Job Search Behavior over the Business Cycle*

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Abstract

In this paper, we study nonemployed workers' job search behavior. In particular, we analyze how search behavior changes over the business cycle. Theoretically, we show that job search intensity can either be procyclical or countercyclical depending on various factors. Empirically, we first examine how aggregate job search intensity changes over the business cycle. Second, we examine job search behavior at the individual level and analyze how various factors affect individuals' job search behavior.

Keywords: job search, time use, business cycles
JEL Classifications: E24, E32, J22, J64

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1 Introduction

Search effort of firms and workers is one of the most important determinants of aggregate employment. In a frictional labor market, a higher number of matches are formed when both firms and workers make more effort to find a suitable counterpart. Understanding the factors that influence search effort on both the firm and the worker sides, therefore, is essential in analyzing the behavior of aggregate employment.

Firms' recruiting effort decision over the business cycle has been studied extensively in the past. For example, studies of Beveridge curves find that firms make higher recruiting effort by posting more vacancies during booms.[1] A recent paper by Davis, Faberman, and Haltiwanger (2010) argues that firms' recruiting effort in addition to posting vacancies also contributes to the cyclical pattern of how firms match with workers. Relatedly, Davis, Faberman, and Haltiwanger criticize the standard Diamond-Mortensen-Pissarides (DMP) framework for limiting the firm's recruiting effort just to the number of vacancies—they emphasize the importance of other inputs in accounting for the microeconomic patterns of hiring.

In this paper, we focus on the worker side of the labor market to analyze how workers' job search effort varies over the business cycle. We show that there is a significant cyclicality in search intensity per nonemployed (or unemployed) worker, and thus just counting the number of nonemployed workers (or unemployed workers) is not sufficient to measure workers' job search effort. In that sense, our paper complements Davis, Faberman, and Haltiwager's (2010) argument and extends their critique to the measurement of search effort on the worker side.

Workers' search effort has not been studied much in the macroeconomic literature both theoretically and empirically. In the basic DMP model (as in Pissarides (1985) and Shimer (2005)), a firm makes an explicit recruiting effort choice by deciding how many vacancies to post, while a nonemployed worker waits passively until a job offer arrives. In other words, the basic DMP search and matching models abstract from workers' *intentional* choice of search

[1] See, for example, Blanchard and Diamond (1990) and Shimer (2005).

effort and workers' search decisions play no role in facilitating match formation.

There are a few recent theoretical papers that analyzes the worker's search effort explicitly. In the model of Christiano, Trabandt, and Walentin (2012), search effort by nonemployed households moves procyclically, and this generates procyclical employment. In Veracierto (2008) and Shimer (2011), a nonemployed worker can choose whether being "unemployed" or "inactive," and only unemployed workers have a positive probability of finding a job (while they have to incur a cost of search). This discrete choice between "unemployed" or "inactive" can be considered as a discrete choice of search effort.

In some of these models, such as Veracierto (2008) and Christiano, Trabandt, and Walentin (2012), the fluctuations of employment and unemployment are driven solely by the worker's search effort. In other words, in these models, the employment fluctuations are entirely *supply driven*, while in the basic DMP model, employment fluctuations are entirely *demand driven*. These are completely opposite views on the aggregate labor market fluctuations, and the procyclical search effort by workers is an essential part of the cyclical dynamics in the former class of models. Thus, examining the cyclical behavior of workers' search effort can provide valuable information on the source of the fluctuations in the labor market.

Despite its importance, there is even less work done on the empirical analysis of the worker's search effort that goes beyond the measurement of unemployment.[2] The main reason for this oversight is the lack of high quality data on job search behavior. We overcome this obstacle by combining two datasets as we describe later.

Beyond the determination of aggregate employment, workers' search effort also has important implications for policy design. For example, in the recent studies of optimal unemployment insurance over the business cycle, such as Kroft and Notowidigdo (2011) and Landais, Michaillat, and Saez (2011), moral hazard in worker's search effort (and how it varies over the business cycle) is the central focus in determining the optimal policy.

The paper consists of three parts. We first construct a simple model in order to obtain

[2] There are a few important exceptions, which we discuss below.

theoretical predictions on how economic environment influences the worker's job search effort. One insight we learn from the model is that there is no ex ante reason to believe that the job search effort is procyclical or countercyclical. There are many effects at work, and it is an empirical question whether some effects dominate others.

Second, we document the macroeconomic time series properties of job search effort. We use the American Time Use Survey (ATUS) and the Current Population Survey (CPS) in order to measure job search effort at the aggregate and individual level. Both datasets have their own shortcomings, and our innovation is to combine the information from both surveys in order to obtain a nationally-representative and monthly time series of job search effort. In an analogy to the labor supply literature, we distinguish two different margins of search effort: the "extensive margin" and the "intensive margin." The "extensive margin" refers to "how many nonemployed workers engage in search activities," while the "intensive margin" refers to "how intensely each searcher is searching." Aggregate search effort in the economy then can be calculated as the product of the extensive and intensive margins.

Third, we explore the determinants of the job search effort, by looking at the individual level. In particular, we run regressions of individual search effort on worker characteristics and measures of their economic environment. We are particularly interested in the relationship of search effort with with labor-market tightness and wealth level.

There are existing papers that utilize the ATUS and the CPS to measure the search effort. Shimer (2004) is an early critic of the way search effort is modeled in typical search-matching models. Shimer uses a measure of job search intensity based on the CPS and shows that the procyclicality of search effort, which is the implication of existing models of job search, is not supported by the data. Krueger and Mueller (2010) and Aguiar, Hurst, and Karabarbounis (2012) are two more recent papers which make use of the ATUS to analyze job search behavior. DeLoach and Kurt (2012) look at ATUS and analyze the determinants of the search time at the micro level. Compared to these studies, our analysis has the advantage of a better measure of job search effort that utilizes information from both the ATUS and the CPS.

This paper is organized as follows. Section 2 presents a simple model in order to uncover the elements that affect the cyclicality of search behavior at the macro and micro level. Section 3 describes the data and explains how we combine the information from two datasets. Section 4 analyzes the cyclicality of search effort at the macro level. Section 5 investigates why we observe the countercyclical search effort from the micro level. Section 6 concludes.

2 Model

In this section, we formulate a simple static model of individual search decision. The model serves two purposes. First, it shows that whether nonemployed workers' search effort is procyclical or countercyclical is an *empirical question*—within reasonable settings of the model, search effort can be procyclical or countercyclical. The models of Appendix A confirm this finding in a more elaborate, dynamic setting. Second, it clarifies the intuition regarding the channels that contribute to the cyclicality of search effort. In particular, the model focuses on the effect of labor-market tightness (how many vacancies there are compared to the number of unemployed workers), wages, unemployment compensations, and wealth.

2.1 Setting

Consider a worker who is currently nonemployed. In the beginning of the period, she decides the intensity of job search effort, $s \in \mathbb{R}_+$. Search effort is costly, and we assume that the cost (in utility term) is $c(s)$ where $c'(\cdot) > 0$ and $c''(\cdot) > 0$. The job-finding probability is assumed to take the form $f(s, \bar{s}, \theta)$ where f is increasing and concave in s. The variable $\bar{s}$ is the search effort of other workers. $\bar{s}$ affects the job-finding probability of a given worker when there is an externality: for example, it may be the case that when some workers search harder, it reduces the odds of other workers finding a job. θ is a parameter that represents the labor market conditions that the worker is facing. Later, θ is represented by vacancy-unemployment ratio. We assume that f is increasing in θ.

A special case is the standard DMP model, which postulates a constant-returns-to-scale matching function $M(u, v)$. There, the number of matches, $M(u, v)$, is increasing in both the number of unemployed workers u and the number of vacancies posted v. Given the constant returns, the probability of a worker matching with a job is $M(u, v)/u = M(1, \theta)$, where θ is defined as the vacancy-unemployment ratio v/u. This formulation is a special case in the sense that $f(s, \bar{s}, \theta) = M(1, \theta)$ and it does not depend on s and $\bar{s}$.

A less trivial special case is the one analyzed by Pissarides (2000, Chapter 5) where job search effort is explicitly modeled. The matching function at the aggregate level (assuming that the individuals are atomistic) is assumed to take the form $M(\bar{s}u, v)$ where $M(\bar{s}u, v)$ is constant-returns-to-scale (and increasing) in these two terms. For each individual, the probability of finding a job is $sM(\bar{s}u, v)/(\bar{s}u)$ which can be rewritten as[3]

$$f(s, \bar{s}, \theta) = sM\left(1, \frac{1}{\bar{s}}\theta\right). \tag{1}$$

where θ is defined as v/u.

Denote the utility that the worker receives from finding a job as $\mathcal{W}$ and the utility from being unemployed as $\mathcal{U}$. Clearly, $\mathcal{W}$ and $\mathcal{U}$ are influenced by the characteristics of the worker and also by the labor market conditions that the worker faces (possibly including θ, as we will discuss later). We will specify $\mathcal{W}$ and $\mathcal{U}$ in more detail later on. Here, we only assume that $\mathcal{W} > \mathcal{U}$. The optimization problem for the worker is

$$\max_{s} \quad f(s, \bar{s}, \theta)\mathcal{W} + (1 - f(s, \bar{s}, \theta))\mathcal{U} - c(s).$$

2.2 Findings

We next analyze how job search effort responds to various changes in the economic environment.

Proposition 1 *Given $\bar{s}$ and θ, job search intensity s is increasing in $(\mathcal{W} - \mathcal{U})$. It is increasing in θ if and only if $f_{13}(s, \bar{s}, \theta) > 0$, where $f_{ij}(s, \bar{s}, \theta)$ represents the cross derivative of $f(s, \bar{s}, \theta)$*

[3]This formulation is used by, for example, Merz (1995) and Gomme and Lkhagvasuren (2012) in their quantitative analysis.

in ith and jth terms.

Proof. The first order condition is

$$c'(s) = f_1(s, \bar{s}, \theta)(\mathcal{W} - \mathcal{U}), \tag{2}$$

where $f_i(s, \bar{s}, \theta)$ is the partial derivative of $f(s, \bar{s}, \theta)$ with respect to ith term. From the Implicit Function Theorem,

$$\frac{ds}{d(\mathcal{W} - \mathcal{U})} = \frac{f_1(s, \bar{s}, \theta)}{c''(s) - f_{11}(s, \bar{s}, \theta)(\mathcal{W} - \mathcal{U})}$$

Since $c''(s) > 0$, $f_{11}(s, \bar{s}, \theta) \leq 0$, and $f_1(s, \bar{s}, \theta) \geq 0$, $ds/d(\mathcal{W} - \mathcal{U}) \geq 0$. Similarly,

$$\frac{ds}{d\theta} = \frac{f_{13}(s, \bar{s}, \theta)(\mathcal{W} - \mathcal{U})}{c''(s) - f_{11}(s, \bar{s}, \theta)(\mathcal{W} - \mathcal{U})}$$

and since $c''(s) > 0$ and $f_{11}(s, \bar{s}, \theta) \leq 0$, and $\mathcal{W} - \mathcal{U} > 0$, $ds/d\theta$ has the same sign as $f_{13}(s, \bar{s}, \theta)$.

■

In words, $f_{13}(s, \bar{s}, \theta) > 0$ means that the individual's search effort s and the labor market condition θ are *complementary*—when θ increases, the "marginal product" of s increases. This is the situation where it is productive to search harder when the firms are posting many vacancies. The opposite case, $f_{13}(s, \bar{s}, \theta) < 0$, can be considered as the case where s and θ are *substitutive* in the job matching process. This happens, for example, in a situation where matches are formed no matter what individual workers do because firms are sending out many offers to everyone.

Note that in the standard DMP model, $(\mathcal{W} - \mathcal{U})$ also has a direct link to θ in general equilibrium, which we ignore here.[4] Appendix A shows that even in a fully dynamic and

[4] There, both θ and $(\mathcal{W} - \mathcal{U})$ are endogenous, and it is difficult to think of an experiment of "moving θ exogenously" as we do here. In that case, if, for example, the outcome of the match is expected to be good, the high surplus from the match is divided between firms and workers through Nash bargaining (therefore a high $(\mathcal{W} - \mathcal{U})$), while a high surplus for firms leads to more vacancy posting today (therefore a high θ). This effect increases both $(\mathcal{W} - \mathcal{U})$ and θ at the same time. Perhaps a more straightforward "partial equilibrium" intuition is that θ at time t would affect the unemployment at time $t+1$, and this affects $(\mathcal{W} - \mathcal{U})$ in the next period. This intuition is correct only in a partial-equilibrium model. In the general equilibrium of Pissarides (1985) model, $(\mathcal{W} - \mathcal{U})$ is not affected by u at time $t+1$ and thus there is no effect going through this channel.

general equilibrium model, an equation similar to (2) determines s and the main message of this section (the cyclicality of s depends on the setting of the model) carries through.

Proposition 1 provides an analysis of individual search effort decisions. When we look at the data, we need to take into account that $\bar{s}$ is also determined (by the choice of s of other people) in the economy and influenced by the economic environment. For simplicity, suppose that the economy consists of homogeneous workers. Then, in a symmetric equilibrium, $\bar{s} = s$ has to hold. Under this assumption, we can show prove the "equilibrium version" of Proposition 1. First, we need an additional assumption.

Assumption 1 $c''(s) - (f_{11}(s, s, \theta) + f_{12}(s, s, \theta))(\mathcal{W} - \mathcal{U}) > 0$ *for all* s *and* θ*.*

This is satisfied when $f_{12}(s, s, \theta)$ is sufficiently small. It is, for example, satisfied under (1) since there $f_{12}(s, s, \theta)$ is negative. Under Assumption 1, it is straightforward to show the following.

Proposition 2 *Given* θ*, job search intensity,* s*, is increasing in* $(\mathcal{W} - \mathcal{U})$*. It is increasing in* θ *if and only if* $f_{13}(s, s, \theta) > 0$*.*

The proof is omitted since it is similar to the proof of Proposition 1. Thus the result of this "equilibrium outcome" is similar to the outcome of the decision problem in Proposition 1. Note that this result is still not "general equilibrium" in the sense of Pissarides (2000), since variables such as θ, $\mathcal{W}$, and $\mathcal{U}$ are assumed to be exogenous. We take the current approach because we are interested in the workers' search effort decision in a given environment.

To characterize the determinants of $\mathcal{W}$ and $\mathcal{U}$, we make the following additional assumptions. First, the utility from consumption is represented by a strictly increasing and strictly concave utility function $u(c)$, where c is consumption. The worker has an asset level a. If he works, he receives the wage w, and if he is unemployed, he receives the unemployment compensation b. Thus, $c = w + a$ if he works and $c = b + a$ if he is unemployed. Then, $\mathcal{W} = u(w + a)$ and $\mathcal{U} = u(b + a)$. (In a dynamic model, c also depends on the expectations on future income.) Assume that $w > b$. Then it is straightforward to show the following.

