by calibrating and estimating the model via SMM using monthly data on the U.S. economy. In the model, the resolution of uncertainty about match quality occurs right after match formation, whereas the empirical analysis on SIPP data shows that learning happens gradually over time. However, the estimated hazard rates indicate that the risk of separation for workers who move on-the-job is mostly concentrated in the first twelve months of tenure, and then
it declines sharply. I calibrate the ex ante risk of new matches to capture the estimated risk of separation within the first year of tenure. In particular, I consider two calibration approaches: one based on matching the empirical risk of separation observed in the first eight months of tenure; and one based on matching the risk of separation in the first twelve months. I numerically solve for the equilibrium steady state of the model in order to simulate the conditions of the U.S. economy in May 2007, when the unemployment rate was at its lowest level before the recession. I then simulate the effects of the Great Recession by generating drops in aggregate productivity and in the job-matching probabilities, which are as large as those observed during the period May 2007-October 2009.

In my model, there are two mechanisms that deliver lower job-to-job transitions during recessions. The first is the new mechanism that I introduce, which operates through labor supply. The second is the drop in the matching probabilities for employed workers, which can result from a decrease in labor demand. The latter mechanism has been analyzed in Barlevy (2002): when aggregate productivity declines, firms can generate less surplus through the formation of new matches. As a consequence, labor demand declines, firms post fewer vacancies, and workers searching on-the-job have fewer chances to move to new firms. The main objective of my empirical estimation is to assess the effects on workers’ reallocation of both the demand-side mechanism emphasized by the literature, and the new, supply-based mechanism proposed in this paper.

The first step in my empirical analysis is to consider a calibration of the model in which the risk of separation after a new match formation matches the estimated cumulative hazard in the first eight months of tenure. I find that the increase in employed workers’ reservation wages generates a drop in the employer-to-employer transition rate by 8.5%, while the decrease in matching probability generates a 40% decline. Then, I consider the alternative calibration approach in which the risk of separation matches the cumulative hazard of the first twelve months. In this case, workers’ reluctance to move during the recession generates a drop in the job-to-job transition rate by 10%. Hence, the mechanism operating through labor supply accounts for about 20% of the overall decline in the job-to-job transitions generated by the model.

Finally, I quantify the effects of the supply-based mechanism on productivity through lower workers’ reallocation. I find that the increase in employed workers’ reservation wages during the recession generates a productivity loss of about 1%. Productivity declines because workers do not reallocate from smaller, less productive firms to larger, more productive ones. Due to workers’ reluctance to move, firms would need to offer higher wages to compensate for the risk related to a job-to-job transition. However,
during a recession, many employers are forced to either reduce their wage or keep it constant to make non-negative profits. As a result, they can attract fewer workers from less productive firms. This result is consistent with the empirical evidence presented in Moscarini and Postel-Vinay (2014), who show that there has been a sharp decline in job-to-job transitions from small to large firms during the last recession.

Related Literature

The paper contributes to the theoretical and empirical literature on employment dynamics in general equilibrium. I build upon the framework developed in Burdett and Mortensen (1998) and extend it to incorporate the risk of early dissolution in new match formation. The novel insight of my model is that employed workers’ propensity to move on-the-job is contingent on the state of the labor market, and in particular it decreases when it is hard for unemployed workers to find a new job. The empirical estimation points out that my proposed mechanism is quantitatively important, and it complements the traditionally emphasized labor demand channel in explaining the decline of the employer-to-employer transition rate during recessions. As discussed in the introduction, my work is also related to Barlevy (2002), who shows that lower reallocation of workers, due to firms’ lower demand, has negative effects on aggregate productivity. Differently from his model, I evaluate the effects of workers’ unwillingness to reallocate during recessions, and quantify the effects on productivity. More recently, Gertler, Huckfeldt, and Trigari (2014) introduce endogenous search intensity of employed workers in a random search model. During recessions, employed workers exert less search effort, and job-to-job transitions decline. Their paper is related to mine, in that it also focuses on a supply-based mechanism. Their proposed mechanism does not conflict with the main mechanism of my model but rather complements it. Moreover, differently from Gertler, Huckfeldt, and Trigari (2014), I incorporate heterogeneity in firm productivity. This allows me to match the empirical relationship between firm size and workforce distributions observed in U.S. data, and to characterize the reallocation of workers across different firm size classes.

In my model, I explicitly capture the uncertainty about new match formation by introducing the risk of separation at the beginning of a new match. Other papers, such as Moscarini (2005), have introduced learning about match quality in random-search, general equilibrium models. In Moscarini (2005), imperfect information about match quality determines an equilibrium wage density that is consistent with the main features of empirical wage distributions. Unlike this paper, my focus is on understanding how
the uncertainty about new matches affects the propensity of workers to move on-the-job during recessions and on quantifying the effects of this mechanism on reallocation and productivity.

On the empirical side, this paper is related to Moscarini (2003) and Pries (2004). By using CPS Tenure Supplement data, the authors estimate the hazard rate function of U.S. workers and show that it is high at the beginning of the employment relationship, and then it declines with tenure. Their analysis includes both jobs of workers who have directly moved from another employer, and jobs of workers who have been hired while unemployed. One of the contributions of my paper is the estimation of hazard rates of separation for workers who move on the job. I show that these hazard rates are very similar to those of workers who are hired from unemployment. These findings provide empirical support for the main mechanism of my model, which hinges on the presence of a sizable risk of early match dissolution associated with job-to-job transitions.

Finally, as mentioned in the Introduction, the paper relates to the recent findings presented in Moscarini and Postel-Vinay (2014). By using newly available data on gross worker flows by establishment size from the Job Openings and Labor Turnover Survey (JOLTS), the authors show that, during the Great Recession, there was a sharp decline in the flow of workers moving from small to large employers. Consistent with these findings, in my model, the increase in workers’ reluctance to move on-the-job during recessions prevents workers from moving from smaller, less productive firms to larger, more productive firms.

**Layout** The paper is organized as follows. Section 2.1 illustrates the empirical facts about workers’ reallocation during recessions, while Section 2.2 reports the results of the estimation of the hazard rates of separation from SIPP data. The theoretical model is presented in Section 3. In Section 4, I estimate the model and assess the effects on reallocation and productivity of workers’ reluctance to move on-the-job during recessions. Section 5 concludes.

## 2 Empirical Evidence

### 2.1 Labor Marker Dynamics

Figure 2.1 shows the Employer-to-Employer transition rate, estimated by Fallick and Fleischman (2004) from monthly gross worker flows in CPS data, from September 1995 to July 2014. Figure 2.1 also reports the monthly civilian unemployment rate from the Bureau of Labor Statistics (BLS) for the same time period. As the graph clearly shows,
Employer-to-Employer transition rates are negatively correlated with the unemployment rate. Declines in Employer-to-Employer rate are concentrated around recessions: in particular, during the Great Recession, the rate dramatically decreased, going down by 46% from May 2007 to October 2009, the months with the lowest and the highest level of unemployment around the Great Recession. The drop in job-to-job transitions is also reflected in the decline of workers’ voluntary quits: Figure 2.1 shows that the monthly quits rate of nonfarm workers sharply declines in recessions, and in particular, it fell by almost 40% during the last recession.

As discussed in the Introduction, the literature has traditionally explained these dynamics through mechanisms based on labor demand, as in Barlevy (2002): with lower productivity, firms post less vacancies, hence aggregate labor demand declines and workers have fewer opportunities to move on the job. However, the observed freeze in quits may also reflect the unwillingness of workers to leave their current job during recessions. This hypothesis has recently been formulated, amongst others, by the Federal Reserve Chair, Janet Yellen, in her March 31, 2014 speech, while commenting on the state of labor markets:

“[...] the number of people who voluntarily quit their jobs is noticeably below levels before the recession; that is an indicator that people are reluctant to risk leaving their jobs because they worry that it will be hard to find another. It is also a sign that firms may not be recruiting very aggressively to hire workers away from their competitors. [...]”

Concerns about workers’ reluctance to quit their current job during a recession are also expressed by employers who are hiring. For example, as reported by the Wall Street Journal, the president of the recruiting firm, Jobplex, has recently declared that young workers are becoming more cautious about job transitions in the aftermath of the Great Recession compared to the past, and that it has become harder for employers to poach workers away from other firms, even with offers of a higher salary.

In this paper, I explicitly model this mechanism: the model presented in Section 3 captures the higher reluctance of workers to start a new career with a different employer during a recession, compared to normal times. In the model, even if offered higher wages by poaching firms, workers are more cautious during recessions because the match with a new employer can end up in a separation, which would force workers to look for another job when it is harder to find it.

Figure 1: Unemployment Rate (percentage points, right axis) from BLS, and Employer-to-Employer Transition Rate (percentage points, left axis) from CPS. Shaded Areas: NBER Recessions

Figure 2: Quits Rate - Total Nonfarm, from JOLTS. Shaded Areas: NBER Recessions
2.2 Hazard Rates Estimation: SIPP Data

In order to provide empirical support for the mechanism described in the previous subsection, I estimate the hazard rates of separation for workers who move on-the-job by using SIPP data. I find that there is indeed a sizable risk of early separation for U.S. workers who quit their current job to form a match with a new employer.

The Survey of Income and Program Participation is a household-based statistical survey conducted by the United States Census Bureau. The Survey contains several panels, reporting a nationally representative sample of individuals that are interviewed over a multi-year period. Each panel lasts from 2.5 to 4 years, containing 14,000 to 37,000 households. Within each panel, households are interviewed every four months (an interval of time defined as “wave”), and in each interview, they provide detailed information about the employment history of every household member during the previous four months. Hence, it is possible to obtain the employment history of each individual in the sample for at most 48 months. Moreover, the dataset allows me to distinguish hires that result from employer-to-employer transitions from hires of workers who come from unemployment.

Other datasets, such as the Panel Survey of Income Dynamics (PSID), provide information about workers’ employment histories. Compared to the PSID, the SIPP data contains a much larger sample size. Moreover, it tracks workers’ labor market conditions at a higher frequency, which allows me to better identify hires from unemployment and hires from employment. As a result, SIPP data provides more accurate information for the estimation of the hazard rates of separation for the two groups of hires.

For each panel of workers, respondents are asked to report at most two jobs held during the previous four months. If a respondent has more than one job in a given month, she is asked to specify which one is the primary job. For the empirical analysis performed in this section, I focus on primary jobs. Then, for each worker’s history, I calculate the duration in months of each reported job and separate jobs in two groups: 1) jobs originating from employer-to-employer transitions, occurring when there is no unemployment time between the end of the old job and the beginning of the new one; 2) jobs originating from hires of unemployed workers, occurring when the worker experiences unemployment between the old and the new job.

