The Unemployment Volatility Puzzle: 
The Role of Matching Costs Revisited

José I. Silva and Manuel Toledo*

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Abstract

Pissarides (2009) has argued that the standard search model with sunk fixed matching costs increases unemployment volatility without introducing an unrealistic response of wages of new matches to productivity shocks. We revise the role of matching costs and show that when these costs are not sunk and, therefore, can be partially passed on to new hired workers in the form of lower wages, the amplification mechanism of fixed matching costs is considerably reduced. Finally, we observe that an empirical reasonable share of sunk costs is not able to match the volatility of unemployment without introducing unrealistic sensitivity to unemployment benefits. (JEL E32, J32, J64)

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I Introduction

The Mortensen-Pissarides (MP) search and matching model (Mortensen and Pissarides, 1994; Pissarides, 1985, 2000) studies the dynamics of unemployment in an environment where jobs are continuously created and destroyed. A sequence of papers by Costain and Reiter (2008), Hall (2005) and Shimer (2005) have questioned the model’s ability to match the observed cyclical fluctuations of the unemployment rate in the U.S. For example, Shimer shows that under a reasonable calibration strategy, the MP model predicts that the vacancy-unemployment ratio and the average labor productivity should have nearly the same volatility. In contrast, the standard deviation of the vacancy-unemployment ratio in the U.S. is almost 20 times as large as the standard deviation of average labor productivity. This large discrepancy between the volatility implied by the model and the data constitutes an empirical puzzle, known as the unemployment volatility puzzle.

Pissarides (2009) shows that introducing fixed matching costs into the model (e.g., training costs) can significantly increase the volatility of labor-market outcomes, such as tightness and the job finding rate. He points out that this result is obtained without inducing a counterfactually low volatility in the wages of new jobs. In his quantitative exercise, Pissarides only considers sunk fixed matching costs and argues that non-sunk fixed training costs play a similar role. More in detail, Pissarides (2009, p.1364) writes the following with respect to matching costs: “they are sunk once the wage bargain is concluded and the worker takes up the position, but this property is not important for the volatility, because training costs that are not sunk play a similar role”. He shows that when these costs increase from zero to 40% of average labor productivity, the volatility of the
The vacancies-unemployment ratio (measured by its elasticity) increases almost twofold, and it matches the observed volatility in the U.S. labor market.

In this paper we evaluate the amplification mechanism of non-sunk fixed matching costs, and examine whether the cyclical volatility predicted by the model is substantially augmented. We show that when these costs are not sunk and, therefore, can be partially passed on to workers through lower wages, the volatility of the vacancy-unemployment ratio is approximately an order of magnitude less responsive to variations in these costs. Thus, from a quantitative standpoint, the contribution of matching costs in explaining labor market volatility depends not only on the level, but also on what proportion of these costs is sunk. We also show that the model with fixed costs is equivalent to the standard model with lower labor productivity and non-constant flow hiring costs. When we calibrate the model considering a share of sunk costs of 28% consistent with the empirical estimate of a small or a nearly neutral effect of training costs on the starting wage, the model is able to reproduce 96% of the observed volatility in the U.S. labor market tightness. We observe, however, that this share of sunk costs introduces an unrealistic sensitivity to unemployment benefits (see Costain and Reiter, 2008, for an explanation of this issue).

The paper is organized as follows. In Section II we incorporate non-sunk fixed costs in the standard MP model. Section III presents the calibration and the simulated elasticities. In Section IV, we present evidence related to the effect of training on the starting wage and check whether empirically reasonable training costs are able to match the volatility of unemployment. Finally, we present our conclusions in Section V.
II The model

Given that our model is essentially the same as Pissarides’ (2009), its presentation is reduced to a minimum. In this economy, there is a continuum of risk-neutral, infinitely-lived workers and firms which discounts future payoffs at a common rate \( r \); capital markets are perfect; and time is continuous.

