THE SLOW JOB RECOVERY IN A MACRO MODEL OF SEARCH AND RECRUITING INTENSITY

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Abstract. Despite steady declines in the unemployment rate and increases in the job openings rate after the Great Recession, the hiring rate in the United States has lagged behind. A significant gap remains between the actual job filling rate and that predicted from the standard labor search model. To examine the forces behind the slow job recovery, we generalize the standard labor search model to incorporate endogenous variations in search intensity and recruiting intensity. Our model features a vacancy creation cost, which implies that firms rely on variations in both the number of vacancies and recruiting intensity to respond to aggregate shocks, in contrast to the textbook model with costless vacancy creation and thus constant recruiting intensity. Cyclical variations in search and recruiting intensity drive a wedge into the matching function even absent exogenous changes in match efficiency. Our estimated model suggests that fluctuations in search and recruiting intensity help substantially bridge the gap between the actual and model-predicted job filling rates in the aftermath of the Great Recession.

I. Introduction

The U.S. labor market has improved substantially since the Great Recession. The unemployment rate declined steadily from its peak of about 10 percent in 2009 to about 5 percent in 2015, accompanied by a steady rise in the job openings rate. However, the recovery in the hiring rate has continued to lag behind. Thus, despite the rise in job openings, the job filling rate has dropped significantly, while the job finding rate has recovered only sluggishly (see the solid blue lines in Figure 1).

These patterns present a puzzle for the standard labor search model. In the standard model, hiring is related to unemployment and job vacancies through a matching function of

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the form

$$m_t = \mu u_t^{\alpha} v_t^{1-\alpha}, \tag{1}$$

where m_t denotes new job matches in period t, u_t and v_t denote unemployment and job vacancies, respectively, α measures the elasticity of matching with respect to unemployment, and μ is a scale parameter that captures the average match efficiency. With this standard matching function, the job filling rate (denoted by q_t^v) and the job finding rate (denoted by q_t^u) are respectively given by

$$q_t^v \equiv \frac{m_t}{v_t} = \mu \left(\frac{v_t}{u_t}\right)^{-\alpha}, \quad q_t^u \equiv \frac{m_t}{u_t} = \mu \left(\frac{v_t}{u_t}\right)^{1-\alpha}. \tag{2}$$

Thus, the job filling rate is inversely related to the labor market tightness measured by the vacancy-unemployment (v-u) ratio, and the job finding rate is positively related to the labor market tightness. When the vacancy rate increases and the unemployment rate falls, as it has been the case since the Great Recession, the v-u ratio rises and pushes the job finding rate up and the job filling rate down. However, Figure 1 shows that feeding the observed behavior of the unemployment and vacancy rates in this standard matching function with α calibrated to 0.5 implies a much more gradual decline in the job filling rate than observed in the data. The standard theory also implies a much more rapid increase in thevjob finding rate that in the data (see the dashed red lines vs. the solid blue lines). The reason for these patterns is that the actual hiring rate has not increased as much as that predicted by theory.[1]

To understand the forces behind this slow job recovery, we develop and estimate a DSGE framework that incorporates endogenous variations in two additional margins of labor-market adjustment: search intensity and recruiting intensity. We consider a matching function that generalizes the standard matching function to include these intensive margins:

$$m_t = \mu \left(s_t u_t\right)^{\alpha} \left(a_t v_t\right)^{1-\alpha}, \tag{3}$$

where s_t and a_t denote, respectively, search and recruiting intensity. Our approach to modelling search and recruiting intensity builds on the textbook framework of Pissarides (2000). The benchmark model economy is populated by a large number of identical and infinitely lived households. The representative household is a family of workers, some employed and others are not. In each period, unemployed workers search for jobs and decide how much effort to put into their search. Greater search intensity raises the probability of finding a job, but also incurs higher costs of searching. Firms post vacancies at a fixed cost and choose the level of advertising effort —our concept of recruiting intensity. Optimal level of advertising

[1]The job filling rate and the job finding rate implied by the standard matching function are calculated based on the v-u ratio in Equation (2) and actual data for u and v.

results from the tradeoff between the marginal benefit of raising the probability of filling the job opening and the costs of advertising.

Our first contribution is to provide a microeconomic foundation for endogenous aggregate variations in recruiting intensity by assuming that vacancy creation incurs a sunk cost. In the textbook model with recruiting intensity (Pissarides, 2000), vacancy creation is costless and when economic conditions change firms vary the number of vacancies, which is costless, to meet their new hiring needs and choose the level of recruiting intensity to minimize the cost of posting each vacancy. This behavior implies that recruiting intensity is independent of macoeconomic fluctuations. Instead, with a sunk cost of creating vacancies, firms adjust both the number of vacancies and recruiting intensity in response to aggregate shocks, generating business-cycle variations in recruiting intensity.[2]

Our second contribution is to examine the quantitative importance of search and recruiting intensity for the job filling and job finding rates. To do so, we estimate the model using Bayesian methods, fitting the time-series data of the unemployment rate and the job vacancy rate. Our estimation suggests that cyclical variations in search and recruiting intensity have important implications for the dynamics of hiring. In the wake of the Great Recession, our model predicts a slow recovery in the hiring rate resulting from a below-trend recovery of search and recruiting intensity. Therefore, our estimated model predicts a slow job recovery, with a sharp decline in the job filling rate and a sluggish increase in the job finding rate. The model's predictions are more in line with the data than those from the standard model without intensive margins, as shown in Figure 1.

Our work is inspired by Davis et al. (2013), who construct a measure of recruiting intensity based on the Job Openings and Labor Turnover Survey (JOLTS) at the establishment level. They present evidence that employers rely not just on the number of vacancies, but also heavily on other instruments for hiring. They show that incorporating recruiting intensity, which captures employers' hiring instruments other than vacancies, into the standard matching function helps deliver a better-fitting Beveridge curve for the post Great Recession period. Our paper complements their work by building and estimating a DSGE framework with optimizing agents and with endogenous variations in both recruiting intensity and search intensity at the aggregate level.

Our paper is related to the literature on the shifts of the Beveridge curve, which describes the relationship between steady-state u and v. The Beveridge curve has experienced

[2]Fujita and Ramey (2007) introduce a fixed cost of creating vacancies in a search model to account for the sluggish responses of employment and the unemployment to vacancy ratio following productivity shocks, although they do not model recruiting intensity. See Coles and Kelishomi (2011) for a detailed discussion of the implications of costly entry for the labor market dynamics.

a significant outward movement following the Great Recession (Daly et al., 2012). While alternative explanations for this shift have been offered, including mismatch (Kocherlakota, 2010), variations in labor force participation (Diamond, 2013; Christiano et al., 2013), and more generous unemployment benefits (Mulligan, 2010)), the debate remains inconclusive.[3] Our model suggests that cyclical variations in search and recruiting intensity are also important factors.

Our work also complements recent work on screening, an implicit form of recruiting intensity. For instance, Ravenna and Walsh (2012) examine the effects of screening on the magnitude and persistence of unemployment following adverse technology shocks in a search model with heterogeneous workers and endogenous job destruction. Relatedly, Sedláček (2014) empirically studies the fluctuations in matching efficiency and proposes countercyclical changes in hiring standards as an underlying force.

Finally, by examining the interaction between search and recruiting intensity, our work also complements the analysis of Gomme and Lkhagvasuren (2013), who study how the addition of search intensity and directed search can amplify the responses of the unemployment and vacancy rates following productivity shocks, although their model is not estimated to fit time-series data.

