The Role of On-the-Job Search in Hiring Dynamics and Matching Efficiency: A Bayesian-Estimated DSGE Model

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Abstract

Conventional DSGE models that include labor search-and-matching frictions assume that only unemployed workers are job seekers. Without taking the behavior of employed job seekers into account, these standard models overestimate the true magnitude of fluctuations in the entire population of job seekers. Hence, this paper proposes augmenting the standard DSGE model with on-the-job search by employed workers. Using Bayesian estimation methods, I show that this augmented model not only well explains the 25 percent decline in hiring that was seen during the Great Recession, but also successfully predicts the subsequent actual five-year-long recovery period of hiring. In contrast, the standard models, which do not incorporate employed workers’ on-the-job searches, fail to explain the sharp declines in hiring seen during the Great Recession and the slow job recovery afterward. Furthermore, I find that if on-the-job-search is incorporated in the model, the decline in matching efficiency of the unemployed workers would explain 54 percent of the increase in U.S. unemployment during the Great Recession, as opposed to 27 percent suggested by the standard DSGE models without on-the-job search.

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1 Introduction

Standard Dynamics Stochastic General Equilibrium (DSGE) models that include labor search-and-matching frictions, along the line of Mortensen and Pissarides (1994), conventionally assume that only unemployed workers are job seekers. However, the number of all new jobs in the United States filled by employed workers is one and a half times as large as that of unemployed workers. In addition, Faberman et al. (2017) showed that the number of offers that employed job seekers received is no less than that of the unemployed. The actual population of job seekers is composed of both unemployed workers and employed workers who want to change jobs, thus raising the question of whether unemployed workers are an appropriate proxy for the entire population of total job seekers. By investigating hiring dynamics and matching efficiency, I find that omitting employed job seekers in the models is problematic.

The differences in search behavior and matching processes between employed and unemployed job seekers are actually nontrivial. As shown in Figure 1, these two groups trend in different directions: the number of the unemployed workers increases during recessions, while the population of employed job seekers declines. In the models with labor search-and-matching frictions, hires (as output) are positively related to job seekers and vacancies (as input), through matching functions. In addition, the components in total hires that cannot be explained by changes in job seekers or vacancies in matching functions are accounted for by fluctuations in matching efficiency (or mismatch) shock (see, e.g., Blanchard and Diamond 1989 and Elsby et al. 2015b). In particular, the changes in matching efficiency played an important role in the labor market dynamics during the Great Recession. For example, researchers such as Barnichon and Figura (2015) have claimed that the decline in matching efficiency during 2008–2012 caused the job finding rate to decrease by 30 percent. Because of the dissimilitude between employed and unemployed job seekers, the assumption about the composition of job seekers is particularly important for the models to correctly predict hiring and estimate matching efficiency.2

This paper first assesses the ability of DSGE models that include labor search-and-matching frictions in explaining hiring dynamics. Because these standard models do not take the behavior of employed job seekers into account, and instead consider only job seekers who are unemployed, the standard models predicted a much smaller decline in hiring than actually took place during the Great Recession (only 10 percent, as opposed to the 25 percent that actually occurred). In addition, they indicated that hiring


2 In this paper, employed workers also face employed-specific matching efficiency shock which influences the fluctuations in the number of employed job seekers, as seen in Figure 1. For the sake of clarity, I call employed-specific matching efficiency as employed workers’ matching technology shock. From now on, matching efficiency or mismatch always apply to that of the unemployed.
would return to pre-recession levels in two years, rather than the actual five-year-long recovery period that transpired. Then, I show that the models incorporating on-the-job searching by employed job seekers are able to depict sharp declines in hiring and subsequent slow job recovery, such as was seen during and after the Great Recession. Third, I examine the accuracy of the models’ estimates of matching efficiency. I find that in the standard models that assume only unemployed workers are job seekers, matching efficiency declined less than half as much as the estimates of the models that incorporate on-the-job search during the Great Recession; therefore, around 27 percent of the increase in unemployment attributed to the changes in matching efficiency during the Great Recession is not included in the standard models.

These standard models fail to correctly predict hiring and accurately offer the estimates of matching efficiency because they do not paint a complete picture of the entire population of job seekers. During the Great Recession, the number of unemployed workers (i.e., job seekers in the standard models) increased by 50 percent, while vacancies decreased by 60 percent. Because the increase in unemployment canceled out the decrease in vacancies, these standard models therefore only predicted a moderate decline in hiring. After the Great Recession, the number of unemployed workers remained higher than had been the case before the Great Recession. According to the standard models, hiring should have returned to pre-recession levels much sooner—in

Figure 1: Job Seekers

*Note: The green dotted solid line represents unemployment, while the black solid line represents employed job seekers, as constructed in this paper. The blue dashed line with circle markers represents vacancies. The gray shaded areas indicate NBER recession periods. Data source for unemployment and vacancies: Federal Reserve Economic Data (FRED).*
less than half the five years that, in fact, passed before hiring again reached these levels. This failure of the standard models to accurately predict hiring dynamics has also been explored by Leduc and Liu (2017). Because the numbers of employed and unemployed job seekers move in distinctive directions, a model that incorporates both groups into the population of total job seekers can portray hiring dynamics that are mainly determined by fluctuations in vacancies. Because vacancies declined dramatically during the Great Recession, this model would predict that a sharp decline in hiring occurred. Therefore, this model can explain the slowness of job recovery, as witnessed in the aftermath of the Great Recession, when the number of vacancies and employed job seekers recovered sluggishly. Therefore, introducing on-the-job searches of employed workers into standard models can better match the hiring dynamics.

Without taking the dynamics of the number of employed job seekers into account, the standard models overestimate the magnitude of the decline in labor market tightness, defined as the ratio of vacancies to unemployment. This causes the standard models to fail to offer accurate estimates of matching efficiency. In the labor search-and-matching model, during the recession, the decline in unemployed workers’ job finding rates can be attributed to two procyclical components: fluctuations in matching efficiency and fluctuations in labor market tightness. During the Great Recession, because of the marked increase in unemployment together with the decrease in vacancies, the standard models suggest a sharp drop in market tightness. In contrast, the models that incorporate both unemployed and employed job seekers into the population of total job seekers suggest less of a decline in labor market tightness because unemployment is countercyclical while job searches from employment move procyclically. Therefore, when the models consider the behavior of employed job seekers, the fraction of the decline in the job finding rate during the Great Recession that is attributed to the changes in matching efficiency enlarges. This paper shows that in the model that incorporated employed job seekers, matching efficiency declined more than twice as much as the estimates of the standard models did during the Great Recession. Therefore, these standard models only suggest that approximately 27 percent of the unemployment increase during the Great Recession are accounted for by matching efficiency while the models that incorporate on-the-job searching by employed job seekers explained more of the decline.

Unlike this paper, Leduc and Liu (2017) used a standard model that assume that only unemployed workers are searching jobs. Their paper only focused on slow job recovery and proposed workers’ search intensity and firms’ recruiting effort in the standard model as a solution. In contrast, this paper argues that the models that incorporate the behavior of employed job seekers can well explain both the sharp declines and the slow job recovery.
seekers suggest 54 percent.

In the real world, matching efficiency shock can be composed of, for example, skill or demographic mismatches (e.g., Şahin et al. 2014 or Herz and van Rens 2015). The composition of heterogeneity among unemployed workers (e.g., Barnichon and Figura 2015) also influences matching efficiency fluctuations. In addition, the changes of matching efficiency shock are also related to firms’ search behavior, such as recruiting efforts (as emphasized by Davis et al. 2013) and hiring standards (as presented in Sedláček 2014); and to workers’ search efforts, which were studied by Hornstein and Kudyak (2016). Therefore, this paper argues that these factors should be further examined for researchers and policy makers to better decompose the source of matching efficiency to understand the increase in unemployment rate during the Great Recession.

Another potential issue resulting from the underestimation of the decline in matching efficiency shock during the Great Recession is that the standard models could overestimate the contribution of other channels to unemployment fluctuations. One such channel that is frequently cited in the literature is unemployment insurance. I incorporate unemployment insurance according to Zhang (2017) because her paper analyzed both matching efficiency and unemployment insurance by a standard model. I find that after on-the-job searching by employed job seekers is introduced to the standard models, the percentage of increase in the unemployment rate during the Great Recession attributed to changes in unemployment insurance decreased by 15 percent.

I conducted my analysis in the framework of an estimated medium-scale DSGE model that included labor search-and-matching frictions featuring two mechanisms: on-the-job search and time-varying matching efficiency. Both unemployed and employed workers are considered job seekers. In this revised model, different search behavior of both unemployed and employed job seekers can be generated to account for the distinctive shocks each faces in their job finding rates. Following other estimated medium-scale DSGE models, I introduce standard supply-side, demand-side, and labor market-related shocks that can often be seen in literature (e.g., Gertler et al. 2008 or Brzoza-Brzezina and Kolasa 2013). The purpose of incorporating these shocks is to avoid incorrectly attributing unemployment rate increases caused by these channels to fluctuations of matching efficiency. In my model, when employed workers switch to new jobs, they are recognized as experienced workers with higher productivity. According to the Nash bargaining problem, workers and firms split the total surplus so that employed workers receive higher wage incomes than they received at previous jobs. Therefore, employed workers have incentives to search jobs. I introduce the mechanism of on-the-job search based on Martin and Pierrard (2014), but their model

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5Researchers therefore also refer matching efficiency shock to mismatch shock. See Furlanetto and Groshenny (2016) and Sedláček (2016).
only considers technology shock and labor only. In contrast, my model incorporates multiple shocks, including matching efficiency shock and the features of the medium-scale DSGE models.

To evaluate the models’ performances in predicting hires, variables such as total hires or the flows from unemployment or employment to new hires are not used in the estimation. For comparability, the data used for the estimation are standard macroeconomic variables, which have been used by, for example, Gertler et al. (2008) and Cheremukhin and Restrepo-Echavarria (2014), among others. The baseline model is a real business cycle (RBC) model that does not include price stickiness. Because the New Keynesian (NK) DSGE models are also widely used, in robustness checks, I modified the proposed model to a NK DSGE model based on seminal works such as those of Christiano et al. (2005) and Smets and Wouters (2007) so that sticky prices, nominal interest rates, and inflation could be considered. This paper’s main results about hiring dynamics and matching efficiency still hold in my NK DSGE model.

This paper is related to the following areas of literature. First, this work belongs to studies on improving the performance of DSGE models that include labor search-and-matching frictions. According to Shimer (2005), such DSGE models fail to accurately generate a high volatility of unemployment and vacancies (volatility puzzle). One potential solution is incorporating on-the-job searches by employed workers in the model.\(^6\) Although the issue of on-the-job searches has been widely discussed in the partial equilibrium literature since Pissarides (1994), the importance of on-the-job search in improving the performance of DSGE models has been examined by only a few researchers. Krause and Lubik (2006), Zandweghe (2010), and Krause and Lubik (2012) introduced two types of jobs (good and bad) as a mechanism to generate on-the-job search. Tüzemen (2017) extended their models by incorporating capital and workers from outside of the labor force. Tasci (2007) and Êva Nagypál (2007) introduced on-the-job search through matching quality. In their models, employed workers only switch to new jobs (matches) with a higher quality than that of their current jobs. They use these models to address the volatility puzzle. Martin and Pierrard (2014) determined when on-the-job search helps to generate a high degree of volatility in unemployment rates and vacancies.\(^7\) My contribution is that I show the importance of incorporating

\(^6\)Other potential solutions include introducing wage rigidity or procyclical vacancy costs in a model. For wage rigidity, Hagedorn and Manovskii (2008) proposed a calibration strategy related to the wage bargain to introduce wage rigidity. Gertler et al. (2008) introduced wage rigidity based on staggered Nash bargaining and Furlanetto and Groshenny (2016) considered a wage adjustment cost. Christiano et al. (2016) proposed a model in which the real wage is determined through alternating offer bargaining, so that wage rigidity emerges endogenously. For mechanisms to generate procyclical vacancy costs, for example, Fujita and Ramey (2007) proposed costly entry, and Petrosky-Nadeau (2014) connects vacancy postings to credit constraints.

