Unemployment Benefits and Matching Efficiency in an Estimated DSGE Model with Labor Market Search Frictions*

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Abstract

To explain the high and persistent unemployment rate in the U.S. during and after the Great Recession, this effort develops and estimates a DSGE model with search and matching frictions and shocks to unemployment benefits and matching efficiency. It finds that the unemployment benefits play an important role in the cyclical movement of unemployment through their effects on labor demand, a channel overlooked in previous studies. From the second half of 2008 to 2011, extended unemployment benefits may have increased the overall unemployment rate by 1 percentage point. In contrast, matching efficiency changes have less effect on the cyclical movement of unemployment for the same period, but significantly slowed down the recovery after 2012.

Keywords: DSGE, search and matching frictions, unemployment benefits, matching efficiency

JEL codes: E24, E32, E52

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1 Introduction

The effects of unemployment benefits on unemployment are the subject of an active policy debate. Most existing empirical literature investigating the effects of unemployment benefits have focused on the micro effect – namely, the unemployment benefits reduce workers' search efforts – but ignore two potentially large general equilibrium effects. The first of these is that unemployment benefits may have a stimulative effect on aggregate demand. The second effect is unemployment benefits reduce firm vacancy creation, which is consistent with the Mortensen-Pissarides framework. The latter effect was studied by Hagedorn, Karahan, Manovskii, and Mitman (2013, 2015) and Mitman and Rabinovich (2014). The model in Mitman and Rabinovich (2014) was designed to study the effect on vacancy creation, but does not incorporate the impact of unemployment benefits on aggregate demand. However, these two effects work in opposite directions, so a DSGE model incorporating both effects is necessary to assess their magnitudes quantitatively. The empirical methodology in Hagedorn et al. (2013, 2015) is based on differences between states and border counties and thus it differences out part of the stimulative effect of unemployment benefits that affects those counties symmetrically. An aggregate model is needed to assess the magnitude of this stimulative effect. This paper offers a model to assess the overall effects of the extended unemployment benefits policy, and is the main contribution of the paper.

In this paper, a DSGE model is built to include labor market search and matching frictions and unemployment benefits shocks. Different from most existing models with search and matching frictions, this model does not exogenously set real wages to be rigid by assuming staggered Nash bargaining or Calvo-type wage stickiness. Instead, it matches the inertial wage dynamics in the data by estimating the value of leisure and other labor market structural parameters. The advantage is generating inertia wage endogenously. This strategy is used by Christiano, Eichenbaum and Trabandt (2013) as well, however, they used an alternative bargaining set-up, which is much more complicated than but does deliver similar results to the Nash bargaining process used here.

Zhang (2014) also investigated the effect of unemployment benefits program from the aspect of labor demand. However, there are two main differences between this current paper and Zhang (2014). First, this paper provides an estimated model, while Zhang (2014) studied a calibrated model and referred to the estimation results in this paper when calibrating the parameters related to unemployment benefits policies. Second, this paper models the economy for the past 40 years and uses data from 1976 to the present, while Zhang (2014) focused on the Great Recession and introduced the zero lower bound on the nominal interest rate and liquidity shocks to capture the main characteristics of the Great Recession only. I do not introduce the zero lower bound and liquidity shocks here for three reasons. First of all, the nonlinearity problem caused by the zero lower bound is more difficult to deal with during the estimation procedure than in a calibrated model. Second, the labor market issues during the Great Recession are the motivation and one application, but those are not the whole picture in this paper, and the zero lower bound and liquidity shocks, which mainly influence aggregate demand, do not affect the labor demand channel focused on in this paper. Introducing too many other aspects can contaminate the main message in this paper. Third, in Zhang (2014), a comparison between the zero lower bound case and the normal case shows that under both circumstances, positive unemployment benefits shocks slow down the labor market recovery, and the key difference between these two scenarios is that positive unemployment benefits shocks have a larger stimulative effect at the beginning of the recession if the zero lower bound is binding due to a non-increasing real interest rate. However, none of the results in this current paper either indicate or rely on that the initial rise in unemployment during the Great Recession was mainly caused by unemployment benefits shocks. Thus, difference between these two scenarios is not crucial in this current study. Considering these three reasons, the model is kept simple, and the zero lower bound issue is not discussed in this paper.

One of the primary findings of this paper is that shocks to unemployment benefits have historically played a very important role in unemployment fluctuations. In the model offered here, shocks to unemployment benefits account for more than 27% of the variation in unemployment over the long term. During the Great Recession and the early recovery period (from the second half of 2008 to the end of 2011), unemployment benefits shocks contributed to the high unemployment rate. Particularly, during the period from the end of 2009 to 2011, unemployment benefits shocks increased the unemployment rate by more than one percentage point. While the unemployment benefits shocks accounted for a large proportion of the high unemployment during 2009 to 2011, matching efficiency shocks significantly slowed down the labor market recovery from 2011 to the end of 2013. However, when unemployment benefits shocks are not taken into account, over 40% of unemployment variations can be explained by matching efficiency shocks, which is grossly overestimated since the effects of unemployment benefits shocks are largely picked up by the matching efficiency shocks.

The remainder of this paper is structured as follows. Section 2 sets up the model. Section 3 presents the estimation of the model parameters. Section 4 presents the results for the baseline model. Section 5 gives the results of robustness checks. Finally, Section 6 concludes the paper.

2 The Model

The primary framework of the model I use follows Smets and Wouters (2007). The model considers three types of agents: households, intermediate goods firms, and final goods firms. And like Smets and Wouters (2007), I introduce a number of exogenous shocks in the model.

2.1 Household

There is a representative household in the economy and there are a continuum of members, indexed by i, measured on $[0, 1]$ in the household. Every member has the same period utility function: $\frac{(c_t - h\mathcal{C}_{t-1})^{1-\sigma}}{1-\sigma}$, where the utility depends not only on their own consumption of final goods c_t, but also on the past aggregate consumption in the economy, $\mathcal{C}_{t-1}$. I define h as the habit formation parameter. Unlike Smets and Wouters (2007), I don't include the intensive margin of employment, because Gertler, Sala and Trigari (2008) found that most of the cyclical variation in employment in the United States is on the extensive margin and including the intensive margin does not affect the model very much. Leisure is not considered in the utility function here. Instead, it appears in the budget constraint. That is, the value of being unemployed is measured in consumption goods and considered a part of the household's income. People in a household pool their income together for consumption. The household does not make the labor supply decision. All unemployed members search on the job market and the frictional search and matching process determines who is employed. The representative household maximizes:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{(C_t - h\mathcal{C}_{t-1})^{1-\sigma}}{1-\sigma} \tag{1}$$

s.t.

$$\begin{aligned} C_t + I_t + \frac{B_t}{\epsilon_t^b r_t P_t} = & \int_0^1 \chi_{it} W_{it} di + \frac{B_{t-1}}{P_t} + r_t^k d_t K_{t-1}^H - D(d_t) K_{t-1}^H \\ & + D_t + \int_0^1 (1-\chi_{it})(A_t + G_t^u) di - T_t \end{aligned} \tag{2}$$

The inter-temporal discount factor is β, and the consumption of the family members at period t is C_t. The consumption C_t is a CES function over a continuum of goods with elasticity of substitution ϵ_t^p,

$$C_t = [\int_0^1 (C_{\widetilde{j}t})^{\frac{\epsilon_t^p - 1}{\epsilon_t^p}} d\widetilde{j}]^{\frac{\epsilon_t^p}{\epsilon_t^p - 1}}, \epsilon_t^p > 1$$

where $\widetilde{j}$ is the index of the differentiated final consumption goods, and ϵ_t^p follows $\log \epsilon_t^p = (1-\psi_p)\log \epsilon^p + \psi_p \log \epsilon_{t-1}^p - \mu^p \nu_{t-1}^p + \nu_t^p$. All innovations in this paper, including ν_t^p, are *i.i.d.* random variables with mean 0.

The price for the consumption good is P_t. The investment is represented by I_t. The bond holding is B_t, and the gross nominal interest rate controlled by the central bank is r_t. The risk premium shock is ϵ_t^b, which follows $\log \epsilon_t^b = \psi_b \log \epsilon_{t-1}^b + \nu_t^b$.

The household's disposable real labor income earned by member i is represented by W_{it}. The indicator for employment status, χ_t, equals 1 when the person is employed in period t, and 0 otherwise. The flow value from unemployment includes unemployment benefits paid by the government G_t^u, as well as other factors (such as leisure) that can be measured in units of consumption goods $A_t = \iota^t A$, where ι is the deterministic growth rate of output. I assume A_t has the same deterministic growth rate as output does; in this way, leisure wouldn't become less and less valuable as the economy grows.

The stock of capital at the end of period $t-1$ held by the household is K_{t-1}. The net return to capital is expressed as the return on the capital used minus the cost associated with variations in the degree of capital utilization: $(r_t^k d_t K_{t-1}^H - D(d_t) K_{t-1}^H)$. The income from renting out capital services depends on the level of capital stock and its utilization rate d_t. The cost of capital utilization is assumed to be zero when capital is fully used (*i.e.* $D(1) = 0$).

The profit from the final goods sector is D_t; the lump-sum tax is T_t.

The accumulation of capital obeys the following rule:

$$K_t^H = (1-\delta) K_{t-1}^H + \epsilon_t^I [1 - \psi(I_t / I_{t-1})] I_t, \tag{3}$$

where $\psi(\cdot)$ is the investment adjustment costs, which equals zero when the investment grows at the deterministic growth trend ι ($\psi(\iota) = 0$). The adjustment cost function also satisfies $\psi'(\iota) = 0$ and $\psi''(\iota) > 0$. ϵ_t^I is the shock to installation cost, which follows $\log \epsilon_t^I = \psi_I \log \epsilon_{t-1}^I + \nu_t^I$.

The representative household maximizes its utility by choosing consumption, bond holdings, investment, capital stock, and the capital utilization rate. The first order conditions for the household's problem are:

$$C_t : (C_t - h\mathcal{C}_{t-1})^{-\sigma} = \widetilde{\lambda}_{1t} \tag{4}$$

$$B_t : \widetilde{\lambda}_{1t} = \beta \mathbb{E}_t(\widetilde{\lambda}_{1t+1}\epsilon_t^b r_t \frac{P_t}{P_{t+1}}) \tag{5}$$

$$\begin{aligned} I_t : Q_t\psi'(\frac{I_t}{I_{t-1}})\frac{\epsilon_t^I I_t}{I_{t-1}} - \beta\mathbb{E}_t[Q_{t+1}\frac{\widetilde{\lambda}_{1t+1}}{\widetilde{\lambda}_{1t}}\psi'(\frac{I_{t+1}}{I_t})\frac{\epsilon_{t+1}^I I_{t+1}}{I_t}\frac{I_{t+1}}{I_t}] + 1 \\ = Q_t\epsilon_t^I(1 - \psi(\frac{I_t}{I_{t-1}})) \end{aligned} \tag{6}$$

$$K_t^H : Q_t = \beta\mathbb{E}_t\{\frac{\widetilde{\lambda}_{1t+1}}{\widetilde{\lambda}_{1t}}[Q_{t+1}(1-\delta) + d_{t+1}r_{t+1}^k - D(d_{t+1})]\} \tag{7}$$

$$d_t : r_t^k = D'(d_t) \tag{8}$$

where

$$Q_t = \frac{\widetilde{\lambda}_{2t}}{\widetilde{\lambda}_{1t}}. \tag{9}$$

Tobin's q is represented by Q_t, and the Lagrangian multipliers for the budget constraint and capital accumulation constraint are represented by $\widetilde{\lambda}_{1t}$ and $\widetilde{\lambda}_{2t}$ respectively.

2.2 Intermediate Goods Sector

The intermediate goods sector is perfectly competitive; each firm hires one worker and rents capital to produce identical intermediate goods.

Matching

At the beginning of period t, existing matches are terminated with an exogenous probability $0 \leq \rho < 1$, N_t pairs of matched workers and firms survive from the separation, and $U_t = 1 - N_t$ workers are unemployed.

After the separation process, remaining matches enter production, all unemployed workers go to the labor market, and new matches between workers and firms are formed. The number of new matches in period t is M_t. These new matches enter production in the next period, after surviving both separations. The total number of matches evolves according to:

$$N_{t+1} = (1 - \rho)(N_t + M_t). \tag{10}$$

The number of new matches in period t depends on the amount of vacancies posted by the firms, V_t, and the number of unemployed workers, U_t. The matching function $M_t(U_t, V_t)$ takes the form $\epsilon_t^M \mathcal{M} U_t^{\zeta} V_t^{1-\zeta}$, where $\mathcal{M}$ is the scale parameter representing the aggregate matching efficiency. The matching efficiency shock ϵ_t^M follows $\log \epsilon_t^M = \psi_M \log \epsilon_{t-1}^M + \nu_t^M$. In the literature, many papers have attempted to estimate the matching efficiency. They found that the matching efficiency does change pro-cyclically. A shock to the scale parameter of the matching function allows fluctuations in the matching efficiency in the model. An increase in the degree of the mismatch, such as the skill mismatch and geographic mismatch, worsens the efficiency of the labor market, and could be considered a negative matching efficiency shock.

