Labor Turnover Costs and the Cyclical Behavior of Vacancies and Unemployment

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Abstract

This paper extends the Diamond-Mortensen-Pissarides (DMP) matching model with endogenous job destruction by introducing post-match labor turnover costs (PMLTC). We consider training and separation costs which create heterogeneity among workers. In particular, there are two types of employed workers: (i) new entrants who need training in order to become fully productive, and (ii) incumbents.

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who are fully productive and whose departure from the firm imposes costs on it.

We find that our calibrated model, relative to the standard DMP model, comes
closer to the data regarding the volatility of vacancies and unemployment without
introducing unrealistic sensitivity to policy changes. Moreover, our extended model
nearly reproduces the downward-sloping Beveridge curve, which is unusual when
there exists endogenous job destruction in this type of models.

*Keywords*: Labor Markets, Search, Matching, Turnover costs, Business Cycles.
1 Introduction

The existence of labor market frictions in macroeconomic fluctuations has been increasingly recognized. In recent years, the Diamond (1982), Mortensen (1982) and Pissarides’ (1985) (henceforth DMP) matching model has become a widely used theory of equilibrium unemployment. However, recent studies by Costain and Reiter (2008), Hall (2005) and Shimer (2005) have questioned the model’s ability to match the U.S. data in at least one important dimension: the cyclical variations in unemployment and vacancies in response to shocks of reasonable size. This large discrepancy between the volatility of the model and the data constitutes an empirical puzzle.

In this paper we extend the DMP model with endogenous job destruction by introducing labor turnover costs that are generated once a job match has been established, which we call post-match labor turnover costs (PMLTC). In particular, we focus on training and separation costs. The standard model only considers hiring costs. However, survey information reveals that PMLTC are considerably higher than the former.

The main objective of this paper is to investigate whether our extended model amplifies business cycle fluctuations of labor market outcomes. To that end we calibrate the model to the U.S. economy. The simulation results reveal that our model generates cyclical fluctuations in vacancies and labor market tightness more than two times larger than what the standard model predicts. Despite this noticeable improvement, the model still falls short of what we observe in the data. That is, the model only explains one tenth of the observed volatility in labor market tightness. This volatility is increased by an additional 40% when the response of job destruction to aggregate productivity shocks is reduced to a minimum. Thus, endogenous job destruction significantly damps the
response of labor market tightness.

The intuition for this result is simple. Larger PMLTC induce a smaller surplus of a new match because newly hired workers are less productive and separations are more costly to firms. Therefore, a given productivity shock has a relatively larger impact on the value of a new position and, in consequence, in job creation and market tightness.¹

As it is well known, the matching model has two fundamental elements. First, an exogenous matching function capturing the uncoordinated, time-consuming, and costly search process for both firms and workers. Second, wages are set through Nash bargaining at the individual level. Some of the studies questioning this model precisely highlight the role of this assumption. Hall (2005) and Shimer (2004) argue that this wage determination scheme is the crucial reason why the model does not exhibit good performance. It introduces a high degree of wage flexibility to the model. As a result, almost all variation in productivity is absorbed by wages, leaving only a softened response of vacancies and unemployment.

According to Mortensen and Nagypal (2007), the failure of the DMP model does not lie in the degree of flexibility of wages but in the large difference between labor productivity and the opportunity cost of a match implied by the calibrated exercise. Thus, even a fixed wage scheme needs an employment opportunity cost parameter near average labor productivity to account for the observed volatility of vacancies and unemployment.

Hagedorn and Manovskii (2008) prove Mortensen and Nagypal’s point. They argue that Shimer’s choice of the opportunity cost of employment is too low because it only considers unemployment benefits. In contrast, this parameter should also include the value of leisure or home production forgone when employed. They recalibrate both the
opportunity cost of employment and the wage share parameter to match the cyclical response of wages and the average profit rate. Using this alternative calibration, the simulated model is able to match the data.

Their exercise, however, introduces a counterfactual response of unemployment to policy changes. This observation has been raised by Costain and Reiter (2008). They argue that the standard matching model can generate sufficiently large cyclical fluctuations in unemployment, or a sufficiently small unemployment response to changes in unemployment benefits (UB), but it cannot do both. In Hagedorn and Manovskii (2008), the response of the steady-state unemployment rate to long-run UB changes is three times larger than the conservative value estimated by Costain and Reiter.

Along this line, another important finding is that our model is capable of amplifying these fluctuations without inducing an unrealistic response of the steady-state unemployment rate to changes in UB. The origin of this result lies in the way the elasticity of both the job finding rate and the separation rate with respect to the employment opportunity cost is affected by PMLTC. On the one hand, the elasticity of the job finding rate increases with PMLTC as the surplus of a new match falls. On the other hand, these costs make job destruction less sensitive to UB. These two opposing forces tend to offset each other with respect to their impact on the long-run unemployment rate.

We also find that our calibrated economy, contrary to similar models with endogenous job destruction, nearly matches the observed negative relationship between vacancies and unemployment (i.e. the Beveridge curve). Our model is able to improve in this dimension because job creation becomes relatively more sensitive to aggregate productivity shocks than job destruction. To understand this result let us look at the case with no PMLTC.
In this instance, job destruction is more volatile and plays a bigger role in the cyclical employment adjustment. This dampens the response of job creation to shocks and thereby the correlation of vacancies and unemployment.

Several authors have considered the effect of PMLTC on the labor market. For example, within the search and matching literature, Mortensen and Pissarides (1999), Wasmer (1999), Blanchard and Landier (2002), and Cahuc and Postel-Vinay (2002), among others, have distinguished between insiders and new entrants when these types of costs exist. Our analysis follows the spirit of these papers but differs in scope. We focus on business cycle fluctuations whereas the previous literature has generally taken a long-run perspective.

The paper is organized as follows. In Section 2 we present evidence on labor turnover costs. Section 3 incorporates training and separation costs in the standard DMP model. Section 4 presents the calibration of our extended model. In Section 5, we simulate the model to check whether it can match some of the basic labor market facts for the U.S. economy. Finally, Section 6 presents our conclusions.