Corollary 1 *The job search intensity, s, is increasing in w, decreasing in b, and decreasing in a in the context of both Propositions 1 and 2.*

Proof. We only need to establish how $\mathcal{W} - \mathcal{U}$ responds to these parameters since we can then apply Propositions 1 and 2, we Since $\mathcal{W} - \mathcal{U} = u(w + a) - u(b + a)$, the first two are straightforward. For a,

$$\frac{d(\mathcal{W} - \mathcal{U})}{da} = u'(w + a) - u'(b + a) < 0$$

since $w + a > b + a$. $\blacksquare$

During expansions, θ, w, and a are typically higher. The first can have positive or negative effect in s, depending on the $f(s, \bar{s}, \theta)$ function. The second has a positive effect and the third has a negative effect.[5] Therefore, whether s is procyclical or countercyclical for a nonemployed worker is an empirical issue. This in particular raises two distinct empirical questions: (i) the relative strengths of the effect of w, b, and a, and (ii) the shape of the $f(s, \bar{s}, \theta)$ function. At the macroeconomic level, the number of nonemployed worker also fluctuates, adding one more factor in the fluctuations of the aggregate search effort.

2.3 Generalizing the matching function

Before discussing our empirical analysis, one issue is worth exploring: when is $f_{13}(s, s, \theta)$ negative? This is not a trivial question—for example, when we start from the aggregate matching function, a natural formulation such as (1) cannot generate a negative $f_{13}(s, s, \theta)$: $f_{13}(s, s, \theta)$ is *always positive* as long as $M(su, v)$ is increasing in v. As we discussed earlier, intuitively, it is quite natural to think of a situation where $f_{13}(s, s, \theta)$ is negative—that is, the "marginal product" of individuals' search is smaller when the labor market conditions are better. For example, when there are so many jobs (the firm searches very heavily), that it is almost certain that every worker has a good job offer, additional effort by the worker does not add much to the matching outcome. Based on a similar intuition, Shimer (2004) builds a

[5] If the utility function is linear, the third effect is absent.

concrete micro-founded matching model which does not necessarily result in complementarity between worker search effort and the labor market conditions.

As an example of "generalized" version of (1), we can consider

$$f(s, \bar{s}, \theta) = \chi \left(\alpha s^{\psi} + (1-\alpha) \left(\frac{s}{\bar{s}} \right)^{\xi} \theta^{\psi} \right)^{\eta}. \tag{3}$$

When workers are homogeneous, this aggregates up to the matching function

$$M(\bar{s}, u, v) = \chi \left(\alpha \bar{s}^{\psi} + (1-\alpha) \left(\frac{v}{u} \right)^{\psi} \right)^{\eta} u. \tag{4}$$

We assume that $\chi > 0$, $\alpha \in [0, 1]$, and ψ, ξ, η have the same sign (weakly). This formulation nests some important special cases. For example,

- When $\xi = \alpha = 0$ and $\psi\eta \in (0, 1)$, (3) reduces to the standard DMP matching function in Cobb-Douglas form.
- If we first set $\xi = \psi = 1/\eta$ and take a limit of $1/\eta \to 0$, $f(s, \bar{s}, \theta)$ becomes $s\chi(\theta/\bar{s})^{1-\alpha}$ and $M(\bar{s}, u, v)$ becomes $\chi(\bar{s}u)^{\alpha} v^{1-\alpha}$. Therefore this is a Cobb-Douglas version of (1).

To see that f_{13} can be either positive or negative, consider a simple special case of (3) where $\xi = 0$. Then one can easily show that $f_{13} < 0$ if and only if $\psi(\eta - 1) < 0$. Since ψ and η has the same sign, this means that $\eta \in (0, 1)$.[6] Once again, the takeaway here is that the shape of $f_{13}(s, s, \theta)$ is an empirical question.

3 Measuring search effort

This section explains how we measure workers' job search effort by combining information from the CPS and the ATUS, and creating a measure of job search effort for each worker in the CPS sample at a monthly frequency.

[6] In this case, additional parametric restrictions may be needed in order to guarantee the properties that are usually assumed in the search-matching literature. Also note that it may be necessary to check the second-order condition for optimal choice of s, since f function may not be concave. For example, if $\psi\eta = 1$ and $\eta < 1$, f is convex in s.

Job search activities (050401)
Interviewing (050403)
Waiting associated with job search interview (050404)
Security procedures related to job search/interviewing (050405)
Job search activities, not elsewhere specified (050499)

Table 1: Definitions of job search activities in ATUS

3.1 Data

The CPS is a monthly survey conducted by the U.S. Bureau of Census for the Bureau of Labor Statistics (BLS). It is a primary source of labor force statistics for the population of the United States. The ATUS is conducted by the BLS and individuals are drawn from the exiting samples of the CPS. Respondents are interviewed 2–5 months after their last CPS interview. Through a daily diary, the ATUS collects detailed information on the amount of time respondents devote to various activities during the day preceding their interview. Our sample from the ATUS spans 2003-2011 and our sample for the CPS goes from 1994 through 2011. Following Shimer (2004), we restrict the sample of workers to those between 25 and 70 year old.

Recently, the ATUS has been used to measure job search effort by some researchers, such as Krueger and Mueller (2010), Aguiar, Hurst, and Karabarbounis (2011), and DeLoach and Kurt (2012). The ATUS has the advantage of having a qualifiable measure of job search effort at the "intensive margin," that is, how many minutes each nonemployed worker spends for job search. This is a very natural measure of job search effort, corresponding to the hours worked in measuring the labor input for production. We follow Krueger and Mueller (2010) and identify job search activities as the ones in Table 1. The first category (job search activities) includes contacting employer, sending out resumes, and filling out job application, among others.[7]

[7] See Krueger and Mueller (2010) Table 1 in Appendix A for details. In the analysis below, we exclude the samples who report more than eight hours of job search activities. The results in this and the next section are not affected by this treatment except for a small change in the average level.

The ATUS has two major shortcomings for our purposes—it has small sample size (12,000–21,000 per year) and a short sample period (available only from 2003). The small sample size problem is more severe than it appears—considering that it only contains information about the day before the interview, there are less than 100 observations per day. The short sample is a problem because the U.S. economy has experienced only one recession after 2003 and it may be difficult to detect a recurring cyclical pattern from only one experience.

In order to overcome these shortcomings, we make use of information on job search behavior in the CPS. The CPS has both a larger sample size (150,000 per month) and a longer sample period (we use the surveys after 1994 redesign). Moreover, the question we utilize contains information about the job search behavior over the past month, rather than just one day. In addition to the time diaries, the ATUS includes a follow-up interview in which they ask many of the basic CPS questions.

The question we utilize is regarding the search methods the worker has used: the CPS monthly basic survey and the ATUS follow-up survey both contain a question on the particular search methods used in the previous month. Conditional on the worker being a nonemployed searcher (that is, an unemployed worker who is not on temporary layoff), the interviewer asks what kind of search methods the worker has used in the past month.[8] In the question, respondents are allowed to select from nine active search methods and three passive search methods. Table 2 lists all methods. Shimer (2004) employed the number of methods used by the worker as a proxy of the search intensity. The idea is that if a worker uses six methods in one month, she is likely to be searching more intensely than a worker who uses only one method. The shortcomings of this proxy are that this is not as natural as the "time" measure (once again, the time measure has a natural analogy to the hours worked in the study of labor supply), it is not readily quantifiable, and it is not necessarily obvious whether each method is equally as important.

[8] There is a small group of nonemployed workers other than searchers who report using a strictly positive number of search methods. Since the CPS documentation states that only searchers are asked about their search methods, we interpret these responses as miscoding and replace them with zeros.

Contacting an employer directly of having a job interview
Contacting a public employment agency
Contacting a private employment agency
Contacting friends or relatives
Contacting a school or university employment center
Checking union or professional registers
Sending out resumes or filling out applications
Placing or answering advertisements
Other means of active job search
Reading about job openings that are posted in newspapers or on the internet
Attending job training program or course
Other means of passive job search

Table 2: Definitions of job search methods in CPS and ATUS (the first nine are active, the last three are passive)

3.2 Linking the ATUS and the CPS

Table 2 shows that many activities overlap with the job search activities recorded in the ATUS time diaries and therefore it is likely that similar information is contained in the answers to the "methods" question and the ATUS "time" records. To see how closely these two measures are related, we categorize unemployed workers (limited to searchers) by the number of methods they report using and we plot the average minutes per day that each group spends on job search activities. This, in effect, is a validation exercise for Shimer's (2004) proxy.

Figure 1 indicates that recorded search time and the number of methods used exhibit a strong positive correlation. This implies that the information contained in the "methods" question indeed can be used as a measure of search intensity.

However, as we noted earlier, the number of methods is not necessarily an ideal measure of the search effort. It does not convey any information on the relative importance of each method in workers' job search activities—in reality, it is likely that workers allocate their search time differently across different methods, considering the effectiveness and time

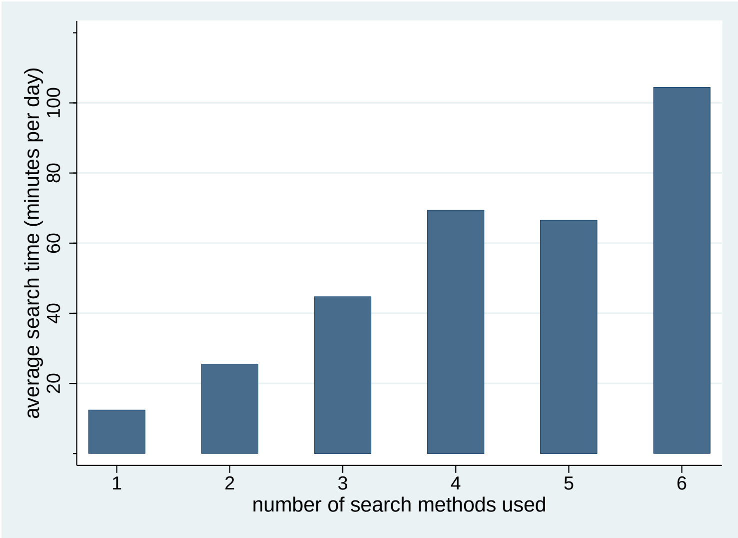


Figure 1: The average minutes (per day) spent for job search activities for the workers with each number of search methods used. Sample of searchers.

intensiveness of various methods.

In this paper, we link the information of the two datasets in order to overcome their shortcomings. In particular, we generate the “imputed search time” spent for job search for each CPS respondent, using the relationship between the “time” question and “methods” question for the ATUS sample. The simplest approach would be to run an OLS regression for the ATUS sample with the “time” on the left-hand side and dummy variables for each method used (and various worker characteristics) on the right-hand side, and use this equation for the imputation of the CPS sample, for which we can only see the methods and other worker characteristics. One shortcoming with this approach is that there are many incidences of negative imputed minutes. Another shortcoming of this approach is that we cannot fully utilize the information contained in “zero” reported search time—since the time measure only contains the information about the day before the survey (while the method measure contains the methods used in the last four weeks), there are a lot of incidences of “zeros” in the left-hand side[9].

[9]Only around 20% of the unemployed searchers reported positive search time on the day of the interview.

To overcome this, the approach we take here involves two steps. In the first step, we estimate the probability of observing positive search time in ATUS—if the worker spent many days during the last four weeks actively searching, it is more likely that the ATUS survey day falls onto a day of active search. This is done by running a probit model with dummy variables for each method and the worker characteristics on the right-hand side. In the second step, we restrict the ATUS samples to the ones who reported strictly positive search time and run a regression with the log of search time on the left-hand side and dummy variables for each method and the worker characteristics on the right-hand side. We can conduct the imputation for the CPS sample by using the estimated coefficients for both steps and multiplying the outcome. The details of the imputation and alternate specifications are explored in Appendix B.2. Figure 2 provides a comparison of the time series of the actual reported minutes and the imputed minutes within the ATUS sample. The imputed minutes track the actual minutes closely, with the exception of 2004 and 2005.

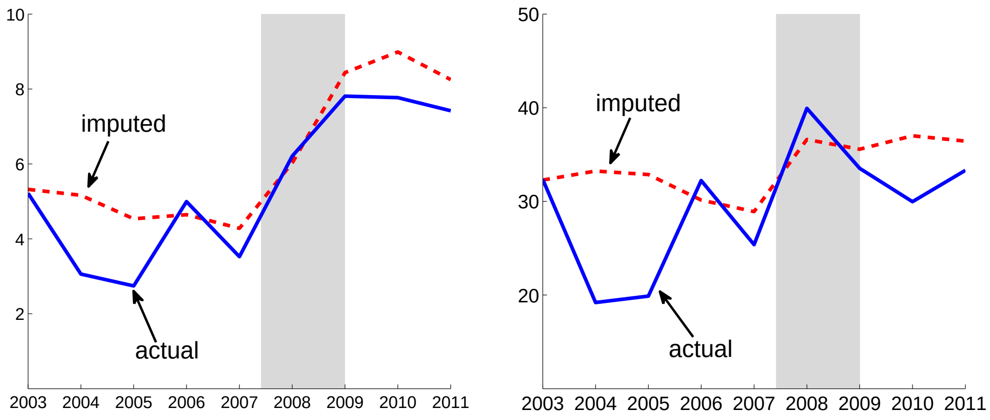
In the remainder of the paper, we use our imputed minutes (denoted $\hat{s}_{it}$ for individual i at time t) as the search effort measure for the CPS sample. This measure is a nontrivial extension of Shimer's measure since it exploits information on job search from the ATUS.[10]

3.3 Determining the extensive margin

As a first step in analyzing the ATUS and the CPS data on job search, it is useful to identify the type of workers who engage in search activity. This information is used when we separate the search intensity into two margins: extensive margin (the number of people who are actively searching) and intensive margin (how much time each active searcher spends searching for a job). Here, we aim at determining the extensive margin by examining which category of workers can be considered as active searchers. Table 3 reports the average time (in minutes per day) spent on job search activities reported in the time diaries of the ATUS for workers in each category of labor market state.

See Appendix B.2 for imputation results using this simple OLS regression.

[10] We have repeated all exercises in Section 4 using Shimer's (2004) measures (see Appendix B.3) and using imputed minutes based on a simple OLS regression described above. All results remain the same qualitatively.



(a) all nonemployed

(b) unemployed

Figure 2: Average search minutes per day for all nonemployed workers and unemployed workers, actual and imputed. ATUS sample.