\(^7\)Unlike these works based on random search, Menzio and Shi (2011) introduce on-the-job search into the directed search framework.
on-the-job search in generating accurate models of hiring dynamics and in correctly identifying the causes of unemployment fluctuations. In contrast to existing DSGE models with on-the-job search, my model considers on-the-job search in the environment of medium-scale DSGE models.

Second, this paper is related to the studies that examine the importance of matching efficiency (or mismatch) in explaining fluctuations in the unemployment rate. Studies based on the DSGE approach all assume that only unemployed workers are job seekers. These works (e.g., Cheremukhin and Restrepo-Echavarria 2014, Furlanetto and Groshenny 2016, and Zhang 2017) showed that mismatch can explain no more than 30 percent of the increase in the unemployment rate during the Great Recession and its aftermath. Among the works based on a partial equilibrium model or matching functions, most follow such standard assumptions. These works, such as Barlevy (2011), Dickens (2009), Sahin et al. (2014), and Barnichon and Figura (2015), reported similar contributions of mismatch as were seen in studies based on DSGE. In contrast, Hall and Schulhofer-Wohl (2015) and Sedláček (2016) relaxed this assumption to incorporate individuals who are employed and job seekers who are outside of the labor force in their estimations based on a non-DSGE approach. Hall and Schulhofer-Wohl (2015) found that mismatch accounts for 40 percent of the fluctuation of the unemployment rate, and Sedláček (2016) suggested that it accounts for 49 percent. My contribution is that this is the first paper which states that even in the DSGE models that fully characterize demand and supply sides, after I take the behavior of employed workers into account, the contribution of mismatch still increases. Moreover, I contribute to this literature by showing that incorporating employed job seekers into DSGE models can also improve their ability to predict hires.

Third, this paper contributes to the work on slow job recovery. Researchers in this area have used different channels in their models to account for slow job recovery. Where Schmitt-Grohe and Uribe (2012) and Shimer (2012b) focused on wage rigidity, Cantore et al. (2014) introduced deep habits in consumption and government expenditure and the constant elasticity of substitution technology, Siemer (2014) considered financial constraints, and Leduc and Liu (2017) introduced firms’ recruiting efforts and workers’ search efforts. However, these authors all assumed that the population of job seekers is comprised only of unemployed workers. I contribute to this literature not only by showing that introducing on-the-job search into models can help generate this feature of hiring but also by indicating that the failure of standard models for generating slow job recovery causes the contribution of matching efficiency to unemployment fluctuations to be underestimated.

They estimate matching efficiency based on matching functions, which incorporate both unemployed and non-unemployed job seekers. Veracierto (2011) uses a similar approach but only considers job seekers from outside of the labor force.
This paper proceeds as follows. Section 2 explains how incorporating job searches from employment affects the prediction of model hiring and the estimates of matching efficiency. Section 3 presents the proposed revised model. Section 4 explains my estimation methodology and the data I used for estimation. Section 5 reports the empirical findings, and Section 6 is the conclusion.

2 Main Mechanism and Concepts

The standard models assume that only unemployed workers should be included as job seekers. In this section, through the lens of the matching function, I first analytically show why it is inappropriate to impose such an assumption. Then, I explain why standard models fail to generate hiring dynamics that have been observed and why these models underestimate the declines in matching efficiency during the Great Recession.

2.1 Hires

Although in reality the total population of job seekers is comprised of both unemployed workers and employed workers looking to switch jobs, standard DSGE models that include labor search-and-matching frictions usually define job seekers as unemployed workers. However, Figure 2 shows that the number of unemployed workers is not an...
appropriate proxy for the total population of job seekers. First, the majority of hiring is from the pool of employed workers rather than unemployed ones. Before the Great Recession, the number of hires from the ranks of the employed was twice as high as those from the ranks of the unemployed; after the Great Recession, hires from both categories were equal. Second, the number of hires from employment is procyclical, while hires from unemployment are countercyclical.

This difference in cyclical dynamics is due to heterogeneity in the job seekers’ search behavior and their matching processes. For example, staying unemployed may erode a worker’s human capital. Due to information asymmetries, employers may also screen workers’ abilities or skills by their unemployment durations. Thus, unemployed workers may feel particularly compelled to accept offers during recessions. In contrast, employed workers are likely to stay at their current jobs and only switch jobs when they get better offers.

Because unemployed and employed job seekers behave differently in searching for jobs, and because most (or at least half of) hires are from those who are employed, unemployed workers cannot serve as a good proxy for total job seekers. The main message of this paper is that unemployed workers are not an appropriate proxy for job seekers, meaning that standard models fail to explain hiring dynamics and are unable to accurately estimate matching efficiency. Therefore, this paper does not consider workers from outside of the labor force as job seekers. Including job search from employment in my model shows the importance of considering non-unemployed job seekers in modeling more generally. As shown in Figure 2, in the comparison with the other two series, the hiring from outside of the labor force is acyclical and does not fluctuate as business cycles change. In the appendices, I show that including workers from outside of the labor force does not influence the argument of this paper.9

To rigorously understand the differences between unemployed workers and all job seekers, I introduce matching functions in the following discussion, and I show how to analytically construct the number of total job seekers based on the observed job finding rates to offer direct evidence.

2.2 Matching Functions and Job Seekers

In the standard DSGE model with labor search-and-matching frictions, the matching process is usually described by a reduced-form matching function,

\[ h_t = m(js_t, v_t), \]  

9Although incorporating job searches from outside of the labor force does not change my argument, it is important to consider worker flows between unemployment and nonparticipation. Elsby et al. (2015a) argued that the flows between individuals who are completely outside of the labor force and those who are just currently unemployed are important for understanding unemployment fluctuations. I do not address this here and recommend future research on the issue.
where the function $m$ is increasing, concave, and homogeneous for both job seekers $j_{st}$ and job vacancies $v_t$. These functional properties are supported by the empirical findings in Petrongolo and Pissarides (2001). In my following analysis, I adopted the Cobb-Douglas matching function with constant returns to scale, as with the majority of the literature.

In the standard models, the matching function is

$$h_t = (\epsilon_t^\mu \cdot u_t)^\xi v_t^{1-\xi},$$

(2.2)

where job seekers are only comprised of unemployed workers, and $\xi$ describes matching elasticity for job seekers. Matching efficiency, $\epsilon_t^\mu$, captures the ability of a market to match unemployed workers and job postings. Because firms may not be able to identify the workers who fulfill their job requirements, workers may not find jobs that satisfy their needs; at the same time, because of factors such as information asymmetry, employers are unsure of workers’ skills and abilities, thus making the matching process time consuming and costly. Matching efficiency is used here for capturing these frictions or mismatches in the labor market.

As job seekers from employment are considered, job seekers $j_{st}$ will consist of not only unemployed workers $u_t$ but also job seekers from employment $\epsilon_t^{n, \mu} n_t$. Here, $n_t$ is the number of employed workers, and $\epsilon_t^{n, \mu}$ can be seen as a combination of the search participation of these employed job seekers and their specific matching technology. After job search from employment is incorporated, the generalized matching function can be written as

$$h_t = (\epsilon_t^\mu u_t + \epsilon_t^{n, \mu} n_t)^\xi v_t^{1-\xi}.$$  

(2.3)

Thus, this generalized matching function is similar to (2.2). The only difference here is that job search from employment, $\epsilon_t^{n, \mu} n_t$, is considered in the total number of job seekers, as seen in, for example, Martin and Pierrard (2014) and Sedláček (2016). This generalized matching function is used in DSGE models with on-the-job search, as seen in Zandweghe (2010), Krause and Lubik (2012), Martin and Pierrard (2014), and Tüzemen (2017), although these previous papers do not consider time-varying matching efficiency shock $\epsilon_t^\mu$ as I do here.\(^{10}\)

Next, I explain the accounting exercise for constructing the pool of employed job seekers from data. Before I move to the details of this exercise, I need to emphasize that this accounting exercise is used for offering brief information regarding the business cycle property of employed job seekers. This paper does not use hires $h_t$ or employed job seekers constructed according to this exercise as observed variables in my estima-
tion. The findings and results of this paper are based on model estimation rather than this accounting exercise.

In this exercise, first, we can rewrite Equation (2.3) as
\[ h_t = (\xi_t)^{\frac{\mu}{1-\xi}} \cdot (u_t + \Phi^n_t n_t)^{\frac{\mu}{1-\xi}}. \]

By the assumption of random search and according to Equation (2.3), the job finding rate for unemployed workers will be\(^{11}\)
\[ f_t^u = \xi_t^{\mu} f_t, \]
and the job finding rate for employed workers will be
\[ f_t^n = \xi_t^{\mu} n_t. \]

Here, job seekers \( j_{st} \) is \( \xi_t^{\mu} u_t + \xi_t^{\mu n_t} \), and \( f_t = h_t / j_{st} \) is the average job finding rate, defined as total hires \( h_t \) divided by total job seekers \( j_{st} \). Because unemployed workers face matching efficiency fluctuations, while employed workers’ job searches also depend on their search participation and specific matching technology, job finding rates for these two types of job seekers are related to these two distinctive shocks. Thus, according to this model structure, we have \( \Phi^n_t = f_t^n / f_t^u \). Second, since job finding rates \( f_t^u \) and \( f_t^u \) are publicly available,\(^{12}\) we can derive \( \Phi^n_t \) from the data. Third, because hires \( h_t \), unemployment \( u_t \), employment \( n_t \), and vacancies, \( v_t \), are all available, matching efficiency can be computed according to (2.3) after we choose specific value \( \xi \), which is estimated by this paper. Therefore, employed job seekers \( \xi_t^{\mu n_t} n_t = \xi_t^{\mu} \Phi^n_t n_t \) can be constructed.

Figure 1 shows the fluctuation of unemployed workers \( u_t \) and employed job seekers based on this accounting exercise. The number of unemployed workers moves countercyclically, while the number of employed job seekers moves procyclically. This difference confirms that the number of unemployed workers is not an appropriate proxy for the total number of job seekers.

### 2.3 Model Hires and Matching Efficiency

As shown in Equation (2.1), whether or not a labor search-and-matching model can generate accurate hires depends on the proxy of job seekers we use. Because the numbers of unemployed and employed job seekers move in different directions, assuming

\(^{11}\) I explain why the assumption of random searches can lead to these job finding rate formulas in the appendices.

only unemployed workers are job seekers thus fails to capture the actual dynamics of job seekers. The standard models thus cannot generate correct estimates of hires.