2 Evidence on labor turnover costs

Turnover of productive workers is a major source of productivity and profit losses in the U.S. For instance, according to the Job Openings and Labor Turnover Survey, during 2003 the monthly average separations relative to total employment in the private sector was 3.4 percent. This means that around four out of ten employees in this sector left their company in 2003. This high rate is almost equal to the rate of hired workers. Estimates of the costs of employee turnover vary widely and depend on whether all costs are recognized, fluctuating between 25 percent and 200 percent of annual compensation.
for a leaving employee.³

In general, these costs can be classified into two categories: (i) Pre-match labor turnover costs, which are those costs incurred by the firm during the hiring process of a new worker, and (ii) post-match labor turnover costs, which take place after the worker and the employer have matched and started an employment relationship.

To examine the relevance of the hiring process, we can use information reported by Dolfin (2006) and Barron, Berger and Black (1997) in the 1982 Employer Opportunity Pilot Project (EOPP), a cross-sectional firm-level survey that contains detailed information on these pre-match labor turnover costs in the U.S. According to the authors, it takes on average 17.2 days to fill a vacancy.⁴ During this time the number of manhours spent by company personnel recruiting, screening, and interviewing applicants to hire one individual for the vacant position is equal to 13.5.⁵ Table 1 presents our approximation to the total average cost that comes from these hours, which represents 3.6 percent of the quarterly wage of a fully productive worker, or 4.3 percent of the quarterly wage of a new hired worker.

The DMP matching model assumes that once the matching process has finished, the new employee or entrant starts her job with a labor productivity equal to that observed by an incumbent employee working in the firm. In other words, the entrant becomes fully productive immediately. However, data sets have identified the existence of both explicit and implicit costs of training by inquiring about the incidence and duration of various on-the-job training activities, and by identifying the presence of time devoted to learning by doing. All this information suggests that newly hired workers do not become fully productive instantaneously, so there are important PMLTC in the labor market. Along
this line, the EOPP survey also considers in a comprehensive way the magnitude of the training costs to the firm. According to Barron, Berger and Black (1997), this survey reveals that about 95 percent of the newly hired workers receive some kind of on-the-job training, spending, on average, 142 hours on this activity during the first three months of work, approximately 30 percent of their working time during that period (see Table 1). Moreover, other workers spend 87.5 hours on average training a new employee. The total average cost of these man-hours of training is about $1,360 per newly hired worker in 1982 dollars, which is approximately equivalent to 55 percent of her quarterly wage.

Using the same EOPP survey, Bishop (1996) shows that simultaneously to the training process, the reported average productivity of a new hired employee increases significantly by roughly a third during the first quarter and by an additional 32 percent between the second quarter and the end of the second year of job tenure in the firm. In other words, assuming that the productivity of a newly hired worker reaches the average productivity of an incumbent employee in a period no longer than two years, we observe a starting productivity gap between these two types of workers equivalent to about 40 percent of the incumbent’s productivity. This gap is closed after a period of both on-the-job training and learning by doing. Clearly, this information reveals that the turnover of fully productive workers is a major source of productivity losses in the U.S.

The training process is not the only source of PMLTC in the U.S. Using the 1982 EOPP, Dolfin (2006) reports that about 12 percent of the firms have a great deal of paperwork involved in firing an employee. Firing costs may include not only administrative and legal charges but also other costs such as efficiency losses due to the disruption of the regular flow of work. Moreover, the 2004 World Bank Doing Business survey, which takes
into account the cost of advanced notice requirements, severance payments and penalties due when firing workers, finds that firing costs in the U.S. are equivalent to 8 weeks of weekly wages of an incumbent employee.

Thus, it is reasonable to argue that, given the magnitude of training and separation costs, hiring decisions should depend crucially not only on the cost of searching for new workers but also on what we call PMLTC.

3 The model

This economy consists of a measure 1 of risk-neutral, infinitely-lived workers and a continuum of risk-neutral, infinitely-lived firms. Workers and firms discount future payoffs at a common rate $\delta$ and capital markets are perfect. In addition, time is discrete.

Workers can be either unemployed or employed. Unemployed workers get $b$ units of the consumption good each period, which could be understood as the value of leisure, home production, or unemployment benefits. Those who are employed can be either entrants ($e$) or incumbent ($i$) employees, and earn a wage $w^e_t$ and $w^i_t$, respectively. We assume that entrants receive training and are less productive than incumbent workers. Unemployed workers are first considered entrants once they find a job. At the beginning of each period, entrants become fully productive with probability $\iota$.

There is a time-consuming and costly process of matching unemployed workers and job vacancies. As in den Haan et al. (2000), we assume that the matching function takes the following form

\[ m(u_t, v_t) = \frac{u_t v_t}{(u_t^\varphi + v_t^\varphi)^{1/\varphi}}, \quad \varphi > 0, \quad (1) \]
where $u_t$ denotes the unemployment rate and $v_t$ are vacancies. This constant-return-to-scale matching function ensures that ratios $m(u_t, v_t)/u_t$ and $m(u_t, v_t)/v_t$ lie between 0 and 1. Due to the CRS assumption they only depend on the vacancy-unemployment ratio $\theta_t$. The former represents the probability at which unemployed workers meet jobs, $f(\theta_t) = m(1, 1/\theta_t)$. Similarly, the latter denotes the probability at which vacancies meet workers, $q(\theta_t) = m(\theta_t, 1)$.

Firms have a production technology that uses only labor. Each firm consists of only one job which is either filled or vacant. Before a position is filled, the firm has to open a job vacancy with cost $c$ per period. A firm’s output depends on aggregate productivity $A_t$, a match-specific term $z_t$, and the worker’s type. In particular, a job filled with an incumbent produces $A_t z_t$ whereas with an entrant it produces $A_t z_t(1 - \xi)$, with $\xi \in (0, 1)$. The parameter $\xi$ represents both training costs and the “average” productivity gap between entrants and incumbents. The match-specific productivity term $z_t$ is assumed to be independent and identically distributed across firms and time, with a cumulative distribution function $G(z)$ and support $[0, \bar{z}]$. We also assume that $\log A_t$ follows a Markovian stochastic process.

