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 2016, 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 ratio.
(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 implies a much slower decline in the job filling rate and a much faster increase in the job finding rate than has actually occurred in recent data. The reason for these discrepancies is that the actual hiring rate has not increased as much as predicted by 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.

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 of whom are employed and the others unemployed. 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.

Our DSGE model 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

\(^1\) 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, \(\alpha\) measures the elasticity of matching with respect to unemployment, and \(\mu\) is a scale parameter that captures the average matching efficiency. With this matching function, the job filling rate is given by \(q^f_t \equiv \frac{m_t}{v_t} = \mu \left(\frac{u_t}{v_t}\right)^{1-\alpha}\) and the job finding rate is given by \(q^u_t \equiv \frac{m_t}{u_t} = \mu \left(\frac{u_t}{v_t}\right)^{-\alpha}\). 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 \(\alpha = 0.5\).
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.\textsuperscript{2}

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 \textit{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. In a recession, the job filling rate falls, and firms respond by exerting less recruiting efforts. However, since the match value and the vacancy value also both decline, the net value of filling a vacancy is ambiguous. Depending on model parameters, recruiting intensity may be pro- or counter-cyclical.

To examine the quantitative importance of cyclical fluctuations in search and recruiting intensity for the job filling and finding rates, we estimate 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 a sharp decline in the job filling rate and a sluggish increase in the job finding rate. These predictions are much more in line with the data than those from the standard model without intensive margins, as shown in Figure 1. Over the recovery period, the gap between our model’s predicted job filling rate and the actual data measured by the root mean square errors is reduced by about two-thirds relative to the gap implied by the standard model. We also obtain a quantitatively important improvement for fitting the job finding rate relative to the standard model.

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 only on the number of vacancies, but

\textsuperscript{2}We are not the first to introduce fixed costs of vacancy creation. Elsby, Michaels, and Ratner (2015) examine the effects of recruiting intensity on the Beveridge curve dynamics in a partial equilibrium model with fixed vacancy 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 u-v 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.
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 work complements theirs by providing a macro perspective on recruiting intensity. Despite the difference in approaches, the aggregate correlation between hiring and recruiting intensity obtained from our estimated DSGE model is remarkably close to that reported in Davis et al. (2013) based on microeconomic evidence.

II. 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 less on exogenous variations in matching efficiency and more on endogenous responses of search and recruiting intensity 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 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. 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 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 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 $N_{t-1}$ workers. A fraction $\delta_t$ of job matches are separated in any given period. We assume that the job separation rate $\delta_t$ is stochastic and follows the stationary process

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

In this shock process, $\rho_\delta$ 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 $\sigma_\delta$. 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

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

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 an entry cost. Newly created vacancies add to the existing stock of vacancies carried over from the previous period. In addition, newly separated jobs also add to the stock of vacancies, provided that the positions are not obsolete. We follow Fujita and Ramey (2007) and assume that a vacant position becomes obsolete at a constant rate of $\rho^o$. The law of motion for job vacancies $v_t$ is described by

$$v_t = (1 - \rho^o)v_{t-1} + (\delta_t - \rho^o)N_{t-1} + n_t, \quad (3)$$

where $n_t$ denotes newly created vacancies.

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

$$m_t = \mu(s_t u_t)^{\alpha}(a_t v_t)^{1-\alpha}, \quad (4)$$

where $m_t$ denotes the number of successful matches, $s_t$ denotes search intensity, $a_t$ denotes recruiting intensity (or advertising), the parameter $\mu$ 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 (i.e., the job filling rate) is given by

$$q_t^v = \frac{m_t}{v_t}. \quad (5)$$
The probability that an unemployed and searching worker finds a job (or the job finding rate) is given by

$$q_u^u = \frac{m_t}{u_t}. \quad (6)$$

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

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

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

$$U_t = u_t - m_t = 1 - N_t. \quad (8)$$

### 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

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

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 $\chi_t$ is a shock to the dis-utility of working, which follows the stationary stochastic process

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

In this shock process, $\rho_{\chi}$ 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 $\sigma_{\chi}$. 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

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

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, $q^u(s_t)$ denotes the job finding rate for the worker with search intensity level of $s_t$, $d_t$ denotes the household’s share of firm profits, and $T_t$ denotes lump-sum taxes. The parameter $\phi$ 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

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

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

$$q_u(s_{it}) = \frac{s_{it}}{s_tu_t}m_t,$$

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

$$\frac{\partial q_u(s)}{\partial s_i} = \frac{m_t}{s_tu_t} = \frac{q_u}{s_t},$$

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

$$h'(s_t) = \frac{q_u}{s_t}S_t^H,$$

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

$$S_t^H = w_t - \phi - \frac{\chi_t}{\Lambda_t} + E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} (1 - \delta_{t+1})(1 - q_u)S_{t+1}^H,$$