II. The model with search and recruiting intensity

In this section, we present a DSGE model with search frictions in the labor market. To study factors that potentially shift the Beveridge curve, we introduce both an exogenous shock to matching efficiency and endogenous intensive margins of adjustments in the matching technology. First, we follow Davis et al. (2013) and introduce recruiting intensity as an additional margin of adjustments for firms. A decline in recruiting intensity leads to a lower vacancy filling rate and therefore an outward shift in the Beveridge curve. Second, we

[3] An important literature examines the role of exogenous fluctuations in matching efficiency and its effects on unemployment and vacancies. For example, Lubik (2013) examines the role of shocks to matching efficiency for the shift in the Beveridge curve in a standard labor search model. He finds that a combination of lower matching efficiency and a decline in productivity are necessary to account for the recent behavior of unemployment and vacancies. Similarly, Barlevy (2011) and Veracierto (2011) infer the decline in matching efficiency from the outward shift in the Beveridge curve to assess the role of structural factors for the rise in unemployment during the Great Recession and the early phase of the recovery. Sahin et al. (2013) develop an empirical framework to assess the extent to which mismatch between the skills of job seekers and the characteristics of job vacancies translate into higher unemployment. Similarly, Sterk (2011) considers geographical mismatch arising from fluctuations in house prices. Our study suggests that the observed matching efficiency contains important endogenous components originating from fluctuations in search and recruiting intensities. See Elsby et al. (2015) for a recent survey of the literature on the shifts of the Beveridge curve.

introduce sunk costs for vacancy creation. In the standard textbook search model, recruiting intensity does not depend on macroeconomic conditions because free-entry implies that an unfilled vacancy has zero value, so that firms rely on varying the number of job vacancies to respond to shocks instead of adjusting recruiting intensity (Pissarides, 2000). With sunk costs for vacancy creation, as we show, firms respond to shocks by adjusting both the number of vacancies (i.e., the extensive margin) and recruiting intensity (i.e., the intensive margin). In addition, having sunk costs in the model generate more interesting dynamics for job vacancies, as shown by Fujita and Ramey (2007); Coles and Kelishomi (2011); Elsby et al. (2015). Third, we also introduce search intensity as an additional adjustment margin for unemployed workers.

The economy is populated by a continuum of infinitely lived and identical households with a unit measure. The representative household consists of a continuum of worker members. The household owns a continuum of firms, each of which uses one worker to produce a consumption good. In each period, a fraction of the workers are unemployed and they search for a job. Searching workers also choose optimally the levels of search effort. New vacancies creation incurs an entry cost. Posting existing vacancies also incurs a per-period fixed cost. The number of successful matches are produced with a matching technology that transforms efficiency units of searching workers and vacancies into an employment relation. Job matches are separated at a given job separation rate. Real wages are determined by Nash bargaining between a searching worker and a hiring firm. The government finances its spending and transfer payments to unemployed workers by lump-sum taxes.

II.1. **The Labor Market.** In the beginning of period t, there are N_{t-1} workers. A fraction δ of job matches are separated. Workers in a separated match go into the unemployment pool. Following Blanchard and Galí (2010), we assume full labor force participation, with the size of the labor force normalized on one. Thus, the number of unemployed workers searching for jobs is given by

$$u_t = 1 - (1-\delta)N_{t-1}. \tag{4}$$

After observing aggregate shocks, new vacancies are created. Following Fujita and Ramey (2007); Coles and Kelishomi (2011), we assume that creating new vacancies incurs an entry cost. Newly created vacancies add to the existing stock of vacancies carried over from the previous period. In addition, a fraction δ of job matches are separated, and those vacant job positions also add to the stock of vacancies. The law of motion for job vacancies v_t is described by

$$v_t = v_{t-1} + \delta N_{t-1} + n_t, \tag{5}$$

where n_t denotes newly created vacancies.

The searching workers and firms with job vacancies form new job matches based on a matching technology described by the Cobb-Douglas function

$$m_t = \mu(s_t u_t)^{\alpha}(a_t v_t)^{1-\alpha}, \tag{6}$$

where m_t denotes the number of successful matches, s_t denotes search intensity, a_t denotes recruiting intensity (or advertising), the parameter μrepresents the scale of matching efficiency, and the parameter $\alpha \in (0,1)$ is the elasticity of job matches with respect to efficiency units of searching workers.

The probability that an open vacancy is filled with a searching worker (i.e., the job filling rate) is given by

$$q_t^v = \frac{m_t}{v_t}. \tag{7}$$

The probability that an unemployed and searching worker finds a job (or the job finding rate) is given by

$$q_t^u = \frac{m_t}{u_t}. \tag{8}$$

New job matches add to the employment pool so that aggregate employment evolves according to the law of motion

$$N_t = (1-\delta)N_{t-1} + m_t. \tag{9}$$

At the end of the period t, the searching workers who failed to find a job match remains unemployed. The unemployment rate is given by

$$U_t = u_t - m_t = 1 - N_t. \tag{10}$$

II.2. **The households.** There is a continuum of infinitely lived and identical households with a unit measure. The representative household has a utility function given by

$$E\sum_{t=0}^{\infty}\beta^t\left(\ln C_t - \chi_t N_t\right), \tag{11}$$

where $E[\cdot]$ is an expectation operator, C_t denotes consumption, and N_t denotes the fraction of household members who are employed. The parameter $\beta \in (0,1)$ denotes the subjective discount factor.

The term χ_t is a shock to the dis-utility of working, which follows the stationary stochastic process

$$\ln\chi_t = (1-\rho_\chi)\ln\bar{\chi} + \rho_\chi \ln\chi_{t-1} + \varepsilon_{\chi t}. \tag{12}$$

In this shock process, ρ_χ is the persistence parameter and the term $\varepsilon_{\chi t}$ is an i.i.d. normal process with a mean of zero and a standard deviation of σ_χ. The term $\bar{\chi}$ is the steady-state level of the disutility shock.

The representative household chooses consumption C_t, saving B_t, and search intensity s_t to maximize the utility function in (11) subject to the sequence of budget constraints

$$C_t + \frac{B_t}{r_t} = B_{t-1} + w_t N_t + \phi u_t (1 - q^u(s_t)) - u_t h(s_t) + d_t - T_t, \quad \forall t \geq 0, \tag{13}$$

where B_t denotes the household's holdings of a risk-free bond, r_t denotes the gross real interest rate, w_t denotes the real wage rate, $h(s_t)$ denotes the resource cost of search efforts, $q^u(s_t)$ denotes the job finding rate for the worker with search intensity level of s_t, d_t denotes their share of firms' aggregate profits, and T_t denotes lump-sum taxes. The parameter ϕ measures the flow benefits of unemployment.

We follow Pissarides (2000) and assume that the cost of searching is an increasing and convex function of the level of search effort s_i for an individual unemployed worker i. In particular, the search cost function is given by

$$h_{it} = h(s_{it}), \quad h'(s_{it}) > 0, h''(s_{it}) \geq 0, \tag{14}$$

where h_{it} is the search cost in consumption units and applies only for unemployed members of the household.

Raising search intensity, while costly, may increase the job finding rate. For each efficiency unit of searching workers supplied, there will be $m/(su)$ new matches formed. For a worker who supplies s_{it} units of search effort, the probability of finding a job is

$$q^u(s_{it}) = \frac{s_{it}}{s_t u_t} m_t, \tag{15}$$

where s (without the subscript i) denotes the average search intensity. The household takes the economy-wide variables s, u, and m as given when choosing the level of search intensity s_i. A marginal effect of raising search intensity on the job finding rate is given by

$$\frac{\partial q^u(s)}{\partial s_i} = \frac{m_t}{s_t u_t} = \frac{q_t^u}{s_t}, \tag{16}$$

which depends only on aggregate economic conditions.

As we show in the Appendix A, the household's optimal search intensity decision (in a symmetric equilibrium) is given by

$$h'(s_t) = \frac{q_t^u}{s_t} S_t^H, \tag{17}$$

where S_t^H is the household's surplus of employment (relative to unemployment). Thus, at the optimal level of search intensity, the marginal cost of searching equals the marginal benefit, which is the increased odds of finding a job multiplied by the surplus value of employment.

The employment surplus S_t^H itself, as we show in the same appendix, is given by the Bellman equation

$$S_t^H = w_t - \phi - \frac{\chi_t}{\Lambda_t} + \mathrm{E}_t \frac{\beta \Lambda_{t+1}}{\Lambda_t}(1-\delta)(1-q_{t+1}^u) S_{t+1}^H, \tag{18}$$

where $\Lambda_t = \frac{1}{C_t}$ denotes the marginal utility of consumption.

The employment surplus has a straightforward economic interpretation. If the household adds a new worker in period t, then the current-period gain would be wage income net of the opportunity costs of working, including unemployment compensations and the disutility of working. The household also enjoys the continuation value of employment if the employment relation continues. Having an extra worker today adds to the employment pool tomorrow (if the employment relation survives job separation); however, adding a worker today would also reduce the pool of searching workers tomorrow, a fraction q_{t+1}^u of whom would be able to find jobs. Thus, the marginal effect of adding a new worker in period t on employment in period $t+1$ is given by $(1-\delta)(1-q_{t+1}^u)$, resulting in the effective continuation value of employment shown in equation (18).