Firms may endogenously terminate employment relationships, for which they may incur a cost. In particular, firms lose $\gamma$ when a match with an incumbent worker is destroyed by the firm. This cost is assumed to be fully wasted and not a transfer, reflecting firing restrictions imposed by the government. In contrast, we assume that laying off entrant workers is costless. One way to justify this assumption is that firms can avoid dismissal protections during the on-the-job training or screening process of new workers. There are also exogenous separations with probability $\phi$ and no firing costs.
In order to describe the firms’ behavior, let us define the Bellman equations characterizing the value of vacancies, \( V_t \), and filled positions, \( J^e_t(z_t) \) and \( J^i_t(z_t) \), \(^9\)

\[
V_t = -c + \delta E_t \left[ q(\theta_t) \int_{\tilde{z}^{e}_{t+1}}^{\tilde{z}} J^e_{t+1}(z) dG(z) + [1 - q(\theta_t)(1 - G(\tilde{z}^{e}_{t+1}))]V_{t+1} \right],
\]

\[
J^e_t(z_t) = A_t z_t (1 - \xi) - w^e_t(z_t) + \delta (1 - \phi) E_t \left[ \int_{\tilde{z}^{e}_{t+1}}^{\tilde{z}} J^e_{t+1}(z) dG(z) + G(\tilde{z}^{e}_{t+1})V_{t+1} \right] + (1 - \iota) \left( \int_{\tilde{z}^{e}_{t+1}}^{\tilde{z}} J^e_{t+1}(z) dG(z) + G(\tilde{z}^{e}_{t+1})V_{t+1} \right) + \delta \phi E_t V_{t+1},
\]

\[
J^i_t(z_t) = A_t z_t - w^i_t(z_t) + \delta (1 - \phi) E_t \left[ \int_{\tilde{z}^{i}_{t+1}}^{\tilde{z}} J^i_{t+1}(z) dG(z) + G(\tilde{z}^{i}_{t+1}) (V_{t+1} - \gamma) \right] + \delta \phi E_t V_{t+1},
\]

where \( \tilde{z}^j_{t+1}, j = \{e, c, i\} \), are match-specific productivity thresholds defined such that nonprofitable matches (i.e., with negative surplus) are severed. \(^{10}\) These thresholds (also called reservation productivities) must satisfy the following conditions:

\[
J^e_t(\tilde{z}^{e}_t) - V_t = 0,
\]

\[
J^i_t(\tilde{z}^{i}_t) - V_t = 0,
\]

\[
J^i_t(\tilde{z}^{i}_t) - V_t + \gamma = 0.
\]

Expressions (5) and (7) define the reservation productivity for entrant and incumbent workers, respectively, whereas condition (6) refers to those entrants on the verge of becoming incumbents. That is, those who become fully productive with probability \( \iota \).

Notice that firms have the option to avoid entrant-to-incumbent conversion by laying off workers before legal restrictions become operational. In this case the firm does not have to pay \( \gamma \) if it chooses to break up the match.

It follows that the incumbent and entrant workers separate with probabilities

\[
s^j_t = \phi + (1 - \phi)G(\tilde{z}^{j}_t),
\]

11
Moreover, job creation takes place with probability $q(\theta_t)(1 - G(\tilde{z}_{t+1}^c))$ when a firm and a worker meet and agree on a contract. Similarly, unemployed workers find a job with probability $f(\theta_t)(1 - G(\tilde{z}_{t+1}^e))$.

On the workers’ side the values of the different statuses - unemployed, $U_t$; entrant employee, $W_t^e(z_t)$; and incumbent employee, $W_t^i(z_t)$ - are given by the following expressions:

\begin{equation}
U_t = b + \delta E_t \left[ f(\theta_t) \int_{\tilde{z}_t+1}^{\tilde{z}} W_{t+1}^e(z) dG(z) + [1 - f(\theta_t)(1 - G(\tilde{z}_{t+1}^e))]U_{t+1} \right], \tag{10}
\end{equation}

\begin{equation}
W_t^e(z_t) = w_t^e(z_t) + \delta(1 - \phi) E_t \left[ \iota \left( \int_{\tilde{z}_t+1}^{\tilde{z}} W_{t+1}^i(z) dG(z) + G(\tilde{z}_{t+1}^i)U_{t+1} \right) + (1 - \iota) \left( \int_{\tilde{z}_t+1}^{\tilde{z}} W_{t+1}^e(z) dG(z) + G(\tilde{z}_{t+1}^e)U_{t+1} \right) + \delta \phi E_t U_{t+1} \right], \tag{11}
\end{equation}

\begin{equation}
W_t^i(z_t) = w_t^i(z_t) + \delta E_t \left[ (1 - \phi) \left( \int_{\tilde{z}_t+1}^{\tilde{z}} W_{t+1}^i(z) dG(z) + G(\tilde{z}_{t+1}^i)U_{t+1} \right) + \phi U_{t+1} \right]. \tag{12}
\end{equation}

To close the model, we need first to incorporate two more assumptions. One is the free entry condition for vacancies: firms will open vacancies until the expected value of doing so becomes zero. Therefore, in equilibrium we must have

\begin{equation}
V_t = 0. \tag{13}
\end{equation}

The other assumption is that wages are set through Nash bargaining. The Nash solution is the wage that maximizes the weighted product of the worker’s and firm’s net return from the job match. The first-order conditions for entrants and incumbent employees yield the following two conditions,

\begin{equation}
(1 - \beta)(W_t^e(z_t) - U_t) = \beta(J_t^e(z_t) - V_t), \tag{14}
\end{equation}

\[ s_t^e = \phi + (1 - \phi) [(1 - \iota)G(\tilde{z}_t^e) + \iota G(\tilde{z}_t^i)]. \tag{9} \]
\[(1 - \beta)(W_t^i(z_t) - U_t) = \beta(J_t^i(z_t) - V_t + \gamma),\]  

(15)

where \(\beta \in (0, 1)\) denotes workers bargaining power relative to firms. Notice that the Nash condition for incumbents (15) has an extra term \(\gamma\). The interpretation is that the firm’s threat point when negotiating with an incumbent employee is no longer the value of a vacancy \(V_t\) but \((V_t - \gamma)\) because now separation costs are relevant.

Using (2)-(15), we can now solve for the equilibrium wages as a function of the current state \(A_t z_t\) and \(\theta_t\),

\[w_t^e(z_t) = (1 - \beta)b + \beta \theta_t c + \beta A_t z_t (1 - \xi) - \delta \beta \nu (1 - \phi) [1 - G(\tilde{z}_{t+1})] \gamma;\]  

(16)

\[w_t^i(z_t) = (1 - \beta)b + \beta \theta_t c + \beta A_t z_t + \beta [1 - \delta (1 - \phi)] \gamma.\]  

(17)

Introducing PMLTC decreases entrants’ wages (16) by a fraction of both the training costs and the separation costs. In contrast, the incumbent wage (17) is higher because incumbents are fully productive workers and separation costs are now operational, which increase their “implicit” bargaining power.