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 $q_u$ 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 \( (1 - \delta_{t+1})(1 - q_{t+1}^a) \), 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

\[
1 = E_t \beta \Lambda_{t+1} r_t. \tag{17}
\]

### 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.\(^3\) 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 \( \varepsilon_{zt} \) is an i.i.d. normal process with a zero mean and a finite variance of \( \sigma_z^2 \). 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 \( 1 - \delta_{t+1} \)), the firm continues; if the match breaks down, the firm posts a new job vacancy at a flow cost of \( \kappa_{jt} \), with the value \( J_{V_{j,t+1}} \). The value of a firm with a match is therefore given by the Bellman equation

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

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 an entry cost of \( x \) drawn from an i.i.d. distribution \( F(\cdot) \). A new vacancy is created if and only if \( x \leq J_{V_t} \), 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 $\eta$ is a scale parameter and $\xi$ 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 $\xi$ 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 posting a vacancy is an increasing and convex function of the level of advertising. In particular, we follow Pissarides (2000) and assume that

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

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

$$q^v(a_{jt}) = \frac{a_{jt}}{a_tv_t} m_t, \quad (22)$$

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

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

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

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

where, from (22), we have

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

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

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

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 falls, and firms respond by exerting less recruiting efforts. However, since the match value $J^F$ and the vacancy value $J^V$ both decline, the net value of filling a vacancy—the difference between $J^F$ and $J^V$—is 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

$$\kappa(a_t) = q_v^n J^F_t. \quad (27)$$

Furthermore, the optimal advertising choice (26) reduces to

$$\kappa'(a_t) = q_v^n a_t J^F_t. \quad (28)$$

These two equations together implies that

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

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 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.

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

$$\max_{w_t} \left( S^H_t \right)^b \left( J^F_t - J^V_t \right)^{1-b}, \quad (30)$$

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

$$b \left( J^F_t - J^V_t \right) \frac{\partial S^H_t}{\partial w_t} + (1 - b) S^H_t \frac{\partial \left( J^F_t - J^V_t \right)}{\partial w_t} = 0, \quad (31)$$
where, from the household surplus equation (16), we have \( \frac{\partial S^H}{\partial w_t} = 1 \); and from the firm’s value function (19), we have \( \frac{\partial (J^F_t - J^V_t)}{\partial w_t} = -1 \).

Define the total surplus as
\[
S_t = J^F_t - J^V_t + S^H_t.
\] (32)
The polishing solution is given by
\[
J^F_t - J^V_t = (1 - b)S_t, \quad S^H_t = bS_t.
\] (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 \( w^N_t \) satisfies the Bellman equation
\[
\frac{b}{1 - b} (J^F_t - J^V_t) = w^N_t - \phi - \frac{\chi_t}{\Lambda_t} + E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} \left[ (1 - \delta_{t+1})(1 - q^u_{t+1}) \frac{b}{1 - b} (J^F_{t+1} - J^V_{t+1}) \right].
\] (34)

III.5. Wage Rigidity. In general, however, equilibrium real wage may be different from the Nash bargaining solution. Indeed, Hall (2005a) and Shimer (2005) point out that real wage rigidity is important to generate empirically plausible volatilities of vacancies and unemployment.\(^4\) 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,
\[
w_t = w^N_{t-1}(w^N_t)^{1-\gamma},
\] (35)
where \( \gamma \in (0, 1) \) represents the degree of real wage rigidity.\(^5\)

III.6. Government policy. The government finances unemployment benefit payments \( \phi \) for unemployed workers through lump-sum taxes. We assume that the government balances the budget in each period so that
\[
\phi(1 - N_t) = T_t.
\] (36)

\(^4\)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.
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

\[ B_t = 0. \]  
(37)

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

\[ Y_t = Z_t N_t. \]  
(38)

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

\[ C_t + h(s_t)u_t + \kappa(a_t)v_t + n_t J^V_t = Y_t, \]  
(39)

where the last term on the left-hand 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 \( J^V_t \).

IV. **Empirical strategies**

We solve the DSGE model by log-linearizing 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

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

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

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.