<table>
<tr><td colspan="5">All workers
1.6</td></tr>
<tr><td rowspan="4">Employed
0.5</td><td colspan="4">Nonemployed
4.6</td></tr>
<tr><td colspan="2">Unemployed
27.6</td><td colspan="2">Not in the labor force
0.5</td></tr>
<tr><td>Temp layoff
10.2</td><td>Searchers
30.6</td><td>Non-searchers
2.3</td><td>Other NILF
0.5</td></tr>
<tr><td></td><td colspan="2">Attached workers
25.0</td><td></td></tr>
</table>

Table 3: Average search time (minutes per day) from the ATUS

In addition to standard categorizations (employed and nonemployed; employed, unemployed, and not in the labor force [NILF]), we divide unemployed workers into two categories ("temporary layoffs" and "searchers") and non-participants into two categories ("non-searchers" and "other NILF").[11] Searchers are defined to be the unemployed workers who are not on temporary layoff, and non-searchers are the workers who are not in the labor force but who report that they "want a job."[12] The sum of searchers and non-searchers are categorized as "attached workers."

Table 3 reveals large differences in search time among different categories. Not so surprisingly, unemployed workers spend much more time searching for a job compared to either employed workers or those not in the labor force. There is also some difference in search time between workers on temporary layoff and searchers, but workers on temporary layoff do spend significant time searching. Therefore, it is clear from Table 3 that the answer to "who are actively searching?" is "the unemployed workers." Thus in the next section we identify the extensive margin of search by the unemployed workers.

4 Cyclicality of search effort

In this section, we describe how nonemployed workers' search behavior has changed over time. As we described above, we divide the search intensity into two margins: the extensive margin and the intensive margin. Given that we will use the unemployed workers as the extensive margin, our main departure from the DMP literature is the measurement of the intensive margin.

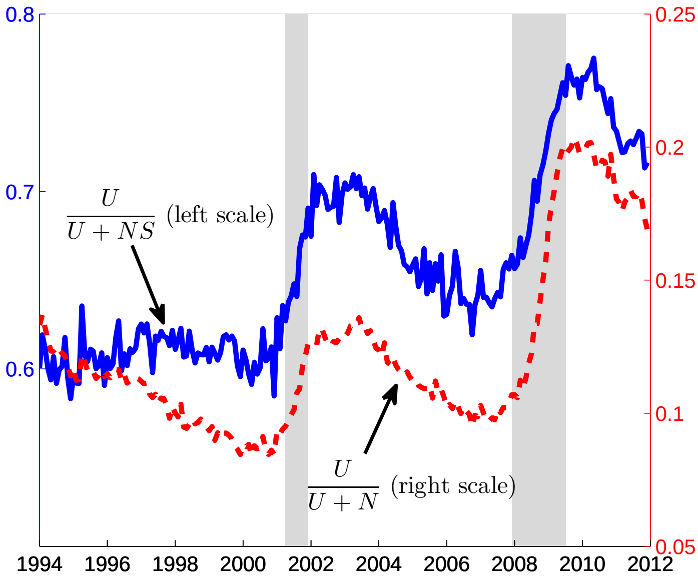


Figure 3: The time series of extensive margins: $U/(U+N)$ and $U/(U+NS)$

4.1 The extensive margin

As we discussed in the previous section, the most reasonable answer to "who is searching?" is "the unemployed workers." Figure 3 plots the ratio of unemployed worker (U) to all nonemployed workers (N) and the ratio of unemployed workers to the sum of the number of unemployed workers and the number of nonsearchers (NS).[13] Here, the denominator is meant to represent the "entire population of potential workers." In the most general context, it corresponds to the "entire population who are in the appropriate age range."[14] In that case, the appropriate denominator is all nonemployed workers. Another reasonable choice is to exclude workers who do not want to work, in which case the sum of unemployed workers

[11] This classification, as well as the terminology of "searchers," "non-searchers," and "attached workers," follows Shimer (2004).

[12] This is a larger category than "marginally attached workers"—a marginally attached worker has to be available for working and have searched during the past 12 months (but not past four weeks), in addition to reporting that she wants a job.

[13] This sum corresponds to "generalized unemployment" in the language of Krusell et al. (2010).

[14] In this paper, the age range is from 25 to 70.

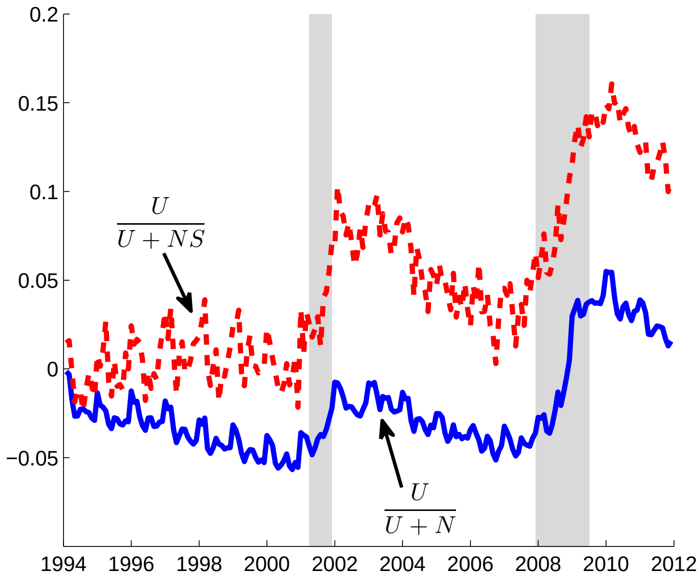


Figure 4: The time series of the time dummies μ_s. The sample population is $U + N$ for the dotted line and $U + NS$ for the solid line.

and the nonsearchers is the appropriate denominator.

Figure 3 clearly shows that the extensive margin is countercyclical. This is not a surprising observation given that the strong countercyclicality of unemployment has been widely documented. In order to control for the changes in composition of the nonemployed pool over the business cycle, we estimate a linear probability model that is similar to that in Shimer's (2004). We run the regression (using the $U + N$ and $U + NS$ sample)

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\delta} + \sum_s \mu_s m_s + \varepsilon_{it}, \tag{5}$$

where y_{it} is 1 if $i \in U$ and 0 if $i \notin U$, $\mathbf{x}_{it}$ is the same set of controls as in (4) with the coefficient vector $\boldsymbol{\delta}$, and m_s is the month dummy that takes 1 if $s = t$ and 0 otherwise. Figure 3 plots the coefficients on the month dummy, μ_s, for each s. These coefficients provide an estimate of how much being in a particular month raises the probability of being in U given that you are not employed. Like Figure 3, this time series is also countercyclical.

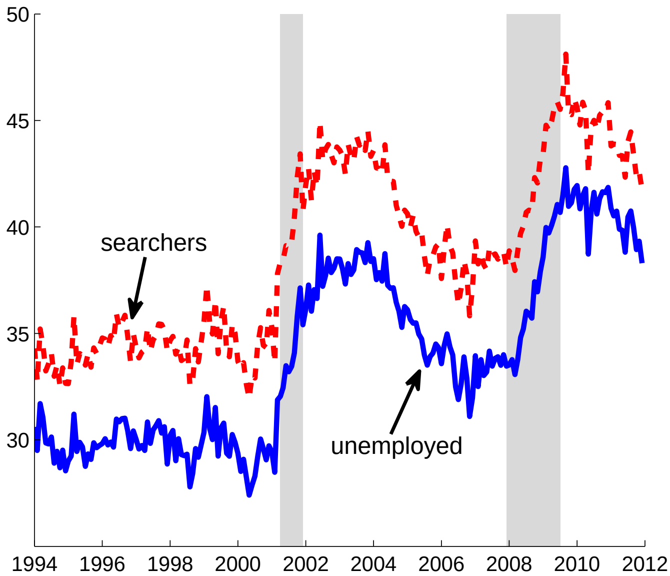


Figure 5: The time series of the estimated average search effort (minutes per day) for unemployed workers and searchers

Although the results on the extensive margin provide some useful information about search effort decision, this is a rough measure of each worker's search effort. In addition, in the context of many search models, the extensive margin is effectively irrelevant, since typically the "entire population of workers" is considered as employment plus unemployment. Thus we examine the "intensive margin" in the next subsection.

4.2 The intensive margin

We use the imputed minutes, $\hat{s}_{it}$, calculated in Section 3.2, as our measure of search effort at the intensive margin. Figure 5 plots the time series of the average $\hat{s}_{it}$ in minutes per day. The solid line is the average minutes per day that an unemployed worker spends on search activities and the dotted line is the corresponding number for searchers. They clearly also exhibit a countercyclical pattern.

In order to see if the same pattern holds after controlling for the composition of unem-

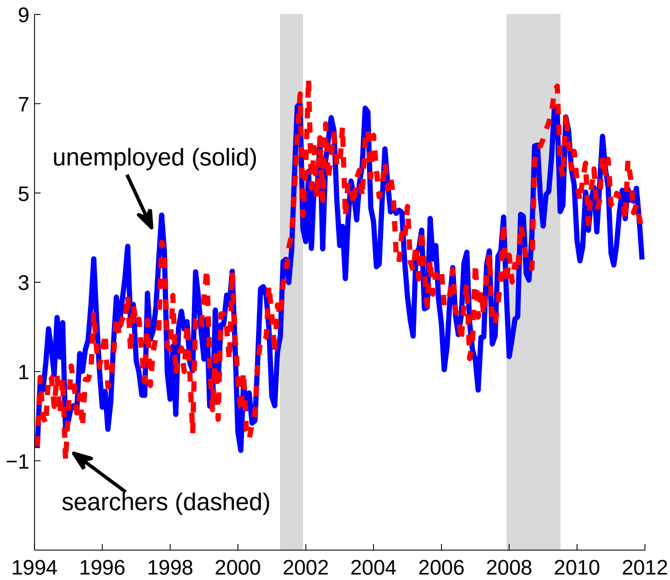


Figure 6: The time series of the time dummies, for unemployed workers and searchers

ployed workers, we run a similar regression as (5) with $\hat{s}_{it}$ for the unemployed worker on the left-hand side. Figure 6 plots the coefficients on the month dummies and shows that the countercyclical pattern remains even after controlling for observed changes in composition.

4.3 Total

The total search effort by nonemployed workers in the economy can be calculated as [the fraction of unemployed in the population]×[intensive margin]. This is the counterpart of s (and $\bar{s}$) in the nonemployed worker's matching probability $f(s, \bar{s}, \theta)$ in Section 2. Figure 7 plots three measures of total search effort which depend on the group of workers included in the calculations. The lowest line is the minutes of search of searchers only (that is, the minutes of all other nonemployed workers are set to zero). The next highest line uses the minutes of all unemployed workers, and the highest line measures the minutes of all nonemployed workers. Since unemployment is the measure at the extensive margin, the total search effort of all unemployed workers is the most natural measure. However, because only "searchers"

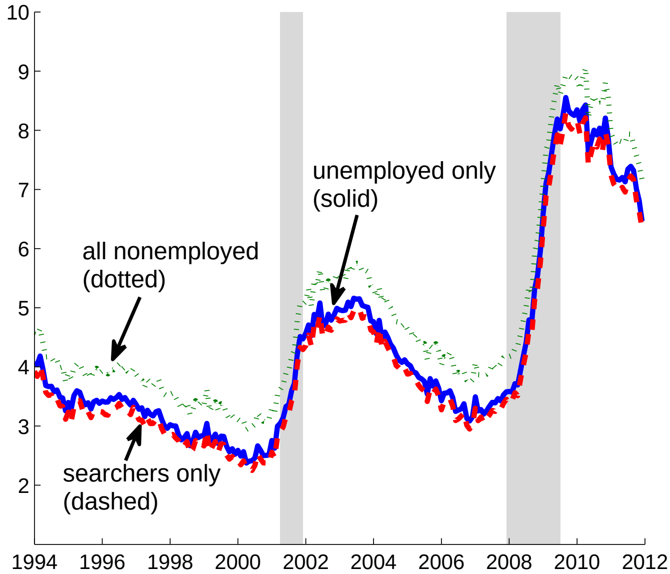


Figure 7: The total search effort (sum of all minutes divided by the total nonemployed population), using the minutes of only searchers, only unemployed workers, and all nonemployed

(unemployed workers who are not on the temporary layoff) are asked about their search methods, searchers' $\hat{s}_{it}$ is the most accurately measured and because some non-participants report nonzero search time in the ATUS, we include all three measures. As one can infer from the previous two sections' results, total search effort in Figure 7 for all three groups also exhibits a countercyclical pattern.

If we multiply the series in Figure 7 by $(U + N)/(U + N + E)$, we obtain the total search effort in the economy. This is the natural counterpart of the input su in the matching function $M(su, v)$ in Section 2. These series are plotted in Figure 8 and again exhibit a countercycical pattern.

4.4 Implications

Our result that the aggregate search effort by nonemployed workers is countercyclical has several important implications for macroeconomic analysis of the labor market. Below we

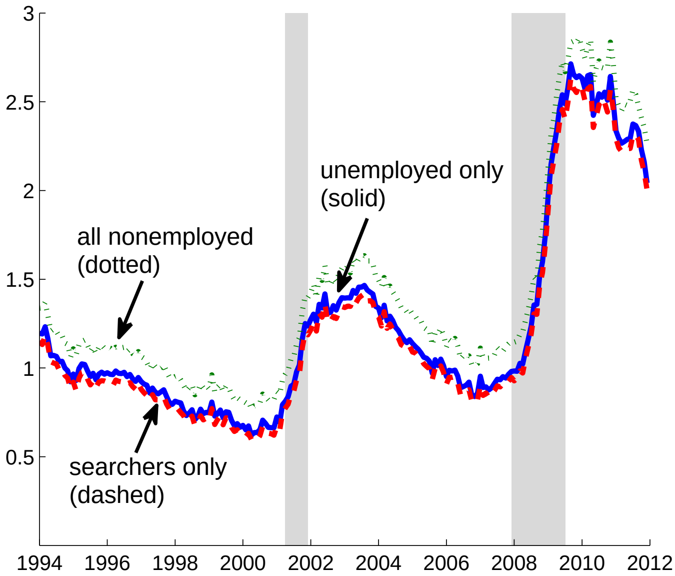


Figure 8: The total search effort (sum of all minutes divided by the total population), using the minutes of only searchers, only unemployed workers, and all nonemployed

discuss two of these.

4.4.1 Implications: driver of the aggregate labor market fluctuations

What does our result tell us about the source of cyclical fluctuation of the labor market? The fact that workers are making more effort in searching for a job in recessions rules out the possibility that labor supply is the sole determinant of the cyclical movement of employment and unemployment—the employment decline in recessions is not because workers are not looking for a job as hard as in booms.

Here, one has to be careful in making distinction between the cyclicality of *aggregate effort* and *individual effort*. When workers are heterogeneous, it is possible that the aggregate search effort is countercyclical while the individual effort is not. We have controlled for the observable characteristics of the workers in the previous section, but the unobservable characteristics may remain, as we will discuss further in Section 5.1.

However, for analyzing aggregate dynamics of the labor market, aggregate effort still provides useful information. In fact, Appendix C shows that, in the context of the DMP-style model, the aggregate search effort has to be *procyclical* if aggregate employment and unemployment are entirely supply-driven. This result casts doubts on the empirical plausibility of a class of models whose employment dynamics is entirely supply-driven, such as Veracierto (2008) and Christiano, Trabandt, and Walentin (2012).

