

The University of Adelaide School of Economics

Research Paper No. 2013-09 July 2013

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Francesco Furlanetto and Nicolas Groshenny



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Abstract

We investigate the macroeconomic consequences of fluctuations in the effectiveness of the labor-market matching process with a focus on the Great Recession. We conduct our analysis in the context of an estimated medium-scale DSGE model with sticky prices and equilibrium search unemployment that features a shock to the matching efficiency (or mismatch shock). We find that this shock is almost irrelevant for unemployment fluctuations in normal times. However, it plays a somewhat larger role during the Great Recession when it contributes to raise the actual unemployment rate by 1.25 percentage points and the natural rate by 2 percentage points. Moreover, it is the only shock that generates a positive conditional correlation between unemployment and vacancies.

Keywords: Search and matching frictions; Unemployment; Natural rates.

JEL codes: E32, C51, C52

^{*}First version: September 2011. This version: 27 June 2013. We are especially grateful to Regis Barnichon and Murat Tasci for generously sharing their data and to our discussants Federico Ravenna, James Morley, Pascal Michaillat, Shigeru Fujita and Makoto Nakajima for their comments. We also thank Klaus Adam, Michael Bordo, Efrem Castelnuovo, Larry Christiano, Marco Del Negro, Richard Dennis, Wouter Den Haan, Rochelle Edge, Chris Edmond, Paolo Gelain, Pedro Gomes, James Hansen, Steinar Holden, Peter Ireland, Nicolas Jacquet, Alejandro Justiniano, Jinill Kim, Dirk Krueger, François Langot, Jesper Linde, Ellen McGrattan, Elmar Mertens, Claudio Michelacci, Ed Nelson, Samad Sarferaz, Martin Seneca, Tommy Sveen, Fabien Tripier, Lawrence Uren, Karl Walentin, Jake Wong and participants in several conferences and seminars for their suggestions. The views expressed in this paper do not necessarily reflect the views of Norges Bank.

[†]Corresponding author. Address: Norges Bank, Bankplassen 2, PB 1179 Sentrum, 0107 Oslo, Norway. E-mail: francesco.furlanetto@norges-bank.no. Telephone number: +47 22316128.

[‡]Address: University of Adelaide, School of Economics. Email: nicolas.groshenny@adelaide.edu.au.

"The primary role for monetary policy is to offset the impact of nominal rigidities — that is, the sluggish adjustment of prices and inflation expectations to shocks. To offset nominal rigidities, monetary policy accommodation should track the gap between the observed unemployment rate u and the natural rate u^* . The challenge for monetary policymakers is that u^* changes over time and is unobservable." Narayana Kocherlakota (2011)

1 Introduction

During the Great Recession the unemployment rate in the United States increased markedly from a value of 4.5 percent in mid-2007 to a peak of 10 percent in fall 2009. Since then the labor market has recovered slowly. Nearly three years after its peak, the unemployment rate was still above 8 percent. Some policymakers have related the persistently high rate of unemployment to an increase in sectoral and geographical mismatch between the vacant jobs that are available and the workers who are unemployed (Kocherlakota 2010; Plosser 2010; and Lacker 2012). This view has received some support from a series of studies that identify a decline in the effectiveness of the process by which the aggregate labor market matched vacant jobs with unemployed workers during the Great Recession (cf. Elsby, Hobijn, and Sahin 2010; Barnichon and Figura 2011, among others). In this paper, we take a general equilibrium perspective and we estimate a medium-scale New Keynesian model with search and matching frictions in the labor market to measure the macroeconomic consequences of the observed decline in matching efficiency – in particular, its impact on the unemployment rate and the unemployment gap.

The spirit of our exercise is quantitative. Our model features the standard frictions and shocks that help in obtaining a good fit of the macro data (Christiano, Eichenbaum, and Evans 2005; Smets and Wouters 2007). In many respects, our model is similar to the one proposed by Gertler, Sala, and Trigari (2008) (henceforth GST) with three main differences: (i) we introduce a shock to the efficiency of the matching function (or "mismatch shock" for short); (ii) we treat this shock as an observable variable in our estimation; and (iii) we use the specification of the hiring cost function proposed by Yashiv (2000a, 2000b, and 2006) which combines a pre-match and a post-match component. We discuss each deviation from the GST (2008) benchmark in turn.

Matching efficiency shocks are already present in the seminal paper by Andolfatto (1996), which interprets them as sectoral reallocation shocks of the kind emphasized by Lilien (1982).¹ These shocks can be seen as the Solow residual of the matching function and as catch-all shocks for structural features in the labor market. These disturbances reflect variations in factors such as the degree of skill mismatch between jobs and workers (Sahin, Song, Topa, and Violante 2012; Herz and Van Rens 2011); the importance of geographical mismatch that might have been exacerbated by house-locking effects (Nenov 2012; Sterk 2011); workers' search intensity that may have been reduced by the extended duration of unemployment benefits (Fujita 2011; Baker and Fradkin 2012); firms' recruiting efforts (Davis, Faberman, and Haltinwanger 2010); and shifts in the composition of the unemployment pool, such as a rise in the share of long-term unemployed or fluctuations in participation due to demographic factors (Barnichon and Figura 2012). If these structural factors played an important role during the Great Recession, matching efficiency shocks should emerge as a prominent driver of the surge in the unemployment rate. Our goal is to quantify their contribution.

Our econometric strategy consists of two steps. First, we construct a time series for matching efficiency by adopting an approach inspired by Barnichon and Figura (2011). We use quarterly observations on the job-finding rate and the labor market tightness and feed these data into a subset of the equilibrium conditions provided by our model. By calibrating two parameters, the elasticity of the matching function and the steady-state separation rate, we are able to back out an implied time series for matching efficiency prior to the estimation. In line with Barnichon and Figura (2011) and Elsby, Hobijn, and Sahin (2010), our series for matching efficiency exhibits a large decline during the Great Recession. In the second step, we estimate our DSGE model using Bayesian techniques and quarterly data from 1957:Q1 to 2010:Q3 for eight aggregate variables, including matching efficiency. Treating matching efficiency as an observable variable facilitates identification

¹More recently, DSGE models featuring matching efficiency shocks have been considered by Beauchemin and Tasci (2012), Cheremukhin and Restrepo-Echevarria (2010), Furlanetto and Groshenny (2012), Justiniano and Michelacci (2011), Krause, Lopéz-Salido, and Lubik (2008) and Lubik (2009) among others.

of key parameters and puts discipline in the estimation exercise. Importantly, our shock has a clear empirical counterpart in keeping with the recommendation in Chari, Kehoe, and McGrattan (2009).

In our model, firms' hiring costs consist of a pre-match and a post-match component. The pre-match component is the search cost of advertising vacancies, a standard ingredient of models with search and matching frictions in the labor market (Pissarides 2000). The post-match component is the cost of adjusting the hiring rate. We can think of it as capturing training costs (GST 2008 and Pissarides 2009). In Furlanetto and Groshenny (2012), we show that the nature of hiring costs is crucial for the propagation of matching efficiency shocks. In particular, when firms do not face any pre-match costs, as in GST (2008), matching shocks exert no effects on the unemployment rate. Therefore, the share of pre-match costs in total hiring costs is a key parameter that we estimate in our analysis.

We find that matching efficiency shocks are almost irrelevant for business cycle fluctuations. This is due to the fact that the data favor a dominant role for the post-match component in the generalized hiring cost function. However, these shocks played a somewhat larger role during the Great Recession as matching efficiency literally collapsed. In this episode mismatch shocks explain about 1.25 percentage points of the increase in the unemployment rate. It is interesting that our general equilibrium model estimated on aggregate data delivers results that are consistent with Barnichon and Figura (2012) who find, by using disaggregated data, that reduced matching efficiency increased unemployment by at most 1.5 percentage points during the Great Recession. Sahin, Song, Topa, and Violante (2012) also use disaggregated data to measure the share of unemployment due to mismatch (which is one important driver of matching efficiency, but not the only determinant) and in their baseline scenario find that mismatch increased unemployment by 0.75 points during the Great Recession. Our results suggest that the bulk of the rise in the unemployment rate during the Great Recession was driven by a series of negative demand shocks, in particular risk premium shocks and investment-specific technology shocks.