Finally, for each of the two groups of jobs, I estimate

\[ \text{2In the empirical analysis, I use the CEPR SIPP Uniform Extracts. These extracts combine variables from the SIPP Core, Topical, and Longitudinal files and convert the data in a “person-month” panel format, such that each SIPP respondent has a unique identification variable, and for each person-month in the panel there are no repeated observations.}

\[ \text{3An additional useful information contained in the dataset is the reason for the termination of a given job. I am interested in estimating the hazard rates of jobs that result from voluntary job-to-job transitions,}

\]
## Table 1: Monthly Cumulative Hazard Rates of Separations and Confidence Interval for E-to-E jobs, from SIPP 2004 Panel

<table>
<thead>
<tr>
<th>Month</th>
<th>Cum. Haz.</th>
<th>95% C.I.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0314</td>
<td>[0.0266, 0.0369]</td>
</tr>
<tr>
<td>2</td>
<td>0.0713</td>
<td>[0.0638, 0.0797]</td>
</tr>
<tr>
<td>3</td>
<td>0.1155</td>
<td>[0.1056, 0.1263]</td>
</tr>
<tr>
<td>4</td>
<td>0.1647</td>
<td>[0.1525, 0.1779]</td>
</tr>
<tr>
<td>5</td>
<td>0.2098</td>
<td>[0.1956, 0.2250]</td>
</tr>
<tr>
<td>6</td>
<td>0.2483</td>
<td>[0.2325, 0.2651]</td>
</tr>
<tr>
<td>7</td>
<td>0.2830</td>
<td>[0.2658, 0.3013]</td>
</tr>
<tr>
<td>8</td>
<td>0.3154</td>
<td>[0.2968, 0.3351]</td>
</tr>
<tr>
<td>9</td>
<td>0.3514</td>
<td>[0.3313, 0.3726]</td>
</tr>
<tr>
<td>10</td>
<td>0.3815</td>
<td>[0.3602, 0.4041]</td>
</tr>
<tr>
<td>11</td>
<td>0.4092</td>
<td>[0.3866, 0.4331]</td>
</tr>
<tr>
<td>12</td>
<td>0.4450</td>
<td>[0.4208, 0.4706]</td>
</tr>
</tbody>
</table>

The hazard rates of separation through nonparametric methods.

I perform the estimation on the 2004 and the 2008 SIPP panels, obtaining similar results across the two panels (see Appendix). In this section, I focus on the estimation performed on the 2004 panel, which tracks the employment histories of 131,585 individuals from 2004 to 2008. I identify 4,592 hires from employment, and 11,559 hires from unemployment, and I calculate their durations in months. For each of the two groups, I estimate the cumulative hazard function using the Nelson-Aalen nonparametric estimator, defined as:

$$
\hat{H}(t) = \sum_{j \mid t_j < t} \frac{d_j}{n_j},
$$

where $t_j$, $j = 1, 2, \ldots$ are the times at which separations occur, $n_j$ is the number of jobs at risk of separation just before time $t_j$, and $d_j$ is the number of separations at time $t_j$. Table 2.2 shows the estimated cumulative hazard rates of separation in the first year of tenure, for jobs starting after employer-to-employer transitions. The risk of separation seems to be quite large in the first year, as the cumulative hazard rate reaches 44% in the twelfth month.

I then use the cumulative hazard functions $\hat{H}(t)$ to obtain an estimate of the hazard function. I first calculate the estimated hazard contributions, $\Delta \hat{H}(t_j) = \hat{H}(t_j) - \hat{H}(t_{j-1})$, therefore I exclude from the group of “hires from employment” the cases in which the worker quits the old job for reasons that do not depend on her will. Specifically, I exclude cases in which the respondents report the following reasons for quitting the old job: “On layoff,” “Discharged/Fired,” “Job was temporary and ended.”
and then estimate the hazard function through a kernel smooth of the hazard contributions. The estimated hazard rates of separation for both hires from employment and hires from unemployment are illustrated in Figure 2.2. Hazard rates are overall higher for hires from unemployment, compared to hires from employment, however, the shape of the two functions is similar: hazard rates are high in the first year of tenure, and then they sharply decline. The shape of the hazard function estimated on hires from unemployment is similar to the ones obtained in Moscarini (2003) and Pries (2004) using CPS data. The novel finding is that this function is very similar to the hazard function estimated only on hires from employment. This result indicates that the choice of moving on-the-job is actually risky for workers. In the next section, I explicitly incorporate this risk in the Burdett and Mortensen (1998) set-up and analyze its effects on workers’ reallocation. Then, I use the cumulative hazard rates of separation estimated in this section to calibrate the parameters of the model in Section 4.

3 The Model

The model builds on Burdett-Mortensen (1998). There is a unit-mass of ex ante identical workers who can be either employed or unemployed. Unemployed workers’ value of nonlabor activities is equal to $b$, while employed workers receive a wage $w$ each period. There is a measure $N$ of active firms, with constant returns to scale technology, that use labor as the only input. Each firm has a specific productivity $p$, distributed according to c.d.f. $\Gamma$ on the positive interval $[\underline{p}, \bar{p}]$. Workers and firms are both risk neutral and infinitely lived, and they share a common discount factor $\beta \in (0, 1)$.

Workers in the labor market can search both when unemployed and when employed. Because of search frictions, in each period $t$, unemployed workers can only search with probability $\lambda_0 \in (0, 1]$, while employed workers can search with probability $\lambda_1 = s\lambda_0$, where $s \in (0, 1]$ represents the relative search intensity of employed workers. As in Moscarini and Postel-Vinay (2013), workers that are allowed to search in period $t$ can only send one job application to firms. The sampling of firms by workers is not uniform, but, as in Moscarini and Postel-Vinay (2008), I assume that each $p$-firm has a sampling weight $q(p) > 0$. Allowing for sampling weights $q(p)$ that are increasing in $p$ helps the model to match the distribution of firm sizes observed in the data for the U.S. The resulting sampling c.d.f. is defined as $\Phi(p) := \int_p^\bar{p} q(x) d\Gamma(x)$, hence the sampling weights are appropriately scaled in such a way that $\Phi(\bar{p}) = 1$. As a result, the sampling weight of a type-$p$ firm is given by $\varphi(p) = q(p) \gamma(p)$. In each period, a given firm $p$ posts the
Figure 3: Hazard Rates as Function of Months of Tenure, E-to-E jobs (top) and U-to-E jobs, (bottom), estimated from SIPP 2004 Panel
wage \( w(p) \) offered to new potential workers. There is a one sided-commitment: once the worker accepts the wage offered, the firm commits to pay that wage each period until separation (if any). Workers, however, are free to quit in every period (for example, whenever they decide to join a new firm). I denote by \( L(p) \) the size of each type-\( p \) firm, that is, the measure of workers employed by each type-\( p \) firm. Then, the mass of employed workers is given by \( N \int_p^\rho L_t(p) \, d\Gamma(p) = 1 - u_t \), where \( u_t \) is the unemployment rate. Finally, it is assumed that, in each period, every employed worker can become unemployed with exogenous separation probability \( \delta \in (0, 1) \).

I then introduce the risk of early match dissolution in this set-up. In particular, I assume that newly formed matches produce per-period output \( y = \mu \times p \), where \( \mu \) is stochastic and match-specific, unknown ex ante, and perfectly learned by both the worker and the firm right after the match is created, before production takes place. The variable \( \mu \) is distributed according to a Bernoulli p.d.f., hence it takes value 1 with probability \( \rho \in [0, 1] \) and value 0 with probability \( 1 - \rho \). When a worker forms a match with a firm, the \( \mu \) shock realizes: if \( \mu \) is equal to 1, the match survives and production happens; if instead \( \mu = 0 \), the match dissolves and worker and firm separate. In this case, the worker cannot go back to the previous job and becomes unemployed. As a consequence, a worker who is currently working with a given firm, and accepts an offer from a poaching firm, can become unemployed with probability \( 1 - \rho \). Hence, the decision of the worker to accept or reject the offer of a poaching firm also depends on the value of unemployment, since the new match can be unsuccessful and the worker can potentially be separated from the new employer. If being unemployed is particularly undesirable - for example, because the probability of finding a new job while unemployed is very low - then a worker may be reluctant to move to a poaching firm, even if the new firm offers a wage that is higher than the wage currently earned by the worker.

The stochastic shock \( \mu \) can be interpreted as any factor, unknown ex ante and specific to each match, that could potentially lead to separation after the formation of a new match. This parameter captures both factors influencing the worker’s decision to quit (for example, she discovers that she does not like the new working conditions) and factors determining the employer’s decision to separate from the worker (for example, the employer learns that the worker is not a good fit for the firm due to her set of skills and/or personal characteristics).

The assumption that the worker and the firm perfectly learn the quality of the match right after its formation allows me to simplify the model substantially. An alternative approach, followed by Moscarini (2005), postulates that \( \mu \) is gradually learned as the worker and the firm interact over time. However, the estimated hazard rates of sepa-
ration shown in the previous section suggest that most of the uncertainty about match quality is resolved within the first year of tenure. In light of this evidence, assuming that $\mu$ is learned immediately after match formation appears to be a reasonable approximation of reality.

The timing of the economy is the following. In each period $t$, given the allocation of workers across employment states and across firms in $t - 1$:

1. Benefit $b$ is paid to each unemployed worker, firms produce output, and wages are paid to each employed worker;

2. A fraction $\delta$ of all matches is destroyed;

3. Firms post wages;

4. Previously unemployed workers submit one job application with probability $\lambda_0$ and decide whether to remain unemployed or join the offer (if any). Among the $(1 - \delta)$ surviving matches, each worker submits one job application with probability $\lambda_1$ and decides whether to accept or reject the offer (if any). Fraction $1 - \rho$ of all workers who have joined a new firm becomes unemployed.

In the next sections, I define the problem of workers and firms, and I derive the equilibrium of the model.

### 3.1 Workers

Before presenting the optimization problem of workers, I need to define the distribution of wage offers $F_t$. As mentioned in the previous section, each firm $p$ posts a wage $w(p)$, taking as given the actions of the other firms. The c.d.f. of offered wages is defined as:

$$F_t(w) = \int_p F[w(x) \leq w] q(x) d\Gamma(x),$$

where $I[\cdot]$ is the indicator function. Hence, $F_t$ is the cumulative distribution of wages that workers face when sampling job offers at time $t$.