4.4.2 Implications: matching function

Our observation that the intensive margin of search effort exhibit strong cyclicality has important implications on the theoretical models that relies on the matching function. If we consider only the number of unemployed workers as the input to the matching function as in the standard DMP model, we are implicitly measuring the search effort only using the extensive margin. Figure 9 plots total search effort measures using only the extensive margin ($U/(E+U+N)$) against a measure that uses the intensive margin as well ($\bar{s}U/(E+U+N)$),[15]

[15] Note that this is an appropriate input of the matching function in the context of (1) but may not be appropriate in the context of (3).

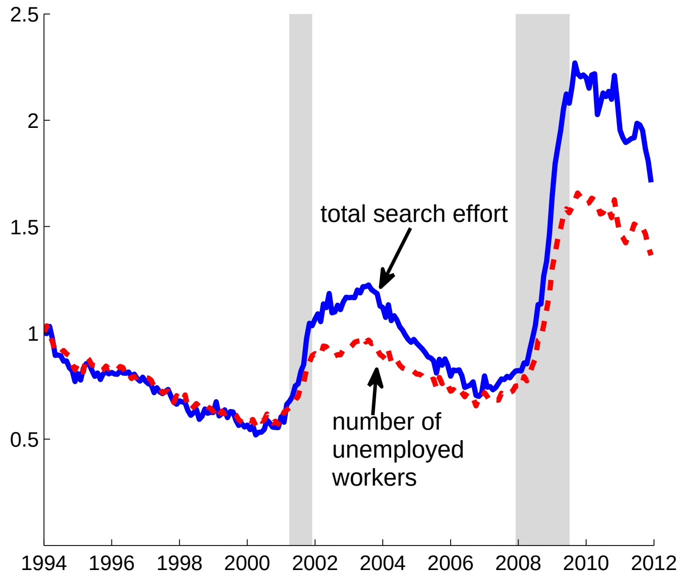


Figure 9: The total search effort (sum of all minutes divided by the total population), using the minutes of unemployed workers ($\bar{s}U/(E+U+N)$), compared to the number of unemployed workers $U/(E+U+N)$. Both are normalized to 1 at the beginning of 1994.

normalizing the initial levels to one. We see that, especially in recent years, the two lines diverge significantly, illuminating the importance of appropriately taking the intensive margin into account.

We can further measure the importance of the intensive margin by estimating the matching function. Here, we consider simple linear regressions under the constant returns to scale assumption.[16] There is a large literature on estimating matching functions (earlier literature was surveyed by Petrongolo and Pissarides, 2001) but none have considered the worker's search intensity, except for Yashiv (2000).

We use the data from JOLTS and CPS from December 2000 to December 2011. The job finding probability f_t is obtained by dividing the "hires" variable in JOLTS by the number of unemployed in CPS. The variable θ_t is obtained by dividing the "vacancy" variable in

[16]See Appendix D for the interpretation in the context of the exact matching function in the form of (4).

JOLTS by the number of unemployed in CPS. We consider the formulation

$$\ln(f_t) = \delta_0 + \delta_\theta \ln(\theta_t) + \delta_s \ln(\bar{s}_t) + \delta_d d_t + \tau_t + \epsilon_t, \tag{6}$$

where f_t is the job-finding probability, $\theta_t \equiv v_t/u_t$ where v_t is vacancy and u_t is unemployment, τ_t is the month dummy, and ϵ_t is the error term. $\bar{s}_t$ is the aggregate value for intensive margin of search effort (for each unemployed worker), measured in Section 4.2. d_t is a dummy variable that takes one for t before July 2009—this is to control for a recent large decline in matching efficiency.

Table 4 shows the results of a simple OLS regression of the form (6), with and without $\ln(\bar{s}_t)$. The first column is the conventional matching function estimation, and the result is within the range of the OLS results in the literature—see, for example, Borowczyk-Martins, Jolivet, and Postel-Vinay (2013). The second column adds our search intensity variable estimated from CPS, $\bar{s}$. As is expected by the theory, the coefficient of $\ln(\bar{s})$ is positive and significant at 1% level. The inclusion of this variable also changes the estimated coefficient of $\ln(\theta_t)$ upwards.

	Without $\ln(\bar{s}_t)$	With $\ln(\bar{s}_t)$
$\ln(\theta_t)$	0.731^{***}	0.831^{***}
	(0.019)	(0.036)
$\ln(\bar{s}_t)$	–	0.522^{**}
	–	(0.164)

Table 4: Matching function estimation: OLS. Standard errors are in the parenthesis. *** indicates being significant at 0.1% level. ** indicates being significant at 1% level.

As is argued by Borowczyk-Martins, Jolivet, and Postel-Vinay (2013), however, the OLS estimate is likely biased. In particular, they argue that θ_t is endogenous in the conventional matching function estimation when there are shocks to the matching efficiency. In our formulation, their argument also can be applied to $\bar{s}_t$. They devised a GMM estimation method that is immune from this endogeneity bias. In particular, they assume that ϵ_t in (6) has an ARMA structure and estimate the AR parameters ϵ_t together with the coefficients β_i using the lagged values of $\ln(\theta_t)$ as instrumental variables. We extend their method to incorporate another endogenous variable $\ln(\bar{s}_t)$. Following their method, we assume that ϵ_t follows ARMA(3,3). We use $\ln(\theta_{t-i})$ and $\ln(\bar{s}_{t-i})$ where $i = 4, 5, 6, 7, 8, 9$ as the instrumental variables. (Note that here the system is over-identified.) Following Borowczyk-Martins, Jolivet, and Postel-Vinay (2013), we repeat the estimation also with $\ln(f_{t-4})$ included in the list of instrumental variables.

	Lags of $\ln(\theta_t)$ and $\ln(\bar{s}_t)$ used as IV	$\ln(f_t)$ lag also included as IV
$\ln(\theta_t)$	0.793^{***}	0.658^{***}
	(0.143)	(0.091)
$\ln(\bar{s}_t)$	0.055	-0.094
	(0.436)	(0.392)

Table 5: Matching function estimation: GMM method based on Borowczyk-Martins, Jolivet, and Postel-Vinay (2013). Standard errors are in the parenthesis. *** indicates being significant at 0.1% level.

Table 5 shows the result. In both cases, the coefficient of $\ln(\theta_t)$ is significant at 0.1% significance level and also in line with the estimates in the previous studies (in Borowczyk-Martins, Jolivet, and Postel-Vinay (2013), the corresponding numbers are 0.706 and 0.692). The point estimates of both coefficients are lower than the OLS estimates, as the theory would predict. Unfortunately, the coefficients of $\ln(\bar{s})$ have large standard errors and thus cannot provide a conclusive evidence on the effect of $\bar{s}_t$. We also experimented with adding more instruments, including S&P-500 index and nation-wide house price index, but they did not improve the estimates. This is because (i) the measurement of $\bar{s}_t$ is not as precise as θ_t and (ii) the instruments are not very strong for $\bar{s}_t$, and (iii) the negative externality among workers may wash out the individual effect at the aggregate level. Further exploring this issue and precisely identifying the sign and the magnitude of $\bar{s}_t$ coefficient is left for future research.

In principle, the estimation of the matching function would also shed light on how the worker's effort and the firm's effort are related technologically. In particular, as Appendix

D shows, (under the assumption of no externality in s) if the coefficient on the cross-term is negative, these are "substitutive" rather than "complementary." Table 6 shows the result. All variables are transformed as the log-deviation from their sample means, so that the coefficients are easily interpretable. The OLS estimates are potentially biased because of the endogeneity of θ_t and $\bar{s}_t$. Once again, except for $\ln(\theta_t)$, the coefficients in the GMM IV estimation (with the ARMA(3,3) specification and the same number of lags used as the instruments as above) are not significantly different from zero. It remains as a future research topic to estimate these coefficients more precisely.

	OLS	Lags θ_t, $\bar{s}_t$ variables as IV	$\ln(f_t)$ lag also included as IV
$\ln(\theta_t)$	0.858***	0.585***	0.654***
	(0.045)	(0.089)	(0.081)
$\ln(\bar{s}_t)$	0.695**	−0.279	−0.110
	(0.209)	(0.356)	(0.346)
$\ln(\theta_t)^2$	0.057	0.038	0.050
	(0.071)	(0.077)	(0.080)
$\ln(\bar{s}_t)^2$	1.979	0.100	0.664
	(1.483)	(1.511)	(1.545)
$\ln(\theta_t)\ln(\bar{s}_t)$	0.601	−0.031	0.168
	(0.660)	(0.631)	(0.654)

Table 6: Matching function estimation: GMM method based on Borowczyk-Martins, Jolivet, and Postel-Vinay (2013), all variables are log-deviations from their mean value. Standard errors are in the parenthesis. *** indicates being significant at 0.1% level. ** indicates being significant at 1% level.

Overall, the matching function estimation indicates that $\bar{s}_t$ matters for the estimation outcome. Unfortunately, our measurement is not sufficient for providing a conclusive evidence on how it matters in the IV estimation, and a further examination is left for the future research.

5 Why is the search effort countercyclical?

Our results in Section 4 indicate that the search effort is countercyclical, both at the intensive and the extensive margins. This section analyzes the reasons behind this countercyclicality, especially in the intensive margin.

Note that, as is mentioned in the previous section and we will discuss further below, unobserved heterogeneity is an important issue in the measurement of the cyclicality of the intensive margin in the aggregate, since the pool of searchers change over time. We have shown that aggregate search effort is countercyclical, and this holds for the intensive margin as well. This observation is true even after controlling for *observed* heterogeneity. However, in addition to changes in observed characteristics of searchers, there is a countercyclical bias stemming from unobserved heterogeneity when we consider individual-level effort. We deal with this issue of unobserved heterogeneity by exploiting the panel aspect of the CPS and find that unobserved heterogeneity indeed has some effect on analyzing the response of individual search effort to external environment.

5.1 The individual decision rules

In the context of our simple model in Section 2, job search behavior is strongly influenced by either labor market conditions, θ, and present value of wealth, a. We run various individual-level regressions to uncover the factors that influence individuals' decision for s. The regression equation is

$$\hat{s}_{it} = \theta_{it}\delta_{\theta} + w_{it}\delta_{w} + \mathbf{x}_{it}'\boldsymbol{\delta}_{x} + \varepsilon_{it}, \tag{7}$$

where θ_{it} is a measure of labor market conditions with δ_{θ} as the associated coefficient, w_{it} is the wealth variable with the associated coefficient δ_{w}, and $\mathbf{x}_{it}$ is the vector of controls and $\boldsymbol{\delta}_{x}$ is the associated coefficient vector. ε_{it} is the error term. The controls include the usual demographic controls (a quartic in age, marital status, race, sex, and education), four occupation dummies,[17] a quartic function of unemployment duration, and month dummies.

[17] We use the occupation categorization in Acemoglu and Autor (2011), in which occupations are divided into four categories, cognitive/non-routine, cognitive/routine, manual/non-routine, and manual/routine.

5.2 Individual response to aggregate condition

First, we run the individual-level regression (7), with the individual $\hat{s}_{it}$ on the left-hand side, and using the aggregate-level θ_t (we use the vacancy-unemployment ratio) and the aggregate-level measure of wealth on the right-hand side. We restrict the sample to the searchers, whose imputed time is based on the search methods used in addition to the individual characteristics. Table 7 shows the regression results for equation (7) using two alternative measures of aggregate labor market conditions and two alternative measures of wealth. The two measures of labor market conditions come from the vacancy series in the JOLTS and HWOL datasets, which we use to compute the aggregate labor market tightness (vacancy-unemployment ratio) v/u. The JOLTS survey starts in 2001 and gives us a longer time series while the HWOL series start in 2005. For wealth, we use S&P 500 and the aggregate Core-Logic house price index. Full results of the regression are reported in Appendix E.

	JOLTS		HWOL	
Market Tightness (θ)	-0.930^{***}	-1.098^{***}	-2.146^{***}	-2.857^{***}
	(0.118)	(0.118)	(0.248)	(0.336)
S&P 500	-0.005^{***}	–	-0.003^{***}	–
	(0.001)	–	(0.001)	–
House Price Index	–	-0.025^{***}	–	-0.004
	–	(0.002)	–	(0.006)

Table 7: Regression results using aggregate measures of labor market tightness and wealth. Standard errors are in the parenthesis. *** indicates being significant at 0.1% level. Full regression results are reported in Appendix E Table 15.

Table 7 suggests that searchers tend to reduce their search effort when aggregate labor market conditions are favorable (that is, when θ_t is high). These results are consistent with the matching function being "substitutive" rather than "complementary" between s_t and θ_t. We also find that workers search harder in periods where aggregate wealth measures are low.

5.3 Individual response to local labor market condition

It is most likely that the labor-market condition θ_t for a particular individual is not the aggregate-level θ_t but is determined within a more narrow labor market. Ideally, we would like to see the effect of the labor market conditions that an individual faces in her job search and her current level of wealth. Unfortunately, it is impossible to observe the labor market conditions that an individual is facing in her job search for two reasons: (i) there is no good information about the market that a particular individual is searching at in the currently available data sources and (ii) computing labor market tightness requires knowing the number of unemployed in very small markets—due to the small sample size of the CPS, unemployment counts become unreliable for small labor markets making it impossible to compute the corresponding labor market tightness. In addition, available data sources do not provide us any information on individuals' wealth.

What we do here is to run the regression (7) using several different measures of labor market conditions and wealth. In particular, we use market tightness at the census region and state level in order to capture more individual-specific labor markets and a state-level house price index to get closer to personal wealth. In addition, we also try the interaction of occupations and locations as the definition of the individuals's labor market—specifically, we define $4 \times 4 = 16$ labor markets which are the interaction of four occupation categories[18] and four Census regions.

Table 8 summarizes the results and shows that, similarly to when we used aggregate measures, the searchers respond negatively to labor market conditions and wealth when we also use more disaggregated measures.

5.4 The issue of unobserved heterogeneity

As we discussed earlier, an important issue is unobserved heterogeneity that could potentially create a cyclical composition bias. For example, suppose that searchers are heterogeneous

[18] The categories are the same as the footnote 17.