The probability of a worker finding a job (the job-finding rate) is given by

$$\rho_t^w = \frac{M_t(U_t, V_t)}{U_t} = \epsilon_t^M \mathcal{M} \theta_t^{1-\zeta}, \tag{11}$$

and the probability of a vacancy being filled (the vacancy-filling rate) is

$$\rho_t^f = \frac{M_t(U_t, V_t)}{V_t} = \epsilon_t^M \mathcal{M} \theta_t^{-\zeta}, \tag{12}$$

where $\theta_t = V_t / U_t$ is the labor market tightness.

Firm's Decision

The production function of a matched firm j follows

$$Y_{jt}^I = z_t \iota^{t(1-\alpha)} K_{jt}^{\alpha}. \tag{13}$$

The common technology shock z_t follows an AR(1) process: $\log z_t = \psi_z \log z_{t-1} + \nu_t^z$. And ι is the deterministic labor-augmenting growth rate. Intermediate goods are sold in a competitive market at the given price P_t^I.

Firms that survived from the separation choose capital optimally by maximizing

$$\frac{z_t K_{jt}^{\alpha} \iota^{t(1-\alpha)}}{\mu_t} - r_t^k K_{jt},$$

where $\mu_t = \frac{P_t}{P_t^I}$ is the price markup. The optimal capital level is:

$$K_{jt}^* = \iota^t \left(\frac{\alpha z_t}{\mu_t r_t^k}\right)^{\frac{1}{1-\alpha}}. \tag{14}$$

Since all firms are identical ex-ante, the subscript j can be eliminated. Unmatched firms seeking workers have to pay a cost, $\gamma \iota^t$, to post a vacancy. The vacancy posting cost grows at the same deterministic rate as output. The vacancy could be filled with probability ρ_t^f and the filled vacancy could be separated with probability $1-\rho$ before entering the production process in period $t+1$. The unmatched firm will only post a vacancy when the discounted expected future value of doing so is bigger than or equal the cost. Free entry ensures that unmatched firms post vacancies until

$$\gamma \iota^t = \beta \rho_t^f \mathbb{E}_t\left[\frac{\widetilde{\lambda}_{1t+1}}{\widetilde{\lambda}_{1t}}(1-\rho) J_{t+1}\right] \tag{15}$$

where J_{t+1} is the expected future value of a matched firm; this is identical for all firms.

The value of a matched firm can be expressed as the net profit obtained from this period's production plus the discounted expected future value of the firm:

$$J_t = \frac{Y_t^I}{\mu_t} - W_t - r_t^k K_t^* + \beta \mathbb{E}_t\left[\frac{\widetilde{\lambda}_{1t+1}}{\widetilde{\lambda}_{1t}}(1-\rho) J_{t+1}\right], \tag{16}$$

where Y_t^I/μ_t is the firm's revenue from selling intermediate goods evaluated in terms of final goods, and W_t is the worker's real wage in terms of final goods.

A matched worker's value, H_t, is equal to the real wage he/she can get from the work in this period, plus the discounted future value of the work:

$$H_t = W_t + \beta \mathbb{E}_t \{ \frac{\widetilde{\lambda}_{1t+1}}{\widetilde{\lambda}_{1t}} [(1-\rho)H_{t+1} + \rho X_{t+1}] \}, \tag{17}$$

where X_t is the value of an unemployed worker:

$$X_t = G_t^u + \beta \mathbb{E}_t \{ \frac{\widetilde{\lambda}_{1t+1}}{\widetilde{\lambda}_{1t}} [(1-\rho)\rho_t^w H_{t+1} + (1-(1-\rho)\rho_t^w) X_{t+1}] \}. \tag{18}$$

The value of the unemployed worker comprises the total unemployment compensation in current period and expected income, irrespective of future employment.

The economic surplus of a match is $J_t + H_t - X_t$. The real wage resulting from the Nash bargaining is:

$$W_t = \epsilon_t^\theta \Theta [\frac{Y_t}{\mu_t} - r_t^k K_t^* + \gamma \tau_t] + (1 - \epsilon_t^\theta \Theta)(A + G_t^u),$$

where Θ is the steady state bargaining power of workers, and ϵ_t^θ is the shock to the bargaining power following an AR(1) process: $\log \epsilon_t^\theta = \psi_\theta \log \epsilon_{t-1}^\theta + \nu_t^\theta$.

The total or average output net of the vacancy posting costs of the economy is defined as

$$Y_t^{NI} = N_t z_t \iota^{t(1-\alpha)} K_t^\alpha - \iota^t \gamma V_t \tag{19}$$

2.3 Final Goods Sector

The final goods sector is monopolistically competitive. Each final good firm, indexed by $\widetilde{j}$, buys the output of the intermediate goods firms at the price P_t^I. They then convert this output into a differentiated final good, $Y_{\widetilde{j}t}$, with no cost and sells the final goods in the market at price $P_{\widetilde{j}t}$. The demand for each variety is:

$$Y_{\widetilde{j}t} = (\frac{P_{\widetilde{j}t}}{P_t})^{-\epsilon_t^p} Y_t \tag{20}$$

and the aggregate price is

$$P_t = [\int_0^1 (P_{\widetilde{j}t})^{1-\epsilon_t^p} d\widetilde{j}]^{\frac{1}{1-\epsilon_t^p}}. \tag{21}$$

Prices are sticky in the final goods sector. In the following analysis, the index $\widetilde{j}$ is eliminated, because every firm faces an identical problem. Following Calvo(1983), during each period, only a fraction of $(1-\omega)$ firms can choose their prices optimally. For the firms which could not re-optimize their prices at period t, they can adjust their prices according to the past inflation rate: $P_t = P_{t-1}\Pi_{t-1}^{\xi}$. Now, let P_t^* be the optimal price set by firms that can reoptimize prices in period t. The optimization problem for a final goods firm is:

$$\max_{P_t^*} \sum_{s=0}^{\infty} \omega^s \mathbb{E}_t \{\Lambda_{t,t+s}[P_t^* \Pi_{t+s-1,t-1}^{\xi} Y_{t,t+s} - P_{t+s}^I Y_{t,t+s}]\}$$

where

$$Y_{t,t+s} = (\frac{P_t^* \Pi_{t+s-1,t-1}^{\xi}}{P_{t+s}})^{-\epsilon_{t+s}^p} C_{t+s}$$

The result of the optimization problem is:

$$P_t^* = \frac{\mathbb{E}_t \sum_{s=0}^{\infty} \omega^s \Lambda_{t,t+s} C_{t,t+s} \epsilon_{t+s}^p \mu_{t+s}^{-1} P_{t+s}^{1+\epsilon_{t+s}^p} \Pi_{t+s-1,t-1}^{-\xi\epsilon_{t+s}^p}}{\mathbb{E}_t \sum_{s=0}^{\infty} \omega^s \Lambda_{t,t+s} C_{t,t+s} (\epsilon_{t+s}^p - 1) P_{t+s}^{\epsilon_{t+s}^p} \Pi_{t+s-1,t-1}^{\xi(1-\epsilon_{t+s}^p)}} \tag{22}$$

where $\mathbb{E}_t\Lambda_{t,t+s} \equiv \beta^s \mathbb{E}_t[(\widetilde{\lambda}_{1t+s}/\widetilde{\lambda}_{1t})(P_t/P_{t+s})]$ is the stochastic discount factor for nominal payoffs, and $\Pi_{t+s,t} = P_{t+s}/P_t$. So the aggregate price is given by

$$P_t = [\omega(P_{t-1}(\frac{P_{t-1}}{P_{t-2}})^{\xi})^{1-\epsilon_t^p} + (1-\omega)(P_t^*)^{1-\epsilon_t^p}]^{\frac{1}{1-\epsilon_t^p}}. \tag{23}$$

2.4 Government

In order to close the model, we need to specify the monetary policy, fiscal policy, and unemployment benefits policy. Here, the monetary policy obeys the following simple Taylor rule:

$$\widehat{r}_t = (1-\phi_r)(\phi_\pi \widehat{\pi}_t + \phi_y \widehat{y}_t) + \phi_r \widehat{r}_{t-1} + \widehat{\epsilon}^r_t, \tag{24}$$

where $\widehat{x}_t$ is the log-deviation from the steady state value and the temporary interest rate shock is given by $\log \epsilon^r_t = \psi_r \log \epsilon^r_{t-1} + \nu^r_t$.

The government budget constraint is of the form:

$$G_t + G^{utotal}_t + \frac{B_{t-1}}{P_t} = T_t + \frac{B_t}{r_t P_t} \tag{25}$$

where $G^{utotal}_t = G^u_t U_t$ is the total unemployment benefits.

The steady state unemployment benefits obtained by each unemployed person are $G^u = \overline{rr}W$, where $\overline{rr}$ is the replacement rate – the steady state ratio between unemployment benefits and the average real wage. The changes in unemployment benefits depend on an exogenous shock on the unemployment benefits, $\epsilon^{g^u}_t$, and changes in real wages and past unemployment rate: $\widehat{g}^u_t = \widehat{\epsilon}^{g^u}_t + \widehat{w}_t + \phi_u \widehat{u}_{t-1}$. The unemployment benefits shock $\epsilon^{g^u}_t$ follows $\log \epsilon^{g^u}_t = \psi_{g^u} \log \epsilon^{g^u}_{t-1} + \nu^{g^u}_t$. Figure 1 plots the growth rate of benefits per unemployed worker[1] and the growth rate of the real wage, which reflects that besides wages and unemployment, there is something else causing the change in the benefits. That is where the shocks come into the model.

In order to maintain the simplicity of the model, the setup of the unemployment benefits here is not exactly the same as that in the real economy. However, both setups reflect how generous the unemployment benefits program is. We can obtain a mapping from the setup in the model to that of the real economy. A 1% permanent increase in G^u at period t in

[1] One of the observed variables used in estimating the baseline model is the total unemployment benefits paid by the government, so here the benefits per unemployed worker is obtained by dividing the total unemployment benefits paid by the government by the number of unemployed workers receiving the benefits.

the model implies that the lifetime expected benefits obtained by an unemployed worker can increase by $\mathbb{E}_t \sum_{\tau=t}^{\infty} \beta^\tau \Pi_{s=t}^{\tau}(1-\rho_s^w)$. Suppose $\mathbb{E}_t \rho_s^w \equiv \overline{\rho}^w$, then the increase in expected benefits will be $\frac{1}{1-\beta(1-\overline{\rho}^w)}$. If the 1% increase in G^u is transitory, which means there is a 1% positive unemployment benefits shock with autocorrelation ρ^{g^u}, then the increase in expected benefits obtained will be $\frac{1}{1-\beta\rho^{g^u}(1-\overline{\rho}^w)}$, which is around 1.64% according to my parameter calibration and estimation. In the real world, the unemployment benefits program extends from T weeks to T' weeks, then the expected benefits increase from $\mathbb{E}_t \sum_{\tau=t}^{t+T} \beta^\tau \Pi_{s=t}^{\tau}(1-\rho_s^w)G_\tau^u$ to $\mathbb{E}_t \sum_{\tau=t}^{t+T'} \beta^\tau \Pi_{s=t}^{\tau}(1-\rho_s^w)G_\tau^u$, which equals $\mathbb{E}_t \sum_{\tau=t+T}^{t+T'} \beta^\tau (1-\overline{\rho}^w)^\tau G_\tau^u$ with the assumption that $\mathbb{E}_t \rho_s^w \equiv \overline{\rho}^w$. If the benefits program in the real world extends from 39 weeks to 99 weeks, the expected benefits increase by less than 11%, which is equivalent to a 7% positive unemployment benefits shock in the model.

Government spending expressed relative to steady state output $g_t^y = \frac{G_t}{Y_t t}$ follows the process: $\log g_t^y = (1-\psi_g)\log g^y + \psi_g \log g_{t-1}^y + \nu_t^g + \mu^{gz}\nu_t^z$.

2.5 Market Equilibrium

To obtain the goods market equilibrium, the production should equal the household's demand for consumption and investment, and the government spending:

$$Y_t = C_t + I_t + G_t + \psi(d_t)K_{t-1}^H \tag{26}$$

The equilibrium condition for the capital market is obtained by equalizing the capital used in the intermediate good sector and the capital stock times the utilization rate:

$$n_t K_t^* = d_t K_{t-1}^H. \tag{27}$$

3 Parameter Estimation

3.1 Estimation Equations

The previously defined model is detrended and estimated with Bayesian method using nine key macroeconomic quarterly US time series as observed variables: the log difference of real GDP ($dGDP_t$), log difference of real consumption ($dCONS_t$), log difference of real investment ($dINV_t$), log difference of the real wage ($dWAG_t$), log difference of the GDP deflator (INF_t), the federal funds rate (FFR_t), log deviation of the unemployment rate from its mean ($\log(UNEM_t - \overline{UMEM})$), log deviation of vacancies from its mean ($\log(VAC_t - \overline{VAC})$), and log difference of the total government unemployment insurance ($dINS_t$). Every observable is in percentage points; population growth is extracted, since the variables in the model are all in per capita terms. The time period of the data is from 1976Q1 to 2014Q4.[2]

The details of the data are described in Table 1 to 2 in the appendix. The first 6 observed variables are the same as those in Smets and Wouters (2007) and Gertler, Sala and Trigari (2008). The 7th variable I use is the unemployment rate, which corresponds with the unemployment in my model directly. I add 2 new observed variables: vacancies and unemployment insurance. I also add 2 new structural shocks, a matching technology shock and an unemployment benefits shock, to correspond to the two newly added observables so that the number of observables and the number of shocks are equal.