For given distribution $F_t(w)$ resulting from the optimal wage posting of the firms, unemployed workers’ utility at time $t$ can be expressed in recursive form as follows:

$$U_t = b + \beta \left[ (1 - \lambda_0) U_{t+1} + \lambda_0 \int_0^\infty \max \{U_{t+1}; \rho V_{t+1}(x) + (1 - \rho) U_{t+1}\} dF_{t+1}(x) \right].$$

(3)
An unemployed worker at time $t$ enjoys $b$, interpreted as unemployment benefit plus value of nonlabor activities, while at time $t+1$ with probability $1 - \lambda_0$ she cannot sample any job offer and remains unemployed. With probability $\lambda_0$, she receives an offer $w(p)$ drawn from sampling distribution $F_{t+1}(x)$. The worker can then decide whether to accept the offer or stay unemployed, and in the case she accepts, the worker stays with the firm and receives the value of being employed, $V(w)$, only in the case that the match is successful, hence only with probability $\rho$.

Employed workers’ utility at time $t$ can be expressed as follows:

$$V_t(w) = w + \beta \left\{ \delta U_{t+1} + (1 - \delta) (1 - \lambda_1) V_{t+1}(w) \right\} + (1 - \delta) \lambda_1 \left[ \int_0^\infty \max \{V_{t+1}(w); \rho V_{t+1}(x) + (1 - \rho) U_{t+1}\} \, dF_{t+1}(x) \right].$$

(4)

A worker employed by a firm paying wage $w$ receives the wage $w$ at time $t$, while at $t+1$ with probability $\delta$ she will be exogenously separated from the firm. If not separated, with probability $(1 - \lambda_1)$, the worker cannot sample new job offers, while with probability $\lambda_1$, she can sample a job offer from the $F$ distribution. As in the case of the unemployed worker, if the worker decides to quit and join the new firm, then the new match can dissolve with probability $(1 - \rho)$ and the worker becomes unemployed.

Let me now consider the optimal choice of each class of workers in the steady state, in which $V_t(w) = V(w)$ and $U_t = U$. The unemployed worker’s reservation wage, $R$, equates the the value of being unemployed, $U$, with the value of accepting the offer of a given firm offering wage $w$. Hence, the optimal choice of an unemployed worker receiving an offer $w$ is $\max \{\rho V(w) + (1 - \rho); U\}$. Accordingly, the wage $R$ that makes the worker indifferent must satisfy $\rho V(R) + (1 - \rho) U = U$, which reduces to the condition $V(R) = U$: this is the same condition obtained when there is no ex ante uncertainty about match quality. The intuition for this result is simple: for any $w > R$, the worker will always accept the job offer, even if there is a probability $(1 - \rho)$ that the match will dissolve. If this is the case, the worker becomes again unemployed and obtains the same utility $U$ as before, while if the match is successful the worker obtains $V(w) > U$.

As far as the employed worker is concerned, a worker currently earning wage $w$ who receives an offer $w' \neq w$ from a poaching firm, will accept the outside offer if and only if the expected value of accepting is higher than the value of staying with the current employer, hence if the following condition is satisfied:

$$V(w) < \rho V(w') + (1 - \rho) U$$
It is immediate to verify that, as long as the value of unemployment, \( U \), is finite and lower than \( V (w) \) - which is true by definition for any worker currently earning a wage \( w > R \) - then it holds that \( \rho V (w) + (1 - \rho) U \leq V (w) \) for any \( \rho \in [0, 1] \). Given this result, and since the value function \( V (w) \) is continuous and strictly increasing in \( w \), there exists one threshold function of the wage, \( w^* : \mathbb{R}_+ \to \mathbb{R}_+ \), such that \( w^* (w) \geq w \ \forall w \), that satisfies the following indifference condition:

\[
\rho V (w^* (w)) + (1 - \rho) U = V (w) .
\] (5)

As a result, any worker currently earning \( w \) will accept the offer \( w' \) from a poaching firm if and only if \( w' \geq w^* (w) \). This condition is quite different from the standard Burdett and Mortensen (1998) model, in which there is no uncertainty about match quality, and therefore \( \rho = 1 \). In this case, \( w^* (w) = w \) always, and the worker will move to a new firm for any wage above the current one. From condition (5) it is possible to derive the following expression for \( w^* (w) \):

\[
w^* (w) = V^{-1} \left[ \frac{1}{\rho} (V (w) - (1 - \rho) U) \right] .
\] (6)

Hence, from (6) it is possible to observe that the optimal threshold \( w^* (w) \) depends on the value of unemployment: in particular, as \( U \) decreases, the optimal threshold \( w^* \) rises. As a result, a lower \( U \) increases workers’ reluctance to accept new job offers. The intuition for this result is simple: given that there is a probability \( (1 - \rho) \) that the worker becomes unemployed after a job-to-job transition and receives utility \( U \), the expected value of accepting an offer while on-the-job is lower for a small \( U \). Moreover, the value of unemployment is decreasing in the job contact rate \( \lambda_0 \), since \( U \) is lower if it is harder to find a new job. This is the key mechanism of the model that triggers the increase in workers’ reluctance to quit during recessions. Its effects are explored in the quantitative analysis in Section 4, in which I estimate the model and simulate the effects of a decrease in the job arrival rates during a recession.

3.2 Firms

The profit maximization problem of the firms depends, among other things, on the cross-sectional allocation of workers across different firms obtained in \( t - 1 \). This distribution is defined as follows:
\[ G_t(w) = \frac{1}{\int_p L_t(x) \, d\Gamma(x)} \int_p L_t(x) \times I_{[w(x) \leq w]} d\Gamma(x). \]  

(7)

In each period \( t \), firms participate in a noncooperative simultaneous game of wage posting: they take as given the optimal strategies of workers currently unemployed or employed in each firm, and take as given the optimal wage posting strategies of other firms. Firms pursue a stationary wage policy, hence the wage that is initially accepted by the workers continues to be paid each period as long as the working relationship lasts, that is, as soon as the worker quits after accepting a better offer from another firm. As a result, each firm chooses a wage in order to maximize expected profit per worker contacted:

\[ w = \arg\max_{w > R} \pi(p, w) = h(w) J(p, w), \]

where \( h(w) \) is the probability that offer \( w > R \) is accepted by a randomly contacted worker (who can be either employed or unemployed), and \( J(p, w) \) is the present discounted value of net profits from hiring a worker.

The function \( h(w(p)) \) is equal to:

\[ h(w(p)) = \frac{q(p) \lambda_0 u + \lambda_1 (1 - \delta) (1 - u) G(\tilde{w}(w))}{N \lambda_0 u + \lambda_1 (1 - \delta) (1 - u)}; \]

(8)

the ratio \( q(p) / N \) determines the expected number of workers contacted by each employer \( p \). In the second fraction, the denominator is the total mass of employed and unemployed workers looking for a job, while the numerator represents the mass of searching workers who would potentially accept a given wage offer \( w(p) \). The function \( \tilde{w}(w) \) appearing in the numerator is defined as the inverse of function \( w^*(w) \), that is,

\[ \tilde{w}(w) := (w^*)^{-1}(w). \]

Hence, \( \tilde{w}(w) \) represents the wage earned by a worker who is exactly indifferent between accepting a given offer \( w \) and continuing to work for the current employer at wage \( \tilde{w} \). In other words, \( \tilde{w} \) is such that \( w^*(\tilde{w}(w)) = w \). As a result, a firm offering wage \( w \) has the opportunity to successfully poach only workers who earn at most \( \tilde{w}(w) \leq w \), that is, \( (1 - u) G(\tilde{w}(w)) \), while any worker who is currently unemployed would be certainly hired as long as \( w > R \). Accordingly, the ratio \( h(w) \) represents the fraction of searching workers that a firm posting wage \( w \) can potentially hire. Note that as \( w \) goes up, also \( \tilde{w}(w) \) increases and \( G(\tilde{w}(w)) \) tends to one. In this case, \( h(w) = 1 \), and the firm would be sure to hire any worker contacted. It is also important to note that, in the no-uncertainty
case (when \( \rho = 1 \)), \( \tilde{w}(w) \) would be exactly equal to \( w \), and a firm would be able to hire workers earning \( w - \varepsilon \), for arbitrarily small \( \varepsilon > 0 \). Differently from this case, when \( \rho < 1 \) we have that \( \tilde{w}(w) < w \), and the firm offering \( w \) cannot win those workers earning \( w' \in (\tilde{w}(w), w) \).

As derived in the Appendix, the present discounted value of net profits per worker receiving wage \( w \) is:

\[
J(p, w) = \frac{\rho (p - w)}{1 - \beta (1 - \delta) [1 - \lambda_1 (1 - F(w^*(w)))].}
\]

(9)

The numerator is the expected difference between the output produced by the worker-firm match in each period, \( p \), and the wage paid, while the denominator is instead the discount rate, given by the probability of match destruction. As a result, the profit function is:

\[
\pi(p, w) = \rho q(p) \frac{\lambda_0 u + \lambda_1 (1 - \delta) (1 - u) G(\tilde{w}(w))}{N \left[ \lambda_0 u + \lambda_1 (1 - \delta) (1 - u) \right] \left[ 1 - \beta (1 - \delta) [1 - \lambda_1 (1 - F(w^*(w)))] \right]} (p - w).
\]

(10)

The profit function reveals that the optimal choice of the wage by a firm has to balance two intertemporal effects. On the one hand, a higher wage posted decreases \( (p - w) \), the earnings per worker, but on the other hand it increases both the probability that a randomly contacted worker accepts the job offer - due to a higher \( G(\tilde{w}(w)) \) - and the probability that the worker does not quit in the future - due to a higher \( F(w^*(w)) \). In other words, a higher offered wage earns a firm a larger workforce size, due to more successful recruiting and retention, but it decreases the profit per worker. Facing this tradeoff, each firm chooses the optimal wage, taking as given the wage strategies of other firms, summarized by the function \( F(w) \), the cross-sectional distribution of wages paid to each worker, \( G(w) \), and taking as given the optimal threshold function \( w^*(w) \) of the workers.

Given the formula of the expected profit function, two more important properties can be derived, as shown in Proposition 1:

**Proposition 1**

1. The optimal wage strategy, conditional on firm’s \( p \), is an increasing function of firm’s productivity;

2. Each firm’s size is increasing in its own productivity \( p \).
Proof: See Appendix.

The fact that firms’ optimal wages are an increasing function of firms’ productivity implies that, in equilibrium, workers rank firms on the basis of their productivity. As a result, the fraction of wage offers that are smaller than or equal to \( w(p) \) corresponds to the fraction of firms with productivity \( p \) or less, weighted by their sampling weights \( q(p) \). This implies that the following relationship holds in equilibrium:

\[
F(w(p)) = \Phi(p). \tag{11}
\]

Moreover, the cross-sectional distribution of workers across different wage levels reflects the allocation of workers to firms of different productivity levels, that is:

\[
(1 - u) G(w(p)) = N \int_{p} q(x) d\Gamma(x). \tag{12}
\]

Hence, the fraction of workers currently earning a wage \( w(p) \) or less corresponds to the fraction of employed workers at firms with productivity \( p \) or less.

