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

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Abstract. An estimated model with labor search frictions and endogenous variations in search intensity and recruiting intensity does well in explaining the slow job recovery after the Great Recession. The model features a sunk cost of vacancy creation, under which firms rely on adjusting both the number of vacancies and recruiting intensity to respond to aggregate shocks. This stands in contrast to the textbook model with free entry, which implies constant recruiting intensity. Our estimation suggests that fluctuations in search and recruiting intensity help substantially bridge the gap between the actual and model-predicted job filling and finding rates.

I. Introduction

The U.S. labor market has improved substantially since the Great Recession. The unemployment rate has declined steadily from its peak of about 10 percent in 2009 to less than 5 percent in 2017, accompanied by a steady increase in the job openings rate. However, the hiring rate has been much more subdued in comparison.

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. The matching function implies that the job filling rate—defined as new hires per job vacancy—is inversely related to labor market tightness measured by the vacancy-unemployment

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(v-u) ratio. It also implies that the job finding rate—defined as new job matches per unemployed worker—is positively related to labor market tightness. Thus, when the vacancy rate increases and the unemployment rate falls, as has been the case during the recent recovery, the v-u ratio rises, pushing the job finding rate up and the job filling rate down.

The standard theory fails to predict the slow job recovery. As shown in Figure 1, the theory's predicted job filling rate and job finding rate are both significantly higher than that occurred in recent data. The reason for these discrepancies is that the actual hiring rate has not increased as much as predicted by the theory with the standard matching function.[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 examine the quantitative importance of cyclical fluctuations in search and recruiting intensity for the job filling and finding rates in our estimated general equilibrium model.

We make three contributions to the literature. First, we develop a DSGE model that allows for endogenous variations in recruiting intensity because vacancy creation incurs a sunk cost. In the textbook model with recruiting intensity (Pissarides, 2000), vacancy creation is costless (i.e., there is free entry). When macroeconomic conditions change, firms vary the number of vacancies—which are costless to create or destroy—to meet new hiring needs and choose the level of recruiting intensity to minimize the cost of posting each vacancy. As shown by Pissarides (2000), this behavior implies that recruiting intensity is independent of macroeconomic fluctuations. However, in the more plausible case where vacancy creation incurs a sunk cost, as we assume in our model, firms adjust both the number of vacancies and recruiting intensity in response to aggregate shocks, generating business-cycle variations in recruiting intensity.[2]

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[1]The standard matching function takes the form $m_t = \mu u_t^{\alpha} v_t^{1-\alpha}$, where m_t denotes new job matches, 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 matching efficiency. With this matching function, the job filling rate is given by $q_t^v \equiv \frac{m_t}{v_t} = \mu \left(\frac{v_t}{u_t}\right)^{-\alpha}$ and the job finding rate is given by $q_t^u \equiv \frac{m_t}{u_t} = \mu \left(\frac{v_t}{u_t}\right)^{1-\alpha}$. The job filling and finding rates implied by the standard matching function shown in Figure 1 are calculated by using the observed data on job openings (from JOLTS) and the unemployment rate (from BLS), with $\alpha = 0.5$. By construction, the job filling rate and the job finding rate implied by the standard matching function are perfectly negatively correlated. To highlight the changes of the job filling and finding rates implied by the model relative to those in the data, we transform each series into log units and normalize each series by setting the first observation to zero (so that all subsequent observations are log-deviations from the first observation). Under this normalization, the scale parameter μ in the matching function becomes irrelevant.

[2]We are not the first to introduce fixed costs of vacancy creation. Elsby et al. (2015) examine the effects of recruiting intensity on the Beveridge curve dynamics in a partial equilibrium model with fixed vacancy

In our model, the cyclical properties of recruiting intensity are a priori ambiguous. Optimal recruiting intensity results from a tradeoff between the marginal costs of recruiting efforts and the marginal benefit of raising the probability of filling a job opening, thus obtaining the *net* value of a filled position. Although by filling a position the firm gains the value of an employment match, it also loses the value of an open vacancy, which is non-zero in equilibrium because of costly entry. Because the match value and the vacancy value both decline in a recession, the net value of filling a vacancy is ambiguous. Depending on model parameters, recruiting intensity may be pro- or counter-cyclical.

Our second contribution is to quantitatively examine the importance of cyclical fluctuations in search and recruiting intensity for the job filling and finding rates. We do so by estimating the model using Bayesian methods, fitting three monthly time series data of the U.S. labor market: the unemployment rate, the job vacancy rate, and a measure of search intensity to help discipline the model.

The model estimation shows that recruiting intensity is procyclical and positively correlated with aggregate hiring and it interacts with cyclical variations in search intensity to amplify labor market dynamics. In the aftermath of the Great Recession, our model predicts a slow recovery of the hiring rate driven by a below-trend recovery of search and recruiting intensity. Therefore, our estimated model predicts a slow job recovery, with much lower job filling and job finding rates than those from the standard model without intensive margins, and much more in line with the data, as shown in Figure 1.

Finally, our third contribution is to show that, despite our macro approach, the aggregate correlation between hiring and recruiting intensity obtained from our estimated DSGE model is remarkably close to estimates derived from micro data. In particular, Davis et al. (2013) 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 only on the number of vacancies, but also heavily on other instruments for hiring, which they call recruiting intensity. Under the assumption that their microeconomic estimates hold at the macro level, Davis et al. (2013) document a strong correlation between recruiting intensity and hiring at the aggregate level. Our work complements theirs by directly providing a macro perspective on the relationship between recruiting intensity and hiring.

creation costs. 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 v-u 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.

II. Other related literature

Our paper contributes to the recent theoretical literature on cyclical variations in recruiting intensity. For example, Kaas and Kircher (2015) study a competitive search environment with heterogeneous firms facing a recruiting cost function that is convex in the number of open vacancies. In their model, since the marginal cost of recruiting increases with the number of vacancies, growing firms do not rely solely on vacancy posting to attract workers; they also rely on varying their posted wage offers. Gavazza et al. (2014) assume a recruiting cost function similar to that in Kaas and Kircher (2015) and study the importance of financial shocks for shifting the Beveridge curve through their impact on firms' recruiting intensity. We add to this literature by introducing an alternative departure from the textbook search model. In particular, we relax the free entry condition to allow for business cycle fluctuations in recruiting intensity. The resulting tractability of our framework has the added advantage of making it straightforward to estimate the model to fit time-series data using standard techniques.

Motivated by the observed patterns in labor adjustments at the establishment level, Cooper et al. (2007) estimate a labor search model with non-convexities in vacancy posting costs and firing costs using simulated methods of moments to match aggregate unemployment, vacancies, and hours. Our work is also motivated by micro-level facts about search intensity and recruiting intensity. We use these micro-level facts to discipline an aggregate DSGE model and we estimate the model to understand aggregate fluctuations in the labor market.

Lubik (2009) estimate a macro model with the standard labor search frictions, and he finds that the model relies heavily on exogenous shocks to matching efficiency to fit time series data of unemployment and vacancies. Our model enriches the standard model with search and recruiting intensity and thus relies on endogenous responses of search and recruiting intensity (instead of exogenous variations in matching efficiency) to explain the observed labor market dynamics.

Our paper is also related to 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.

By examining the interaction between search and recruiting intensity, our work also complements the analysis of Gomme and Lkhagvasuren (2015), 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.

III. The model with search and recruiting intensity

In this section, we present a DSGE model with search frictions in the labor market. To study the underlying forces behind the slow job recovery from the Great Recession, we introduce endogenous intensive-margin adjustments in the matching technology. First, we follow Davis et al. (2013) and introduce recruiting intensity as an additional margin of adjustments for firms. Second, we 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 vacancy 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 exogenously separated each period. Real wages are determined by Nash bargaining between a searching worker and a hiring firm. The government finances transfer payments to unemployed workers by lump-sum taxes.

III.1. **The Labor Market.**

In the beginning of period t, there are N_{t-1} employed workers. A fraction δ_t of job matches are separated in each period. We assume that the job separation rate δ_t is stochastic and follows the stationary process

$$\ln \delta_t = (1 - \rho_\delta) \ln \bar{\delta} + \rho_\delta \ln \delta_{t-1} + \varepsilon_{\delta t}. \tag{1}$$

In this shock process, ρ_δ is the persistence parameter and the term $\varepsilon_{\delta t}$ is an i.i.d. normal process with a mean of zero and a standard deviation of σ_δ. The term $\bar{\delta}$ denoted the steady state rate of job separation.

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

$$u_t = 1 - (1 - \delta_t) N_{t-1}. \tag{2}$$

After observing aggregate shocks, new vacancies are created. Following Fujita and Ramey (2007) and Coles and Kelishomi (2011), we assume that creating new vacancies incurs a sunk cost. Newly created vacancies add to the existing stock of vacancies carried over from the previous period. We follow Fujita and Ramey (2007) and assume that a vacant position becomes obsolete at a constant rate of ρ^o. A fraction of the open vacancies in the previous period are filled with job matches, and those filled vacancies subtract from the stock of vacancies carried over into the current period provided that they are not obsolete. In addition, newly separated jobs also add to the stock of vacancies if those positions are not obsolete.