We first calibrate a subset of model parameters using steady-state restrictions. These parameters include \( \beta \), the subjective discount factor; \( \chi \), the average dis-utility of working; \( \alpha \), the elasticity of matching with respect to searching workers; \( \mu \), the average matching efficiency; \( \bar{\delta} \), the average job separation rate; \( \rho^v \), the vacancy obsolescence rate; \( \phi \), the flow unemployment benefits; \( b \), the Nash bargaining weight; \( \kappa_0 \) and \( \kappa_1 \), the intercept and the slope of the vacancy cost function; \( h_1 \), the slope parameter of the search cost function; \( \gamma \),
the parameter that measures real wage rigidities; \( \xi \), the elasticity parameter in the vacancy-creation condition (20).

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; \( \kappa_2 \), the curvature of the vacancy-posting cost function; and \( h_2 \), the curvature of the search cost function. The shock parameters include \( \rho_z \) and \( \sigma_z \), the persistence and the standard deviation of the technology shock; \( \rho_\chi \) and \( \sigma_\chi \), the persistence and the standard deviation of the disutility shock, and \( \rho_\delta \) and \( \sigma_\delta \), 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 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 \( \rho_o = 0.0317 \). 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 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 \( \kappa_0 \) so that the total cost of posting vacancies is about 1 percent of gross output. To assign a value of \( \kappa_0 \) 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 \( \bar{\delta} = 0.034 \), 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 \( \kappa_1 = 0.10 \) 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 \( \bar{s} = 1 \).

---

\(^6\)Given our monthly job filling rate of \( q_v = 0.338 \), the quarterly filling rate is given by \( q_v + (1-q_v)q_v + (1-q_v)^2q_v = 0.71 \), which is the same value as in den Haan et al. (2000).
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 $\gamma = 0.95$, 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 November 2015, which is the available range of data from JOLTS.

The unemployment rate in the data (denoted by $U_{\text{data}}^t$) 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

$$\ln(U_{\text{data}}^t) - \ln(U_{\text{data}}) = \hat{U}_t,$$  \hspace{1cm} (42)

where $U_{\text{data}}$ 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

$$\ln(v_{\text{data}}^t) - \ln(v_{\text{data}}) = \hat{v}_t,$$  \hspace{1cm} (43)

where $v_{\text{data}}$ 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

$$s_t = A - Bd_t,$$  \hspace{1cm} (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.
IV.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 $K$, $\kappa_2$, and $h_2$ each follow 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 $\kappa_2$ 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 $\rho_z$, $\rho_\chi$, and $\rho_\delta$ each follow the beta distribution and the priors of $\sigma_z$, $\sigma_\chi$, and $\sigma_\delta$ each follow 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 18.189, with a 90% confidence interval from 14.058 to 23.448. The curvature parameter $\kappa_2$ of the vacancy-posting cost function has a posterior mean of 1.039 and a 90% confidence interval from 0.805 to 1.232. The curvature parameter $h_2$ of the search cost function has a posterior mean of 0.965 and a 90% confidence interval from 0.851 to 1.102. The posterior estimates are significantly different from the priors. Thus, the data seem to be quite informative about these structural parameters.

V. Economic implications

We now discuss the 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 an 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 job filling rate
in our model also declines because hiring drops more than does the number of vacancies. The decline in vacancies is also 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.

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 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 falls 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 (26), 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 \( q_v \) in the short run, 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 matching efficiency falls, as shown in the last panel of Figure 3. The measured matching efficiency here is defined as

\[
\Omega_t = \mu s_t^\alpha a_t^{1-\alpha}.
\]

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

Figures 4 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 declines in the stock of vacancies, leads to a gradual increase in the job filling rate.

Figures 5 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, newly 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 should also rise.

However, equilibrium adjustments of the hiring rate also depend on the responses of the intensive margins. In particular, since the job separation shock reduces the present value of a job match, firms respond by reducing recruiting intensity. This reduction in recruiting intensity, combined with an increase in unemployment, leads to a decline in the job finding rate for unemployed workers. Thus, households respond by reducing their search intensity. The reductions in both recruiting intensity and search intensity dampens the rise in the hiring rate. Accordingly, the job filling rate initially rises (since the vacancy rate rises slowly) and then falls below the steady state.

V.2. The Great Recession and the slow job recovery. The impulse responses show that search and recruiting intensity react procyclically to the shocks in our environment. We now illustrate 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 generating these observations. In particular, the standard model predicts incorrectly that the job filling and finding rates should have been higher than those observed in the data for most of the recovery period following the Great Recession.

Incorporating search and recruiting intensity in the model helps bring the job filling rate and the job finding rate much closer to those observed in the data. For instance, in our sample, the root mean squared error (RMSE) between the actual job filling rate and that predicted by the standard model is 0.287. In contrast, the RMSE between the actual data and that predicted from our estimated model is only 0.093, which is about one-third 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. Over the same period, the RMSE between the actual job finding rate and that predicted by the standard model is also about 0.287, whereas our estimated model implies a smaller RMSE of 0.16.