### 3.3 Steady State Equilibrium

In order to derive the steady state equilibrium, it is necessary to describe how aggregate endogenous variables evolve from period \( t \) to \( t + 1 \). In particular, each firm \( p \)'s size evolves as:

\[
L_{t+1}(p) = L_t(p)(1 - \delta) [1 - \lambda_1 \bar{F}_{t+1}(w^*(w(p)))] + \rho \frac{q(p)}{N} [\lambda_0 u_t + \lambda_1 (1 - \delta) (1 - u_t) G_{t+1}(\bar{w}(w(p)))]. \tag{13}
\]

The size of firm \( p \) after exogenous separation is \( L_t(p)(1 - \delta) \). The first addendum of Formula (13) subtracts from this term the fraction of workers who accept an outside offer higher than \( w^*(w(p)) \), \( L_t(p)(1 - \delta) \lambda_1 \bar{F}_t(w^*(w(p))) \). The second addendum represents the new workers that the firm gains at \( t + 1 \), and that survive after the realization of the \( \mu \)-shock at the beginning of the match formation. Hence, \( \rho \frac{q(p)}{N} [\lambda_0 u_t] \) is the number of new recruits coming from unemployment, while:

\[
\rho \frac{q(p)}{N} [\lambda_1 (1 - \delta) (1 - u_t) G_{t+1}(\bar{w}(w(p)))]
\]

is the number of recruits successfully poached from other firms. Note that the pool of workers from which the firm offering \( w(p) \) can successfully poach new workers includes
workers earning at most wage \( \bar{w} (w (p)) \leq w (p) \). In steady state, the expression for each firm \( p \)'s size is the following:

\[
L (p) = \frac{\rho \sigma (p)}{1 - (1 - \delta) [1 - \lambda (w (p))]} \left[ \lambda_0 u + \lambda_1 (1 - \delta) (1 - u) G (\bar{w} (w (p))) \right].
\]  

(14)

Second, unemployment evolves as:

\[
u_{t+1} = u_t + \delta (1 - u_t) - \rho \lambda_0 u_t + (1 - \rho) \lambda_1 (1 - \delta) (1 - u_t) \left[ \int_{w}^{\bar{w}} [1 - F_{t+1} (w^* (x))] g_{t+1} (x) \, dx \right],
\]

where \( \delta (1 - u_t) \) is the size of employed workers who are exogenously separated at the beginning of period \( t \) and join unemployment; \( \rho \lambda_0 u_t \) is the fraction of unemployed who leave unemployment because they receive an offer from a firm and draw a value \( \mu = 1 \). Finally, the fourth addendum represents the fraction of all employed workers who move to a poaching firm, but draw \( \mu = 0 \), hence becoming unemployed. The expression inside the integral, \( [1 - F_{t+1} (w^* (x))] g_{t+1} (x) \), is the total number of workers employed at wage \( x \) who make a job-to-job transition because they receive an offer higher than \( w^* (x) \). Hence, the fourth addendum represents the fraction of all employed workers who join a new firm, but draw \( \mu = 0 \), and return to unemployment. The resulting expression for steady state unemployment is:

\[
u = \frac{\delta + (1 - \rho) \lambda_1 (1 - \delta) \left[ \int_{w}^{\bar{w}} [1 - F (w^* (x))] \, g (x) \, dx \right]}{\rho \lambda_0 + \delta + (1 - \rho) \lambda_1 (1 - \delta) \left[ \int_{w}^{\bar{w}} [1 - F (w^* (x))] \, g (x) \, dx \right]}.
\]  

(16)

Finally, the law of motion of \( G (w) \) for each level of \( w \) is the following:

\[
(1 - u_{t+1}) G_{t+1} (w) = (1 - \delta) (1 - u_t) G_t (w) + \rho \lambda_0 F_t (w) u_t - \lambda_1 (1 - \delta) (1 - u_t) \times
\]

\[
\times \left\{ [1 - F_t (w)] G_t (\bar{w} (w)) + (1 - \rho) \int_{w}^{\bar{w}} [F_t (w) - F_t (w^* (x))] \, dG_t (x) + \int_{w}^{\bar{w}} [1 - F_t (w^* (x))] \, dG_t (x) \right\}.
\]  

(17)

The first addendum in the right-hand side is the fraction of workers earning at most wage \( w \) who have survived the \( \delta \) shock, while the second addendum is the fraction of unemployed workers who successfully move to firms paying \( w \) or less. Finally, the
third addendum accounts for the effects on $G(w)$ of two outflows: 1) workers earning a wage $w' \in [w, \bar{w}(w)]$ who receive a wage offer higher than $w$ and move to these firms: $[1 - F_l(w)] G_l(\bar{w}(w))$; 2) workers earning a wage $w' \in [w, \bar{w}(w)]$ who receive a wage offer $w''$ smaller than $w$ and higher than their reservation, $w'' > w^*(w')$, who drew a value $\mu = 0$ upon moving to the new firms: $\rho \int_{\bar{w}(w)}^{w} \left[ F_l(w) - F_l(w^*(x)) \right] dG_l(x)$; 3) workers currently earning wage $w' \in (\bar{w}(w), w)$ who received an offer higher than $w^*(w') > w$: $\int_{\bar{w}(w)}^{w} \left[ F_l(w) - F_l(w^*(x)) \right] dG_l(x)$. Note that in the case in which $\rho = 1$, workers leave a firm for any offer slightly more generous than the current wage, hence the expression in the curly brackets simplifies to $[1 - F_l(w)] G_l(w)$.

In steady state, $G_l = G$:

$$G(w) = \frac{\rho \lambda_0}{\delta} F(w) \frac{u}{1 - u} - \lambda_1 \left( \frac{1 - \delta}{\delta} \right) \left\{ (1 - F(w)) G(\bar{w}(w)) + \right.$$  

$$+ (1 - \rho) \int_{\bar{w}(w)}^{w} \left[ F(w) - F(w^*(x)) \right] dG_l(x) + \int_{\bar{w}(w)}^{w} \left[ 1 - F(w^*(x)) \right] dG(x).$$  

(18)

It is now possible to define the equilibrium:

**Definition 1.** A steady state equilibrium solution to the model is an optimal threshold function $w^*(w)$, wage offer c.d.f. $F(w)$, an unemployment rate $u$, and a c.d.f. of earned wages $G(w)$ that satisfy the steady state conditions (16), (18), and the requirement that every wage offered maximizes each firm’s expected profit per worker contacted.

Given that the equilibrium threshold function $w^*$ is expressed implicitly as a function of the value functions $V$ and $U$, the model can only be solved numerically, not analytically. In the next section, I provide the details of the computational algorithm used to obtain the steady state equilibrium.

### 3.4 Computational Algorithm

Given values of the model parameters determined by the calibration performed in Section 4, the model is solved computationally as a fixed point of the following endogenous aggregate variables:

$$\{N, F(\cdot), G(\cdot), u\}$$  

(19)
I solve for the steady state equilibrium by initially guessing values for the variables in (19), then solving for the new optimal decisions of workers and firms, and finally verifying the initial guess. In particular, starting from a guess of the variables in (19), the algorithm proceeds as follows:

1. Given the guess on (19), compute the optimal reservation wage of the unemployed, \( R \), the optimal threshold function of the employed, \( w^* (w) \);

2. Given the guess on (19), and given the updated rules \( R \) and \( w^* (w) \) from Step 1, calculate the optimal wages set by the firms and update the offer distribution, \( F \), and the number of active firms, \( N \);

3. Using the guess on \( G \) and \( u \) and the updated values of \( N \) and \( F \), derive the steady state firm sizes \( L (p) \) for each productivity level \( p \) according to Formula (14);

4. Use the updated sizes to calculate the new \( u \) using the definition \( u = 1 - \int_{p}^{\bar{p}} L (p) d\Gamma (p) \);

5. Use updated \( u \) and firm sizes \( L \), update \( G \) using (12);

6. Given all the updated guesses, repeat from Step 1 until convergence.

This algorithm delivers the equilibrium values of (19) as the fixed point.

4 Estimation

In order to quantitatively assess the importance of workers’ increasing unwillingness to reallocate during recessions, in this section I estimate the model and simulate the effects of a recession on reallocation and productivity. During a recession, reallocation freezes both because workers’ job arrival rates decrease, and because, for given number of job offers, workers are more reluctant to leave their current jobs. The performed estimation delivers two important results: 1) workers’ unwillingness to move substantially contributes to the overall drop in employer-to-employer transitions during recessions; 2) it has important effects on aggregate productivity.

The benchmark for the model estimation is the U.S. economy in the years of the Great Recession. I calibrate and estimate the parameters of the model in order to fit key empirical moments of the U.S. economy at the peak before the crisis, and characterize the steady state before the recession. Then, I look at the combined effect of shocks that match by magnitude the ones observed during the Great Recession: 1) a negative aggregate
productivity shock, 2) a drop in the job-finding rates of both employed and unemployed workers, \( \lambda_0 \) and \( \lambda_1 \).

In order to better capture the effects of a recession I extend the model to endogenize the number of firms \( N \). In particular, I assume that the productivity parameter \( p \) of each firm is \( p = \omega \times \theta \), where \( \omega \) is the aggregate productivity component and \( \theta \) is the idiosyncratic component, as in Moscarini and Postel-Vinay (2008). Moreover, I assume that there is a measure 1 of potential firms in the economy, which can be either active or inactive (while \( N \leq 1 \) represents the measure of active firms). Each firm has a fixed value of the idiosyncratic productivity \( \theta \), where \( \theta \sim \Gamma_0 (\cdot) \). The aggregate productivity component \( \omega \) is set equal to 1 in the boom steady state. Therefore, in the boom steady state, \( p = \theta \) and the number of active firms \( N \) is an endogenous variable, determined by the number of firms whose productivity \( p = \theta \) is larger than or equal to the equilibrium reservation wage of unemployed workers. Firms with a productivity \( \theta < R \) cannot hire any worker because \( R \) is the lowest wage that a worker is willing to accept, thus they are inactive. As a result, the c.d.f. of active firms during the boom is equal to \( \Gamma (p) = (\Gamma_0 (p) - \Gamma_0 (R)) / (1 - \Gamma_0 (R)) \). In order to simulate the effects of a recession on firms’ exit, I assume that the lowest wage determined in the boom equilibrium corresponds to the legal minimum wage of the economy, hence \( w = R \). During a recession, the aggregate productivity component goes down to \( \omega' = \omega - \epsilon \), shifting to the left the distribution of productivities. As a result, active firms must satisfy \( \theta \geq (w/\omega') \), which implies that there is a net exit of firms equal to \( [\Gamma_0 (w/\omega') - \Gamma_0 (w)] \) from boom to recession. As a result, the recession distribution of productivities among active firms is equal to:

\[
\Gamma (p) = \frac{\Gamma_0 (p/\omega') - \Gamma_0 (w/\omega')}{1 - \Gamma_0 (w/\omega')}
\]

### 4.1 Basic Calibration and Estimation, \( \rho = 1 \)

Let me first consider the case in which there is no match quality uncertainty, hence \( \rho = 1 \). The values of the calibrated parameters are reported in Table 2. The model is calibrated at monthly frequency, and the discount factor \( \beta \) is set equal to 0.9956 to obtain a 5% annual discount rate. The values of the model’s parameters in the pre-recession steady state are calibrated to fit key moments of U.S. data observed in May 2007, the month in which unemployment rate reached its lowest level (4.4%) in the economic expansion phase preceding the Great Recession, hence in the period 2001:12 - 2007:12. The value of the the job-finding probability of the unemployed, \( \lambda_0 \), during the boom is set equal
to 0.269, which is the value of the unemployment-to-employment exit rate observed in May 2007, as measured by Fallick and Fleischman (2004) using CPS data. The value of the job-finding probability of the employed, \( \lambda_1 \), is not directly observed empirically, and it is usually set as equal to a constant fraction of \( \lambda_0 \), hence \( \lambda_1 = s\lambda_0 \). The value of \( s \) is estimated through the SMM procedure explained below. The parameter \( \delta \) is set equal to the employment-to-unemployment exit rate for May 2007, hence \( \delta = 0.013 \).

