Job Matching and Propagation*

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Abstract

In the U.S. labor market, the vacancy-unemployment ratio and employment react sluggishly to productivity shocks. We show that the job matching model in its standard form cannot reproduce these patterns due to excessively rapid vacancy responses. Extending the model to incorporate sunk costs for vacancy creation yields highly realistic dynamics. Creation costs induce entrant firms to smooth the adjustment of new openings following a shock, leading the stock of vacancies to react sluggishly.

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1 Introduction

It is widely recognized that aggregate employment adjusts sluggishly in response to business cycle shocks. This pattern has proven difficult to rationalize, however. In the standard Real Business Cycle model, for example, shocks to total factor productivity are propagated quickly to the labor market, and subsequent employment adjustments exhibit little of the sluggishness seen in the data.

The dynamics of employment can be tied to frictions in the labor market, as manifested in unemployed workers and unfilled job vacancies. Figure 1 depicts detrended series for labor productivity, employment, and the ratio of vacancies to unemployment, often referred to as *market tightness*.[1] Fluctuations of productivity in the top panel are closely tracked by swings in employment and market tightness, shown in the bottom panel. This suggests an important role for frictions in explaining the link between productivity shocks and employment adjustments.

The Diamond-Mortensen-Pissarides job matching model has been proposed as a framework for understanding the relationship between employment adjustment and labor market frictions. In an early theoretical analysis of this model, Pissarides (1985) showed that productivity shocks can generate movements in market tightness that qualitatively resemble those shown in Figure 1. The quantitative performance of the model in accounting for these patterns has yet to be fully assessed, however. This paper attempts to fill this gap by evaluating a standard version of the model in terms of its ability to propagate productivity shocks to market tightness and employment.

In U.S. data, productivity shocks induce distinctive hump-shaped patterns of adjustment in market tightness and employment, with employment lagging market tightness by one quarter. We demonstrate that the calibrated matching model does not reproduce these patterns: in simulated data, the response of market tightness closely mimics the dynamics of productivity, exhibiting none of the sluggishness observed in the empirical data. The employment response builds slightly for one quarter, then dies away quickly in line with productivity. Thus, the matching model does not provide a mechanism for propagating shocks in a realistic manner.

To gain further insight into the mechanics of propagation, we decompose the empirical market tightness responses into separate vacancy and unemployment components. The patterns of adjustment to productivity shocks are quite similar, albeit in opposite direc-

[1] The variables are detrended by regressing their logs on cubic time polynomials.

tions, with vacancies and unemployment having roughly equal importance in explaining the dynamics of market tightness. The standard matching model cannot reproduce this pattern of sluggish vacancy adjustment, since it treats vacancies as a jump variable that closely tracks market conditions.

These findings suggest that the empirical behavior of vacancies might be rationalized by introducing costs that slow their adjustment. To this end, we extend the standard matching model by introducing a sunk cost for creation of new job positions, which rises with the number of positions created. Once created, positions remain active, whether filled or unfilled, until destroyed by obsolescence. This modification transforms vacancies into a predetermined variable, with entrant firms having an incentive to smooth the creation of new positions. Simulated data from the creation cost version of the matching model exhibit more realistic dynamics: productivity shocks lead to hump-shaped responses for both market tightness and employment, resembling those observed in the empirical data.

We conclude that costs of creating new job positions may play a central role in accounting for the observed patterns of employment adjustment. While direct evidence on new job openings is lacking, we are able to construct an indirect measure using data from the Job Opening and Labor Turnover Survey (JOLTS), starting in 2001. The recent business cycle recovery corresponds to a strong upward movement in new openings, leading the upward adjustment of vacancies. Although this evidence is limited, it serves to reinforce our conclusion that costs for creating new job positions, in conjunction with matching frictions, can account for the sluggish labor market adjustment observed in the data.

Labor market dynamics in the matching context have previously been considered by Fujita (2004), who stresses the inability of the matching model to explain the behavior of gross worker flows and the dynamic correlations of unemployment and vacancies. Fujita studies a version of the matching model in which job matches may separate endogenously, and his results are driven in part by surges of vacancy postings following spikes in job destruction. In Fujita (2003) the matching model with endogenous separation is expanded to incorporate planning lags in vacancy creation along with "mothballing" of unfilled vacancies by firms.

The present paper focuses on a simpler specification in which separation occurs for exogenous reasons only, and it ties the dynamics of market tightness and employment directly to the rapid adjustment of vacancies following productivity shocks. The paper also shows that a simple sunk creation cost specification can yield significant improvements in the model's ability to explain labor market dynamics. In related work, Yashiv (2006) evaluates a version of the matching model in which firms must incur a hiring cost upon matching with workers. Increasing marginal hiring costs are shown to produce a more realistic autocorrelation of vacancies. Propagation of shocks is not considered, however.

Several papers have demonstrated that embedding labor market frictions into the Real Business Cycle model improves the model's ability to propagate shocks. Merz (1995), Andolfatto (1996), and Den Haan, Ramey, and Watson (2000), for example, combine the Real Business Cycle model with standard versions of the matching model, while Burnside, Eichenbaum, and Rebelo (1993), Burnside and Eichenbaum (1996), and Cogley and Nason (1995) consider other types of frictions. These papers combine labor frictions with a measure of intertemporal substitution in consumption. In the currrent paper, we establish that the matching model can provide realistic propagation in the linear utility case, so that intertemporal substitution is not necessary.

The paper proceeds as follows. Section 2 lays out a standard version of the job matching model. Empirical evidence and evaluation of the standard model are presented in Section 3. Section 4 considers the role of vacancies in accounting for the poor performance of the standard model. This section also introduces and evaluates a version of the matching model that incorporates creation costs. Section 5 discusses the relationship between our findings and the recent work on amplification of shocks in the matching model, and Section 6 concludes.

2 Job Matching Model

Model description. We adopt a discrete-time version of the matching model presented in Pissarides (2000, chap. 1). The model consists of a unit mass of persons who are available for work and an infinite mass of firms. Let u_t indicate the number of unemployed workers in period t. Unemployed workers receive a flow payoff of b per period, which may be interpreted as utility from leisure, home production, and unemployment insurance payments. Firms may be either matched with a worker, unmatched and posting a vacancy, or inactive. Let v_t denote the number of vacancies posted in period t. Firms that post vacancies must pay a posting cost of c per period.

At the start of each period, matched worker-firm pairs negotiate contracts that divide the period t surplus according to the Nash bargaining solution, where π gives workers' bargaining weight and separation constitutes the threat point. Given that they agree to continue, an output level z_t is produced during the period. Let z_t evolve according to the following process:

$$\ln z_t = \rho \ln z_{t-1} + \varepsilon_t, \tag{1}$$

where ε_t is normally distributed with mean zero and standard deviation σ. The realized value of z_t is observed by all agents in the economy at the start of each period, and potential entrant firms choose whether or not to post vacancies in period t after observing z_t.

While production is taking place, unemployed workers and vacancy-posting firms attempt to form matches. The net number of new matches created in period t is given by the matching function $m(u_t, v_t)$. We adopt the usual Cobb-Douglas specification with constant returns to scale:

$$m(u_t, v_t) = A u_t^{\alpha} v_t^{1-a}. \tag{2}$$

A worker's probability of finding a job in period t is $A\theta_t^{1-\alpha}$, while $A\theta_t^{-\alpha}$ gives the probability of filling a vacancy, where $\theta_t = v_t/u_t$ indicates market tightness. Finally, matches that produce in the current period separate with probability λ at the end of the period.

Equilibrium. Let S_t represent the value of surplus for a match that exists at the start of period t. A worker in the u_t pool receives the flow payoff b along with a proportion of the future surplus from any match made in period t. Thus, the expected present value of current and future payoffs for an unemployed worker is given by

$$U_t = b + \beta E_t \Big[A\theta_t^{1-\alpha} \pi S_{t+1} + U_{t+1} \Big], \tag{3}$$

where β indicates the discount factor. Similarly, for a firm in the period t matching pool, the expected present value of current and future payoffs is

$$V_t = -c + \beta E_t \Big[A\theta_t^{-\alpha} (1-\pi) S_{t+1} + V_{t+1} \Big]. \tag{4}$$

The value of a match that produces in period t is

$$M_t = z_t + \beta E_t \Big[(1-\lambda) S_{t+1} + U_{t+1} + V_{t+1} \Big], \tag{5}$$

and equilibrium surplus is defined by

$$S_t = M_t - U_t - V_t. \tag{6}$$

Plugging (3), (4), and (5) into (6) gives the evolution of the surplus:

$$S_t = z_t - b + c + \beta \Big[(1-\lambda) - A\theta_t^{1-\alpha}\pi - A\theta_t^{-\alpha}(1-\pi) \Big] E_t S_{t+1}. \tag{7}$$

Because of free entry into the vacancy pool, $V_t = 0$ must hold for all t, yielding the following equilibrium condition:

$$c = \beta E_t \left[A\theta_t^{-\alpha}(1-\pi)S_{t+1} \right]. \tag{8}$$

Equations (7) and (8) determine equilibrium paths of S_t and θ_t for a given process z_t. The equilibrium law of motion for u_t is

$$u_t = u_{t-1} + \lambda(1-u_{t-1}) - A\theta_{t-1}^{1-\alpha}u_{t-1}. \tag{9}$$

The second term on the right-hand side of (9) represents workers who had produced in period $t-1$ and separated at the end of the period. The third term represents workers who formed new matches during period $t-1$.