We also show in the appendix that the household's optimizing consumption/saving decision implies the intertemporal Euler equation

$$1 = \mathrm{E}_t \beta \frac{\Lambda_{t+1}}{\Lambda_t} r_t. \tag{19}$$

II.3. **The firms.** A firm can produce the final consumption goods only if it successfully matches with a worker. The production function for firm j with one worker is given by

$$y_{jt} = Z_t,$$

where y_{jt} is output and Z_t is an aggregate technology shock.[4] The technology shock follows the stochastic process

$$\ln Z_t = (1-\rho_z) \ln \bar{Z} + \rho_z \ln Z_{t-1} + \varepsilon_{zt}. \tag{20}$$

The parameter $\rho_z \in (-1, 1)$ measures the persistence of the technology shock. The term ε_{zt} is an i.i.d. normal process with a zero mean and a finite variance of σ_z^2. The term $\bar{Z}$ is the steady-state level of the technology shock.

If a firm j finds a match, it obtains a flow profit in the current period after paying the worker. In the next period, if the match survives (with probability $1-\delta$), the firm continues; if the match breaks down, the firm posts a new job vacancy at a flow cost of κ_{jt}, with the value $J_{j,t+1}^V$. The value of a firm with a match is therefore given by the Bellman equation

$$J_{jt}^F = Z_t - w_t + E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} \left\{ (1-\delta) J_{j,t+1}^F + \delta J_{j,t+1}^V \right\}. \tag{21}$$

[4]The model can be easily extended to allow for trend growth. We do not present that version of the model to simplify presentation.

Here, the value function is discounted by the representative household's marginal utility because all firms are owned by the household.

Following Coles and Kelishomi (2011), we assume that vacancy creation incurs an entry cost of x drawn from an i.i.d. distribution $F(\cdot)$. A new vacancy is created if and only if $x \leq J_t^V$, or equivalently, if and only if its net value is non-negative. Thus, the number of new vacancies n_t equal to $F(J_t^V)$–the cumulative density of entry costs at the value of vacancy. With appropriate assumptions about the functional form of the distribution function $F(\cdot)$, the number of new vacancies created is related to the value of vacancies through the equation

$$n_t = \eta (J_t^V)^{\xi}, \tag{22}$$

where η is a scale parameter and ξ measures the elasticity of new vacancies with respect to the value of the vacancy. The special case with $\xi = \infty$ corresponds to the standard DMP model with free entry. In general, a smaller value of ξ would imply a less elastic response of new vacancies to changes in aggregate conditions (through changes in the value of vacancies). In the baseline model, we assume that entry costs are uniformly distributed, so that $\xi = 1$, which is the case studied by Fujita and Ramey (2007).

The flow cost of positing a vacancy is an increasing and convex function of the level of advertising. In particular, we follow Pissarides (2000) and assume that

$$\kappa_{jt} = \kappa(a_{jt}), \quad \kappa'(\cdot) > 0, \quad \kappa''(\cdot) \geq 0, \tag{23}$$

where a_{jt} is firm j's level of advertising.

Advertising efforts also affect the probability of filling a vacancy. For each efficiency unit of vacancy supplied, there will be m/av new matches formed. Thus, for a firm that supplies a_{jt} units of advertising efforts, the probability of filling a vacancy is

$$q^v(a_{jt}) = \frac{a_{jt}}{a_t v_t} m_t, \tag{24}$$

where a_t is the average advertising efforts by firms.

If the vacancy is filled (with probability q_{jt}^v), the firm obtains the value of a match J_{jt}^F. If the vacancy remains unfilled, then the firm goes into the next period and obtains the continuation value of the vacancy. Thus, the value of an open vacancy is given by

$$J_{jt}^V = -\kappa(a_{jt}) + q^v(a_{jt}) J_{jt}^F + (1 - q^v(a_{jt})) E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} J_{j,t+1}^V. \tag{25}$$

The firm chooses advertising efforts a_{jt} to maximize the value of vacancy J_{jt}^V. The optimal level of advertising is given by the first order condition

$$\kappa'(a_{jt}) = \frac{\partial q^v(a_{jt})}{\partial a_{jt}} \left[J_{jt}^F - (1 - \rho^o) E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} J_{j,t+1}^V \right], \tag{26}$$

where, from (24), we have

$$\frac{\partial q^v(a_{jt})}{\partial a_{jt}} = \frac{m_t}{a_t v_t} = \frac{q_t^v}{a_t}. \tag{27}$$

We concentrate on a symmetric equilibrium in which all firms make identical choices of the level of advertising. Thus, in equilibrium, we have $a_{jt} = a_t$. In such a symmetric equilibrium, the optimizing advertising decision (26) can be written as

$$\kappa'(a_t) = \frac{q_t^v}{a_t}\left[J_t^F - E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} J_{t+1}^V\right]. \tag{28}$$

If the firm raises advertising effort, it incurs a marginal cost of $\kappa'(a_t)$. The marginal benefit of raising advertising efforts is that, by increasing the probability of forming a job match, the firm obtains the match value J_t^F, although it loses the continuation value of the vacancy, which represents the opportunity cost of filling the vacancy.

In the special case with free entry, the value of vacancy would be driven down to zero. Thus, equation (25) reduces to

$$\kappa(a_t) = q_t^v J_t^F. \tag{29}$$

Furthermore, the optimal advertising choice (28) reduces to

$$\kappa'(a_t) = \frac{q_t^v}{a_t} J_t^F. \tag{30}$$

These two equations together implies that

$$\frac{\kappa'(a_t) a_t}{\kappa(a_t)} = 1. \tag{31}$$

In this case, the level of advertising is chosen such that the elasticity of the cost of advertising equals 1 and it thus is invariant to macroeconomic conditions, as in the textbook model of Pissarides (2000).

This special case highlights the importance of the incorporating costs of vacancy creation. Absent any vacancy creation cost, as in the textbook models, firms can freely adjust vacancies to respond to changes in macroeconomic conditions and choose the level of advertising to minimize the cost of each vacancy. In this case, the optimal level of advertising is independent of market variables. In contrast, if vacancy creation is costly, as we assume in our model, firms would rely on adjusting both the level of advertising and the number of vacancies to respond to changes in macroeconomic conditions.

II.4. **The Nash bargaining wage.** Firms and workers bargain over wages. The Nash bargaining problem is given by

$$\max_{w_t} \quad \left(S_t^H\right)^b \left(J_t^F - J_t^V\right)^{1-b}, \tag{32}$$

where $b \in (0,1)$ represents the bargaining weight for workers. The first-order condition implies that

$$b\left(J_t^F - J_t^V\right)\frac{\partial S_t^H}{\partial w_t} + (1-b)S_t^H \frac{\partial\left(J_t^F - J_t^V\right)}{\partial w_t} = 0, \quad (33)$$

where, from the household surplus equation (18), we have $\frac{\partial S_t^H}{\partial w_t} = 1$; and from the firm's value function (21), we have $\frac{\partial\left(J_t^F - J_t^V\right)}{\partial w_t} = -1$.

Define the total surplus as

$$S_t = J_t^F - J_t^V + S_t^H. \quad (34)$$

The the bargaining solution is given by

$$J_t^F - J_t^V = (1-b)S_t, \quad S_t^H = bS_t. \quad (35)$$

The bargaining outcome implies that firm surplus is a constant fraction $1-b$ of the total surplus S_t and the household surplus is a fraction b of the total surplus.

The bargaining solution (35) and the expression for household surplus in equation (18) together imply that the Nash bargaining wage w_t^N satisfies the Bellman equation

$$\frac{b}{1-b}(J_t^F - J_t^V) = w_t^N - \phi - \frac{A_t \chi_t}{\Lambda_t} + E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t}\left[(1-\delta)\left(1-q_{t+1}^u\right)\frac{b}{1-b}(J_{t+1}^F - J_{t+1}^V)\right]. \quad (36)$$

II.5. **Wage Rigidity.** In general, however, equilibrium real wage may be different from the Nash bargaining solution. Indeed, Hall (2005) and Shimer (2005) point out that real wage rigidity is important to generate empirically plausible volatilities of vacancies and unemployment. We follow the literature and consider real wage rigidity. We assume that the real wage is a geometrically weighted average of the Nash bargaining wage and the realized wage rate in the previous period. That is,

$$w_t = w_{t-1}^{\gamma}(w_t^N)^{1-\gamma}, \quad (37)$$

where $\gamma \in (0,1)$ represents the degree of real wage rigidity.[5]

II.6. **Government policy.** The government finances unemployment benefit payments ϕ for unemployed workers through lump-sum taxes. We assume that the government balances the budget in each period so that

$$\phi_t(1-N_t) = T_t. \quad (38)$$

[5]We have examined other wage rules as those in Blanchard and Galí (2010) and we find that our results do not depend on the particular form of the wage rule.