The proxy of job seekers we use also affects the accuracy of the estimates of matching efficiency. In the labor search-and-matching model, the employment transition equation can be written as follows 13:

\[ n_t = (1 - s) \cdot (n_{t-1} + f_t^u u_t), \]

where \( s \) is the exogenous separation rate, and the unemployed workers’ job finding rate \( f_t^u \) is \( \hat{e}^u (v_t / j_t s_t)^{1 - \xi} \) according to Cobb-Douglas matching functions. In steady state, this equation can be written as

\[ s \cdot n = (1 - s) e^{\hat{e}u} (\frac{v}{j s})^{1-\xi} u, \]

which explained that the total separation from employment (left-hand side) is equal to hiring from unemployment (right-hand side). Therefore, unemployed workers’ job finding rate is \( f_t^u = sn / ((1 - s) \cdot u) = e^{\hat{e}u} (\hat{\theta})^{1-\xi} \), where \( \theta \) is labor market tightness, the ratio of vacancy \( v \) to total job seekers \( j s \). The fluctuations of the unemployed workers’ job finding rate can be decomposed to an exogenous shock, matching efficiency, and an endogenous variable, labor market tightness. We can further derive

\[ \hat{f}_t^u = e^{\hat{e}u} (1 - \xi) \cdot (\hat{\theta} - \hat{j}_s). \]

I place a hat over a variable to denote this variable’s log deviation from the mean (i.e., fluctuations). Because the numbers of unemployed and employed job seekers move in different directions, fluctuations in the number of job seekers decrease after employed job seekers are incorporated into the population of job seekers. Because standard models differ from the models that incorporate employed job seekers only in the definition of the population of job seekers, the models that include employed job seekers suggest that during the recession, the larger decline in the job finding rate is attributed to the decrease in matching efficiency. Therefore, matching efficiency in the models that include employed job seekers declined more than in the standard models during the recession.

We can also show this argument on matching efficiency above analytically. By \( s \cdot n = (1 - s) e^{\hat{e}u} (\frac{v}{j s})^{1-\xi} u \), and normalizing labor force as unity \((u + n = 1)\), we can have

\[ \frac{j s^{1-\xi}}{e^{\hat{e}u}} = \frac{1 - s}{s} \cdot \frac{v^{1-\xi}}{1 - u}. \]

For standard models, by Equation (2.2), job seekers \( j s \) is equal to \( e^{\hat{e}u} u \), so we have

\[ \frac{(e^{\hat{e}u})^{1-\xi}}{e^{\hat{e}u}} = \frac{1 - s}{s} \cdot \frac{v^{1-\xi}}{1 - u}. \]

13Section 3 explains how this equation is derived.
However, in the models that consider employed job seekers, total job seekers $js$ becomes $e^\mu u + e^{\mu,n}n$. Therefore, we have

$$\frac{(e^\mu \cdot u + e^{\mu,n} \cdot n)^{1-\xi}}{e^\mu u} = \left( \frac{1}{(e^\mu u)^\xi} + \frac{e^{\mu,n} \cdot n}{(e^\mu u)^{1-\xi}} \right)^{1-\xi} = \frac{1-s}{s} \cdot \frac{v^{1-\xi}}{1-u}.$$

Given the same separation rate $s$ and matching elasticity $\xi$, when observed unemployment $u$ and vacancy $v$ are fed back to both models, the models that incorporate employed job seekers have higher estimates of the decline in matching efficiency $e^\mu$ during the Great Recession because of the decline in effective employed job seekers $e^{\mu,n} \cdot n$. In my analysis, I actually use dynamic models and estimate matching elasticity $\xi$ rather than the same fixed value for both models. I find that this argument about matching efficiency still holds.

To quantify these biases in hiring and matching efficiency, I developed a DSGE model with on-the-job search featuring matching efficiency shock in the dynamic environment.

3 Model

This section presents the model used for measuring bias in hiring and for quantifying the bias in estimated matching efficiency in standard models. The baseline model is a RBC medium-scale DSGE model with labor search-and-matching frictions. In the appendices, I extend the model to a NK DSGE model with labor search friction to check its robustness.

My proposed model builds on standard medium-scale DSGE models with labor search frictions, such as those presented in Gertler et al. (2008), Cheremukhin and Restrepo-Echavarria (2014), and Christiano et al. (2016), among others, but I introduce the on-the-job search based on Martin and Pierrard (2014). Thus, this proposed model bridges DSGE models with on-the-job search and medium-scale DSGE models.

3.1 Labor Market

The processes by which firms and workers meet are described by the generalized matching functions presented in (2.3), as I consider employed job seekers in my model. I first impose the assumption of random search, following Mortensen and Pissarides (1994). Second, I assume no flows between the labor force and outside of it. Therefore, the labor force is normalized to unity.

According to the matching function shown in equation (2.3) and the assumption of random search, the job finding rate for unemployed workers is $f^u_t = \epsilon^u_t \cdot h_t/js_t$, the job finding rate for employed workers is $f^n_t = \epsilon^{\mu,n}_t \cdot h_t/js_t$ and the vacancy filling rate
is $q_t = h_t/v_t$. After the job finding rate and vacancy filling rates are defined, I discuss the dynamics of employment and unemployment in the labor markets.

In each period, there are three consecutive stages: matching, separation, and production. In the beginning of a period, firms and workers meet, and a new match is formed. Here, I assume that when a match is formed, workers in this new match cannot search again until the matching stage in the next period. After the matching stage, separation occurs with exogenous probability $s$. For the matches that suffer separation, workers become unemployed and cannot search for jobs until the next period, and only those unseparated matches that survive in the production stage are productive.

To create on-the-job search, the productivity of a new match depends on the workers’ labor force status in the last period. For firms, the new matches with employed workers generate higher productivity than those with unemployed workers because employed job seekers are experienced workers. For those employed workers who cannot find a new job, their matches with firms have the same productivity as the new matches with unemployed workers. However, following Martin and Pierrard (2014), I assume that the human capital of these experienced workers decays and the increase in productivity only lasts for one period. I make this assumption about employed workers’ productivity particularly for comparability purposes. By this assumption, all employed workers are going to search in each period in my model so that I can use the matching function as seen in Equation (2.3). Because this is the first paper using DSGE models to examine the changes in the estimates of matching efficiency after the behavior of employed job seekers is incorporated into the population of job seekers, I can only compare my results with existing works based on non-DSGE approaches, such as Sedláček (2016), which used similar matching functions to those in Equation (2.3). In addition, this assumption helps me avoid keeping track of the distribution of matching quality and workers’ labor force status. Without creating history dependence, the difficulty of estimating this model is greatly reduced so that I can conduct the analysis based on DSGE model estimation. This allows me to compare my model’s prediction of hiring and the estimates of matching efficiency with previous works based on DSGE models that do not consider on-the-job search.

Because of higher productivity, employed workers who switch to new jobs can receive higher wages for one period, while unemployed workers who find jobs or other employed workers who stay at current jobs receive lower wages. In my model, I normalize the productivity of unemployed workers as unity, and the relative productivity of employed workers is $\chi > 1$ to induce on-the-job search to occur.

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14 This sequence of stages is based on Christiano et al. (2016).

15 Although Krause and Lubik (2007) and Trigari (2006) consider endogenous separation in their models, based on the findings of Shimer (2012a), separation only explains one-quarter of the fluctuations in unemployment rates. This paper thus assumes a constant separation rate in the model.
Thus, in the beginning of period $t$, the total number of employed workers includes the new hires (matches) from unemployment $f_{t-1}^u u_{t-1}$ and employment at the end of period $t-1$, which is $n_{t-1}$. After the matching stage, separation occurs, and the total number of employed workers at the end of the period is represented by those who are not separated from their current jobs. Hence, the law of motion of aggregate employment $n$ can be written as

$$n_t = (1 - s) \cdot (n_{t-1} + f_{t-1}^u u_{t-1}). \tag{3.1}$$

At the end of period $t$, in the production stage, $n_t$ workers are hired by firms for producing goods. Because on-the-job search is introduced into the model, two equations that describe the hiring dynamics of employed workers: one that applies to those who find a new job and a second one for those who do not. For those employed workers who find new jobs, the transition equation is

$$n_t^n = (1 - s) \cdot f_t^n \cdot n_{t-1}. \tag{3.2}$$

Here, the superscript $n$ stands for new (or high-wage) jobs, and $n_t^n$ are the employed workers who switch to new jobs in the end of period $t$. In the beginning of period $t$, $f_t^n \cdot n_{t-1}$ matches from employment are formed. Then separation occurs, so in the end of the period $t$, only $(1 - s) \cdot f_t^n \cdot n_{t-1}$ matches can survive in the production stage. Because these workers have higher productivity, they can receive the higher wage $w_t^n$. For those unemployed workers who find jobs or for currently employed workers who fail to switch to new jobs, the transition equation is

$$n_t^o = n_t - n_t^n = (1 - s) \cdot ((1 - f_t^n) \cdot n_{t-1} + f_{t-1}^u u_{t-1}). \tag{3.3}$$

Here, $o$ stands for their old (that is, current or lower-wage) jobs. In the matching stage, $(1 - f_t^n) \cdot n_{t-1}$ employed workers are going to stay at current jobs, and $f_{t-1}^u u_{t-1}$ new matches are formed from unemployment. After the separation stage, only $(1 - s) \cdot ((1 - f_t^n) \cdot n_{t-1} + f_{t-1}^u u_{t-1})$ matches survive and can be productive in the production stage. These workers receive lower wage $w_t^o$.

These wages $w_t^n$ and $w_t^o$ are determined through the Nash bargaining problem in this model. The size of the labor force in the end of time $t$ is normalized as one:

$$u_t + n_t = 1. \tag{3.4}$$

Here, $u_t$ is the number of unemployed workers.

### 3.2 The Representative Household

The representative household consists of a continuum of infinitely lived family members of measure one. Following Merz (1995), in the model, the family members pool
their consumption risk. Following Christiano et al. (2016), Furlanetto and Groshenny (2016), and Zhang (2017), for a representative household, utility depends on consumption \( C_t \). The expected lifetime utility of the representative household is

\[
E_0 \sum_{t=0}^{\infty} \beta^t e^{pt} \left[ \frac{(C_t - \xi^c C_{t-1})^{1-\sigma^c}}{1-\sigma^c} \right],
\]

where \( E \) is the expectation operator, \( \beta \) is the discounter factor, \( \xi^c \) is the habit formation parameter, and \( \sigma^c \) is risk aversion. Here, I follow Brzoza-Brzezina and Kolasa (2013) and introduce preference shock to capture fluctuations in consumption. The representative household chooses consumption \( C_t \) and bonds \( B_t \) for saving to maximize their expected lifetime utility, subject to budget constraints,

\[
C_t + \frac{B_t}{r_t} + T_t = w^n_t \cdot n^n_t + w^o_t \cdot n^o_t + b_t u_t + \Pi_t + B_{t-1},
\]

where \( r_t \) is the real interest rate. The representative household uses labor income from employed workers who find new jobs, \( w^n_t \cdot n^n_t \), labor income from employed workers who stay in their old jobs, \( w^o_t \cdot n^o_t \), unemployment insurance, \( b_t u_t \), dividends \( \Pi_t \) from capital producers, and final goods firms for expenditure and lump-sum taxes \( T_t \). The first-order conditions (FOCs) are

\[
\begin{align*}
\partial C_t : & \quad \lambda_t = e^{pt} U'(C_t) \\
\partial B_t : & \quad \lambda_t = \beta r_t E_{t+1} \lambda_{t+1},
\end{align*}
\]

where \( \lambda_t \) is the Lagrange multiplier associated with Equation (3.6). The first equation in (3.7) is the marginal utility of consumption, and the second equation is the Euler equation. With Equation (3.7), I define \( \beta_{t+1} = \beta \lambda_{t+1}/\lambda_t \) as a stochastic discount factor.