Davis et al. (2013) study establishment-level data and construct a measure of recruiting intensity. 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. 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.

Our model also implies a smoothed time-series of recruiting intensity conditional on the estimated parameters and shocks. Compared to Davis et al. (2013), we have followed a very different approach to obtaining an empirical measure of recruiting intensity \( (a_t) \). 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 0.82, which is, remarkably, the same as that reported by Davis et al. (2013), despite the clear differences in empirical methodologies. This surprising 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. We first compare the impulse responses in the benchmark model with two alternative counterfactual scenarios, one with constant search intensity (but variable recruiting intensity), and the other with constant recruiting intensity (and variable search intensity). We then examine the quantitative importance of using information from search intensity in the data by re-estimating the same model using an alternative measure of search intensity or estimating the model abstracting from data on search intensity.

V.3.1. Impulse responses under alternative model specifications. To compare impulse responses of our benchmark model with alternative specifications, we keep the parameters and the shock processes the same as in the estimated benchmark model. We focus on the effects of a negative technology shock.

Figure 6 shows the impulse responses to a negative technology shock in the benchmark model (the black solid lines), the counterfactual model with constant search intensity (the blue dashed lines), and the counterfactual with constant recruiting intensity (the red dashed and dotted lines).

The figure highlights that, when either intensive margins is held constant, the responses of the job finding and filling rates and the measured match efficiency are about half that in the benchmark model. The counterfactual models also imply more muted increases in the unemployment rate and smaller declines in the hiring rate. When recruiting intensity is held constant, firms rely more on varying the number of vacancies to respond to the negative technology shock. Thus, the vacancy rate declines slightly more than in the benchmark case. Overall, Figure 6 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.

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).\(^7\)

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 estimating our model using a less procyclical search intensity measure. For instance, we set the value of \(B\) in equation (44) to a smaller value of 0.9 (instead of 1.54), following the alternative estimate of Davis (2011). In addition, we also report results when we only fit the model to the unemployment and vacancy rates, without using information of search intensity in the data.

When we use a less procyclical measure of search intensity (with \(B = 0.9\) instead of 1.54), we obtain similar qualitative estimation results. Figure 7 shows the job filling and

\(^7\)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.
finding rates from this re-estimated model and compare them to those in the data and
from the standard model without search and recruiting intensity. The figure shows that
the model estimated with the less procyclical search intensity series also outperforms the
standard model without search and recruiting intensity in fitting the observed time series of
job filling and finding rates. Compared to the actual data, the job filling rate predicted by
the estimated model with less procyclical search intensity has an RMSE of 0.086 over our
sample period, similar to our benchmark model and substantially smaller than that implied
by the standard matching function (0.287). The job finding rate predicted by the estimated
mode has also a much smaller RMSE relative to the data than that implied by the standard
matching function (0.187 vs. 0.287).

The results obtained in our benchmark model are also robust when we re-estimate the
model to fit unemployment and vacancies, without using search intensity data (see Figure 8).
In this case, the RMSEs for the job filling and finding rates predicted by the estimated
model are 0.116 and 0.200, respectively, both are smaller than those implied by the standard
matching function (0.287), but somewhat higher than under our benchmark estimation.

However, when we fit the model to a less procyclical search intensity series or without
fitting to any search intensity series, the hiring 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 0.62 when the model is
fitted to a less procyclical search intensity series, and it becomes even lower at 0.32 when the
model is estimated without fitting to any search intensity series. In comparison, under our
benchmark estimation, the model implied hiring has a significantly higher correlation with
the data (0.69). 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 fit the model to a less procyclical search intensity, the
model-implied recruiting intensity and hiring display a much smaller correlation than in the
benchmark estimation (0.10 vs. 0.82). Similarly, the correlation between recruiting intensity
and hiring is small when we do not use any information from search intensity to estimate the
model (0.22). The correlations obtained in these two alternative cases are also much weaker
than those 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 Recession. 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 incorporate endogenous job separations and labor force participation for understanding labor market fluctuations and for policy designs. Our work provides a step forward along this research agenda.
Table 1. Calibrated parameters