The comparison of the observed variables and shocks used in Smets and Wouters (2007) and Gertler, Sala and Trigari (2008), as well as in this paper, is summarized in Table 3. Table 4 illustrates the mapping between each observed variable and the shock. Equation (28) are the measurement equations, where d means the first difference, $\overline{X}$ is the mean of X, $\bar{\iota} = 100 * (\iota - 1)$ is the quarterly trend growth rate to the real GDP, $\bar{r} = 100 * (r - 1)$ is

[2] I chose 1976 as the initial year because I use the dataset constructed by Fujita and Ramey (2009) to calibrate parameters, form the priors of the labor market parameters, and use their data on the job-finding rate to conduct the robustness check; their data was constructed using CPS micro data back to 1976. I attempted to use data back to 1966 in the baseline estimation, which is the same as Smets and Wouters (2007), and the results are not affected. Therefore, in order to maintain consistency with the data used in the robustness checks, I restrict the dataset to the period starting from 1976.

the quarterly average steady state net nominal interest rate, and $\overline{\pi}_c = 100 * (\pi - 1)$ is the quarterly steady state inflation rate.

$$\begin{bmatrix} dGDP_t \\ dCONS_t \\ dINV_t \\ dWAG_t \\ INF_t \\ FFR_t \\ UNEM_t - \overline{UNEM} \\ VAC_t - \overline{VAC} \\ dINS_t \end{bmatrix} = \begin{bmatrix} \bar{\iota} \\ \bar{\iota} \\ \bar{\iota} \\ \bar{\iota} \\ \overline{\pi}_c \\ \overline{r} \\ 0 \\ 0 \\ \bar{\iota} \end{bmatrix} + \begin{bmatrix} \widehat{y}_t - \widehat{y}_{t-1} \\ \widehat{c}_t - \widehat{c}_{t-1} \\ \widehat{i}_t - \widehat{i}_{t-1} \\ \widehat{w}_t - \widehat{w}_{t-1} \\ \widehat{\pi}_t \\ \widehat{r}_t \\ \widehat{u}_t \\ \widehat{v}_t \\ \widehat{g}_t^{utotal} - \widehat{g}_{t-1}^{utotal} \end{bmatrix} \tag{28}$$

3.2 Prior and Posterior of the Parameters

Several parameters are calibrated in this current effort and are shown in Table 5. The quarterly depreciation rate δ is fixed at 0.025; the elasticity of the production function α is set to be 0.33; the discount factor β is assumed to be 0.99. Government spending, as a proportion of output, is fixed at 0.18. The elasticity of substitution among the differentiated final goods, ϵ^p, is set at 11. These parameters are conventionally fixed in the literature. There are eight new parameters coming from the modified labor market when compared Smets and Wouters' model, and one of these is fixed here: the separation rate is set to 0.105. The reason for fixing these parameters is that we cannot obtain information about them from the data used for estimation. As such, these parameters would be difficult to estimate unless they were used directly in the measurement equations.

The priors of the stochastic processes are set based on the setup in Smets and Wouters (2007): the standard errors for the exogenous innovations are drawn from an Inverse-Gamma distribution with a mean of 0.10 and standard deviation 0.15. The persistence of the $AR(1)$ processes is Beta distributed with mean 0.5 and standard deviation 0.2. The top panel of Table 6 illustrates the prior and posterior distribution of the shock processes.

The priors for the conventional structural parameters are consistent with the papers in the literature. For the new parameters related to the labor market, I set the mean to be consistent with the data and the calibration results found in the literature. I choose priors that are reasonably loose. The bottom panel of Table 6 shows the prior and posterior distribution of the estimated parameters.

Of all the estimated parameters, there is one steady state value of an endogenous variable, τ, the steady state labor market tightness. Meanwhile, one exogenous parameter, the matching technology $\mathcal{M}$, is not estimated, as there is a one-to-one mapping between these two parameters when other parameters are given and it is easier to solve the analytical solution of the model at the steady state when τ is given. The estimated labor market tightness is 0.75, and the implied matching technology is 0.35. The estimated ratio between vacancy posting cost and real wage is 0.10, implying the vacancy posting cost is 1.6% of output. The estimated value of leisure is 35% of the steady state value of average real wage. The estimated steady state labor market tightness θ is 0.76.

The estimates for the conventional parameters are very close to the results found in both Smets and Wouters (2007) and Gertler, Sala and Trigari (2008).

The main statistics of labor market variables both in the data and in the estimated models are reported in Table 7. The top panel reports the statistics for the data, and the following four panels report the statistics for the baseline model and three robustness check models respectively. The statistics reported include standard deviations, quarterly autocorrelations, and correlation matrices. The standard deviations of the labor market variables are all relative to the standard deviation of output. Table 7 shows that the models can generate labor market variables with large enough volatilities, reasonable persistence, and realistic correlations.

4 Sources of Fluctuations

This section examines the sources of the labor market fluctuations by investigating impulse responses, variance decomposition and historical decomposition of variables with respect to the estimated shocks in the model.

4.1 Impulse Responses

Figure 2 to Figure 4 indicates the impulse responses of nine key variables to three of the structural shocks. Six of these variables are labor market variables, including the unemployment rate, vacancies, the vacancy-filling rate, the job-finding rate, the real wage, and the unemployment benefits. The remaining three variables are consumption, the inflation rate, and the nominal interest rate. The three structural shocks are the technology shock, the matching efficiency shock, and the unemployment benefits shock. These impulse responses are calculated using parameter values at the posterior means. The x-axis represents the time in quarters and the y-axis represents the deviation from the steady state in percentage points in response to a one standard deviation positive shock. The grey shaded areas indicate the highest posterior density intervals.

As illustrated in Figure 2, a positive technology shock benefits the economy as a whole. Consumption increases, and the labor market conditions improve. Unemployment decreases and firms post more vacancies. The vacancy-filling rate decreases and the job finding rate largely increases, both because of the rise in the labor market tightness caused by the increase in the number of vacancies and the decrease in the number of people unemployed.

In Figure 3, a positive matching efficiency shock increases the efficiency of the matching process, hence, effectively and largely increasing the job-finding rate and vacancy-filling rate, so that unemployment decreases. As expected, unemployment and vacancies move in the same direction. This co-movement in unemployment and vacancies implies a shift in the Beveridge curve.

Figure 4 shows the impulse responses to a positive unemployment benefits shock. The co-movement of unemployment and vacancies in response to an unemployment benefits shock differs from that in response to a matching efficiency shock. In this figure, unemployment and vacancies change and move in the opposite directions. Increased unemployment and decreased vacancies lower the labor market tightness, in turn, raising the vacancy-filling rate and lowering the job-finding rate.

4.2 Variance Decomposition

Table 9 and Table 10 illustrate the variance decompositions of five key variables in the model right after and then 40 quarters after the shocks. These five variables are consumption, the unemployment rate, vacancies, labor market tightness, and the job-finding rate.

The unemployment benefits shock is ignored in other papers, but it appears to be empirically important. Over 35% of the unemployment variation is caused by this shock in the short term. In the long run, the shock is even more important and accounts for more than 27% of the fluctuations in unemployment. The unemployment benefits shock accounts for over 40% and 33% of these changes in vacancies in the short run and long run respectively.

The matching efficiency shock does not account for as much of the fluctuations in unemployment as the unemployment benefits shock does, especially in the short term. Around 17% and 22% of unemployment fluctuations can be explained by the matching efficiency shock in the short run and the long run respectively. However, the matching efficiency shock only explains less than 7% of the fluctuations in vacancies both in the short run and long run.

4.3 Application: Unemployment over 2007-2014

Figure 5 summarizes the historical contribution of the shocks to unemployment fluctuations during and after the recent recession, starting from 2007Q1. The solid line is the log deviation of the unemployment rate from its average level. The darkest bars with white dots are the contribution of unemployment benefits shocks, the gray area with slashes represents the contribution of matching efficiency shocks, and the white area with black dots notes the contribution of all other shocks. This decomposition is based on the estimation of the baseline model. Figure 7 plots the estimated smoothed shocks used in the historical decomposition, and the y-axis of each subplot indicates how many percentage points each corresponding shock deviates from the zero steady state.

Unemployment benefits shocks accounted for a large proportion of the increase in unemployment during the Great Recession and the early phase of recovery (from 2008Q3 to 2012Q2). Without these unemployment benefits shocks, the unemployment rate could have been lowered by at least 1 percentage point during 2009Q1 and 2011Q2. This number is smaller than the estimation results in Hagedorn et al (2013, 2015), which show that the unemployment benefits shocks increased the unemployment rate by 2.5 percentage points during this period. The main reason that the effect of unemployment benefits in my model is smaller than that in Hagedorn et al (2013, 2015) is the stimulative effect on aggregate demand is larger in my model. Many papers with search and matching frictions feature higher unemployment rates than that observed in the data, and this can be justified by interpreting the unemployed, or more precisely, the unmatched workers in the model as being both unemployed and out of the labor force in the real world. For example, Andolfatto (1996) had $u = 0.52$, Trigari (2009) had $u = 0.29$, and Krause and Lubik (2007) had $u = 0.12$. The steady state unemployment rate in my model is 27%, which is also much higher than that in the data, so the same amount of increase in unemployment benefits per unemployed worker will result in a much larger increase in the total income of households in the model, implying that the stimulative effect on aggregate demand is 3 to 5 times larger in the model and then offsets a larger part of the negative effects of unemployment benefits shock on labor demand. Introducing labor force participation decisions and distinguish people who are unemployed and people who are out of the labor force can results in a model with a more appropriate unemployment rate and size of the stimulus effect, and then generate a result much closer to the empirical results in Hagedorn et al (2013, 2015). However, this will make the model even more complicated. Given that despite the stimulus effect is overestimated in this model, the direct effect of unemployment benefits on labor demand still dominates and results in a one percentage higher unemployment during 2009 and 2011, I believe that using the current relatively easier and standard way to model the labor market is sufficient.

While the unemployment benefits shocks increased the unemployment rate by at least one percentage point during 2009 and 2011, the matching efficiency shocks did not play an important role during the same period. The contribution of matching efficiency shocks on unemployment was much smaller than was the contribution of unemployment benefits shocks in each quarter from 2008Q3 to 2011Q1. This result is consistent with the result in Valletta and Kuang (2010), namely, that there was a limited increase in structural unemployment during 2008 and 2010. From the second half of 2012, the two types of shocks affected unemployment in opposite directions. Matching efficiency shocks continued to contribute to the high unemployment rate until the end of 2013. However, the unemployment benefits shocks has been contributing to decreasing the unemployment rate from 2012Q3. Thus, unemployment benefits shocks increased the unemployment rate during the Great Recession and prevented unemployment from decreasing in the early phase of the recovery period, while matching efficiency shocks contributed more to the slow recovery in unemployment from 2011 to the second half of 2013.

Figure 6 summarizes the historical contribution of the shocks to vacancy fluctuations starting in 2007Q1. From 2008Q2 to 2012Q1, the unemployment benefits shocks decreased vacancies. Particularly, from the end of 2008Q4 to 2010Q2, 20% of the decrease in vacancies was caused by the unemployment benefits shocks. Unemployment benefits shocks turned to help the recovery of vacancy postings from 2012Q2. In the meantime, matching efficiency shocks had a very limited effect on vacancies.

Figure 8 supports the results drawn from the historical decomposition of unemployment. The figure shows the actual Beveridge curve (the black solid line) and its counterfactual counterparts during 2007Q1 and 2014Q4. The x-axis represents how many percentage points the unemployment rate moved away from its mean; the y-axis shows how many percentage points the vacancies moved away from its mean. To obtain the counterfactual Beveridge curve with only the unemployment benefits shocks (the line with dots), the estimated shocks on the unemployment benefits are inputted to the estimated model and all other shocks are set to 0. In this way, the effect of the unemployment benefits shocks on the Beveridge curve is isolated. It is clear that the unemployment benefits shocks first pushed the labor market down along the Beveridge curve during the Great Recession, and then in the opposite direction during the recovery period. To obtain the counterfactual Beveridge curve with only the matching efficiency shocks (the line with triangles), the estimated shocks on matching efficiency are inputted to the estimated model and other shocks are set at 0. The matching efficiency shocks shifted the Beveridge curve to the right. The two counterfactual Beveridge curves show that the unemployment benefits shocks caused an increase in unemployment and a decrease in vacancies at the same time while the matching efficiency shocks mainly caused an increase in unemployment, but it had a very limited effect on vacancies. These findings are consistent with the results for the historical decomposition analysis.[3]

4.4 Why are the Unemployment Benefits Shocks so Important?

In the literature, people study the effect of unemployment benefits from the aspect of labor supply and focus on how changes in unemployment benefits affect workers' search efforts. However, they ignore the effects of those benefits on labor demand, which is the main focus of the current paper. Empirical studies, such as Rothstein (2011), and Farber and Valetta (2013), measure the micro effect of unemployment benefits extensions, and find that the expansion on unemployment benefits did increase the unemployment rate during and after the Great Recession, but the smaller search effort is not the main channel. Since there is

[3]The model generates much flatter Beveridge curve than that in the data. This is because in the quarterly model, vacancies respond to shocks right away but new matches start producing only from next quarter, hence, unemployment responds to changes in vacancies with a lag of one quarter.

empirical evidence showing that the labor supply is not the main channel through which unemployment benefits affect the labor market, it is certainly worth investigating the effects of unemployment benefits on labor demand as well.