I use \( V^o_t \) as the marginal value from having one additional worker employed from unemployment. We can also interpret \( V^u_t \) as the marginal asset value from having one additional employed worker who stays at their old job. Due to on-the-job search, I also define the marginal asset value from having one additional employed worker who switches jobs as \( V^n_t \). The marginal value from having one additional worker separated from employment is denoted by \( V^u_t \). Because employment and unemployment evolve according to Equations (3.1), (3.2), (3.3), and (3.4), these asset values can be written as

\[
\begin{align*}
V^u_t &= b_t + E_t \beta_{t+1} \left[ (1 - f^u_t(1 - s))V^u_{t+1} + f^u_t(1 - s)V^o_{t+1} \right], \\
V^o_t &= w^o_t + E_t \beta_{t+1} \left[ (1 - s)((1 - f^o_t)V^o_{t+1} + f^o_t V^n_{t+1}) + sV^u_{t+1} \right], \text{ and} \quad (3.8) \\
V^n_t &= V^o_t + w^n_t - w^o_t.
\end{align*}
\]

The first equation denotes that the asset value of unemployed workers consists of unemployment benefit \( b_t \) and the expected return of the job searches. Because separation
occurs after new matches are formed, when unemployed workers find jobs, they can be productive with probability \( f^n_t (1 - s) \) and enjoy the asset value of being employed \( V^u_{t+1} \); otherwise, they become unemployed and receive the asset value of being unemployed \( V^o_{t+1} \). The second equation shows that employed workers who stay at their current jobs receive wages \( w^o_t \) and future expected returns from on-the-job searches. Because separation occurs after the matching stage, the probability that employed job seekers can be productive in new jobs at the end of the period is \( (1 - s) f^n_t \), and these workers receive the asset value \( V^n_t \). In contrast, the probability for those who can be productive in current jobs at the end of the period is \( (1 - f^n_t) (1 - s) \), and these workers still receive \( V^o_{t+1} \). In the separation stage, workers become unemployed with probability \( s \) and receive \( V^u_{t+1} \). When workers find new jobs, they receive a higher wage than workers who stay in their old jobs. Thus, \( w^n_t \) is larger than \( w^o_t \). In the following period, new jobs become old ones, and workers receive \( w^o_t \), so the wage premium \( w^n_t - w^o_t \) of new jobs only lasts for one period. The marginal asset value for employed workers who find new jobs \( V^n_t \) in the third equation is, therefore, the wage premium \( w^n_t - w^o_t \) plus the asset value of employed workers who stay at their old jobs \( V^o_t \). When there is no on-the-job search, the wage premium returns back to zero, so \( V^o_t = V^n_t \).

### 3.3 Capital Goods Producers

For model tractability, I introduce capital goods producers by following Brzoza-Brzezina and Kolasa (2013). These capital goods producers are identical and act in a perfectly competitive environment. They purchase the final goods as investment \( I_t \) for accumulating physical capital \( \tilde{K}_t \), according to

\[
\tilde{K}_t = (1 - \delta) \tilde{K}_{t-1} + \epsilon^I_t \left[ 1 - \frac{\kappa_I}{2} \left( \frac{I_t}{I_{t-1}} - 1 \right)^2 \right] I_t, \tag{3.9}
\]

where \( \epsilon^I_t \left( \frac{I_t}{I_{t-1}} - 1 \right)^2 \) is the adjustment cost for investment. The first part, \( (1 - \delta) \tilde{K}_{t-1} \), is the undepreciated capital. The second part, \( \epsilon^I_t \left[ 1 - \frac{\kappa_I}{2} \left( \frac{I_t}{I_{t-1}} - 1 \right)^2 \right] I_t \), is the new capital produced at time \( t \). Here, \( \epsilon^I_t \) is the investment-specific technology shock, which is used to capture dynamics in investment. Capital goods producers also choose capital utilization \( \mu^k_t \) and transform \( \tilde{K}_{t-1} \) to effective capital \( K_t \), according to linear transformation technology, which is

\[
K_t = \mu^k_t \tilde{K}_{t-1}, \tag{3.10}
\]

and the corresponding cost of capital utilization \( \mu^k_t \) is

\[
a(\mu^k_t) = \phi_1 (\mu^k_t - 1) + \phi_2 \frac{(\mu^k_t - 1)^2}{2}, \tag{3.11}
\]

where the steady state of \( \mu^k_t \) is set at one. Capital goods producers own capital and rent this effective capital to final goods firms to earn a real capital return \( r^k_t \). Thus, the
optimization problem of these capital goods producers is
\begin{equation}
\max E_t \sum_{t=0}^{\infty} \beta^t \frac{\lambda_t}{\lambda_0} \left[ r_t^K K_t - I_t \right]
\end{equation}
and is subject to equations (3.9), (3.10), and (3.11). Hence, the investment demand $I_t$, supplies of effective capital, and optimal utilization of capital are, respectively,
\begin{equation}
\begin{aligned}
\frac{\partial I_t}{\partial t} : & = \kappa_t E_t \left[ \beta_{t+1} \lambda_{t+1}^q \epsilon_{t+1}^T \left( \frac{I_{t+1}}{I_t} - 1 \right) \left( \frac{I_{t+1}}{I_t} \right)^2 \right] + \\
& \quad \lambda_t^q \epsilon_t^T \left[ 1 - \kappa_t \left( \frac{I_t}{I_{t-1}} - 1 \right)^2 - \kappa_t \left( \frac{I_t}{I_{t-1}} - 1 \right) \frac{I_t}{I_{t-1}} \right], \\
\frac{\partial K_t}{\partial t} : & = \lambda_t^q = E_t \beta_{t+1} \left[ (1 - \delta) \lambda_{t+1}^q + r_{t+1}^k \mu_{t+1}^k - a(\mu_{t+1}^k) \right], \text{ and} \\
\frac{\partial \mu_{t}^k}{\partial t} : & = r_t^k = a'(u_t^k).
\end{aligned}
\end{equation}

### 3.4 Final Goods Firm

Final goods firms use capital and labor as inputs and face a perfectly competitive environment. The production function of a final goods firm is
\begin{equation}
Y_t = a_t (\chi n_t^n + n_t^o)^{\alpha} K_t^{-\alpha}.
\end{equation}
where $Y_t$ is the output, $n_t^n$ are the workers who switch to new jobs, and $n_t^o$ are the workers who find jobs from unemployment (or those who stay at their current jobs). Employed workers who switch to new jobs are experienced workers and, thus, have relatively higher productivity $\chi > 1$. The aggregate technology shock is denoted by $a_t$. Due to search-and-matching frictions, these final goods firms need to post vacancies $v_t$ with unit costs $c^o$ to recruit workers. The lifetime real profit for final goods firms is
\begin{equation}
E_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_t}{\lambda_0} \left[ a_t (\chi n_t^n + n_t^o)^{\alpha} K_t^{-\alpha} - w_t^n n_t^n - w_t^o n_t^o - r_t^K K_t - c^o v_t \right],
\end{equation}
which describes how final goods firms rent capital and hire labor for producing goods, but need to pay wages to households, capital rent to capital goods producers, and vacancy costs. Thus, we can solve the firms’ FOCs as follows:
\begin{equation}
\begin{aligned}
\frac{\partial n_t^n}{\partial t} : & = j_t^n = \chi a_t y_t / \left( \chi n_t^n + n_t^o \right) - w_t^n + E_t \left[ \beta_{t+1} (1 - s) (1 - f_t^n) j_{t+1}^n \right], \\
\frac{\partial n_t^o}{\partial t} : & = j_t^o = a_t y_t / \left( \chi n_t^n + n_t^o \right) - w_t^o + E_t \left[ \beta_{t+1} (1 - s) (1 - f_t^o) j_{t+1}^o \right], \text{ and} \\
\frac{\partial K_t}{\partial t} : & = r_t^K = Y_t / K_t.
\end{aligned}
\end{equation}
Here, we can interpret $J_t^n$ as the marginal asset value function when firms hire one additional worker from employment, while $J_t^o$ is the marginal asset value function
when firms hire one additional worker from unemployment. For a firm–worker match, firms can receive workers’ marginal productivity, but they need to pay wages to the workers. When these workers are unable to switch to new jobs and these matches survive the separation stage, the probability that firms can maintain the asset value of existing matches is $(1 - s) \cdot (1 - f^u)$.

Because new jobs become old jobs in the following period, the asset value of this existing match is $J_{t+1} + \mu_{t+1}$. The last equation, the first-order condition with regard to capital, describes the capital demand of final goods firms. The free entry condition for firms is

$$c^v = q_t(1 - s)\beta_{t+1} \frac{\epsilon_t^\mu u_t J_{t+1}^o + \epsilon_t^{n\mu} n_t J_{t+1}^u}{\epsilon_t^\mu u_t + \epsilon_t^{n\mu} n_t},$$

(3.17)

When a vacancy is posted in the stage of matching, a firm meets job seekers with probability $q_t$. Due to the assumption of random search, the probability that this firm can meet employed workers (or unemployed workers) depends on their percentage of total job seekers, which is $\mu_t n_t / j_s$ (or $\mu_t u_t / j_s$). Here, job seekers are denoted by $j_s = \epsilon_t^\mu u_t + \epsilon_t^{n\mu} n_t$. Although these matches are formed, only $1 - s$ of them can be productive.

3.5 Wage Determination

The flexible wage is determined through the Nash bargaining problem over the total surplus.\(^{16}\) The bargaining problem for the firm–employed worker match is

$$\max_{\omega_t^e} (V_t^e - V_t^o)^{\eta_t} (J_t^e - V_t^f)^{1 - \eta_t},$$

(3.18)

and for the employer–unemployed worker match, it is

$$\max_{\omega_t^o} (V_t^o)^{\eta_t} (J_t^o - V_t^f)^{1 - \eta_t}.$$  

(3.19)

Through the FOCs of these bargaining problems, wages $\omega_t^e$ and $\omega_t^o$ are determined according to

$$\eta_t (J_t^e - V_t^f) = (1 - \eta_t)(V_t^e - V_t^o),$$

and

$$\eta_t (J_t^o - V_t^f) = (1 - \eta_t)(V_t^o - U_t),$$

(3.20)

Here, I introduce bargaining power shock $\epsilon_t^\eta$, proposed by Shimer (2005), to capture the fluctuation in wages. The average wage $w_t$ is defined as $w_t = (n_t^e \omega_t^e + n_t^o \omega_t^o) / n_t$.

\(^{16}\)When the production function is decreasing return to scale, researchers also use Nash bargaining over the marginal surplus, as proposed by Stole and Zwiebel (1996), such as in Michaillat (2012) and Elsby and Michaels (2013). I do not follow this approach, however, since most works in the DSGE literature use total surplus splitting.
3.6 Closing the Model

The resource constraint in the model is

\[ Y_t = C_t + I_t + G_t + c_v v_t + a(u^k_t)K_t. \]  

(3.21)

Total output will be used for consumption, investment, government expenditures, vacancy costs, and capital utilization cost. The budget constraint of government is

\[ T_t + \frac{B_t}{r_t} = u_t b_t + G_t + B_{t-1}. \]  

(3.22)

As in standard medium-scale DSGE models, I assume fiscal policy as

\[ G_t = \frac{G^y_t}{y_t}, \]

where \( y^G_t \) is the steady-state ratio of government spending \( G_t \) to total output \( y_t \). Here, \( g^G_t \) is government spending shock, which captures demand-side fluctuations. In the baseline estimation, I assume unemployment insurance as a constant \( b_0 \), which will be calibrated in the next section. I consider the time-varying unemployment benefit only when I attempt to qualify its contribution to unemployment fluctuations after on-the-job search is considered.

Seven exogenous shocks are included in this proposed revised model. These shocks can be divided into three groups. Technology shock \( a_t \) represents supply-side shock. Preference shock \( \epsilon^p_t \), investment specific shock \( \epsilon^I_t \), and government spending shock \( \epsilon^G_t \) represent demand-side shocks. The third group is labor market-related shocks: match efficiency shock \( \epsilon^\mu_t \), employed workers’ matching technology \( \epsilon^\mu_{tn} \), and bargaining power shock \( \epsilon^n_t \). I assume that logarithms of these shocks follow the AR(1) process with coefficient \( \rho_j \) and innovation \( \epsilon_{j,t} \), which follows \( N(0, \sigma^2_j) \). Here, \( j \) is the index for these shocks. The shock propagation process in the model is

\[ \ln j_t = (1 - \rho_j) \ln \bar{j} + \rho_j \ln j_{t-1} + \epsilon_{j,t}, \]

where \( \bar{j} \) is the steady state of these shocks.