To fully characterize the dynamics of the model economy, we need to define the law of motion for the unemployment rate \(u_t\), and the mass of entrant and incumbent workers, \(n_t^e\) and \(n_t^i\), respectively. These evolve according to the following difference equations:

\[u_t = u_{t-1} + s_t n_{t-1}^e + s_t n_{t-1}^i - f(\theta_{t-1})(1 - G(\tilde{z}_t^e))u_{t-1},\]  

(18)

\[n_t^e = n_{t-1}^e + f(\theta_{t-1})(1 - G(\tilde{z}_t^e))u_{t-1} - s_t n_{t-1}^e - (1 - \phi) \nu (1 - G(\tilde{z}_t^e)) n_{t-1}^e,\]  

(19)

\[n_t^i = n_{t-1}^i + (1 - \phi) \nu (1 - G(\tilde{z}_t^e)) n_{t-1}^e - s_t n_{t-1}^i,\]  

(20)

\[1 = u_t + n_t^e + n_t^i.\]  

(21)
Finally, the average separation probability is equal to

\[ s_t = \frac{s_t^e n_t^e + s_t^i n_t^i}{(1 - u_t - 1)}. \]  

(22)

4 Calibration

We calibrate the model at quarterly frequency in order to match several empirical facts of the U.S. economy between 1953 and 2003. Following Blanchard and Diamond (1990), we target an average unemployment rate \( u^* \) of 11%. This value is consistent with the fraction of unmatched workers in the U.S. when we consider not only the officially unemployed but also those not in the labor force who want a job.

We match a steady-state job separation probability \( s^* \) equal to 0.10 per quarter, which is widely used in the literature and consistent with empirical estimates.\(^\text{11}\)

Our calibration also targets an elasticity of the matching function with respect to unemployment in the steady state \( \varepsilon_{m,u}^* = 0.72 \) as in Shimer (2005).

Following Costain and Reiter (2008), we do not want the unemployment rate to be counterfactually responsive to unemployment benefits. Therefore, we target the semielasticity of the unemployment rate with respect to unemployment benefits equal to 2, which represents the benchmark calibrated value used by them.

We set the discount factor \( \delta = 0.99 \), which implies a reasonable quarterly interest rate of nearly 1 percent.

We normalize the average aggregate labor productivity \( A^* \) to 1. We assume that \( \log A_t \) follows a first-order autoregressive process of the form

\[ \log A_t = \rho \log A_{t-1} + \epsilon_t, \]
where $\epsilon_t$ is an i.i.d. $N(0, \sigma_\epsilon)$ random variable. The parameters of the AR(1) process, the autoregressive coefficient $\rho$ and the standard deviation of the white noise process $\sigma_\epsilon$, are calibrated to match the cyclical volatility (0.02) and persistence (0.88) of the average U.S. labor productivity $y_t/(1 - u_t)$ between 1953 and 2003.\(^\text{12}\) Thus, we set $\rho = 0.96$ and $\sigma_\epsilon = 0.01$.

Regarding the exogenous separation probability $\phi$, we follow den Haan et al. (2000), and interpret exogenous separations as worker-initiated separations. Hence, only endogenous separations are associated with the layoff rate. According to evidence from the Job Opening Labor Turnover Survey (JOLTS) shown by Davis, Faberman, and Haltiwanger (2006), and from the Census’ Survey of Income and Program Participation (SIPP) shown by Nagypal (2004), layoffs represent on average about 35% of total separations. Thus, we set $\phi = 0.065$, which is close to the one used by den Haan et al. (2000).

We now turn to the labor turnover cost parameters $c$, $\iota$, $\xi$, and $\gamma$. As mentioned in Section 2, the 1982 EOPP and the 1992 SBA surveys estimate total hiring costs to be about 4.3 percent of the quarterly compensation of a new hired worker. Therefore, we set $c$ such that in the steady state it is equal to $0.043w^{\epsilon*}$.

Barron, Berger and Black (1997) document the average time that a newly hired worker takes to become fully trained according to two surveys: the above mentioned 1982 EOPP survey and the 1992 Small Business Administration (SBA) survey. They find that it takes on average between 20.2 and 22.2 weeks to become fully trained.\(^\text{13}\) The 1992 SBA survey also suggests that the most intense training period is the first three months on the job. They estimate that around 70 percent of training spells are finished within this period. However, a new employee needs more than on-the-job training to fill the productivity
gap; learning by doing is also part of the training process. As shown in Table 1, Bishop (1996) reports an increase of 34 percent in the productivity of a newly hired worker during the first three months, coinciding with the most intense on-the-job training period, and another 32 percent between the first quarter and the end of the second year, which we consider to be mostly due to learning by doing. In the absence of additional information, we assume that a new entrant takes on average 1 year to become fully productive. Hence, new hired workers become fully productive with probability $\iota = 0.25$.

The parameter $\xi$ can be thought of as consisting of two main components: the actual productivity gap between entrant and incumbent workers, and the cost of training. We denote the average productivity gap during the training process as $\psi$. We consider training costs as forgone production while training takes place. It consist of both the time devoted to on-the-job training by new entrants, $\tau^e$, and the time spent by incumbents training new employees, $\tau^i$. Thus, we can write $\xi = \psi + (1 - \psi)\tau^e + \tau^i$. The second term, $(1 - \psi)\tau^e$, represents what the trainee fails to produce during the training process while the other term, $\tau^i$, describes incumbents’ forgone productivity while training new entrants.

Section 2 argues that the initial productivity gap between a new entrant and an incumbent worker is around 40 percent of the latter’s productivity. If we assume for simplicity that this initial gap is filled at a constant rate each quarter, the average productivity gap during the training process is about 20 percent. Thus, we set $\psi = 0.20$ as the average productivity gap between entrants and incumbents during training.

Barron, Berger and Black (1997) report an average time spent on on-the-job training for new hires of about 142 hours during the first three months on the job. Notice that this figure is a truncated estimate of the average total hours of training. Indeed, about
30 percent of the training spells last for more than three months. To obtain \( \tau^e \) we assume that these 142 hours of on-the-job training are evenly distributed across the whole training process, which lasts for 1 year on average. Thus, \( \tau^e = 142/(480 \times 4) = 0.074 \).\(^{\text{14}}\) We subtract hours of watching others (54.5) from total hours of training to calculate \( \tau^i \) because we assume that those hours do not represent a productivity loss for incumbents. Thus, \( \tau^i = (142 - 54.5)/(480 \times 4) = 0.046 \). Having set \( \psi, \tau^e \) and \( \tau^i \), we get \( \xi = 0.31 \).