3 Propagation of Shocks

Empirical evidence. The job matching model predicts the behavior of market tightness and employment for a given exogenous productivity process. We evaluate the model using quarterly U.S. data on productivity, vacancies, unemployment, and employment.[2]

To characterize the dynamic relationship among those three variables, we first estimate the following reduced-form vector autoregression (VAR):

$$A(L) \begin{bmatrix} \ln z_t \\ \ln \theta_t \\ \ln e_t \end{bmatrix} = \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^\theta \\ \varepsilon_t^e \end{bmatrix}, \tag{10}$$

where $\ln z_t$, $\ln \theta_t$ and $\ln e_t$ denote the logs of labor productivity, market tightness and the employment-population ratio, respectively; ε_t^z, ε_t^θ and ε_t^e are the reduced-form residuals of the three equations; and $A(L)$ is a lag polynomial matrix, with $A(0)$ being the identity matrix.

[2] Labor productivity is measured as real GDP divided by civilian employment, 16 years and over. For market tightness we take quarterly averages of the index of newspaper help-wanted advertising divided by the number of unemployed, 16 years and over. We measure employment as the ratio of employment, 16 years and over, to the civilian noninstitutional population. The sample period is 1951:Q1 to 2005:Q4. Availability of the help-wanted index determines the length of the sample. All variables are detrended by regressing their logs on cubic time polynomials prior to VAR estimation. The data were obtained from the FRED II database maintained by the Federal Reserve Bank of St. Louis. Our analysis of labor market dynamics builds on the pioneering work of Blanchard and Diamond (1989).

In the context of evaluating the models presented in this paper, we are interested in identifying the structural shock to labor productivity, and then tracing its effects on the other two variables. For identification of the structural productivity shock, we adopt a recursive identification scheme wherein the shock to productivity comes first in the ordering. Under this identifying assumption, the reduced form residual ε_t^z is interpreted as a structural shock to productivity.[3]

In addition, the productivity equation in the identified VAR allows market tightness and employment to have feedback effects on labor productivity through the lagged values. In fact, pairwise Granger causality tests between measured productivity and the other two variables show that each variable has a statistically significant impact on productivity. These feedbacks derive from demand shocks, composition effects, and other factors. The models presented in this paper do not include these factors, but instead treat labor productivity as an exogenous driving force. Accordingly, we evaluate the models based on the identified productivity shocks, which most closely resemble the concept used in the models.[4]

The exogenous component of productivity, denoted by $\ln \widehat{z}_t$, can be determined from the structural shocks as follows:

$$\widehat{A}_{11}(L) \ln \widehat{z}_t = \widehat{\varepsilon}_t^z, \tag{11}$$

where $\widehat{A}_{11}(L)$ is the estimated value of the polynomial in the first row and first column of $A(L)$, and $\widehat{\varepsilon}_t^z$ indicates the estimated structural shock from (10); The series $\widehat{z}_t$ is obtained by taking $\widehat{\varepsilon}_t^z$ and the estimate of the lag polynomial associated with $\ln z_t$, $\widehat{A}_{11}(L)$, from (10). Further, to remove the feedback effects, we set the lag polynomials $\widehat{A}_{12}(L)$ and $\widehat{A}_{13}(L)$, which are associated with labor market tightness and employment, respectively, to zeros.

With the exogenous productivity series in hand, we may assess the cyclical behavior

[3]The system (10) was estimated with lag lengths of three quarters for each equation. Changing the lag lengths has little effect on the results. Moreover, we tried other orderings and found that they changed the results little. Notably, the ordering of the remaining two variables does not matter when productivity is placed first in the ordering.

[4]A similar point has been made concerning the responses of the Solow residual to other macroeconomic variables (see Evans (1992), for example).

of $\ln \theta_t$ and $\ln e_t$ by means of the following quasi-VAR system:[5]

$$B(L) \begin{bmatrix} \ln \theta_t \\ \ln e_t \end{bmatrix} = C(L) \ln \widehat{z}_{t-1} + D\widehat{\varepsilon}_t^z + \begin{bmatrix} \eta_t^\theta \\ \eta_t^e \end{bmatrix}, \tag{12}$$

where $B(0)$ is the identity matrix; η_t^θ and η_t^e are the innovations to $\ln \theta_t$ and $\ln e_t$ in the above system; and $B(L)$, $C(L)$ and D indicate a polynomial matrix, a polynomial vector and a real vector, respectively.[6] Impulse response functions to a one-standard-deviation productivity shock, based on the system (12), are depicted in Figure 2. As seen in the top panel, $\ln \widehat{z}_t$ jumps by about 0.7 percent as a result of the shock, then returns monotonically to its steady state after oscillating slightly for two quarters.[7] The middle panel shows that $\ln \widehat{\theta}_t$ responds immediately to the shock, jumping up by about 5 percent. Subsequent adjustments follow a hump-shaped pattern, with $\ln \widehat{\theta}_t$ rising rapidly for four quarters and peaking at roughly 12 percent above its steady state value. The variable $\ln \widehat{e}_t$, in the bottom panel, does not jump in the period of the shock, but otherwise its response closely mimics that of $\ln \widehat{\theta}_t$, with a one-quarter lag and a peak of about 0.35 percent above the steady state. This suggests that the adjustment of employment is closely tied to the behavior of market tightness.

Figure 3 reports the correlations of $\ln \widehat{\theta}_t$ and $\ln \widehat{e}_t$ with $\ln \widehat{z}_t$ at various leads and lags, providing alternative measures of the effects of productivity shocks on market tightness and employment. Observe that market tightness and employment are highly correlated with lagged values of exogenous productivity, with peak correlations at lags of 0-1 quarters for market tightness and 1-2 quarters for employment.

Overall, the results indicate that productivity shocks are propagated only gradually to the labor market, with market tightness and employment continuing to respond strongly even as the productivity shock dies away. In other words, the adjustments are sluggish.

[5] In estimating the following system (12), we use lag lengths of three quarters in order to maintain consistency with the previous specification.

[6] An alternative approach would be to take the estimated lag polynomial matrix in (10) and calculate the impulse response functions under the restrictions $A_{12}(L) = A_{13}(L) = 0$. In this case, the impulse response functions also measure the effects of the identified productivity shock under a no-feedback assumption, but the effect of productivity on $\ln \theta_t$ and $\ln e_t$ is still based on $A_{21}(L)$ and $A_{31}(L)$, that is, based on an empirical system with endogenous productivity as explanatory variable. This alternative approach has given us very similar results to the results we present in this paper.

[7] The estimated impulse response for $\ln \widehat{z}_t$ is very close to the one generated by the technology process $\ln z_t = 0.95 \ln z_{t-1} + \varepsilon_t$, with $\sigma = 0.007$, that is standard in RBC analysis.

Calibration. We evaluate the matching model by comparing the estimates obtained using simulated data to the empirical estimates reported above. The model is calibrated at monthly frequency by matching steady state properties of the model to U.S. data. Parameter choices are summarized in Table 1.

Consider first the steady state version of (9):

$$0 = \lambda(1-u) - A\theta^{1-\alpha}u. \tag{13}$$

Following Shimer (2005), we adopt a monthly worker matching probability of $A\theta^{1-\alpha} = 0.45$. Including marginally attached workers in the worker search pool gives an adjusted unemployment rate of $u = 0.08$; see Castillo (1998). Equation (13) then implies a separation rate of $\lambda = 0.039$.

Next consider the parameters of the matching function. Estimates using micro data suggest $\alpha = 0.50$ as a reasonable estimate of the elasticity parameter; see Petrongolo and Pissarides (2001). As discussed by Blanchard and Diamond (1989), vacancies have an average duration of roughly three weeks, and thus the average vacancy filling rate is 0.33 per week. This implies a monthly rate of $A\theta^{-\alpha} = 0.90$. Combining these estimates yields the value $A = 0.636$ for the scale parameter.

The monthly discount factor β is chosen to be 0.9967, which implies an annual interest rate of 4 percent. We select the standard value for the worker's bargaining weight, i.e., $\pi = 0.5$, given the lack of direct evidence. Based on our estimates from the preceding section, the values $\rho = 0.975$ and $\sigma = 0.0044$ are used to parameterize (1) at monthly frequency.[8]

It remains to specify the parameters b and c. Combining the steady state versions of (7) and (8) gives the following expression:

$$\frac{z-b+c}{1-\beta[1-\lambda-\pi A\theta^{1-\alpha}-(1-\pi)A\theta^{-\alpha}]} = \frac{c}{\beta(1-\pi)A\theta^{-\alpha}}. \tag{14}$$

The parameter choices specified thus far imply the steady state value $\theta = 0.5$. Equation (14) then contains two unknown variables, b and c. We solve this equation for c under a

[8]Note that the empirically identified productivity series (11) follows an AR(3) process at quarterly frequency, whereas productivity in the model is assumed to follow an AR(1) process at monthly frequency. The monthly productivity process in the model is parameterized so that the time-aggregated quarterly productivity series in the model can closely mimic the properties of the empirically identified quarterly productivity process. Specifically, $\rho = 0.975$ and $\sigma = 0.0044$ allow us to closely match the variance and first order autocorrelation of the quarterly productivity process.

given value of b. To fix b, we exploit the fact that the variability of employment in the matching model is highly sensitive to the level of b (Shimer (2005)); b is selected to match the standard deviation of employment to its empirical value. This procedure yields the choices $b = 0.90$ and $c = 0.17$.