4 Econometrics Strategy

My quantitative analyses are based the model proposed in Section 3. I estimate the log-linearized approximation of both the proposed model with on-the-job search and the one without it.\(^{17}\) Because the data used for estimating the log-linearized models are

\(^{17}\)The model without on-the-job search is based on the model in Section 3. When \( \chi \) is equal to 1, because new jobs filled by employed workers cannot generate higher productivity, firms have no incentives to reallocate these employed workers from current jobs to new jobs. Thus, firms only hire workers from unemployment to increase the labor numbers. Therefore, the free entry condition in Equation (3.17) also becomes the one in standard models: all new vacancy postings are filled by unemployed workers. Moreover, \( \chi = 1 \) also leads the wage premium to be equal to zero. All settings in the model and value functions in Equations (3.8) and (3.16) are those seen in the standard models without on-the-job searches. Therefore, as \( \chi \) is equal to one, my proposed model is the same as the standard model without on-the-job search.
detrended or demeaned, the parameters related to steady states cannot be determined in the estimation procedure. I pin down such parameters using external information rather than data for estimation. The remaining free parameters unrelated to steady states are estimated using the Bayesian method.

4.1 Data

I use quarterly, seasonally adjusted U.S. data spanning the 1959:Q1–2017:Q1 periods for estimation. These data are drawn from Federal Reserve Economic Data (FRED), Fallick and Fleischman (2004), and Barnichon (2010). The number of shocks is the same as the observed variables. For the model without on-the-job search, I use data on the following six variables: real output \((y)\), real consumption \((c)\), real investment \((I)\), real wage \((w)\), unemployment rate \((u)\), and vacancies \((v)\). Because job openings from FRED are only available after 2000:Q4, I use the composite Help-Wanted Index constructed by Barnichon (2010) for vacancies before then. Because the model with on-the-job search has one additional shock, which is employed workers’ matching technology shock \(\epsilon_{m,n}\), I use the ratio of the job finding rate of employed workers \(f_n^t\) to the job finding rate of unemployed workers \(f_u^t\) as one of the observed variables. These job finding rates are taken from Fallick and Fleischman (2004).

Although \(f_n^t / f_u^t\) begins from 1994:Q1, in the estimation, I treat \(f_n^t / f_u^t\) before 1994:Q1 as the unobserved latent variable so that I do not have to omit data on other observed variables with longer durations to match the length of \(f_n^t / f_u^t\).

For the robustness check, I estimate the NK DSGE model modified based on my proposed model in Section 3. In the estimation of the NK model, except for the variables above, I include the nominal interest rates and inflation. During the zero lower bound (ZLB) period, under the observed Federal Effective Rate, the Taylor rule is inadequate for describing the central bank’s monetary policy in a log-linearized model. To avoid this issue, I replace the interest rate during the ZLB period with the shadow rate constructed by Wu and Xia (2016) so that interest continues to decrease during this period. Therefore, the Taylor rule can better capture the central bank’s monetary policy during the ZLB period. The connection between the shadow rate and monetary policy during the ZLB period can be seen in Wu and Zhang (2017). When I estimate the importance of unemployment insurance in explaining unemployment fluctuations, I use real unemployment insurance \((b)\) as an additional observed variable. Trending data such as output, consumption, investment, and wage are detrended by removing the linear trend from their logs, and I demean the remaining variables in the logarithm.

In the appendices, I provide my data sources in detail and explain how these data series are constructed.

\(^{18}\)The job finding rates they offer are seasonally unadjusted. I transform them to seasonally adjusted data using Census X-13ARIMA-SEATS.
Table 1: Calibration

<table>
<thead>
<tr>
<th>Parameters/Steady State</th>
<th>Value</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steady-State Unemployment Rate: $\bar{u}$</td>
<td>0.058</td>
<td>Sample Average (1959:Q1–2017:Q1)</td>
</tr>
</tbody>
</table>

**Structure Parameter**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount Factor: $\beta$</td>
<td>0.99</td>
<td>Convention</td>
</tr>
<tr>
<td>Risk Aversion: $\sigma^c$</td>
<td>2</td>
<td>Convention</td>
</tr>
<tr>
<td>Capital Depreciation Rate: $\delta$</td>
<td>0.025</td>
<td>Convention</td>
</tr>
<tr>
<td>Gov’t Spending to</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gross Output Ratio: $G/Y$</td>
<td>0.2</td>
<td>Convention</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Separation Rate: $s$</td>
<td>0.1</td>
<td>Sample Average: Shimer (2012a)</td>
</tr>
<tr>
<td>Labor Elasticity: $\alpha$</td>
<td>0.677</td>
<td>Labor Share: 2/3, Michaillat (2012)</td>
</tr>
<tr>
<td>Unit Vacancy Cost: $c^v$</td>
<td>0.121</td>
<td>$c^v/\bar{w} = 0.01$ (Pissarides (2009))</td>
</tr>
<tr>
<td>Bargaining Power: $\eta$</td>
<td>0.804</td>
<td>$\bar{b}/\bar{w} = 0.4$ (Christiano et al. (2016))</td>
</tr>
</tbody>
</table>

**On-the-Job-Search-Related Parameters**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quit Rate: $f^n$</td>
<td>0.06</td>
<td>Zandweghe (2010)</td>
</tr>
<tr>
<td>Relative Productivity: $\chi$</td>
<td>1.5</td>
<td>Tüzemen (2017), Davis et al. (2013)</td>
</tr>
</tbody>
</table>

*Note: This table reports non-estimated parameters as quarterly frequencies based on the strategy reported in Section 4.*

### 4.2 Calibration

Table 1 summarizes how the parameters that affect steady state are calibrated according to their corresponding targets. As in most works, such as Michaillat (2012) and Christiano et al. (2016), I set the steady-state unemployment rates in my model as sample averages. The discount factor $\beta$ is set at 0.99. The quarterly separation rate $s$ is set according to the monthly separation rate constructed by Shimer (2012a). The capital depreciation rate $\delta$ is chosen by following convention. According to Michaillat (2012), the output elasticity of labor $\alpha$ is set such that the model labor share is two-thirds. The unit cost of a vacancy posting $c^v$ is set such that the total vacancy costs-to-wages ratio is 1% of wages per the suggestion of Pissarides (2009). Moreover, the bargaining power of workers is set so that the steady-state unemployment insurance-to-wage ratio is 0.4, as recommended by Furlanetto and Groshenny (2016) and Christiano et al. (2016). For the model with on-the-job search, employed workers’ job finding rate (or quit rate) $f^n$ is set as 0.06 according to Zandweghe (2010). The relative productivity $\chi$ of employed workers who switch jobs is set according to the strategy of Tüzemen (2017), which in turn was based on the findings in Davis et al. (2013). As in Christiano et al. (2016) (and indeed most literature), I set the ratio of government spending to output as 0.2. Based on these chosen values, all model steady-state variables can be derived. For the NK models, I follow a similar strategy to pin down these parameters but only choose a steady-state price markup of 10%.
Table 2: Prior Distribution

<table>
<thead>
<tr>
<th>Name</th>
<th>Prior Shape</th>
<th>(Mean, Std.)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumption Habit Persistence: ( \xi^c )</td>
<td>( \mathcal{B} )</td>
<td>(0.7, 0.1)</td>
</tr>
<tr>
<td>Matching Elasticity of Job Seekers: ( \xi )</td>
<td>( \mathcal{B} )</td>
<td>(0.5, 0.15)</td>
</tr>
<tr>
<td>Inv. Adjustment Cost ( \kappa^I )</td>
<td>( \mathcal{IG} )</td>
<td>(5.0, 1.5)</td>
</tr>
<tr>
<td>Capital Utilization Cost ( \phi^2 )</td>
<td>( \mathcal{IG} )</td>
<td>(0.5, 0.1)</td>
</tr>
<tr>
<td><strong>AR(1) Coefficients &amp; Std.</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \rho^j )</td>
<td>( \mathcal{B} )</td>
<td>(0.5, 0.2)</td>
</tr>
<tr>
<td>( \sigma^j )</td>
<td>( \mathcal{IG} )</td>
<td>(0.01, ( \infty ))</td>
</tr>
<tr>
<td><strong>Unemployment Insurance</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment Relation: ( \phi^u )</td>
<td>( \mathcal{N} )</td>
<td>(0.2, 0.1)</td>
</tr>
<tr>
<td>Wage Relation: ( \phi^w )</td>
<td>( \mathcal{N} )</td>
<td>(0.25, 0.1)</td>
</tr>
<tr>
<td><strong>New Keynesian</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phillips Curve</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price Indexation: ( \zeta^p )</td>
<td>( \mathcal{B} )</td>
<td>(0.5, 0.2)</td>
</tr>
<tr>
<td>Calvo Probability: ( \phi^p )</td>
<td>( \mathcal{B} )</td>
<td>(0.6, 0.1)</td>
</tr>
<tr>
<td><strong>Taylor Rule</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interest Smoothing: ( \phi^R )</td>
<td>( \mathcal{B} )</td>
<td>(0.7, 0.1)</td>
</tr>
<tr>
<td>Feedback to Output: ( \phi^y )</td>
<td>( \mathcal{N} )</td>
<td>(0.5, 0.1)</td>
</tr>
<tr>
<td>Feedback to Inflation: ( \phi^\pi )</td>
<td>( \mathcal{N} )</td>
<td>(1.5, 0.1)</td>
</tr>
</tbody>
</table>

Note: This table reports prior distributions (together with mean and standard deviation) for parameters in the baseline model and additional parameters in a NK DSGE model.

### 4.3 Bayesian Estimation

The estimated parameters are consumption habit persistence \( \xi^c \), matching elasticity \( \xi \), investment adjustment cost \( \kappa_I \), capital utilization cost \( \phi^2 \), unemployment insurance-related parameters, AR(1) coefficients, and standard deviation for shocks. For the NK model, price indexation \( \zeta^p \), Calvo probability \( \phi^p \), and the Taylor Rule parameters are also estimated. Table 2 summarizes the prior distributions of these parameters. First, if the parameter value lies between zero and one, I will choose Beta distribution as prior density. Second, if the parameter value is larger than zero, then Inverse Gamma distribution is used. Third, for parameters with no restriction on their ranges, I use normal distribution. The prior mean and standard deviation are chosen so that possible parameters suggested in the literature are more likely to be drawn from prior distributions. In the estimation, I connect the model to observed data series \( X_t \) through the measurement equations, and use a log-linearized model as a transition equation. The state space model can be written as

\[
X_t = \Phi_0 Z_t + \Phi_1 e^m_t, \\
Z_t = \Psi_0 Z_{t-1} + \Psi_1 e_t. 
\]  

(4.1)
The first equation is a measurement equation, and the second one is the log-linearized model. In Equation (4.1), I define the vector of observed data as $X_t$, the vector of model variables as $Z_t$, the vector of measurement error as $e^m_t$, and the vector of structural shocks as $e_t$. Table 3 contains the posterior mode and 90% credible set results. The parameters estimates for the model with on-the-job search and the one without it are both reported. I obtained the posterior distribution of parameters using the Metropolis-Hastings algorithm. I ran 1,000,000 draws from two chains and dropped the first half of each chain.