In this paper, unemployment benefits shocks affect unemployment by affecting labor demand. That mechanism is described as follows. An increase in the unemployment benefits raises the value of being unemployed, X_t, and hence, pushes up the workers' reservation wage. A higher value of X_t means lower economic surplus of a match, $J_t + H_t - X_t$. Since firms and works split the economic surplus through a Nash bargaining process, decreased surplus implies firms can gain less profits from the bargaining process and firm value, J_t, also goes down. Facing a lowered surplus, there are two potential ways to offset the decrease in profits for firms.[4] One way is to reduce wage payments. However, due to the high value of leisure, A, and steady state unemployment benefits, which account for 35% and 43% of the steady state real wage (or 21% and 26% of labor productivity) respectively, the total value of non-market activity reaches 47% of labor productivity and causes the wage dynamics to exhibit inertial behavior, so it becomes impossible for firms to offset their decrease in profits through large and immediate adjustments in wages.[5] The second possible response of firms is to reduce vacancy posting. Vacancy posting by a firm is determined by Eq. (15). Given the vacancy posting cost, the left-hand-side of Eq. (15), is constant in the detrended model, the benefit of posting vacancies, the right-hand-side of Eq. (15), changes in the same direction as J_t does. Vacancy posting decisions are made solely by firms, so firms can control the number of vacancies and offset their decrease in profits through cutting vacancies. The changes in vacancy posting in response to an unemployment benefits shock, can be supported by the impulse responses in Figure 4 and the variance decomposition in Table 9 and Table 10. Figure 4 shows that in response to a positive unemployment benefits shock, vacancies

[4] A third way for firms to respond to an decrease in profits is firing more workers through raising the separation rate in the model with endogenous separation. Details will be provided in Section 5.3.

[5] There is no agreed value for the non-market activity in the literature. For example, Shimer (2005) calibrated the value of non-market activity to be 40% of labor productivity, and Gertler, Sala, and Trigtari (2008) got the estimated value to be 73%.

do decrease significantly, and the variance decompositions imply that 40% of fluctuations in vacancies are caused by unemployment benefits shocks in the short run; even in the long term this number is still above 33%. The reduced vacancies lower the labor market tightness and the job-finding rate, hence, unemployment becomes higher. Thus, on the labor demand side, firms will reduce their vacancy posting in response to higher unemployment benefits, and their response increases unemployment and makes the labor market situation worse. The key driving force of this labor demand channel is the wage inertia caused by the high value of leisure and high unemployment benefits at the steady state. Without wage inertia, firms would decrease wages in response to higher unemployment benefits; hence, both vacancies and unemployment would be affected less.

Of course, only considering the partial equilibrium effects on the labor market is not convincing enough, since the labor market is closely related to other parts of the economy, and the unemployment benefits policy can affect the economy through other channels, such as aggregate demand. President Obama's Council of Economic Advisors has suggested that Mitman and Rabinovich (2014) did not model the aggregate demand effects of benefit extensions, which are claimed to be "the key channel through which EUC can aid economic growth and the recovery". In a simple model, it is true that not every aspect of the economy can be taken into consideration. However, in the medium scale DSGE model investigated in this paper, aggregate demand is sufficiently considered. Even so, consumption still decreases in response to a positive unemployment benefits shock, which is opposite to the Council's statement. Thus, according to the rich macroeconomic model, the stimulative effects of extended unemployment benefits cannot overcome their detrimental effect on job creation.[6]

[6]Extended unemployment benefits also have detrimental effect on job separation if separation is endogenously determined.

5 Robustness Checks

This section reports on the results of robustness checks. These results show that although the estimated parameters are inevitably different when using different observables and models in the estimation, the relative importance of shocks during and after the Great Recession, as implied by the variance decomposition and historical decompositions, is indeed very robust.

5.1 Estimation with Job-finding Rate and Labor Market Tightness as Observables

In this section, the job-finding rate and labor market tightness is used as observables to obtain a realistic matching efficiency series and substitute the vacancies for one observed variable in estimation.

Furlanetto and Groshenny (2012) found that when using the unemployment rate and vacancies as observables, it can be difficult to see much decline in a model generated matching efficiency during the Great Recession; when using the job finding rate and labor market tightness as observables, the implied matching efficiency series matches the data better. In the baseline model here, implied matching efficiency does not decline much. Does that smaller decrease in matching efficiency cause an underestimation of the role played by matching efficiency on unemployment? To determine whether the importance of unemployment benefits and the irrelevance of matching efficiency obtained in the previous sections depends on observables used, in this part, I follow Furlanetto and Groshenny (2012) and use the job-finding rate data constructed by Fujita and Ramey (2009) and the labor market tightness data to calculate the matching efficiency series. I then use that series to substitute for vacancies during the estimation.[7] Figure 9 plots the matching efficiency series used here as well as the series implied by the estimated baseline model. The solid line is the matching efficiency

[7] I also use the job-finding rate data in Furlanetto and Groshenny (2012), which differs from the Fujita-Ramey dataset in terms of dealing with the margin error. Similar results were found using this specification. The analysis is based on data from 1976Q1 to 2011Q2 due to data availability.

series implied by the baseline model, and the dashed line represents the series implied by the model estimated using the job-finding rate and labor market tightness data. The dashed line presents a very similar pattern to that derived by Furlanetto and Groshenny (2012) and Barnichon and Figura (2011), and also captures the sharp decline in matching efficiency in recent years.

Although different data is used herein, I do find that estimation results from this estimation are very similar to what were obtained before by comparing the second and third columns in Table 8. Matching efficiency shocks are still less important for unemployment, as shown in the second and third column in Table 11. Matching efficiency shocks explain about 8% of the unemployment fluctuations, while unemployment benefits shocks may explain 24% of them in the long run. From the historical decomposition of unemployment reported in Figure 10, we can obtain the same result as in the baseline model, namely, that the unemployment benefits shock raised the unemployment rate by more than one percentage point from 2009 to 2011. Since this model captures the large decline in matching efficiency during the Great Recession, the decrease in matching efficiency did increase the unemployment rate more from 2007 to 2011 than it did in the baseline case. However, the impact of unemployment benefits shocks is not affected by the larger decline in matching efficiency. Unemployment benefits shocks still account more than one-percentage-point increase in the unemployment rate during 2009Q2 and 2011Q2. Figure 11 shows the actual Beveridge curve (black line) and its counterfactual counterparts (lines with dots and triangles) during 2007Q1 and 2011Q2. The inputs of this analysis are the shocks estimated using data on the job-finding rate and labor market tightness. The solid line represents the actual Beveridge curve, the line with dots represents the Beveridge curve generated with only estimated unemployment benefits shocks, and the line with triangles represents the curve generated with only estimated matching efficiency shocks. Like the result found in the baseline model, the unemployment benefits shocks pushed the labor market down along the Beveridge curve and matching efficiency shocks shifted the curve to the right.

Based on these previous analyses, the main results from the baseline model on the relative importance of the unemployment benefits shocks and the matching efficiency shocks are still maintained when the job-finding rate and the labor market tightness data are used to estimate the model.

5.2 Model with No Unemployment Benefits Shocks

Since the unemployment benefits shock is a new concept in this paper, what would happen if there were no unemployment benefits shock? Would matching efficiency shocks become more important for affecting unemployment fluctuations? This section reports the analysis and the results of a model without unemployment benefits shocks. Different from the baseline case, unemployment benefits shocks are shut down and the estimation procedure is conducted without the data on total unemployment insurance.

The estimation results for the structural parameters are reported in the fourth column of Table 8, and the variance decomposition of unemployment is shown in the fourth column of Table 11. The estimated structural parameters are indeed very similar to the baseline case. The variance decomposition result is different from the baseline case: Matching efficiency shocks cause more than 40% of unemployment. However, the contribution of matching efficiency shocks on unemployment in terms of historical decomposition does not change much. Figure 12 shows that these matching efficiency shocks did not contribute much to the high unemployment rate during the Great Recession and early phase of the recovery period, but did keep preventing the decrease in unemployment from 2011 to the end of 2013, the same implication as that for the baseline model. So even without unemployment benefits shocks, matching efficiency shocks still did not account for more increase in unemployment in the past 6 years comparing with that in the baseline case. The reason is that matching efficiency shocks cannot generate the co-existence of high unemployment and low vacancies we observed during the Great Recession.

5.3 Model with Endogenous Separation

The baseline model assumes that job separations happen exogenously with a constant probability. However, in the real economy, the separation rate is changing over time in a business cycle, and there are papers finding that endogenous separation can fit the data better (e.g., Den Hann, Ramey and Watson (2000)). This section reports the results of a model with endogenous separation.

At the beginning of period t, a match is terminated with an exogenous probability $0 \leq \rho^x < 1$. The remaining matched workers and firms, indexed by j, jointly observe the realization of social common productivity z_t, and match-specific productivity a_{jt}, which follows a Lognormal distribution with mean 0 and standard deviation σ_a, and then decide whether to continue the match. If a_{jt} is larger than some threshold $\widetilde{a}_{jt}$, the match continues and production occurs. Since all the intermediate good firms are identical ex ante, we can eliminate the subscript j. All the matches with match specific productivity lower than $\widetilde{a}_t$ are endogenously terminated. So the endogenous separation rate is given by

$$\rho_t^n = F(\widetilde{a}_t) = \int_{-\infty}^{\widetilde{a}_t} f(a_t)da_t \tag{29}$$

The total separation rate is $\rho_t = \rho^x + (1 - \rho^x)\rho_t^n$. The production function of the matched firms follows

$$Y^I(a_{jt}) = z_t a_{jt} \iota^{t(1-\alpha)} K_{jt}^{\alpha}. \tag{30}$$

Following Krause and Lubik (2007), since under small shocks, real wages are always above workers' reservation wage, the critical value of a_t below which endogenous separation takes place is given by $J(\widetilde{a}_t) = 0$. Substituting the real wage and capital use at $\widetilde{a}_t$, the separation threshold is determined by the following equation:

$$\frac{^I(\widetilde{a}_t)}{\mu_t} - W(\widetilde{a}_t) - r_t^k K^*(\widetilde{a}_t) + \frac{\gamma \iota^t}{\rho_t^f} = 0 \tag{31}$$

The rest of the model is the same as the baseline setup.

The estimation results for the structural parameters are reported in the last column of Table 8, and the variance decomposition of unemployment is shown in the last column of Table 11. The results are very similar to those obtained in the baseline case, in the sense that unemployment benefits shocks account for a large proportion of unemployment fluctuations. Figure 13 shows that unemployment benefits shocks can explain more than one percentage point increase in the unemployment rate during the recovery from the Great Recession and their negative effect on labor market lasts even longer than that in the baseline case. This is because in the model with endogenous separation, firms can not only decrease vacancy postings but also fire more workers through raising the endogenous separation rate in response to their loss in profits. So in the baseline case, in response to a positive unemployment benefits shock, firms can only reduce the flow out of unemployment through posting less vacancies, while in the model with endogenous separation, firms can also increase the flow into unemployment through separating more matches endogenously.

6 Conclusions

In an estimated medium-scale DSGE model with labor market frictions, the unemployment benefits shocks are responsible for a large proportion of unemployment fluctuations. Over 27% of the unemployment variation is caused by these unemployment benefits shocks in the long term. During the Great Recession and the early recovery period (the second half of 2008 to the end of 2011), unemployment benefits shocks contributed to the increase in the unemployment rate. The effect of unemployment benefits shocks was particularly large between 2009 and 2011. Indeed, the unemployment rate could have been one percentage point lower without these unemployment benefits shocks during this period. In the later recovery period (from 2012 to the present), unemployment benefits shocks have had a positive effect on lowering the unemployment rate. The deterioration of matching efficiency had a very limited effect on unemployment from 2009 to 2011, however it did play a major role in preventing the decrease in unemployment from 2011Q2 to 2013Q3, and this negative effect lasted until the beginning of 2014.