II.7. **Search equilibrium.** In a search equilibrium, the markets for bonds and goods all clear.

Since the aggregate supply of bond is zero, the bond market-clearing condition implies that

$$B_t = 0. \tag{39}$$

Aggregate output Y_t is related to employment through the aggregate production function

$$Y_t = Z_t N_t. \tag{40}$$

Goods market clearing requires that real spendings on consumption, search efforts, recruiting efforts, and vacancy creation equal to aggregate output. This requirement yields that the aggregate resource constraint

$$C_t + h(s_t)u_t + \kappa(a_t)v_t + n_t J_t^V = Y_t, \tag{41}$$

where the last term on the left-had side of the equation corresponds to the aggregate cost of creating n_t job vacancies, with the cost of each equal to the value of a vacancy J_t^V.

III. Empirical strategies

We solve the DSGE model by log-linearzing the equilibrium conditions around the deterministic steady state. Appendix B summarizes the equilibrium conditions, the steady state, and the log-linearized system. We calibrate a subset of the parameters to match steady-state observations and estimate the remaining structural parameters and shock processes to fit the U.S. time series data.

We begin with parameterizing the vacancy cost function $\kappa(a)$ and search cost function $h(s)$. We assume that

$$\kappa(a_t) = \kappa_0 + \kappa_1(a_t - \bar{a}) + \frac{\kappa_2}{2}(a_t - \bar{a})^2, \tag{42}$$

$$h(s_t) = h_1(s_t - \bar{s}) + \frac{h_2}{2}(s_t - \bar{s})^2, \tag{43}$$

where we normalize the steady-state levels of recruiting intensity and search intensity so that $\bar{a} = 1$ and $\bar{s} = 1$. We also assume that the search cost is zero in the steady state.

The structural parameters to be calibrated in our model include β, the subjective discount factor; χ, the average dis-utility of working; α, the elasticity of matching with respect to searching workers; μ, the average matching efficiency; δ, the job separation rate; ϕ, the flow unemployment benefits; b, the Nash bargaining weight; κ_0 and κ_1, the intercept and the slope of the vacancy cost function; h_1, the slope parameter of the search cost function; γ, the parameter that measures real wage rigidities; ξ, the elasticity parameter in the vacancy-creation condition (22).

The scale parameter $K \equiv \frac{1}{\eta}$ of the vacancy creation cost, the curvature parameter κ_2 of the vacancy-posting cost function, and the curvature parameter h_2 of the search cost function cannot be identified through steady-state restrictions. We estimate these structural parameters along with the parameters in the shock processes ρ_k and σ_k, for $k \in \{z, \chi\}$ using Bayesian methods to fit the time-series data of the unemployment rate and the vacancy rate.

III.1. **Calibration.** The calibrated values of the model parameters are summarized in Table 1.

We consider a monthly model. Thus, we set $\beta = 0.9967$, so that the model implies a steady-state annualized real interest rate of about 4 percent. We set $\alpha = 0.5$ following the literature (Blanchard and Galí, 2010; Gertler and Trigari, 2009). We set the steady-state job separation rate to $\delta = 0.034$ per month, consistent with the Job Openings and Labor Turnover Survey (JOLTS) for the period from December 2000 to April 2015. We also set the monthly vacancy obsolescence rate to $\rho^o = 0.0317$. FollowingHall and Milgrom (2008), we set $\phi = 0.25$ so that the unemployment benefit is about 25 percent of normal earnings. We set $b = 0.5$ following the literature. In our baseline experiment, we focus on the case with $\xi = 1$, as in Fujita and Ramey (2007) and Coles and Kelishomi (2011).

We set a value for the steady-state level of vacancy cost κ_0 so that the total cost of posting vacancies is about 1 percent of gross output. To assign a value of κ_0 then requires knowledge of the steady-state number of vacancies v and the steady-state level of output Y. We calibrate the value of v such that the steady-state vacancy filling rate $q^v = 0.338$ per month, which matches the quarterly job filling rate of 0.71 calibrated by den Haan et al. (2000).[6]

We also calibrate the steady-state unemployment rate to be $U = 0.055$. Given the job separation rate of $\delta = 0.034$, we obtain the steady-state hiring rate of $m = \delta(1-U) = 0.0321$. Thus, we have $v = \frac{m}{q^v} = 0.0951$. To obtain a value for Y, we use the aggregate production function that $Y = ZN$ and normalize the level of technology such that $Z = 1$. This procedure yields a calibrated value of $\kappa_0 = 0.0994$. We set $\kappa_1 = 0.10$ so that the steady-state recruiting intensity is $\bar{a} = 1$. We set $h_1 = 0.1089$ so that the steady-state search intensity is $\bar{s} = 1$.

Given the steady-state values of m, u, and v, we use the matching function to obtain an average matching efficiency of $\mu = 0.353$. To obtain a value for $\bar{\chi}$, we solve the steady-state system so that $\bar{\chi}$ is consistent with an unemployment rate of 5.5 percent. The process results in $\bar{\chi} = 0.666$. Finally, we set the real wage rigidity parameter to $\gamma = 0.8$.

[6] Given our monthly job filling rate of $q^v = 0.338$, the quarterly filling rate is given by $q^v + (1 - q^v)q^v + (1 - q^v)^2 q^v = 0.71$, which is the same value as in den Haan et al. (2000).

III.2. **Estimation.** The structural parameters to be estimated include K, the scale of the vacancy-creation cost function; κ_2, the curvature parameter of the vacancy-posting cost function; h_2, the curvature parameter of the search cost function. In addition, we need to estimate the parameters in the two shock processes. These shock parameters include ρ_z and σ_z, the persistence and the standard deviation of the technology shock; and ρ_χ and σ_χ, the persistence and the standard deviation of the disutility shock.

III.2.1. *Data and measurement.* We use Bayesian methods to estimate these parameters. We fit the model to 2 monthly time-series data in the United States: the unemployment rate and the job vacancy rate. The sample covers the period from December 2000 to March 2015, which is the available range of data from JOLTS.

The unemployment rate in the data (denoted by U_t^{data}) corresponds to the end-of-period unemployment rate in the model U_t. We demean the unemployment rate data (in log units) and relate it to our model variable according to

$$\ln(U_t^{data}) - \ln(U^{data}) = \hat{U}_t, \tag{44}$$

where U_t^{data} denotes the unemployment rate data and $\hat{U}_t$ denotes the log-deviations of the unemployment rate in the model from its steady-state value.

Similarly, we relate the demeaned vacancy rate data (also in log units) and relate it to the model variable according to the relation

$$\ln(v_t^{data}) - \ln(v^{data}) = \hat{v}_t, \tag{45}$$

where v^{data} denotes the vacancy rate data and $\hat{v}_t$ denotes the log-deviations of the vacancy rate in the model from its steady-state value.

III.2.2. *Prior distributions and posterior estimates.* The prior and posterior distributions of the estimated parameters are displayed in Table 2.

The priors of the structural parameters K, κ_2, and h_2 each follows the gamma distribution. We assume that the prior mean of K is 10 with a standard deviation of 5. The mean value of K is close to the calibrated value in Coles and Kelishomi (2011). The prior distribution of κ_2 and h_2 each has a mean of 0.5 and a standard deviation of 0.1.

For the shock parameters, we follow the literature and assume that the priors of ρ_z and ρ_χ each follows the beta distribution and the priors of σ_z and σ_χ each follows an inverse gamma distribution.

The posterior estimates and the 90% confidence interval for the posterior distributions are displayed in the last 3 columns of Table 2. The scale of the vacancy-creation cost function has a posterior mean of 25.50, with a 90% confidence interval from 17.93 to 32.94. The posterior mean is remarkably close to that calibrated by Fujita and Ramey (2007). The curvature parameter κ_2 of the vacancy-posting cost function has a posterior mean of 0.68 and a 90% confidence interval from 0.51 to 0.85. The curvature parameter h_2 of the search cost function has a posterior mean of 1.05 and a 90% confidence interval from 0.88 to 1.23. The posterior estimates are significantly different from the priors. Thus, the data seem to be quite informative about these structural parameters.

The posterior estimates also show that both shocks are highly persistent and volatile. Shocks to the disutility of working is more persistent and more volatile than technology shocks. This is not surprising in light of the Shimer puzzle: models driven by technology shocks have difficulties to account for the observed fluctuations in unemployment and vacancies. Although our model with search and recruiting intensity contains an additional amplification mechanism, it still relies on preference shocks that directly affect the reservation value of workers to fit the time series behaviour of the labor market variables.