From the perspective of a monetary policymaker, looking at the drivers of the actual unemployment rate is not sufficient. As Kocherlakota (2011) puts it, monetary policy should focus on offsetting the effects of nominal rigidities. To do so, monetary policy may aim at closing the gap between the actual and the natural rate of unemployment. As stressed by Kocherlakota (2011), a big challenge for policymakers is that the natural rate is unobservable and fluctuates over time. To address this issue, we use our estimated DSGE model to infer the path of the natural rate. We define the natural rate as the counterfactual rate of unemployment that emerges in a version of the model with flexible prices and wages, constant price mark-up, and constant bargaining power, in keeping with the previous literature (Smets and Wouters 2007; Sala, Söderström and Trigari 2008; Groshenny 2009 and 2012). Even though matching efficiency shocks have limited importance for fluctuations in actual unemployment, we find that these shocks are a dominant source of variation in the natural rate. This result is due to the fact that nominal rigidities dampen the propagation of matching efficiency shocks and enhance the effects of all the other shocks. We find that the deterioration in the effectiveness of the aggregate labor market matching process during the Great Recession contributed to raising the actual unemployment rate by 1.25 percentage points and the natural rate by 2 percentage points. Hence, negative matching efficiency shocks helped close the gap between the actual and the natural rate of unemployment. We estimate that in 2010:Q3the natural rate of unemployment was slightly below 8 percent and that the size of the unemployment gap was fairly small, just above 1 percentage point.

Our paper is related to two strands of the literature. We contribute to the literature initiated by Lilien (1982) on the importance of reallocation shocks, and more generally of structural factors, as a source of unemployment fluctuations.² Abraham and Katz (1986) and Blanchard and Diamond (1989) look at shifts in the sectoral composition of demand and estimate a series of regressions to disentangle the importance of reallocation shocks and aggregate demand shocks. Both papers emphasize the primacy of aggregate demand shocks in producing unemployment fluctuations and find that reallocation shocks

 $^{^{2}}$ In this sense we follow the seminal contribution by Andolfatto (1996) and we interpret the shock to the matching efficiency as a reallocation shock: if job creation is easier within sectors than across sectors, as seems plausible, reallocation shocks will affect aggregate matching efficiency. This seems to be a natural choice in the context of a one-sector model. An alternative approach that would allow for a more rigorous treatment of reallocation shocks would be the use of multisector models that have, however, a less tractable structure (Garin, Pries, and Sims 2011).

are almost irrelevant at business cycle frequencies (although they have some explanatory power at low frequencies). Our contribution to this literature is the use of an estimated dynamic stochastic general equilibrium model (DSGE) rather than a reduced-form model.

Our paper also relates to the literature that studies the output gap derived from estimated New Keynesian models (Smets and Wouters 2007; Justiniano, Primiceri, and Tambalotti 2013). Often in this literature, the labor market is modeled only along the intensive margin (hours worked). Notable exceptions are Galí, Smets and Wouters (2011) and Sala, Söderström, and Trigari (2008). Galí, Smets, and Wouters (2011) estimate a model with unemployment and also compute a measure of the natural rate. However, in their model, unemployment is due only to the presence of sticky wages (there are no search and matching frictions) so that the natural rate fluctuates only in response to wage mark-up shocks. In our model, unemployment is due to both nominal rigidities and search and matching frictions. Moreover, our measure of the natural rate fluctuates in response to several shocks. Sala, Söderström, and Trigari (2008) provide a similar model-based measure of the natural rate. Their model, however, does not feature matching efficiency shocks which are, according to our estimates, prominent drivers of the natural rate, and their sample period does not include the Great Recession.

The paper proceeds as follows: Section 2 lays out the model. Section 3 explains our econometric strategy. Sections 4 and 5 discuss the effects of the decline in the effectiveness of the labor market matching process during the Great Recession on the *actual* unemployment rate and the *natural* unemployment rate respectively. Section 6 concludes.

2 Model

Our model builds upon Groshenny (2009, 2012) and merges the New Keynesian model with the search and matching model of unemployment.³ The model incorporates the standard features introduced by Christiano, Eichenbaum, and Evans (2005) to help the

³The use of search and matching frictions in business cycle models was pionereed by Merz (1995) and Andolfatto (1996) in the real business cycle (RBC) literature. More recently, the same labor market frictions have been studied in the New Keynesian model by Blanchard and Galí (2010), Christiano, Trabandt, and Walentin (2011), Christoffel, Kuester, and Linzert (2009), GST (2008), Groshenny (2009 and 2012), Krause and Lubik (2007a), Krause, López-Salido, and Lubik (2008), Ravenna and Walsh (2008 and 2011), Sveen and Weinke (2009), Trigari (2009), and Walsh (2005), among many others.

model fit the postwar U.S. macro data. Moreover, as in the benchmark quantitative macroeconometric model of Smets and Wouters (2007), fluctuations are driven by multiple exogenous stochastic disturbances. Including the matching efficiency shock, the model features eight disturbances. The remaining seven shocks are: 1) a shock to the growth rate of total factor productivity (TFP), 2) an investment-specific technology shock, 3) a risk-premium shock, 4) a price markup shock, 5) a wage bargaining shock, 6) a government spending shock and 7) a monetary policy shock. GST (2008) have shown that such a model fits the macro data as accurately as the Smets and Wouters (2007) model.

Our model is similar to GST (2008) with three main differences, as already outlined in the introduction. We include an extra stochastic disturbance, namely the mismatch shock, we treat matching efficiency as an observable variable in the estimation, and we use a generalized hiring function as in Yashiv (2000a, 2000b, and 2006). There are other small differences compared to GST (2008). First, as in Smets and Wouters (2007), we have a risk premium shock, rather than a preference shock, to capture disturbances originating in the financial markets. Given the financial flavor of the Great Recession, we believe it is important to have a financial shock in the model. Second, we use the timing proposed by Ravenna and Walsh (2008) in the law of motion for employment: new hires become productive in the current period and separated workers start searching for a job immediately so that they do not have necessarily to be unemployed for one period (see below). Third, we simplify the model in some dimensions that are not essential for our analysis by using quadratic adjustment costs in prices (Rotemberg 1982) and wages (Arsenau and Chugh 2008) instead of staggered time-dependent contracts. We also use a Dixit-Stiglitz aggregator with constant elasticity of substitution across goods instead of the Kimball aggregator with endogenous elasticity.

The model economy consists of a representative household, a continuum of intermediate goods-producing firms, a representative finished goods-producing firm, and monetary and fiscal authorities which set monetary and fiscal policy respectively.

The representative household There is a continuum of identical households of mass one. Each household is a large family, made up of a continuum of individuals of

measure one. Family members are either working or searching for a job. The model abstracts from the labor force participation decision. Following Merz (1995), we assume that family members pool their income before allowing the head of the family to optimally choose per capita consumption.

The representative family enters each period t = 0, 1, 2, ..., with B_{t-1} bonds and \overline{K}_{t-1} units of physical capital. Bonds mature at the beginning of each period, providing B_{t-1} units of money. The representative family uses some of this money to purchase B_t new bonds at nominal cost B_t/R_t , where R_t denotes the gross nominal interest rate between period t and t + 1.

The representative household owns the stock of physical capital \overline{K}_t which evolves according to

$$\overline{K}_{t} \leq (1-\delta) \,\overline{K}_{t-1} + \mu_{t} \left[1 - \pounds \left(\frac{I_{t}}{I_{t-1}} \right) \right] I_{t},\tag{1}$$

where δ denotes the depreciation rate. The function \pounds captures the presence of adjustment costs in investment, as in Christiano, Eichenbaum, and Evans (2005). An investment-specific technology shock μ_t affects the efficiency with which consumption goods are transformed into capital. This shock follows the process

$$\ln \mu_t = \rho_\mu \ln \mu_{t-1} + \varepsilon_{\mu t},\tag{2}$$

where $\varepsilon_{\mu t}$ is *i.i.d.N* $(0, \sigma_{\mu}^2)$.