We use the value of the total firing cost provided by the 2004 World Bank Doing Business survey shown in Table 1. According to this survey, firing costs in the U.S. represent 8 weeks of weekly wages of an incumbent employee. Hence, \( \gamma = 8/12 = 0.67 \).

The idiosyncratic productivity \( z_t \) is assumed to be log-normally distributed with parameters \( (\mu, \sigma_z) \). We choose the mean of \( \log z_t \) to be zero. That is, \( \mu = 0 \). The standard deviation parameter \( \sigma_z \) is calibrated together with the hiring cost \( c \), the matching technology parameter \( \varphi \), workers’ bargaining power \( \beta \), and the employment opportunity cost \( b \).

We select these parameters such that the steady-state equilibrium satisfies our calibration targets \( w^* = 0.11, s^* = 0.10, \xi^*_{m,u} = \theta^{s\varphi}/(1 + \theta^{s\varphi}) = 0.72 \), the semielasticity of the unemployment rate with respect to unemployment benefits equal to 2, and \( c = 0.043w^{e*} \). This yields \( \sigma_z = 0.170, c = 0.034, \varphi = 1.553, \beta = 0.748, \) and \( b = 0.677 \).

5 Simulation

We now simulate both the basic DMP model and our extended version, and turn to a discussion of their business cycle statistics. Notice that for the simulation of the basic model (without PMLTC), we set \( \xi = \gamma = 0 \), and adjust the parameters \( b, \beta, c, \sigma \) and \( \varphi \) in
order to maintain our calibration target values. In this case, we set \( b = 0.60, \beta = 0.837, c = 0.0565, \sigma_z = 0.47 \) and \( \varphi = 1.891 \).

We simulate the model presented above 10,000 times. Each time we simulate the economy for 1,212 “quarters” and throw away the first 1,000 of them in order to obtain the U.S. post Second World War period (212 quarters between 1951-2003). We detrend the generated data using an HP filter with \( 10^5 \) smoothing parameter and, finally, we calculate the standard deviations, autocorrelation coefficients and correlation matrix.

5.1 Results

Table 3 presents the summary statistics of the U.S. labor market. Tables 4 and 5 show the simulation results of the model without and with PMLTC, respectively.

The most important difference between both versions of the model lies in the volatility of vacancies and, consequently, \( \theta \) and the job finding rate \( f(\theta) \). As in Shimer (2005) (see his Table 5), we find that in the standard model with job destruction and without training and separation costs the variables above show relatively low variability, with standard deviations that are at most 20 percent as volatile as in U.S. data. In contrast, our extended version of the DMP model notably increases those standard deviations. The volatility of \( v \) (0.062), \( \theta \) (0.105) and \( f(\theta) \) (0.030) are more than two times higher than what we observe in the standard model without PMLTC (0.007, 0.043 and 0.015, respectively). The standard deviation of unemployment also increases but in a smaller magnitude (from 0.039 to 0.049). In spite of the larger fluctuations predicted by our model, it still underestimates the U.S. labor market volatility by a considerable margin.

In turn, vacancies become more persistent with PMLTC. The autocorrelation coeffi-
cient is 0.738 compared to 0.123 in the standard model and 0.940 in the data. Similarly, the negative correlation between vacancies and unemployment is considerably increased from -0.377 to -0.808, which comes much closer to the observed correlation of -0.894 in the U.S. Finally, the standard deviation of the job destruction rate $s$ is the nearly the same in both models and 60 percent smaller than the value observed in the data (0.075).

5.2 Discussion

To understand why the cyclical fluctuations of vacancies and unemployment increase when we introduce PMLTC into the model we need to consider the total match surplus of a new entrant. Let us define the new entrant’s match surplus as

$$S_e^e(z_t) = J_e^e(z_t) - V_t + W_t^e(z_t) - U_t.$$ 

After some substitutions we obtain the following expression:

$$S_e^e(z_t) = A_t z_t (1 - \xi) - b - t \delta (1 - \phi)(1 - G(\tilde{z}_{t+1})) \gamma - \delta \beta f(\theta_t) E_t \left[ \int_{\tilde{z}_{t+1}}^{\tilde{z}} S_{t+1}^e(z) dG(z) \right] + (1 - \phi) \delta \left( t E_t \left[ \int_{\tilde{z}_{t+1}}^{\tilde{z}} S_{t+1}^i(z) dG(z) \right] + (1 - t) E_t \left[ \int_{\tilde{z}_{t+1}}^{\tilde{z}} S_{t+1}^e(z) dG(z) \right] \right) \quad (23)$$

where $S_i^i(z_t) = J_i^i(z_t) - V_t + \gamma + W_t^i(z_t) - U_t$ represents the incumbent’s match surplus. Notice that for every productivity level $A_t z_t$ the match surplus of a new entrant is lower when we account for training $\xi$ and firing costs $\gamma$. However, since our parameterizations of the extended and the standard models yield different parameter values for $\sigma$, $b$, $c$, $\varphi$ and $\beta$, a more meaningful comparison between both versions of the model is to look at their calibrated match surplus $S^e$ across different levels of aggregate productivity $A$.

Figure 1 shows that $S^e$ is lower for every level of $A$ when PMLTC are accounted for. This implies that in the extended model productivity shocks have a relatively greater impact on $S_e^e(z_t)$ and, consequently, on the value of a newly filled position $J_e^e(z_t) = (1 - \beta) S_e^e(z_t)$. 

19
As Hornstein, Krusell and Violante (2005) point out, given the equilibrium job creation condition,
\[(1 - \beta)\delta E_t \left[ \int_{\tilde{z}_{t+1}} E_{t+1}^e(z) dG(z) \right] = c/q(\theta_t),\]
a larger percentage change in \(S^e\) induces a greater response in labor market tightness \(\theta^{17}\). Hence a higher volatility of vacancies and unemployment. Figures 2 and 3 show the response of the conditional mean of \(S^e_t\), \(E[S^e_t(z)|z \geq \tilde{z}_t^e]\), to a 1 percent increase in \(A_t = A^*\) with and without PMLTC. On impact, the average surplus increases by more than two times in the former case relative to the latter, magnifying the initial response of labor market variables.