Denote by q_t^v the job probability of filling a vacancy in period t, and by n_t the number of newly created vacancies. The law of motion for the stock of job vacancies v_t is described by

$$v_t = (1 - q_{t-1}^v)(1 - \rho^o) v_{t-1} + (\delta_t - \rho^o) N_{t-1} + n_t. \tag{3}$$

The searching workers and firms with job vacancies form new job matches based on the matching function

$$m_t = \mu (s_t u_t)^\alpha (a_t v_{t-1})^{1-\alpha}, \tag{4}$$

where m_t denotes the number of successful matches, s_t denotes search intensity, a_t denotes recruiting intensity (or advertising), the parameter μ represents 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 is given by

$$q_t^v = \frac{m_t}{v_t}. \tag{5}$$

The probability that an unemployed and searching worker finds a job is given by

$$q_t^u = \frac{m_t}{u_t}. \tag{6}$$

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

$$N_t = (1 - \delta_t) N_{t-1} + m_t. \tag{7}$$

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

$$U_t = u_t - m_t = 1 - N_t. \tag{8}$$

III.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

$$E \sum_{t=0}^{\infty} \beta^t \left(\ln C_t - \chi_t N_t \right), \tag{9}$$

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

$$\ln \chi_t = (1-\rho_\chi) \ln \bar{\chi} + \rho_\chi \ln \chi_{t-1} + \varepsilon_{\chi t}. \tag{10}$$

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 (9) subject to the sequence of budget constraints

$$C_t + \frac{B_t}{r_t} = B_{t-1} + w_t N_t + \phi(1-N_t) - u_t h(s_t) + d_t - T_t, \quad \forall t \geq 0, \tag{11}$$

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, d_t denotes the household's share of firm 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 satisfies the conditions

$$h_{it} = h(s_{it}), \quad h'(s_{it}) > 0, h''(s_{it}) \geq 0, \tag{12}$$

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 probability. 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

$$q^u(s_{it}) = \frac{s_{it}}{s_t u_t} m_t, \tag{13}$$

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 probability is given by

$$\frac{\partial q^u(s)}{\partial s_i} = \frac{m_t}{s_t u_t} = \frac{q_t^u}{s_t}, \tag{14}$$

which depends only on aggregate economic conditions.

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

$$h'(s_t) = \frac{q_t^u}{s_t}\left[w_t - \phi - \frac{\chi_t}{\Lambda_t} + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\delta_{t+1})(1-q_{t+1}^u)S_{t+1}^H\right], \tag{15}$$

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 net benefit of employment, including both the contemporaneous net flow benefits and the continuation value of employment.

The employment surplus S_t^H itself, as we show in the appendix, satisfies the Bellman equation

$$S_t^H = w_t - \phi - \frac{\chi_t}{\Lambda_t} + \frac{h(s_t)}{1-q_t^u} + \mathrm{E}_t \frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\delta_{t+1})(1-q_{t+1}^u)S_{t+1}^H, \tag{16}$$

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 contemporaneous benefit also includes saved search cost because it reduces the pool of job seekers, the measure of which is $1 - q_t^u$ at the end of period t. In addition, 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 $(1-\delta_{t+1})(1-q_{t+1}^u)$, resulting in the effective continuation value of employment shown in equation (16).

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

$$1 = \mathrm{E}_t \beta \frac{\Lambda_{t+1}}{\Lambda_t} r_t. \tag{17}$$

III.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. The technology shock follows the stochastic process

$$\ln Z_t = (1 - \rho_z) \ln \bar{Z} + \rho_z \ln Z_{t-1} + \varepsilon_{zt}. \tag{18}$$

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.[3]

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 $1 - \delta_{t+1}$), 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 $J^V_{j,t+1}$. The firm's match value therefore satisfies the Bellman equation

$$J^F_{jt} = Z_t - w_t + E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} \left\{ (1 - \delta_{t+1}) J^F_{j,t+1} + (1 - \rho^o) \delta_{t+1} J^V_{j,t+1} \right\}. \tag{19}$$

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 a non-negative entry cost of x drawn from an i.i.d. distribution $F(\cdot)$. A new vacancy is created if and only if $x \leq J^V_t$, or equivalently, if and only if its net value is non-negative. Thus, the number of new vacancies n_t equal to $F(J^V_t)$—the cumulative density of entry costs at the value of a 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

$$n_t = \eta (J^V_t)^{\xi}, \tag{20}$$

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 (i.e., $J^V_t = 0$). 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) and Coles and Kelishomi (2011).

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

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

$$\kappa_{jt} = \kappa(a_{jt}), \quad \kappa'(\cdot) > 0, \quad \kappa''(\cdot) \geq 0, \tag{21}$$

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

$$q^v(a_{jt}) = \frac{a_{jt}}{a_t v_t} m_t, \tag{22}$$

where a_t is the average advertising efforts by firms.

If the vacancy is filled (with probability q^v_{jt}), the firm obtains the value of a match J^F_{jt}. 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

$$J^V_{jt} = -\kappa(a_{jt}) + q^v(a_{jt}) J^F_{jt} + (1-\rho^o)(1-q^v(a_{jt})) E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} J^V_{j,t+1}. \tag{23}$$

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

$$\kappa'(a_{jt}) = \frac{\partial q^v(a_{jt})}{\partial a_{jt}} \left[J^F_{jt} - (1-\rho^o) E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} J^V_{j,t+1} \right], \tag{24}$$

where, from (22), we have

$$\frac{\partial q^v(a_{jt})}{\partial a_{jt}} = \frac{m_t}{a_t v_t} = \frac{q^v_t}{a_t}. \tag{25}$$

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 (24) can be written as

$$\kappa'(a_t) = \frac{q^v_t}{a_t} \left[J^F_t - (1-\rho^o) E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} J^V_{t+1} \right]. \tag{26}$$

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^F_t, although it loses the continuation value of the vacancy, which represents the opportunity cost of filling the vacancy.

The optimizing recruiting intensity (advertising) decision equation (26) reveals that the cyclical properties of recruiting intensity are a priori ambiguous. In a recession, the job filling rate rises (see Figure 1), and firms respond by exerting more recruiting efforts. However, in a recession, the match value J^F and the vacancy value J^V both decline, so that changes in the net value of filling a vacancy—the difference between J^F and J^V—are in general ambiguous. Depending on model parameters, recruiting intensity can be pro- or counter-cyclical.

In the special case with free entry, the value of vacancy would be driven down to zero. Thus, equation (23) reduces to

$$\kappa(a_t) = q_t^v J_t^F. \tag{27}$$

Furthermore, the optimal advertising choice (26) reduces to

$$\kappa'(a_t) = \frac{q_t^v}{a_t} J_t^F. \tag{28}$$

These two equations together implies that

$$\frac{\kappa'(a_t)a_t}{\kappa(a_t)} = 1. \tag{29}$$

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 incorporating sunk 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.

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

$$\max_{w_t} \quad \left(S_t^H\right)^b \left(J_t^F - J_t^V\right)^{1-b}, \tag{30}$$

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

$$b\left(J_t^F - J_t^V\right)\frac{\partial S_t^H}{\partial w_t} + (1-b)S_t^H \frac{\partial\left(J_t^F - J_t^V\right)}{\partial w_t} = 0, \tag{31}$$

where, from the household surplus equation (16), we have $\frac{\partial S_t^H}{\partial w_t} = 1$; and from the firm's value function (19), we have $\frac{\partial\left(J_t^F - J_t^V\right)}{\partial w_t} = -1$.

Define the total surplus as

$$S_t = J_t^F - J_t^V + S_t^H. \tag{32}$$

Then the bargaining solution is given by

$$J_t^F - J_t^V = (1-b)S_t, \quad S_t^H = bS_t. \tag{33}$$

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 (33) and the expression for household surplus in equation (16) together imply that the Nash bargaining wage w_t^N satisfies the Bellman equation

$$\frac{b}{1-b}(J_t^F - J_t^V) = w_t^N - \phi - \frac{\chi_t}{\Lambda_t} + \frac{h(s_t)}{1-q_t^u} + E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} \left[(1-\delta_{t+1}) \left(1 - q_{t+1}^u\right) \frac{b}{1-b} (J_{t+1}^F - J_{t+1}^V) \right]. \tag{34}$$

III.5. **Wage Rigidity.** In general, however, equilibrium real wage may be different from the Nash bargaining solution. Hall (2005a) and Shimer (2005) point out that real wage rigidities are important for generating empirically plausible volatilities of vacancies and unemployment relative to the volatility of labor productivity.[4] 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,

$$w_t = w_{t-1}^{\gamma} (w_t^N)^{1-\gamma}, \tag{35}$$

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

III.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

$$\phi(1-N_t) = T_t. \tag{36}$$

III.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

$$B_t = 0. \tag{37}$$

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

$$Y_t = Z_t N_t. \tag{38}$$

[4]The recent literature identifies several sources of real wage rigidities. For example, Christiano et al. (2015) report that an estimated DSGE model with wages determined by an alternating offer bargaining game in the spirit of Hall and Milgrom (2008) fits the data better than the standard model with Nash bargaining. Liu et al. (2016) show that, in an estimated DSGE model with labor search frictions and collateral constraints, endogenous real wage inertia can be obtained conditional on a housing demand shock even if wages are determined from the standard Nash bargaining game.

[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.

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

$$C_t + h(s_t)u_t + \kappa(a_t)v_t + \int_0^{J_t^V} x dF(x) = Y_t, \tag{39}$$

where the last term on the left-hand side of the equation corresponds to the aggregate cost of creating job vacancies. With a uniform distribution of the vacancy creation cost x in the interval $[0, K]$, the aggregate cost of vacancy creation is given by $\int_0^{J_t^V} x dF(x) = \frac{1}{2}\frac{(J^V)^2}{K}$, where $K = \frac{1}{\eta}$. Using the relation between the number of job vacancies and the value of an open vacancy in equation (20), the aggregate resource cost for vacancy creation can be written as $\frac{1}{2} n_t J_t^V$.