	Census Region		State		Occupation×Region	
Market Tightness (θ)	-1.121^{***}	-1.500^{***}	-0.339^{**}	-0.454^{**}	-1.122^{***}	-1.862^{**}
	(0.113)	(0.103)	(0.124)	(0.140)	(0.181)	(0.142)
S&P 500	-0.004^{***}	–	-0.006^{***}	–	-0.004^{***}	–
	(0.001)	–	(0.001)	–	(0.001)	–
House Price Index	–	-0.017^{***}	–	-0.018^{***}	–	-0.015^{***}
	–	(0.002)	–	(0.002)	–	(0.002)

Table 8: Regression results using market-specific measures of labor market tightness and wealth. The Census Region regressions use the JOLTS and the others are based on the HWOL. Full regression results are reported in Appendix E Table 16.

in their desire to work and that a worker with a strong preference to work tends to make higher search effort and tends to transit to employment more quickly than other workers. In booms, workers tend to transit to employment more quickly, and "high search effort" workers may disappear from the unemployment pool faster. As a result, during booms, the unemployment pool would be dominated by workers with less desire to work. This channel could create a countercyclical bias in the observed average effort per nonemployed through composition changes.

To address this issue, we attempt to control for the desire to work in various ways. One component of the unobserved heterogeneity that can affect the cyclicality of job search effort is the individual's labor market attachment, which is typically hard to observe and effects the individual's desire to work. We attempt to control for labor force attachment by following Elsby, Hobijn, and Şahin (2012) who show that the composition of the unemployment pool gets skewed towards workers who are more attached to the labor force during recessions. We follow their analysis and use prior labor market status of unemployed workers as a proxy for labor force attachment. To do this, we use the CPS microdata matched across all eight survey months and only include people who were unemployed at some point in the 5th to the 8th month in the survey and who we are able to match to their survey exactly one year ago. We define their prior status as their labor market status 12 months ago. We find that workers who were nonparticipants a year ago, and thus had the lowest degree of attachment, have the lowest job search effort. Workers who were in the labor force a year ago search harder, with those who were employed a year ago searching more intensity than those who were unemployed. Table 9 shows that while job search effort still responds negatively to better labor market conditions, prior employment status is an important determinant of job search effort and that those with a stronger desire to work search more intensely.

	JOLTS		HWOL	
Market Tightness (θ)	-0.577^{***}	-0.924^{***}	-1.476^{***}	-3.574^{***}
	(0.213)	(0.214)	(0.451)	(0.607)
S & P 500	-0.005^{***}	–	-0.004^{***}	–
	(0.001)	–	(0.001)	–
House Price Index	–	-0.023^{***}	–	0.011
	–	(0.004)	–	(0.010)
Employed 1 year ago	6.015^{***}	6.029^{***}	5.975^{***}	5.981^{***}
	(0.216)	(0.216)	(0.271)	(0.271)
Unemployed 1 year ago	4.918^{***}	4.821^{***}	4.910^{***}	4.856^{***}
	(0.255)	(0.254)	(0.306)	(0.306)

Table 9: Regression results using aggregate measures of labor market tightness and wealth with eligibility. Full regression results are reported in Appendix E Table 17.

As another attempt to control for the unobserved heterogeneity in desire to work, below we exploit the full panel structure of the CPS and run regressions with individual fixed effects. Assuming that an individual's desire to work does not change over the sample period, this some directly control for the unobserved compositional bias. When we control for individual fixed effects, we only use the individuals with at least 2 periods of unemployment in the eight months in which they are surveyed. In Tables 10 and 11, we report regression results with fixed effects. Since this sample is smaller than the overall sample we used for the regressions reported in Tables 7 and 8, we report the results without fixed effects for the same sample in Table 19 in Appendix E. A comparison of the results with and without individual fixed effects on the same sample suggests that introducing individual fixed effects decreases the estimated effect of labor market conditions on search effect in some cases. This result indicates that the unobserved heterogeneity and the changing composition of the unemployed pool is potentially important in shaping the cyclicality of job search effort.

	JOLTS		HWOL	
Market Tightness (θ)	-0.551	-1.322^{**}	-1.696^{*}	-4.362^{***}
	(0.506)	(0.475)	(0.675)	(0.665)
S&P 500	-0.003^{**}	–	-0.002	–
	(0.001)	–	(0.001)	–
House Price Index	–	-0.008	–	0.096^{***}
	–	(0.013)	–	(0.02)

Table 10: Regression results using aggregate measures of labor market tightness and wealth with individual fixed effects.

	Census Region		State		Occupation×Region	
Market Tightness (θ)	-0.230	-0.927^{*}	-0.504	-1.347^{**}	0.356	0.127
	(0.452)	(0.414)	(0.474)	(0.447)	(0.214)	(0.208)
S&P 500	-0.003^{***}	–	-0.003^{***}	–	-0.004^{***}	–
	(0.001)	–	(0.001)	–	(0.001)	–
House Price Index	–	-0.015	–	0.013	–	-0.014
	–	(0.012)	–	(0.017)	–	(0.016)

Table 11: Regression results using market-specific measures of labor market tightness and wealth with fixed effects. The Census Region regressions use the JOLTS and the others are based on the HWOL.

5.5 Unemployment insurance benefits

The link between job search effort and unemployment insurance (UI) has received a significant attention in both labor economics literature and macroeconomics literature. Our model in Section 2 as well as various models in the literature[19] predict that a more generous unemployment insurance discourages workers from searching for jobs and causes longer unemployment spells.

We first examine the effect of unemployment insurance by comparing the search effort of eligible and ineligible unemployed workers. We define eligibility following Rothstein (2011) and assume that unemployed workers who report being job losers or temporary job enders

[19]See, for example, Shavell and Weiss (1979), Wang and Williamson (1996), Hopenhayn and Nicolini (1997), and Chetty (2008).

as the eligible worker pool. Table 12 shows eligible unemployed workers search more than the rest of the unemployed and that the effect is statistically significant.

	JOLTS		HWOL	
Market Tightness (θ)	-0.247^{**}	-0.457^{***}	-1.086^{***}	-2.331^{***}
	(0.1584)	(0.119)	(0.250)	(0.173)
S&P 500	-0.0040^{***}	–	-0.003^{***}	–
	(0.0005)	–	(0.001)	–
House Price Index	–	-0.023^{***}	–	0.003^{***}
	–	(0.002)	–	(0.006)
Eligibility	5.151^{***}	5.135^{***}	4.843^{***}	4.826^{***}
	(0.101)	(0.101)	(0.125)	(0.125)

Table 12: Regression results using aggregate measures of labor market tightness and wealth with eligibility. Full regression results are reported in Appendix E Table 18.

The next question is whether workers' search behavior change depending on the number of weeks they have left on their benefits. For example, do we see unemployed workers searching harder as they get closer to the expiration of UI benefits? To examine this issue, we estimate the effect of weeks left on UI on the job search effort using only the sample of unemployed workers who are eligible for UI benefits.[20] Table 20 in the Appendix E shows that search effort responds negatively to the number of weeks left on UI. In other words, workers who get closer to the expiration of their UI benefit respond by increasing their search effort.

At the first sight, the first result seems contrary to the dominant view in the literature that the existence unemployment insurance reduce the incentive for job search. However, note that the eligible workers and noneligible workers are different in many dimensions other than the eligibility. In particular, eligible workers are more attached to employment than noneligible workers and we suspect that this is the main cause of their higher effort. This interpretation is also consistent with the result in Section 5.4. The second result is consistent with the standard theory. As the unemployment duration lengthens during the recession, this effect also contributes to the countercyclical aggregate search effort.

[20]Due to the availability of benefits data, this regression goes from January 2004 to March 2011.

5.6 Taking stock

In this section, we have examined how individual search effort is affected by various factors. As our model in Section 2 suggests, the wealth level has consistently negative effects in various regressions. The labor market environment, represented by the vacancy-unemployment ratio, tend to have negative a effect on search effort. This suggests that the job-finding technology may be "substitutive" between individual search effort and the labor market condition. Thus the elements that we highlighted in Section 2 indeed seem to contribute to the countercyclical pattern of job search effort.

There is also an indication that unobserved heterogeneity is important. Workers who are eligible for UI benefits incur more efforts than the noneligible workers, and the effort level increases as the expiration date becomes closer. There are other controls that show interesting relationship with the search effort—Appendix F highlights two examples, age and unemployment duration.

6 Conclusion

This paper examined the cyclical pattern of job search effort by nonemployed workers. Our innovation is to combine the information in ATUS and CPS in order to overcome the shortcomings of each dataset.

We found that the job search effort by nonemployed workers is countercyclical at the aggregate level, in both extensive and intensive margin. This finding casts a doubt on the validity of the models that relies entirely on worker's search effort (the supply side of the labor market) in explaining procyclical employment. This also implies that ignoring the intensive margin in the matching function may quantitatively miss the fluctuation of the worker's side of the search input.

The individual-level regression found that a worker's search effort negatively responds to wealth, as is predicted by the model. The labor market condition tends to have a negative effect on search as well. These results are suggestive in accounting for the countercyclical aggregate search effort, but far from conclusive, given that we don't have a good measure of individual wealth and the information on how labor market is segmented. Further examination of the potential causes of the countercyclicality, as well as a further analysis on the role of unobserved heterogeneity, is left for future research.

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Appendix

A A general equilibrium search-matching model

This section presents an infinite-horizon general equilibrium model.

A.1 General setup

The aggregate number of matches at each period is dictated by the matching function $M(u_t, v_t; \bar{s}_t)$, where $\bar{s}_t$ is the average search effort in the economy, v_t is the aggregate vacancy, and u_t is the number of unemployed workers at time t. At the individual level, matching is stochastic, and the probability of worker i finding a job is $f(s_{it}, \bar{s}_t, \theta_t)$, where s_{it} is his search effort and $\theta_t \equiv v_t/u_t$. The probability of a firm finding a worker is $q(\bar{s}_t, \theta_t)$. The separation probability of a matched job-worker pair is σ. The job-worker match produces z_t unit of consumption goods, and z_t follows a Markov process.

A.1.1 Unemployment dynamics

The total population is 1, and therefore the number of employed workers is $1 - u_t$. The dynamics of the unemployment is dictated by

$$u_{t+1} = \sigma(1 - u_t) + (1 - f(s_{it}, \bar{s}_t, \theta_t))u_t. \tag{8}$$

A.1.2 Value functions

Let the (aggregate) state variable at time t be $S_t \equiv (u_t, z_t)$. From a firm's perspective, the value of being matched with a worker, $J(S_t)$, is:

$$J(S_t) = z_t - w(S_t) + \beta E[(1 - \sigma)J(S_{t+1}) + \sigma V(S_{t+1})], \tag{9}$$

where $V(S_t)$ is the value of vacancy and $w(S_t)$ is the wage paid to the worker. The expectation $E[\cdot]$ is taken with the information of S_t. The value of vacancy is

$$V(S_t) = -\kappa + \beta E[q(\bar{s}_t, \theta_t)J(S_{t+1}) + (1 - q(\bar{s}_t, \theta_t))V(S_{t+1})]. \tag{10}$$

For the worker's side, the value of being employed, $W(S_t)$, is

$$W(S_t) = w(S_t) + \beta E[(1-\sigma)W(S_{t+1}) + \sigma U(S_{t+1})], \tag{11}$$

and the value of being unemployed, $U(S_t)$, is

$$U(S_t) = \max_{s_{it}} \{b - c(s_{it}) + \beta E[f(s_{it}, \bar{s}_t, \theta_t)W(S_{t+1}) + (1 - f(s_{it}, \bar{s}_t, \theta_t))U(S_{t+1})]\}. \tag{12}$$

The first-order condition for the right hand side is:

$$c'(s_{it}) = \beta f_1(s_{it}, \bar{s}_t, \theta_t)E[W(S_{t+1}) - U(S_{t+1})]. \tag{13}$$

Denote s_{it} that satisfies (13) by s_{it}^*.

A.1.3 Wage determination

Let

$$\tilde{J}(w; S_t) = z_t - w + \beta E[(1-\sigma)J(S_{t+1}) + \sigma V(S_{t+1})|S_t]$$

and

$$\tilde{W}(w; S_t) = w + \beta E[(1-\sigma)W(S_{t+1}) + \sigma U(S_{t+1})].$$

The wage is determined by the generalized Nash bargaining with the worker's bargaining power $\gamma \in (0,1)$. Then w solves

$$(1-\gamma)(\tilde{W}(w; S_t) - U(S_t)) = \gamma(\tilde{J}(w; S_t) - V(S_t)). \tag{14}$$

A.1.4 Free entry and equilibrium

We assume free entry to vacancy posting, $V(S_t) = 0$. From (10),

$$\kappa = \beta q(\bar{s}_t, \theta_t)E[J(S_{t+1})] \tag{15}$$

holds, and (9) can be rewritten as

$$J(S_t) = z_t - w(S_t) + \beta(1-\sigma)E[J(S_{t+1})].$$

Therefore,

$$J(S_t) = z_t - w(S_t) + \frac{(1-\sigma)\kappa}{q(\bar{s}_t, \theta_t)}.$$

Using this to the right-hand side of (15) yields

$$\kappa = \beta q(\bar{s}_t, \theta_t) E\left[z_{t+1} - w(S_{t+1}) + \frac{(1-\sigma)\kappa}{q(\bar{s}_{t+1}, \theta_{t+1})}\right]. \tag{16}$$

From (11) and (12),

$$W(S_t) - U(S_t) = w(S_t) - b + c(s_{it}^*) + \beta E[(1 - \sigma - f(s_{it}^*, \bar{s}_t, \theta_t))(W(S_{t+1}) - U(S_{t+1}))].$$

This can be rewritten as

$$w(S_t) = W(S_t) - U(S_t) + b - c(s_{it}^*) - \beta E[(1 - \sigma - f(s_{it}^*, \bar{s}_t, \theta_t))(W(S_{t+1}) - U(S_{t+1}))].$$

From (14),

$$W(S_t) - U(S_t) = \frac{\gamma}{1-\gamma} J(S_t).$$

Thus

$$w(S_t) = \frac{\gamma}{1-\gamma} J(S_t) + b - c(s_{it}^*) - \beta(1 - \sigma - f(s_{it}^*, \bar{s}_t, \theta_t)) \frac{\gamma}{1-\gamma} E[J(S_{t+1})].$$

Once again, from (15),

$$w(S_t) = \frac{\gamma}{1-\gamma} J(S_t) + b - c(s_{it}^*) - \frac{\gamma}{1-\gamma} \frac{(1 - \sigma - f(s_{it}^*, \bar{s}_t, \theta_t))\kappa}{q(\bar{s}_t, \theta_t)}.$$

Forwarding one period, taking expectation, and using (15) once again,

$$E[w(S_{t+1})] = \frac{\gamma}{1-\gamma} \frac{\kappa}{\beta q(\bar{s}_t, \theta_t)} + b - E[c(s_{i,t+1}^*)] - \frac{\gamma}{1-\gamma} E\left[\frac{(1 - \sigma - f(s_{i,t+1}^*, \bar{s}_{t+1}, \theta_{t+1}))\kappa}{q(\bar{s}_{t+1}, \theta_{t+1})}\right]. \tag{17}$$

Let us impose the equilibrium condition and denote $s_t = s_{it}^* = \bar{s}_t$. Then combining (16) and (17) we obtain

$$\frac{\kappa}{1-\gamma} = \beta q(s_t, \theta_t) E\left[z_{t+1} - b + c(s_{t+1}) + \frac{1 - \sigma - \gamma f(s_{t+1}, s_{t+1}, \theta_{t+1})}{1-\gamma} \frac{\kappa}{q(s_{t+1}, \theta_{t+1})}\right]. \tag{18}$$

The equation (13) can be rewritten as

$$c'(s_t) = f_1(s_t, s_t, \theta_t) \frac{\gamma}{1-\gamma} \frac{\kappa}{q(s_t, \theta_t)}. \tag{19}$$

Equations (18) and (19) determine the dynamics of θ_t and s_t. Note that the variable u do not appear in both (18) and (19). This implies that the dynamics of θ_t and s_t (both jump variables) are not influenced by u (only influenced by z). Once we know the dynamics of θ_t and s_t from (18) and (19), we can determine the dynamics of unemployment by (8) and u_0.