In our view, this is a legitimate calibration procedure, given that there is little direct empirical evidence on the value of b. Our choice of b may nonetheless be controversial. Recent work has focused on the role of the b parameter in determining the ability of the matching model to *amplify* productivity shocks. We are instead concerned with the model's ability to *propagate* shocks, which is a separate issue. In Section 5 below we demonstrate that our propagation results continue to hold for lower values of b, under which the model does not generate realistic amplification. Thus, the question of amplification may be considered separately from our analysis of propagation.

Model evaluation. The model is solved by linearizing around the deterministic steady state and computing the unique rational expectations solution. Using the solution, we compute the monthly impulse response functions and then convert them into the quarterly responses by time averaging, so that the model's responses are comparable to the empirical responses. Quarterly impulse responses are reported in Figure 4. The positive productivity shock induces a sharp upward jump in market tightness, followed by a monotonic decline that tracks the path of productivity. This response exhibits none of the sluggish adjustment observed in the empirical impulse response.

This discrepancy shows up clearly in the cross correlations estimated from the simulated data, depicted in Figure 5.[9] In terms of the contemporaneous correlation between productivity and market tightness, the standard model and observed data are reasonably close, both exhibiting a high correlation between the two variables (0.99 in the model vs. 0.92 in the data). However, the cross-correlations based on data generated from the standard model fall sharply and symmetrically from their peak at zero lag. This contrasts with the empirical correlations, which are flatter and show a pronounced negative phase shift.

The impulse response of employment, shown in the bottom panel of Figure 4, exhibits a counterfactually large jump on impact, followed by another large jump in the initial quarter. Subsequent adjustments closely track the path of productivity. Cross correlations

[9] To compute the summary statistics of the model, we first generate 30,300 periods of simulated monthly data and discard the first 300 periods. We then take quarterly averages to obtain 10,000 periods of data.

of productivity and employment are given in the lower panel of Figure 5. The model generates very high correlations between employment and productivity at lags of zero and one quarters, while the empirical correlations are lower and have their peaks at lags of one and two quarters. Thus employment responses are too sharp and too rapid.

It follows that the standard matching model generates unrealistic dynamics. Labor market adjustments occur contemporaneously with or immediately following productivity disturbances, displaying little of the sluggishness seen in the data.

4 Vacancy Dynamics

Empirical evidence. The poor performance of the standard model is tied to the dynamic behavior of vacancies. This can be seen by decomposing the adjustment of market tightness into separate vacancy and unemployment components. For this purpose we estimate the following quasi-VAR:

$$F(L)\begin{bmatrix}\ln v_t\\ \ln u_t\end{bmatrix} = G(L)\ln\widehat{z}_{t-1} + H\widehat{\varepsilon}_t^z + \begin{bmatrix}\eta_t^v\\ \eta_t^u\end{bmatrix}, \tag{15}$$

where $\ln v_t$ and $\ln u_t$ represent the logs of vacancies and unemployment, respectively; η_t^v and η_t^u are innovations to vacancies and unemployment, respectively; and $F(L)$, $G(L)$ and $H(L)$ indicate a polynomial matrix, a polynomial vector and a real vector, respectively.[10]

Figure 6 displays the estimated impulse responses generated by the empirical data and by the model. The empirical impulse responses for vacancies and unemployment are nearly identical, albeit of opposite sign: on impact the variables jump by about 2 percent, and reach their peak responses four to five quarters later at roughly 6 percent from the steady state. In the simulated data, vacancies jump by a full six percentage points on impact, then move rapidly toward the steady state. Moreover, the unemployment response displays little of the sluggishness seen in the empirical response.

These findings suggest that the poor performance of the matching model stems from excessively rapid adjustment of vacancies. Introducing costs that induce smoothing of vacancy adjustment has the potential to improve the model's performance.

Matching model with vacancy creation costs. To explore the possibility that vacancy smoothing may improve model performance, we extend the standard model by

[10] As in the previous estimation, vacancies and unemployment are detrended by regressing on cubic polynomial time trends prior to VAR estimation, and the lag lengths are set to three quarters.

introducing a sunk cost for vacancy creation. Assume that potential entrant firms must pay a cost of Kn_t for creating a new job position, where n_t indicates the total number of positions created in period t.[11] Creation occurs at the start of the period, after z_t is observed. Once a position is created, it continues to exist, either filled or unfilled, until eliminated by obsolescence. Firms post vacancies to fill newly created positions as well as preexisting positions that become vacant for reasons other than obsolescence.

Let λ^o denote the probability that a job position becomes obsolete at the end of a period. For an active worker-firm match, obsolescence means the worker enters the unemployment pool in the following period, whereas the position disappears. Let λ^n indicate the probability that an active worker-firm match experiences a non-obsolescence, or "normal," separation at the end of a period. In this case, both the worker and firm enter the matching pools in the following period. The overall separation probability in the extended model is $\lambda^o + (1-\lambda^o)\lambda^n$.

In the extended model, the value of an unemployed worker, given by (3) in the standard model, is now given by

$$U_t = b + \beta E_t\Big[(1-\lambda^o)A\theta_t^{1-\alpha}\pi S_{t+1} + U_{t+1}\Big]. \tag{16}$$

Note that this expression is slightly different from the corresponding expression for the standard model (3), as it reflects the possibility that newly formed matches are severed due to job obsolescence. Similarly, (4) and (5), which represent the value of a vacant and filled position, respectively, in the standard model, are replaced by

$$V_t = -c + \beta E_t\Big[(1-\lambda^o)A\theta_t^{-\alpha}(1-\pi)S_{t+1} + (1-\lambda^o)V_{t+1}\Big], \tag{17}$$

$$M_t = z_t + \beta E_t\Big[(1-\lambda^o)(1-\lambda^n)S_{t+1} + U_{t+1} + (1-\lambda^o)V_{t+1}\Big]. \tag{18}$$

Observe that the expected future value of a vacant job position is affected by the obsolescence probability, while expected future match surplus is further affected by the normal separation probability. Substituting (16), (17), and (18) into the surplus sharing rule (6) yields surplus evolution similar to the standard model (7), with slight modifications due to the distinction between obsolescence and normal separation:

$$S_t = z_t - b + c + \beta(1-\lambda^o)\Big[(1-\lambda^n) - A\theta_t^{1-\alpha}\pi - A\theta_t^{-\alpha}(1-\pi)\Big]E_t S_{t+1}. \tag{19}$$

[11] Importantly, marginal creation costs are assumed to be increasing in the total number of positions created. This assumption can be motivated by adjustment costs based on scale or technology, scarcity of profitable opportunities, or limited managerial resources. See the Conclusion for further discussion.

Free entry equates the vacancy value to the creation cost:

$$V_t = Kn_t. \tag{20}$$

Plugging (20) into the continuation value for a vacant job (17) relates new openings n_t to expected surplus:

$$Kn_t = -c + \beta E_t \Big[(1-\lambda^o) A\theta_t^{-\alpha}(1-\pi)S_{t+1} + (1-\lambda^o)Kn_{t+1} \Big]. \tag{21}$$

The implied laws of motion for unemployment and vacancies are

$$u_t = u_{t-1} + (\lambda^o + (1-\lambda^o)\lambda^n)(1-u_{t-1}) - (1-\lambda^o)A\theta_{t-1}^{1-\alpha}u_{t-1}, \tag{22}$$

$$v_t = (1-\lambda^o)v_{t-1} + (1-\lambda^o)\lambda^n(1-u_{t-1}) - (1-\lambda^o)A\theta_{t-1}^{-\alpha}v_{t-1} + n_t. \tag{23}$$

Importantly, vacancies become a predetermined variable in the extended model. The existence of a sunk cost for creating job positions means unfilled positions have positive value in equilibrium. This leads firms to repost vacancies following normal separations. As a consequence, the vacancy pool will be affected by the numbers of new positions created in prior periods.

The dynamic paths of the economy are determined by (19) and (21) under the laws of motion for unemployment (22) and vacancies (23), and the exogenous productivity process (1). To compute equilibria of the model, we first linearize the system around the deterministic steady state and then find its unique rational expectation solution.

Calibration. First consider the steady state version of (22):

$$0 = (\lambda^o + (1-\lambda^o)\lambda^n)(1-u) - (1-\lambda^o)A\theta^{1-\alpha}u. \tag{24}$$

Additional information is needed to identify the parameters λ^o and λ^n. For this purpose, we draw on the evidence from the Business Employment Dynamics (BED) program. According to Faberman (2004), the quarterly job destruction rate in the private sector averaged around 8 percent over the period 1990 through 2003, meaning that, on average, 92 percent of job positions filled at the start of a quarter remain filled one quarter later. This suggests the following relationship:

$$\begin{aligned} \lambda^o + (1-\lambda^o)\lambda^o + (1-\lambda^o)^2\lambda^o + (1-\lambda^o)^3 \Big[\lambda^n \Big((1-A\theta^{-\alpha})^2 + A\theta^{-\alpha}\lambda^n \Big) \\ + (1-\lambda^n)\lambda^n(1-A\theta^{-\alpha}) + (1-\lambda^n)^2\lambda^n \Big] = 0.08. \end{aligned} \tag{25}$$

The first three terms in (25) indicate the probability that obsolescence occurs within the quarter. The bracketed term incorporates the various patterns of normal separation and rematching that culminate in an unfilled vacancy at the end of the quarter, given that obsolescence does not occur. Using our earlier measurements of matching and unemployment rates, we solve (24) and (25) to obtain the values $\lambda^o = 0.021$ and $\lambda^n = 0.018$.