As far as the parameter \( b \) is concerned, it is usually interpreted as the monetary compensation of the unemployed worker, hence it should be set equal to the average replacement rate for the U.S., that is, the ratio between average unemployment benefits and the average wage. In other words, \( b \) should be equal to a fraction \( \tau \in (0, 1) \) of the average wage:

\[
b = \tau \cdot E(w)
\]

As discussed in Hornstein et al. (2005), the OECD (1996) provides estimates of the average replacement rates across countries, and for the U.S. this value is equal to 0.20, while Shimer (2005) sets \( \tau = 0.41 \) on the basis of average unemployment insurance replacement rates. It is important to remark that the value of \( \tau \) usually calibrated in the wage dispersion literature is very low or even negative. As explained in Hornstein et al. (2011), models that generate realistic amounts of equilibrium wage dispersion - including the Burdett and Mortensen (1998) model - can be consistent with the high job-finding rates observed in the data only if an extremely low utility of nonemployment is assumed, which implies that \( b \) is usually calibrated as equal to zero or even negative. The reason is that a high dispersion of wages makes workers more patient when unemployed, since the option value of waiting is higher with higher wage dispersion. Hence, these models can be consistent with low duration of unemployment spells observed in the data only if workers have an implausibly low value of nonemployment. Interpreting \( w \) as the hourly wage, we observe \( E(w) = \$19.14 \) from the 2007 data of US private sector wages in the Current Population Survey (CPS). I thus set \( b \) equal to \$5, which implies a value of \( \tau = 0.25 \). By setting \( \tau = 0.25 \), I obtain a more realistic value of \( b \), but as direct consequence of the points made in Hornstein et al. (2011), the calibrated model generates a smaller wage dispersion compared to what is observed in the data.

Finally, I need to calibrate the sampling distribution of firms, \( \Phi_0(p) \), and the under-
lying distribution of firm productivities, $\Gamma_0(p)$. Following Moscarini and Postel-Vinay (2008), I calibrate these two distributions in order to allow the model-generated distribution of wages in the boom to fit the distribution of wages observed in CPS data for 2007, while the sampling weights $\varphi(p)$ are calibrated to match the relationship between firm size and employment share observed in the Quarterly Census of Employment and Wages (QCEW) for March 2007. In particular, I assume that $\Phi_0(p)$ is Lognormal, with parameters $(\mu_\Phi, \sigma_\Phi)$. The assumption of lognormality allows me to simplify the calibration of the $\Phi_0$ distribution to only two parameters, $(\mu_\Phi, \sigma_\Phi)$. The distribution $\Gamma$ is also Lognormal with parameters $(\mu_\Gamma, \sigma_\Gamma)$, where $\mu_\Gamma$ and $\sigma_\Gamma$ can be different from $(\mu_\Phi, \sigma_\Phi)$. As previously argued, the variance of the sampling distribution needs to be larger than the actual variance of the firm-type distribution, in order for the model to be consistent with the fact that, empirically, a large share of workers is allocated to few, very large firms.

Given the set of parameters $\{\beta, \lambda_0, \delta, b, \}$ that have been previously calibrated, I estimate the set of remaining parameters $\{s, \mu_\Phi, \sigma_\Phi, \mu_\Gamma, \sigma_\Gamma\}$ with Simulated Method of Moments. In particular, I compute the moments implied by the model by implementing the computational algorithm described in Section 3.4 and then I compare these model-generated moments with the ones implied by U.S. data in order to minimize the following objective function:

$$\min \sum_{j=1}^J \frac{|\text{model (j)} - \text{data (j)}|}{\text{data (j)}},$$

where $J$ is the total number of moments to be matched. Hence, the SMM algorithm calculates moment-generated data under different values of the parameters $\{s, \mu_\Phi, \sigma_\Phi, \mu_\Gamma, \sigma_\Gamma\}$ and selects those values of the parameters that make the model’s moments the closest to the empirical moments.

The first targeted moment is the job-to-job transition rate for May 2007, which is equal to 2.4%. Then I target the mean and the standard deviation of the cross-sectional distribution of wages observed in the business sector data from CPS in 2007. The empirical moments are, respectively, $\text{mean (w)} = 19.14$ and $\text{st.dev (w)} = 14.7572$. Moreover, I target nine more moments, which describe the relationship between firm size and employment shares in U.S. firms, as reported in the Quarterly Census of Employment and Wages (QCEW) for March 2007. In particular, I target the allocation of workers across size classes of firms as summarized in Table (3).

To sum up, parameters $\{\beta, \lambda_0, \delta, b, \}$ are calibrated through direct match with their empirical counterparts, while the parameters $\{s, \mu_\Phi, \sigma_\Phi, \mu_\Gamma, \sigma_\Gamma\}$ are estimated through
### Table 3: The firm size - worker share relationship (from QCEW, March 2007)

<table>
<thead>
<tr>
<th>Size Class</th>
<th>Firm Size CDF</th>
<th>Total Employment CDF</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 – 4</td>
<td>60.54%</td>
<td>6.8%</td>
</tr>
<tr>
<td>5 – 9</td>
<td>77%</td>
<td>15.1%</td>
</tr>
<tr>
<td>10 – 19</td>
<td>88%</td>
<td>26.3%</td>
</tr>
<tr>
<td>20 – 49</td>
<td>95.42%</td>
<td>43.7%</td>
</tr>
<tr>
<td>50 – 99</td>
<td>98%</td>
<td>57.16%</td>
</tr>
<tr>
<td>100 – 249</td>
<td>99.45%</td>
<td>73.8%</td>
</tr>
<tr>
<td>250 – 499</td>
<td>99.8%</td>
<td>83.07%</td>
</tr>
<tr>
<td>500 – 999</td>
<td>99.94%</td>
<td>89.72%</td>
</tr>
<tr>
<td>≥ 1000</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

SMM by targeting, in total, 12 empirical moments: the job-to-job transition rate, the mean and dispersion of wages, and the quantiles of the distribution of workers across classes of firm size.

#### 4.1.1 Equilibrium Before the Recession, $\rho = 1$

In this section, I present the results of the estimation described above, and characterize the endogenous variables in the boom steady state equilibrium. The estimation delivers a value of $s = 0.6$, while the $\Phi_0$ distribution is a truncated Lognormal defined on the support $[\underline{p}, \bar{p}] = [6, 800]$ with estimated parameters $(\mu_\Phi, \sigma_\Phi) = (-1.05, 1.25)$. The $\Gamma_0$ distribution is also a truncated Lognormal, on the same support, with estimated parameters $(\mu_\Gamma, \sigma_\Gamma) = (-1.05, 0.98)$. It is important to remark that these are the distributions of potential firms, while the actual distributions of active firms are endogenously determined in equilibrium. Hence, given the equilibrium reservation wage $R$, the sampling distribution and the productivity distribution of active firms are equal to, respectively, $\Phi(p) = (\Phi_0(p) - \Phi_0(R)) / (1 - \Phi_0(R))$ and $\Gamma(p) = (\Gamma_0(p) - \Gamma_0(R)) / (1 - \Gamma_0(R))$, and the implied sampling weights are given by $q(p) = \varphi(p) / \gamma(p)$. In Table 4, I report the moments generated by the model with the corresponding empirical targets.

The estimation procedure delivers a very good fit for the relationship between firm size and employment share. This feature is very important for realistically measuring the effects of workers’ reallocation on productivity during a recession, as is done in the next section. The model also does a good job at matching the job-to-job transition rate, which is equal to 1.9% and a bit lower than the corresponding value observed in May 2007, equal to 2.4%.

The model is less good at fitting the mean and the dispersion of the wage distribution.
### Table 4: Comparison of Model and Data Moments

<table>
<thead>
<tr>
<th>Firm Size CDF</th>
<th>Total Employment CDF - Model</th>
<th>Total Employment CDF - Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>60.54%</td>
<td>9%</td>
<td>6.8%</td>
</tr>
<tr>
<td>77%</td>
<td>13.1%</td>
<td>15.1%</td>
</tr>
<tr>
<td>88%</td>
<td>21%</td>
<td>26.3%</td>
</tr>
<tr>
<td>95.42%</td>
<td>36.2%</td>
<td>43.7%</td>
</tr>
<tr>
<td>98%</td>
<td>56.28%</td>
<td>57.16%</td>
</tr>
<tr>
<td>99.45%</td>
<td>71.5%</td>
<td>73.8%</td>
</tr>
<tr>
<td>99.8%</td>
<td>81.17%</td>
<td>83.07%</td>
</tr>
<tr>
<td>99.94%</td>
<td>91.1%</td>
<td>89.72%</td>
</tr>
<tr>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

However, this result is not surprising in light of the discussion made above on Hornstein et al. (2011): since $b = 5$, the amount of frictional wage dispersion that the model can generate is limited. On the other hand, the model in equilibrium still delivers sizable wage dispersion and preserves the feature that the optimal wage set by the firms is increasing in firms’ own productivity, as shown in Figure 4. The wage function $w(p)$ is increasing in firms’ productivity and concave. This is due to the fact that, for high levels of wage, the elasticity of the labor supply of a firm is low, since the quit rate of workers is lower at high-paying jobs and the workers have a small chance to move to better-paying firms. Thus, wages in the upper quantiles of the distribution are less responsive to the increase in productivity of the firms. From Figure 1, it is possible to see that the wage function is quite steep up to $p = 50$, and then it flattens out.