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A Model Appendix

A.1 Stationary Model

$$u_t = 1 - n_t \tag{32}$$

$$n_{t+1} = (1-\rho)(n_t + m(u_t, v_t)) = (1-\rho_{t+1})(n_t + \epsilon_t^M E u_t^{\zeta} v_t^{1-\zeta}) \tag{33}$$

$$\rho_t^w = m(u_t, v_t)/u_t = \epsilon_t^M \mathcal{M} u_t^{\zeta} v_t^{1-\zeta}/u_t = \epsilon_t^M \mathcal{M} \tau_t^{1-\zeta} \tag{34}$$

$$\rho_t^f = m(u_t, v_t)/v_t = \epsilon_t^M \mathcal{M} u_t^{\zeta} v_t^{1-\zeta}/v_t = \epsilon_t^M \mathcal{M} \tau_t^{-\zeta} \tag{35}$$

$$\overline{\beta}\mathbb{E}_t\{\frac{\lambda_{1t+1}}{\lambda_{1t}}(1-\rho)\rho_t^f[\frac{1-\alpha}{\alpha} r_{t+1}^k k_{t+1}^* - w_{t+1} + \frac{\gamma}{\rho_{t+1}^f}]\} = \gamma/\iota \tag{36}$$

$$w_t = \epsilon_t^{\Theta}\Theta(\frac{1-\alpha}{\alpha} r_t^k k_t^* + \gamma\tau_t) + (1-\epsilon_t^{\eta}\eta)(A + g_t^u) \tag{37}$$

$$1 = \overline{\beta} r_t \mathbb{E}_t[\frac{\lambda_{1t+1}}{\lambda_{1t}}\frac{P_t}{P_{t+1}}] \text{ where } \overline{\beta} = \beta\iota^{-\sigma} \text{ and } \lambda_{1t} = \widetilde{\lambda}_{1t}\iota^{\sigma t} \tag{38}$$

$$Q_t = \overline{\beta}\mathbb{E}_t\{\frac{\lambda_{1t+1}}{\lambda_{1t}}[Q_{t+1}(1-\delta) + d_{t+1} r_{t+1}^k - D(d_{t+1})]\} \tag{39}$$

$$\begin{aligned} Q_t\psi'(\frac{\iota i_t}{i_{t-1}})\frac{\epsilon_t^I \iota i_t}{i_{t-1}} - \overline{\beta}\mathbb{E}_t[Q_{t+1}\frac{\lambda_{t+1}}{\lambda_t}\psi'(\frac{\iota i_{t+1}}{i_t})\frac{\epsilon_{t+1}^I \iota i_{t+1}}{i_t}\frac{\iota i_{t+1}}{i_t}] + 1 \\ = Q_t(1-\psi(\frac{\iota i_t}{i_{t-1}})) \end{aligned} \tag{40}$$

$$r_t^k = D'(d_t) \tag{41}$$

$$k_t^H = \frac{1-\delta}{\iota} k_{t-1}^H + \epsilon_t^I(1-\psi(\frac{\iota i_t}{i_{t-1}}))i_t \tag{42}$$

$$k_t^* = (\frac{\alpha z_t}{\mu_t r_t^k})^{\frac{1}{1-\alpha}} \tag{43}$$

$$n_t \iota k_t^* = d_t k_{t-1}^H \tag{44}$$

$$\lambda_{1t} = (c_t - h/\iota c_{t-1})^{-\sigma} \tag{45}$$

$$y_t = n_t \frac{\mu_t r_t^k}{\alpha} k_t^* - \gamma v_t \tag{46}$$

$$y_t = c_t + i_t + g_t + D(d_t)k^H_{t-1}/\iota \tag{47}$$

$$P_t^{1-\epsilon_t^P} = \omega(P_{t-1}\Pi_{t-1}^{\xi})^{1-\epsilon_t^P} + (1-\omega)(P_t^*)^{1-\epsilon_t^P} \text{ where } \Pi_t = \frac{P_t}{P_{t-1}} \tag{48}$$

$$r_t = \epsilon_t^r r_{t-1}^{\phi_r}(\pi_t^{\phi_\pi} y_t^{\phi_y})^{1-\phi_r} \tag{49}$$

$$g_t^y = \frac{g_t}{y} \tag{50}$$

$$g_t^{utotal} = g_t^u u_t = (\epsilon_t^{g^u} w_t^{\overline{rr}} u_{t-1}^{\phi_u})u_t \tag{51}$$

A.2 Steady State

$$u = 1 - n \tag{52}$$

$$\rho n = m(u,v) = (1-\rho)\mathcal{M}u^{\zeta}v^{1-\zeta} \tag{53}$$

$$\rho^w = \frac{m(u,v)}{u} = \mathcal{M}\tau^{1-\zeta} \tag{54}$$

$$\rho^f = \frac{m(u,v)}{v} = \mathcal{M}\tau^{-\zeta} \tag{55}$$

$$\overline{\beta}\rho^f(1-\rho)(\frac{1-\alpha}{\alpha}r^k k^* - w + \frac{\gamma}{\rho^f}) = \gamma/\iota \tag{56}$$

$$w = \Theta(\frac{1-\alpha}{\alpha}r^k k^* + \gamma\tau) + (1-\Theta)(A + g^u) \tag{57}$$

$$\overline{\beta} = \frac{\pi}{r} \tag{58}$$

$$q = 1 \text{ where } \Psi'(\frac{I}{K}) = 1 \tag{59}$$

$$1 = \overline{\beta}(1 - \delta + r^k) \tag{60}$$

$$r^k = D'(1) \text{ where } d = 1 \tag{61}$$

$$\frac{i}{k^H} = 1 - \frac{1-\delta}{\iota} \tag{62}$$

$$k^* = (\frac{\alpha}{\mu r^k})^{\frac{1}{1-\alpha}} \tag{63}$$

$$\widetilde{k}^{*} = (\frac{\alpha}{\mu r^{k}})^{\frac{1}{1-\alpha}} \tag{64}$$

$$n k^{*} \iota = k^{H} \tag{65}$$

$$y = \frac{n \mu r^{k} k^{*}}{\alpha} - \gamma v \tag{66}$$

$$y = c + i + g \tag{67}$$

$$\lambda_{1} = c^{-\sigma}(1 - h/\iota)^{-\sigma} \tag{68}$$

$$\mu = \frac{\epsilon^{P}}{\epsilon^{P} - 1} \tag{69}$$

$$g = g^{y} y \tag{70}$$

$$g^{utotal} = g^{u} u = w^{\overline{rr}} u + u^{\phi_{u}} u \tag{71}$$

A.3 Log-linear Model

$$\widehat{u}_{t} = -\frac{n}{u} \widehat{n}_{t} \tag{72}$$

$$\widehat{n}_{t+1} = (1-\rho)\widehat{n}_{t} + \rho[\widehat{\epsilon}_{t}^{M} + \zeta \widehat{u}_{t} + (1-\zeta)\widehat{v}_{t}] \tag{73}$$

$$\widehat{\rho}_{t}^{w} = \widehat{\epsilon}_{t}^{M} + (\zeta - 1)\widehat{u}_{t} + (1-\zeta)\widehat{v}_{t} \tag{74}$$

$$\widehat{\rho}_{t}^{f} = \widehat{\epsilon}_{t}^{M} + \zeta \widehat{u}_{t} - \zeta \widehat{v}_{t} \tag{75}$$

$$-\widehat{\rho}_{t}^{f} = \widehat{\lambda}_{1t+1} - \widehat{\lambda}_{1t} + \frac{\frac{1-\alpha}{\alpha} r^{k} k^{*}(\widehat{r}_{t+1}^{k} + \widehat{k}_{t+1}^{*}) - w \widehat{w}_{t+1} - \frac{\gamma}{\rho^{f}} \widehat{\rho}_{t+1}^{f}}{\frac{1-\alpha}{\alpha} r^{k} k^{*} - w + \frac{\gamma}{\rho^{f}}} \tag{76}$$

$$W \widehat{w}_{t} = \Theta[\frac{1-\alpha}{\alpha} r^{k} k^{*}(\widehat{r}_{t}^{k} + \widehat{k}_{t}^{*}) + \gamma \tau(\widehat{v}_{t} - \widehat{u}_{t})] + (1-\Theta) g^{u} \widehat{g}_{t}^{u} + (\frac{1-\alpha}{\alpha} r^{k} k^{*} + \gamma \tau - A - g^{u}) \widehat{\epsilon}_{t}^{\theta} \tag{77}$$

$$\widehat{\lambda}_{1t} = \widehat{r}_{t} + \mathbb{E}_{t}(\widehat{\lambda}_{1t+1} - \widehat{\pi}_{t+1}) + \widehat{\epsilon}_{t}^{b} \tag{78}$$

$$\widehat{q}_{t} = -(\widehat{r}_{t} - \mathbb{E}_{t}\widehat{\pi}_{t+1}) + \overline{\beta}(1-\delta)\mathbb{E}_{t}\widehat{q}_{t+1} + (1 - \overline{\beta}(1-\delta))\mathbb{E}_{t}\widehat{r}_{t+1}^{k} - \widehat{\epsilon}_{t}^{b} \tag{79}$$

$$\widehat{i}_{t} = \frac{1}{1+\overline{\beta}\iota}\widehat{i}_{t-1} + \frac{\overline{\beta}\iota}{1+\overline{\beta}\iota}\widehat{i}_{t+1} + \frac{\phi}{\iota^{2}(1+\overline{\beta}\iota)}\widehat{q}_{t} - \frac{1}{1+\overline{\beta}\iota}\widehat{\epsilon}_{t}^{I} \text{ where } \phi = \frac{1}{\psi''(\iota)} \tag{80}$$

$$\widehat{r}_t^k = \sigma_d \widehat{d}_t \tag{81}$$

$$\widehat{k}_t^H = \frac{1-\delta}{\iota}\widehat{k}_{t-1}^H + \delta \widehat{i}_t \tag{82}$$

$$\widehat{k}_t^* = \frac{1}{1-\alpha}(\widehat{z}_t - \widehat{\mu}_t - \widehat{r}_t^k) \tag{83}$$

$$\widehat{k}_{t-1}^H = \widehat{n}_t + \widehat{k}_t^* - \widehat{d}_t \tag{84}$$

$$\widehat{\lambda}_{1t} = \frac{-\sigma}{1-h/\iota}\widehat{c}_t + \frac{\sigma h}{\iota - h}\widehat{c}_{t-1} \tag{85}$$

$$\widehat{y}_t = (1+\gamma\frac{v}{y})(\widehat{n}_t + \widehat{\mu}_t + \widehat{r}_t^k + \widehat{k}_t^*) - \gamma\frac{v}{y}\widehat{v}_t \tag{86}$$

$$\widehat{y}_t = \frac{c}{y}\widehat{c}_t + \frac{i}{y}\widehat{i}_t + \widehat{g}_t + \frac{r^k k^H}{y\iota}\widehat{k}_{t-1}^H \tag{87}$$

$$\widehat{\pi}_t = \frac{\overline{\beta}}{1+\overline{\beta}\xi}\mathbb{E}_t\widehat{\pi}_{t+1} + \frac{\xi}{1+\overline{\beta}\xi}\widehat{\pi}_{t-1} - \frac{(1-\overline{\beta}\omega)(1-\omega)}{\omega(1+\overline{\beta}\xi)}\widehat{\mu}_t + \widehat{\epsilon_t^P} \tag{88}$$

$$\widehat{r}_t = (1-\phi_r)(\phi_\pi \widehat{\pi}_t + \phi_y \widehat{y}_t) + \phi_r \widehat{r}_{t-1} + \widehat{\epsilon}_t^r \tag{89}$$

$$\widehat{g}_t = \widehat{g}_t^y \tag{90}$$

$$\widehat{g}_t^u = \widehat{\epsilon}_t^{g^u} + \widehat{w}_t + \phi_u \widehat{u}_{t-1} \tag{91}$$

There are 20 equations and 20 unknown variables (u_t, n_t, v_t, ρ_t^f, ρ_t^w, w_t, r_t, π_t, Q_t, d_t, i_t, k_t^H, y_t, μ_t, c_t, g_t, g_t^u, λ_t, r_t^k, k_t^*).

B Tables and Figures

Table 1: Data Description and Sources

Data Title	Data Description	Data Sources
GDPC96	Real Gross Domestic Product Billions of Chained 1996 Dollars Seasonally Adjusted Annual Rate	U.S. Department of Commerce: Bureau of Economic Analysis
GDPDEF	Gross Domestic Product Implicit Price Deflator, 1996=100 Seasonally Adjusted	U.S. Department of Commerce: Bureau of Economic Analysis
PCEC	Personal Consumption Expenditure Billions of Dollars Seasonally Adjusted Annual Rate	U.S. Department of Commerce: Bureau of Economic Analysis
CE16OV	Civilian Employment Sixteen Years & Over, Thousands Seasonally Adjusted, 1996=100	U.S. Department of Labor: Bureau of Labor Statistics
FEDR	Federal Funds Rate Averages of Daily Figures Percent	Board of Governors of the Federal Reserve System
LNS10000000	Labor Force Status Civilian noninstitutional population Seasonally Adjusted	U.S. Department of Labor: Bureau of Labor Statistics
LNSindex	LNS10000000(1992:3)=1	
FPI	Fixed Private Investment Billions of Dollars Seasonally Adjusted Annual Rate	U.S. Department of Commerce: Bureau of Economic Analysis
RWAGE	Nonfarm Business, All Persons Hourly Compensation Seasonally Adjusted, 2009=100	U.S. Department of Labor: Bureau of Labor Statistics
UNRATE	Unemployment Rate Civilian Unemployment Rate Seasonally Adjusted	U.S. Department of Labor: Bureau of Labor Statistics
HELPWANT	Index of Help-Wanted Advertising 1987=100 Seasonally Adjusted	Composite Help-Wanted Index by Barnichon (2010)
UNINS	Unemployment Insurance Billions of Dollars Seasonally Adjusted	U.S. Department of Commerce: Bureau of Economic Analysis

Table 2: Definition of Data Variables

Data Variable	Mnemonic	Formula
Output	GDP	$= \log(GDPC96/LNSindex) * 100$
Consumption	CONS	$= \log(PCED/(GDPDEF * LNSindex)) * 100$
Investment	INV	$= \log(FPI/(GDPDEF * LNSindex)) * 100$
Real wage	WAG	$= \log(RWAGE/GDPDEF) * 100$
Unemployment insurance	INS	$= \log(UNINS/(GDPDEF * LNSindex)) * 100$
Unemployment	UNEM	$= \log(UNRATE) * 100$
Inflation	INF	$= \log(GDPDEF/GDPDEF(-1)) * 100$
Federal funds rate	FFR	$= FEDR/4$
Vacancy	VAC	$= \log(HELPWANT/LNSindex) * 100$

Table 3: Observed Variables and Shocks Comparison

SW (2007)[1]		GST (2008)[2]		This paper]	
Obs. Var.	Shocks	Obs. Var.	Shocks	Obs. Var.	Shocks
GDP	Gov. Spending	GDP	Gov. Spending	GDP	Gov. Spending
CONS	Risk Prem.	CONS	Risk Prem.	CONS	Risk Prem.
INV	Invest. Tech.	INV	Invest. Tech.	INV	Invest. Tech.
WAG	Wage Markup	WAG	Bargain Power	WAG	Bargain Power
INF	Price Markup	INF	Price Markup	INF	Price Markup
FFR	Monetary	FFR	Monetary	FFR	Monetary
Employ	Technology	Employ	Technology	UNEM	Technology
-	-	-	-	VAC	Matching
-	-	-	-	INS/REPR	Unemp. Ben.