Next consider the steady state value of n. Our measured worker and firm matching probabilities imply a steady state value $\theta = 0.50$. From this we compute $v = \theta u = 0.04$. The steady state version of (23) is

$$0 = -\lambda^o v + (1-\lambda^o)\lambda^n(1-u) - (1-\lambda^o)A\theta^{-\alpha}v + n, \tag{26}$$

from which we obtain the value $n = 0.024$.

Finally, we must choose the parameters b, c, and K. Combining the steady state versions of (19) and (20) results in the following expression:

$$\frac{z-b+c}{1-\beta(1-\lambda^o)[1-\lambda^n-\pi A\theta^{1-\alpha}-(1-\pi)A\theta^{-\alpha}]} = \frac{Kn[1-\beta(1-\lambda^o)]+c}{\beta(1-\lambda^o)(1-\pi)A\theta^{-\alpha}}. \tag{27}$$

To facilitate comparison of the standard and creation cost models, we maintain the value $b = 0.90$. The previous parameter choices together with the implied steady state values of θ and n leave two unknowns c and K in (27). As we did for the calibration of the standard model, we choose c and K to satisfy (27) as well as to match the empirical standard deviation of employment. This procedure yields the values $c = 0.13$ and $K = 26.94$. In Section 5 we demonstrate that our propagation results continue to hold for lower values of b, assuming that the ratio of c to K remains constant for each value of b.

Model evaluation. We repeat the evaluation procedure described above for the calibrated creation cost model. Impulse responses of the creation cost model are shown in Figure 7. The creation cost model yields much more realistic contemporaneous reactions to a productivity shock: on impact, the responses of both market tightness and employment are close to their empirical values. This contrasts with the standard model, for which the contemporaneous responses are much too large.

The creation cost model also exhibits a strong propagation effect. The simulated response of market tightness builds in magnitude for four quarters, matching the timing of the empirical response. Although the peak value of the simulated response is only about half that of the empirical response, the creation cost model nevertheless affords an important improvement relative to the standard model. Furthermore, the employment response in the creation cost model closely matches the empirical response, with the simulated response lying within the 90 percent error band for all quarters. Notably, employment jumps by a small amount at impact and attains its peak five quarters following the shock, in common with the empirical response.

Figure 5 reports cross correlations for both the standard and creation cost models, along with the empirical correlations. As far as the dynamics of market tightness and productivity, the creation cost model generates highly realistic phasing, with peak correlations spread out over lags of 0-3 quarters. This contrasts dramatically with the standard model, where the correlations fall sharply from their peak at zero lag. Similar observations hold for employment.

We conclude that the calibrated creation cost model successfully reproduces key features of the empirical data, encompassing the impact effects of shocks and the timing of the market tightness and employment responses. In particular, the extended model provides a mechanism for propagating shocks in a realistic manner. Compared with the standard model, the creation cost model offers a clear improvement in explaining labor market dynamics.

Sources of propagation. The dynamic properties of the creation cost models are linked to the behavior of vacancies. This is illustrated in Figure 8, which depicts the vacancy and unemployment responses of the model along with those estimated from the empirical data based on (15). In the creation cost model, vacancies jump by 2.5 percent in the period of the shock, close to the 2 percent jump observed empirically. The vacancy response for the creation cost model also displays a pronounced hump shape.

This contrasts sharply with the vacancy response for the standard model, shown in Figure 6, where vacancies jump by over six percentage points on impact and the response dies away quickly. We conclude that the behavior of vacancies is a key factor underlying the improved performance of the creation cost model relative to the standard model.

The impulse responses for unemployment are presented in the bottom panel of Figure 8. Although the simulated response exhibits an unrealistically small jump on impact, subsequent unemployment dynamics are qualitatively similar to the empirical dynamics. For the standard model, the jump in unemployment on impact is more realistic, but the subsequent dynamics do not resemble the empirical responses, as may be seen in Figure 6.[12]

[12] It should be noted that employment and unemployment are rigidly linked in the matching framework

In the creation cost model, adjustments in the stock of vacancies are driven by a rich pattern of underlying flows. To evaluate this pattern we decompose the net change in the vacancy stock into separate gross outflows and inflows, using (23):

$$\Delta v_t = \underbrace{-\lambda^o v_{t-1}}_{\text{obsolescence}} \underbrace{-(1-\lambda^o)A\theta_{t-1}^{-\alpha}v_{t-1}}_{\text{hires}} + \underbrace{(1-\lambda^o)\lambda^n(1-u_{t-1})}_{\text{repostings}} + \underbrace{n_t}_{\text{new openings}} .$$

Observe that the net changes comprise gross outflows due to obsolescence and hires, together with gross inflows due to repostings following normal separations and new openings. Figure 9 plots the impulse responses for these gross flows.[13] The graph clearly shows that vacancy adjustment is driven almost entirely by new openings and hires. Furthermore, the inflows from new openings lead the outflows from hires, which are tied to the timing of the matching process. In the four quarters following the shock, new opening inflows exceed hiring outflows, accounting for the propagation effect observed in Figure 8.

According to Figure 9, entrant firms spread out the creation of new positions following a shock. This smoothing behavior arises in a familiar way from the assumption of increasing marginal creation costs. Moreover, since job positions are durable, entrant firms will not choose to leave the vacancy pool once they have entered it, either initially or following a normal separation. These factors together underlie the sluggish vacancy adjustment observed in the creation cost model. Similar reasoning applies with respect to negative productivity shocks: a lower volume of new openings reduces marginal creation costs, causing entrant firms to spread out their responses; and durability means that reductions in new openings have a more persistent effect on the vacancy stock.

Evidence from JOLTS. Although new openings play a crucial role in shaping vacancy adjustment in the creation cost model, the available vacancy data do not permit a direct empirical assessment of this role. JOLTS, however, does provide information about vacancy stocks, quits, layoffs, and hires for 2001:Q1 to 2006:Q1, and this allows us to obtain

considered here, since the framework abstracts from labor force participation. A more complete specification would incorporate movements into and out of the labor force, which might generate a more empirically valid unemployment response while preserving the realistic employment response.

[13]The responses in Figure 9 are expressed in levels, as opposed to the responses in Figures 6 and 8, which are expressed in logs.

an indirect measure of new openings via the following stock-flow relationship:

$$vac_t = (1 - \lambda^o)vac_{t-1} + quits_t - hires_t + n_t. \tag{28}$$

Our calibration of the model suggests $\lambda^o = 0.021$ as a reasonable estimate of the monthly vacancy withdrawal rate. We can combine this figure with the JOLTS data to impute an estimate of n_t from (28).

Consider the first quarter of 2001, which we view as the most typical within the limited JOLTS sample. For this quarter, the ratio of cumulative hires to end-of-quarter vacancy stock is about 3.5. Our imputed inflow of new openings amounts to 1.5 times the end-of-quarter stock. Thus, new openings amount to nearly half of total hires within the quarter.

Figure 10 plots indices of imputed new openings, vacancies, hires, and quits, based on quarterly averages of the monthly series and treating 2001:Q1 as the base period. The four series fluctuate by comparable amounts over the sample period, and, in particular, new openings exhibit significant variability. Moreover, new openings move strongly upward in 2003:Q2, leading the upward movement of vacancies by roughly four quarters. The upward movements of hires and quits lag those of new openings and are less steep. Based on this limited evidence, it appears that new openings adjust sooner and by a greater magnitude in comparison with the other components.

5 Amplification and Propagation

Recent research has considered the amplification of shocks in the context of the job matching model.[14] Attention has focused on the sensitivity of model-generated volatility to the unemployment payoff b. In the absence of other information, our calibration exploits this sensitivity by selecting the value $b = 0.90$ in order to match the empirical standard deviation of employment. It is of interest, however, to assess the robustness of our propagation results to the selection of this parameter.

To address this issue, we recalibrate the standard and creation cost versions of the matching model under the alternative values $b = 0.65$ and $b = 0.4$. Table 2 gives the values of the parameter c that are implied by the free entry condition in the standard model. For the creation cost model, our calibration procedure does not pin down both c

[14] See Hagedorn and Manovskii (2005), Hall (2005), Hornstein, Krusell, and Violante (2005), Mortensen and Nagypál (2005), and Shimer (2005).

and K in these cases, since the model cannot match the empirical volatility of employment under lower values of b. We handle this by fixing the ratio of K to c at the value determined in the original calibration, i.e., $K/c = 207.23$.

Table 3 presents standard deviations of employment, market tightness, unemployment, and vacancies calculated using empirical and simulated data. The empirical values are based on the estimated systems (12) and (15). For both the standard and creation cost versions of the matching model, the value $b = 0.90$ produces a close match with the standard deviations of employment and vacancies, while market tightness and unemployment display insufficient volatility. The table also shows that lower values of b imply lower standard deviations, as previous authors have stressed.