IV. Economic implications

We now discuss the mechanism through which recruiting intensity and search intensity help amplify the impact of shocks on labor market dynamics. We do this with the help of impulse responses. We estimate our model with two shocks, a technology shock and a preference shock. For clarify of discussion, we focus here on the effects of a negative technology shock. We present the impulse responses to a preference shock that increases the disutility of working in the appendix (see Appendix E).

Figure 2 shows the impulse responses of several key labor market variables to a one-standard deviation drop in TFP. The decline in TFP reduces the value of new job matches. Firms respond by reducing hiring and vacancy posting. These responses lead to a drop in workers' job finding rate and an increase in the unemployment rate. The job filling rate initially declines because hiring drops more than does the number of vacancies. Over time, however, the job filling rate rises above the steady-state level as hiring recovers while the number of vacancies remain persistently low. The persistence of vacancy dynamics stems from entry costs. Unlike the standard model with free entry, our model with costly vacancy creation implies that the value of an unfilled vacancy is positive. Thus, the number of vacancies becomes a state variable that evolves slowly over time according to the law of motion in Equation (5). This gives rise to persistent dynamics in vacancies, as shown in Figure 2. The decline in vacancies is also attributable to declines in entry (or new vacancy creation). Since the value of a new job match is now lower and the hiring rate also falls, the value of creating a new vacancy becomes lower.

The figure also shows that a contractionary technology shock reduces both search intensity and recruiting intensity. The household's optimizing decisions for search intensity (Eq. (17))

reveals that search intensity increases with the job finding rate and the employment value, which is proportional to the match surplus from Nash bargaining. Since a decline in TFP reduces both the job finding rate and the match surplus, it reduces search intensity as well.

Recruiting intensity falls following the negative technology shock, partly because the job filling rate declines in the short run and the expected value of a job match also declines. This can be seen from firms' optimizing decision for recruiting intensity in Equation (28), which shows that recruiting intensity increases with both the job filling rate (q^v) and the value of a new job match (J^F) relative to the value of an unfilled vacancy (J^V). Since the technology shock reduces both J^F and J^V, the net effect on recruiting intensity (a) can be ambiguous. However, the shock unambiguously reduces the job filling rate q^v, which discourages firms from exerting recruiting efforts. With our estimated parameters, a contractionary technology shock on net reduces recruiting intensity.

Finally, declines in search and recruiting intensity imply an outward shift of the Beveridge curve, because the measured match efficiency falls, as shown in the last panel of Figure 2. The measured match efficiency here is defined as

$$\Omega_t = \mu s_t^{\alpha} a_t^{1-\alpha}. \tag{46}$$

Thus, even if there is no exogenous changes in true match efficiency (i.e., if μ is constant), measured match efficiency (Ω) still fluctuates with endogenous variations in search and recruiting intensity.

To understand the importance of cyclical variations in search and recruiting intensity, we compare the impulse responses to a technology shock in the benchmark model with two alternative counterfactual scenarios, one with a constant search intensity (but variable recruiting intensity), and the other with a constant recruiting intensity (and a variable search intensity). These impulse responses are displayed in Figure 3.

Compared to the benchmark case (the solid lines), when search intensity is held constant (the dotted lines) or recruiting intensity is held constant (the dashed lines), there is a smaller decline in measured match efficiency and thus a small drop in hiring. All else equal, a smaller decline in hiring implies a smaller reduction in the job filling rate and the job finding rate. Of course, the fill rate and finding rate both depend on the responses of unemployment and vacancies. When search intensity or recruiting intensity is held constant, the more muted response of hiring dampens the increase in unemployment. The smaller increase in unemployment, combined with the muted decline in hiring, lead to a smaller decline in the job finding rate. However, since entry declines more in each counterfactual case with search or recruiting intensity held constant, the response of the stock of vacancies is amplified relative to the benchmark case.

Overall, Figure 3 shows that allowing search and recruiting intensity to endogenously respond to changes in macroeconomic conditions helps amplify the responses of the job filling rate and the job finding rate following a technology shock.

IV.1. **The Great Recession and the slow job recovery.** The impulse responses show that search and recruiting intensity in our model helps amplify the effects of shocks on labor market variables. We now illustrates the ability of the model to explain the slow job recovery after the Great Recession.

As shown in Figure 1, the job filling rate declined sharply and the job finding rate rose slowly after the Great Recession. The standard model without search and recruiting intensity has difficulties for generating these observations. In particular, the standard model predicts incorrectly that the job filling rate should remain elevated for most of the period after the Great Recession and that the job opening rate should rise quickly. Incorporating search and recruiting intensity in the model helps bring the fill rate and finding rate much closer to those observed in the data.

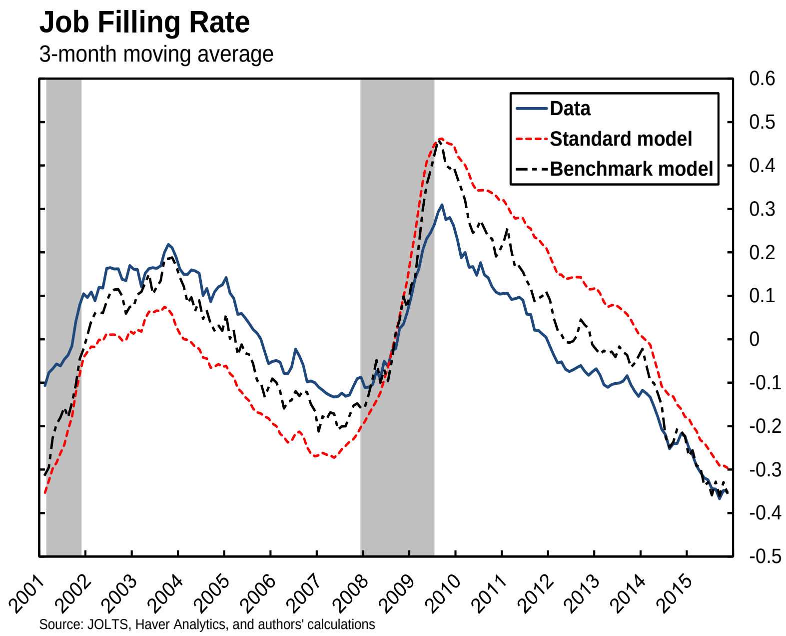
V. Conclusion

Table 1. Calibrated parameters

	Parameter Description	value
β	Subjective discount factor	0.9967
ϕ	Unemployment benefit	0.25
α	Elasticity of matching function	0.50
μ	Matching efficiency	0.353
δ	Job separation rate	0.034
ρ^o	Vacancy obsolescence rate	0.0317
κ_0	Steady-state advertising cost	0.0994
κ_1	Slope of vacancy posting cost	0.10
h_1	Slope of search cost	0.1089
b	Nash bargaining weight	0.50
γ	Real wage rigidity	0.80
ξ	Elasticity of vacancy creation	1
$\bar{\chi}$	Mean value of preference shock	0.666
$\bar{Z}$	Mean value of technology shock	1

TABLE 2. Estimated parameters

	Parameter description	Prior type[mean, std]	Posterior		
			Mean	5%	95%
K	scale of vacancy creation	gamma[10, 5]	25.4965	17.9265	32.9391
κ_2	curvature of vacancy posting	gamma[0.5, 0.1]	0.6838	0.5099	0.8488
h_2	curvature of search cost	gamma[0.5, 0.1]	1.0528	0.8765	1.2328
ρ_z	AR(1) of technology shock	beta[0.3333, 0.2357]	0.9344	0.9126	0.9556
ρ_χ	AR(1) of preference shock	beta[0.3333, 0.2357]	0.9949	0.9902	0.9995
σ_z	std of technology shock	inv gamma[0.01, 1]	0.0511	0.0433	0.0585
σ_χ	std of preference shock	inv gamma[0.01, 1]	0.1751	0.1522	0.1974