<table>
<thead>
<tr>
<th>Parameter Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$ Subjective discount factor</td>
<td>0.9967</td>
</tr>
<tr>
<td>$\phi$ Unemployment benefit</td>
<td>0.25</td>
</tr>
<tr>
<td>$\alpha$ Elasticity of matching function</td>
<td>0.50</td>
</tr>
<tr>
<td>$\mu$ Matching efficiency</td>
<td>0.353</td>
</tr>
<tr>
<td>$\bar{\delta}$ Job separation rate</td>
<td>0.034</td>
</tr>
<tr>
<td>$\rho^o$ Vacancy obsolescence rate</td>
<td>0.0317</td>
</tr>
<tr>
<td>$\kappa_0$ Steady-state advertising cost</td>
<td>0.0994</td>
</tr>
<tr>
<td>$\kappa_1$ Slope of vacancy posting cost</td>
<td>0.10</td>
</tr>
<tr>
<td>$h_1$ Slope of search cost</td>
<td>0.1089</td>
</tr>
<tr>
<td>$b$ Nash bargaining weight</td>
<td>0.50</td>
</tr>
<tr>
<td>$\gamma$ Real wage rigidity</td>
<td>0.95</td>
</tr>
<tr>
<td>$\xi$ Elasticity of vacancy creation</td>
<td>1</td>
</tr>
<tr>
<td>$\bar{\chi}$ Mean value of preference shock</td>
<td>0.666</td>
</tr>
<tr>
<td>$\bar{Z}$ Mean value of technology shock</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 2. Estimated parameters

<table>
<thead>
<tr>
<th>Parameter description</th>
<th>Prior type[mean, std]</th>
<th>Posterior</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>$K$  scale of vacancy creation</td>
<td>gamma[10, 5]</td>
<td>18.1893</td>
</tr>
<tr>
<td>$\kappa_2$ curvature of vacancy posting</td>
<td>gamma[0.5, 0.1]</td>
<td>1.0390</td>
</tr>
<tr>
<td>$h_2$ curvature of search cost</td>
<td>gamma[0.5, 0.1]</td>
<td>0.9652</td>
</tr>
<tr>
<td>$\rho_z$ AR(1) of technology shock</td>
<td>beta[0.3333, 0.2357]</td>
<td>0.8971</td>
</tr>
<tr>
<td>$\rho_X$ AR(1) of preference shock</td>
<td>beta[0.3333, 0.2357]</td>
<td>0.5980</td>
</tr>
<tr>
<td>$\rho_\delta$ AR(1) of job separation shock</td>
<td>beta[0.3333, 0.2357]</td>
<td>0.8507</td>
</tr>
<tr>
<td>$\sigma_z$ std of technology shock</td>
<td>inv gamma[0.01, 1]</td>
<td>0.0229</td>
</tr>
<tr>
<td>$\sigma_X$ std of preference shock</td>
<td>inv gamma[0.01, 1]</td>
<td>0.4143</td>
</tr>
<tr>
<td>$\sigma_\delta$ std of preference shock</td>
<td>inv gamma[0.01, 1]</td>
<td>0.0729</td>
</tr>
</tbody>
</table>
Figure 1. Job filling rate and job finding rate: Data, standard model, and benchmark DSGE model. The shaded areas indicate recession dates.
**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 positive disutility shock
Figure 5. Impulse responses to a positive job separation shock
Figure 6. Impulse responses to a negative technology shock: Alternative models
Figure 7. Job filling rate and job finding rate: Data, standard model, and DSGE model estimated with less procyclical search intensity. The shaded areas indicate recession dates.
Figure 8. 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. 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

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

subject to

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

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

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

$$
u_t = 1 - (1 - \delta_t) N_{t-1}. \quad (A3)$$

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

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

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

$$
\frac{\partial N_t}{\partial s_t} = \frac{\partial q^u(s_t)}{\partial s_t} [1 - (1 - \delta_t) N_{t-1}]. \quad (A5)
$$
To derive the optimizing decisions for the household, we rewrite the household’s problem in the recursive form

\[ V_t(B_{t-1}, N_{t-1}) \equiv \max A_t [\ln C_t - \chi_t N_t] + \beta E_t V_{t+1}(B_t, N_t), \]  

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

\[ \Lambda_t = \frac{A_t C_t}{\lambda_t}. \]  

(A7)

Optimal choice of search intensity \( s_t \) implies that

\[ \Lambda_t h'(s_t) = \frac{q^u_{s_t}}{s_t} \left[ \Lambda_t (w_t - \phi) - A_t \chi_t + \beta E_t \frac{\partial V_{t+1}(B_t, N_t)}{\partial N_t} \right] \]  

(A8)

where we have used equation (14) to replace the term \( \frac{\partial q^u(s_t)}{\partial s_t} \) by \( \frac{q^u_{s_t}}{s_t} \). The envelope condition implies that

\[ \frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_{t-1}} = \left[ \Lambda_t (w_t - \phi) - A_t \chi_t + \beta E_t \frac{\partial V_{t+1}(B_t, N_t)}{\partial N_t} \right] \frac{\partial N_t}{\partial N_{t-1}} - \Lambda_t (w_t - \phi - A_t \chi_t) \Lambda_t \]  