IV. Empirical strategies

We solve the DSGE model by log-linearzing the equilibrium conditions around the deterministic steady state. Appendix C 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 these cost functions are both quadratic and take the forms

$$\kappa(a_t) = \kappa_0 + \kappa_1(a_t - \bar{a}) + \frac{\kappa_2}{2}(a_t - \bar{a})^2, \tag{40}$$

$$h(s_t) = h_1(s_t - \bar{s}) + \frac{h_2}{2}(s_t - \bar{s})^2, \tag{41}$$

where we normalize the steady-state levels of recruiting intensity and search intensity so that $\bar{a} = 1$ and $\bar{s} = 1$.[6] We also assume that the search cost is zero in the steady state.

We first calibrate a subset of model parameters using steady-state restrictions. These parameters 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; $\bar{\delta}$, the average job separation rate; ρ^o, the vacancy obsolescence 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 (20).

[6] The quadratic form of the search cost function is supported by the empirical evidence provided by Yashiv (2000) and Christensen et al. (2005).

We estimate the remaining structural and shock parameters using Bayesian methods to fit the time-series data of unemployment, vacancies, and search intensity. The structural parameters to be estimated include $K \equiv \frac{1}{\eta}$, the scale of the vacancy-creation cost function; κ_2, the curvature of the vacancy-posting cost function; and h_2, the curvature of the search cost function. The shock parameters include ρ_z and σ_z, the persistence and the standard deviation of the technology shock; ρ_χ and σ_χ, the persistence and the standard deviation of the disutility shock, and ρ_δ and σ_δ, the persistence and the standard deviation of the job separation shock.

IV.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 $\bar{\delta} = 0.034$ per month, consistent with the JOLTS data for the period from December 2000 to April 2015. Following Hall 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 follow the literature and focus on the case with $\xi = 1$, as in Fujita and Ramey (2007) and Coles and Kelishomi (2011).[7]

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 probability $q^v = 0.338$ per month, which matches the quarterly job filling probability of 0.71 calibrated by den Haan et al. (2000).[8]

[7]To examine the sensitivity of our results to ξ, we re-estimate the baseline model with two alternative calibrations, one with $\xi = 2$ and the other with $\xi = 10$. With a larger value of ξ, the model becomes closer to one with free entry, in which case firms rely more on variations in the number of vacancies to respond to macroeconomic shocks than on varying recruiting intensity. Thus, the exercise here also helps evaluate the quantitative importance of cyclical variations in recruiting intensity for labor market dynamics. We find that, in terms of the model's predictions for the job filling and finding rates and the hiring rate, the quantitative results with $\xi = 2$ are similar to those in the baseline case with $\xi = 1$. However, if $\xi = 10$, the fit of the estimated model becomes significantly worse than the baseline case, and the predicted job filling and job finding rates become closer to those from the standard matching function. To conserve space, we report these results in an online appendix. See `http://www.frbsf.org/economic-research/files/wp2016-09_appendix.pdf`.

[8]Given our monthly job filling probability of $q^v = 0.338$, the quarterly filling probability 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).

We also calibrate the steady-state unemployment rate to be $U = 0.055$. Given the job separation rate of $\bar{\delta} = 0.034$, we obtain the steady-state hiring rate of $m = \bar{\delta}(1-U) = 0.0321$. 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 $\kappa_1 = 0.1124$ so that the steady-state recruiting intensity is $\bar{a} = 1$. We set $h_1 = 0.1178$ 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 $\mu = 0.353$. We calibrate the vacancy obsolescence rate to $\rho^o = 0.0338$, so that the steady-state ratio of newly created vacancies to employment in the model equals 0.036, the same ratio as that estimated by Davis et al. (2013) based on establishment-level JOLTS data.

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 $\bar{\chi} = 0.6579$. Finally, we set the real wage rigidity parameter to $\gamma = 0.95$, which lies at the high end of the literature (Hall, 2005b).

IV.2. **Estimation.** We now describe our data and estimation approach.

IV.2.1. *Data and measurement.* We fit the DSGE model to three monthly time-series data of the U.S. labor market: the unemployment rate, the job vacancy rate, and a measure of search intensity that helps discipline the predictions of the model. The sample covers the period from December 2000 to December 2016, 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

$$\ln(U_t^{data}) - \ln(U^{data}) = \hat{U}_t, \tag{42}$$

where U^{data} denotes the sample average of the unemployment rate in the 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

$$\ln(v_t^{data}) - \ln(v^{data}) = \hat{v}_t, \tag{43}$$

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

Our measure of search intensity is constructed by Davis (2011). He combines mean unemployment spells from the Current Population Survey (CPS) and regression results from Krueger and Mueller (2011), who find that search intensity declines as the duration of unemployment increases in high-frequency longitudinal data. In particular, Davis (2011) postulates that

$$s_t = A - Bd_t, \tag{44}$$

where s_t is search intensity and d_t is the mean spell duration of unemployed workers. Based on Krueger and Mueller (2011)'s regressions, B is set to 1.54 and A to 139.8. Figure 2 displays this measure of aggregate search intensity. Clearly, search intensity declined substantially during the Great Recession and its aftermath, as the duration of unemployment lengthened. We discuss in Section V.3.2 the importance of using the time series data of search intensity to discipline the estimation of our DSGE model.

IV.2.2. *Prior distributions and posterior estimates.* The prior and posterior distributions of the estimated parameters from our benchmark model are displayed in Table 2 (Panel A).

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 5 with a standard deviation of 1. The prior distribution of κ_2 and h_2 each has a mean of 1 and a standard deviation of 0.1. For the shock parameters, we follow the literature and assume that the priors of ρ_z, ρ_χ, and ρ_δ each follows the beta distribution and the priors of σ_z, σ_χ, and σ_δ each follows an inverse gamma distribution.

The posterior estimates and the 90% confidence interval for the posterior distributions are displayed in the last three columns of Table 2. The scale of vacancy creation costs K has a posterior mean of 12.64, with a 90% confidence interval from 11.12 to 14.18. The posterior estimate of K is significantly different from the priors. Thus, the data seem to be quite informative about this parameter. The posterior estimate of $K = 12.64$ implies that the sunk cost of vacancy creation is about 0.77 percent of steady-state output. The curvature parameter κ_2 of the vacancy-posting cost function has a posterior mean of 1.15 and a 90% confidence interval from 1.01 to 1.33, which is also significantly different from its prior mean. The curvature parameter h_2 of the search cost function has a posterior mean of 0.92 and a 90% confidence interval from 0.80 to 1.01. The data are less informative on this particular structural parameter since the prior mean lies within the 90% confidence band of the posterior distribution.

The estimation also suggests that technology shocks are more persistent and less volatile than the other two shocks. The disutility shock has an estimated standard deviation (0.36) that is an order of magnitude larger than the other two shocks. As we discuss below, this large standard deviation of the disutility shock is required to fit the time series data of search intensity, given the estimate of the fixed cost.

V. Economic implications

We now discuss the economic mechanism through which search and recruiting intensity help amplify the impact of shocks on labor market dynamics. We do this with the help of impulse responses and counterfactual simulations in which one or both of the intensive margins of adjustments are turned off.

V.1. **The model's transmission mechanism.** We first examine the model's transmission mechanism through impulse responses.

Figure 3 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 postings. These responses lead to a drop in workers' job finding rate and a persistent increase in the unemployment rate.

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 (3). This gives rise to persistent dynamics in vacancies, as shown in Figure 3. The decline in vacancies is also partly attributable to declines in entry or new vacancy creation (not shown in the figure). Since the value of a new job match is now lower and the hiring rate also falls, the value of creating a new vacancy declines. With both hiring and vacancies declining following the negative technology shock, the response of the job filling rate—which is the ratio of hires to vacancies— can be ambiguous. With our estimation, the job filling rate declines initially and then overshoots its steady state before returning to the steady state.

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. (15)) show that search intensity increases with the job finding probability 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 falls in the short run and the expected value of a job match also declines. This can be seen from the optimizing decision for recruiting intensity in Equation (26), which shows that recruiting intensity increases with both the job filling probability and the value of a new job match (J^F) relative to the value of an unfilled vacancy (J^V). However, note that because the technology shock reduces both J^F and J^V, the net effect on recruiting intensity

(a) can be ambiguous. Under our estimated parameters, the net surplus falls following a contractionary technology shock. Thus, recruiting intensity falls as well.

Declines in search and recruiting intensity imply an outward shift of the Beveridge curve, because the measured matching efficiency falls, as shown in the last panel of Figure 3. The measured matching efficiency here is defined as

$$\Omega_t = \mu s_t^{\alpha} a_t^{1-\alpha}. \tag{45}$$

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

As search intensity and recruiting intensity both declines following a negative technology shock, our model implies that hiring declines more than the stock of job vacancies in the short run. Accordingly, the job filling rate declines in the short run before rising persistently above its steady state.