Tables 4 and 5 present the cross correlations in tabular form. As the tables demonstrate, lowering the value of b has a minuscule effect on the dynamic relationships between market tightness, employment, and productivity. Thus, our findings with respect to the model's dynamic performance are unaffected by the level of the b parameter. More broadly, the amplification and propagation properties of the matching model can be viewed as separate dimensions. The unemployment payoff greatly affects amplification, but our results show that the unemployment payoff has no effect on propagation.

6 Conclusion

The job matching model has become the standard framework for analyzing the business cycle behavior of vacancies, unemployment, and employment. The model has met with considerable empirical success in accounting for the size and variability of these magnitudes, along with the gross flows of jobs and workers.[15] In this paper, however, we demonstrate that the model fails to capture key dynamic properties of labor market adjustment. The sluggish adjustment observed in the empirical data does not emerge from the matching model in its standard form, where the rapid responses of vacancies induce counterfactually sharp adjustments of market tightness and employment.

We extend the matching model by introducing a simple specification of sunk costs for creating new job positions. Creation costs cause entrant firms to smooth vacancy creation over time. This leads to much more realistic dynamics: in simulated data, productivity shocks induce contemporaneous responses and subsequent adjustment patterns that closely

[15] See, for example, Andolfatto (1996), Den Haan, Ramey, and Watson (2000), Mortensen (1994), Mortensen and Pissarides (1994), Merz (1995, 1999) and Yashiv (2006).

mimic those found in the empirical data.

Although the creation cost model performs well in capturing the main features of the empirical dynamics, the magnitudes of the peak responses in the simulated data fall short of the empirical magnitudes. This shows up in the excessively high conditional correlations of market tightness and employment with lags of productivity. Our creation cost specification could be extended to incorporate planning lags that might induce bunching of vacancy creation several quarters after a shock. Such bunching might also occur if established job positions could be "mothballed" following a normal separation; shocks might then lead to reposting of a large number of mothballed vacancies after several quarters. These ideas, explored in Fujita (2003), represent important avenues for future research.

A number of further extensions may be of interest. Diseconomies in new job creation, associated with increasing marginal creation costs, could be considered in greater detail. These may arise from explicit costs of adjustment at the establishment or firm level, limited availability of key capital inputs, or technical constraints associated with R&D activity. Aggregate adjustment may be influenced by entry and exit of establishments. These factors may introduce important additional sources of propagation, including the possibility of longer-run feedbacks from the labor market to productivity. Relatedly, the assumed equivalence of newly created and preexisting job positions could be modified by incorporating a vintage structure, whereby new jobs enjoy higher productivity. This would permit the endogenous obsolescence of jobs and the turnover of workers to be considered as separate flows within a common framework.[16] Finally, we have ignored the effects of cyclical variation in the relative sizes of the pools of unemployed workers, workers out of the labor force but available for work, and workers out of the labor force and unavailable. Changes in the characteristics of these pools may, however, represent another important source of longer-run propagation effects.

[16] Aghion and Howitt (1994), Caballero and Hammour (1994), and Mortensen and Pissarides (1998), for example, analyze endogenous obsolescence in models that combine embodied technological progress with search/matching frictions. None of those papers distinguish between worker and job turnover. In recent work, Hornstein, Krusell, and Violante (2004) adopt a specification similar to ours for purposes of analyzing the unemployment experiences of the U.S. and Europe. They focus on comparison of steady states, however, rather than cyclical adjustment.

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Table 1: Benchmark Parameter Values

symbol	description	standard	creation cost
λ	total separation rate	0.039	n.a.
λ^o	obsolescence rate	n.a.	0.021
λ^n	normal separation rate	n.a.	0.018
α	elasticity parameter for matching function	0.50	same
A	scale parameter for matching function	0.636	same
β	discount factor	0.9967	same
π	worker bargaining weight	0.5	same
ρ	autoregressive parameter for productivity process	0.975	same
σ	standard deviation of productivity innovation	0.0044	same
b	unemployment payoff	0.90	same
c	vacancy posting cost	0.17	0.13
K	creation cost parameter	n.a.	26.94

Table 2: Alternative Parameter Values

symbol	standard			creation cost		
b	0.40	0.65	0.9	0.40	0.65	0.90
c	1.01	0.59	0.17	0.78	0.455	0.13
K	n.a.			161.65	94.30	26.94

Table 3: Standard Deviations

	empl.	market tightness	vacancies	unempl.
empirical	0.0078	0.2976	0.1310	0.1790
standard model				
$b = 0.90$	0.0083	0.2084	0.1203	0.0919
0.65	0.0023	0.0573	0.0323	0.0260
0.40	0.0013	0.0334	0.0188	0.0152
creation cost model				
$b = 0.90$	0.0079	0.1951	0.1082	0.0884
0.65	0.0022	0.0549	0.0302	0.0251
0.40	0.0013	0.0320	0.0176	0.0147

Notes: empl.: employment. unempl.: unemployment. Reported statistics are based on logged values of the corresponding series expressed as quarterly averages of the monthly series. Volatilities of the empirical data are conditional on the productivity process identified by (11). Those of empirical employment and market tightness series are based on the estimated system (12), and those of vacancies and unemployment series are based on the estimated system (15). To compute the summary statistics of the model, we first generate 30,300 periods of simulated monthly data and discard the first 300 periods. We then take quarterly averages to obtain 10,000 periods of data. Parameter values for generating the artificial data from the two models are put together in Table 1 and Table 2.

Table 4: Cross correlations between market tightness at t and productivity at $t+i$

$i =$	-3	-2	-1	0	1	2	3
empirical	0.82	0.89	0.93	0.92	0.86	0.81	0.75
standard model							
$b = 0.90$	0.79	0.86	0.94	0.99	0.94	0.86	0.79
0.65	0.80	0.87	0.95	1.00	0.95	0.87	0.80
0.40	0.80	0.87	0.95	1.00	0.95	0.87	0.80
creation cost model							
$b = 0.90$	0.91	0.96	0.98	0.96	0.89	0.81	0.75
0.65	0.92	0.96	0.98	0.96	0.89	0.82	0.75
0.40	0.92	0.96	0.98	0.96	0.89	0.82	0.75

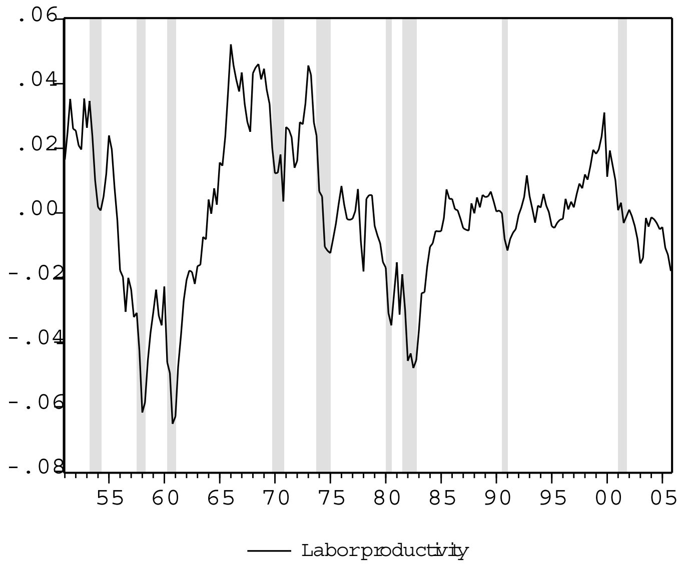
Notes: Reported statistics are based on logged values of the corresponding series expressed as quarterly averages of the monthly series. Cross correlations of the empirical data are conditional on the productivity process identified by (11). Those of empirical employment and market tightness series are based on the estimated system (12), and those of vacancies and unemployment are based on the estimated system (15). To compute the summary statistics of the model, we first generate 30,300 periods of simulated monthly data and discard the first 300 periods. We then take quarterly averages to obtain 10,000 periods of data. Parameter values for generating the artificial data from the two models are put together in Table 1 and Table 2.

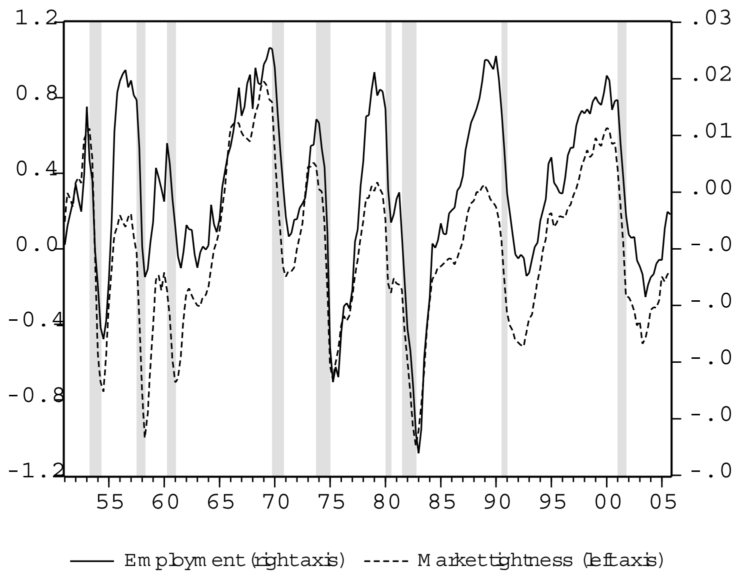
Table 5: Cross correlations between employment at t and productivity at $t+i$

$i =$	-3	-2	-1	0	1	2	3
empirical	0.85	0.91	0.92	0.85	0.80	0.74	0.69
standard model							
$b = 0.90$	0.85	0.92	0.98	0.96	0.89	0.82	0.75
0.65	0.86	0.93	0.99	0.98	0.90	0.83	0.76
0.40	0.86	0.93	0.99	0.98	0.91	0.83	0.76
creation cost model							
$b = 0.90$	0.94	0.97	0.96	0.91	0.83	0.76	0.70
0.65	0.95	0.98	0.97	0.92	0.84	0.77	0.71
0.40	0.95	0.98	0.97	0.92	0.85	0.78	0.71

Notes: see the notes for Table 4.