(A9)

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

\[ S^H_t = \frac{1}{\Lambda_t} \frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_t} = \frac{1}{\Lambda_t} \frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_{t-1}} \frac{\partial N_{t-1}}{\partial N_t} = \frac{1}{\Lambda_t} \frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_{t-1}} (1 - \delta_t)(1 - q^u(s_t)). \]  

(A10)

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

\[ S^H_t = w_t - \phi - \frac{A_t \chi_t}{\Lambda_t} + E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} (1 - \delta_t)(1 - q^u_{t+1}) S^H_{t+1}. \]  

(A11)

The employment surplus \( S^H_t \) derived here corresponds to equation (16) 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:

\[ h'(s_t) = \frac{q^u_{s_t}}{s_t} \left[ w_t - \phi - \frac{A_t \chi_t}{\Lambda_t} + E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} (1 - \delta_t)(1 - q^u_{t+1}) S^H_{t+1} \right] = \frac{q^u_{s_t}}{s_t} S^H_t. \]  

(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 (15) in the text.

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

$$\frac{\Lambda_t}{r_t} = \beta E_t \frac{\partial V_{t+1}(B_t, N_t)}{\partial B_t}.$$  \hfill (A13)

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

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

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

$$1 = E_t \frac{\beta \Lambda_{t+1}}{\Lambda_t} r_t,$$ \hfill (A15)

which is the intertemporal Euler equation (17) 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

$$[C_t, \Lambda_t, m_t, q^u_t, q^v_t, N_t, u_t, U_t, Y_t, r_t, v_t, J^F_t, w^N_t, w_t, n^e_t, a_t, s_t].$$

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

1. Household’s bond Euler equation:

$$1 = E_t \beta \frac{\Lambda_{t+1}}{\Lambda_t} r_t,$$ \hfill (B1)

2. Marginal utility of consumption

$$\Lambda_t = \frac{1}{C_t},$$ \hfill (B2)

3. Search intensity

$$h_1 + h_2(s_t - \bar{s}) = \frac{q^u_t}{s_t} \frac{b}{1-b}(J^F_t - J^V_t),$$ \hfill (B3)

4. Matching function

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

5. Job finding rate

$$q^u_t = \frac{m_t}{u_t},$$ \hfill (B5)

6. Vacancy filling rate

$$q^v_t = \frac{m_t}{v_t},$$ \hfill (B6)
(7) **Employment dynamics:**
\[ N_t = (1 - \delta_t)N_{t-1} + m_t, \]  
(B7)

(8) **Number of searching workers:**
\[ u_t = 1 - (1 - \delta_t)N_{t-1}, \]  
(B8)

(9) **Unemployment:**
\[ U_t = 1 - N_t, \]  
(B9)

(10) **Law of motion for vacancies:**
\[ v_t = (1 - \rho^o)v_{t-1} + (\delta_t - \rho^o)N_{t-1} + n_t, \]  
(B10)

(11) **Aggregate production function:**
\[ Y_t = Z_tN_t \]  
(B11)

(12) **Aggregate Resource constraint:**
\[ C_t + h(s_t)u_t + \kappa(a_t)v_t + Kn^{1+\xi}_t = Y_t, \]  
where the search cost function and the recruiting cost function are given by
\[ h(s_t) = h_1(s_t - \bar{s}) + \frac{h_2}{2}(s_t - \bar{s})^2 \]
\[ \kappa(a_t) = \kappa_0 + \kappa_1(a_t - \bar{a}) + \frac{\kappa_2}{2}(a_t - \bar{a})^2 \]  
(B12)

(13) **Value of vacancy:**
\[ Kn_t = -\kappa(a_t) + q^v_tJ^F_t + (1 - q^v)(1 - \rho^o)E_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}Kn_{t+1}^{\xi}. \]  
(B13)

(14) **Recruiting intensity:**
\[ \kappa_1 + \kappa_2(a_t - \bar{a}) = \frac{q^v_t}{\alpha_t}\left[J^F_t - (1 - \rho^o)E_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}Kn^{\xi}_t\right]. \]  
(B14)

(15) **Match value:**
\[ J^F_t = Z_t - w_t + E_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}\left\{(1 - \delta_{t+1})J^F_{t+1} + \delta_{t+1}Kn_{t+1}^{\xi}\right\}. \]  
(B15)