There is a time-consuming and costly process of matching workers and job vacancies, captured by a standard constant-returns-to-scale matching function \( m(u, v) = m_o u^\eta v^{1-\eta} \), where \( u \) denotes the unemployment rate, \( v \) is the vacancy rate, and \( \eta \) and \( m_o \) are the function parameters. Unemployed workers find jobs at the rate \( f(\theta) = m(u, v)/u \), and vacancies are filled at the rate \( q(\theta) = m(u, v)/v \), where \( \theta = v/u \) denotes labor market tightness. From the properties of the matching function, the higher the number of vacancies with respect to the number of unemployed workers, the easier it is to find a job, \( f'(\theta) > 0 \), and the more difficult it is to fill vacancies, \( q'(\theta) < 0 \).

A job can be either filled or vacant. Before a position is filled, the firm has to open a job vacancy with a flow cost \( c \). Firms have a linear technology with labor as the only production factor. Each filled job yields instantaneous profit equal to the difference between labor productivity \( p \) and the wage. When the worker arrives, the firm pays fixed costs \( H \) which is sunk. Moreover, it pays non-sunk fixed costs \( T \) right after both the firm and the worker agree to start a working relationship. A job remains “new” until a shock with arrival rate \( \lambda \) hits the match and changes its status to a continuing job. In that case, the worker and the firm renegotiate wages. Notice that \( T \) becomes sunk after the initial negotiation. Therefore, new and continuing jobs will have different wages \( w^n \) and \( w^c \), respectively. Thus, the value of vacancies \( V \), the value of a new job \( J^n \), and the value of a
continuing job $J^c$ are represented by the following Bellman equations:

$$rV = -c + q(\theta)(J^n - H - T - V),$$

(1)

$$rJ^n = p - w^n + s(V - J^n) + \lambda(J^c - J^n),$$

(2)

$$rJ^c = p - w^c + s(V - J^c),$$

(3)

When finding a job, the unemployed worker first belongs to a new job. At rate $\lambda$, it becomes a continuing job. All employed workers separate from their firm at the constant rate $s$. Unemployed and employed workers’ Bellman equations are given by

$$rU = z + f(\theta)(W^n - U),$$

(4)

$$rW^n = w^n + s(U - W^n) + \lambda(W^c - W^n),$$

(5)

$$rW^c = w^c + s(U - W^c),$$

(6)

where $z$ represents the flow utility from leisure.

As is standard, we assume that there is free entry for vacancies. Therefore, in equilibrium:

$$V = 0.$$

(7)

We also assume that wages in new jobs are determined through bilateral Nash bargaining between the worker and the firm. The first-order conditions for entrant employees yield the following equation:

$$(1 - \beta)(W^n - U) = \beta(J^n - T),$$

(8)
where $\beta \in (0, 1)$ denotes the workers’ bargaining power relative to the firms’. Note that the Nash condition depends on matching costs $T$ but not on $H$ because the former are not sunk to new jobs, and therefore they are explicitly considered in the wage negotiation with new entrants.

This sharing rule implies that $J^n - T = (1 - \beta)S^n$, where $S^n = J^n + W^n - T$ is the surplus of a new job (net of sunk cost $H$). By substituting the free entry condition into equation (1) and then the Nash sharing rule we obtain

$$\frac{c}{q(\theta)} + H = J^n - T,$$

$$\frac{c}{q(\theta)} + H = (1 - \beta)S^n. \tag{10}$$

Then, by using the asset-value equations (1)-(6), we find the following expression for the surplus of a new job,

$$S^n = \left(\frac{p}{r} - rU\right)/(r + s) - T. \tag{11}$$

We now substitute $(W^n - U) = \frac{\beta}{1 - \beta}(c/q(\theta) + H)$, which is given by the Nash sharing rule and equation (9), into asset-value (4) and get

$$rU = z + \frac{\beta}{1 - \beta}(c\theta + f(\theta)H). \tag{12}$$

Then, we substitute this expression into (11) and, finally, the resulting $S^n$ into (10) in order to obtain the equilibrium job creation condition:

$$\frac{[(1 - \beta)(p - z) - \beta(c\theta + f(\theta)H)]}{(r + s)} = \frac{c}{q(\theta)} + H + (1 - \beta)T. \tag{13}$$