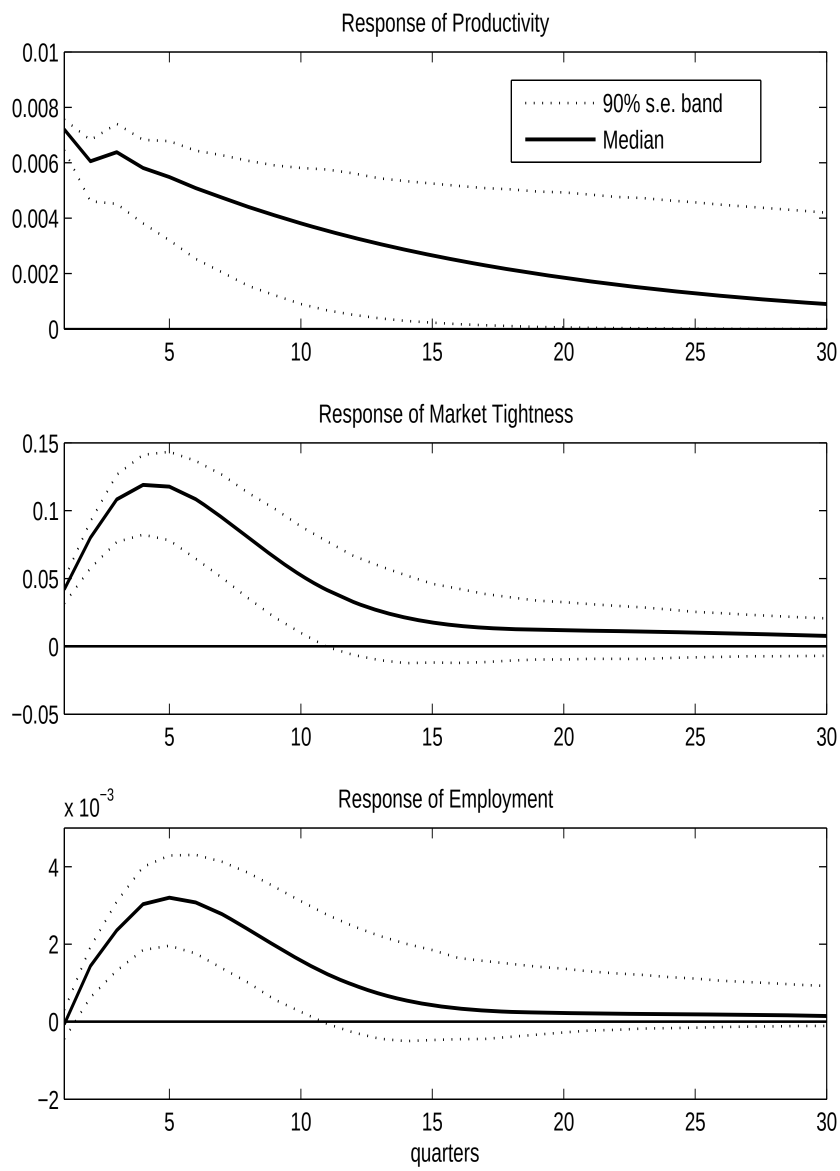
Figure 1: Cyclical movements of labor productivity, market tightness, and employment





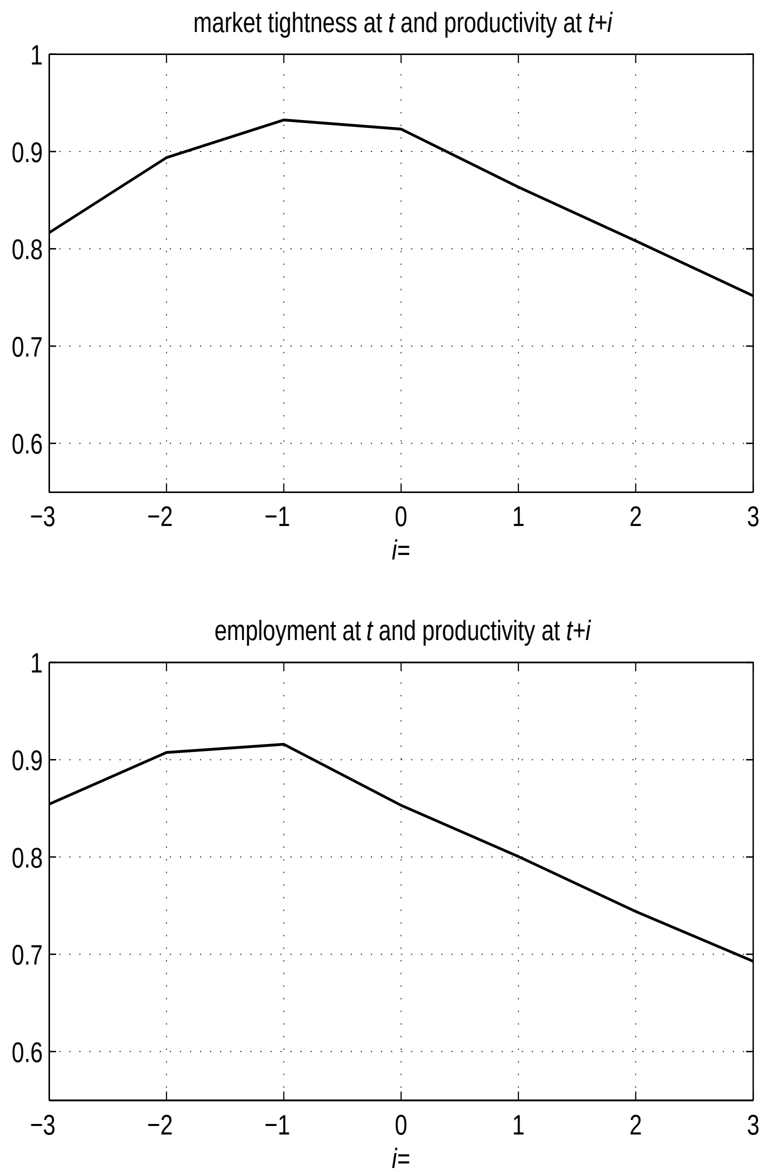
Notes: Data are expressed as log deviations from the cubic polynomial trends. Monthly employment and market tightness series are converted into quarterly data by averaging. Shaded areas indicate NBER dated recessions. Labor productivity: real GDP divided by the number of employed. Employment: employment-population ratio. Market tightness: the number of help-wanted ads divided by the number of unemployed. See footnote 2 for more details of the data sources.

Figure 2: Empirical impulse responses to one-s.d. productivity shock



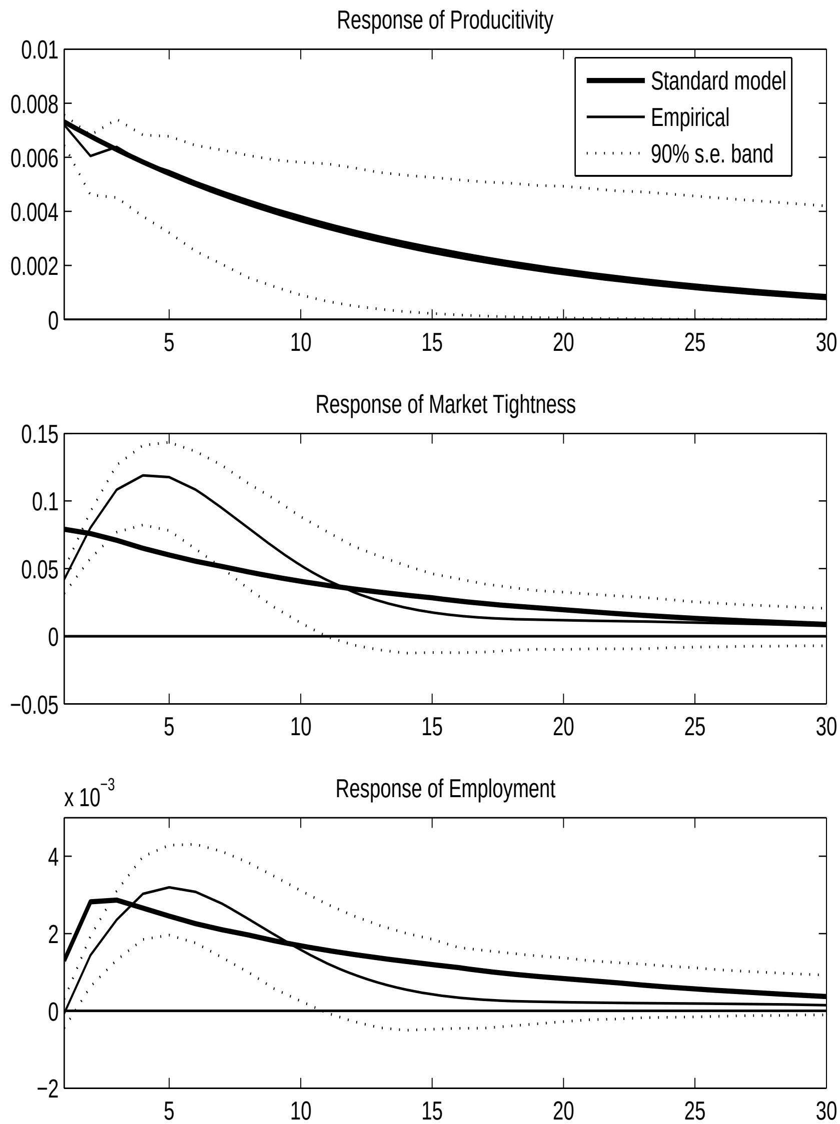
Notes: The impulse responses are based on the estimated system (12). Dotted lines are 90% confidence bands computed via Monte-Carlo simulations with 1,000 replications under the assumption of normality of the error term.