#### 4.2 Effects of the Recession

In order to simulate the effects of the recession, I first consider the model’s steady state equilibrium before the recession, as estimated in the previous section. The chosen parameters of the model fit the key empirical moments of the U.S. economy in the month of lowest unemployment during the expansion period preceding the crisis, that is, in May 2007. Then I look at the joint effect of two shocks: a negative aggregate productivity shock, and a drop in the job-findings rates, $\lambda_0$ and $\lambda_1$. 

<table>
<thead>
<tr>
<th>Moments</th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Wage</td>
<td>13.5</td>
<td>19.14</td>
</tr>
<tr>
<td>St. Dev. Wage</td>
<td>5.2621</td>
<td>14.7572</td>
</tr>
<tr>
<td>E-to-E Transition Rate</td>
<td>1.9</td>
<td>2.4</td>
</tr>
</tbody>
</table>
In order to evaluate the effects of these shocks, I compare the steady state equilibrium before the shocks with the steady state equilibrium after the realization of the shocks: this analysis allows me to study the medium-run effects on workers’ reallocation and productivity. In order to analyze the short-run effects of the shocks, I perform the following exercise, which approximates the actual short-run response of the economy. After the shocks realize, I derive the new wage policies of the firms and the new reservation wages of the workers that are mutual best responses, under the assumption that the cross-sectional allocation of workers, $G$, is constant and equal to its pre-recession level. This can be considered as an accurate approximation of the behavior of the economy in the aftermath of the recessionary shocks, since the distribution of workers, $G$, adjusts only slowly after the shocks, due to the small values of the monthly job-finding rates, $\lambda_0$ and $\lambda_1$, whereas the distribution of the new wage offers and the reservation wages of workers can immediately adjust. This approximation is necessary to understand the short-run effects of the shocks. In fact, in the context of this model, it is not possible to derive analytical transitional dynamics to stochastic shocks. The time-varying state space is infinite-dimensional, as it depends on the cross-sectional allocation of workers across different firms. Moscarini and Postel-Vinay (2014) solve the problem of the dimensionality of the state space by showing that, in their setting with no uncertainty about match quality, the workers rank firms according to their productivity, and the rank of firms is fixed in all dates. Hence, workers and firms do not need to keep track of the time-varying distribution of wages and firm sizes in order to solve their optimization problems in each period. In my set-up, this property does not hold: for the reasons discussed in Section 3, due to the uncertainty about the quality of new matches, it is possible for workers to reject a job offer from a firm that is more productive than the current one, and which
Table 5: Productivity and Matching Probabilities

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Pre-Recession</th>
<th>Recession</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate Productivity: $\omega$</td>
<td>1</td>
<td>0.97</td>
</tr>
<tr>
<td>Unemployed, Matching Probability: $\lambda_0$</td>
<td>0.269</td>
<td>0.162</td>
</tr>
<tr>
<td>Employed, Matching Probability: $\lambda_1 = 0.6 \times \lambda_0$</td>
<td>0.1614</td>
<td>0.0972</td>
</tr>
</tbody>
</table>

offers a higher wage. Hence, workers’ reservation wages depend in each period on the infinite-dimensional distribution of wage offers, which is endogenously determined in equilibrium by firms’ offer strategies that are mutual best responses.

I will now describe in detail the simulation of the recession. I calibrate the drop in productivity by matching the observed drop in aggregate TFP, as measured in John Fernald’s utilization-adjusted quarterly TFP series. The reference period is, as mentioned above, the interval of time between the trough and the peak in unemployment during the last recession episode, that is, May 2007 - October 2009. Since Fernald’s data is quarterly, I consider the period 2007:Q2 - 2009:Q3. For this time period, we observe a total drop in measured TFP by about 3%. As a result, aggregate productivity in the recession is equal to $\omega = 0.97$.

In order to calibrate the drop in $\lambda_0$, I consider the monthly time series of Unemployment-to-Employment (UE) transition rates from CPS. In the period May 2007 - October 2009, the rate drops from 26.9% to 16.2%, a decline of 39.8%. As a result, I set the recessionary job contact rate $\lambda_0$ equal to 0.169, in order to exactly match the drop observed in the data. Moreover, since $\lambda_1 = s \times \lambda_0$, this implies that during the recession, the arrival rate of job offers for employed workers drops by the same amount. This discussion is summarized in Table 4.2.

As described above, I look at the short-run effects and at the medium-run effects of these shocks on the equilibrium job-to-job transition rate. In particular, I consider the short-run equilibrium response in which the agents optimally respond to the shocks, while keeping $G$ fixed at its pre-recession level. Then, I consider the new steady state equilibrium in which the distribution $G$ of workers has adjusted as well. In other words, I follow these steps:

1. Start from the boom steady state values of the endogenous variables and let aggregate productivity $\omega$ and job arrival rates $\lambda_0$ and $\lambda_1$ drop, as specified in Table 4.2.

2. Keeping the distribution $G$ fixed, derive the optimal equilibrium response of work-
ers and firms - hence, the new reservation wages $w^*$ and the new p.d.f. of offered wages, $F$ - and calculate the new job-to-job quit rate, 

$$\frac{\lambda_1}{1-u} \int P \left(1 - F \left(w^* (w (p))\right)\right) L (x) d\Gamma (x);$$

3. Finally, calculate the job-to-job quit rate in the new steady state equilibrium, in which also $G$ has fully adjusted.

### 4.2.1 Short-Run Effects

In this section, I perform the analysis described in Steps 1 and 2. Starting from the boom steady state and letting the shocks hit, I numerically solve for the equilibrium optimal responses of firms and workers. The shock to aggregate productivity causes the immediate exit of firms at the bottom of the distribution of active firms. In particular, the minimum wage in the pre-recession equilibrium is equal to $8.1$, and the share of exiting firms relative to active firms is equal to $\left[\Gamma_0 \left(\frac{8.1}{0.97}\right) - \Gamma_0 (8.1)\right] / 1 - \Gamma_0 (8.1) = 10.2\%$. The immediate effect of the shock is the reduction in the number of active firms, which increases in the size of unemployment rate. Given the steady state allocation of workers across firms, the exit of firms at the bottom decreases employment by $0.88\%$. Then, I derive the short-run equilibrium response of active firms’ offered wages and workers’ reservation wages, in response to the drop in productivity and in the matching probabilities of the workers, as described in Table 4.2. The reduction in firms’ aggregate productivity affects the equilibrium wages offered by the firms, which generally decrease for each $p-$type firm, as shown in Figure 5.

The new level of job-to-job transition rates, defined as:

$$\frac{\lambda_1}{1-u} \int P \left(1 - F \left(w (x)\right)\right) L (x) d\Gamma (x);$$

is equal to $1.13\%$ in the new equilibrium. Hence, the job-to-job transition rate declines from the pre-recession level of $1.9\%$ to $1.13\%$, a drop of $40.5\%$. The main reason why the job-to-job rate declines in the recession is that $\lambda_1$, the rate of arrival of job offers for workers who search on-the-job, declines by $39.8\%$ in the recession. As discussed in Section 2, this is the demand-based mechanism traditionally emphasized by the literature: in a recession, workers have fewer opportunities to move on-the-job, hence the employer-to-employer transition rate declines. This mechanism is quantitatively important in my model, since it generates a large decline in job-to-job transition rate. As a reference, during the Great Recession, the U.S. job-to-job transition rate dropped from $2.4\%$ to $1.3\%$ in the period May 2007 - October 2009, a decline of $45.8\%$. In Section 4.3, I assess the
Figure 5: Optimal Hourly Wages as a Function of Firms’ Productivities, Boom vs. Recession

relative importance of this demand-based mechanism vis-a-vis the new, supply-based mechanism proposed in this paper.

4.2.2 Medium-Run Effects

Considering the full transition to the new recession steady state - hence, letting also $G$ adjust - the new level of the job-to-job flows is equal to 1.39%, which implies a drop of just 27% with respect to its pre-recession level. The reason why the drop is smaller compared to the drop obtained in the previous section is that, in the new steady state, firm sizes have fully adjusted to an equilibrium in which workers have lower opportunities to move to other employers on-the-job. Hence, compared to the case in which $G$ is fixed at the pre-recession level, in the new steady state, less productive firms retain more workers and are larger. As a result, the fraction of workers in “bad” matches is larger, and there are more workers in each period that move on the job, compared to the short-run equilibrium.

To sum up, the estimation just performed shows that the model with no uncertainty about match quality ($\rho = 1$) generates a large decline (40%) in job-to-job transition rates in the short-run and a smaller decline (27%) in the medium-run. In the next section, I perform the same estimation on the full model, in which there is a positive probability of early match dissolution.
4.3 Equilibrium with Match Quality Uncertainty: $\rho < 1$

I now consider the model with match quality uncertainty. The value of the parameters are assigned by following the same procedure described in the first part of Section 4.1 for the case in which $\rho = 1$, the only difference being that here I need to calibrate $\rho < 1$. As discussed in Section 3, the parameter $\rho \in [0,1]$ corresponds to the fraction of “successful” job-to-job transitions: a low value of $\rho$ delivers high rates of separation upon the formation of new matches, and increases the risk of moving on-the-job perceived by the workers. Based on the estimation of the hazard rates performed in Section 2, cumulative hazard rates are quickly increasing during the initial months of new matches formed after a job-to-job transition. For example, after only eight months, the cumulative risk of separation is about 0.3, which means that there is a risk of 30%. The $\rho$ parameter is calibrated in order to match this initial uncertainty. In particular, I consider two calibration approaches: one based on matching the empirical risk of separation observed in the first eight months; and one based on matching the risk of separation in the first twelve months. In the first case, the implied value of $\rho$ is 0.7, while in the second case implies $\rho = 0.55$.

As in the previous section, for both calibrations I numerically solve for the equilibrium steady state of the model to match key moments of the U.S. economy in May 2007, when the unemployment rate was at its lowest level before the recession. I then simulate the effects of a recession by generating drops in aggregate productivity and in the job-matching probabilities, which are as large as those observed during the period May 2007-October 2009. The calibration and SMM estimation of the remaining parameters of the model are performed in the same way as the model with $\rho = 1$. The results of the SMM estimation are reported in the Appendix.

4.4 Effects of the Recession, $\rho = 0.7$ and $\rho = 0.55$

In this section I perform the simulation of the effects of a recession for the two calibration approaches in the same way as reported in Section 4.2. I follow Steps 1-3 and look at the effects of the shocks described in Table 4.2.