[1] SW (2007): Smets and Wouters (2007)
[2] GST (2008): Gertler, Sala, and Trigari (2008)

Table 4: Mapping Between Observables and Shocks

Variables		Shocks
dGDP	$\Leftarrow$	Government Spending
dCONS	$\Leftarrow$	Risk Premium
dINV	$\Leftarrow$	Investment Specific Technology
dWAG	$\Leftarrow$	Bargaining Power
dINS & dAWB	$\Leftarrow$	Unemployment Benefit
INF	$\Leftarrow$	Price Markup
FFR	$\Leftarrow$	Monetary Policy
UEMP	$\Leftarrow$	Technology
VAC	$\Leftarrow$	Matching Efficiency

Table 5: Calibrated Parameters

β	δ	α	g^y	$\bar{\epsilon}^P$	ρ
0.99	0.025	0.33	0.18	11	0.105

Table 6: Prior and Posterior Distribution of Shocks and Structural Parameters

		Prior Distribution			Posterior Distribution			
		Distribution	Mean	St. Dev.	Mode	Mean	5 percent	95 percent
Standard deviations								
Risk premium	σ_b	InvGamma	0.10	0.15	0.23	0.26	0.20	0.31
Bargaining power	σ_η	InvGamma	0.10	0.15	1.50	1.52	1.35	1.70
Investment	σ_I	InvGamma	0.10	0.15	0.66	0.66	0.58	0.74
Price markup	σ_p	InvGamma	0.10	0.15	0.49	0.51	0.39	0.62
Technology	σ_z	InvGamma	0.10	0.15	0.71	0.71	0.64	0.78
Matching efficiency	σ_m	InvGamma	0.10	0.15	3.10	3.13	2.83	3.44
Government	σ_g	InvGamma	0.10	0.15	0.48	0.48	0.43	0.53
Unemployment benefits	σ_{g^u}	InvGamma	0.10	0.15	2.16	2.19	1.82	2.58
Monetary	σ_r	InvGamma	0.10	0.15	0.26	0.28	0.24	0.31
Risk premium	ψ_b	Beta	0.50	0.20	0.96	0.95	0.92	0.99
Bargaining power	ψ_η	Beta	0.50	0.20	0.98	0.98	0.97	0.99
Investment	ψ_I	Beta	0.50	0.20	0.80	0.80	0.74	0.86
Price markup	ψ_p	Beta	0.50	0.20	0.96	0.96	0.93	0.98
	μ_p	Beta	0.50	0.20	0.36	0.34	0.21	0.48
Technology	ψ_z	Beta	0.50	0.20	0.99	0.99	0.97	0.99
Matching efficiency	ψ_m	Beta	0.50	0.20	0.97	0.97	0.94	0.99
Government	ψ_g	Beta	0.50	0.20	0.97	0.96	0.94	0.98
	μ_{gz}	Beta	0.50	0.20	0.55	0.55	0.45	0.64
Unemployment benefits	ψ_{g^u}	Beta	0.50	0.20	0.99	0.99	0.98	0.99
Monetary	ψ_r	Beta	0.50	0.20	0.13	0.21	0.06	0.35
Structural parameters								
Taylor rule inertia	ϕ_r	Beta	0.75	0.10	0.74	0.71	0.65	0.78
Taylor rule: inflation	ϕ_π	Normal	2.20	0.10	2.33	2.37	2.22	2.53
Taylor rule: output	ϕ_y	Normal	0.13	0.05	0.05	0.05	0.03	0.08
Consumption habit	h	Beta	0.50	0.10	0.22	0.23	0.16	0.30
Steady-state growth rate	$\bar{\iota}$	Normal	0.40	0.10	0.50	0.49	0.45	0.54
Inv. Adj. cost elast.	ϕ	Normal	0.70	0.05	0.78	0.79	0.70	0.87
Price indexation	ξ	Beta	0.50	0.15	0.46	0.47	0.25	0.67
Bargaining power	θ	Beta	0.30	0.05	0.67	0.67	0.64	0.71
Calvo price para.	ω	Normal	0.50	0.05	0.47	0.47	0.42	0.51
Capital util. adj. cost elast.	σ_d	Normal	1.30	0.05	1.33	1.33	1.25	1.41
Steady-state inflation	$\overline{\pi}_c$	Beta	0.50	0.20	0.98	0.97	0.94	0.99
Labor market tightness	τ	Normal	0.63	0.05	0.76	0.75	0.69	0.82
Replacement rate	rr	Normal	0.25	0.05	0.43	0.43	0.35	0.51
Matching function para.	ζ	Normal	0.50	0.05	0.53	0.52	0.48	0.56
Unempl. Policy: unempl.	ϕ_u	Normal	0.20	0.05	0.28	0.28	0.20	0.35
Vacancy posting cost	γ/W	Normal	0.10	0.05	0.10	0.10	0.02	0.17
Value of leisure	A/W	Normal	0.30	0.05	0.35	0.35	0.27	0.43

Table 7: Labor Market Summary Statistics of the U.S. Economy and Model Economy

Summary Statistics of the U.S. Labor Market				
	u	v	τ	ρ^w
Standard deviation	5.61	4.71	9.70	4.92
Quarterly autocorrelation	0.97	0.95	0.96	0.93
		Correlation matrix		
u	1.00	-0.85	-0.96	-0.93
v		1.00	0.96	0.85
τ			1.00	0.92
ρ^w				1.00

Summary Statistics of the Baseline Model				
	u	v	τ	ρ^w
Standard deviation	4.50	5.39	9.33	4.88
Quarterly autocorrelation	0.98	0.98	0.99	0.99
		Correlation matrix		
u	1.00	-0.78	-0.93	-0.99
v		1.00	0.95	0.79
τ			1.00	0.94
ρ^w				1.00

Summary Statistics of the Model Estimated with Job-finding Rate and Labor Market Tightness				
	u	v	τ	ρ^w
Standard deviation	6.97	5.82	12.36	7.56
Quarterly autocorrelation	0.98	0.98	0.99	0.99
		Correlation matrix		
u	1.00	-0.87	-0.97	-0.99
v		1.00	0.96	0.89
τ			1.00	0.98
ρ^w				1.00

Summary Statistics of the Model Estimated with No Unemployment Benefits Shocks				
	u	v	τ	ρ^w
Standard deviation	4.39	4.42	7.75	4.76
Quarterly autocorrelation	1.00	1.00	1.00	1.00
		Correlation matrix		
u	1.00	-0.55	-0.88	-0.99
v		1.00	0.88	0.57
τ			1.00	0.88
ρ^w				1.00

Summary Statistics of the Model with Endogenous Separation				
	u	v	τ	ρ^w
Standard deviation	4.64	6.76	10.96	5.02
Quarterly autocorrelation	0.99	0.97	0.99	0.98
		Correlation matrix		
u	1.00	-0.94	-0.98	-0.97
v		1.00	0.99	0.98
τ			1.00	0.99
ρ^w				1.00

[1] The standard deviations of all variables are relative to output.

[2] All variables in the top panel are reported as deviations from an HP trend (with smoothing parameter 10^5) following Shimer (2005). The data for the unemployment rate (u), vacancies (v), and labor market tightness (τ) are seasonally adjusted U.S. quarterly data from 1976-2014. The job-finding rate data, ρ^w, is from 1976 to 2007 due to data availability.

Table 8: Model Sensitivity – Estimation Results for Structural Parameters in Robustness Checks

		Baseline	Job-finding Rate as Observable	No Unemp. Benefits Shock	Model with Endogenous Separation
Taylor rule inertia	ϕ_r	0.74	0.76	0.69	0.88
Taylor rule: inflation	ϕ_π	2.33	2.31	2.48	2.36
Taylor rule: output	ϕ_y	0.05	0.07	0.01	0.24
Consumption habit	h	0.22	0.23	0.18	0.53
Steady-state growth rate	$\bar{\iota}$	0.50	0.48	0.44	0.42
Inv. Adj. cost elast.	ϕ	0.78	0.78	0.79	0.64
Price indexation	ξ	0.46	0.44	0.45	0.93
Bargaining power	θ	0.67	0.59	0.51	0.50
Calvo price para.	ω	0.47	0.47	0.49	0.36
Capital util. adj. cost elast.	σ_d	1.33	1.33	1.36	1.53
Steady-state inflation	$\overline{\pi}_c$	0.98	0.97	0.99	0.86
Labor market tightness	τ	0.76	0.71	0.70	0.80
Replacement rate	rr	0.43	0.43	0.46	0.25
Matching function para.	ζ	0.53	0.42	0.53	0.55
Unempl. Policy: unempl.	ϕ_u	0.28	0.23	0.30	0.03
Vacancy posting cost	γ/W	0.10	0.10	0.11	0.06
Value of leisure	A/W	0.35	0.35	0.34	0.36
Threshold of endo. Sep.	$\widetilde{a}$	-	-	-	0.72

Table 9: Variance Decomposition of Key Variables (on impact in %)

Shocks \ Variables	c	u	v	τ	ρ^w
Technology	68.57	4.14	4.78	4.97	4.14
Bargaining power	5.01	41.51	47.85	49.84	41.52
Investment	5.39	0.04	0.04	0.04	0.04
Price markup	0.81	1.25	1.47	1.50	1.25
Monetary	0.00	0.00	0.01	0.00	0.00
Matching efficiency	3.09	17.31	4.86	0.67	17.25
Government	12.23	0.06	0.10	0.06	0.05
Unemployment benefits	4.90	35.67	40.88	42.90	35.74
Risk premium	0.00	0.01	0.01	0.01	0.00

Table 10: Variance Decomposition of Key Variables (40 Quarters in %)

Shocks \ Variables	c	u	v	τ	ρ^w
Technology	49.52	3.23	3.94	4.13	3.24
Bargaining power	5.57	44.84	53.91	57.29	44.86
Investment	11.67	0.04	0.05	0.05	0.04
Price markup	0.79	1.65	2.00	2.09	1.64
Monetary	0.00	0.01	0.01	0.01	0.00
Matching efficiency	4.98	22.56	6.66	0.89	22.39
Government	23.87	0.06	0.11	0.07	0.05
Unemployment benefits	3.59	27.60	33.30	35.46	27.77
Risk premium	0.01	0.01	0.02	0.01	0.01

Table 11: Variance Decomposition of Unemployment in the Baseline Model and Models for Robustness Checking (on impact / 40 quarters, in %)

Shocks \ Models	Baseline	Job-finding Rate as Observable	No Unemploy. Benefits Shock	Model with Endogenous Separation
Technology	5.51/3.48	5.72/4.01	17.96/14.94	2.67/3.96
Bargaining power	40.45/45.11	57.09/60.34	28.19/30.85	61.93/53.36
Investment	0.03/0.04	0.09/0.09	0.30/80.27	0.76/0.27
Price markup	1.12/1.54	2.70/2.83	10.19/10.76	3.72/6.22
Monetary	0.00/0.01	0.01/0.01	0.01/0.01	0.00/0.00
Matching efficiency	16.53/22.77	6.69/8.22	43.07/42.93	1.13/1.90
Government	0.06/0.06	0.08/0.06	0.26/0.21	0.03/0.02
Unemployment benefits	36.28/26.97	27.62/24.43	–	29.76/34.27
Risk premium	0.01/0.01	0.01/0.01	0.02/0.03	0.00/0.00