Figure 3: Empirical cross correlations



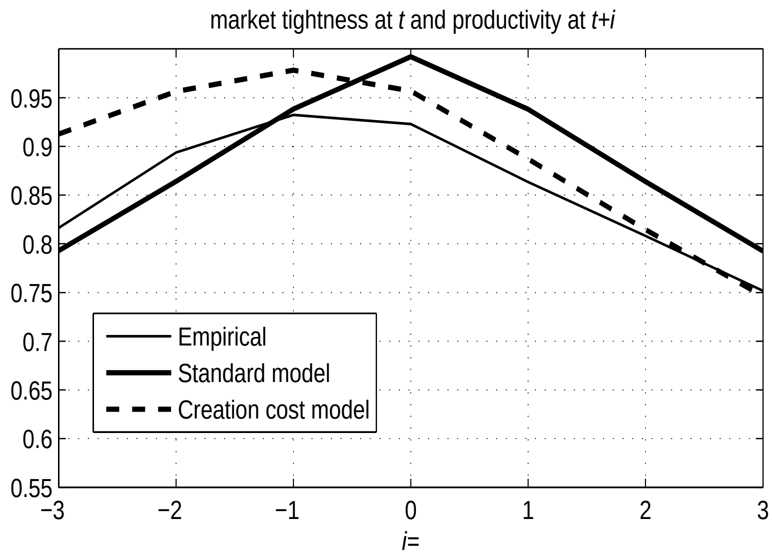
Notes: The above graphs plot the empirical cross correlations presented in Tables 4 and 5. See notes for the tables.

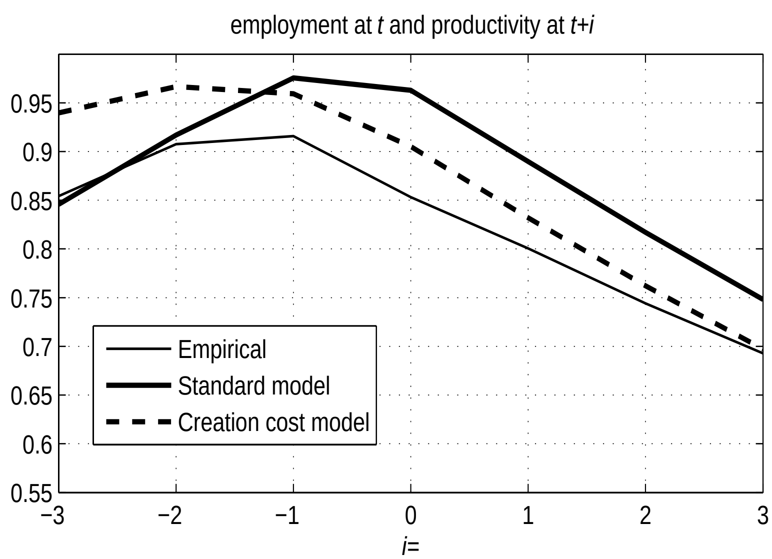
Figure 4: Comparison of impulse responses: empirical vs. standard model



Notes: See notes for Figure 2 for explanation of empirical impulse responses. Quarterly impulse responses of the model plotted above are obtained by time-averaging the monthly impulse responses. Parameter values used for solving the model are summarized in Table 1. The size of the productivity shock for the model is chosen to match one standard deviation of the productivity shock, empirically identified at quarterly frequency.

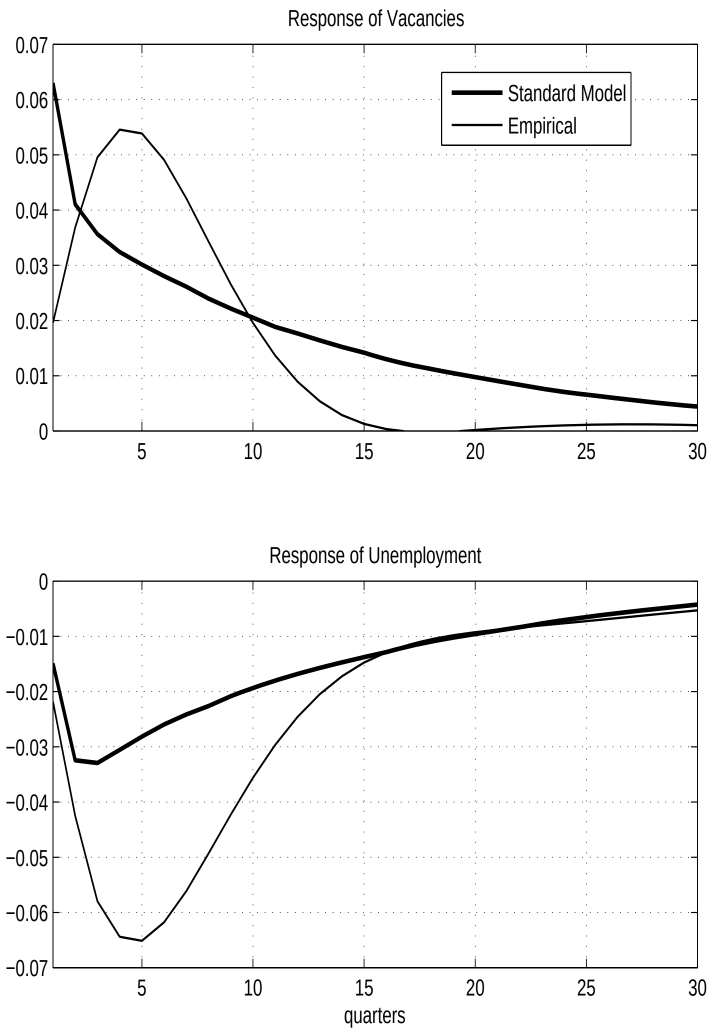
Figure 5: Comparison of cross correlations





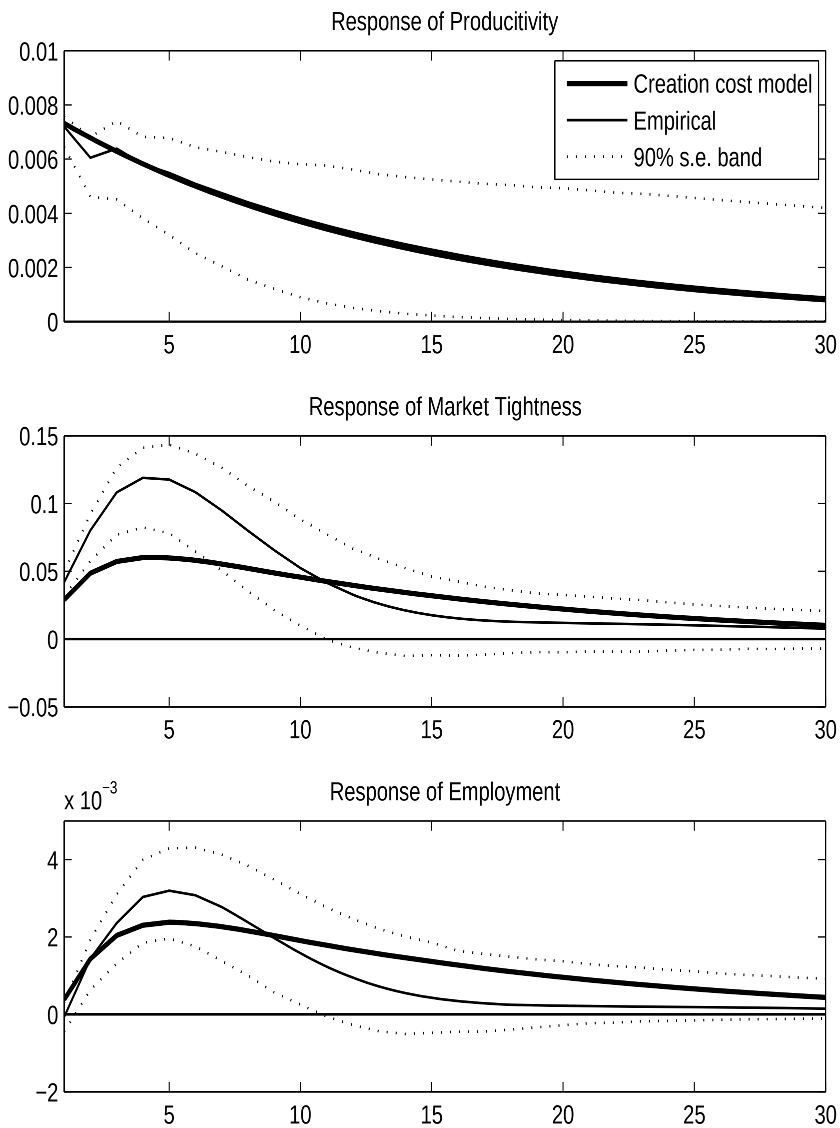
Notes: The above graphs plot the cross correlations presented in Tables 4 and 5. The correlations for the models correspond to the $b = 0.9$ case. See notes for those tables.