According to Costain and Reiter (2008), the standard matching model with exogenous job destruction can generate sufficiently large cyclical fluctuations in unemployment, or a sufficiently small response of unemployment to unemployment benefits, but it cannot do both. As stressed by these authors, this result depends crucially on the surplus of a match. The smaller this surplus is, the higher the response of the job-finding probability \(f(\theta)\) to changes in UB. Given the job destruction probability, unemployment becomes more sensitive.

This puzzle is still present with endogenous job destruction because higher levels of UB not only increase unemployment through reductions in \(f(\theta)\) but also through increments in \(s\). However, our extended model with PMLTC leads to a greater amplification of productivity shocks without introducing “unrealistic” sensitivity to policy changes. The origin of this result lies in the lower response of the job destruction probability to an increase in UB.

This point can be verified in Table 6. On the one hand, \(S^e\) is about 50 percent lower when the model accounts for PMLTC than in the case when these costs are omitted. As a result, the elasticity of \(f(\theta)\) with respect to the employment opportunity cost \(b\) in the
steady state, $\varepsilon_{f,b}$, is about two times higher (in absolute value) in the former case (-1.1 with respect to -0.5 when PMLTC are excluded). On the other hand, the elasticity of job destruction probability with respect to $b$, $\varepsilon_{s,b}$, is more than 3 times higher when there are no training and separation costs in the model (2.1 with PMLTC versus 0.6). Intuitively, when firing a worker becomes more costly, firms choose to keep relatively more employees in response to an increase in $b$. Thus, the elasticity of unemployment with respect to $b$ changes only slightly from 2.2 to 1.8.

It is well known that endogenous job destruction tends to induce positive correlation between unemployment and vacancies in the DMP model. For example, Shimer (2005) shows a correlation coefficient of 0.95 between these two variables when there are only stochastic shocks to the job destruction rate. He also shows that the model with labor productivity shocks and a constant job destruction rate is quantitatively consistent with the observed correlation coefficient in the data (-0.894). Costain and Reiter (2008) show similar results. Our simulated results show that our extended model is also quantitatively consistent with the observed downward-sloping Beveridge curve (the simulated correlation coefficient is -0.809). As before, this result takes place because training and separation costs make job creation much more sensitive than job destruction. Hence, employment dynamics is mostly driven by the former. To understand why this induces a more negative correlation, let us think about the opposite case where separations play a bigger role in employment fluctuations. In that case, when a positive productivity shock hits the economy, firms lay off fewer workers which reduces unemployment but dampens vacancy creation because firms do not need to recruit as many workers now.

Finally, notice that in our extended version of the model the correlation coefficient
between the average wage and labor productivity remains almost as high as in the basic model because there is no change in the Nash Bargaining scheme. Therefore, we can argue that without introducing wage rigidities it is possible to improve the performance of the model.

5.3 Endogenous job destruction and the amplification mechanism

To study how endogenous separations affect vacancies and unemployment fluctuations, we now reduce to a minimum the response of job destruction to aggregate productivity shocks by making all separations exogenous in the steady state. Thus, we set the exogenous separation probability $\phi$ to 0.10. This does not necessarily mean that all separations will be exogenous. Out of the steady state, particularly for low levels of aggregate productivity, there could still be endogenous separations.

We also recalibrate parameters $b$, $\beta$, $c$, $\sigma$ and $\psi$ in order to maintain our calibration target values. In this case, we set $b = 0.776$, $\beta = 0.564$, $c = 0.0424$, $\sigma = 0.071$ and $\psi = 1.551$. The simulation results are shown in Table 7.

Compared with our baseline simulation results in Table 5, the volatility of vacancies nearly doubles (from 0.062 to 0.115). In contrast, the standard deviation of unemployment is reduced by 28% (from 0.049 to 0.036). As a result, the volatility of labor market tightness increases from 0.105 to 0.146. Thus, a higher response of endogenous job destruction to aggregate shocks significantly dampens the response of vacancies and labor market tightness.
6 Conclusions

In this study we argue that introducing post-match labor turnover costs in the standard DMP matching model with endogenous job destruction helps increase the labor market volatility in response to labor productivity shocks of reasonable magnitude.

In particular, the simulation of our model shows that with reasonable parameter values for training and separation costs the volatility of vacancies and labor market tightness more than doubles with respect to the model with no PMLTC. Moreover, in contrast to the standard matching model with endogenous job destruction, our extended model comes close to matching the observed negative relationship between vacancies and unemployment because job creation becomes relatively more sensitive to aggregate productivity shocks than job destruction.

The crucial reason behind this result is the lower value of a new match since (i) entrants need training before being fully productive as incumbent employees, and (ii) firms may become liable to separation costs in the future. This amplifies the volatility of the model because productivity shocks account for a larger fraction of the value of a newly filled position. Therefore, firms’ reaction, namely job creation, is more volatile. Thus, both vacancies and labor market tightness fluctuate more over the business cycle.

Finally, considering Costain and Reiter’s (2008) observation, our matching model generates not only larger cyclical fluctuations in labor market variables but also a sufficiently small response of unemployment to changes in unemployment benefits. This result is driven by how PMLTC affect the elasticity of both the job finding probability and the separation probability with respect to the employment opportunity cost. On the one hand, the elasticity of the former increases with training and separation costs as the sur-
plus of a new match falls. On the other hand, higher PMLTC make job destruction less sensitive to policy changes. These two opposing forces counterbalance each other with respect to their impact on the unemployment rate.

Notes

1See Hornstein, Krusell and Violante (2005) for a similar mechanism at work in the standard model when labor productivity is close to the value of being unemployed.


3See for example, Ahr and Ahr (2000).

4See Table 1 from Barron, Berger and Black (1997).

5See Table 1 from Dolfin (2006).

6The EOPP project contains a set of four questions concerning various types of on-the-job training related to the total number of hours spent during the first three months of employment (a) by specially trained personnel providing formal training to the most recently hired worker, (b) by line supervisors providing the new worker with informal individualized training and extra supervision and (d) by the worker watching others perform tasks. Contrary to the EOPP project, others surveys such as the Current Population Survey (CPS) and the National Longitudinal Survey of Youth (NLSY) have received criticism since they lack all or most of the informal training information. See Loewenstein and Spletzer (1994) for a detailed analysis.

7The 1992 Small Business Administration (SBA) survey is a more recent survey that reports a similar number of hours spent on on-the-job training during the first three months of employment (150 hours). See Barron, Berger and Black (1997).