The procyclical pattern of the job filling rate conditional on technology shocks appears inconsistent with the countercyclical pattern of that variable in the data (see Figure 1). This result suggests that our model faces a tradeoff between generating slow-moving vacancy dynamics and countercyclical job filling rate fluctuations conditional on technology shocks. To see this, we compare in Figure 4 the impulse responses of the labor market variables to a negative technology shock from our benchmark model to those from a counterfactual model with a lower sunk cost of vacancy creation (with $K = 2.25$ instead of 12.64).[9] With a lower vacancy creation cost, the model would be closer to the standard DMP model with free entry, in which case the number of job vacancies is a jump variable instead of a slow-moving state variable. Consistent with our intuition, the figure shows that, in the model with lower vacancy creation costs, a negative technology shock leads to a sharper decline in job vacancies relative to hiring. Accordingly, the job filling rate rises persistently. In contrast, our estimation of the benchmark model implies a large vacancy creation cost to match the persistent vacancy dynamics. With slow-moving vacancies and a large response of hiring (driven in part by endogenous search intensity and recruiting intensity), our model implies a procyclical response of the job filling rate in the short run following a technology shock.

The tradeoff between vacancy dynamics and the cyclical behaviors of the job filling rate illustrated here represents an additional challenge for the class of DMP models to fit labor market dynamics. This challenge is different from the well-known Shimer puzzle. Shimer

[9]The value of $K = 2.25$ is obtained when we estimate the model without fitting the time-series of search intensity (see Table 2 below).

(2005) shows that technology shocks cannot generate the observe large volatility of unemployment relative to that of labor productivity unless real wages are rigid. Our finding here suggests that, even if real wage rigidities are imposed in the model, it is still difficult to generate a countercyclical job filling rate in response to technology shocks without sacrificing persistent vacancy dynamics.

Our model thus relies on other shocks in addition to technology shocks to match the time series data. We now turn to discussing the impulse responses following the other two shocks in our model.

Figures 5 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 through an income effect. As both recruiting intensity and search intensity decline, the measured matching efficiency also declines. Furthermore, the large and persistent increase in the unemployment rate alleviates the fall in hiring which, combined with persistent declines in the stock of vacancies, leads to a persistent increase in the job filling rate. Thus, in contrast to technology shocks, the job filling rate is countercyclical following a disutility shock.

Figures 6 shows the impulse responses following a positive shock to the job separation rate. With a higher rate of job separation, the unemployment rate rises. At the same time, separated jobs add to the stock of vacancies, so that the vacancy rate rises as well. Since both u and v increase, the hiring rate also rises. Equilibrium adjustments of hiring also depend on the responses of the intensive margins. The job separation shock reduces both the match value J^F and the vacancy value J^V, rendering the net effect on recruiting intensity ambiguous. Under our estimation, recruiting intensity edges down slightly following the separation shock. On the other hand, since firms reduce the number of newly created vacancies in response to the shock, households choose to reduce search intensity slightly. On net, the responses of these intensive margins are small relative to those of unemployment and vacancies, leading to a persistent increase in hiring. The increase in hiring slightly dominates the increase in vacancies, implying that the job filling rate rises slightly in the short run before it eventually declines in about 6 months after the shock.

V.2. **The Great Recession and the slow job recovery.** The impulse responses show that search and recruiting intensity are procyclical in our estimated model. We now illustrate the ability of the model to explain the slow job recovery after the Great Recession.

In the data, the job filling rate declined sharply after the Great Recession, while the job finding rate rose gradually, as shown in Figure 1 (the blue solid lines). These patterns are consistent with a relatively slow recovery in hiring.

The standard model without search and recruiting intensity has difficulties in replicating these observations. As Figure 1 shows (the red dashed lines), the predicted job filling rate and the job finding rate from the model with the standard matching function both stayed persistently higher than those observed in recent data.

In comparison, our model with endogenous search intensity and recruiting intensity performs much better than the standard model in explaining the slow job recovery. As shown in Figure 1 (the black dashed and dotted lines), the predicted job filling and finding rates from our benchmark model track the actual data closely.

To get a quantitative sense of the goodness of fit of our model relative to the standard model, we consider the root mean squared errors (RMSE) for the variables of interest in each model. We calculate the RMSEs based on demeaned series in the data and in each model.[10] As shown in Table 3, the standard model's predicted job filling rate has an RMSE of 0.1565 relative to the data. In contrast, the RMSE of the job filling rate predicted from our estimated benchmark model is 0.0864, which is slightly over half of that implied by the standard model. Our model with search and recruiting intensity also improves the fit for the job finding rate relative to the standard model, with a similar magnitude of improvement.

The ability of our benchmark model to predict the recovery paths of the job filling and finding rates suggests that the model is also able to predict the observed slow job recovery. This is indeed the case, as shown in Figure 8, which displays the times series of the hiring rate in the data and the smoothed hiring series from our estimated model. While our model misses the timing of the trough in hiring, the correlation between the model's predicted hiring rate and the actual hiring rate is still about 0.70. This correlation is surprisingly high because our model is not fitted to the observed time-series data of hiring.

Our model also implies that recruiting intensity is highly correlated with the hiring rate, as found by Davis et al. (2013), despite clear differences in the approaches. Davis et al. (2013) construct a measure of recruiting intensity based on establishment-level data. They show that recruiting intensity delivers a better-fitting Beveridge curve and accounts for a large share of fluctuations in aggregate hires. They further impute an aggregate relation between recruiting intensity and the hiring rate based on their estimated microeconomic relations.

[10]The series shown in Figure 1 are normalized based on the demeaned series, so that the first observation of each series is indexed to 0. We do not calculate the RMSEs based on the normalized series, but instead, we use the "raw" demeaned series.

They show that this aggregate measure of recruiting intensity is highly correlated with the aggregate hiring rate, with a sample correlation of about 0.82.

We have followed a very different approach to obtaining an empirical measure of recruiting intensity (a_t) in our estimated macro model. To assess how our measure of recruiting intensity behaves over the business cycle, we calculate the sample correlation between the model-based time series of recruiting intensity and the hiring rate, and we obtained a correlation of 0.72, which is remarkably close to that reported by Davis et al. (2013). This finding strengthens the argument by Davis et al. (2013) that recruiting intensity plays an important role in explaining cyclical fluctuations in aggregate hires.

V.3. **The importance of search and recruiting intensity.** To understand the importance of cyclical variations in search and recruiting intensity, we conduct two sets of counterfactual experiments. In the first experiment, we consider a counterfactual model with both search intensity and recruiting intensity held constant. In the second experiment, we re-estimate the benchmark model to fit time-series data on unemployment and vacancies only, without using data on search intensity.

V.3.1. *A counterfactual model with constant search and recruiting intensity.* We first consider a counterfactual model that holds search and recruiting intensity constant. In particular, we keep the parameters and the shock processes the same as in the estimated benchmark model, but we force the search intensity and recruiting intensity to stay constant at their steady-state levels. We focus on the effects of a negative technology shock.

Figure 7 shows the impulse responses to a negative technology shock in the counterfactual model with constant search and recruiting intensity (the blue dashed lines), along with those in the benchmark model (the black solid lines).

The figure highlights that a negative technology shock leads to a more muted decline in hiring and a smaller increase in unemployment in the counterfactual model than those predicted by the benchmark model with endogenous intensive-margin adjustments. Without variations in search and recruiting intensity, hiring is solely determined by the number of job-seekers and the number of job vacancies according to the matching function. Since the number of job seekers entering the matching function is predetermined and the stock of job vacancies is a slow-moving state variable, the responses of hiring in the counterfactual model are more muted than in the benchmark model. Given the muted declines in hiring, the drop in job vacancies following a negative technology shock leads to an increase in the job filling rate in the counterfactual model. However, the ability of the counterfactual model to generate a countercyclical job filling rate comes at the cost of predicting muted responses of other labor market variables, including hiring, unemployment, and the job finding rate.

Overall, Figure 7 shows that endogenous adjustments in search and recruiting intensity to changes in macroeconomic conditions help amplify the responses of the labor market variables in general.

V.3.2. *The importance of using information from search intensity data.* In estimating our benchmark model, we have used three time series data: the unemployment rate, the job vacancy rate, and search intensity. We followed Davis (2011) and constructed a time series of search intensity based on unemployment duration. The resulting search intensity series is procyclical, as shown in Figure 2. The procyclical behavior of search intensity is consistent with the textbook model (Pissarides, 2000).[11]

Yet, the empirical literature is not conclusive about whether search intensity is procyclical. For example, in an influential study, Shimer (2004) argues that search intensity is countercyclical based on cross-sectional data of the average number of search methods used by job seekers observed in the Current Population Survey (CPS). Mukoyama et al. (2014) combine information from the CPS data and the American Time Use Survey (ATUS) and obtain similar results.

On the other side of the debate, Tumen (2014) criticizes the interpretation of the cyclical behavior of search intensity measured by cross-sectional average number of search methods in the CPS. He emphasizes that these cross-sectional measures are likely to suffer from a composition bias if a job seeker with stronger labor-market attachment also uses more search methods, since the share of job seekers with stronger labor-market attachment increases during a recession. When this composition bias is corrected, Tumen (2014) finds that search intensity is procyclical. Gomme and Lkhagvasuren (2015) make a similar argument about the composition bias. They use merged data from the ATUS and the CPS to study cyclical variations in search intensity. They find that, when the composition bias is corrected, the evidence suggests procyclical search intensity.

Given this debate, we assess the robustness of our findings by fitting our model to the observed unemployment rate and the vacancy rate only. Under this alternative estimation, we do not use information of search intensity in the data. In this alternative estimation, we keep the priors of the parameters the same as in our benchmark estimation.