Figure 1: Growth Rates of the Unemployment Benefits and Real Wage

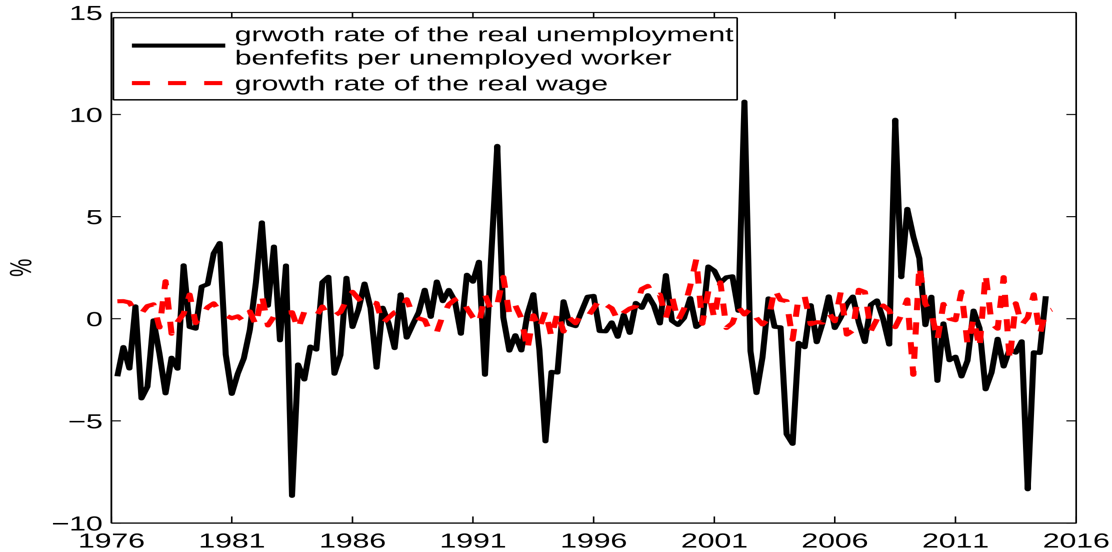
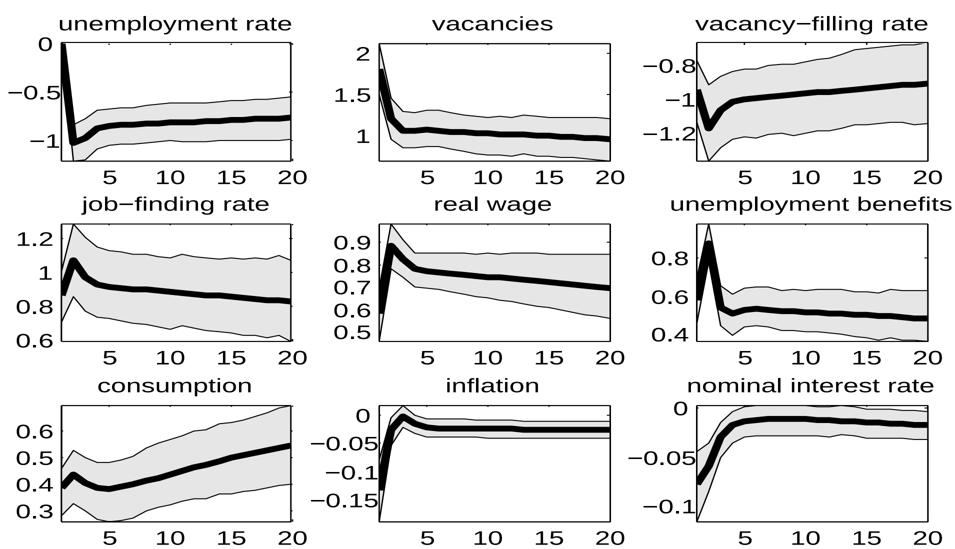
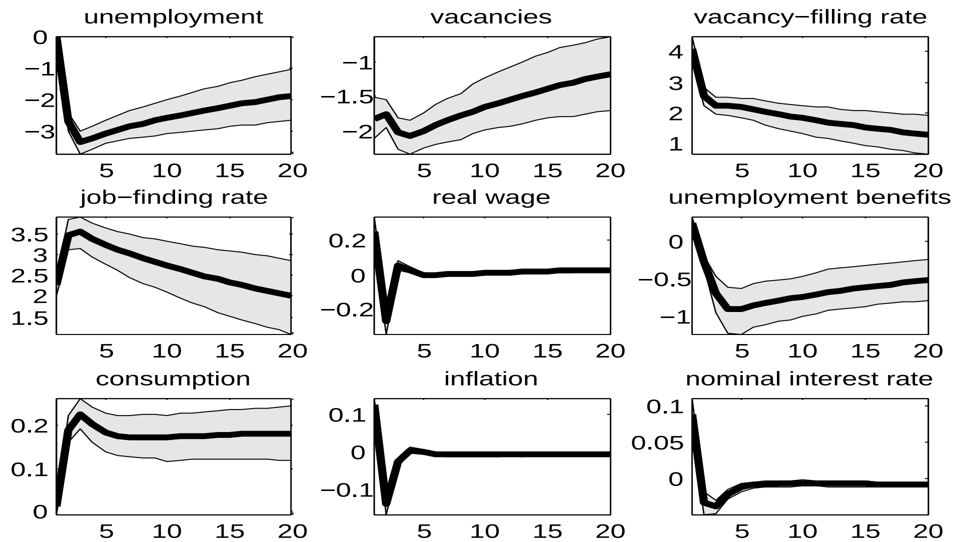


Figure 2: Impulse Responses to a Positive Technology Shock



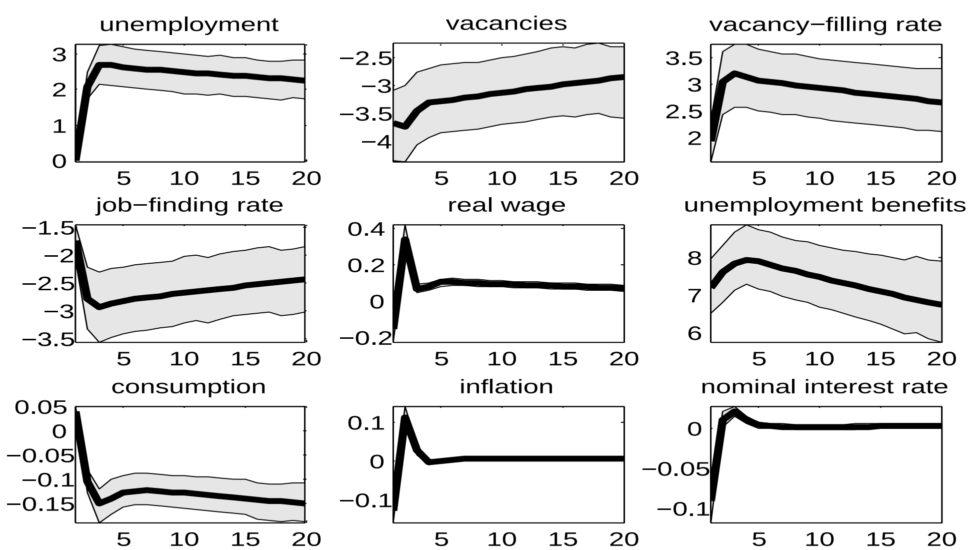
Notes: This figure reports the impulse responses of 9 key variables to one standard deviation positive technology shock. These impulse responses are calculated with parameter values at the posterior means. The shaded areas provide the highest posterior density intervals. The x-axis represents the time in quarters and the y-axis is the deviation from the steady state in percentage points.

Figure 3: Impulse Responses to a Positive Matching Efficiency Shock



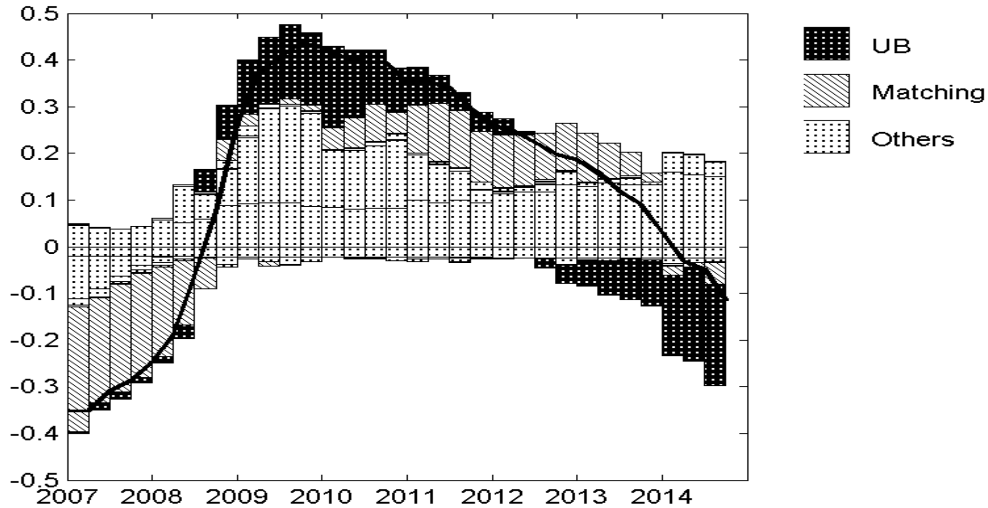
Notes: This figure reports the impulse responses of 9 key variables to one standard deviation positive matching efficiency shock. These impulse responses are calculated with parameter values at the posterior means. The shaded areas provide the highest posterior density intervals. The x-axis represents the time in quarters and the y-axis is the deviation from the steady state in percentage points.

Figure 4: Impulse Responses to a Positive Unemployment Benefit Shock



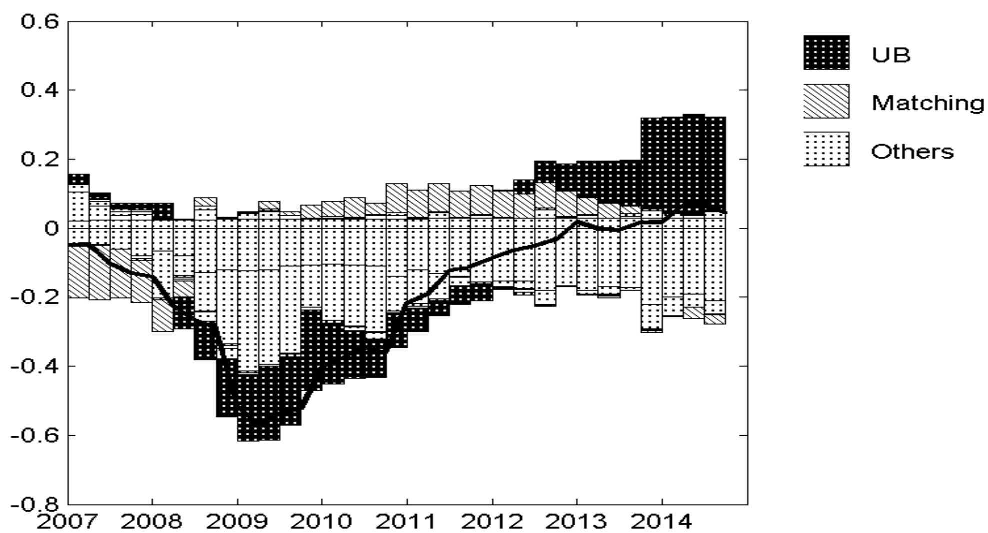
Notes: This figure reports the impulse responses of 9 key variables to one standard deviation positive unemployment benefits shock. These impulse responses are calculated with parameter values at the posterior means. The shaded areas provide the highest posterior density intervals. The x-axis represents the time in quarters and the y-axis is the deviation from the steady state in percentage points.

Figure 5: Historical Decomposition for Unemployment: 2007Q1 - 2014Q4



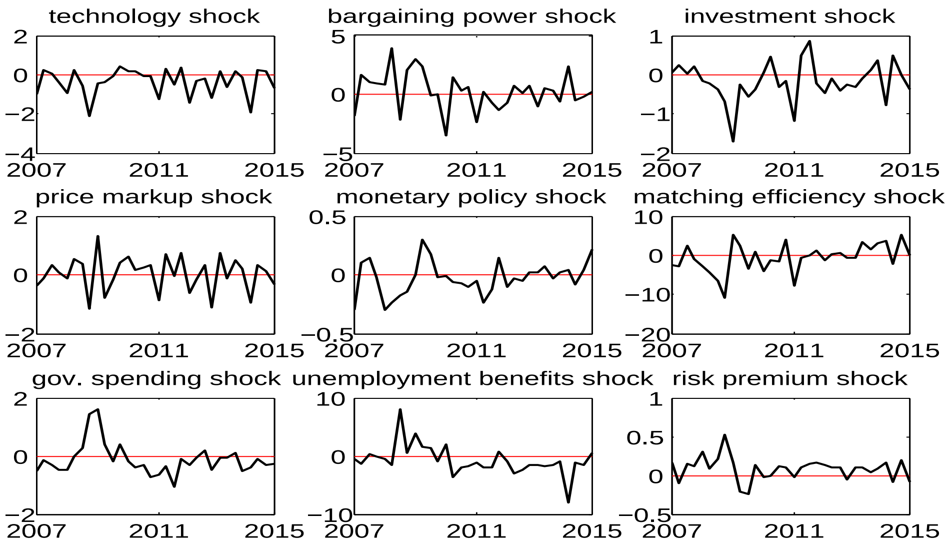
Notes: The estimated model and smoothed shocks reported in Figure (7) are used to obtain the historical decomposition. The black line is the log-deviation of the unemployment rate from its mean. The dark area with white dots, grey area with slash lines, and white area with black dots represent the contribution of the unemployment benefits shocks, matching efficiency shocks, and all other shocks to the deviation, respectively.