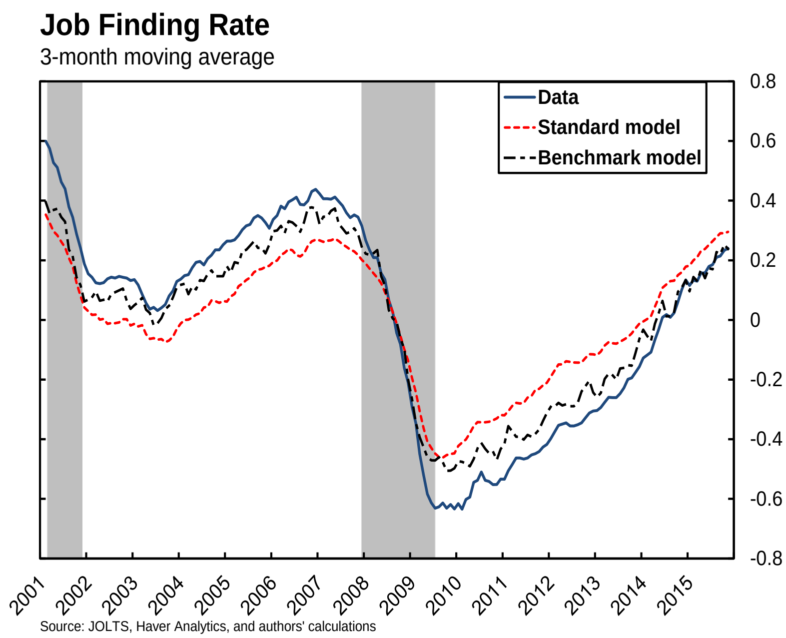


FIGURE 1. Job filling rate and job finding rate: Data versus alternative models

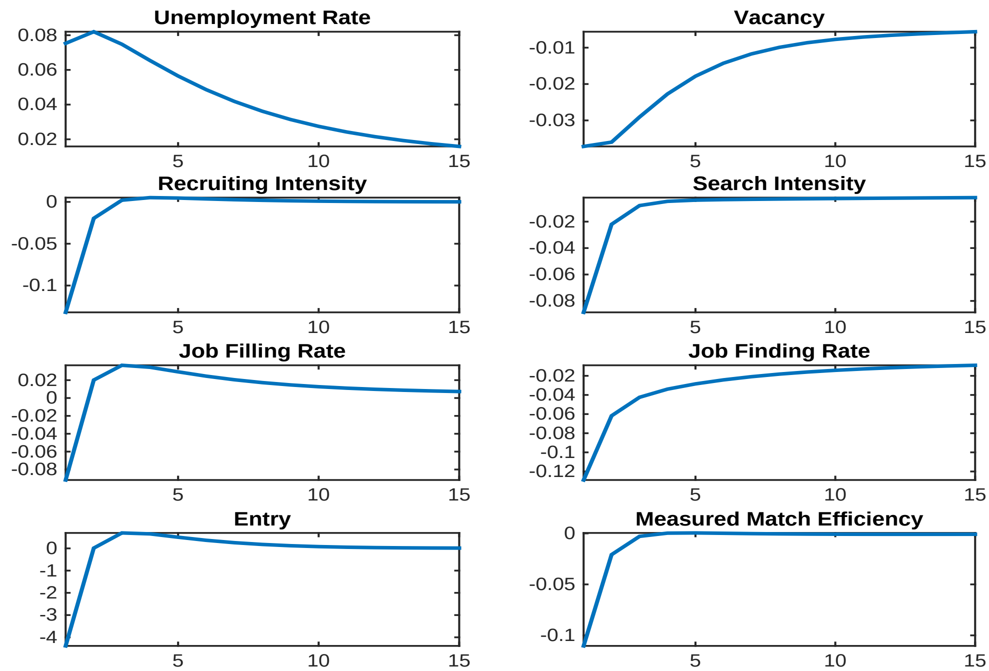


FIGURE 2. Impulse responses to a negative technology shock: Benchmark model

FIGURE 3. Impulse responses to a negative technology shock: Alternative models

Appendix A. Derivations of household's optimizing conditions

Our approach to incorporating search intensity in the DSGE model builds on the textbook treatment by Pissarides (2000). The basic idea is that the representative household can choose the effort level that is devoted to searching for those members who are unemployed. Increasing search effort incurs some resource costs, but it also creates the benefits of increasing the individual searching worker's job finding rate.

We now derive the optimal search intensity decision from the first principle. To economize notations, we do not carry around the individual index i in describing the household's optimizing problem. Keep in mind that, in choosing the individual search intensity and employment, the household takes the economy-wide variables as given. In a symmetric equilibrium, the individual optimal choices coincide with the aggregate optimal choices.

The household's optimizing problem is given by

$$\max \quad \mathrm{E}\sum_{t=0}^{\infty} \beta^t A_t \left[\log C_t - \chi_t N_t\right]$$

subject to

$$C_t + \frac{B_t}{r_t} = B_{t-1} + w_t N_t + \phi u_t (1 - q^u(s_t)) - u_t h(s_t) + d_t - T_t, \quad \forall t \geq 0, \tag{A1}$$

$$N_t = (1-\delta)N_{t-1} + q^u(s_t)u_t, \tag{A2}$$

where the beginning-of-period fraction of searching workers is given by

$$u_t = 1 - (1-\delta)N_{t-1}. \tag{A3}$$

The household chooses C_t, B_t, N_t, and s_t, taking prices and the average job finding rate as given.

Note that equation (A2) implies that

$$\frac{\partial N_t}{\partial N_{t-1}} = (1-\delta)(1 - q^u(s_t)). \tag{A4}$$

Thus, having an additional worker carried over from the previous period increases the number of workers in the current period, but it also reduces the number of searching workers, each of whom has a probability of $q^u(s_t)$ of finding a new job. Thus, after exogenous job separation (due to vacancy obsolescence and normal separation), the net marginal effect of having an additional worker from $t-1$ on current-period employment is given by the right-hand side of equation (A4). Further, we have

$$\frac{\partial N_t}{\partial s_t} = \frac{\partial q^u(s_t)}{\partial s_t}\left[1 - (1-\delta)N_{t-1}\right]. \tag{A5}$$

To derive the optimizing decisions for the household, we rewrite the household's problem in the recursive form

$$V_t(B_{t-1}, N_{t-1}) \equiv \max\ A_t\left[\ln C_t - \chi_t N_t\right] + \beta \mathrm{E}_t V_{t+1}(B_t, N_t), \tag{A6}$$

subject to equation (A1). Here, we have substituted out u_t using equation (A3) and we will use the relation of N_t with N_{t-1} and with s_t shown in equations (A4) and (A5) to derive the Euler equations.

Denote by Λ_t the Lagrangian multiplier for the budget constraint (A1). The first-order condition with respect to consumption implies that

$$\Lambda_t = \frac{A_t}{C_t}. \tag{A7}$$

Optimal choice of search intensity s_t implies that

$$\Lambda_t h'(s_t) = \frac{q_t^u}{s_t}\left[\Lambda_t(w_t - \phi) - A_t\chi_t + \beta \mathrm{E}_t \frac{\partial V_{t+1}(B_t, N_t)}{\partial N_t}\right], \tag{A8}$$

where we have used equation (16) to replace the term $\frac{\partial q^u(s_t)}{\partial s_t}$ by $\frac{q_t^u}{s_t}$. The envelope condition implies that

$$\begin{aligned}\frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_{t-1}} &= \left[\Lambda_t(w_t - \phi) - A_t\chi_t\right]\frac{\partial N_t}{\partial N_{t-1}} + \beta \mathrm{E}_t \frac{\partial V_{t+1}(B_t, N_t)}{\partial N_t}\frac{\partial N_t}{\partial N_{t-1}} \\ &= (1-\delta)(1-q^u(s_t))\left\{\Lambda_t(w_t - \phi) - A_t\chi_t + \beta \mathrm{E}_t \frac{\partial V_{t+1}(B_t, N_t)}{\partial N_t}\right\}. \end{aligned} \tag{A9}$$

Define the employment surplus (i.e., the value of employment relative to unemployment) as

$$S_t^H = \frac{1}{\Lambda_t}\frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_t} = \frac{1}{\Lambda_t}\frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_{t-1}}\frac{\partial N_{t-1}}{\partial N_t} = \frac{1}{\Lambda_t}\frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_{t-1}}\frac{1}{(1-\delta)(1-q^u(s_t))}. \tag{A10}$$

Thus, S_t^H is the value for the household to send an additional worker to work in period t. Then the envelope condition (A9) implies that

$$S_t^H = w_t - \phi - \frac{A_t\chi_t}{\Lambda_t} + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\delta)(1-q_{t+1}^u)S_{t+1}^H. \tag{A11}$$

The employment surplus S_t^H derived here corresponds to equation (18) in the text and it is the relevant surplus for the household in the Nash bargaining problem.

We then use the envelope condition (A9) to rewrite the optimal search intensity decision (A8) in terms of employment surplus:

$$h'(s_t) = \frac{q_t^u}{s_t}\left[w_t - \phi - \frac{A_t\chi_t}{\Lambda_t} + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\delta)(1-q_{t+1}^u)S_{t+1}^H\right] = \frac{q_t^u}{s_t}S_t^H. \tag{A12}$$

Thus, at the optimum, the marginal cost of search intensity equals the marginal benefit, where the benefit derives from the increased job finding rate and the net value of employment. This last equation corresponds to equation (17) in the text.