The posterior estimation results are shown in Table 2 (Panel B). Compared to the benchmark estimation, this alternative estimation without using information from search intensity

[11]The measure of search intensity that we use, which is the same measure used by Davis (2011), has an advantage in that it is constructed based on longitudinal data that track unemployed workers' amount of time spent for job searching as well as the number of weeks they have been unemployed. A drawback of this method is that it is based on answers from interviews conducted over a 24-week period during the fall of 2009 and winter of 2010, so it has a relatively short time-series dimension.

data results in a few notable changes in the posterior distributions of the structural parameters and the shock parameters. Specifically, the posterior mean of K is much smaller than that obtained from the benchmark estimation (2.25 vs. 12.64), although it is still significantly different from the prior, suggesting that the data are still informative about this parameter. The estimated curvature parameter κ_2 of the vacancy posting cost function is very similar to the benchmark estimation. However, the estimated curvature parameter of the search cost function h_2 is significantly larger than obtained from the benchmark estimation (1.21 vs. 0.92). These results suggest that the search intensity data carry information that is important for identifying K and h_2, but less important for identifying κ_2.

Furthermore, technology shocks are less persistent and preference shocks are more persistent under the alternative estimation than under the benchmark estimation. The most striking change, however, is the standard deviation of the preference shock, which goes down from 0.358 under the benchmark estimation to 0.014 under the alternative estimation. Thus, when the model is not required to fit the search intensity data, the estimated size of the preference shock becomes an order of magnitude smaller. This finding suggests that the preference shock plays an important role for fitting the model to search intensity data.

Despite these differences in the estimation results, our model with endogenous variations in search and recruiting intensity still outperforms the standard model without these intensive margins. Figure 9 shows that, even if we do not use search intensity data for estimating our model, the predicted job filling rate and the job finding rate (the black dashed and dotted lines) still track the data (the blue solid lines) more closely than those from the standard model (the red dashed lines). Table 3 shows that the RMSEs for the job filling rate and the job finding rate predicted from our model under this alternative estimation are greater than those from the benchmark estimation, but still lower than those from the standard model.

However, when we estimate the model without fitting to the search intensity series, the hiring rate implied by the model displays a weaker correlation with that in the data compared to our benchmark estimation. Specifically, the correlation between model-implied hiring and actual hiring is about 0.37, much smaller than than obtained under the benchmark estimation (0.70). These results suggest that fluctuations in search intensity are important to account for fluctuations in hiring.

Furthermore, cyclical fluctuations in search intensity also help amplify cyclical fluctuations in recruiting intensity. When we do not use information from search intensity to estimate the model, the correlation between recruiting intensity and hiring becomes much weaker than under the benchmark estimation (0.38 vs. 0.72) and that obtained by Davis et al. (2013).

Overall, these exercises suggest that using our measure of search intensity in estimating the DSGE model helps discipline the estimation. It also suggests that there are important general equilibrium interactions between search intensity and recruiting intensity that amplify the impact of shocks on labor market variables through their procyclicality and help improve the predictions for the job filling and job finding rates.

VI. Conclusion

The slow job recovery after the Great Recession has presented a challenge for the standard model of labor search and matching. We have developed and estimated a DSGE model that generalizes the standard model to incorporate cyclical fluctuations of search and recruiting intensity. We find that these intensive margins of labor-market adjustments are quantitatively important. During the recovery period, the job filling rate and the job finding rate predicted from our estimated model are much closer to the actual time-series data than those implied by the standard model without search and recruiting intensity. Our model suggests that the observed slow job recovery stems to a large extent from below-trend recovery in search and recruiting intensity.

To allow for aggregate fluctuations in recruiting intensity, we modify the standard model by assuming that firms need to pay a fixed cost to create a new job vacancy. This simple modification facilitates tractability and makes it straightforward to estimate the model to fit time-series data using standard techniques. Interestingly, our macro emphasis nonetheless yields predictions of the cyclical movements in recruiting intensity that are very much in line with those postulated in Davis et al. (2013) based on establishment-level data. In particular, both approaches highlight a high positive correlation between the hiring rate and recruiting intensity. But our empirical findings also point to an important interaction between search and recruiting intensity that helps account for the observed behavior of the job filling and job finding rates since the end of the Great Recession.

To better highlight the mechanism, we focus on three particular sources of business cycle fluctuations: technology, preference, and separation shocks. All are arguably reduced-form representations of some microeconomic frictions or policy distortions that are not considered in our model. For example, the preference shock in our model reflects changes in workers' reservation value, including variations in unemployment benefits. Our model also assumes that job separations vary exogenously, while in reality, job separations occur endogenously in reaction to the state of the economy.

Our model also restricts the labor force participation rate to be constant. Relaxing this assumption can have important implications for labor market dynamics. For example, Diamond (2013) argues that incorporating flows into and out of the labor force helps better understand the shifts of the Beveridge curve after the Great Recesison. Kudlyak and Schwartzman (2012) show that persistent declines in labor force participation contributed to the large increases in unemployment during the Great Recession and also to the subsequent slow decline in unemployment. Future research should extend our framework to incorporate endogenous job separations and labor force participation to study their potential interactions with search and recruiting intensity. Such a framework should be useful for better understanding labor market fluctuations and for policy designs. Our work provides a step forward for this promising research agenda.

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
$\bar{\delta}$	Job separation rate	0.034
ρ^o	Vacancy obsolescence rate	0.0338
κ_0	Steady-state advertising cost	0.0994
κ_1	Slope of vacancy posting cost	0.1124
h_1	Slope of search cost	0.1178
b	Nash bargaining weight	0.50
γ	Real wage rigidity	0.95
ξ	Elasticity of vacancy creation	1
$\bar{\chi}$	Mean value of preference shock	0.6579
$\bar{Z}$	Mean value of technology shock	1

Table 2. Estimated parameters

	Parameter description	Prior type [mean, std]	Posterior Mean	Posterior 5%	Posterior 95%
	A. Benchmark estimation				
K	scale of vacancy creation	gamma [5, 1]	12.6446	11.1224	14.1829
κ_2	curvature of vacancy posting	gamma [1, 0.1]	1.1530	1.0106	1.3298
h_2	curvature of search cost	gamma [1, 0.1]	0.9160	0.8015	1.0094
ρ_z	AR(1) of technology shock	beta [0.3333, 0.2357]	0.8919	0.8736	0.9072
ρ_χ	AR(1) of preference shock	beta [0.3333, 0.2357]	0.5513	0.4798	0.6238
ρ_δ	AR(1) of job separation shock	beta [0.3333, 0.2357]	0.7992	0.7079	0.8663
σ_z	std of technology shock	inv gamma [0.01, 1]	0.0199	0.0171	0.0225
σ_χ	std of preference shock	inv gamma [0.01, 1]	0.3581	0.2949	0.4269
σ_δ	std of separation shock	inv gamma [0.01, 1]	0.0720	0.0653	0.0787
	B. Alternative estimation (no search intensity data)				
K	scale of vacancy creation	gamma [5, 1]	2.2465	1.7177	2.9397
κ_2	curvature of vacancy posting	gamma [1, 0.1]	1.1512	0.9892	1.3063
h_2	curvature of search cost	gamma [1, 0.1]	1.2101	1.0444	1.3688
ρ_z	AR(1) of technology shock	beta [0.3333, 0.2357]	0.0575	0.0001	0.1298
ρ_χ	AR(1) of preference shock	beta [0.3333, 0.2357]	0.9766	0.9611	0.9955
ρ_δ	AR(1) of job separation shock	beta [0.3333, 0.2357]	0.6137	0.5110	0.6870
σ_z	std of technology shock	inv gamma [0.01, 1]	0.0025	0.0019	0.0029
σ_χ	std of preference shock	inv gamma [0.01, 1]	0.0135	0.0104	0.0168
σ_δ	std of separation shock	inv gamma [0.01, 1]	0.0776	0.0698	0.0844

Table 3. Out-of-sample predictions of alternative models: RMSE

Variable	Standard model	Benchmark model	Alternative estimation
Job filling rate	0.1565	0.0864	0.1238
Job finding rate	0.1565	0.0862	0.1437

Note: The numbers in this table are root mean squared errors calculated based on demeaned data and predictions from each model. The standard model implies that the job filling rate and the job finding rate are both functions of the labor market tightness (the v-u ratio) and are perfectly negatively correlated. Thus, the RMSEs for both variables from the standard model are identical.