As Pissarides (2009) points out, this job creation condition is independent of the specific wage determination scheme for continuing jobs. If, in particular, we assume a Nash wage rule for contin-
using matches as well, we obtain the following equilibrium wages:

\[ w^n = (1 - \beta)z + \beta(c\theta + p + f(\theta)H - (r + s + \lambda)T), \quad (14) \]

\[ w^c = (1 - \beta)z + \beta(c\theta + p + f(\theta)H). \quad (15) \]

Since \( H \) are sunk, they increase the implicit bargaining power of all workers and, therefore, their wages. In contrast, firms can pass on part of the non-sunk matching costs \( T \) to new employees in the form of lower wages.

A steady-state equilibrium in this economy is a triplet of labor market tightness and wage rates \((\theta^*, w^n^*, w^c^*)\) that solves equations (13), (14), and (15) for the steady-state productivity level \( p^* \).

### III Parameter values and elasticities

For comparison purposes, we use the same targets and parameter values as in Pissarides (2009), and calibrate the model at monthly frequency without fixed matching costs, \( T = H = 0 \) (benchmark). We calibrate the job conversion rate \( \lambda \) by assuming that “new” jobs are converted to continuing jobs at the end of the training period. According to Barron, Berger and Black (1997), a new hired worker becomes fully trained after 20.2 weeks on average. Thus, the average duration of a new job is 5.1 months, so \( \lambda = 0.196 \) (i.e., \( 1/\lambda = 5.1 \)). Notice that the value of \( \lambda \) is irrelevant when \( T = 0 \). See Table 1 for all the parameter values of our benchmark calibration.

The quantitative exercise we carry out in this section is very simple. We increase either the sunk \((H)\) or non-sunk \((T)\) matching costs and adjust the free vacancy parameter \( c \) in order to maintain
the same steady-state value for the labor market tightness $\theta^*$ and, therefore, the equilibrium unemployment rate $u^* = s/(s + f(\theta^*))$.2

[Insert Table 1 Here]

The central question in this paper is whether this extended MP matching model with fixed matching costs can explain the size of the business cycle fluctuations in labor-market tightness and unemployment given the separation rate. To explore this issue, we find the elasticities of the vacancy-unemployment ratio, $\varepsilon_\theta$, and wages in new jobs, $\varepsilon_{w^n}$, with respect to labor productivity $p$. Thus, from the job creation condition (13) and the wage equations (14), we obtain

$$\varepsilon_\theta = \frac{(1/\eta)(1 - \beta)p^*}{(1 - \beta)(p^* - z) + \beta \left(1 - \frac{\eta}{\eta} \right) c\theta^* - \left[r + s + \beta \left(1 - \frac{2\eta}{\eta} \right) f(\theta^*) \right] H - (r + s)(1 - \beta)T}, \quad (16)$$

and

$$\varepsilon_{w^n} = \beta \left[p^* + \varepsilon_\theta (c\theta^* + f(\theta^*)(1 - \eta)H) \right]/w^*. \quad (17)$$

Table 2 shows these elasticities for different values of $H$ and $T$. We find that the volatility of the vacancies-unemployment ratio $\theta$ is much higher when sunk fixed matching costs $H$ are increased. For example, the elasticity of the vacancies-unemployment ratio is multiplied almost by two (from 3.67 to 7.24) when these costs increase from 0 to 40% of the average labor productivity. In contrast, this elasticity only increases approximately 6% (from 3.67 to 3.88) for the same variation in the non-sunk matching costs $T$.