(16) **Nash bargaining wage:**
\[ \frac{b}{1 - b}(J^F_t - Kn_{t}^{\xi}) = w^N_t - \phi - \chi_t\frac{A_t}{\Lambda_t} + E_t\frac{\beta\Lambda_{t+1}}{\Lambda_t}\left[(1 - \delta_{t+1})(1 - q^v_{t+1})\frac{b}{1 - b}(J^F_{t+1} - Kn_{t+1}^{\xi})\right]. \]  
(B16)

(17) **Actual real wage (with real wage rigidity)**
\[ w_t = w^\gamma_{t-1}(w^N_t)^\gamma, \]  
(B17)
THE SLOW JOB RECOVERY

APPENDIX C. STEADY STATE

(1) Household’s bond Euler equation:
\[ 1 = \beta r, \]  
(C1)

(2) Marginal utility of consumption
\[ \Lambda = \frac{1}{C}, \]  
(C2)

(3) Search intensity
\[ h_1 = \frac{q^u}{s} \frac{b}{1-b} (J^F - Kn^\xi), \]  
(C3)

(4) Matching function
\[ m = \mu(\bar{s}u)^\alpha(\bar{a}v)^{1-\alpha}, \]  
(C4)

(5) Job finding rate
\[ q^u = \frac{m}{u}, \]  
(C5)

(6) Vacancy filling rate
\[ q^v = \frac{m}{v}, \]  
(C6)

(7) Employment dynamics:
\[ m = \delta N, \]  
(C7)

(8) Number of searching workers:
\[ u = U + m, \]  
(C8)

(9) Unemployment:
\[ U = 1 - N, \]  
(C9)

(10) Vacancies:
\[ \rho^o v = (1 - \rho^o) \rho^s N + n, \]  
(C10)

(11) Aggregate production function:
\[ Y = ZN \]  
(C11)

(12) Aggregate Resource constraint:
\[ C + \kappa_0 v + Kn^{1+\xi} = Y, \]  
(C12)

(13) Value of vacancies:
\[ q^v J^F - \kappa_0 = [1 - \beta (1 - q^v)(1 - \rho^o)] Kn^\xi \]  
(C13)

(14) Recruiting intensity:
\[ \kappa_1 \bar{a} = q^v [J^F - \beta(1 - \rho^o)Kn^\xi], \]  
(C14)
(15) Match value:
\[ [1 - \beta (1 - \delta)] J^F = Z - w + \beta \delta Kn^\xi, \]  
(C15)

(16) Nash bargaining wage:
\[ w^N = \phi + \frac{\chi}{\Lambda} + \frac{b}{1 - b} [1 - \beta (1 - \delta)(1 - q^n)] (J^F - Kn^\xi), \]  
(C16)

(17) Actual real wage
\[ w = w^N, \]  
(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
\[ [\hat{\bar{C}}_t, \hat{\Lambda}_t, \hat{r}_t, \hat{Y}_t, \hat{\bar{m}}_t, \hat{\bar{u}}_t, \hat{\bar{v}}_t, \hat{\bar{q}}^u_t, \hat{\bar{q}}^v_t, \hat{\bar{N}}_t, \hat{\bar{U}}_t, \hat{\bar{J}}^F_t, \hat{\bar{w}}^N_t, \hat{\bar{w}}_t, \hat{\bar{n}}_t, \hat{\bar{a}}_t, \hat{\bar{s}}_t]. \]

(1) Household’s bond Euler equation:
\[ 1 = E_t \hat{\Lambda}_{t+1} \hat{r}_t, \]  
(D1)

(2) Marginal utility of consumption
\[ \hat{\Lambda}_t = \frac{1}{\hat{C}_t}, \]  
(D2)

(3) Search intensity
\[ h_1 + h_2 \hat{s}_t (\hat{s}_t - 1) = \frac{q^n \hat{q}^u}{\hat{s}_t} \frac{b}{1 - b} (J^F \hat{J}^F_t - Kn^\xi \hat{n}^\xi_t), \]  
(D3)

(4) Matching function
\[ \hat{m}_t = \exp(\hat{\mu}_t) (\hat{s}_t \hat{u}_t)^{\alpha} (\hat{a}_t \hat{v}_t)^{1-\alpha}, \]  
(D4)

(5) Job finding rate
\[ \hat{q}^u_t = \frac{\hat{m}_t}{\hat{u}_t}, \]  
(D5)

(6) Vacancy filling rate
\[ \hat{q}^v_t = \frac{\hat{m}_t}{\hat{v}_t}, \]  
(D6)

(7) Employment dynamics:
\[ \hat{N}_t = (1 - \delta \hat{\delta}_t) \hat{N}_{t-1} + \frac{m}{N} \hat{m}_t, \]  
(D7)