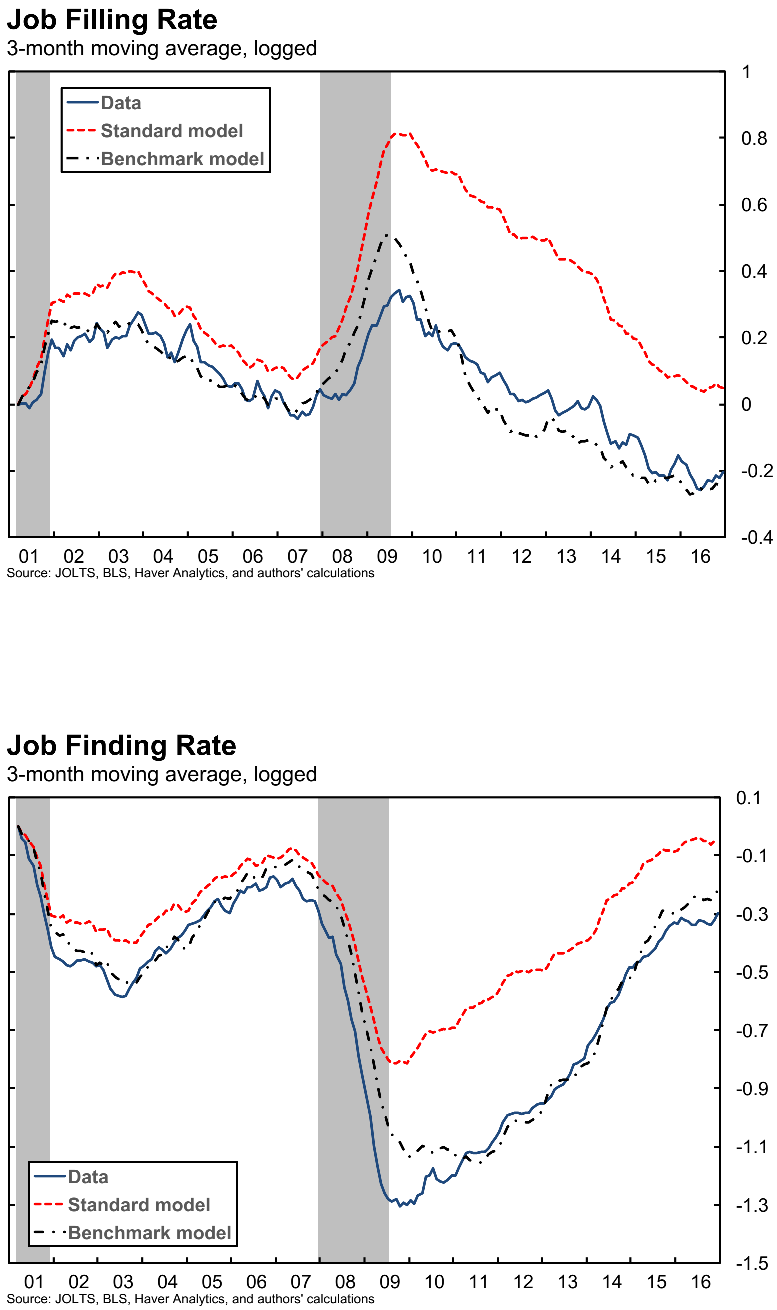

FIGURE 1. Job filling rate and job finding rate: Data, standard model, and benchmark DSGE model. The shaded areas indicate the NBER recession dates. The job filling rate is the ratio of hires to the end-of-period stock of job vacancies and the job finding rate is the ratio of hires to the end-of-period unemployment. Each plotted series is normalized so that the first observation is zero.

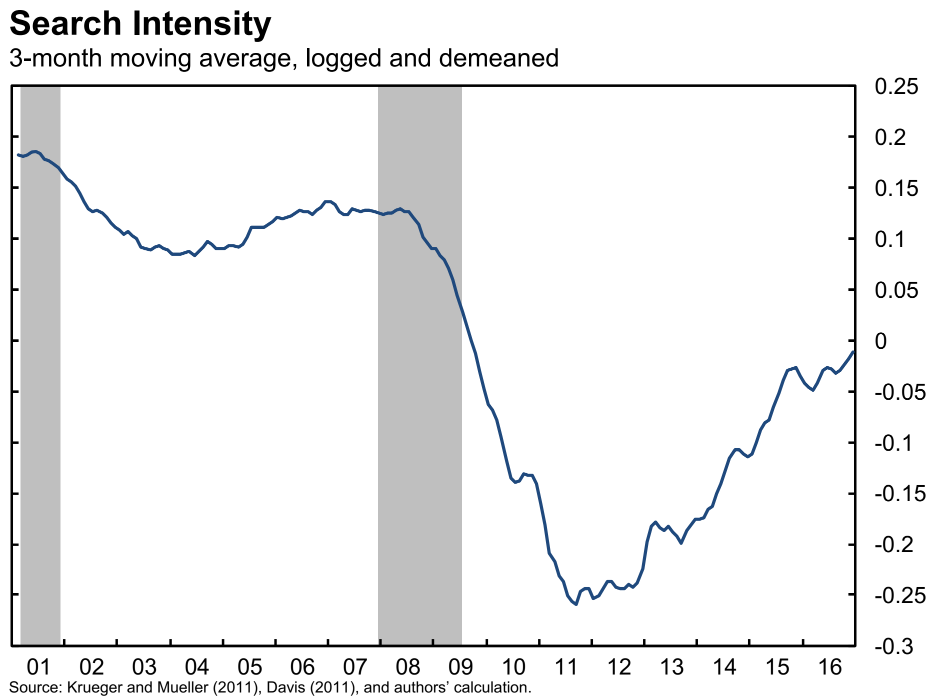

FIGURE 2. Time series of search intensity. The shaded areas indicate recession dates.

FIGURE 3. Impulse responses to a negative technology shock: Benchmark model

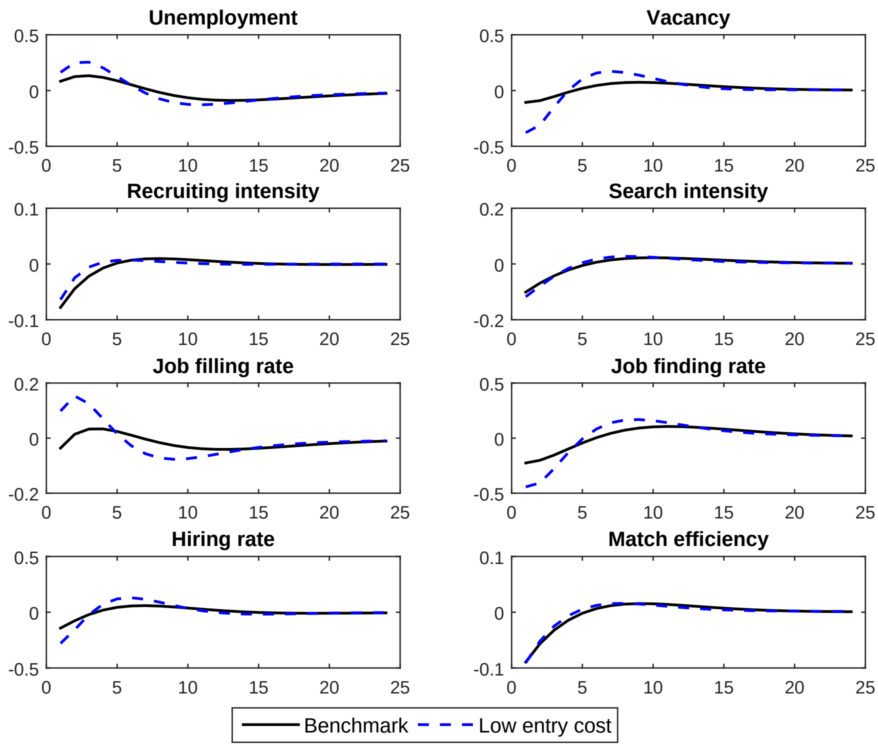

FIGURE 4. Impulse responses to a negative technology shock: Benchmark model vs. counterfactual model with low entry cost