The household chooses the capital utilization rate, u_t , which transforms physical capital into effective capital according to

$$K_t = u_t \overline{K}_{t-1}.$$
(3)

Following Christiano, Eichenbaum, and Evans (2005), the household faces a cost $a(u_t)$ of adjusting the capacity-utilization rate. The household rents effective capital services to firms at the nominal rate r_t^K .

Each period, N_t family members are employed. Each employee works a fixed amount

of hours and earns the nominal wage W_t . The remaining $(1 - N_t)$ family members are unemployed and each receives nominal unemployment benefits b_t , financed through lumpsum taxes. Unemployment benefits b_t are proportional to the nominal wage along the steady-state balanced growth path $b_t = \tau W_{ss,t}$. The fact that unemployment benefits grow along the balanced growth path ensures that unemployment remains stationary. During period t, the representative household receives total nominal factor payments $r_t^K K_t + W_t N_t + (1 - N_t) b_t$ as well as profits D_t . The family uses these resources to purchase finished goods for both consumption and investment purposes.

The family's period t budget constraint is given by

$$P_{t}C_{t} + P_{t}I_{t} + \frac{B_{t}}{\epsilon_{bt}R_{t}} \leq B_{t-1} + W_{t}N_{t} + (1 - N_{t})b_{t} + r_{t}^{K}u_{t}\overline{K}_{t-1}$$

$$-P_{t}a(u_{t})\overline{K}_{t-1} - T_{t} + D_{t}.$$
(4)

As in Smets and Wouters (2007), the shock ϵ_{bt} drives a wedge between the central bank's instrument rate R_t and the return on assets held by the representative family. As noted by De Graeve, Emiris, and Wouters (2009), this disturbance works as an aggregate demand shock and generates a positive comovement between consumption and investment. The risk-premium shock ϵ_{bt} follows the autoregressive process

$$\ln \epsilon_{bt} = \rho_b \ln \epsilon_{bt-1} + \varepsilon_{bt},\tag{5}$$

where $0 < \rho_b < 1$, and ε_{bt} is *i.i.d.N* $(0, \sigma_b^2)$.

The family's lifetime utility is described by

$$E_t \sum_{s=0}^{\infty} \beta^s \ln \left(C_{t+s} - h C_{t+s-1} \right),$$
(6)

where $0 < \beta < 1$ and h > 0 captures internal habit formation in consumption.

The representative intermediate goods-producing firm Each intermediate goods-producing firm $i \in [0, 1]$ enters in period t with a stock of $N_{t-1}(i)$ employees. Before production starts, $\rho N_{t-1}(i)$ old jobs are destroyed. The job destruction rate ρ is constant. Those workers who have lost their jobs start searching immediately and can potentially still be hired in period t (Ravenna and Walsh 2008). Employment at firm ievolves according to $N_t(i) = (1 - \rho) N_{t-1}(i) + m_t(i)$, where the flow of new hires $m_t(i)$ is given by $m_t(i) = q_t V_t(i)$. $V_t(i)$ denotes vacancies posted by firm i in period t and q_t is the aggregate probability of filling a vacancy,

$$q_t = \frac{m_t}{V_t},\tag{7}$$

where $m_t = \int_0^1 m_t(i) di$ and $V_t = \int_0^1 V_t(i) di$ denote aggregate matches and vacancies respectively. Aggregate employment $N_t = \int_0^1 N_t(i) di$ evolves according to

$$N_t = (1 - \rho) N_{t-1} + m_t.$$
(8)

The matching process is described by an aggregate constant-returns-to-scale Cobb-Douglas matching function,

$$m_t = \zeta_t S_t^{\sigma} V_t^{1-\sigma},\tag{9}$$

where S_t denotes the pool of job seekers in period t,

$$S_t = 1 - (1 - \rho) N_{t-1}, \tag{10}$$

and ζ_t is a time-varying scale parameter that captures the efficiency of the matching technology. It evolves exogenously following the autoregressive process,

$$\ln \zeta_t = \left(1 - \rho_\zeta\right) \ln \zeta + \rho_\zeta \ln \zeta_{t-1} + \varepsilon_{\zeta t},\tag{11}$$

where ζ denotes the steady-state matching efficiency and $\varepsilon_{\zeta t}$ is *i.i.d.N* $(0, \sigma_{\zeta}^2)$. Aggregate unemployment is defined by $U_t \equiv 1 - N_t$.

At this stage we want to emphasize the importance of the timing assumption that we borrow from Ravenna and Walsh (2008) and that has been adopted also by Sveen and Weinke (2009) and Christiano, Eichenbaum, and Trabandt (2012). At the beginning of the period, which is a quarter in our model, exogenous separation takes place before production starts. Separated workers immediately look for a job and may find one with a probability given by the current job-finding rate. After matching has taken place, those who remaining unmatched enter in the unemployment pool and will search for a job in the next period. Newly hired workers become productive in the current period. As recently pointed out by Christiano, Eichenbaum, and Trabandt (2012), this timing convention implies that our model features a kind of job-to-job transition which is highly cyclical, given that it depends on the job-finding rate. Therefore, the flow from employment to unemployment is not constant. It increases during recessions, even if we have a model with exogenous separation. In bad times, when the job-finding rate is low, few workers will have a direct job-to-job transition and more workers will flow from employment to unemployment.

Firms face hiring costs $H_t(i)$ measured in terms of the finished good and given by a generalized hiring function proposed by Yashiv (2000a, 2000b, and 2006) that combines a pre-match and a post-match component in the following way,

$$H_t(i) = \frac{\kappa}{2} \left(\frac{\phi_V V_t(i) + (1 - \phi_V) m_t(i)}{N_t(i)} \right)^2 Y_t,$$
(12)

where κ determines to the output-share of hiring costs and $0 \leq \phi_V \leq 1$ governs the relative importance of the pre-match component. When ϕ_V is equal to 0 we are back to the model with only post-match hiring costs (GST 2008). Instead, when ϕ_V is equal to 1 we obtain a model with quadratic pre-match hiring costs (Pissarides 2000). Interestingly, the empirical literature has so far preferred a specification with post-match hiring costs, that can be interpreted as training costs. In the context of our model it is essential to include a pre-match component because shocks to the matching efficiency do not affect unemployment in a model that only includes post-match hiring costs (Furlanetto and Groshenny 2012).

Each period, firm *i* combines $N_t(i)$ homogeneous employees with $K_t(i)$ units of efficient capital to produce $Y_t(i)$ units of intermediate good *i* according to the constant-

returns-to-scale technology described by

$$Y_t(i) = A_t^{1-\alpha} K_t(i)^{\alpha} N_t(i)^{1-\alpha}.$$
(13)

 A_t is an aggregate labor-augmenting technology shock whose growth rate, $z_t \equiv A_t/A_{t-1}$, follows the exogenous stationary stochastic process,

$$\ln z_t = (1 - \rho_z) \ln z + \rho_z \ln z_{t-1} + \varepsilon_{zt},\tag{14}$$

where z > 1 denotes the steady-state growth rate of the economy and ε_{zt} is *i.i.d.N* $(0, \sigma_z^2)$.

Intermediate goods substitute imperfectly for one another in the production function of the representative finished goods-producing firm. Hence, each intermediate goodsproducing firm $i \in [0, 1]$ sells its output $Y_t(i)$ in a monopolistically competitive market, setting $P_t(i)$, the price of its own product, with the commitment of satisfying the demand for good i at that price. Each intermediate goods-producing firm faces costs of adjusting its nominal price between periods, measured in terms of the finished good and given by

$$\frac{\phi_P}{2} \left(\frac{P_t(i)}{\pi_{t-1}^{\varsigma} \pi^{1-\varsigma} P_{t-1}(i)} - 1 \right)^2 Y_t.$$
(15)

The term ϕ_P governs the magnitude of the price adjustment cost. The expression $\pi_t = \frac{P_t}{P_{t-1}}$ denotes the gross rate of inflation in period t. The steady-state gross rate of inflation is denoted by $\pi > 1$ and coincides with the central bank's target. The parameter $0 \le \varsigma \le 1$ governs the importance of backward-looking behavior in price setting (Ireland 2007).