**Calibration 1: $\rho = 0.7$**

First, I consider the model with $\rho = 0.7$. The main difference with the previous model in which $\rho = 1$ is that, here, a worker who earns a given wage $w$ will accept offers from a poaching firm if and only if the offered wage is larger than or equal to an endogenous reservation wage $w^*(w) \geq w$, as defined by Formula 5. Figure 6 shows the optimal
reservation wage $w^*$ as a function of the wage currently earned by workers in the pre-recession steady state. For each value of $w$ on the horizontal axis, the vertical distance between the red and the blue line indicates by how much the reservation wage $w^* (w)$ is higher than the wage $w$ that the worker is currently earning. A larger difference between $w^*$ and $w$ indicates that the worker is more reluctant to move on-the-job, since any wage between $w$ and $w^* (w)$ would be too low to compensate the worker for the risk of unemployment associated with the job-to-job transition. In particular, the difference between $w^* (w)$ and $w$ is increasing in $w$: a worker who is in a “good” match is more reluctant to accept outside offers, due to the risk of becoming unemployment and losing a high wage. It is important to stress that, in the case of $\rho = 1$, the red line always coincides with the blue line: for any $w$, $w^* (w) = w$. In other words, the reservation wage of workers coincides with the current wage, and any offer that is slightly higher than $w$ is accepted by the worker.

One key property of workers’ reservation wages is that they depend on the value of unemployment, because a match with a new firm can be unsuccessful. In a recession, the value of unemployment decreases, since unemployed workers have fewer opportunities to find a new job. This has direct effects on employed workers as well, and in particular, the lower value of unemployment makes them more reluctant to move. In order to show the effects of this mechanism on workers’ reallocation, I consider the pre-recession steady state and derive the short-run equilibrium responses of firms and workers after the realization of the shocks described in Table 4.2. When $\lambda_0$ decreases, the value of unemployment goes down, since it becomes harder for unemployed workers to find a job. Hence, employed workers’ option value of moving to a new firm goes down, and employed workers’ reservation wages increase.

This mechanism is clearly depicted in Figure 7. The green line represents workers’ new reservation wages in the recession. This line lies above the red one, which represents workers’ reservation wages in the pre-recession steady state. The increase in workers’ reservation makes workers more reluctant to leave their current jobs, and this causes a decline in the aggregate job-to-job transition rate. Intuitively, workers need higher offered wages during recessions, to compensate them for the higher cost of unemployment. However, after aggregate productivity declines, firms need to reduce their wages to make non-zero profits. As shown in Figure 8, firms’ offered wages generally decrease in the recession. The only exception is the behavior of the firms with productivity $p > 140$ (the top 0.00001 in the productivity distribution), which can set higher wages in order to compensate for the increase in workers’ reservation wages.

After deriving optimal workers’ reservation wages and firms’ offered wages, I cal-

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Figure 6: Wage and Reservation Wages of Employed Workers, $\rho = 0.7$

Figure 7: Reservation Wages, Boom vs. Recession, $\rho = 0.7$
culate the new level of job-to-job transition rate, which is equal to 0.69%. Hence, the job-to-job transition rate drops from a pre-recession level of 1.34% to 0.69%, a decline of 48.5%. This decline is due to the combined effect of two mechanisms: the decrease in the job arrival rate of employed workers, $\lambda_1$; and the increase in worker’s reluctance to move on-the-job during the recession.

In order to single out the net effect of workers’ higher unwillingness to reallocate, I perform the following exercise. I exogenously keep fixed reservation wages of employed workers at their pre-recession steady state and calculate the equilibrium after the shocks in Table 4.2. This way, I shut down the increase in workers’ reluctance to quit due to the recession. Then, I calculate the drop in job-to-job transitions in the new equilibrium. The new value of the job-to-job transition rate is 0.83%, hence without the shift in workers’ reservation wages, this rate would only decline by 39.5%. As a result, the drop in $\lambda_1$ generates a drop in the job-to-job transition rate by 39.5%, while workers’ increased reluctance to move on-the-job accounts for the residual effect, equal to $(48.5\% - 39.5\%) = 9\%$, which represents about 18% of the overall decline in job-to-job transitions.

Finally, I consider the medium-run effects of the shocks by deriving the new steady state in which $G$ can adjust. In this steady state, the value of the job-to-job transition rate is equal to 0.94%, which implies a decline of 30% from the pre-recession value (1.34%). Also in this case, the freeze in job-to-job transitions is due to the combined effects of the demand-based mechanism (the drop in $\lambda_1$) and the supply-based one (the increase in workers’ reservation wages). In order to quantify the importance of the latter, I repeat the same exercise described above: I impose that workers keep the same reservation wages fixed at the pre-recession level and calculate the drop in the employer-to-employer transition rate in the new equilibrium. In this case, the supply-based channel generates a drop in the transition rate of 5.3%, which again represents about 18% of the overall decline.

**Calibration 2: $\rho = 0.55$**

Now, I consider the second calibration, where $\rho = 0.55$ matches the risk of separation estimated for the first 12 months of tenure for workers who move on-the-job. In this case, the effects of a recession on workers’ unwillingness to move on-the-job are even stronger, since the unemployment state is more likely after the formation of a new match, compared to the case in which $\rho = 0.7$. Hence, workers’ reluctance to move generates a larger drop in the number of workers moving on-the-job.

Following the same steps as in Calibration 1, I first look at the effects of the shocks described in Table 4.2 by deriving the short-run equilibrium response of firms and work-
The job-to-job rate declines from a level of 1.27% in the pre-recession steady state to a level of 0.62% in the recession, a drop of 51%. Also in this case, this drop results from the combined effect of the supply and the demand-based mechanisms. I isolate the contribution of the supply-based mechanism by following the same procedure described above and find that it generates a drop in the employer-to-employer rate by 10%. Hence, this mechanism accounts for about 20% of the total drop in job-to-job transitions generated by the model.

Looking at the effects of the shock on the medium-run equilibrium, the total decline in the job-to-job rate is about 35%, and also in this case, the supply-based mechanism accounts for about 20% of the model-generated decline in the transition rate.

4.5 The Effects on Measured Productivity

Finally, I consider the effects of workers’ increased reluctance to move on-the-job on aggregate productivity during recessions. In the model, workers who move from less to more productive firms contribute to increasing the average quality of matches. As a consequence, a lower propensity of workers to move to better firms during recessions decreases the average quality of matches and measured productivity. In order to quantify these effects, I consider Calibration 2, in which $\rho = 0.55$. I compare aggregate productivity in the pre-recession steady state, and in the medium-run equilibrium following the shocks described in Table 5. This comparison allows me to measure the drop in productivity, which is due to the effect of both the demand and the supply-based mechanism. In
order to identify the effects of the latter, I impose that workers keep the same reservation wages exogenously fixed at their pre-recession level and calculate the drop in productivity.

I calculate productivity as aggregate output divided by the total number of employed workers. I find that productivity declines by about 10% from the pre-recession steady state to the new steady state. Productivity is lower due to three effects: 1) the negative shock to the common component of firms’ productivity; 2) the decline in workers’ job-finding rate, $\lambda_1$; 3) the increase in workers’ reluctance to move on-the-job. Following the above-described procedure, I find that the shift in workers’ reservation wages alone generates a productivity loss of about 0.9%. This loss in productivity is due to workers’ reluctance to move to new firms, which prevents reallocating workers from the low to the high quantiles of the firm productivity distribution. In order to illustrate this mechanism, I derive in Figure 9 the difference between the density of employed workers across firms’ productivity levels between the equilibrium in which workers’ reservation wages are kept exogenously fixed and the equilibrium in which these reservation wages can adjust. Hence, Figure 9 shows the difference in the allocation of workers across firms between the equilibrium in which workers do not become more reluctant to move in recessions and the equilibrium in which this happens. Figure 9 clearly shows that the increase in workers’ unwillingness to move in recessions increases the mass of workers concentrated in low productivity firms (those with $p < 25$) and reduces the mass of workers in higher productivity firms (with $p > 25$). In aggregate, this is reflected in a lower measured productivity.

Finally, the mechanism through which workers’ reluctance to move to new firms reduces workers’ reallocation is consistent with the recent findings of Moscarini and Postel-Vinay (2014). The authors use JOLTS data to document that the Great Recession was characterized by a dramatic decline in the flow of workers moving from small to large employers. In the model, more productive firms are also larger, hence an increase in workers’ unwillingness to move on-the-job during recessions prevents workers from moving from smaller, less productive firms to larger, more productive ones.

5 Conclusions

In this paper, I investigate the implications of workers’ unwillingness to move on-the-job during recessions, providing a novel, labor-supply based explanation for why economic downturns are characterized by fewer job-to-job transitions. The mechanism I highlight operates through a risk of early match dissolution for new jobs, which makes workers
more reluctant to change employers during recessions and complements the demand-side channel traditionally emphasized by the literature. I first document that jobs originating after job-to-job transitions carry a high risk of separation during the first twelve months of employment, by estimating the hazard rate function of these jobs using data from SIPP. In light of this new evidence, I introduce the risk of early match dissolution in the job-ladder model of Burdett and Mortensen (1998). I find that my proposed mechanism complements the traditionally emphasized labor demand channel. In particular, I find that my mechanism can generate a drop in job-to-job transition rates by 10% in a recession as large as the Great Recession. Workers’ increased reluctance to quit during recessions also has implications for aggregate productivity, as it hinders worker reallocation from smaller, less productive firms to larger, more productive ones. I find that this mechanism results in an aggregate productivity loss of 1% between the boom and the recession steady state. Having established that match uncertainty on the supply side can have implications for productivity, a natural question then arises concerning the role of policy in spurring labor reallocation during recessions. In particular, these findings suggest that there is a role for unemployment insurance, not only as a means to provide consumption-smoothing and risk sharing, but also as a way to counteract the unwillingness of employed workers to move to better firms during recessions. Unemployment insurance can affect the incentives of employed workers by raising the option value of moving on-the-job. In a set-up similar to the one developed in this paper, but with workers’ risk aversion and endogenous search effort of unemployed workers, unemployment insurance would not only induce workers to decrease search effort, reducing employ-

Figure 9: Percentage Difference in the Cross-Sectional Distributions of Workers across Firms’ Productivity Levels
ment and output, but it would also affect the composition of existing matches by favoring the formation of more matches with high productivity firms. Analyzing these tradeoffs and their implications for the optimal unemployment insurance in booms and recessions is the subject of a companion paper currently in progress.

References


Appendix

A Estimation of the Hazard Rate Functions

In this section, I report the estimation of the hazard rate functions for the 2008 SIPP panels. This panel tracks the employment histories of 126,275 individuals from 2008 to 2012. I identify 11,276 hires from unemployment and 2,792 hires from employment, and I calculate their durations in months. As described in Section 2.1, for each of the two groups, I estimate the cumulative hazard function using the Nelson-Aalen nonparametric estimator and then estimate the hazard function through a kernel smooth of the hazard contributions. The estimated hazard rates of separation for both hires from employment and hires from unemployment are illustrated in Figure 10. Hazard rates are overall similar to the ones obtained on the SIPP 2004 panel.