(8) Number of searching workers
\[ \hat{u} \hat{u}_t = 1 - (1 - \delta \hat{\delta}_t) N \hat{N}_{t-1}, \]  
(D8)
(9) Unemployment:
\[ U_\hat{U}_t = 1 - N \hat{N}_t, \]  
\text{(D9)}

(10) Vacancies:
\[ v_\hat{v}_t = (1 - \rho^o)v_\hat{v}_{t-1} + (\delta_\hat{\delta}_t - \rho^o)N \hat{N}_{t-1} + n_\hat{n}_t^\xi, \]  
\text{(D10)}

(11) Aggregate production function:
\[ \hat{Y}_t = \exp(\hat{\gamma}_t) \hat{N}_t \]  
\text{(D11)}

(12) Aggregate Resource constraint:
\[ \hat{Y}_t = \left[ h_1 s(\hat{s}_t - 1) + \frac{h_2 s^2}{2} (\hat{s}_t - 1)^2 \right] \frac{u}{Y} \hat{u}_t + \left[ \kappa_0 + \kappa_1 \bar{a} (\hat{a}_t - 1) + \frac{\kappa_2 \bar{a}^2}{2} (\hat{a}_t - 1)^2 \right] \frac{v}{Y} \hat{v}_t 
+ \frac{C}{Y} \hat{C}_t + \frac{K n^{1+\xi}}{Y} \hat{n}_t^{1+\xi}, \]  
\text{(D12)}

(13) Value of vacancy:
\[ Kn^\xi \hat{n}_t^\xi = - \left[ \kappa_0 + \kappa_1 \bar{a} (\hat{a}_t - 1) + \frac{\kappa_2 \bar{a}^2}{2} (\hat{a}_t - 1)^2 \right] + \]
\[ q^v J^F \hat{q}^v_\bar{a} \hat{J}^F + (1 - q^v \hat{q}^v_\bar{a})(1 - \rho^o)E_t \frac{\beta \hat{\Lambda}_{t+1}}{\Lambda_t} Kn^\xi \hat{n}_t^{\xi+1}, \]  
\text{(D13)}

(14) Recruiting intensity:
\[ \kappa_1 + \kappa_2 \bar{a} (\hat{a}_t - 1) = \frac{q^v \hat{q}^v_\bar{a}}{\bar{a} \hat{a}_t} \left[ J^F \hat{J}^F - (1 - \rho^o)E_t \frac{\beta \hat{\Lambda}_{t+1}}{\Lambda_t} Kn^\xi \hat{n}_t^{\xi+1} \right]. \]  
\text{(D14)}

(15) Match value:
\[ J^F \hat{J}^F_t = Z \hat{Z}_t - w_\hat{w}_t + E_t \frac{\beta \hat{\Lambda}_{t+1}}{\Lambda_t} \left\{ (1 - \delta_\hat{\delta}_t) J^F \hat{J}^F_{t+1} + \delta_\hat{\delta}_t Kn^\xi \hat{n}_t^{\xi+1} \right\}, \]  
\text{(D15)}

(16) Nash bargaining wage:
\[ \frac{b}{1 - b} (J^F \hat{J}^F_t - Kn^\xi \hat{n}_t^\xi) = w_\hat{w}_t^N - \phi - \chi \frac{A \exp(\hat{\chi}_t + A_t)}{\Lambda \hat{\Lambda}_t} \]
\[ + E_t \frac{\beta \hat{\Lambda}_{t+1}}{\Lambda_t} \left[ (1 - \delta_\hat{\delta}_t) (1 - q^v \hat{q}^v_\bar{a}) \frac{b}{1 - b} (J^F \hat{J}^F_{t+1} - Kn^\xi \hat{n}_t^{\xi+1}) \right]. \]  
\text{(D16)}

(17) Actual real wage (with real wage rigidity)
\[ \hat{w}_t = \hat{w}_{t-1}^\gamma (\hat{w}_t^N)^\gamma, \]  
\text{(D17)}

(18) Preference shock process
\[ \hat{\chi}_t = \rho_\chi \hat{\chi}_{t-1} + \varepsilon_{\chi t}, \]  
\text{(D18)}
(19) Technology shock process

\[ \dot{z}_t = \rho_z \dot{z}_{t-1} + \varepsilon_{zt}, \]  
(D19)

(20) Job separation shock process

\[ \dot{\delta}_t = \rho_{\delta} \dot{\delta}_{t-1} + \varepsilon_{\delta t}, \]  
(D20)
References


Federal Reserve Bank of San Francisco