We model nominal wage rigidities as in Arsenau and Chugh (2008). Each firm faces quadratic wage-adjustment costs which are proportional to the size of its workforce and measured in terms of the finished good,

$$\frac{\phi_W}{2} \left(\frac{W_t(i)}{z \pi_{t-1}^{\varrho} \pi^{1-\varrho} W_{t-1}(i)} - 1 \right)^2 N_t(i) Y_t, \tag{16}$$

where ϕ_W governs the magnitude of the wage adjustment cost. The parameter $0 \le \rho \le 1$ governs the importance of backward-looking behavior in wage setting. Firms take the

nominal wage as given when maximizing the discounted value of expected future profits.⁴

Wage setting The nominal wage $W_t(i)$ is determined through bilateral Nash bargaining,

$$W_t(i) = \arg\max\left(\Delta_t(i)^{\eta_t} J_t(i)^{1-\eta_t}\right).$$
(17)

The worker's surplus, expressed in terms of final consumption goods, is given by

$$\Delta_t(i) = \frac{W_t(i)}{P_t} - \frac{b_t}{P_t} + \beta \chi E_t \left(1 - s_{t+1}\right) \frac{\Lambda_{t+1}}{\Lambda_t} \Delta_{t+1}(i) , \qquad (18)$$

where $\chi \equiv 1 - \rho$. Λ_t denotes the household's marginal utility of wealth and $s_t = m_t/S_t$ is the aggregate job finding rate. The firm's surplus in real terms is given by

$$J_{t}(i) = \xi_{t}(i)(1-\alpha)\frac{Y_{t}(i)}{N_{t}(i)} - \frac{W_{t}(i)}{P_{t}} - \frac{\phi_{W}}{2}\left(\frac{W_{t}(i)}{z\pi_{t-1}^{\varrho}\pi^{1-\varrho}W_{t-1}(i)} - 1\right)^{2}Y_{t} + \frac{\kappa}{N_{t}(i)}\left(\frac{\phi_{V}V_{t}(i) + (1-\phi_{V})q_{t}V_{t}(i)}{N_{t}(i)}\right)^{2}Y_{t} + \beta\chi E_{t}\frac{\Lambda_{t+1}}{\Lambda_{t}}J_{t+1}(i), \quad (19)$$

where $\xi_t(i)$ denotes firm *i*'s real marginal cost (Krause and Lubik 2007a). The worker's bargaining power η_t evolves exogenously according to

$$\ln \eta_t = (1 - \rho_\eta) \ln \eta + \rho_\eta \ln \eta_{t-1} + \varepsilon_{\eta t}, \tag{20}$$

where $0 < \eta < 1$ denotes the steady-state worker's bargaining power and $\varepsilon_{\eta t}$ is *i.i.d.N* $(0, \sigma_{\eta}^2)$.

The representative finished goods-producing firm During each period t = 0, 1, 2, ..., the representative finished good-producing firm uses $Y_t(i)$ units of each intermediate good $i \in [0, 1]$, purchased at the nominal price $P_t(i)$, to produce Y_t units of the finished good according to the constant-returns-to-scale technology described by

$$\left(\int_0^1 Y_t\left(i\right)^{\left(\theta_t-1\right)/\theta_t} di\right)^{\theta_t/\left(\theta_t-1\right)} \ge Y_t,\tag{21}$$

 $^{^{4}}$ We abstract from intrafirm bargaining. Krause and Lubik (2007b) show that the effects of intrafirm bargaining on business cycle fluctuations is negligible.

where θ_t is a shock to the intermediate goods-producing firm's markup. This shock follows the autoregressive process

$$\ln \theta_t = (1 - \rho_\theta) \ln \theta + \rho_\theta \ln \theta_{t-1} + \varepsilon_{\theta t}, \tag{22}$$

where $0 < \rho_{\theta} < 1$, $\theta > 1$, and $\varepsilon_{\theta t}$ is *i.i.d.N* $(0, \sigma_{\theta}^2)$.

Monetary and fiscal authorities The central bank adjusts the short-term nominal gross interest rate R_t by following a Taylor-type rule similar to the one proposed by Justiniano, Primiceri and Tambalotti (2013):

$$\ln\frac{R_t}{R} = \rho_r \ln\frac{R_{t-1}}{R} + (1 - \rho_r) \left(\rho_\pi \ln\frac{(P_t/P_{t-4})^{1/4}}{\pi} + \rho_y \ln\frac{(Y_t/Y_{t-4})^{1/4}}{z}\right) + \ln\epsilon_{mpt}.$$
 (23)

The degree of interest-rate smoothing ρ_r and the reaction coefficients ρ_{π} and ρ_y are all positive. The monetary policy shock ϵ_{mpt} follows an AR(1) process

$$\ln \epsilon_{mpt} = \rho_{mp} \ln \epsilon_{mpt-1} + \varepsilon_{mpt}, \tag{24}$$

with $0 \leq \rho_{mp} < 1$ and $\varepsilon_{mpt} \sim i.i.d.N\left(0, \sigma_{mp}^2\right)$.

The government budget constraint takes the form,

$$P_t G_t + (1 - N_t) b_t = \left(\frac{B_t}{R_t} - B_{t-1}\right) + T_t,$$
(25)

where T_t denotes total nominal lump-sum transfers. Public spending is an exogenous time-varying fraction of GDP,

$$G_t = \left(1 - \frac{1}{\epsilon_{gt}}\right) Y_t,\tag{26}$$

where ϵ_{gt} evolves according to

$$\ln \epsilon_{gt} = \left(1 - \rho_g\right) \ln \epsilon_g + \rho_g \ln \epsilon_{gt-1} + \varepsilon_{gt},\tag{27}$$

with $\varepsilon_{gt} \sim i.i.d.N\left(0,\sigma_g^2\right)$.

Model solution Real output, consumption, investment, capital and wages share the common stochastic trend induced by the unit root process for neutral technological progress. In the absence of shocks, the economy converges to a steady-state growth path in which all stationary variables are constant. We first rewrite the model in terms of stationary variables, and then log-linearize the transformed economy around its deterministic steady state. The approximate model can then be solved using standard methods.

3 Econometric Strategy

Calibrated parameters Due to identification problems, we calibrate 14 parame-Table 1 reports the calibration. The quarterly depreciation rate is set equal to ters. 0.025. The capital share of output is calibrated at 0.33. The elasticity of substitution between intermediate goods is set equal to 6, implying a steady-state markup of 20 percent as in Rotemberg and Woodford (1995). The vacancy-filling rate is set equal to 0.70, which is just a normalization. The steady-state government spending/output ratio is set equal to 0.20. The steady-state values of output growth, inflation, the interest rate, and the unemployment rate are set equal to their respective sample average over the period 1957:Q1–2010:Q3. Calibrated values for the steady state quarterly separation rate range in literature from 0.05 in Krause, Lopéz-Salido, and Lubik (2008) to 0.15 in Andolfatto (1996). We use the conventional value 0.085, in line with most of the literature (Yashiv 2006). We set the elasticity of the matching function with respect to unemployment at 0.4, in keeping with Blanchard and Diamond (1989) and Yashiv (2006). The calibration of the replacement rate is a conservative value based on Shimer (2005) and Yashiv (2006). These choices avoid indeterminacy issues that are widespread in this kind of model, as shown by Kurozumi and Van Zandweghe (2010) among others. Based on results from preliminary estimation rounds we set the degree of indexation to past inflation equal to zero and the hiring cost/output ratio equal to 0.3 percent. Table 2 reports the parameters whose values are derived from the steady-state conditions.

Bayesian estimation We estimate the remaining 26 parameters using Bayesian techniques. The estimation period is 1957:Q1–2010:Q3. We choose to estimate our model with data through 2010:Q3, therefore including the Great Recession in our sample period. We are aware that the use of a linearized model in a period where shocks are large and the zero-lower bound is binding can be problematic. On the other hand, we see the benefit of including four years of data with rich dynamics. Moreover, Stock and Watson (2012) show that during the Great Recession the economy responded in an historically predictable way to shocks that were significantly larger than the ones previously experienced. According to their finding, the use of a linearized model may be less problematic than what was previously thought. Nevertheless, our estimated series of monetary policy shocks should be taken with a grain of salt.