The estimation results for the model without on-the-job search are in line with those from the previous related literature (see e.g., Pace and Villa (2016)). Because this is the first paper estimating a DSGE model with on-the-job search, I compare my estimations results with those in Sedláček (2016), which uses a non-DSGE approach. Unlike my paper estimating a full DSGE model, he only estimates a matching function similar to Equation (2.3), which includes job seekers from employment and outside of the labor force, and also considers matching efficiency shock. Although Sedláček (2016) does not estimate a DSGE model with on-the-job search, his work considers employed job seekers and matching efficiency so I use his estimation results as the benchmarks. The main difference between my estimation and his is in matching elasticity $\xi$. In my
estimation, the posterior mode of $\xi$ is 0.55, regardless of whether or not employed job seekers are included in my estimation. This finding is different from Sedláček (2016). His work found that after non-unemployed job seekers were considered in the estimation, $\xi$ increased from 0.5 to 0.76, which is higher than most other studies suggest. This difference comes from the two sources. First, we use different variables for estimation. Particularly, Sedláček (2016) directly uses hiring for estimation, while I do not use it. Second, different estimation strategies are used. Sedláček (2016) uses the extended Kalman filter for estimation. However, I use log-linearized models. In addition to $\xi$, in my estimation, parameters ($\rho^\mu$, $e^\mu$) related to propagation in matching efficiency processes are also similar whether or not on-the-job search is incorporated. Thus, any biases in matching efficiency that I show are due to a difference in models, rather than differences in parameters.

5 Analysis

In this section, I first argue that models that include employed job seekers better fit the data, particularly hiring dynamics. Second, I show that models that consider only unemployed workers as job seekers (i.e., the models without on-the-job search) underestimate the decline of matching efficiency during the Great Recession. Third, due to this underestimation, these models without on-the-job search also fail to correctly identify sources of unemployment fluctuations. The model parameters are set based on Table 1 and the posterior mode.

5.1 Model Evaluation

I first examine model performance by comparing model-generated moments with their empirical counterparts in U.S. data. I focus on the volatility and autocorrelation of output $y$, consumption $c$, investment $I$, unemployment rate $u$, and vacancies $v$ and the correlations between these variables. These moments are standard for evaluating model performance and widely used in the literature (e.g., Michaillat 2012). I consider two models here: one is my proposed revised model with on-the-job search, and the another one is a standard model that only considers unemployed workers as job seekers (i.e., my proposed model with $\chi = 1$). Table 4 contains data moments and the moments generated based on both models. Overall, both models fit these important moments well. Both of them can generate autocorrelations that are similar to the scenarios demonstrated by the data. In particular, whether or not on-the-job search is introduced into the model, both can generate a relatively higher volatility of labor

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19Because I want to indicate the hiring biases in DSGE models that consider only unemployed workers as job seekers, I have not used hiring as an observed variable in this paper.
Table 4: Data Moments and Model Moments

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Proposed Model with On-the-Job Search</th>
<th>Standard Model without On-the-Job Search</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volatility</td>
<td>1 0.889 2.111 5.622 4.8</td>
<td>1 0.949 2.695 3.102 5.525</td>
<td>1 1.180 2.049 3.049 3.590</td>
</tr>
<tr>
<td>Autocorrelation</td>
<td>0.971 0.964 0.968 0.977 0.950</td>
<td>0.989 0.995 0.985 0.858 0.888</td>
<td>0.99 0.985 0.972 0.844 0.787</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.234 0.805 -0.663 0.435 1</td>
<td>0.78 0.883 -0.566 0.588 1</td>
<td>0.912 0.861 -0.417 0.321 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 0.446 -0.223 0.213 1</td>
<td>1 0.709 -0.353 0.257 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 -0.483 0.581 1</td>
<td>1 -0.441 0.338 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1 -0.722 1</td>
</tr>
</tbody>
</table>

Note: Data moments are based on quarterly, detrended, and seasonally adjusted data series. The sample period is 1957:Q1–2017:Q1. Model theoretical moments are generated based on a log-linearized model based on the posterior mode and calibrated values. Volatility is defined as the variable of standard deviation relative to the output.
unemployment rates and vacancies. As observed in the data, the relationship between
unemployment rates and vacancies is negative in both models. However, when a model
incorporates on-the-job search, it can generate higher volatility of these labor market
variables; in addition, the magnitude of correlation between the unemployment rates
and vacancies are then closer to the correlation shown in the data. Thus, introducing
on-the-job search improves the model performance, and this finding is consistent with
other works based on DSGE models with on-the-job search, such as Tüzemen (2017).

5.1.1 Hiring Dynamics: In-Sample Fit

In addition to data moments, I evaluate the models’ performance by hiring dynamics.
When the models do not consider on-the-job search, they fail to generate the hiring
dynamics during the Great Recession and its aftermath. Figure 3 compares the esti-
mates of model hires and data hires. When the models (i.e., the standard models in
the literature) consider only unemployed workers as job seekers, they can predict only
40 percent of the total decline in hiring during the Great Recession. In addition, these
models also fail to explain the sluggishness of hiring growth seen after the Great Reces-
sion. In contrast, the proposed model with on-the-job search can generate a roughly
similar decline in hiring during the Great Recession. After the Great Recession, hiring
in my proposed model returns to the pre-recession level after five years, consistent
Table 5: In-Sample Predictions: RMSEs

<table>
<thead>
<tr>
<th></th>
<th>$h_t$</th>
<th>$h_t/u_t$</th>
<th>$q_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Model</td>
<td>0.0894</td>
<td>0.101</td>
<td>0.099</td>
</tr>
<tr>
<td>On-the-Job Search</td>
<td>0.0701</td>
<td>0.060</td>
<td>0.074</td>
</tr>
<tr>
<td>Improvement</td>
<td>22%</td>
<td>40%</td>
<td>26%</td>
</tr>
</tbody>
</table>

Note: This table reports the numbers of RMSEs calculated based on detrended data and predictions from both models. Improvement is defined as the percentage decrease in the RMSEs after the model considers the number of employed job seekers.

with what can be observed.

To better understand the goodness of fit of my model, I follow Leduc and Liu (2017) and compute the root mean squared errors (RMSEs) for hiring $h_t$, vacancy filling rate $q_t$, and hiring-to-unemployment ratio $h_t/u_t$. As shown in Table 5 incorporating on-the-job search improves the model’s fit in these variables. Because the vacancy filling rate is defined as hiring divided by total number of vacancies, and the conventional job finding rate is defined as hiring divided by the total number of unemployed workers, the accuracy of the estimates of these two rates depend on whether or not a model can correctly generate hiring. Therefore, my model with on-the-job search explains these two rates better.

This discrepancy, between the standard models’ predictions and the actual hires, emerges because the number of unemployed workers is not a good proxy for the entire population of job seekers. During the Great Recession, the unemployment rate rose from 6 percent to its peak of around 10 percent. Because the numbers of job seekers and vacancies positively affect hires through matching functions, when a model only considers unemployed workers as job seekers, the increases in unemployment during the Great Recession push hires up, and therefore less decline in hiring is generated. After the Great Recession, the number of unemployed workers remained higher than it was before recession until 2014Q3. Hence, when the population of job seekers is comprised of only unemployed workers, the high level of unemployed workers and the increases of vacancies together boost these models’ hires. The sluggish recovery of hires during the post-recession period therefore cannot be predicted by these models that do not take into account on-the-job search.

After on-the-job search is incorporated, the fluctuations of job seekers are smaller than unemployment fluctuations; this is because the number of employed job seekers moves procyclically, while the number of unemployed workers moves countercycli-
Table 6: Out-of-Sample Predictions: RMSEs

<table>
<thead>
<tr>
<th></th>
<th>( h_t )</th>
<th>( h_t/u_t )</th>
<th>( q_t )</th>
<th>( v_t )</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>One Period Ahead</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Model</td>
<td>0.200</td>
<td>0.225</td>
<td>0.101</td>
<td>0.229</td>
</tr>
<tr>
<td>On-the-Job Search</td>
<td>0.132</td>
<td>0.131</td>
<td>0.075</td>
<td>0.152</td>
</tr>
<tr>
<td>Improvement</td>
<td>34%</td>
<td>42%</td>
<td>26%</td>
<td>34%</td>
</tr>
<tr>
<td><strong>Two Periods Ahead</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Model</td>
<td>0.223</td>
<td>0.431</td>
<td>0.248</td>
<td>0.436</td>
</tr>
<tr>
<td>On-the-Job Search</td>
<td>0.201</td>
<td>0.339</td>
<td>0.168</td>
<td>0.349</td>
</tr>
<tr>
<td>Improvement</td>
<td>10%</td>
<td>21%</td>
<td>32%</td>
<td>20%</td>
</tr>
</tbody>
</table>

Note: This table reports the numbers of RMSEs calculated based on detrended data and predictions from both models for the out-of-sample exercise. Improvement is defined as the percentage decrease in the RMSEs after the model considers the number of employed job seekers.

The reason is the low level of the total number of job seekers. As seen in Figure 1, the economic recovery leads the number of unemployed workers to be lower than the pre-recession level after 2014:Q3. In addition, the number of employed job seekers never rose back to the pre-recession level. Because both models can well explain the dynamics in the number of job seekers, they suggest a smaller pool of job seekers.
Therefore, both models predict that firms are less likely to meet job seekers and that firms’ incentives to post job vacancies will decrease, rather than predicting the rise in the vacancies as observed after 2014:Q3. Because hiring is positively related to vacancies and job seekers, both models therefore fail to explain the increase in hiring after 2014:Q3.

Table 6 reports the numbers of RMSEs for one period and the two periods ahead forecast for hiring $h_t$, hiring-to-unemployment ratio $h_t/u_t$, vacancy filling rate $q_t$, and vacancies $v_t$. Although the goodness of fit of both models decreases in the out-of-sample prediction exercises, my proposed model with on-the-job search still fits these variables better than the standard models.

5.2 Bias in Matching Efficiency

When the models include employed job seekers, they predict smaller fluctuations in labor market tightness, which increases the magnitude of decline in matching efficiency, as discussed in Section 2 through steady-state equations. Figure 4 shows the evidence supporting the fact that my argument in Section 2 still holds in the dynamic models. In this graph, I compare the estimates of matching efficiency shocks based on the proposed model that includes on-the-job searches and the one based on the models that assume only unemployed workers are job seekers. When on-the-job searching by employed workers is incorporated into the model, the predicted matching efficiency declines 40 percent for the Great Recession and its aftermath. By contrast, in the models that consider only unemployed workers as job seekers, the matching efficiency declines by around 20 percent.

Although this paper is the first work that shows such differences in the estimates of matching efficiency by the use of DSDE models, Sedláček (2016) offered similar conclusions by estimating the matching function, rather than a DSGE model. In spite of similar conclusions in the estimates of matching efficiency, the underlying mechanisms are different. In his work, he directly used hires as an observed variable. His argument is based on omitted variable errors. Because fewer employed workers search for jobs during a recession, unemployed workers are more likely to find jobs. Hence, without including employed job seekers in the estimation, the decline in matching efficiency is underestimated. He only focused on the biases in the estimates of matching efficiency.

However, my argument is based on the nature of the model with labor search-and-matching frictions. The fluctuations in unemployed workers’ job finding rate $f_t^u$ in such models depends on the changes in labor market tightness and that in matching efficiency. As shown in Section 2, because the number of employed job seek-

\textsuperscript{21}In the appendices, I compare my estimates of matching efficiency with Seláček’s.
ers moves procyclically while unemployment is countercyclical, the models that include job searches from employment predict lower fluctuations in job seekers and thus smaller changes in labor market tightness. My proposed model with on-the-job search consequently shows that the fraction of the changes in $f^{u}_t$ that should be attributed to the fluctuations in matching efficiency would increase.