8Using also the 1982 EOPP survey, Dolfin (2006) finds that “[t]he average new employee spends 201 hours […] in training activities during the first three months of work, while other employees spend on average 146 hours […] training her. The total average cost of these 347 manhours to the firm is
approximately $2,119. This figure is within the range found by other studies, and may understate the total cost of training a new worker if the training period exceeds three months.” So, if anything, our estimate of training costs is rather conservative.

9For exposition reasons, we omit writing the aggregate state variables \{A_t, \theta_t\} as arguments of these value functions.

10 Since the value of a match is increasing in \(z_t\), we can prove that there exists a threshold \(\tilde{z}_t \in [0, \tilde{z}]\) below which matches are no longer profitable.

11See, for example, Shimer (2005), den Haan et al. (2000).

12Total output \(y_t\) is equal to \(y_t = A_t \tilde{z}_t n^i + A_t \tilde{z}_e (1 - \xi) n^e\), where \(\tilde{z} = E[z|z \geq \tilde{z}]\). As in Shimer (2005), the average labor productivity is the seasonally adjusted real average output per person in the non-farm business sector, constructed by the Bureau of Labor Statistics (BLS) from the National Income and Product Accounts and the Current Employment Statistics. It is reported in logs as deviations from an HP trend with a smoothing parameter of \(10^5\).

13For details, see Table 3.4 in Barron, Berger and Black (1997).

14We assume that every quarter workers work 480 hours, equivalent to 40 hours per week.

15Notice that as \(\xi\) and \(\gamma\) approach zero, \(\iota\) becomes irrelevant since \(w^e\) and \(J^e\) tend to approach \(w^i\) and \(J^i\), respectively.

16Table 3 reproduces Table 1 from Shimer (2004, 2005) available at the AER and Shimer’s webpage.

17The equilibrium job creation condition comes from equations (2) and (13).

References


Bishop, John H. (1996) What We Know About the Employer-Provided Training:


Shimer, Robert (2005) The Cyclical Behavior of Equilibrium Unemployment and


Table 1: Labor turnover costs in the U.S. Data from the 1982 EOPP Survey

<table>
<thead>
<tr>
<th>General information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source: Dolfin (2006)</td>
</tr>
<tr>
<td>(1) Supervisor’s hourly wage (1982 dollars)</td>
</tr>
<tr>
<td>(2) New entrant’s hourly wage (1982 dollars)</td>
</tr>
<tr>
<td>(3) Incumbent’s hourly wage (1982 dollars)</td>
</tr>
<tr>
<td>(4) Hours of work during a quarter</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hiring costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source: Dolfin (2006) and Barron, Berger and Black (1997)</td>
</tr>
<tr>
<td>(5) Duration of vacancy in days</td>
</tr>
<tr>
<td>(6) Number of hours spent recruiting, screening, and interviewing applicants (total number hours/ number hired)</td>
</tr>
<tr>
<td>(7) Total hiring cost per newly hired worker (6)×(1)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Training costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source: Barron, Berger and Black (1997)</td>
</tr>
<tr>
<td>(8) Incidence rate of on-the-job training</td>
</tr>
<tr>
<td>(9) Weeks to become fully trained</td>
</tr>
<tr>
<td>During the first 3 months of work:</td>
</tr>
<tr>
<td>(10) Hours of formal training</td>
</tr>
<tr>
<td>(11) Hours of informal training by supervisor</td>
</tr>
<tr>
<td>(12) Hours of informal training by co-worker</td>
</tr>
<tr>
<td>(13) Hours of watching others</td>
</tr>
<tr>
<td>(14) Total training cost per newly hired worker</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Increase in productivity of a newly hired worker (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source: Bishop (1996)</td>
</tr>
<tr>
<td>(15) Between first 2 weeks and next 10 weeks</td>
</tr>
<tr>
<td>(16) Between first 3 months and the end of the 2 year</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Separation costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>(17) Costly firing documentation (% of firms)</td>
</tr>
<tr>
<td>(18) Weeks of wages</td>
</tr>
</tbody>
</table>
### Table 2: Calibrated parameter values for the U.S. economy

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ave. aggregate productivity, $A^*$</td>
<td>1</td>
<td>Normalization</td>
</tr>
<tr>
<td>Stand. dev. of agg. prod. shock, $\sigma_\epsilon$</td>
<td>0.01</td>
<td>U.S. data</td>
</tr>
<tr>
<td>Persistence of agg. productivity, $\rho$</td>
<td>0.96</td>
<td>U.S. data</td>
</tr>
<tr>
<td>Mean of log $z$, $\mu$</td>
<td>0</td>
<td>Normalization</td>
</tr>
<tr>
<td>Standard deviation of log $z$, $\sigma_z$</td>
<td>0.17</td>
<td>Calibrated</td>
</tr>
<tr>
<td>Exogenous separation probability, $\phi$</td>
<td>0.065</td>
<td>Own assumptions</td>
</tr>
<tr>
<td>Discount rate, $\delta$</td>
<td>0.99</td>
<td>Shimer (2005)</td>
</tr>
<tr>
<td>Employment opportunity cost, $b$</td>
<td>0.677</td>
<td>Calibrated</td>
</tr>
<tr>
<td>Matching function parameter, $\varphi$</td>
<td>1.553</td>
<td>Calibrated</td>
</tr>
<tr>
<td>Workers’ bargaining power, $\beta$</td>
<td>0.748</td>
<td>Calibrated</td>
</tr>
<tr>
<td>Cost of vacancy, $c$</td>
<td>0.034</td>
<td>Barron et al. (1997)</td>
</tr>
<tr>
<td>Separation costs, $\gamma$</td>
<td>0.67</td>
<td>World Bank (2004) indicator</td>
</tr>
<tr>
<td>Training cost, $\xi$</td>
<td>0.31</td>
<td>Barron et al. (1997), Bishop</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1996), and own assumptions</td>
</tr>
<tr>
<td>Entrants’ conversion probability, $\iota$</td>
<td>0.25</td>
<td>Barron et al. (1997), Bishop</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1996), and own assumptions</td>
</tr>
</tbody>
</table>
Table 3: Summary statistics for the quarterly U.S. data, 1951-2003