The model includes as many shocks as observables. The estimation uses quarterly data on eight key macro variables: 1) the growth rate of real output per capita, 2) the growth rate of real consumption per capita, 3) the growth rate of real investment per capita, 4) the growth rate of real wages, 5) the inflation rate, 6) the short-term nominal interest rate, 7) the unemployment rate, and 8) matching efficiency. Our priors are standard (Smets and Wouters 2007; GST 2008). We normalize the price-markup shock and the wage-markup shock, so that these enter with a unit coefficient in the model's equations. Such procedure facilitates the identification of the standard deviations of these two disturbances. We use the random walk Metropolis-Hasting algorithm to generate 250,000 draws from the posterior distribution. The algorithm is tuned to achieve an acceptance ratio between 25 and 30 percent. We discard the first 125,000 draws. Tables 3 and 4 summarize the priors and the posteriors.

Using data on matching efficiency helps in identifying some key parameters and imposes some discipline on our estimation exercise. To construct a time series for matching efficiency, we follow an approach inspired by Barnichon and Figura (2011). Namely, we use quarterly observations on the job-finding rate and the vacancy/unemployment ratio and we feed these data into a subset of the model's equilibrium conditions.⁵ Like

 $^{^{5}}$ We thank Larry Christiano for suggesting the current approach to us. In a previous version of this paper, we were using data on vacancies instead of matching efficiency. This approach was problematic as it was producing estimates of matching efficiency shocks which were at odds with the evidence found

technology shocks in the context of the neoclassical production function, matching efficiency shocks have a clear empirical counterpart. Moreover, our empirical strategy enables us to exploit information from two key observables, the job-finding rate and the vacancy/unemployment ratio, without introducing an additional, possibly dubious structural, shock.⁶ The appendix describes the dataset and the empirical strategy in detail. In Figure 1 we plot our matching efficiency series, which exhibits a large drop during the Great Recession when it reaches unprecedented low levels. The cyclical properties of our series are in line with the evidence provided by Barnichon and Figura (2011).

At this point we want to underscore that matching efficiency shocks have a broad interpretation. We see them as catch-all disturbances that soak up changes in various features of the aggregate labor market, not only mismatch. Like the Solow residual of the neo-classical production function, matching efficiency is likely to incorporate a non negligible endogenous component. For example, search intensity by workers and firms may play a nontrivial role, as does variable capacity utilization in the production function. Our paper is only a first step in the identification of structural factors in the labor market. More generally, we believe there is scope for future research on how to "purify" the matching function's Solow residual, as has been done for the production function (Basu, Fernald, and Kimball 2006). Borowczyk-Martins, Jolivet, and Postel-Vinay (2012) and Sedlacek (2012) have made interesting progress in that direction.

4 Mismatch Shocks in the Great Recession

In Tables 3 and 4 we report the outcome of our estimation exercise. Most estimates are in line with the previous literature. A distinctive feature of our model is the use of the generalized hiring cost function proposed by Yashiv (2000a, 2000b, and 2006) which

in the recent literature. In particular, matching efficiency during the Great Recession was estimated to be above its steady-state value and to be improving further. This suggests that the information content of the job finding rate series (that we have used together with labor market tightness) is essential to measure properly matching efficiency. We also tried to estimate the model using data on the job finding rate (instead of vacancies as in the previous version, or matching efficiency as in the current version). However, the standard deviation of matching shocks was not well identified.

⁶A possible alternative that would estimate the model in one step is to use data on the job-finding rate, unemployment, and vacancies as observables. Then, we could introduce a shock to the separation rate in addition to the shock to the matching efficiency to achieve identification.

combines a pre-match and a post-match component. The estimate of the parameter ϕ_V , the weight of the pre-match component in the convex combination, is therefore particularly interesting. Although we use an agnostic prior centered around 0.5, the data pushes clearly in favour of a large post-match component. In fact, ϕ_V is estimated at 0.04 at the posterior median. Christiano, Trabandt, and Walentin (2011) find a similar result in their estimated model for Sweden. This result is also consistent with Silva and Toledo (2009) and Yashiv (2000a), both of whom estimate the relative shares of pre-match and post-match costs in total hiring costs using disaggregated data. Both studies find a dominant role for the post-match component.

This result has strong implications for the propagation of matching efficiency shocks. As we show in Furlanetto and Groshenny (2012), the larger the post-match component is, the lower is the shock's effect on unemployment and output, and the larger its effect on vacancies. In the limiting case of zero weight on the pre-match component (i.e. when posting vacancies is costless, as in GST 2008), unemployment and output are invariant to matching efficiency shocks. This insight is confirmed in the impulse responses shown in Figure 2 where we see that the response of the unemployment rate is very limited.⁷ Of course the shock has a rather large effect on vacancies given that posting vacancies is almost costless. The same picture emerges in the variance decomposition depicted in Table 5 where we see that the mismatch shock behaves like a supply shock, driving output and inflation in opposite directions.⁸

Given the prevalence of the post-match component, matching efficiency shocks are almost irrelevant for business cycle fluctuations over our sample period. The relevant sources of output fluctuations in the model are neutral technology shocks, investment-

⁷Importantly, our results should be interpreted as an upper-bound for the importance of mismatch shocks given our simplifying assumption of exogenous separation (on the importance of endogenous separation, see Fujita and Ramey 2012). In fact, Justiniano and Michelacci (2011) argue that reallocation shocks, unlike other shocks, move job-finding rates and job separation rates in the same direction. Therefore, in our model a decline in the job-finding rate would be accompanied by a decline in separation in response to a negative mismatch shock. This would reduce the unemployment response even further. More recently, Zhang (2013) confirms this result in an estimated DSGE model with endogenous separation.

⁸A detailed discussion on the propagation of mismatch shocks is provided in Furlanetto and Groshenny (2012).

specific technology shocks, and risk-premium shocks.⁹ Finally, wage-bargaining shocks do not matter for output fluctuations. This result was already present in GST (2008) but, as far as we know, it has not been commented in the literature. Chari, Kehoe, and McGrattan (2009) have criticized the New Keynesian model for its reliance on dubiously structural shocks such as the wage-bargaining (or wage mark-up) shock. Here, we find that this criticism does not apply. Our finding suggests that search and matching frictions in the labor market, and the use of labor market variables in the estimation, absorb the explanatory power of the wage-bargaining shock. Put differently, our estimated DSGE model seems successful at endogenizing the labor wedge.

The limited importance of matching shocks for business cycle fluctuations in general does not rule out that these shocks can play a relevant role in specific episodes. In particular, large matching efficiency shocks can occur in periods when unemployment and vacancies move in the same direction. As we see in Figure 3, our matching shock is the only disturbance that generates a positive conditional correlation between unemployment and vacancies. In Furlanetto and Groshenny (2012) we show that this positive correlation obtains when the shock is sufficiently persistent and prices are rather sticky. In our estimated model, the conditions for matching shocks to generate a positive correlation between unemployment and vacancies are fulfilled. Matching shocks are estimated to be very persistent (ρ_{ζ} is equal to 0.93 at the posterior median) and prices to be fairly sticky. Our posterior median estimate of the price adjustment cost parameter ϕ_P implies that the slope of the New Keynesian Phillips curve is equal to 0.085. This value is consistent with firms resetting prices once every four quarters in a model with nominal rigidities à la Calvo. Hence, in our model, exogenous stochastic variations in the effectiveness of the labor market matching process can be seen as shifter of the empirical Beveridge curve and, as shown in Figure 3, they are the only disturbances that can play this role (for the Beveridge curve's behavior during the Great Recession, see Hobijn and Sahin 2012, and Lubik 2011). We believe that this finding offers a powerful justification for including

⁹Our results are consistent with Justiniano, Primiceri and Tambalotti (2010) and GST (2008) once we take into account that the risk premium shock, proposed by Smets and Wouters (2007), limits somewhat the importance of the investment specific technology shock. This fact confirms the financial friction interpretation of the investment shock proposed by Justiniano, Primiceri, and Tambalotti (2011).

mismatch shocks in estimated DSGE models with a focus on the labor market. This result reinforces the interpretation of mismatch shocks as catch-all shocks to capture structural features of the labor market.