5.3 Sources of Unemployment Rates

The previous subsection demonstrates that standard models, which consider only unemployed workers as job seekers, underestimated the declines in matching efficiency that occurred during the Great Recession. Because the decrease in matching efficiency means that mismatches between firms and workers arise more frequently, matching efficiency negatively affects unemployment. Therefore, the underestimation of the decline in matching efficiency leads standard models to calculate the contributions of matching efficiency to unemployment fluctuations at levels that are lower than those experienced. Because the contributions of matching efficiency are underestimated, standard models overestimate the impact of other channels on unemployment fluctuations. I thus offer quantitative analyses and show that standard models fail to correctly identify the sources of unemployment fluctuations.

In the first exercise, I shut down the fluctuation of matching efficiency during and
after the Great Recession to compute corresponding counterfactual unemployment rates, which fluctuated because of the changes in other channels, except matching efficiency. Therefore, the difference between the observed and counterfactual unemployment rates measures the contribution of mismatching efficiency to unemployment fluctuations. The second analysis is based on historical decomposition, which explains what percentage of the variable (e.g., unemployment) fluctuations can be attributed to a shock. This exercise is used to quantify the overestimation of other channels to unemployment changes during the Great Recession. I use unemployment insurance as the example.

Figure 5 presents the observed and the counterfactual unemployment rates. During the Great Recession, the unemployment rate increased from 5 percent to around 10.5 percent. In the standard models assuming that only unemployed workers are job seekers, after the fluctuation of matching efficiency was shut down, the unemployment rate rose to around 9 percent. Thus, the standard models suggest approximately 27 percent of the increase in the unemployment rate during the Great Recession is accounted for by matching efficiency. This finding is consistent with previous research that does not consider employed job seekers, such as the works based on non-DSGE approaches.
Figure 6: Historical Decomposition: $\epsilon^H_t$

Note: This figure represents the contribution of matching efficiency shock to unemployment fluctuations based on historical decomposition. The dark gray shaded area represents the result based on models without on-the-job search. The light gray shaded area represents the excess contribution of matching efficiency in my model with on-the-job search.

(e.g., Şahin et al. 2014) or those based on DSGE models (e.g., Furlanetto and Groshenny 2016). However, when on-the-job searching by employed job seekers is considered, the counterfactual unemployment rate based on the proposed model rises to approximately 7.5 percent. My proposed model shows that around 54 percent of the increase in the unemployment rate during the Great Recession is attributed to matching efficiency. Therefore, when models do not include employed job seekers, they are unable to identify 27 percent of the increase in the unemployment rate, which actually should be attributed to changes in matching efficiency during the Great Recession.

Additional evidence is based on the historical shock decomposition of the unemployment rate. Figure 6 reports the historical shock decomposition for matching efficiency shock. Two features are worth noting in this figure. First, similar to previous research that does not consider on-the-job search, such as Furlanetto and Groshenny (2016), the importance of matching efficiency in explaining unemployment fluctuations increases after the Great Recession. This result holds whether or not on-the-job search is introduced into the models. Second, after on-the-job search is considered in the model, the contributions of matching efficiency to unemployment fluctuations increase by around 20 percent, which is consistent with the previous counterfactual analysis.

These exercises have important policy implications. In the DSGE model, the de-
Figure 7: Historical Decomposition: $e^b_t$

Note: This figure presents the contribution of unemployment insurance shock to unemployment fluctuations based on historical decomposition. The dark gray shaded area represents the result based on models with on-the-job search. The light gray shaded area represents the excess contribution of unemployment insurance shock in the standard models without on-the-job search.

cline in matching efficiency represents the increases in the degree of skill or demographic mismatches between firms and workers during recessions. As the contribution of matching efficiency is lower in the standard DSGE models, the importance of mismatches in explaining unemployment fluctuations is overlooked in the previous DSGE literature. These exercises suggest that, to decrease the unemployment rate, the government should consider not only fiscal and monetary policies but also the provision of job search assistance.

5.3.1 Other Channels: Unemployment Insurance

Due to biases in hiring, standard models that do not incorporate on-the-job search underestimate the importance of matching efficiency in explaining unemployment fluctuations. Therefore, one may wonder whether the standard models overestimate the contributions of other channels. Some researchers (e.g., Zhang 2017) have relied on the results of DSGE models to emphasized the importance of unemployment insurance in explaining the increases in the unemployment rate during the Great Recession. However, these studies all assume that only unemployed workers are job seekers. I explore the example of unemployment insurance based on Zhang (2017) because her work considered both unemployment insurance and matching efficiency in a standard model...
without on-the-job search. She assumes that unemployment insurance $b_t$ is set as

$$ \frac{b_t}{\bar{b}} = \left( \frac{w_t}{\bar{w}} \right)^{\phi_u} (u_{t-1}/\bar{u})^{\phi_w} \epsilon^b_t, \quad (5.1) $$

which states that the change in unemployment insurance at the end of a given period depends on changes in wages in a current period and the unemployment rate at the beginning of that same period. The exogenous unemployment insurance shock $\epsilon^b_t$ is used to capture spontaneous policy changes. The role of $\epsilon^b_t$ here is similar to that of monetary policy shock in the Taylor rule.

Here, $\bar{b}$, $\bar{w}$, and $\bar{u}$ are steady-state unemployment insurance, wages, and unemployment rates, respectively. I follow the assumptions used by most researchers, including Zhang (2017), and assume the steady state of unemployment insurance as a fraction of wages. Therefore, it is reasonable to assume that the dynamics of unemployment insurance depend on changes in wages. Moreover, as the unemployment rates increase, the government adjusts unemployment insurance accordingly. For example, as shown in Zhang (2017), typically, unemployment insurance rates increase by 10 percent during recessions. It is thus reasonable to assume that changes in unemployment insurance during a period are related to the unemployment rate that the government observes. Parameters $\phi_u$ and $\phi_w$ describe the relationship between unemployment insurance and wages, and the unemployment rate.

Figure 7 reports the historical shock decomposition for unemployment insurance shock. When my models do not consider on-the-job search, during the Great Recession and its aftermath, unemployment insurance accounts for around 25 percent of unemployment fluctuation. In other words, unemployment insurance increased the unemployment rate by 1.5 percent during the Great Recession. This result is consistent with the finding of Zhang (2017). However, when I incorporate employed job seekers in the models, the contribution of unemployment insurance shock decreases by 10 percent. Thus, the standard models, which assume only unemployed workers are job seekers, overestimate the contribution of unemployment insurance to unemployment fluctuations.

6 Conclusion

Standard DSGE models with labor search-and-matching frictions usually assume that the population of job seekers is only comprised of unemployed workers, although in reality, hiring from the ranks of employed workers matches or exceeds hiring from the ranks of the unemployed. To understand and quantify biases caused by this unrealistic assumption, I develop DSGE models that incorporate on-the-job searches. This paper shows that the standard models’ unrealistic assumptions about the full pool of job seekers explain the failure of such models to predict the 25 percent decline in hiring wit-
nessed during the Great Recession and explain why hiring in the post-Great Recession period failed to return to pre-recession levels as quickly as the standard models had predicted. This paper further finds that standard models are unable to identify sources of unemployment fluctuations correctly because of this unrealistic assumption. Without considering on-the-job searches, these standard models generate lower contributions of mismatches between unemployed workers and firms (i.e., matching efficiency) to unemployment fluctuations, while overestimating contributions from other channels, such as unemployment insurance. Based on these findings, future works based on DSGE models with labor search-and-matching frictions should relax this conventional assumption and incorporate employed job seekers and should not overlook the importance of matching efficiency in explaining unemployment fluctuations.

Although the model incorporates employed workers’ searches and exogenous matching efficiency shocks, this paper fixes the labor force as constant and does not introduce endogenous matching efficiency. Elsby et al. (2015a) emphasized the importance of the transition between unemployment and being totally outside of the labor force in explaining unemployment rate fluctuations. In addition, matching efficiency can also be an endogenous variable. Davis et al. (2013) showed the importance of recruiting intensity for understanding fluctuations in hiring. These choices of firms may influence matching efficiency endogenously. This work also does not consider heterogeneity in firms. For example, Decker et al. (2014) examined the importance of firm heterogeneity in explaining employment fluctuation. In addition, the impact of on-the-job search on the transmission of monetary policy based on the Taylor rule is not addressed by my present work. Future research should extend my framework to incorporate those who are out of the labor force, firms’ search efforts, and the heterogeneity of firms. This work provides an important step for this research agenda.
References


Appendix A  New Keynesian Model

In this appendix, I explain how to modify the baseline model to the New Keynesian one. In the New Keynesian model, I introduce intermediate goods firms to create price rigidity. Intermediate goods firms’ problems are similar to final goods firms in the baseline RBC model. Capital goods producers remain the same in the New Keynesian model. In the following discussion, I only list the changed FOCs and constraints in the New Keynesian model.

A.1 Household

In the representative household’s problem, the budget constraint will be

\[ C_t + \frac{B_t}{P_t} + T_t = w^n_t \cdot n^n_t + w^o_t \cdot n^o_t + b_t u_t + \Pi_t + \frac{\varepsilon_{t-1}^{pr} R_{t-1} B_{t-1}}{P_t}, \]

where \( R_t \) is the nominal interest rate and \( P_t \) is the price of final good. Moreover, \( \varepsilon^{pr} \) is the risk premium shock. There is no preference shock in a household’s problem. The FOCs are

\[ \frac{\partial C_t}{\partial \lambda_t} = U_C(C_t) \]

\[ \frac{\partial B_t}{\partial \lambda_t} = \beta \varepsilon^{pr}_t R_t E_t \frac{P_t}{P_{t+1}}. \]

Equation (3.8) remains the same here.

A.2 Intermediate Firm

Intermediate firms require inputs of capital from capital goods producers and labor from households. They sell intermediate goods to final goods firms at real price \( z_t \). The intermediate goods market is perfectly competitive. An intermediate goods firm problem is

\[ E_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_t}{\lambda_0} \left[ z_t y_t - w^n_t n^n_t - w^o_t n^o_t - c_v v_t \right]. \]

Thus, we can solve for FOCs as follows:

\[ \frac{\partial n^n_t}{\partial t} : f^n_t = \chi z_t \alpha y_t / (\chi n^n_t + n^o_t) - w^n_t + (1-s)(1-f^n_t) E_t \left[ \beta_{t+1} f^n_{t+1} \right], \]

\[ \frac{\partial n^o_t}{\partial t} : f^o_t = z_t \alpha y_t / (\chi n^n_t + n^o_t) - w^o_t + (1-s)(1-f^o_t) E_t \left[ \beta_{t+1} f^o_{t+1} \right], \]

\[ \frac{\partial K_t}{\partial t} : r^k_t = z_t y_t / K_t. \]

The only difference here is \( z_t \), which is the price of intermediate goods. The free entry condition in Equation (3.17) remains unchanged.
A.3 Final Goods Firm

The final goods market comprises monopolistic competition. Final goods firms choose the optimal prices but face Cavlo-style price rigidity. In each period, only $\xi_p$ fraction of final goods firms can reoptimize and reset the prices. The demand for each final goods firm is

$$Y_{t+s}(i) = \left( \frac{P^*_t \Pi_{t+s-1,t-1}^{1-\xi_p}}{P_{t+s}} \right)^{-\epsilon_{t+s}} Y_t.$$  

Here, inflation $\Pi_{t+s-1,t-1}$ is defined as $P_{t+s-1}/P_{t-1}$, and $\xi_p$ is the parameter that governs price indexation. The choice $P^*_t$ is the optimal price that the final goods firms reoptimize at period $t$. In other words, $\xi_p$ describes the degree to which firms are looking backwards when they reset prices. In addition, $e_t$ is cost-pushing shock. A final goods firm’s problem is

$$\max E_t \sum_{s=0}^{\infty} \beta^s \lambda_t^{\xi_p} \left[ \frac{P^*_t \Pi_{t+s-1,t-1}^{1-\xi_p}}{P_t} - z_t \right] Y_{t+s}(i). \quad (A.1)$$

Thus, the price choice will be

$$P^*_t = \frac{E_t \sum_{s=0}^{\infty} \gamma_s \beta^s \lambda_t^{\xi_p} \epsilon_t z_{t+s} P^1 P_{t+s}^{1+\epsilon_t} \Pi_{t+s-1,t-1}^{\xi_p} \epsilon_{t+s}}{E_t \sum_{s=0}^{\infty} \gamma_s \beta^s (\epsilon_t - 1) z_{t+s} P^1 P_{t+s}^{1+\epsilon_t} \Pi_{t+s-1,t-1}^{\xi_p (1-\epsilon_{t+s})}}$$

and the aggregate price will be

$$P_t = \left[ \xi_p (P_{t-1} \Pi_{t-1})^{1-\epsilon_t} + (1 - \xi_p) (P^*_t)^{1-\epsilon_t} \right]^{1/(1-\epsilon_t)}.$$  

A.4 Monetary Policy

The central bank will adjust interest $R_t$ according to the Taylor rule

$$\ln(R_t/R) = (1 - \phi_R)(\phi_x \ln(\xi_t/\pi) + \phi_y \ln(y_t/y)) + \phi_R \ln(R_{t-1}/R) + \epsilon^R_t. \quad (A.2)$$

In the New Keynesian model, one additional supply shock ($e_t$: cost-pushing shock) and one additional demand shock ($\epsilon^R_t$: monetary policy shock) exist.