A.2 Pissarides (1985) model (no effort choice)

A special case is when s_t is constant, which boils down to the standard Pissarides (1985) model. This case is easy to analyze. Assume that $f(\theta) = \chi\theta^{1-\eta}$ and $q(\theta) = \chi\theta^{-\eta}$, where $\chi > 0$ and $\eta \in (0, 1)$. Then, log-linearizing (18) around the steady-state yields (the "tilde" ($\tilde{}$) denotes the value at the steady state and the "hat" ($\hat{}$) denotes the log deviation from the steady state)

$$\mathcal{A}\hat{\theta}_t = E[\tilde{z}\hat{z}_{t+1} + \mathcal{B}\hat{\theta}_{t+1}],$$

where $\mathcal{A} \equiv \kappa\eta\tilde{\theta}^{\eta}/(1-\gamma)\beta\chi$ and $\mathcal{B} \equiv [(1-\sigma)\kappa\eta\tilde{\theta}^{\eta}/(1-\gamma)\chi] - [\gamma\kappa\tilde{\theta}/(1-\gamma)]$.

Assume that $\hat{z}_{t+1} = \rho\hat{z}_t + \varepsilon_{t+1}$, where $\rho \in (0, 1)$ and ε_{t+1} is a mean zero random variable (thus $\tilde{z} = 1$). Since the equilibrium $\hat{\theta}$ has to take the form

$$\hat{\theta}_t = \mathcal{C}\hat{z}_t,$$

using the method of undetermined coefficients,

$$\mathcal{C} = \frac{\rho}{\mathcal{A} - \rho\mathcal{B}} = \frac{1-\gamma}{\kappa\tilde{\theta}^{\eta}\left(\left[\frac{1}{\rho\beta} - (1-\sigma)\right]\frac{\eta}{\chi} + \gamma\tilde{\theta}^{1-\eta}\right)}. \tag{20}$$

This makes it clear that, for example, for given $\tilde{\theta}$ the amplification ($\mathcal{C}$) is large when κ is small. This is the background of Hagedorn and Manovskii's (2008) main result. (In order to keep $\tilde{\theta}$ and other parameters constant, a small κ requires a large value of b.) This analytical result that $\mathcal{C}$ is increasing in ρ appears new in the literature.[21] If we normalize $\mathcal{C}$ by multiplying $\sqrt{1-\rho^2}$ so that the unconditional variance of the shock is constant, a sufficient condition for this coefficient being increasing in ρ will become $(1-\sigma)\eta > \gamma\chi\tilde{\theta}^{1-\eta}$.

A.3 Pissarides (2000, Ch 5) model

Now, let's go back to the original model, with (18) and (19). Assume that $c(s) = \phi s^{\omega}/\omega$, where $\omega > 1$. As in Pissarides (2000, Ch 5), assume that the matching function takes the form of $M(\bar{s}u, v)$ and the worker's job finding rate is $f(s, \bar{s}, \theta) = sM(1, \theta/\bar{s})$. In particular, assume a Cobb-Douglas function for the matching function:

$$M(\bar{s}u, v) = \chi(\bar{s}u)^{\eta} v^{1-\eta},$$

where $\chi > 0$ and $\eta \in (0, 1)$. The worker's job finding probability is

$$f(s, \bar{s}, \theta) = \chi s \left(\frac{\theta}{\bar{s}}\right)^{1-\eta}.$$

The probability of a vacancy finding a worker is

$$q(\bar{s}, \theta) = \chi \bar{s}^{\eta} \theta^{-\eta}.$$

The equation (18) is now

$$\frac{\kappa}{1-\gamma} = \beta\chi s_t^{\eta}\theta_t^{-\eta} E\left[z_{t+1} - b + \frac{\phi}{\omega} s_{t+1}^{\omega} + \frac{1-\sigma-\gamma\chi s_{t+1}^{\eta}\theta_{t+1}^{1-\eta}}{1-\gamma} \frac{\kappa}{\chi s_{t+1}^{\eta}\theta_{t+1}^{-\eta}}\right].$$

Rearranging, this can be rewritten as

$$\frac{\kappa}{(1-\gamma)\beta\chi} s_t^{-\eta}\theta_t^{\eta} = E\left[z_{t+1} - b + \frac{\phi}{\omega} s_{t+1}^{\omega} + \frac{(1-\sigma)\kappa}{(1-\gamma)\chi} s_{t+1}^{-\eta}\theta_{t+1}^{\eta} - \frac{\gamma\kappa}{1-\gamma}\theta_{t+1}\right].$$

Log-linearizing this yields

$$\frac{\kappa\tilde{s}^{-\eta}\tilde{\theta}^{\eta}\eta}{(1-\gamma)\beta\chi}(\hat{\theta}_t - \hat{s}_t) = E\left[\tilde{z}\hat{z}_{t+1} + \phi\tilde{s}^{\omega}\hat{s}_{t+1} + \frac{(1-\sigma)\kappa\tilde{s}^{-\eta}\tilde{\theta}^{\eta}\eta}{(1-\gamma)\chi}(\hat{\theta}_{t+1} - \hat{s}_{t+1}) - \frac{\gamma\kappa\tilde{\theta}}{1-\gamma}\hat{\theta}_{t+1}\right]. \tag{21}$$

[21] Most of the papers which characterize the analytical properties of the DMP model rely on the steady-state comparison, which makes it impossible to analyze the effect of ρ. Hornstein, Krusell, and Violante (2005) analyze a stochastic model, but with the shock taking only two points.

The equation (19) can be rewritten as

$$\phi s_t^{\omega-1} = \frac{\gamma\kappa}{1-\gamma}\frac{\theta_t}{s_t}. \tag{22}$$

This can be solved as

$$s_t = \left(\frac{\gamma\kappa}{(1-\gamma)\phi}\theta_t\right)^{\frac{1}{\omega}}.$$

Log-linearizing,

$$\hat{s}_t = \frac{1}{\omega}\hat{\theta}_t. \tag{23}$$

This makes it clear that s_t responds *positively* to θ_t. This is no surprise given our results in the simple model. There is no effect of wealth given the linear utility and b stays constant. The job finding probability is complementary between s and θ, which tends to make s move in the same direction as θ. The effect of wage enhances it, since the wage also tends to be procyclical. It responds less when the curvature of the effort cost function (ω) is larger.

Using (23), (21) can be rewritten as

$$\mathcal{A}\hat{\theta}_t = E[\tilde{z}\hat{z}_{t+1} + \mathcal{B}\hat{\theta}_{t+1}],$$

using the same assumption on $\tilde{z}$ as before and following the same steps (we used the fact that (22) also holds in the steady state), we obtain

$$\hat{\theta}_t = \mathcal{C}\hat{z}_t,$$

where

$$\mathcal{C} = \frac{\omega}{\omega-1}\frac{1-\gamma}{\kappa\tilde{\theta}^{\eta}\left(\left[\frac{1}{\rho\beta}-(1-\sigma)\right]\frac{\eta}{\chi\tilde{s}^{\eta}}+\gamma\tilde{\theta}^{1-\eta}\right)}.$$

This is remarkably similar to (20). The only differences are (i) χ is now replaced by $\chi\tilde{s}^{\eta}$, since now this is the "effective" match efficiency on average, and (ii) the term $\omega/(\omega-1)$ is multiplied in front, since the movement of s influences the cyclical movement of the probability of a vacancy finding a worker, changing the incentive for vacancy posting. There is a "magnification" (when $\chi\tilde{s}^{\eta}$ is replaced by χ), since $\omega/(\omega-1) > 1$. This was observed by Merz (1995) and Gomme and Lkhagvasuren (2011) in related, numericaly-solved models.

A.4 A model with "substitutive" matching function

Now assume that

$$M(\bar{s}, u, v) = \chi\left(\alpha\bar{s}^{\psi} + (1-\alpha)\left(\frac{v}{u}\right)^{\psi}\right)^{\eta} u$$

and

$$f(s, \bar{s}, \theta) = \chi(\alpha s^{\psi} + (1-\alpha)\theta^{\psi})^{\eta},$$

where $\chi > 0$, $\alpha \in (0,1)$,$\eta \in (0,1)$, $\psi > 0$, and $\psi\eta < 1$. Note that this is a special case of (3). It follows that

$$q(\bar{s}, \theta) = \chi(\alpha\bar{s}^{\psi} + (1-\alpha)\theta^{\psi})^{\eta}\theta^{-1}.$$

Note that $f_{13} < 0$ is satisfied in this formulation.

The equation (18) can be rearranged to

$$\begin{aligned}&\frac{\kappa}{(1-\gamma)\beta\chi}(\alpha s_t^{\psi} + (1-\alpha)\theta_t^{\psi})^{-\eta}\theta_t \\ &\quad = E\left[z_{t+1} - b + \frac{\phi}{\omega}s_{t+1}^{\omega} + \frac{(1-\sigma)\kappa}{(1-\gamma)\chi}(\alpha s_{t+1}^{\psi} + (1-\alpha)\theta_{t+1}^{\psi})^{-\eta}\theta_{t+1} - \frac{\gamma\kappa}{1-\gamma}\theta_{t+1}\right] \quad (24)\end{aligned}$$

and the equation (19) is[22]

$$\phi s_t^{\omega-1} = \frac{\alpha\eta\gamma\kappa\psi}{1-\gamma}\frac{s_t^{\psi-1}\theta_t}{\alpha s_t^{\psi} + (1-\alpha)\theta_t^{\psi}}.$$

Rearranging and log-linearizing, we obtain

$$\hat{s}_t = \frac{\alpha\tilde{s}^{\psi} - (\psi-1)(1-\alpha)\tilde{\theta}^{\psi}}{\omega\alpha\tilde{s}^{\psi} + (\omega-\psi)(1-\alpha)\tilde{\theta}^{\psi}}\hat{\theta}_t. \quad (25)$$

Denote the right-hand side as $\Xi\hat{\theta}_t$. Similarly to (23), the absolute value of Ξ is small when ω is large. In contrast to (23), here $\hat{s}$ can react *negatively* to $\hat{\theta}$ (i.e. $\Xi > 0$) if ψ is sufficiently large (or α is sufficiently small). Note that $f_{13} < 0$ is not sufficient for this because the effect from wage still exists.

[22] We also have to check the second-order condition in this case, because the concavity of f in s is not necessarily guaranteed. It is

$$\phi(\omega-1)s_t^{\omega-2} - \frac{\gamma\kappa\eta\psi\alpha s_t^{\psi-2}\theta_t}{(1-\gamma)(\alpha s_t^{\psi} + (1-\alpha)\theta_t^{\psi})}\left((\psi-1) + \frac{\psi(\eta-1)\alpha s^{\psi}}{\alpha s_t^{\psi} + (1-\alpha)\theta_t^{\psi}}\right) > 0.$$

Log-linearizing (24) and using (25), we obtain the equation

$$\mathcal{A}\hat{\theta}_t = E[\tilde{z}\hat{z}_{t+1} + \mathcal{B}\hat{\theta}_{t+1}],$$

where

$$\mathcal{A} = \frac{\kappa}{(1-\gamma)\beta\chi}(\alpha\tilde{s}^{\psi} + (1-\alpha)\tilde{\theta}^{\psi})^{-\eta}\tilde{\theta}\left[1 - \eta\frac{\alpha\psi\tilde{s}^{\psi}\Xi + (1-\alpha)\psi\tilde{\theta}^{\psi}}{\alpha\tilde{s}^{\psi} + (1-\alpha)\tilde{\theta}^{\psi}}\right]$$

and

$$\mathcal{B} = \frac{\kappa}{1-\gamma}\left(\frac{1-\sigma}{\chi}(\alpha\tilde{s}^{\psi} + (1-\alpha)\tilde{\theta}^{\psi})^{-\eta}\tilde{\theta}\left[1 - \eta\frac{\alpha\psi\tilde{s}^{\psi}\Xi + (1-\alpha)\psi\tilde{\theta}^{\psi}}{\alpha\tilde{s}^{\psi} + (1-\alpha)\tilde{\theta}^{\psi}}\right] - \gamma\tilde{\theta}\right) + \phi\tilde{s}^{\omega}\Xi.$$

As before, this can be solved as

$$\hat{\theta}_t = \frac{\rho}{\mathcal{A} - \rho\mathcal{B}}\hat{z}_t.$$

Below we solve this numerically. Several parameter values are given upfront: set $\omega = 4$, $\alpha = 0.1$, $\psi = 2$, and $\eta = 0.3$. One period is assumed to be one month: thus set $\beta = 0.987^{\frac{1}{3}}$ and $\rho = 0.95^{\frac{1}{3}}$ (both from Cooley and Prescott (1995)). Following Shimer (2005), set $\gamma = 0.72$ and $\sigma = 0.034$. Let $\tilde{\theta} = 1$ and $\tilde{s} = 1$ in the steady state (later these will pin down κ and ϕ). Set χ so that the steady-state job finding rate $\chi(\alpha\tilde{s}^{\psi} + (1-\alpha)\tilde{\theta}^{\psi})^{\eta} = \chi(0.1 + 0.9)^{0.3} = 0.45$. We set the value of nonemployment, $b - \phi\tilde{s}^{\omega}/\omega = b - \phi/4 = 0.7$, along the line of Hall and Milgrom (2008). κ and ϕ are set from the steady-state version of (18) and (19).

The resulting parameter values are $\chi = 0.45$, $\phi = 0.0161$, $b = 0.708$, and $\kappa = 0.104$. The movement of endogenous variables are governed by

$$\hat{s}_t = -0.3636\hat{\theta}_t$$

and

$$\hat{\theta}_t = 3.3750\hat{z}_t.$$

Thus in this case s_t reacts negatively to the change in θ_t (and therefore z_t).