Figure 6: Comparison of vacancy and unemployment responses: empirical vs. standard model



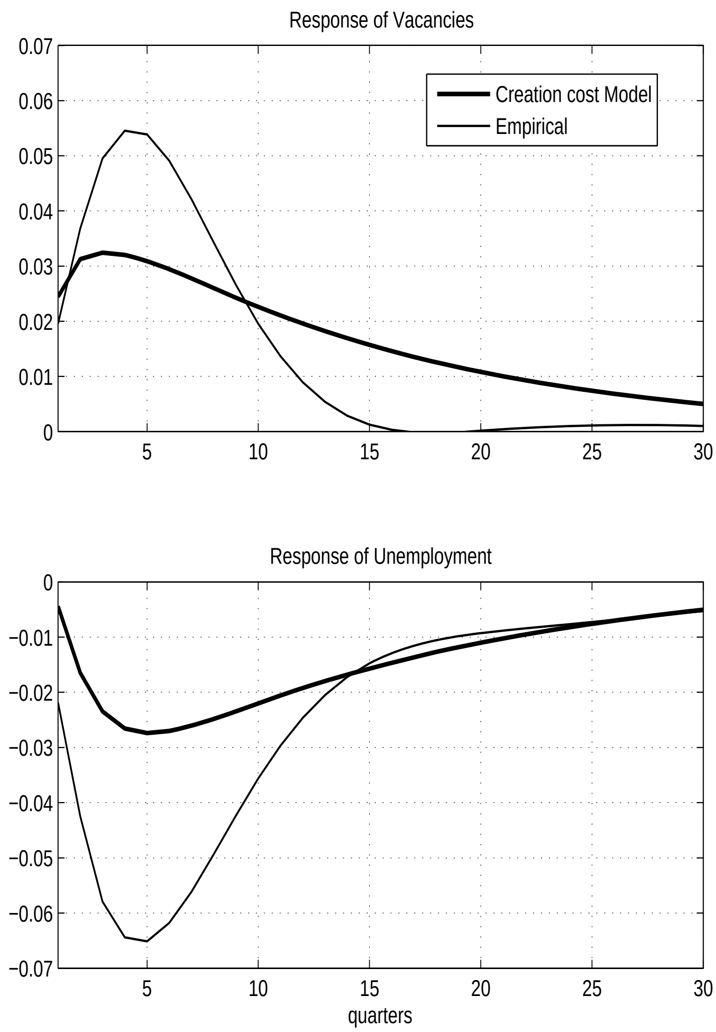
Notes: The empirical responses are based on the estimated system (15). Quarterly impulse responses of the model plotted above are obtained by time-averaging the monthly impulse responses. Parameter values used for solving the model are summarized in Table 1. The size of the productivity shock for the model is chosen to match one standard deviation of the productivity shock that is empirically identified by using the quarterly observations.

Figure 7: Comparison of impulse responses: empirical vs. creation cost model



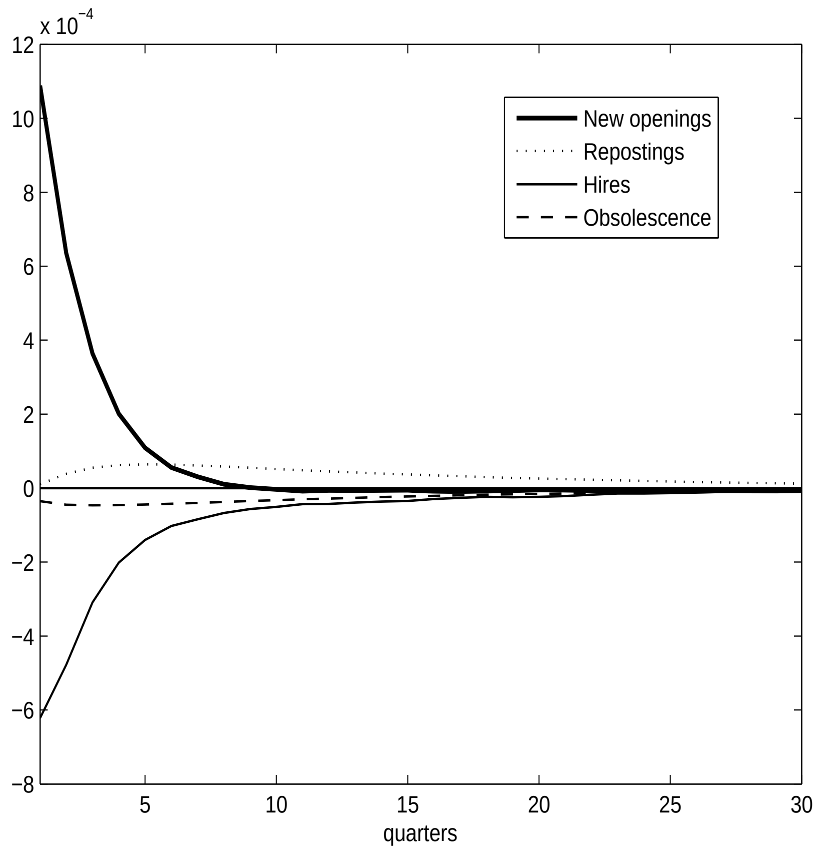
Notes: See notes for Figure 4.

Figure 8: Comparison of vacancy and unemployment responses: empirical vs. creation cost model



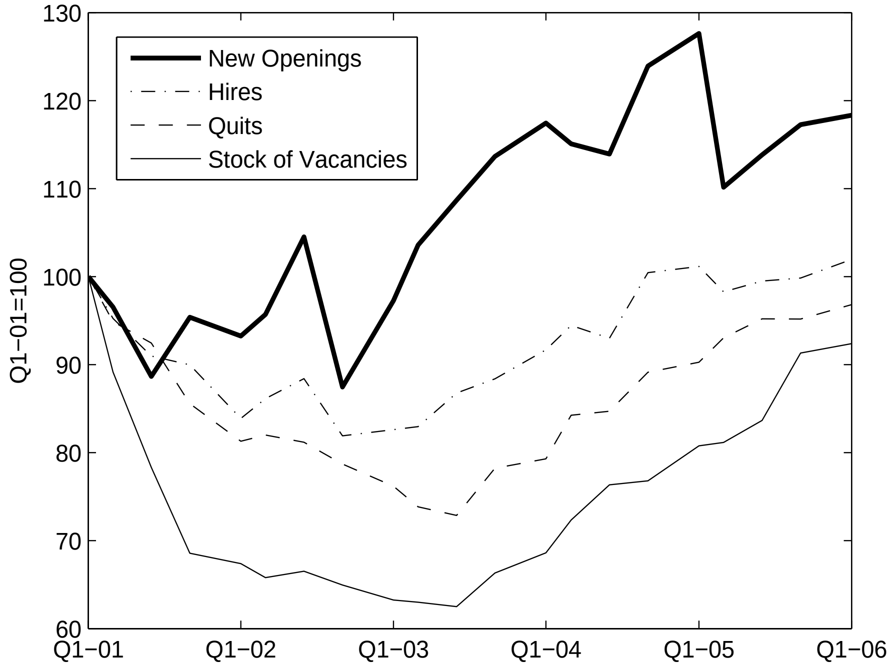
Notes: See notes for Figure 8.

Figure 9: Gross flows of vacancies in the creation cost model



Notes: Level deviations from steady state. Quarterly averages of the monthly responses. Each component is computed based on the following monthly flows; new postings: n_t, repostings: $(1-\lambda^o)\lambda^n(1-u_{t-1})$, hires: $(1-\lambda^o)A\theta_{t-1}^{-\alpha}v_{t-1}$, obsolescence: $\lambda^o v_{t-1}$.

Figure 10: JOLTS data



Notes: We computed out new openings implied by the vacancy stock-flow relationship (28) by using the monthly JOLTS observations on quits, hires and end-of-the-period stock of vacancies, and the calibrated obsolescence rate $\lambda^o = 0.021$. Quarterly averages are then computed. The above figure plots indices that treat 2001:Q1 as the base period.