To understand this result, notice that there are two effects. There is a direct effect associated with the terms that depend on $H$ and $T$ in the denominator of (16). It is easy to see that if $\eta < f(\theta^*)/(2f(\theta^*) - r - s)$, as in our parametrization, then $r + s + \beta ((1 - 2\eta)/\eta) f(\theta^*) > (r+s)(1-\beta)$...
and, consequently, an increase in $H$ has a larger positive impact on $\varepsilon_\theta$. Furthermore, we have an indirect effect through the recalibration of parameter $c$ as explained above. Note that an increase in $H$ causes $\theta^*$ to fall more compared to the impact of $T$. Therefore, in order to keep $\theta^*$ constant, $c$ has to fall more when $H$ increases. Clearly, $\varepsilon_\theta$ is decreasing in $c$. Thus, the indirect effect of a change in fixed matching costs on $\varepsilon_\theta$ through $c$ is larger for $H$. Provided that $\eta < f(\theta^*)/(2f(\theta^*) - r - s)$, both effects are greater in the case of a change in $H$, which explains why $\varepsilon_\theta$ increases more when we raise $H$.

[Insert Table 2 Here]

The question now is to what extent each effect contributes to this result. To assess the size of the direct effect we leave $c$ at its benchmark value and adjust $\theta^*$ in order to satisfy equilibrium condition (13). The difference between both resulting elasticities (again, one recalibrating $c$ and the other letting $\theta$ adjust) can be interpreted as the magnitude of the indirect effect. After all, $\theta^*$ would inevitably change if we keep the remaining parameters constant when fixed costs change. In our alternative exercise, it turns out that the resulting elasticities are in most cases very close to the ones where we change $c$ (see the last column of Table 2). For instance, for $H = 0.1$ or $T = 0.1$, we obtain $\varepsilon_\theta|_{c=.356}$ equal to 4.191 and 3.719, respectively. In these two cases, the actual indirect effect is quite small, in fact negative. This remains the case for other values of $T$. For $H \geq 0.2$, this indirect effect actually becomes positive but it is arguably small relative to the overall change in $\varepsilon_\theta$. Therefore, we can say that our results do not hinge on our particular way of recalibrating the model.
Notice that in Table 2 we obtain very different values of $c$, particularly when we change $H$. One might want to know whether these values are empirically reasonable. Using information reported by Barron et al. (1997) that comes from the 1982 Employer Opportunity Pilot Project (EOPP), a cross-sectional firms-level survey containing detailed information on these labor turnover costs, Silva and Toledo (2009) show that vacancy costs represent, on average, 12.9% (4.3%) of the monthly (quarterly) wage of newly hired workers, $w^n$. In the benchmark calibration without fixed costs ($H = T = 0$), vacancy costs represent 36.4% of $w^n$. On the other end, when fixed costs are $H = 0.40$ and $T = 0$, the vacancy costs only represent 2.7% of $w^n$.

Table 3 presents the simulated results when the vacancy cost parameter $c$ is calibrated so that it is equal to $0.129w^n\ast$. This exercise requires adjusting a different parameter to satisfy the same equilibrium unemployment rate. We choose workers’ bargaining power $\beta$. The resulting elasticities are somewhat similar to the ones shown in Table 2. Thus, the conclusions we draw from this alternative experiment are fundamentally the same.

[Insert Table 3 Here]

Similar to Pissarides (2009), Mortensen and Nagypál (2007) argue that in order to amplify the shocks, it is important to have fixed turnover costs in the model. We can show, however, that our model with fixed costs is equivalent to the standard model with the following flow costs. Let us define the flow cost of vacancy posting as $\tilde{c}(\theta) = c + q(\theta)H$ and labor productivity net of flow (production) costs as $\tilde{p} = p - (r + s + \lambda)T$. Moreover, let $\tilde{J}^n = J^n + T$. Now we can substitute these expressions into equations (1), (2) and (8), and obtain:

$$rV = -\tilde{c}(\theta) + q(\theta)(\tilde{J}^n - V), \tag{18}$$
\[ r\tilde{J}^n = \tilde{p} - w^n + s(V - \tilde{J}^n) + \lambda(J^c - \tilde{J}^n), \tag{19} \]

\[ (1 - \beta)(W^n - U) = \beta\tilde{J}^n. \tag{20} \]

Therefore, the model with fixed costs is isomorphic to the standard model with lower labor productivity \( \tilde{p} \) and non-constant flow vacancy cost \( \tilde{c}(\theta) \).