B Proofs and Equilibrium Steady State Conditions

B.1 Proof of Proposition 1

• Part 1: Consider the profit function in Formula (10). We can write \( \pi(p, w) = A(p, w)^* (p - w) \), where

\[
A(p, w) = \rho \frac{q(p)}{N} \left[ \lambda_0 u + \lambda_1 (1 - \delta) (1 - u) G(\bar{w}(w)) \right] \frac{1 - u}{\left[ \lambda_0 u + \lambda_1 (1 - \delta) (1 - u) \right] \left[ 1 - \beta (1 - \delta) \right] \left[ 1 - \lambda_1 (1 - F(w^*(w))) \right]}.
\]

By definition, the optimal wage chosen by a firm \( p \) is \( w(p) = \arg\max_{w \in \mathbb{R}} A(p, w)^* (p - w) \).

It is also possible to define \( \pi^*(p) = \max_{w \geq R} A(p, w)^* (p - w) \).

Then, taking \( p_2 > p_1 \), and defining \( w_1 := w(p_1); w_2 := w(p_2) \), it holds that:

\[
\pi^*(p_2) = A(p_2, w(p_2)) (p_2 - w(p_2)) \geq A(p_2, w(p_1)) (p_2 - w(p_1))
\]

Figure 10: Hazard Rates as Function of Months of Tenure, E-to-E jobs (top) and U-to-E jobs, (bottom), estimated from SIPP 2008 Panel
\[ > A(p_1, w(p_1)) (p_1 - w(p_1)) = \pi^*(p_1) \]

\[ \geq A(p_1, w(p_2)) (p_1 - w(p_2)), \quad (21) \]

where the first two inequalities come from the definitions of \( \pi^*(p) \) and \( w(p) \), and the third inequality is due to the fact that \( p_2 > p_1 \). Moreover, the relations just derived imply that

\[ (p_2 - p_1) A(p_2, w(p_2)) \geq (p_2 - p_1) A(p_1, w(p_1)), \]

and since \( A(p, w) \) is strictly increasing in \( w \), this implies that \( w(p_2) \geq w(p_1) \).

- Part 2: The fact that the firm size is increasing in each firm’s productivity is a direct consequence of Part 1 of Proposition 2: more productive firms offer higher wages, and since \( A(p, w) \) is increasing in \( w \), a more productive firm has in steady state a higher number of workers due to high offer acceptance rates and low quits.

### B.2 Derivation of the Steady State Conditions

- Firms’ present value of future profits from hiring a worker, \( J_t(p, w) \):

  If the match is successful (with probability \( \rho \)), in period \( t \) the firm obtains profit \((p - w)\). The present value of profit in \( t + 1 \) is equal to:

  \[ \beta (1 - \delta - (1 - \delta) \lambda_1 (1 - F_{t+1}(w_*(w)))) (p - w) \]

  hence, the firm obtains profit \((p - w)\) if the worker is not separated, either exogenously (with probability \( 1 - \delta \)) or endogenously (with probability \( (1 - \delta) \lambda_1 (1 - F_{t+1}(w_*(w))) \)). Iterating from the third period on:

  \[ J_t(p, w) = \rho \left[ (p - w) + \beta (1 - \delta - (1 - \delta) \lambda_1 (1 - F_{t+1}(w_*(w)))) (p - w) + \beta^2 \ldots \right]. \]

  In steady state, \( F_t = F \), and the above expression is equal to Equation 9:

  \[ J(p, w) = \frac{\rho (p - w)}{1 - \beta (1 - \delta) [1 - \lambda_1 (1 - F(w_*(w)))]} \]

- Firm Size
From Equation 13:

\[ L_{t+1}(p) = L_t(p)(1 - \delta) \left[ 1 - \lambda_1 F_{t+1}(w*(w(p))) \right] + \rho \frac{q(p)}{N} \left[ \lambda_0 u_t + \lambda_1 (1 - \delta) (1 - u_t) G_{t+1}(\bar{w}(w(p))) \right]; \]

In steady state: \( L_{t+1} = L_t = L \):

\[ L(p)(1 - (1 - \delta) \left[ 1 - \lambda_1 F_{t+1}(w*(w(p))) \right]) = -\rho \frac{q(p)}{N} \left[ \lambda_0 u_t + \lambda_1 (1 - \delta) (1 - u_t) G_{t+1}(\bar{w}(w(p))) \right]; \]

Hence,

\[ L(p) = \frac{\rho \frac{q(p)}{N} \left[ \lambda_0 u_t + \lambda_1 (1 - \delta) (1 - u_t) G_{t+1}(\bar{w}(w(p))) \right]}{1 - (1 - \delta) \left[ 1 - \lambda_1 F_{t+1}(w*(w(p))) \right]} \]

- Unemployment:

From Equation 15:

\[ u_{t+1} = u_t + \delta (1 - u_t) - \rho \lambda u_t + (1 - \rho) s \lambda (1 - \delta) (1 - u_t) \left[ \int_{w}^{\bar{w}} [1 - F(w*(x))] g(x) dx \right]; \]

In steady state: \( u_{t+1} = u_t = u \):

\[ \rho \lambda u = \delta - \delta u + (1 - \rho) s \lambda (1 - \delta) (1 - u) \left[ \int_{w}^{\bar{w}} [1 - F(w*(x))] g(x) dx \right]; \]

\[ \left( \rho \lambda + \delta + (1 - \rho) s \lambda (1 - \delta) \left[ \int_{w}^{\bar{w}} [1 - F(w*(x))] g(x) dx \right] \right) u = \]

\[ = \delta + (1 - \rho) s \lambda (1 - \delta) \left[ \int_{w}^{\bar{w}} [1 - F(w*(x))] g(x) dx \right]; \]

Hence,

\[ u = \frac{\delta + (1 - \rho) s \lambda (1 - \delta) \left[ \int_{w}^{\bar{w}} [1 - F(w*(x))] g(x) dx \right]}{\rho \lambda + \delta + (1 - \rho) s \lambda (1 - \delta) \left[ \int_{w}^{\bar{w}} [1 - F(w*(x))] g(x) dx \right]}; \]

- \( G \) function:

From Equation 17:
\[(1 - u_{t+1}) G_{t+1}(w) = \rho \lambda F_t(w) u_t + (1 - \delta)(1 - u_t) G_t(w) - s\lambda(1 - \delta)(1 - u_t) \times \]
\[
\times \left\{ [1 - F_t(w)] G_t(\bar{x}(w)) + \int_{\bar{x}(w)}^{w} [1 - F_t(w^*(x))] dG_x(x) + (1 - \rho) \int_{w}^{\bar{x}(w)} [F_t(w) - F_t(w^*(x))] dG_t(x) \right\} ;
\]

In Steady State:

\[(1 - u_t) G(w) = \rho \lambda F(w) u_t + (1 - \delta)(1 - u_t) G(w) - s\lambda(1 - \delta)(1 - u_t) \times \]
\[
\times \left\{ [1 - F(w)] G(\bar{x}(w)) + \int_{\bar{x}(w)}^{w} [1 - F(w^*(x))] dG_x(x) + (1 - \rho) \int_{w}^{\bar{x}(w)} [F_t(w) - F_t(w^*(x))] dG_t(x) \right\} ;
\]

\[G(w) = \rho \lambda F(w) \frac{u_t}{1 - u_t} + (1 - \delta) G(w) - s\lambda(1 - \delta) \times \]
\[
\times \left\{ [1 - F(w)] G(\bar{x}(w)) + \int_{\bar{x}(w)}^{w} [1 - F(w^*(x))] dG_x(x) + (1 - \rho) \int_{w}^{\bar{x}(w)} [F_t(w) - F_t(w^*(x))] dG_t(x) \right\} ;
\]

Hence,

\[G(w) = \rho \frac{\lambda}{\delta} F(w) \frac{u_t}{1 - u_t} - s\lambda \left( \frac{1 - \delta}{\delta} \right) \times \]
\[
\times \left\{ [1 - F(w)] G(\bar{x}(w)) + (1 - \rho) \int_{\bar{x}(w)}^{w} [F_t(w) - F_t(w^*(x))] dG_t(x) + \int_{\bar{x}(w)}^{\bar{x}(w)} [1 - F(w^*(x))] dG(x) \right\} .
\]

### C Estimated Parameters, $\rho = 0.7$ and $\rho = 0.55$

In this section I describe the results of the model calibration and estimation for the cases $\rho = 0.7$ and $\rho = 0.55$, respectively.
** Calibration 1: \( \rho = 0.7 \)**

Parameters \( \{\beta, \lambda_0, b, \} \) are calibrated through direct match with their empirical counterparts, as in the case in which \( \rho = 1 \). Hence, the values of these parameters are reported in Table 2. The parameter \( \delta \) is calibrated as equal to \( \delta = 0.008 \) instead to a value of \( \delta = 0.013 \) when \( \rho = 1 \). Due to \( \rho < 1 \), the presence of separations occurring upon mach formations tends to increase the steady state level of unemployment, compared to the model with \( \rho = 1 \). As a consequence, I set a smaller \( \delta \) in order to obtain a pre-recession level of unemployment equal to 5%.

The remaining parameters, \( \{s, \mu_\Phi, \sigma_\Phi, \mu_\Gamma, \sigma_\Gamma\} \), are estimated through SMM by following the same procedure described in Section 4.1. The value of the estimated parameters are reported in Table 6.
<table>
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<th>Estimated Value</th>
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<td>$\sigma_\Phi$</td>
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<tr>
<td>$\mu_\Gamma$</td>
<td>$-1.05$</td>
</tr>
<tr>
<td>$\sigma_\Gamma$</td>
<td>1.06</td>
</tr>
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</table>

Table 6: Parameter Values, SMM Estimation ($\rho = 0.7$)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimated Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s$</td>
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</tr>
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</table>

Table 7: Parameter Values, SMM Estimation ($\rho = 0.55$)

**Calibration 2: $\rho = 0.55$**

Values of the parameters $\{\beta, \lambda_0, b, \}$ are assigned as in Calibration 1, and summarized in Table 2. Moreover, as argued above, the fact that $\rho < 1$ implies that the calibrated value of $\delta$ must be smaller than in the case in which $\rho = 1$. In particular, a value of $\delta = 0.005$ allows me to obtain a pre-recession level of unemployment equal to 5%.

The remaining parameters, $\{s, \mu_\Phi, \sigma_\Phi, \mu_\Gamma, \sigma_\Gamma\}$, are estimated through SMM as described in Section 4.1. The values of the estimated parameters are reported in Table 7.