B Data Appendix

B.1 Data Description

This appendix describes the various data sources used in this analysis in greater detail. From the ATUS, we use the Multi-Year mictodata files. The advantage to using the multi-year files as opposed to the individual year files is that it provides consistent population weights across years however it comes at the cost of slightly less detailed job search categories. As explained in the **??**, we define define job search activities to include all search, interviews and time sent at the interview location. Because we use the multi-year files which do not provide data at the full level of disaggregation, we do not include the time spent travelling to interviews (180311) in our job search measure. In order to restrict out sample to people who have completed their education and are still active workers, we restrict our respondents to be those between the age of 25 and 70. We also drop individuals who report more than 8 hours of search in each day. This excludes only 33 respondents or around 2.5% of the active searchers.[23] Per year, this leaves us of our sample with around 2,500 nonemployed respondents, around 400 classified unemployed active searchers and 130 respondents who report positive search time.

From the CPS, we use monthly basic samples from January 1994 through December 2011. Again, we restrict out sample to include only respondents between 25 and 70 years old. This leaves us with approximately 20,000 nonemployed individuals and on average 2,000 unemployed searchers each month. In order to run the individual-level regressions in section **??**, we match our sample across the eight survey months.[24] We are able to match 93% of the sample to at least 1 other month of the survey, 60% of respondents to at least 4 months and 40% across all 8 survey months.

[23]Our results are not sensitive to this assumption. We repeated our analysis on the the full sample including all reported search time and found qualitatively similar results

[24]Our methodology matches individuals across samples using the following variables (unicon names in parentheses): household identification numbers (hhid and hhid2), line number (lineno), state (state), serial numbers (serial), gender , race, and the date their first month in the survey (mis).

B.2 Details on the Link between the ATUS and the CPS

Let Y_{it} be the search time we observe in ATUS for worker i at time t. What we are interested in is not Y_{it} per se—Y_{it} contains one day's sample from the search activities in entire period t (one month), and we are interested in the entire month's activity. Denote the "average" search time over the month as $E[Y_{it}]$. Let P_{it} be the probability that i searches strictly positive minutes at the ATUS survey date in period t. Let M_{it} be the minutes that i searches at the survey date of time t, conditional on searching strictly positive minutes. Then the "average" minutes, $E[Y_{it}]$, is

$$E[Y_{it}] = \Pr[Y_{it} > 0]E[Y_{it}|Y_{it} > 0] + \Pr[Y_{it} = 0]E[Y_{it}|Y_{it} = 0] = P_{it}E[M_{it}]$$

from the law of iterated expectations.

Our purpose is to obtain $E[Y_{it}]$ for every CPS sample, but unfortunately we do not observe it, we estimate it from the observed characteristics, including the the search methods she used. We estimate $E[Y_{it}]$ based on the characteristics X_{it} (denote the estimate as $E_X[E[Y_{it}]]$). From the above equation,

$$E_X[E[Y_{it}]] = E_X[P_{it}E[M_{it}]] = E_X[P_{it}]E_X[E[M_{it}]] + cov_X(P_{it}, E[M_{it}]),$$

holds, where $E_X[\cdot]$ denotes the expected value conditional on X and $cov_X(\cdot,\cdot)$ denotes the covariance conditional on X. We assume that $cov_X(P_{it}, E[M_{it}]) = 0$. Then

$$E_X[E[Y_{it}]] = E_X[P_{it}]E_X[E[M_{it}]].$$

This provides us the following two-step strategy for estimating $E_X[E[Y_{it}]]$

1. In order to obtain $E_X[P_{it}]$ for the CPS sample,

    (a) Generate $\{0,1\}$ dummy variable (call y_{it}) based on the minutes value of ATUS sample (zero if the minutes is zero, one if it is strictly positive).

    (b) Run a probit regression with this dummy variable on the left-hand side and the characteristics of the corresponding ATUS sample on the right-hand side. More specifically, maximize the log-likelihood

$$\ln(L) = \sum_{i,t} (y_{it} \ln \Phi(\mathbf{x}'_{it}\beta) + (1 - y_{it}) \ln(1 - \Phi(\mathbf{x}'_{it}\beta))),$$

where $\mathbf{x}_{it}$ is the vector of X_{it}, to obtain the estimated values of β, $\hat{\beta}$.

(c) Use the estimated coefficients above and the characteristics of the CPS sample to calculate the predicted value of P_{it} for the CPS sample. More specifically,

$$E_X[P_{it}] = \Phi(\mathbf{x}'_{it}\hat{\beta}).$$

2. In order to obtain $E_X[E[M_{it}]]$ for the CPS sample,

   (a) Use the subset of the ATUS sample who reports strictly positive minutes. Let minutes be Q_{it}.

   (b) Run the regression

   $$\ln(Q_{it}) = \gamma_0 + \gamma_1 X_{1,it} + ... + \gamma_n X_{n,it} + \epsilon$$

   for the ATUS sample, where ϵ is assumed to be mean zero normal with variance σ^2.

   (c) Then, for the CPS sample, obtain

   $$E_X[E[M_{it}]] = \exp\left(\gamma_0 + \gamma_1 X_{1,it} + ... + \gamma_n X_{n,it} + \frac{\hat{\sigma}^2}{2}\right)$$

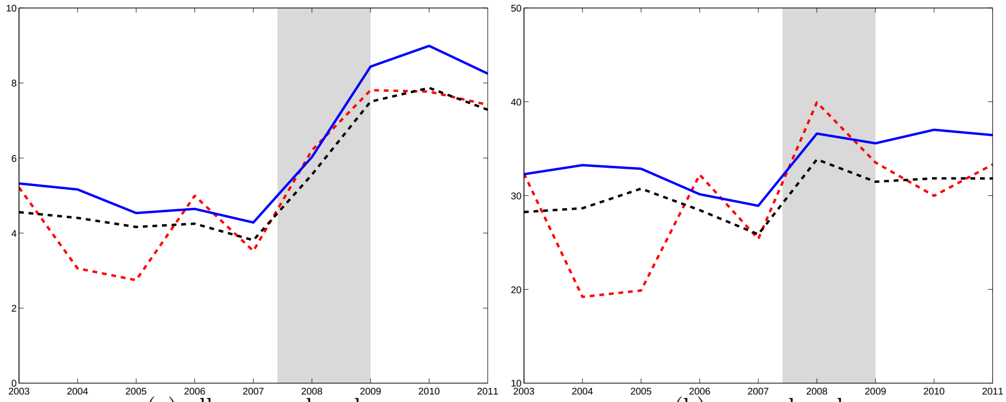
   from the property of the lognormal distribution, where $\hat{\sigma}^2$ is the estimated value of σ^2.

3. In order to obtain $E_X[E[Y_{it}]]$ for the CPS sample, multiply $E_X[P_{it}]$ and $E_X[E[M_{it}]]$ calculated above.

Through this method, we are able to impute a strictly positive amount of search time for all non-employed in both the ATUS and CPS given their reported search methods and observables. Importantly, in addition to including dummies for for each of the twelve search methods, x_{it} contains two sets of observables. The first is a set of worker characteristics which may affect the intensity of their job search. We mostly follow Shimer (2004) in the choice of these controls and include a quartic of age (age_{it}) and dummies for education levels ($educ1_{it}$ for high school diploma, $educ2_{it}$ for some college, and $educ3_{it}$ for college plus), race ($black_{it}$), gender ($female_{it}$), and marital status ($married_{it}$). We also add the interaction term of $female_{it}$ and $married_{it}$ since being married is likely to affect the labor market behavior of men and women differentially. The second set or controls are for labor market status. These controls are intended to capture the search time for the respondents who do not answer the CPS question on job search methods but still report positive search time. Here, we include a dummy for being out of the labor force but not wanting a job ($otherNILF_{it}$), being on temporary layoff ($layoff_{it}$), and being a out of the labor force but wanting a job (NS_{it}).

As mentioned above, a much simpler methods for computing "imputed search time" using the relationship between reported search time and the number of minutes is to run a simple OLS regression using reported "time" on the left-hand side and dummy variables for each method and other worker characteristics on the right-hand side. Figure 10 shows a comparison of the actual reported minutes, the imputed minutes using the 2-part method described in section B.2 and the simple OLS regression. The two imputation methods produce similar results.

In each of these imputation methods, we assume that the search time (or the log search time) for a given search method is constant over time. This assumption is crucial for our imputation exercise but it is not obviously the case. Because the number of search methods is limited both in practice and by the CPS survey design, where people are only able to report up to 6 of 12 possible search methods, individuals could increase their search effort while keeping their number of methods constant by varying the intensity with which they use each method. The topcoding of the number of reportable methods in the CPS question is unlikely to be important for our results - the number of search methods imposed in the ATUS and CPS samples is binding for only 2% in both the ATUS and CPS sample and therefore it is



(a) all nonemployed (b) unemployed

Figure 10: Average search minutes per day for all nonemployed workers and unemployed workers, actual and imputed using OLS regression. ATUS sample.

unlikely to drive the results. However, the possibility remains that individuals increase their search time per method over the business cycle.

To explore this possibility, we first include year dummies in the regression.[25] Results in Table 13 show that the only statistically significant coefficients are in 2004 and 2005 and therefore there is no evidence that the intensity with which people use various methods increased during the recession.

To further explore the possibility that the relationship between search methods and search time varies over time, we break our data into a pre-recession (2003-2007) and a post-recession (2008-2011) sample. We then calculate the imputed minutes for each of the subsamples and explore the in and out of sample fit.

Figure 11 shows that the regression using the pre-recession sample slightly underpredicts the reported search time among both the unemployed only and all nonemployed while using only post-recession data overpredicts the search time in the earlier years.

[25]To produce coefficient estimates that are easy to interpret, we perform this robustness exercise using a simple OLS regression.

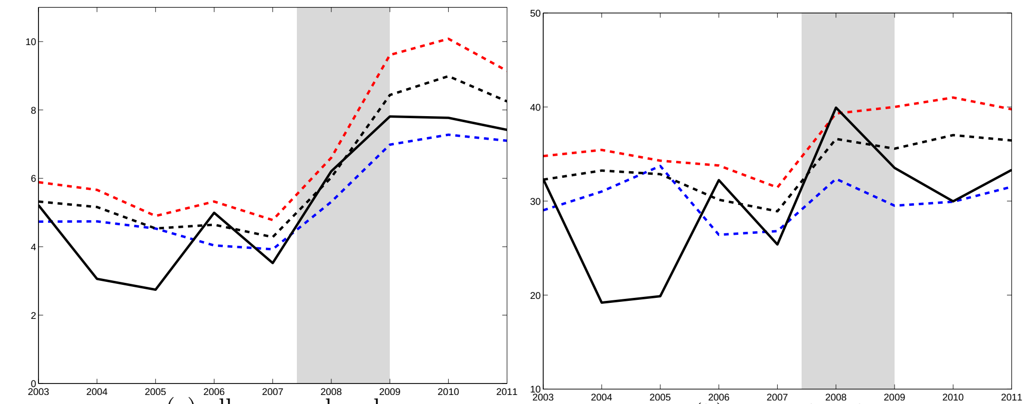
	Search Time
2004	-1.95^{***}
	(0.82)
2005	-2.06^{***}
	(0.81)
2006	0.11
	(1.07)
2007	-0.95
	(0.94)
2008	0.06
	(1.23)
2009	-0.22
	(1.08)
2010	-0.56
	(1.11)
2011	-0.48
	(1.04)

Table 13: Time Dummy Estimates from OLS regression of reported search time on search methods. ATUS sample.

B.3 Additional Results for the Cyclicality of Search Effort

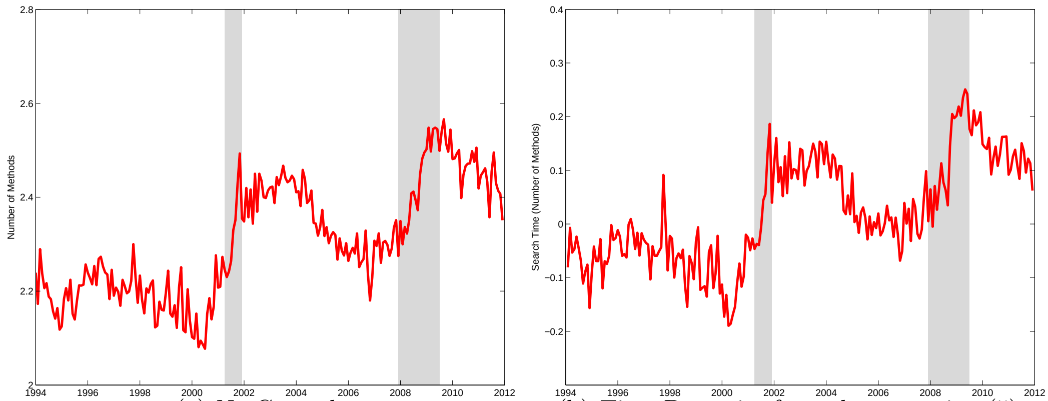
In order to examine the robustness of our results, we present a number of additional measures of the intensive and extensive search margin. Figure 12 shows the average number of search methods used in the CPS sample over our sample period. This more simple measure of search effort shows a countercyclical pattern very similar to Figure 5 and Figure 6.

In order to directly compare the search time information in the ATUS and the CPS, Figure 13 plots search time (left panel) and the average number of search methods (right panel) from the CPS and the ATUS. As discussed in Section 3.1, the ATUS data is very noisy and therefore we plot the annual average. We see that although the ATUS is more volatile, the two search intensity measures are very similar across the datasets, both showing a sharp peak in 2009.



(a) all nonemployed (b) unemployed

Figure 11: Average search minutes per day for all nonemployed workers and unemployed workers, actual and imputed using pre- and post-recession samples of ATUS data



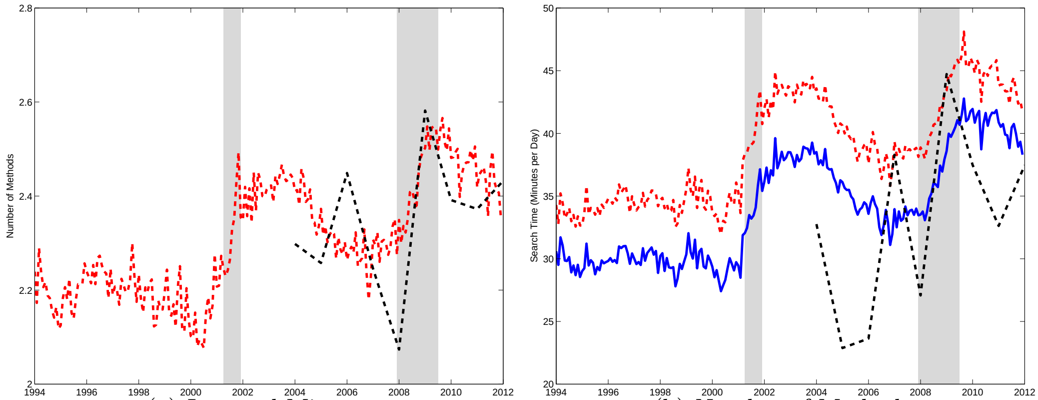
(a) No Controls (b) Time Dummies from the regression (5)

Figure 12: Intensive search margin measures by the average number of search methods used.