In Figure 4 we plot the historical decomposition of the unemployment rate. Over the sample period, matching efficiency shocks generally play a minor role, but have a somewhat larger impact during the Great Recession. Since 2009, negative mismatch shocks are responsible on average for about 1.25 percentage points of the large increase in the unemployment rate.¹⁰ This result is in line with other studies. Barnichon and Figura (2012) decompose movements in the empirical Beveridge curve into the contributions of labor demand, labor supply, and matching efficiency factors. They find that the role of matching efficiency factors is limited and conclude that without any loss in matching efficiency, unemployment would have been about 150 points lower in late 2010 (see also Herz and van Rens, 2011). Both our results and the Barnichon and Figura (2012) results can be interpreted as an upper-bound for mismatch unemployment given that matching efficiency captures also other structural features in the labor market. Two recent studies focus on the implications of the unemployment benefit extension during the Great Recession: Nakajima (2012) finds that the extension increased unemployment by 1.4 percentage points in a calibrated model, whereas Zhang (2013) estimates an increase of 1 per-cent in a DSGE model with endogenous separation. Sahin, Song, Topa, and Violante (2012) confine their attention to the more narrow concept of mismatch unemployment. They combine disaggregated data from JOLTS and HWOL to construct a mismatch index and quantify the importance of mismatch unemployment. In their baseline analysis they find that mismatch unemployment at the 2-digit industry level can account for 0.75 percentage points out of the 5.4 increase in the U.S. unemployment rate from 2006 to the Fall 2009.¹¹ This result is fully compatible with our evidence, given that mismatch is not the

¹⁰Sala, Söderstöm, and Trigari (2012) conduct the same experiment in a similar model with a focus on a cross-country comparison. They find results that are in line with ours for the United States. Interestingly, they find that fluctuations in matching efficiency during the Great Recession are considerably less important in the United Kingdom and Sweden, whereas matching efficiency even improves in Germany. See also Justiniano (2012).

¹¹In a series of extensions they conclude that mismatch unemployment (due to skill mismatch) can account at most for one third of the increase in unemployment whereas geographical mismatch does not play any role.

only driver of matching efficiency. We find it intriguing that studies using very different methodologies and data yield results that are in the same ballpark.

From Figure 4 we see that the large increase in unemployment during the Great Recession is explained by a series of large negative demand shocks like risk-premium shocks (in particular during 2009) and investment shocks. This result is in line with Justiniano, Primiceri, and Tambalotti (2011) who trace the origin of the adverse investment shocks to financial disturbances that are amplified by nominal rigidities. The role of monetary policy shocks is negligible. This finding is partly due to the fact that we include the recent period, when the zero lower bound is binding, in our estimation. Instead, we find that fiscal policy shocks have contributed materially to lower unemployment since 2007. This is somewhat surprising given that the model does not include any of the features that are usually used to amplify the effects of fiscal shocks (like rule-of-thumb consumers, nonseparable preferences, or deep habits). One possible explanation is that, beyond the massive fiscal stimulus package implemented by the U.S. authorities in the aftermath of the crisis, our model interprets as expansionary fiscal shocks some positive impulses stemming from the series of unconventional monetary policy measures taken by the Federal Reserve and the weakening of the US dollar that has helped lifting exports. Finally, we find that negative bargaining power shocks (that is, a reduction in the bargaining power of workers) have contributed to lowering the unemployment rate over the entire period since the jobless recovery that followed the 2001 recession and throughout the Great Recession. This finding may reflect competitive pressures from abroad and threats of offshoring from the domestic market. Arsenau and Leduc (2012) show how the threat to offshore can have large effects on wages even when the actual amount of offshoring in the economy is small.

5 Mismatch Shocks and the Natural Rate

The natural rate of unemployment is unobservable and its estimation is a main challenge for monetary policymakers. In this section, we use our estimated medium-scale DSGE model to infer the path of the natural rate. Following Sala, Söderström, and Trigari (2008), Groshenny (2012) and the related literature on the output gap in DSGE models (Woodford 2003, Justiniano, Primiceri, and Tambalotti 2013), we define the natural rate of unemployment to be the unemployment rate that would prevail if i) prices and wages were perfectly flexible and ii) the markup of price over marginal cost and the bargaining power of workers were constant. With respect to the existing literature on natural rates in DSGE models, a distinguishing feature of our analysis is that we account for variation in structural factors, such as sectoral reallocation, by including a shock to the efficiency of the matching function. We are especially interested in measuring the effects of the deterioration in the aggregate labor market's matching efficiency during the Great Recession (documented in Figure 1) on the natural rate.

We adopt the standard practice of turning off the inefficient shocks to compute the natural rate. Price mark-up shocks and bargaining power shocks are inefficient. The former ones affect the degree of imperfect competition in the goods market. The latter shocks induce deviations from the Hosios condition and so affect the severity of the congestion externality that characterizes the labor market in the search and matching model. This standard definition is in line with the concept of natural rate expressed in Friedman (1968), i.e. a measure of unemployment that fluctuates over time in response to shocks and that is independent from monetary factors. Moreover this definition is also shared by some monetary policymakers. For example, it is consistent with Kocherlakota (2011)'s view of the Fed's mission. Our approach, although dominant in the literature, is not uncontroversial. In particular, the interpretation of labor supply shocks in the New Keynesian model is the object of a recent literature (Chari, Kehoe, and McGrattan 2009; Galí, Smets, and Wouters 2011; Justiniano, Primiceri, and Tambalotti 2013) but is outside the scope of our paper. Note, however, that according to our estimates, wage bargaining shocks are almost white noise. This finding is in keeping with the interpretation of wage markup shocks as measurement errors that is favored by Justiniano, Primiceri, and Tambalotti (2013).

In Figure 5 we plot the observed unemployment rate together with our estimates of the natural rate. Overall, from the 1960s until the onset of the Great Recession, the natural rate has been fairly stable at around 6 percent. Interestingly, according to our model actual unemployment was well below the natural rate over the period 2003–2007. However, during the Great Recession the posterior median estimate of the natural rate rises sharply and stabilizes at around 8 percent in mid-2009. Towards the end of the sample, the posterior distribution of the natural rate becomes rather diffuse. This reflects a standard "end-of-sample problem" typical of two-sided filters such as the Kalman smoother. Here this problem is exacerbated by the fact that recent observations of the unemployment rate are located far away from the mean and look like tail events. Adding more recent observations to the sample may help reduce the uncertainty surrounding our estimates of the natural rate.

If we focus on the very low frequencies just for a while, we see that the natural rate was gently trending upward from the late 1950s until the mid 1970s, and then had been gradually decreasing, reaching a trough just before the 2001 recession. These long-run tendencies are more visible in Figure 6 which only plots the natural rate. The behavior of our natural rate estimates at low frequencies is in line with Staiger, Stock, and Watson (1997) and Ball and Mankiw (2002). Excluding the most recent period, the DSGE-based measure of the natural rate are rather precisely estimated. This aspect of our analysis is at odds with Staiger, Stock, and Watson (1997), who conclude that large confidence bands are a distinguishing feature of the natural rate. Not so surprisingly, we find that the cross-equation restrictions embedded in our estimated DSGE model provide quite a sharp identification strategy of the unobserved natural rate.

In the decade from 1985 to 1995, the natural rate was nearly constant at its sample average, slightly below 6 percent. Around 1995, it started to fall, reaching a trough at 5.5 percent in late 2000. Since then, the natural rate kept rising until mid-2009 when it seems to have stabilized just below 8 percent. Looking at the historical decomposition in Figure 7, we see that the fall during the second half of the 1990s was partly driven by an improvement in matching efficiency, and partly by a reduction in government spending.¹² The improvement in matching efficiency could reflect the firms more widely adopting

¹²In absence of nominal rigidities, an exogenous increase in government spending leads to a rise in the unemployment rate. The negative wealth effect triggered by the fiscal impulse generates a fall in consumption and a rise in the real interest rate. Higher real interest rates provide firms with an incentive to raise the rate of capacity utilization, thereby substituting capital services for labor. This channel is amplified by the inelasticity of labor supply in the search and matching model.

information technologies (the so-called New Economy) and a shift in firms advertising vacancies on the Internet instead of in newspapers (Ball and Mankiw 2002).