This result allows us to explain the underlying intuition behind the amplification mechanism of \( T \) and \( H \). In the first case, the model generates a slightly larger volatility of unemployment because the relative standard deviation of (net) labor productivity increases as \( T \) also increases. Notice that the standard deviation of \( \tilde{p} \) is the same as that of \( p \), but the mean of \( \tilde{p} \) is lower than the average \( p \).

In the case of \( H \), since the vacancy cost \( \tilde{c}(\theta) \) falls with higher values of \( \theta \), firms have an additional incentive to hire workers when a positive labor productivity shock hits the economy.

Now that we understand that sunk costs are crucial for amplifying the shocks, an interesting question is how big these costs are. Moreover, we want to study the implications of empirically reasonable sunk costs on the model’s amplification mechanism.

To answer this question we assume that \( H \) and \( T \) only capture training costs. We find that this source of labor turnover costs is able to match the unemployment volatility if about 36% of them are sunk. We reach this figure as follows. First, we look at some empirical findings regarding on-the-job training in the U.S. Barron et al. (1997), using the EOPP survey, find that 95% of new hired workers received some kind of training and spent, on average, 142 hours in training activities during the first quarter in the firm. When adding the contribution of incumbent workers and supervisors in training new employees, which is 87.5 hours on average, the resulting cost amounts to 55% of the quarterly wage of a new hire. Thus, given our assumption that \( H \) and \( T \) only reflect training
costs, \( H + T = .55 \times 3 \times w^\ast \). Then, we set \( H \) and \( T \) such that this last equation is satisfied and the model matches the observed \( \theta \) elasticity of 7.56 in the U.S. reported by Pissarides (2009). As is shown in the third block of Table 3, we get \( H = 0.524 \) and \( T = 0.921 \) (i.e., \( H/(H + T) = 0.363 \)), which implies \( w^\ast = 0.873 \).

Notice that in this scenario, wages in new matches are about 12.3% more sensitive than labor productivity shocks. This elasticity is above the near-proportionality between wages in new matches and labor productivity estimated in Haefke et al. (2008) as well as in Pissarides (2009).

IV On-the-job training effects on the starting wage:

Empirical evidence and simulated elasticities

Now we ask whether this ratio of sunk to non-sunk training costs is consistent with the empirical evidence. To test the impact of on-the-job training on the starting wage, Barron et al. (1999) employ two data sets: The 1982 EOPP employer survey mentioned before and the 1992 U.S. Small Business Administration (SBA) survey. Both data sets focus on the last hired worker and give detailed retrospective information about the training. Both surveys report a similar number of hours spent on on-the-job training during the first quarter of employment (142 hours in the EOPP and 150 hours in the SBA survey).

To estimate the impact of on-the-job training on starting wages, they specify a wage equation for new hired workers, \( w^n \), augmented by the time spent in on-site training, \( Q \), during the first
three months of employment. Thus, let

$$\ln(w^n) = X\beta_x + \gamma Q + \epsilon,$$

(21)

where $X$ is a vector of firm’s and worker’s characteristics with vector of coefficients $\beta_x$, and $\epsilon$ is an error term with standard properties. After controlling for a set of variables in $X$, they find a positive but statistically insignificant training effect. A similar result is also found in Sicilian (2001) and Veum (1999).

These authors argue that lack of a negative relationship between training and the starting wage may be the result of productivity differences that are not observed in the data. To avoid this problem, Barron et al. (1999) include two more variables in $X$. The first one is the job complexity variable defined as the time to become fully trained and qualified for a standard 40 hour work week using data on the worker’s usual hours worked per week. They expect more-able individuals to match with positions with higher job complexity. With the inclusion of this control variable, the estimated parameter for the on-site training variables becomes negative in both data sets, and for the EOPP sample the elasticity (-0.012) is only significant at the 5% confidence level.