A.5 Parameters

For the New Keynesian model, the calibration strategy is the same as what I use for the baseline model. I only need to calibrate the steady state of $z$ in a New Keynesian model. I follow convention and set the steady state of the cost-pushing shock at $\bar{\epsilon} = 11$. Thus, the steady state of $z$ is $(\bar{\epsilon} - 1)/\bar{\epsilon} = 10/11$. 

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A.6 Analysis

The bias in hiring and estimated shock is robust in the New Keynesian model. Figure 8 in this section demonstrates that the main results in the paper continue to hold in the New Keynesian environment.

First, without considering on-the-job searching by employed workers, standard models fail to explain hiring dynamics during the Great Recession and its aftermath. Second, standard models underestimate the decline of matching efficiency during the Great Recession and its aftermath. Third, standard models underestimate the contribution of matching efficiency to unemployment fluctuations by 20%, while overestimating the contribution of unemployment insurance by approximately 10%.
Figure 8: Robustness Checks: New Keynesian

Note: This figure shows that the main results in this paper still hold in the New Keynesian model. The gray-shaded area indicates NBER Recession periods. Data source: FRED.
Appendix B  Random Search

The assumption of random search means that firms or workers will not direct their searches. In other words, firms will not post vacancies only for workers who belong to a specific category, and workers will also apply for all possible job postings. Therefore, the hiring from employment $h^e_t$ can be written as

$$h^e_t = \frac{h_t}{js_t} \cdot n_t,$$

where job seekers are denoted by $js_t = \epsilon^e_t u_t + \epsilon^n_t n_t$ and $h_t$ represents the total number of new hires. Because of the assumption of random search, unemployed and employed workers are pooled together as job seekers. They also compete with each other for jobs. Thus, the hiring flow from employment divided by the total number of employed job seekers $\epsilon^n_t n_t$ is the probability that a job seeker finds a job (i.e., $h_t / js_t$). In the same way, we can write the hiring from unemployment as

$$h^u_t = \frac{h_t}{js_t} \cdot u_t.$$

The hiring flow data $h^e_t$ and $h^u_t$ are constructed by Fallick and Fleischman (2004) according to CPS data. Because we can observe unemployment $u_t$ and employment $n_t$, job finding rates, $f^u_t = h^u_t / u_t$, and $f^e_t = h^e_t / n_t$, for both types of job seekers can be computed by observed data.
Appendix C Outside of the Labor Force

This appendix section shows that the business cycle properties of job seekers do not change even when workers from outside of the labor force are considered. Based on Equation (2.3), when workers from out of the labor force are considered, the matching function can be modified as

$$h_t = e^\mu_t (u_t + \Phi^o_t n_t + \Phi^o_t o_t)^\xi u_t \xi^{-\xi},$$

where $o_t$ means workers from outside of the labor force and $\Phi^o_t$ can be seen as the combination of search participation and matching technology for workers from outside of the labor force. Thus, $\Phi^o_t \cdot o_t$ can be seen as job seekers from outside of the labor force. Similar to the discussion in Section 2, $\Phi^o_t$ equals the ratio of the job finding rate of workers from outside of the labor force to the job finding rate of unemployed workers. The data of these job finding rates are available from Fallick and Fleischman (2004).

Referring to the accounting exercise explained in Section 2, we can compute $e^\mu_t$ and derive job seekers from employment and outside of the labor force.

In Figure 9, the black solid line shows the dynamics of employed job seekers, while the green dashed line with cross markers represents job seekers from outside of the labor force. Therefore, after we consider workers from outside of the labor force, the number of employed job seekers still moves procyclically. Moreover, since the number of job seekers from outside of the labor force moves acyclically, rather than counter cyclically, incorporating job seekers from outside of the labor force will not help eliminate fluctuations in unemployment, as did those employed job seekers. Thus, although we omit job seekers from outside of the labor force, the main results will not change.
Figure 9: Job Seekers: Outside of the Labor Force

Note: The black line represents the job seekers from employment, while the green dashed line with cross markers represents the job seekers from outside of the labor force. Incorporating those from outside of the labor force or not does not alter the business cycle property of job seekers from employment. The grade shaded areas indicate NBER recession periods.
Appendix D  My Results vs. Sedláček’s

This is the first paper that shows that on-the-job search raises the contribution of matching efficiency to unemployment fluctuations by the use of the DSGE models. Although Sedláček (2016) used a non-DSGE approach and estimated a matching function similar to Equation (2.3), his results are similar to my work. Besides the difference in our estimation approaches, another difference in estimation is that I do not use the number of hires as an observation variable, while he did.

Because the number of hires is the most important variable related to matching efficiency, in this section, I compare my estimates of matching efficiency with those based on his work. I repeat his estimation but exclude job seekers from outside of the labor force. The purpose of this appendix is to show that even though I do not use hiring in the estimation, my paper still suggests similar changes in the estimates of matching efficiency after the number of job seekers from employment is incorporated into the total population of job seekers.

Figure 10 compares the matching efficiency based on my estimation and those based on Sedláček’s estimation approach. This figure shows that the difference in estimation approaches did not change the main message: including job seekers from employment can amplify the decline in matching efficiency during the Great Recession. When we consider only unemployed workers as job seekers, my estimated matching efficiency is similar to Seláček’s, even though I do not consider hires in estimation. However, when employed job seekers are incorporated, the volatility of estimated matching efficiency in my paper is greater than in Seláček’s.

This difference is due to the estimation strategy. My estimation and Seláček’s both transform the nonlinear models to linear models. I follow most DSGE researchers (e.g., Smets and Wouters 2007) and log-linearize my model, while Seláček transforms the model based on the extended Kalman filter. In the models where the population of job seekers is comprised of only unemployed workers, the log-linearized model and extended Kalman Filter suggest the same form of linear matching function. However, given the fact that job search from employment is incorporated, the log-linearized matching function depends on steady states of unemployment and employment in the model. Therefore, in this case, the linear matching function based on the extended Kalman Filter is different from the log-linearized matching function. In spite of this, incorporating job seekers from employment still increases the decline in matching efficiency during the Great Recession.
Figure 10: Matching Efficiency: This Paper vs. Sedláček (2016)

Note: The figure compares the estimates of matching efficiency in my paper and those based on Sedláček (2016). The graph on the left reports the estimated matching efficiency when only unemployed workers are job seekers, while the one on the right reports the estimated matching efficiency when employed job seekers are included in the estimation. In both graphs, the black solid line represents the result based on my estimation, and the blue dashed line represents the result based on the estimation approach in Sedláček (2016).
Appendix E  Data

Table 7: Data: Name & Source

<table>
<thead>
<tr>
<th>Name</th>
<th>Data Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>COMPRNFB</td>
<td>Nonfarm Business Sector: Real Compensation Per Hour</td>
<td>FRED</td>
</tr>
<tr>
<td>FEDFUNDS</td>
<td>Effective Federal Funds Rate</td>
<td>FRED</td>
</tr>
<tr>
<td>JTSJOR</td>
<td>Job Openings: Total Nonfarm</td>
<td>FRED</td>
</tr>
<tr>
<td>UNRATE</td>
<td>Civilian Unemployment Rate</td>
<td>FRED</td>
</tr>
<tr>
<td>W825RC1</td>
<td>Personal current transfer receipts: government social benefits to persons:</td>
<td>FRED</td>
</tr>
<tr>
<td></td>
<td>unemployment insurance</td>
<td></td>
</tr>
<tr>
<td>CLF16OV</td>
<td>Civilian Labor Force</td>
<td>FRED</td>
</tr>
<tr>
<td>PNFI</td>
<td>Private Nonresidential Fixed Investment</td>
<td>FRED</td>
</tr>
<tr>
<td>GDPDEF</td>
<td>Gross Domestic Product: Implicit Price Deflator</td>
<td>FRED</td>
</tr>
<tr>
<td>PCECC96</td>
<td>Real Personal Consumption Expenditures</td>
<td>FRED</td>
</tr>
<tr>
<td>GDPC1</td>
<td>Real Gross Domestic Product</td>
<td>FRED</td>
</tr>
<tr>
<td>JTS1000HIL</td>
<td>Hires: Total Private</td>
<td>FRED</td>
</tr>
<tr>
<td>HWI</td>
<td>Help Wanted Index</td>
<td></td>
</tr>
<tr>
<td>R'</td>
<td>Shadow Rate</td>
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<tr>
<td>f'w</td>
<td>Job Finding Rate for Employed Workers</td>
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<tr>
<td>f'u</td>
<td>Job Finding Rate for Unemployed Workers</td>
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<tr>
<td>h're</td>
<td>Hires for Employment</td>
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</tr>
<tr>
<td>h'u</td>
<td>Hires for Unemployment</td>
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</table>

Note: This table shows data names and corresponding sources.

Table 8: Definition of Observed Variables for Estimation

<table>
<thead>
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<th>Variable</th>
<th>Description</th>
<th>Note</th>
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<tr>
<td>y</td>
<td>ln(GDPC1/CLF16OV)</td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>ln(PCECC96/CLF16OV)</td>
<td></td>
</tr>
<tr>
<td>w</td>
<td>ln(COMPRNFB)</td>
<td></td>
</tr>
<tr>
<td>l</td>
<td>ln(PNFI/(CLF16OV · GDPDEF))</td>
<td></td>
</tr>
<tr>
<td>u</td>
<td>ln(UNRATE)</td>
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</tr>
<tr>
<td>v</td>
<td>ln(HWI/CLF16OV)</td>
<td>Before 2000:Q4</td>
</tr>
<tr>
<td></td>
<td>ln(JTSJOR/CLF16OV)</td>
<td>After 2000:Q4</td>
</tr>
<tr>
<td>φ'w</td>
<td>ln(f′W/f′u)</td>
<td>1994-Q1–Present</td>
</tr>
<tr>
<td>b</td>
<td>ln(W825RC1/(CLF16OV · GDPDEF))</td>
<td></td>
</tr>
<tr>
<td>R</td>
<td>FEDFUNDS/400</td>
<td></td>
</tr>
<tr>
<td>R' /400</td>
<td></td>
<td></td>
</tr>
<tr>
<td>π</td>
<td>ln(GDPDEFt/GDPDEFt−1)</td>
<td>The ZLB Periods</td>
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</tbody>
</table>

Note: This table explains how the observed variables for estimation are constructed.