In Figure 7 we see that matching efficiency shocks are the dominant source of variation in the natural rate. This reflects the fact that these shocks propagate very differently in models with flexible prices and wages than in models with nominal rigidities, as shown in Figure 8 where we plot the impulse responses of the actual and natural unemployment rates to each shock. The mismatch shock is the only shock that propagates more when nominal rigidities are turned off, as explained in Furlanetto and Groshenny (2012). This feature of our model seems to be plausible and intuitive: the mismatch shock captures variations in structural factors (like mismatch, changes in the composition of the unemployment pool, search intensity, and demographic factors, among others) and these structural factors are the drivers of the natural rate in keeping with Friedman (1968).

An additional reason why the natural rate is driven mainly by mismatch shocks is because the other shocks (neutral technology, investment-specific, and government spending shocks) propagate very little under flexible prices and wages. This is a manifestation of the so-called unemployment volatility puzzle emphasized by Shimer (2005) in a RBC model driven only by technology shocks. This happens despite the presence of a dominant post-match component in total hiring costs that, in keeping with Pissarides (2009), guarantees larger unemployment volatility than in a model with pre-match hiring costs. Nominal rigidities are powerful propagators of shocks and these are a possible solution to the unemployment volatility puzzle, at least as long as we are willing to accept that the business cycle is driven by several shocks and not only by neutral technology shocks as in Shimer (2005).

This analysis of the natural rate of unemployment has important policy implications, at least if the Fed's mission is consistent with the view proposed above by Kocherlakota (2011). According to our model and to our definition of the natural rate, expansionary policies are justified by an unemployment gap that has increased from minus 2 percent to 2 percent during the Great Recession (see Figure 9). A series of negative matching efficiency shocks and positive fiscal shocks have contributed to marginally lower the unemployment gap in the last part of our sample (see Figure 10). All in all, our results are consistent with the view that the large increase in unemployment during the Great Recession is largely due to cyclical factors whereas structural factors have contributed only to a limited extent.

6 Conclusion

In this paper we have identified a large decline in matching efficiency during the Great Recession and we have investigated the macroeconomic consequences of this phenomenon in the context of a New Keynesian model with search and matching frictions extended with matching efficiency shocks and a generalized hiring cost function. We find that this large decline in matching efficiency has raised the actual unemployment rate by 1.25 percentage points and the natural rate by 2 percentage points. In normal times mismatch shocks are almost irrelevant for business cycle fluctuations but, nevertheless, these can play a nonnegligible role in certain periods given that these are the only shocks able to generate a positive conditional correlation between unemployment and vacancies. Moreover, mismatch shocks have an economic interpretation, as a catch-all shock capturing structural dynamics in the labor market. This claim is confirmed by the fact that mismatch shocks are relevant for policy analysis. Importantly, a generalized hiring function is essential to capture the transmission mechanism for mismatch shocks.

We believe that this paper contributes to a much broader debate on the performance of models with search and matching frictions in explaining labor market dynamics. Christiano, Eichenbaum, and Trabandt (2012) argue in favour of a specification with only a post-match hiring cost, thus neglecting the importance of search frictions. Michaillat (2012) shows that search frictions do not matter in recessions by using a model where he is able to disentangle the unemployment component due to search frictions from the component due to nominal rigidities. Our results confirm that the data favor a dominant role for the post-match component in total hiring costs and, therefore, imply a very limited role for search frictions in unemployment dynamics. Nevertheless, even a small amount of search frictions can have nonnegligible consequences for unemployment and for the natural rate dynamics in selected periods.

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Appendix

Description of the database Apart from the series for job finding rates (generously provided by Regis Barnichon and Murat Tasci) and for vacancies, that is constructed by Barnichon (Barnichon 2010), we downloaded all other series from the FREDII database maintained by the Federal Reserve Bank of St. Louis. We measure nominal consumption using data on nominal personal consumption expenditures of nondurables and services. Nominal investment corresponds to the sum of personal consumption expenditures of durables and gross private domestic investment. Nominal output is measured by nominal GDP. Per capita real GDP, consumption, and investment are obtained by dividing the nominal series by the GDP deflator and population. Real wages correspond to nominal compensation per hour in the nonfarm business sector, divided by the GDP deflator. Consistently with the model, we measure population by the labor force which is the sum of official unemployment and official employment. The unemployment rate is the official unemployment divided by the labor force. Inflation is the first difference of the log of the GDP deflator. The nominal interest rate is measured by the effective federal funds rate.

Matching efficiency as an observable variable Given that we introduce a new shock in the model (the mismatch shock), we have to use an eighth observable variable to identify it. We put some discipline on the estimation of the shock process by adopting a two-step procedure. In a first step, we construct a time series for matching efficiency by combining quarterly series for the job-finding rate and labor market tightness. In a second step we use the matching efficiency series derived in the first step as an observable variable variable in the estimation of the full DSGE model.

To recover our series for matching efficiency we exploit recursively a system of three equations given by a subset of the log-linearized equilibrium conditions in our model. The system is composed by the definition of the job-finding rate, the definition of the matching function, and the definition of unemployment, and is written as follows:

$$\begin{cases} \widehat{V}_t = \widehat{\Theta}_t - \rho \frac{N}{U} \widehat{s}_t - \left(1 - \rho - \rho \frac{1 - \rho N}{1 - (1 - \rho)N}\right) \frac{N}{U} \widehat{N}_{t-1} \\ \widehat{\zeta}_t = \widehat{s}_t - (1 - \sigma) \left(\widehat{V}_t + \frac{1 - \rho N}{1 - (1 - \rho)N} \widehat{N}_{t-1}\right) \\ \widehat{N}_t = \frac{U}{N} \widehat{\Theta}_t - \frac{U}{N} \widehat{V}_t \end{cases}$$

where $\widehat{\Theta}_t$ represents labor market tightness, defined as the ratio of vacancies over unemployment, in log-deviation from the steady state. Inspired by Barnichon and Figura (2011), we use data on the job-finding rate and on labor market tightness to derive recursively a series for matching efficiency. Our procedure works as follows: we combine the two data series $(\hat{s}_t \text{ and } \hat{\Theta}_t)$, the calibrated parameters $(\rho \text{ and } U)$ and an initial value for \widehat{N}_{t-1} that we set at its steady state value. We obtain a value for \widehat{V}_t that we plug into the second equation (together with σ) to obtain a value for matching efficiency $(\hat{\zeta}_t)$. The third equation is then used to calculate \widehat{N}_t which we then use in the first equation of the system iterated forward one period. These three equilibrium conditions taken in isolation allow us to compute recursively a series for the matching efficiency shock without estimating the full model. In Figure 1 we plot our series for matching efficiency. We identify a large drop in matching efficiency during the Great Recession when it reaches unprecedented low levels. The cyclical properties of the series look similar to the estimated series in Barnichon and Figura (2011). Notice, however, that here we are using a series of equilibrium conditions, and not only the matching function, to identify the shock. Importantly, our measure of matching efficiency is calculated by taking into account the timing convention of our model. Therefore, the separation rate and variations in job-tojob transition affect our measure of matching efficiency, unlike in Barnichon and Figura (2011) where matching efficiency is given by $\hat{\zeta}_t = \hat{s}_t - (1 - \sigma) \left(\hat{V}_t - \hat{U}_t \right)$. In that sense our exercise has a general equilibrium flavor that is a qualifying feature of this paper and that is new in the literature. Notice that the use of a two-step procedure enables us to combine information from two observables (the job-finding rate and labor market tightness) without introducing an additional, possibly dubiously structural, shock.

Obviously, our series for the matching efficiency shock depends on the calibrated parameters (ρ and σ in particular), as is also true for all the other shocks. In this case, given the structure of the model, the dependence is transparent. In this sense, the mismatch

shock has a very general interpretation (it is a catch-all shock capturing structural factors in the labor market, not just mismatch) but at the same time it has also a clear empirical counterpart, unlike other shocks used in the DSGE literature (see Chari, Kehoe, and McGrattan (2009) for a discussion on the wage mark-up shock).