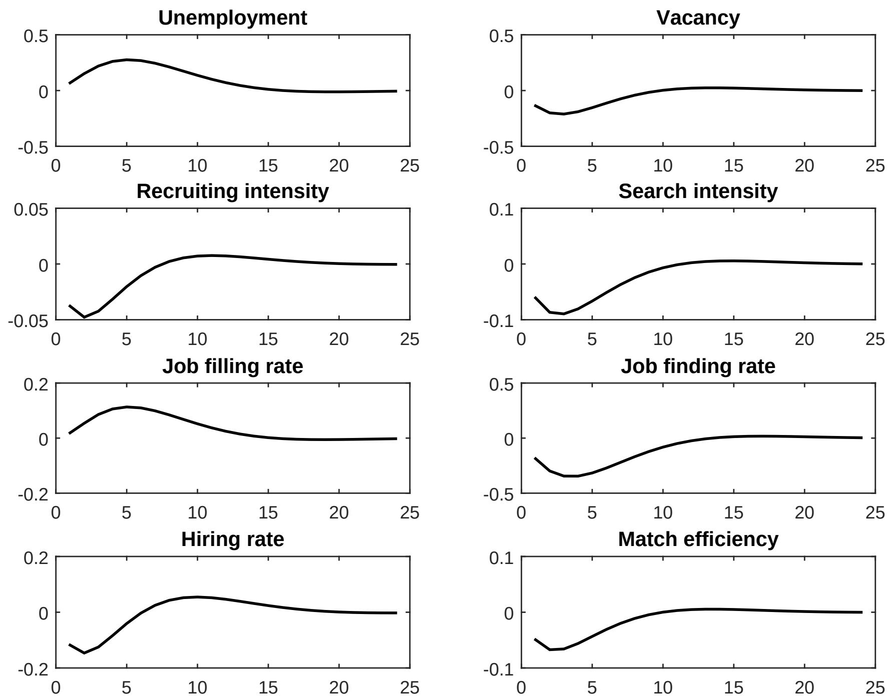

FIGURE 5. Impulse responses to a positive disutility shock

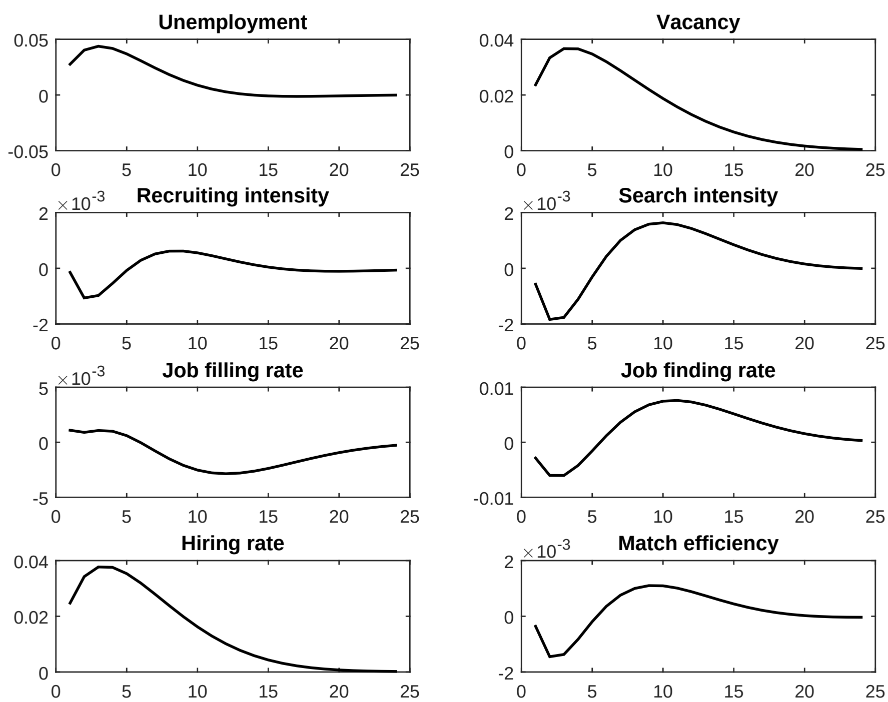

FIGURE 6. Impulse responses to a positive job separation shock

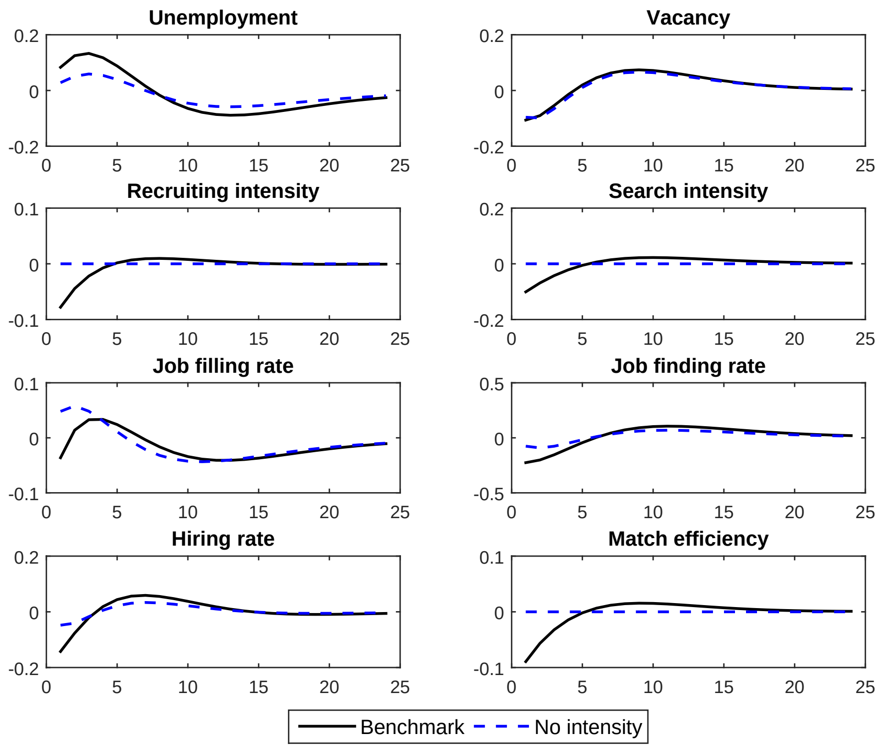

FIGURE 7. Impulse responses to a negative technology shock: Benchmark model vs. counterfactual model with constant search and recruiting intensity

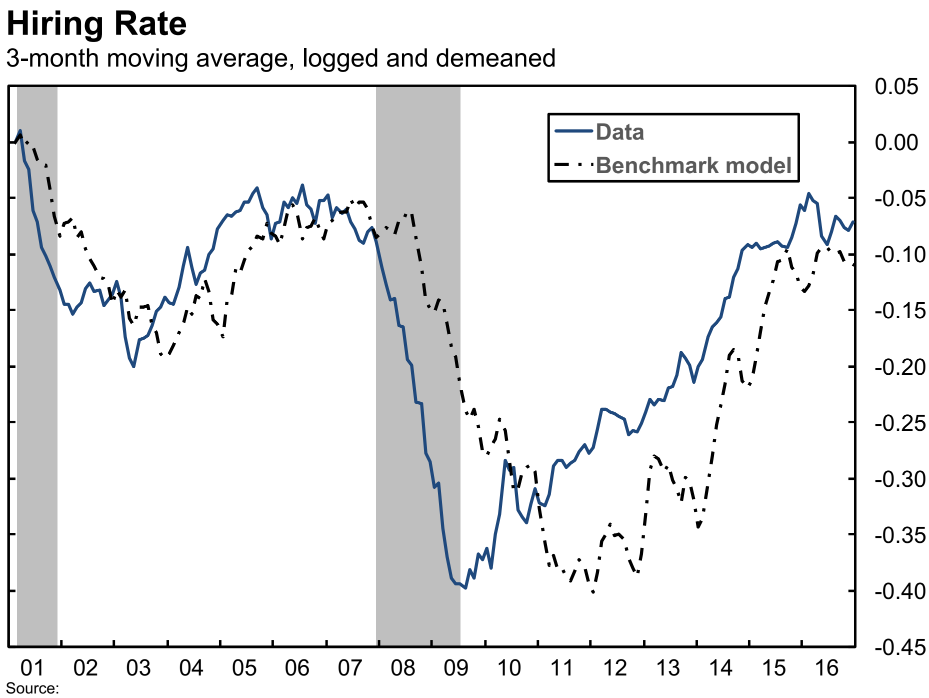

Figure 8. Hiring rate: Data vs. benchmark model. The shaded areas indicate recession dates.

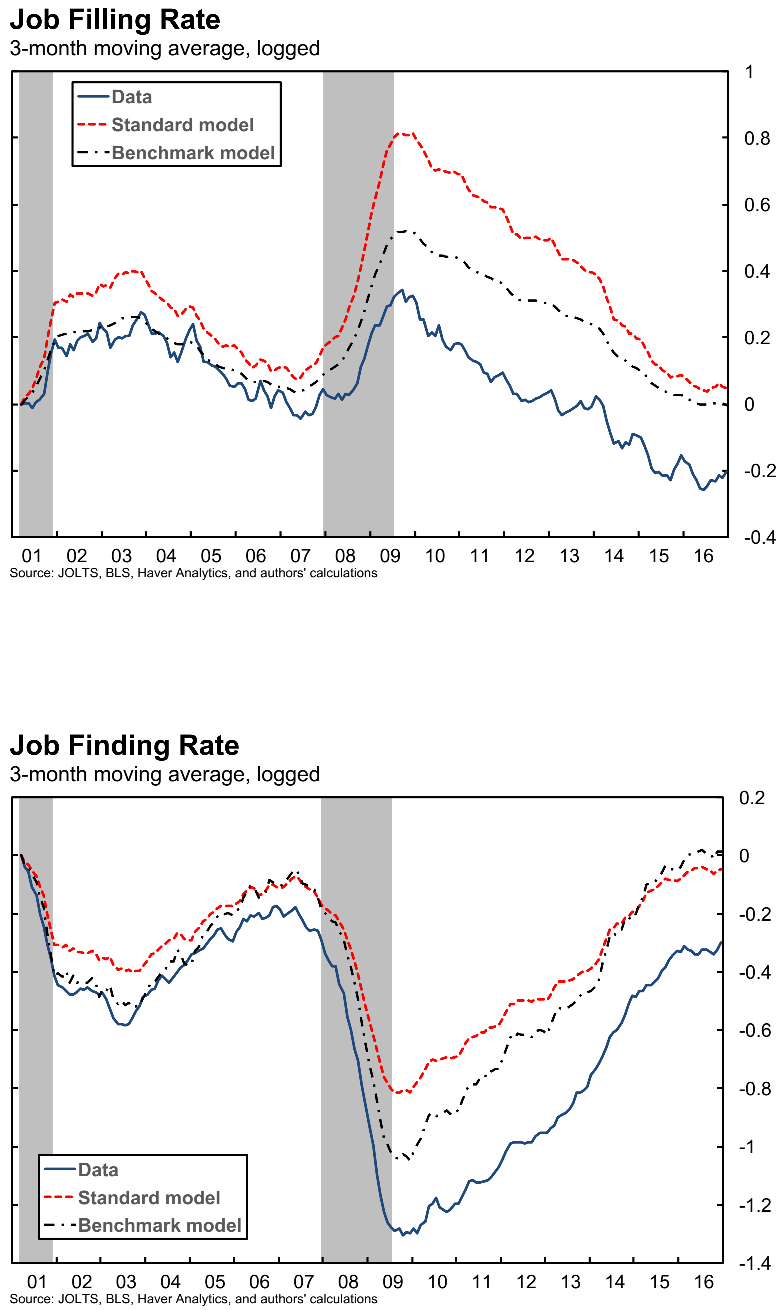

FIGURE 9. Job filling rate and job finding rate: Data, standard model, and DSGE model estimated without using search intensity series. The shaded areas indicate recession dates.