<table>
<thead>
<tr>
<th></th>
<th>$u$</th>
<th>$v$</th>
<th>$\theta$</th>
<th>$f(\theta)$</th>
<th>$s$</th>
<th>$w$</th>
<th>$y/n$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Deviation</td>
<td>0.190</td>
<td>0.202</td>
<td>0.382</td>
<td>0.118</td>
<td>0.075</td>
<td>0.014</td>
<td>0.020</td>
</tr>
<tr>
<td>Quarterly Autocorrelation</td>
<td>0.936</td>
<td>0.940</td>
<td>0.941</td>
<td>0.908</td>
<td>0.733</td>
<td>0.907</td>
<td>0.878</td>
</tr>
</tbody>
</table>

Correlation Matrix

\[
\begin{array}{cccccccc}
 & u & v & \theta & f(\theta) & s & w & y/n \\
 u & 1 & -0.894 & -0.972 & -0.949 & 0.709 & -0.056 & -0.408 \\
v & 1 & 0.975 & 0.897 & -0.684 & -0.004 & 0.364 \\
\theta & 1 & 0.948 & -0.715 & 0.026 & 0.396 \\
f(\theta) & 1 & -0.574 & 0.098 & 0.396 \\
s & 1 & 0.050 & -0.524 \\
w & 1 & 0.178 \\
\frac{y}{(1-u)} & & & & & & 1 \\
\end{array}
\]

Figure 1: Total surplus of new matches versus aggregate labor productivity
Table 4: Simulation results. Standard matching and search model (i.e, $\xi = \gamma = 0$).

<table>
<thead>
<tr>
<th></th>
<th>$u$</th>
<th></th>
<th>$v$</th>
<th>$\theta$</th>
<th>$f(\theta)$</th>
<th>$s$</th>
<th>$w$</th>
<th>$y/n$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Dev.</td>
<td>0.039</td>
<td>0.007</td>
<td>0.043</td>
<td>0.015</td>
<td>0.030</td>
<td>0.019</td>
<td>0.020</td>
<td></td>
</tr>
<tr>
<td>Quart. Autocorr.</td>
<td>0.934</td>
<td>0.123</td>
<td>0.883</td>
<td>0.921</td>
<td>0.883</td>
<td>0.883</td>
<td>0.883</td>
<td></td>
</tr>
</tbody>
</table>

Corr. Matrix

\[
\begin{array}{cccccccc}
  & u & v & \theta & f(\theta) & s & w & y/n \\
-u & 1 & -0.377 & -0.987 & -0.975 & 0.987 & -0.987 & -0.987 \\
v  & 1 & 0.520 & 0.163 & -0.520 & 0.520 & 0.520 & \\
\theta &  & 1 & 0.927 & -1.000 & 1.000 & 1.000 & \\
f(\theta) &  &  & 1 & -0.927 & 0.927 & 0.927 & \\
s &  &  &  & 1 & -1.000 & -1.000 & \\
w &  &  &  &  & 1 & 1.000 & \\
\frac{y}{(1-u)} &  &  &  &  &  & 1 & \\
\end{array}
\]
Table 5: Simulation results. Matching and search model with PMLTC

<table>
<thead>
<tr>
<th></th>
<th>u</th>
<th>v</th>
<th>θ</th>
<th>f(θ)</th>
<th>s</th>
<th>w</th>
<th>y/n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Dev.</td>
<td>0.049</td>
<td>0.062</td>
<td>0.105</td>
<td>0.030</td>
<td>0.027</td>
<td>0.023</td>
<td>0.020</td>
</tr>
<tr>
<td>Quart. Autocorr.</td>
<td>0.954</td>
<td>0.738</td>
<td>0.883</td>
<td>0.885</td>
<td>0.924</td>
<td>0.902</td>
<td>0.883</td>
</tr>
</tbody>
</table>

Corr. Matrix

$$
\begin{array}{ccccccc}
  & u & v & θ & f(θ) & s & w & y/n \\
 u & 1 & -0.808 & -0.938 & -0.979 & 0.971 & -0.962 & -0.959 \\
v & 1 & 0.962 & 0.734 & -0.875 & 0.933 & 0.938 & \\
θ & 1 & 0.885 & -0.964 & 0.993 & 0.995 & \\
f(θ) & 1 & -0.903 & 0.903 & 0.901 & \\
s & 1 & -0.990 & -0.985 & \\
w & 1 & 0.999 & \\
\frac{y}{(1-u)} & & & & 1 & \\
\end{array}
$$

Table 6: Elasticity of the job finding and job destruction probabilities, and unemployment with respect to UB

<table>
<thead>
<tr>
<th>Elasticity with respect to b (%)</th>
<th>$\varepsilon_{f,b}^*$</th>
<th>$\varepsilon_{s,b}^*$</th>
<th>$\varepsilon_{u,b}^*$</th>
</tr>
</thead>
<tbody>
<tr>
<td>With PMLTC</td>
<td>-1.1</td>
<td>0.6</td>
<td>1.8</td>
</tr>
<tr>
<td>Without PMLTC</td>
<td>-0.5</td>
<td>2.1</td>
<td>2.2</td>
</tr>
</tbody>
</table>
Table 7: Simulation results. Matching and search model model with PMLTC and $\phi = 0.10$

<table>
<thead>
<tr>
<th></th>
<th>$u$</th>
<th>$v$</th>
<th>$\theta$</th>
<th>$f(\theta)$</th>
<th>$s$</th>
<th>$w$</th>
<th>$y/n$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std.</td>
<td>0.036</td>
<td>0.115</td>
<td>0.146</td>
<td>0.041</td>
<td>0.000</td>
<td>0.016</td>
<td>0.020</td>
</tr>
<tr>
<td>Quart.</td>
<td>0.900</td>
<td>0.800</td>
<td>0.883</td>
<td>0.883</td>
<td>0.882</td>
<td>0.875</td>
<td>0.880</td>
</tr>
</tbody>
</table>

Corr. Matrix

\[
\begin{array}{cccccccc}
  u & 1 & -0.802 & -0.881 & -0.999 & 0.881 & -0.876 & -0.878 \\
  v & 1 & 0.989 & 0.804 & -0.989 & 0.989 & 0.989 & \\
  \theta & 1 & 0.883 & -1.000 & 0.999 & 0.999 & \ \\
  f(\theta) & 1 & -0.882 & 0.876 & 0.879 & \\
  s & 1 & -0.999 & -0.989 & \ \\
  w & 1 & 0.999 & \ \\
  y/n & 1 & \ 
\end{array}
\]
Figure 2: Impulse response to an aggregate productivity shock (A). *With PMLTC*
Figure 3: Impulse response to an aggregate productivity shock \((A)\). Without PMLTC