The second variable they introduce as a control for worker ability is the time spent by supervisors for applicant interview. Using search theory, these authors argue that more able workers will be hired by employers who spend more time screening each prospective job candidate. When they add this second “ability-control” variable, the SBA estimated coefficient (-0.016) approaches significance at the 10% level and the EOPP estimated coefficient (-0.018) is significant at the 1% level.
According to these results, Barron et al. (1999, p. 244) conclude that “even when the coefficient estimates are negative and statistically significant, their magnitudes are small”. The largest elasticity they estimate is only -0.018 (see their table 2).

Sicilian (2001) also controls heterogeneity bias by estimating first-difference starting-wage regressions using the EOPP survey. More in detail, he takes log differences in starting wages by incorporating information on a second worker hired in the past two years for the same or similar position. Relying on job match theory, the author argues that if employers attempt to fill the same or similar position with a worker with the same or similar ability, then the ability bias inherent in OLS estimates will be reduced once the model is estimated by considering the wage differential between these two workers. Applying this methodology, he finds that total on-the-job training has a statistically significant effect on starting wages, with an estimated elasticity of -0.048. According to Sicilian (2001), this estimated coefficient suggests that every 100 hours of training reduces the starting wages nearly 5%.

Summarizing, the empirical studies that use the EOPP survey have either failed to find a significant negative relationship between on-the-job training and starting wages or find a small negative effect; with the largest elasticity at -0.05.

In order for the model to be consistent with these empirical findings and, therefore, to predict a small or a nearly neutral effect of training costs on the starting wage \( w^n \), it is convenient to express the wage in terms of total on-the-job training costs \( L = H + T \). Let us define the share of sunk training costs as \( \phi = H/L \). We can now rewrite the wage equation (14) as

\[
  w^n = (1 - \beta)z + \beta(c\theta + p + f(\theta)\phi L - (r + s + \lambda)(1 - \phi)L).
\]  

(22)
For training costs to have a neutral effect on \( w^n \), it is necessary that \( f(\theta^*)\phi = (r + s + \lambda)(1 - \phi) \). Thus, given \( f(\theta^*) = 0.594 \), \( r = 0.004 \), \( s = 0.036 \) and \( \lambda = 0.196 \), we obtain \( \phi = (r + s + \lambda)/(f(\theta^*) + r + s + \lambda) = 0.284 \). This value, although lower, is still reasonably close to the ratio of 0.363 implied by \( H = 0.524 \) and \( T = 0.921 \), which are the values of fixed costs required to reproduce the observed elasticity in labor market tightness when vacancy and training costs represent 4.3% and 55% of the quarterly wage of a new hire, respectively (see the third block of Table 3). The last row of the third block in Table 3 shows, however, that when \( H/L = 0.284 \), and still \( c/w^n = 0.129 \) and \( L \) represents 55% of the quarterly starting wage, the elasticity of the vacancy-unemployment ratio is equal to 7.25, which is quite close to the value of 7.56 observed in the data.

Finally, it is interesting to check whether our calibrated model with matching costs generates an unrealistic sensitivity to policy changes. It is well understood from the discussion in Costain and Reiter (2008) that the standard matching model can generate sufficiently large cyclical fluctuations in unemployment, or a sufficiently small unemployment response to changes in unemployment benefits, but it cannot do both. Along this line, the last column of Table 3 shows the calibrated semielasticity of unemployment with respect to the workers outside option, \( \varepsilon_u|_{z=.71} \) in each scenario. Clearly, the introduction of matching costs increases \( \varepsilon_u|_{z=.71} \), especially when these costs are sunk. For \( H \) higher than 0.1, the calibrated semielasticity becomes higher than the conservative value of 2 estimated by Costain and Reiter (2008). When we recalibrate \( z \) to match a semielasticity of 2 as in the bottom two rows of Table 3, we observe no amplification mechanism in training costs since the elasticity of labor market tightness practically does not change when we increase \( H \) and \( T \).
Thus, introducing reasonable sunk and non-sunk fixed costs in the model is basically the same as increasing $z$ in the standard model with no fixed costs, as far as $\varepsilon_\theta$ is concerned.