Figure 6: Historical Decomposition for Vacancies: 2007Q1 - 2014Q4



Notes: The estimated model and smoothed shocks reported in Figure (7) are used to obtain the historical decomposition. The black line is the log-deviation of the vacancies from its mean. The dark area with white dots, grey area with slash lines, and white area with black dots represent the contribution of the unemployment benefits shocks, matching efficiency shocks, and all other shocks to the deviation, respectively.

Figure 7: Shock Inputs of the Historical Decomposition: 2007Q1 - 2014Q4



Notes: The y-axis represents how many percentage points the shocks deviate from their steady state value.

Figure 8: Actual and Counterfactual Beveridge Curves: 2007Q1 - 2014Q4

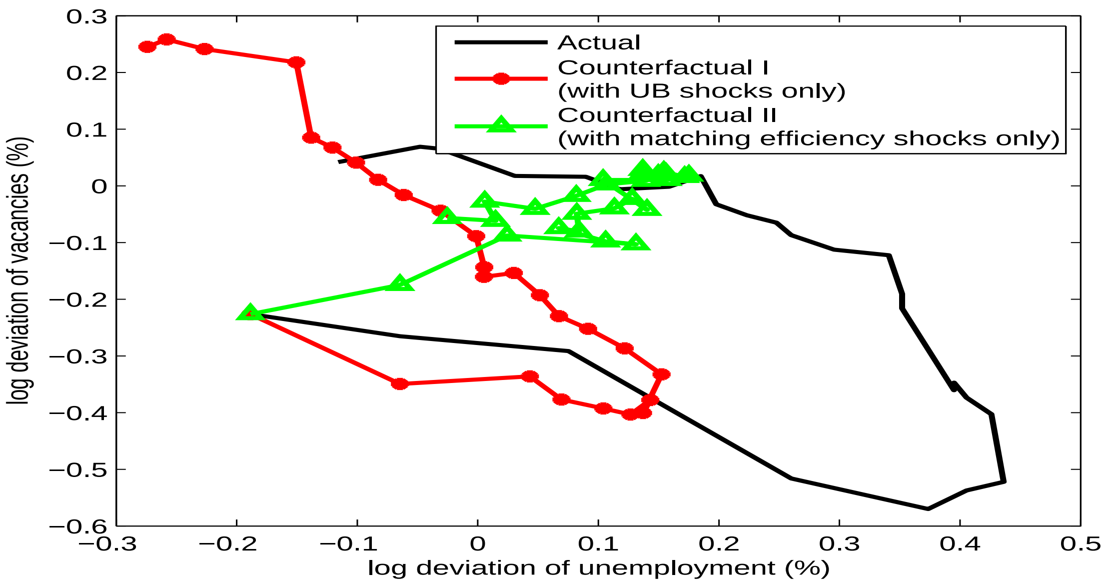


Figure 9: Matching Efficiency Implied by the Estimated Model When the Job-finding Rate and Labor Market Tightness are Used as Observables

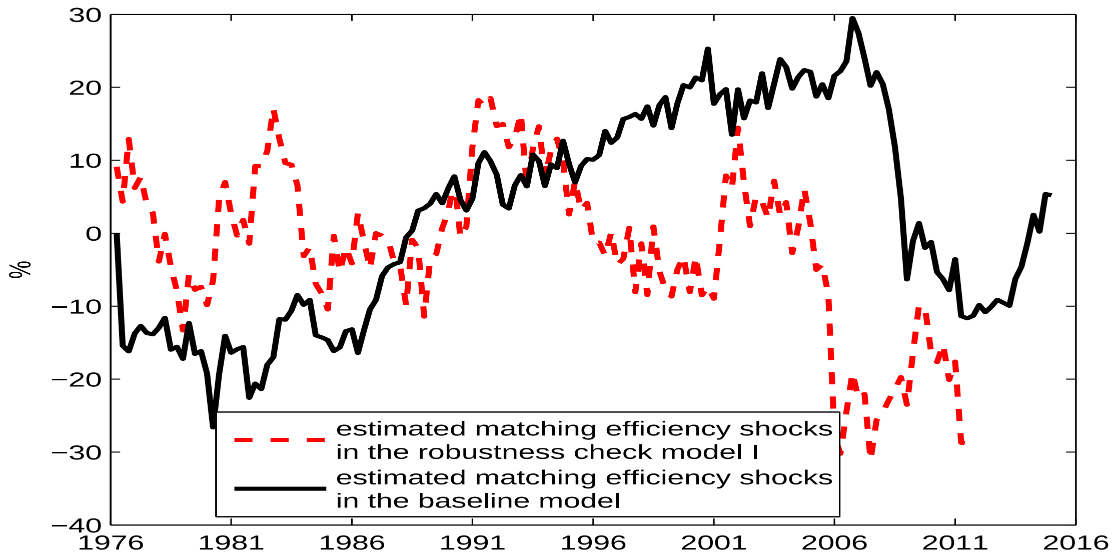
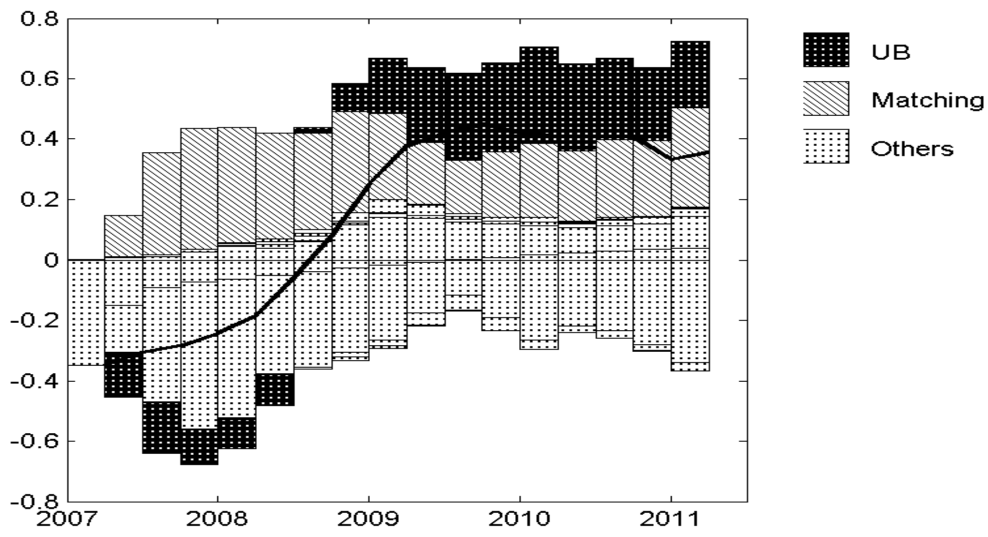


Figure 10: Historical Decomposition for Unemployment: 2007Q1 - 2011Q2 (Using Data on ρ^w and v/u)



Notes: The estimated model and smoothed shocks are used to obtain the historical decomposition. The black line is the log-deviation of the unemployment rate from its mean. The dark area with white dots, grey area with slash lines, and white area with black dots represent the contribution of the unemployment benefits shocks, matching efficiency shocks, and all other shocks to the deviation, respectively.

Figure 11: Actual and Counterfactual Beveridge Curves: 2007Q1 - 2014Q4
(Using Data on ρ^w and v/u)

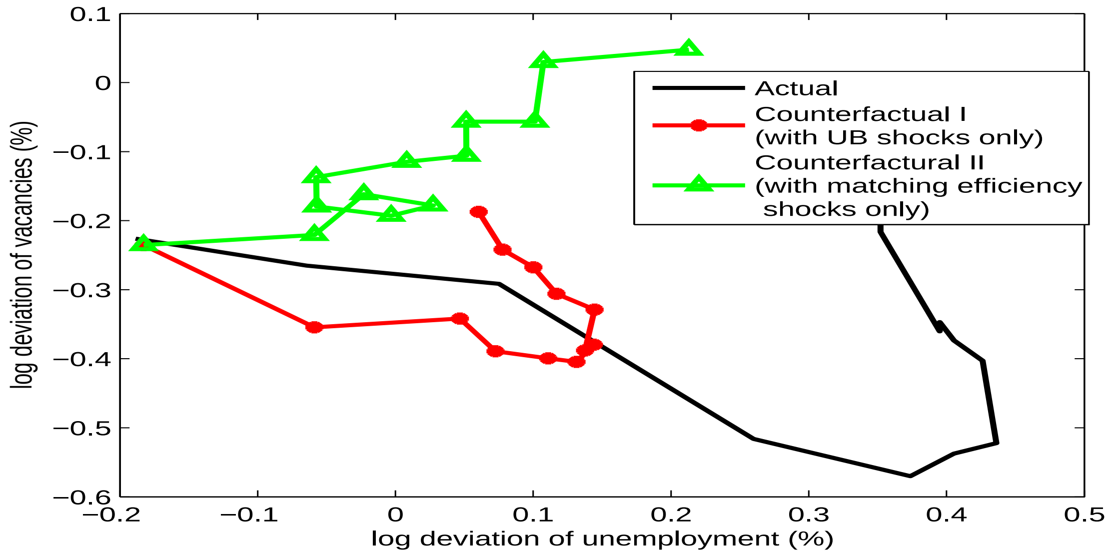
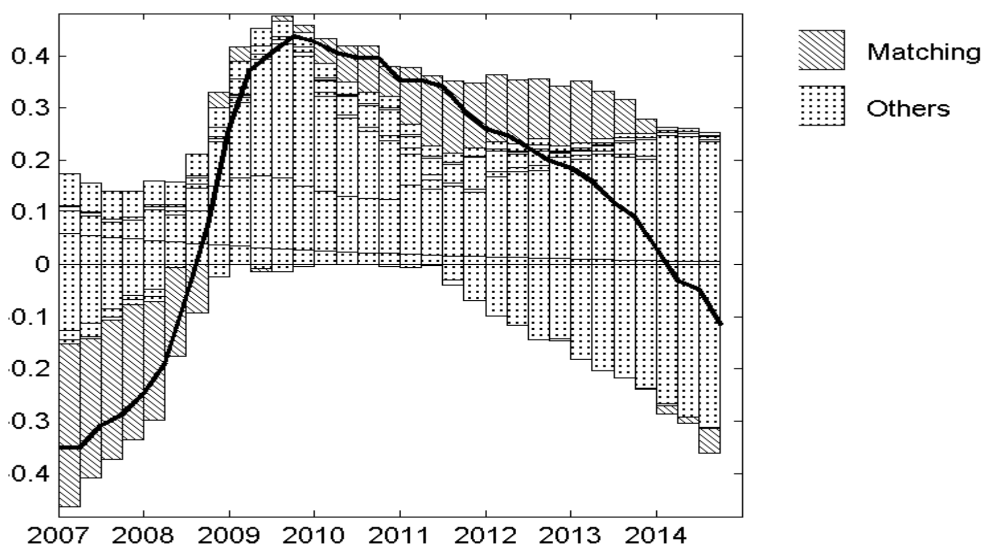
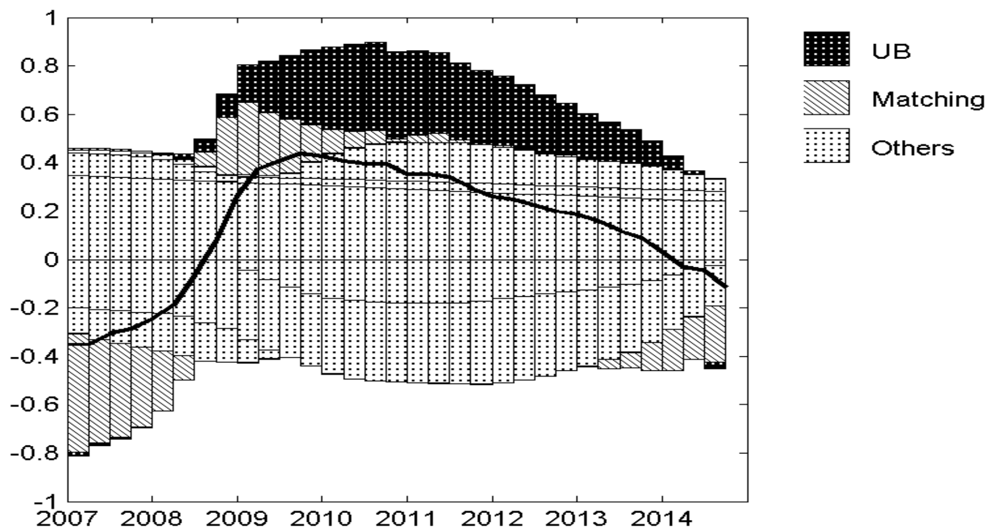


Figure 12: Historical Decomposition for Unemployment: 2007Q1 - 2014Q4
(No Unemployment Benefits Shocks)



Notes: The estimated model and smoothed shocks are used to obtain the historical decomposition. The black line is the log-deviation of the unemployment rate from its mean. The grey area with slash lines and white area with black dots represent the contribution of the matching efficiency shocks and all other shocks to the deviation, respectively.

Figure 13: Historical Decomposition for Unemployment: 2007Q1 - 2014Q4
(Endogenous Separation)



Notes: The estimated model and smoothed shocks are used to obtain the historical decomposition. The black line is the log-deviation of the unemployment rate from its mean. The black area with white dots, grey area with slash lines, and white area with black dots represent the contribution of the unemployment benefits shocks, matching efficiency shocks, and all other shocks to the deviation, respectively.