Finally, optimal choice of B_t that solves the household's utility maximizing problem leads to

$$\frac{\Lambda_t}{r_t} = \beta \mathrm{E}_t \frac{\partial V_{t+1}(B_t, N_t)}{\partial B_t}. \tag{A13}$$

The envelope condition with respect to B_{t-1} implies that

$$\frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial B_{t-1}} = \Lambda_t. \tag{A14}$$

Combining equations (A13) and (A14), we obtain

$$1 = \mathrm{E}_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} r_t, \tag{A15}$$

which is the intertemporal Euler equation (19) in the text.

Appendix B. Summary of equilibrium conditions in the DSGE model

A search equilibrium is a system of 17 equations for 17 variables summarized in the vector

$$\left[C_t, \Lambda_t, m_t, q_t^u, q_t^v, N_t, u_t, U_t, Y_t, r_t, v_t, J_t^F, w_t^N, w_t, n_t^e, a_t, s_t\right].$$

We write the equations in the same order as in the dynare code.

(1) Household's bond Euler equation:

$$1 = \mathrm{E}_t \beta \frac{\Lambda_{t+1}}{\Lambda_t} r_t, \tag{B1}$$

(2) Marginal utility of consumption

$$\Lambda_t = \frac{1}{C_t}, \tag{B2}$$

(3) Search intensity

$$h_1 + h_2(s_t - \bar{s}) = \frac{q_t^u}{s_t} \frac{b}{1-b} (J_t^F - J_t^V), \tag{B3}$$

(4) Matching function

$$m_t = \mu_t (s_t u_t)^{\alpha} (a_t v_t)^{1-\alpha}, \tag{B4}$$

(5) Job finding rate

$$q_t^u = \frac{m_t}{u_t}, \tag{B5}$$

(6) Vacancy filling rate

$$q_t^v = \frac{m_t}{v_t}, \tag{B6}$$

(7) Employment dynamics:

$$N_t = (1-\delta_t)N_{t-1} + m_t, \tag{B7}$$

(8) Number of searching workers:

$$u_t = 1 - (1-\delta_t)N_{t-1}, \tag{B8}$$

(9) Unemployment:

$$U_t = 1 - N_t, \tag{B9}$$

(10) Law of motion for vacancies:

$$v_t = (1-\rho^o)v_{t-1} + (\delta_t - \rho^o)N_{t-1} + n_t, \tag{B10}$$

(11) Aggregate production function:

$$Y_t = Z_t N_t \tag{B11}$$

(12) Aggregate Resource constraint:

$$C_t + h(s_t)u_t + \kappa(a_t)v_t + Kn_t^{1+\xi} = Y_t, \tag{B12}$$

where the search cost function and the recruiting cost function are given by

$$\begin{aligned} h(s_t) &= h_1(s_t - \bar{s}) + \frac{h_2}{2}(s_t - \bar{s})^2 \\ \kappa(a_t) &= \kappa_0 + \kappa_1(a_t - \bar{a}) + \frac{\kappa_2}{2}(a_t - \bar{a})^2 \end{aligned}$$

(13) Value of vacancy:

$$Kn_t^{\xi} = -\kappa(a_t) + q_t^v J_t^F + (1-q_t^v)(1-\rho^o)E_t \frac{\beta\Lambda_{t+1}}{\Lambda_t} Kn_{t+1}^{\xi}, \tag{B13}$$

(14) Recruiting intensity:

$$\kappa_1 + \kappa_2(a_t - \bar{a}) = \frac{q_t^v}{a_t}\left[J_t^F - (1-\rho^o)E_t \frac{\beta\Lambda_{t+1}}{\Lambda_t} Kn_{t+1}^{\xi}\right]. \tag{B14}$$

(15) Match value:

$$J_t^F = Z_t - w_t + E_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}\left\{(1-\delta_{t+1})J_{t+1}^F + \delta_{t+1}Kn_{t+1}^{\xi}\right\}, \tag{B15}$$

(16) Nash bargaining wage:

$$\frac{b}{1-b}(J_t^F - Kn_t^{\xi}) = w_t^N - \phi - \frac{\chi_t A_t}{\Lambda_t} + E_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}\left[(1-\delta_{t+1})\left(1-q_{t+1}^u\right)\frac{b}{1-b}(J_{t+1}^F - Kn_{t+1}^{\xi})\right]. \tag{B16}$$

(17) Actual real wage (with real wage rigidity)

$$w_t = w_{t-1}^{\gamma}(w_t^N)^{\gamma}, \tag{B17}$$

Appendix C. Steady State

(1) Household's bond Euler equation:

$$1 = \beta r, \tag{C1}$$

(2) Marginal utility of consumption

$$\Lambda = \frac{1}{C}, \tag{C2}$$

(3) Search intensity

$$h_1 = \frac{q^u}{s}\frac{b}{1-b}(J^F - Kn^{\xi}), \tag{C3}$$

(4) Matching function

$$m = \mu(\bar{s}u)^{\alpha}(\bar{a}v)^{1-\alpha}, \tag{C4}$$

(5) Job finding rate

$$q^u = \frac{m}{u}, \tag{C5}$$

(6) Vacancy filling rate

$$q^v = \frac{m}{v}, \tag{C6}$$

(7) Employment dynamics:

$$m = \delta N, \tag{C7}$$

(8) Number of searching workers:

$$u = U + m, \tag{C8}$$

(9) Unemployment:

$$U = 1 - N, \tag{C9}$$

(10) Vacancies:

$$\rho^o v = (1-\rho^o)\rho^s N + n, \tag{C10}$$

(11) Aggregate production function:

$$Y = ZN \tag{C11}$$

(12) Aggregate Resource constraint:

$$C + \kappa_0 v + Kn^{1+\xi} = Y, \tag{C12}$$

(13) Value of vacancies:

$$q^v J^F - \kappa_0 = \left[1 - \beta(1-q^v)(1-\rho^o)\right] Kn^{\xi} \tag{C13}$$

(14) Recruiting intensity:

$$\kappa_1 \bar{a} = q^v \left[J^F - \beta(1-\rho^o)Kn^{\xi}\right], \tag{C14}$$

(15) Match value:

$$[1-\beta(1-\delta)]\,J^F = Z - w + \beta\delta K n^{\xi}, \tag{C15}$$

(16) Nash bargaining wage:

$$w^N = \phi + \frac{\chi}{\Lambda} + \frac{b}{1-b}\left[1-\beta(1-\delta)(1-q^u)\right](J^F - Kn^{\xi}), \tag{C16}$$

(17) Actual real wage

$$w = w^N, \tag{C17}$$

Appendix D. Equilibrium system scaled by steady state (used in dynare)

Denote by $\hat{X}_t \equiv \frac{X_t}{X}$ the scaled value of the variable X_t by its steady-state level. The system of equilibrium conditions can be reduced to the following 17 equations to solve for the 17 endogenous variables summarized in the vector

$$[\hat{C}_t, \hat{\Lambda}_t, \hat{r}_t, \hat{Y}_t, \hat{m}_t, \hat{u}_t, \hat{v}_t, \hat{q}^u_t, \hat{q}^v_t, \hat{N}_t, \hat{U}_t, \hat{J}^F_t, \hat{w}^N_t, \hat{w}_t, \hat{n}_t, \hat{a}_t, \hat{s}_t].$$

(1) Household's bond Euler equation:

$$1 = \mathrm{E}_t \frac{\hat{\Lambda}_{t+1}}{\hat{\Lambda}_t}\hat{r}_t, \tag{D1}$$

(2) Marginal utility of consumption

$$\hat{\Lambda}_t = \frac{1}{\hat{C}_t}, \tag{D2}$$

(3) Search intensity

$$h_1 + h_2\bar{s}(\hat{s}_t - 1) = \frac{q^u \hat{q}^u_t}{\bar{s}s_t}\frac{b}{1-b}(J^F \hat{J}^F_t - Kn^{\xi}\hat{n}^{\xi}_t), \tag{D3}$$

(4) Matching function

$$\hat{m}_t = \exp(\hat{\mu}_t)(\hat{s}_t\hat{u}_t)^{\alpha}(\hat{a}_t\hat{v}_t)^{1-\alpha}, \tag{D4}$$