Appendix A. Data

We fit the DSGE model to three monthly time-series data of the U.S. labor market: the unemployment rate, job vacancies, and a measure of search intensity. We also use monthly time-series data of hires to construct our measures of the job filling and finding rates.

(1) Unemployment: Civilian unemployment rate (16 years and over) from the Bureau of Labor Statistics, seasonally adjusted monthly series (LRUSECON in Haver).

(2) Job vacancies: Job openings from the Job Openings and Labor Turnover Survey (JOLTS), seasonally adjusted monthly series (LIJTLA@USECON in Haver).

(3) Search intensity: constructed by Davis (2011) based on the regression relation between search intensity and unemployment duration obtained by Krueger and Mueller (2011) using longitudinal data. The regression relation is

$$s_t = 139.80 - 1.54 d_t, \tag{A1}$$

where s_t denotes search intensity and d_t denotes the seasonally adjusted monthly series of average weeks unemployed for unemployed workers reported in the Current Population Survey (WAAVG@EMPL in Haver).

(4) Hires: Total hires from JOLTS, seasonally adjusted monthly series (LIHTLA@USECON in Haver).

The sample range for all series covers the period from December 2000 to December 2016, corresponding to the available data range in JOLTS.

The job filling rate and the job finding rate in the actual data reported in Figures 1 and 9 are constructed based on the data for hires, unemployment, and vacancies. In particular, the job filling rate in the data is the ratio of hires to the end-of-period stock of job vacancies. The job finding rate is the ratio of hires to the end-of-period unemployment.

Appendix B. 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.

Denote by $V_t(B_{t-1}, N_{t-1})$ the value function for the representative household. The household's optimizing problem can be written in the recursive form

$$V_t(B_{t-1}, N_{t-1}) \equiv \max \ \ln C_t - \chi_t N_t + \beta \mathrm{E}_t V_{t+1}(B_t, N_t), \tag{A2}$$

subject to the budget constraint

$$C_t + \frac{B_t}{r_t} = B_{t-1} + w_t N_t + \phi(1 - N_t) - u_t h(s_t) + d_t - T_t, \tag{A3}$$

and the law of motion for employment

$$N_t = (1 - \delta_t) N_{t-1} + q^u(s_t) u_t, \tag{A4}$$

where the measure of job seekers is given by

$$u_t = 1 - (1 - \delta_t) N_{t-1}. \tag{A5}$$

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

Denote by Λ_t the Lagrangian multiplier for the budget constraint (A3). The first-order condition with respect to consumption implies that

$$\Lambda_t = \frac{1}{C_t}. \tag{A6}$$

The optimizing decision for B_t implies that

$$\frac{\Lambda_t}{r_t} = \beta \mathrm{E}_t \frac{\partial V_{t+1}(B_t, N_t)}{\partial B_t}. \tag{A7}$$

We use the envelope condition with respect to B_{t-1} that

$$\frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial B_{t-1}} = \Lambda_t, \tag{A8}$$

to obtain the intertemporal Euler equation

$$1 = \mathrm{E}_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} r_t, \tag{A9}$$

which is equation (17) in the text.

Optimal choice of search intensity s_t implies that

$$h'(s_t) = \frac{q_t^u}{s_t} \left[w_t - \phi - \frac{\chi_t}{\Lambda_t} + \beta \mathrm{E}_t \frac{\partial V_{t+1}(B_t, N_t)}{\partial N_t} \frac{1}{\Lambda_t} \right], \tag{A10}$$

where we have used equation (14) 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

$$\frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_{t-1}} = \left[\Lambda_t(w_t - \phi) - \chi_t + \beta \mathrm{E}_t \frac{\partial V_{t+1}(B_t, N_t)}{\partial N_t} \right] \frac{\partial N_t}{\partial N_{t-1}} - \Lambda_t h_t \frac{\partial u_t}{\partial N_{t-1}}. \tag{A11}$$

Equations (A4) and (A5) imply that

$$\frac{\partial N_t}{\partial N_{t-1}} = (1-\delta_t)(1-q^u(s_t)) \tag{A12}$$

and that

$$\frac{\partial u_t}{\partial N_{t-1}} = -(1-\delta_t). \tag{A13}$$

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

$$S_t^H = \frac{1}{\Lambda_t}\frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_t} = \frac{1}{\Lambda_t}\frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_{t-1}}\frac{\partial N_{t-1}}{\partial N_t} = \frac{1}{\Lambda_t}\frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_{t-1}}\frac{1}{(1-\delta_t)(1-q^u(s_t))}. \tag{A14}$$

Thus, S_t^H is the value for the household to send an additional worker to work in period t. Then the envelope condition (A11) implies that

$$S_t^H = w_t - \phi - \frac{\chi_t}{\Lambda_t} + \frac{h_t}{1-q_t^u} + \mathrm{E}_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\delta_{t+1})(1-q_{t+1}^u)S_{t+1}^H. \tag{A15}$$

The employment surplus S_t^H derived here corresponds to equation (16) in the text and it is the relevant surplus for the household in the Nash bargaining problem.

Given the definition of employment surplus in equation (A14), the optimal search intensity decision (A10) can be rewritten as

$$h'(s_t) = \frac{q_t^u}{s_t}\left[w_t - \phi - \frac{\chi_t}{\Lambda_t} + \mathrm{E}_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}(1-\delta_{t+1})(1-q_{t+1}^u)S_{t+1}^H\right]. \tag{A16}$$

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 (15) in the text.

Appendix C. 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

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

(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:

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

(11) Aggregate production function:

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

(12) Aggregate Resource constraint:

$$C_t + h(s_t)u_t + \kappa(a_t)v_t + \frac{1}{2}Kn_t^2 = Y_t, \tag{B12}$$

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:

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

(14) Recruiting intensity:

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

(15) Match value:

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

(16) Nash bargaining wage:

$$\frac{b}{1-b}(J_t^F - K n_t) = w_t^N - \phi - \frac{\chi_t}{\Lambda_t} + \frac{h(s_t)}{1-q_t^u} + E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} \left[(1-\delta_{t+1}) \left(1 - q_{t+1}^u\right) \frac{b}{1-b} (J_{t+1}^F - K n_{t+1}) \right]. \tag{B16}$$

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

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

Appendix D. 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

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

(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:

$$[\rho^o + (1-\rho^o) q^v] v = (\delta - \rho^o) N + n, \tag{C10}$$

(11) Aggregate production function:

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

(12) Aggregate Resource constraint:

$$C + \kappa_0 v + \frac{1}{2} K n^2 = Y, \tag{C12}$$

(13) Value of vacancies:

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

(14) Recruiting intensity:

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

(15) Match value:

$$\left[1 - \beta(1-\delta)\right] J^F = Z - w + \beta\delta Kn, \tag{C15}$$

(16) Nash bargaining wage:

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

(17) Actual real wage

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

Appendix E. 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

$$h_1 + h_2\bar{s}(\hat{s}_t - 1) = \frac{q^u \hat{q}^u_t}{\bar{s} s_t} \left\{ \frac{b}{1-b}(J^F \hat{J}^F_t - Kn\hat{n}_t) - \frac{h_1\bar{s}(\hat{s}_t - 1) + \frac{h_2\bar{s}^2}{2}(\hat{s}_t - 1)^2}{1 - q^u \hat{q}^u_t} \right\} \tag{D3}$$

(4) Matching function

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

(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:

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

(8) Number of searching workers

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

(9) Unemployment:

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

(10) Vacancies:

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

(11) Aggregate production function:

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

(12) Aggregate Resource constraint:

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

(13) Value of vacancy:

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

(14) Recruiting intensity:

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

(15) Match value:

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

(16) Nash bargaining wage:

$$\frac{b}{1-b}(J^F \hat{J}_t^F - Kn\hat{n}_t) = w\hat{w}_t^N - \phi - \frac{\chi \exp(\hat{\chi}_t)}{\Lambda\hat{\Lambda}_t} + \frac{h_1\bar{s}(\hat{s}_t - 1) + \frac{h_2\bar{s}^2}{2}(\hat{s}_t - 1)^2}{1 - q^u\hat{q}_t^u}$$
$$+ E_t\frac{\beta\hat{\Lambda}_{t+1}}{\hat{\Lambda}_t}\left[(1 - \delta\exp(\hat{\delta}_{t+1}))\left(1 - q^u\hat{q}_{t+1}^u\right)\frac{b}{1-b}(J^F\hat{J}_{t+1}^F - Kn\hat{n}_{t+1})\right]. \quad \text{(D16)}$$

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

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

(18) Preference shock process

$$\hat{\chi}_t = \rho_\chi\hat{\chi}_{t-1} + \varepsilon_{\chi t}, \quad \text{(D18)}$$

(19) Technology shock process

$$\hat{z}_t = \rho_z\hat{z}_{t-1} + \varepsilon_{zt}, \quad \text{(D19)}$$

(20) Job separation shock process

$$\hat{\delta}_t = \rho_\delta\hat{\delta}_{t-1} + \varepsilon_{\delta t}, \quad \text{(D20)}$$

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