Capital depreciation rate	δ	0.0250
Capital share	α	0.33
Elasticity of substitution btw goods	θ	6
Backward-looking price setting	ς	0.01
Replacement rate	au	0.25
Hiring cost/output ratio	$\frac{\kappa}{2}\aleph^2$	0.003
Job destruction rate	ρ	0.085
Elasticity of matches to unemp.	σ	0.4
Probability to fill a vacancy within a quarter	q	0.7
Exogenous spending/output ratio	g/y	0.2
Unemployment rate	U	0.0595
Quarterly gross growth rate	z	1.0038
Quarterly gross inflation rate	π	1.0087
Quarterly gross nominal interest rate	R	1.0136

Table 1: Calibrated Parameters

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Employment rate	N = 1 - U
Vacancy	$V = \frac{\rho N}{q}$
Matches	m = qV
Discount factor	$\beta = \frac{z\pi}{R}$
Job survival rate	$\chi = 1 - \rho$
Mean of exogenous spending shock	$\epsilon_g = rac{1}{1-g/y}$
Real marginal cost	$\xi = rac{ heta - 1}{ heta}$
Quarterly net real rental rate of capital	$\widetilde{r}^K = rac{z}{eta} - 1 + \delta$
Capital utilization cost first parameter	$\phi_{u1}=\widetilde{r}^K$
Capital/output ratio	$rac{k}{y}=rac{lpha\xi}{\widetilde{r}^{K}}$
Investment/capital ratio	$\tfrac{i}{k} = z - 1 + \delta$
Investment/output ratio	$rac{i}{y} = rac{i}{k}rac{k}{y}$
Consumption/output ratio	$\frac{c}{y} = \frac{1}{\epsilon_g} - \frac{\kappa}{2}\aleph^2 - \frac{i}{y}$
Pool of job seekers	$S = 1 - \chi N$
Matching function efficiency	$\zeta = q\left(\frac{V}{S}\right)^{\sigma}$
Job finding rate	$s = \zeta \left(\frac{V}{S}\right)^{1-\sigma}$
Employees' share of output	$\frac{\widetilde{w}N}{y} = \xi \left(1 - \alpha\right) - \frac{(1 - \beta)\chi}{\rho} 2 \left(\frac{\kappa}{2} \aleph^2\right)$
Bargaining power	$\eta = \frac{1-\tau}{\vartheta - \tau}$
	where $\vartheta \equiv \frac{\xi(1-\alpha) + \left(1 + \beta \chi \frac{s}{\rho}\right) 2\left(\frac{\kappa}{2} \aleph^2\right)}{\frac{\tilde{w}N}{y}}$
Effective bargaining power	$\Omega = \frac{\eta}{1-\eta}$
Std dev of (non-rescaled) markup shock	$\sigma_{\theta} = \left[\left(1 + \beta \varsigma \right) \phi_P \right] \sigma_{\theta^*}$
Std dev of (non-rescaled) bargaining power shock	$\sigma_\eta = (1 - \eta) \sigma_{\eta^*}$

 Table 2: Parameters Derived from Steady-State Conditions

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			Posteriors		
		Priors	5%	Median	95%
Weight of pre-match cost in total hiring cost	ϕ_V	Beta $(0.5, 0.25)$	0.01	0.04	0.09
Habit in consump.	h	Beta (0.7,0.1)	0.60	0.65	0.69
Invest. adj. cost	ϕ_I	IGamma $(5,1)$	2.89	3.48	4.24
Capital ut. cost	ϕ_{u2}	IGamma (0.5,0.1)	0.44	0.59	0.82
Price adjust. cost	ϕ_P	IGamma (50,20)	45.62	58.72	76.04
Wage adjust. cost	ϕ_W	IGamma (50,20)	130.32	207.98	307.31
Wage indexation	ρ	Beta $(0.5, 0.2)$	0.87	0.94	0.98
Interest smoothing	ρ_r	Beta (0.7,0.1)	0.44	0.60	0.69
Resp. to inflation	ρ_{π}	IGamma (1.5,0.2)	1.57	1.70	1.88
Resp. to growth	ρ_y	IGamma (0.5,0.1)	0.39	0.48	0.58

Table 3: Priors and Posteriors of Structural Parameters

				Posteriors	
		Priors	5%	Median	95%
Technology growth	ρ_z	Beta $(0.3, 0.1)$	0.19	0.26	0.33
	$100\sigma_z$	IGamma $(0.1,3)$	1.19	1.27	1.37
Monetary policy	ρ_{mp}	Beta $(0.5, 0.2)$	0.30	0.48	0.70
	$100\sigma_{mp}$	IGamma $(0.1,3)$	0.19	0.21	0.22
Investment	$ ho_{\mu}$	Beta $(0.5, 0.2)$	0.76	0.80	0.85
	$100\sigma_{\mu}$	IGamma $(0.1,3)$	5.52	6.50	7.67
Risk premium	$ ho_b$	Beta $(0.5, 0.2)$	0.66	0.74	0.83
	$100\sigma_b$	IGamma (0.1,3)	0.41	0.63	0.95
Matching efficiency	$ ho_{\zeta}$	Beta $(0.5, 0.2)$	0.89	0.93	0.96
	$100\sigma_{\zeta}$	IGamma $(0.1,3)$	8.59	9.19	9.85
Price markup (rescaled)	$ ho_{ heta^*}$	Beta $(0.5, 0.2)$	0.85	0.92	0.96
	$100\sigma_{\theta^*}$	IGamma $(0.1,3)$	0.10	0.12	0.14
Bargaining power (rescaled)	ρ_{η^*}	Beta $(0.5, 0.2)$	0.08	0.17	0.27
	$100\sigma_{\eta^*}$	IGamma (0.1,3)	130.89	209.25	306.77
Government spending	$ ho_g$	Beta $(0.7, 0.1)$	0.90	0.92	0.94
	$100\sigma_g$	IGamma $(0.1,3)$	0.54	0.58	0.62

 Table 4: Priors and Posteriors of Shock Parameters

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	Output	Unemp.	Vacancy	Inflation
Technology	30	18	11	16
Monetary	3	2	2	2
Investment	27	31	20	57
Matching	0	0.2	38	0
Risk-premium	14	9	8	15
Markup	9	26	12	6
Bargaining	3	12	5	2
Fiscal	14	2	5	2

Table 5: Variance Decomposition (in %)



Figure 1: Time series of matching efficiency, expressed in percentage points, implied by our model when the job finding rate and vacancy/unemployment ratio are treated as observables.



Figure 2: Impulse responses to a one-standard-deviation negative matching efficiency shock, computed at the posterior mode.



Figure 3: Simulated data on vacancies and unemployment conditional on each kind of disturbances. In each panel, the vertical and the horizontal axis correspond respectively to the vacancy rate and the unemployment rate, both expressed in percentage deviations from steady state. Each panel plots 400 pseudo-data points simulated from the model calibrated at the posterior mode and drawing the i.i.d innovations from normal distributions with mean zero and standard deviation set equal to the corresponding posterior mode estimate.



Figure 4: Historical decomposition of the unemployment rate (demeaned), expressed in percentage points, computed at the posterior mode.



Figure 5: Actual and natural rates of unemployment, expressed in percent of the labor force. The solid line depicts the actual unemployment rate. The dashed line represents the posterior median estimate of the natural rate. The shaded area corresponds to the 66% posterior intervals of the natural rate.



Figure 6: Natural rate of unemployment. The solid line shows the posterior median estimate of the natural rate. The dashed line shows the low-fequency component of the natural rate, extracted using the HP filter with a smoothing parameter $\lambda = 10000$.



Figure 7: Historical decomposition of the natural rate of unemployment (demeaned), expressed in percentage points, computed at the posterior mode.



Figure 8: Impulse responses of the actual and natural unemployment rates, expressed in percentage points. The size of each shock is one standard deviation. Responses are computed at the posterior mode.



Figure 9: Unemployment gap, expressed in percentage points. The thick line represents the posterior median. The two thin lines depict the 66% posterior bands.



Figure 10: Historical decomposition of the unemployment gap, expressed in percentage points, computed at the posterior mode.