(5) Job finding rate

$$\hat{q}^u_t = \frac{\hat{m}_t}{\hat{u}_t}, \tag{D5}$$

(6) Vacancy filling rate

$$\hat{q}^v_t = \frac{\hat{m}_t}{\hat{v}_t}, \tag{D6}$$

(7) Employment dynamics:

$$\hat{N}_t = (1-\delta\hat{\delta}_t)\hat{N}_{t-1} + \frac{m}{N}\hat{m}_t, \tag{D7}$$

(8) Number of searching workers

$$u\hat{u}_t = 1 - (1-\delta\hat{\delta}_t)N\hat{N}_{t-1}, \tag{D8}$$

(9) Unemployment:

$$U\hat{U}_t = 1 - N\hat{N}_t, \tag{D9}$$

(10) Vacancies:

$$v\hat{v}_t = (1-\rho^o)v\hat{v}_{t-1} + (\delta\hat{\delta}_t - \rho^o)N\hat{N}_{t-1} + n\hat{n}_t^{\xi}, \tag{D10}$$

(11) Aggregate production function:

$$\hat{Y}_t = \exp(\hat{z}_t)\hat{N}_t \tag{D11}$$

(12) Aggregate Resource constraint:

$$\begin{aligned}\hat{Y}_t &= \left[h_1\bar{s}(\hat{s}_t - 1) + \frac{h_2\bar{s}^2}{2}(\hat{s}_t-1)^2\right]\frac{u}{Y}\hat{u}_t + \left[\kappa_0 + \kappa_1\bar{a}(\hat{a}_t - 1) + \frac{\kappa_2\bar{a}^2}{2}(\hat{a}_t - 1)^2\right]\frac{v}{Y}\hat{v}_t \\ &+ \frac{C}{Y}\hat{C}_t + \frac{Kn^{1+\xi}}{Y}\hat{n}_t^{1+\xi},\end{aligned} \tag{D12}$$

(13) Value of vacancy:

$$\begin{aligned}Kn^{\xi}\hat{n}_t^{\xi} = -\left[\kappa_0 + \kappa_1\bar{a}(\hat{a}_t-1) + \frac{\kappa_2\bar{a}^2}{2}(\hat{a}_t-1)^2\right] + \\ q^v J^F \hat{q}_t^v \hat{J}_t^F + (1-q^v\hat{q}_t^v)(1-\rho^o)\mathrm{E}_t\frac{\beta\hat{\Lambda}_{t+1}}{\hat{\Lambda}_t}Kn^{\xi}\hat{n}_{t+1}^{\xi},\end{aligned} \tag{D13}$$

(14) Recruiting intensity:

$$\kappa_1 + \kappa_2\bar{a}(\hat{a}_t - 1) = \frac{q^v\hat{q}_t^v}{\bar{a}\hat{a}_t}\left[J^F\hat{J}_t^F - (1-\rho^o)\mathrm{E}_t\frac{\beta\hat{\Lambda}_{t+1}}{\hat{\Lambda}_t}Kn^{\xi}\hat{n}_{t+1}^{\xi}\right]. \tag{D14}$$

(15) Match value:

$$J^F\hat{J}_t^F = Z\hat{Z}_t - w\hat{w}_t + \mathrm{E}_t\frac{\beta\hat{\Lambda}_{t+1}}{\hat{\Lambda}_t}\left\{(1-\delta\hat{\delta}_{t+1})J^F\hat{J}_{t+1}^F + \delta\hat{\delta}_{t+1}Kn^{\xi}\hat{n}_{t+1}^{\xi}\right\}, \tag{D15}$$

(16) Nash bargaining wage:

$$\begin{aligned}\frac{b}{1-b}(J^F\hat{J}_t^F - Kn^{\xi}\hat{n}_t^{\xi}) = w\hat{w}_t^N - \phi - \frac{\chi A\exp(\hat{\chi}_t + A_t)}{\Lambda\hat{\Lambda}_t} \\ +E_t\frac{\beta\hat{\Lambda}_{t+1}}{\hat{\Lambda}_t}\left[(1-\delta\hat{\delta}_{t+1})\left(1-q^u\hat{q}_{t+1}^u\right)\frac{b}{1-b}(J^F\hat{J}_{t+1}^F - Kn^{\xi}\hat{n}_{t+1}^{\xi})\right].\end{aligned} \tag{D16}$$

(17) Actual real wage (with real wage rigidity)

$$\hat{w}_t = \hat{w}_{t-1}^{\gamma}(\hat{w}_t^N)^{\gamma}, \tag{D17}$$

(18) Preference shock process

$$\hat{\chi}_t = \rho_{\chi}\hat{\chi}_{t-1} + \varepsilon_{\chi t}, \tag{D18}$$

(19) Technology shock process

$$\hat{z}_t = \rho_z \hat{z}_{t-1} + \varepsilon_{zt}, \tag{D19}$$

Appendix E. Impulse responses to a preference shock

Figures A1 shows the impulse responses of labor market variables following a positive shock to the disutility of working. The shock raises the reservation value of unemployed workers and thus the equilibrium real wage rate. This reduces the value of a new job match. Firms respond by reducing vacancy posting and recruiting intensity. Given the costs of creating new vacancies, the decline in expected value of an open vacancy also reduces entry (the number of new vacancies) and thus the stock of vacancies. The increase in workers' reservation value following the preference shock also reduces workers' search intensity. As both recruiting intensity and search intensity decline, the measured match efficiency also declines. These patterns are similar to the effects of a technology shock. However, since the preference shock is estimated to be highly persistent, its effects on labor market are also highly persistent. Furthermore, the large and persistent increase in the unemployment rate alleviates the fall in hiring. This, combined with the sharp decline in the stock of vacancies, leads to a gradual increase in the job filling rate.

Figure A2 shows the same set of impulse responses to the preference shock in the baseline model (the solid lines), along with those in two different counterfactual cases, one with a constant search intensity (the dotted lines) and the other with a constant recruiting intensity (the dashed lines). Similar to the case with a technology shock, both search and recruiting intensity serve to amplify the effects of preference shocks on the job filling rate, the job finding rate, and the measured match efficiency.

FIGURE A1. Impulse responses to a positive disutility shock: Benchmark model

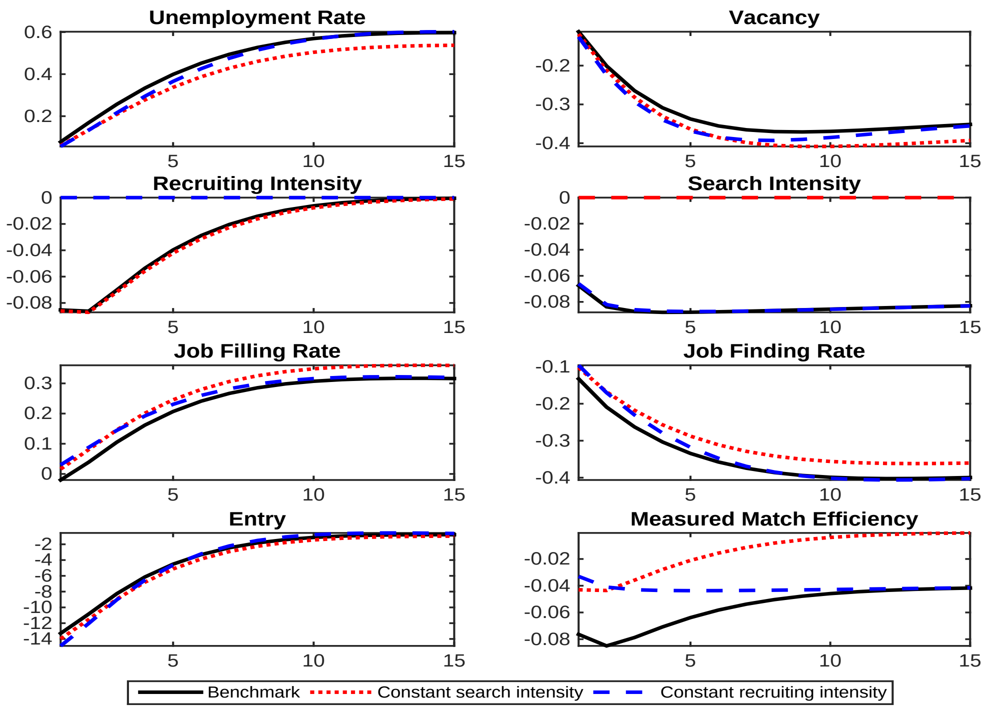


FIGURE A2. Impulse responses to a positive disutility shock: Alternative models

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