In Silva and Toledo (2009), training costs are able to increase the volatility of labor market tightness without introducing unrealistic sensitivity to policy changes because of endogenous job destruction in the model. When the job destruction margin becomes operative, matching costs make job destruction less sensitive to $z$. In contrast, the response of the job finding rate with respect to $z$ increases with higher matching costs. In the end, these two opposing forces tend to offset each other with respect to their impact on the long-run unemployment rate, implying that the semielasticity of unemployment with respect to the workers’ outside option remains unchanged.

V Conclusion

In a recent paper, Pissarides (2009) argues that the presence of fixed matching costs can improve the volatility of unemployment maintaining the one-to-one response of wages to productivity fluctuations observed in the data. In his model, the matching costs are sunk, so new matched workers take actions directed at extracting the quasi-rents created by them. We show that when these fixed matching costs can be partially passed on to workers through lower wages, the volatility of the vacancy-unemployment ratio is significantly reduced. Therefore, not only is the size of these fixed matching costs crucial but also the proportion of this costs that are sunk. We also show that the model with fixed costs is equivalent to the standard model with lower labor productivity and non-constant flow hiring costs.
We calibrated the model under a more realistic scenario with: (i) observed vacancy and training costs equivalent to 4.3% and 55% of the quarterly wage and; (ii) a share of sunk costs of 28% consistent with the empirical estimate of small or a nearly neutral effect of training on the starting wage. Under this scenario the model is able to reproduce 96% of the observed volatility in the U.S. labor market tightness. We observe, however, that reasonable matching costs are not able to match the volatility of unemployment without introducing unrealistic sensitivity to changes in unemployment benefits.

References


Notes

1It is important to notice that the calibrated employment opportunity cost $z$ is considerably higher than the value of 0.4 used in Shimer (2005). It is well known that a higher $z$ decreases the general match surplus and increases the volatility of labor market tightness (see Costain and Reiter, 2008, for a discussion).

2As robustness check of this experiment, later on we calibrate $c$ and $\beta$ differently.

3We thank an anonymous referee for pointing out the equivalence result in the case of non-sunk fixed costs $T$.

4This behavior in hiring costs is consistent with new empirical evidence. In particular, using the Canadian Workplace and Employee Survey, Caponi, Cayahan and Plesca (2010) show that training moves countercyclically with aggregate output fluctuations (e.g., more training in downturns).

5For more information, see Table 1 in Silva and Toledo (2009).

6In this vector $X$, they include years of education, dummy variables to indicate a high school degree and a college degree, the logarithm of the size of the establishment, the logarithm of hours worked, a dummy variable indicating whether the worker is female, a series of dummy variables representing one-digit industry and occupation categories, age, age square, a variable indicating the worker’s union status and working experience as well as its square.

7In the last column, we also target $H + T = 0.55 \times 3 \times w^{n*}$ and $H/(H + T) = 0.284$. 
Table 1:

Calibrated parameter values for the U.S. economy

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Source/Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor productivity, $p^*$</td>
<td>1</td>
<td>Normalization</td>
</tr>
<tr>
<td>Exogenous separation probability, $s$</td>
<td>0.036</td>
<td>Data (Shimer, 2005)</td>
</tr>
<tr>
<td>Interest rate, $r$</td>
<td>0.004</td>
<td>Data</td>
</tr>
<tr>
<td>Employment opportunity cost, $z$</td>
<td>0.71</td>
<td>Hall &amp; Milgrom (2008)</td>
</tr>
<tr>
<td>Matching function elasticity, $\eta$</td>
<td>0.5</td>
<td>Petrongolo &amp; Pissarides (2001)</td>
</tr>
<tr>
<td>Matching function scale, $m_o$</td>
<td>0.7</td>
<td>To match the job finding prob.</td>
</tr>
<tr>
<td>Workers’ bargaining power, $\beta$</td>
<td>0.5</td>
<td>$\beta = \eta$ (efficiency)</td>
</tr>
<tr>
<td>Cost of vacancy, $c$</td>
<td>0.356</td>
<td>Solves (13)</td>
</tr>
<tr>
<td>Sunk fixed matching costs, $H$</td>
<td>0</td>
<td>Benchmark</td>
</tr>
<tr>
<td>Non sunk fixed matching costs, $T$</td>
<td>0</td>
<td>Benchmark</td>
</tr>
<tr>
<td>Job conversion rate, $\lambda$</td>
<td>0.196</td>
<td>To match the ave. duration of training</td>
</tr>
</tbody>
</table>

Variable

| Labor market tightness, $\theta^*$              | 0.72  | JOLTS                       |
| Job finding probability, $f(\theta^*)$         | 0.594 | Shimer (2005)               |
Table 2:
Model results at different combinations of sunk and non-sunken fixed matching costs

| $H$ | $T$ | $c$ | $\varepsilon_\theta$ | $\varepsilon_{w^n}$ | $\varepsilon_{\theta|c=.356}$ |
|-----|-----|-----|-----------------------|----------------------|-----------------------------|
| 0.00| 0   | 0.356| 3.666                 | 0.985                | -                           |
| 0.10| 0   | 0.273| 4.183                 | 0.989                | 4.191                       |
| 0.20| 0   | 0.191| 4.867                 | 0.995                | 4.757                       |
| 0.30| 0   | 0.108| 5.821                 | 1.000                | 5.369                       |
| 0.40| 0   | 0.026| 7.238                 | 1.013                | 6.003                       |
| 0   | 0.00| 0.356| 3.666                 | 0.985                | -                           |
| 0   | 0.10| 0.351| 3.717                 | 0.999                | 3.719                       |
| 0   | 0.20| 0.346| 3.770                 | 1.013                | 3.773                       |
| 0   | 0.30| 0.343| 3.824                 | 1.023                | 3.829                       |
| 0   | 0.40| 0.336| 3.880                 | 1.043                | 3.887                       |
Table 3:

Model results at different combinations of sunk and non-sunk fixed matching costs with targeted vacancy costs \((c/w_n^* = 0.129)\)

| \(H\) | \(T\) | \(\beta\) | \(\varepsilon_\theta\) | \(\varepsilon_{w_n}\) | \(\varepsilon_{u|z=71}\) |
|-------|-------|----------|----------------|----------------|----------------|
| 0.00  | 0     | 0.743    | 3.598          | 0.995          | 1.73           |
| 0.10  | 0     | 0.635    | 4.564          | 0.996          | 2.19           |
| 0.20  | 0     | 0.552    | 5.201          | 0.998          | 2.50           |
| 0.30  | 0     | 0.487    | 5.670          | 1.000          | 2.73           |
| 0.40  | 0     | 0.434    | 6.041          | 1.003          | 2.91           |

| \(H\) | \(T\) | \(\beta\) | \(\varepsilon_\theta\) | \(\varepsilon_{w_n}\) | \(\varepsilon_{u|z=71}\) |
|-------|-------|----------|----------------|----------------|----------------|
| 0     | 0.00  | 0.743    | 3.598          | 0.995          | 1.73           |
| 0     | 0.10  | 0.744    | 3.648          | 1.014          | 1.75           |
| 0     | 0.20  | 0.745    | 3.700          | 1.034          | 1.78           |
| 0     | 0.30  | 0.746    | 3.753          | 1.054          | 1.80           |
| 0     | 0.40  | 0.747    | 3.807          | 1.075          | 1.83           |

<table>
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<tr>
<th>(H)</th>
<th>(T)</th>
<th>(\beta)</th>
<th>(\varepsilon_\theta)</th>
<th>(\varepsilon_{w_n})</th>
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