C Implications of countercylical search effort

This section shows that our evidence goes against a model where the cyclical movement of employment and unemployment are entirely supply-driven. We show that the observed total search effort of such an economy is procyclical.

Consider of an infinite-horizon model with continuum of workers, who are either employed or nonemployed. Workers are heterogeneous and each selects a search effort s when nonemployed. Suppose that the job-finding probability is an increasing function of s: $f(s)$. Employment is purely driven by this search effort, so that s is the only factor that affects the



(a) Imputed Minutes (b) Number of Methods

Figure 13: Intensive search margin measures in the ATUS and the CPS

job-finding probability. The separation probability is the same across workers and constant over time (as in Pissarides (1985)) at δ.

Below we compare the steady states of a "good state" and "bad state". In the U.S. economy, the job-finding probability is sufficiently large so that the cyclical movement is well-approximated by steady state comparisons (see, for example, Shimer (2005)). Below, we assume that $f'(s)s/f(s) \leq 1$ (if we consider $f(s) = s^{\zeta}$, this means that $\zeta \leq 1$).

From the above assumptions, the steady-state probability of a worker with search effort s being nonemployed is $\delta/(f(s)+\delta)$. Suppose that s is distributed across the entire population with the distribution function $G(s)$. Then the steady-state nonemployment rate in the entire economy is

$$\int \frac{\delta}{f(s)+\delta} dG(s) \tag{26}$$

and the observed total search effort by nonemployed workers is

$$\int s \frac{\delta}{f(s)+\delta} dG(s). \tag{27}$$

Suppose that in a boom, $G(s)$ increases in the sense of the first-order stochastic dominance. Then the nonemployment rate (26) falls in the boom and the observed total effort (27) rises. The first is straightforward from the fact that $\delta/(f(s)+\delta)$ is decreasing in s. The second is because $s\delta/(f(s)+\delta)$ is increasing in s when $f'(s)s/f(s) \leq 1$. The effort per nonemployed worker is

$$\int s \frac{\delta}{f(s)+\delta} dG(s) \bigg/ \int \frac{\delta}{f(s)+\delta} dG(s)$$

and this is even more procyclical. Thus we established that, in this model, both total effort of the nonemployed and the effort per nonemployed worker have to be procyclical even under the presence of (unobserved) worker heterogeneity.

D Matching function estimation

This section establishes the link between the matching function estimations in Section 4.4.2 and the shape of the actual matching function. Recall that we consider the matching function (restating (4))

$$M(\bar{s}, u, v) = \chi \left(\alpha \bar{s}^{\psi} + (1-\alpha) \left(\frac{v}{u} \right)^{\psi} \right)^{\eta} u.$$

The average job finding probability for each person in u is (slightly abusing the notation)

$$f(\bar{s}, \theta) = \chi \left(\alpha \bar{s}^{\psi} + (1-\alpha) \theta^{\psi} \right)^{\eta}.$$

When we run a linear regression

$$\ln(f_t) = \delta_0 + \delta_s \ln(\bar{s}_t) + \delta_\theta \ln(\theta_t) + \varepsilon_t,$$

this corresponds to the log-linearized version of the above equation, with

$$\delta_s = \frac{\tilde{f}_s}{\tilde{f}} \tilde{s} = \alpha \psi \eta \tilde{s}^{\psi} \left(\alpha \tilde{s}^{\psi} + (1-\alpha) \tilde{\theta}^{\psi} \right)^{-1}$$

and

$$\delta_\theta = \frac{\tilde{f}_\theta}{\tilde{f}} \tilde{\theta} = (1-\alpha) \psi \eta \tilde{\theta}^{\psi} \left(\alpha \tilde{s}^{\psi} + (1-\alpha) \tilde{\theta}^{\psi} \right)^{-1},$$

where $\tilde{f}_i$ is the partial derivative of $f(s, \theta)$ function with respect to i ($\tilde{s}$ is the value of $\bar{s}$ at the steady-state and $\tilde{\theta}$ is the value of θ at the steady-state). Since we assume that $\alpha \in (0, 1)$ and $\psi\eta > 0$, we expect that both δ_s and δ_θ are positive.

Clearly, ψ and η cannot be distinguished in this log-linear approximation—in order to distinguish them we have to expand the function further.

The higher-order (log) approximation can be conducted by further Taylor expansion. In particular, denoting $\hat{}$ as the log-deviation from the steady-state, we can expand

$$\ln(f) = \ln(f(\tilde{s}e^{\hat{s}}, \tilde{\theta}e^{\hat{\theta}}))$$

with respect to $\hat{s}$ and θ. The second-order approximation yields

$$\ln(f) \approx \sum_{i=s,\theta} \frac{\tilde{f}_i}{\tilde{f}}\tilde{i}\hat{i} + \sum_{i=s,\theta} \frac{1}{2}\left(\frac{\tilde{f}_{ii}\tilde{f} - \tilde{f}_i^2}{\tilde{f}^2}\tilde{i} + \frac{\tilde{f}_i}{\tilde{f}}\right)\tilde{i}\hat{i}^2 + \frac{\tilde{f}_{s\theta}\tilde{f} - \tilde{f}_s\tilde{f}_\theta}{\tilde{f}^2}\tilde{s}\tilde{\theta}\hat{s}\hat{\theta},$$

where f_{ij} is the cross derivative of f function with respect to i and j. $\tilde{f}_s\tilde{s}/\tilde{f}$ and $\tilde{f}_\theta\tilde{\theta}/\tilde{f}$ are the same as above. The other coefficients are:

$$\frac{1}{2}\left(\frac{\tilde{f}_{ss}\tilde{f} - \tilde{f}_s^2}{\tilde{f}^2}\tilde{s} + \frac{\tilde{f}_s}{\tilde{f}}\right)\tilde{s} = \frac{1}{2}\alpha\psi^2\eta\tilde{s}^\psi\left(\alpha\tilde{s}^\psi + (1-\alpha)\tilde{\theta}^\psi\right)^{-1}\left(1 - \alpha\tilde{s}^\psi\left(\alpha\tilde{s}^\psi + (1-\alpha)\tilde{\theta}^\psi\right)^{-1}\right),$$

$$\frac{1}{2}\left(\frac{\tilde{f}_{\theta\theta}\tilde{f} - \tilde{f}_\theta^2}{\tilde{F}^2}\tilde{\theta} + \frac{\tilde{f}_\theta}{\tilde{f}}\right)\tilde{\theta} = \frac{1}{2}(1-\alpha)\psi^2\eta\tilde{\theta}^\psi\left(\alpha\tilde{s}^\psi + (1-\alpha)\tilde{\theta}^\psi\right)^{-1}\left(1 - (1-\alpha)\tilde{\theta}^\psi\left(\alpha\tilde{s}^\psi + (1-\alpha)\tilde{\theta}^\psi\right)^{-1}\right),$$

and

$$\frac{\tilde{f}_{s\theta}\tilde{f} - \tilde{f}_s\tilde{f}_\theta}{\tilde{f}^2}\tilde{s}\tilde{\theta} = -\psi^2\eta\alpha(1-\alpha)s^\psi\theta^\psi\left(\alpha\tilde{s}^\psi + (1-\alpha)\tilde{\theta}^\psi\right)^{-2}.$$

We can run the regression corresponding to this:

$$\begin{aligned}\ln(f_t) &= \delta_0 + \delta_\theta\ln(\theta_t) + \delta_s\ln(\bar{s}_t) + \delta_{\theta\theta}\ln(\theta_t)^2 + \delta_{ss}\ln(\bar{s}_t)^2 \\ &\quad + \delta_{s\theta}\ln(\bar{s}_{kt})\ln(\theta_t) + \varepsilon_t.\end{aligned}$$

The most important coefficient is $\delta_{s\theta}$. In order to have "substitutability" between $\bar{s}$ and θ in the job finding rate, η has to be positive, which implies $\delta_{s\theta} < 0$. Note that the correspondence between $\delta_{s\theta}$ and $f_{13}(s, s, \theta)$ is warranted only when there is no externality coming from other worker's effort—that is, $\xi = 0$ in the context of (3). The variable ξ cannot be estimated from the aggregate data.

E Additional Results for Individual-Level Regressions

Table 14 shows the results for the regressions reported in Table 7 using data from the ATUS. For theta, we find results very similar to full CPS sample using imputed minutes. The rest of this section reports the full regression estimates for the selected tables in section **??**.

	JOLTS		HWOL	
Market tightnesss (θ)	-0.298	-0.572^{**}	-0.089	-0.581^{***}
	(0.264)	(0.181)	(0.486)	(0.202)
S&P 500	0.001	–	-0.000	–
	(0.001)	–	(0.000)	–
House Price Index	–	-0.009	–	-0.005
	–	(0.008)	–	(0.005)

Table 14: Regression results for the ATUS sample using aggregate measures of labor market tightness and wealth. Standard errors are in the parenthesis. *** indicates being significant at 0.1% level.

F Other Determinants of Individual Job Search Effort

F.1 Demographic Characteristics

In our regressions we control for various demographic characteristics that generally affect the labor market behavior of individuals. We find that the effects of these characteristics on search intensity are robust to various specifications.

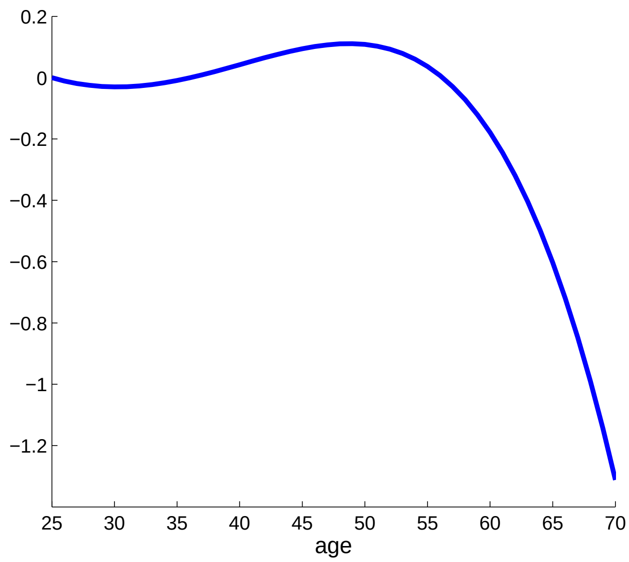


Figure 14: The effect of age on search time. These estimates from the regression in Table 7 column 1 and the first entry is normalized to 0.

Table 15: Full regression results for table 7. Individual regression using aggregate measures of labor market tightness and wealth

	JOLTS		HWOL	
log(theta)	-0.930***	-1.098***	-2.146***	-2.857***
	(0.118)	(0.118)	(0.248)	(0.336)
S & P 500	-0.005***		-0.003***	
	(0.000)		(0.001)	
House Price Index		-0.025***		-0.004
		(0.002)		(0.006)
age	-2.433**	-2.442**	-2.193*	-2.198*
	(0.954)	(0.954)	(1.157)	(1.157)
age^2	-0.023	-0.023	-0.030	-0.030
	(0.033)	(0.033)	(0.040)	(0.040)
age^3	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.001)	(0.001)
age^4	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration	0.585***	0.596***	0.549***	0.551***
	(0.021)	(0.021)	(0.026)	(0.026)
Unemployment Duration^2	-0.007***	-0.007***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment Duration^3	0.000***	0.000***	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration^4	-0.000***	-0.000***	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
black	-2.202***	-2.208***	-1.901***	-1.900***
	(0.123)	(0.123)	(0.154)	(0.154)
married	11.108***	11.109***	10.705***	10.706***
	(0.158)	(0.158)	(0.193)	(0.193)
female	-6.299***	-6.309***	-6.125***	-6.126***
	(0.140)	(0.140)	(0.173)	(0.173)
married*female	-31.512***	-31.509***	-31.216***	-31.211***
	(0.200)	(0.200)	(0.245)	(0.245)
High School	6.393***	6.376***	6.651***	6.638***
	(0.098)	(0.098)	(0.125)	(0.125)
Some College	27.106***	27.087***	27.668***	27.651***
	(0.130)	(0.130)	(0.162)	(0.162)
College	49.402***	49.396***	49.160***	49.148***
	(0.205)	(0.205)	(0.251)	(0.251)
Occupation Groups				
Cognitive Routine	-4.353***	-4.357***	-3.293***	-3.302***
	(0.175)	(0.175)	(0.214)	(0.214)
Manual Non-Routine	-1.023***	-1.022***	-0.381*	-0.381*
	(0.175)	(0.175)	(0.213)	(0.213)
Manual Routine	-6.361***	-6.361***	-5.029***	-5.024***
	(0.179)	(0.179)	(0.220)	(0.220)
Observations	317881	317881	212048	212048

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors. All Regressions include month dummies.

Table 16: Full regression results for table 8 using market-specific measures of labor market tightness and wealth

	Census Region		State		OccXRegion	
log(theta)	-1.121***	-1.499***	-0.339***	-0.454***	-1.122***	-1.862***
	(0.113)	(0.103)	(0.124)	(0.140)	(0.181)	(0.142)
S & P 500	-0.004***		-0.006***		-0.004***	
	(0.000)		(0.000)		(0.000)	
State House Price Index		-0.017***		-0.018***		-0.015***
		(0.001)		(0.002)		(0.002)
age	-2.474***	-2.492***	-2.120*	-2.076*	-2.001*	-2.014*
	(0.954)	(0.954)	(1.157)	(1.158)	(1.165)	(1.165)
age^2	-0.022	-0.021	-0.033	-0.034	-0.037	-0.036
	(0.033)	(0.033)	(0.040)	(0.040)	(0.040)	(0.040)
age^3	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
age^4	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration	0.584***	0.595***	0.554***	0.576***	0.553***	0.561***
	(0.021)	(0.021)	(0.026)	(0.026)	(0.026)	(0.026)
Unemployment $Duration^2$	-0.007***	-0.007***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment $Duration^3$	0.000***	0.000***	0.000	0.000**	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment $Duration^4$	-0.000***	-0.000***	-0.000	-0.000**	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
black	-2.151***	-2.101***	-1.909***	-1.880***	-1.994***	-1.995***
	(0.123)	(0.123)	(0.154)	(0.155)	(0.155)	(0.155)
married	11.107***	11.088***	10.705***	10.690***	10.713***	10.689***
	(0.158)	(0.158)	(0.193)	(0.193)	(0.195)	(0.195)
female	-6.294***	-6.327***	-6.147***	-6.208***	-6.161***	-6.197***
	(0.140)	(0.140)	(0.173)	(0.173)	(0.174)	(0.174)
married*female	-31.509***	-31.489***	-31.224***	-31.200***	-31.299***	-31.275***
	(0.200)	(0.200)	(0.245)	(0.245)	(0.247)	(0.247)
High School	6.384***	6.324***	6.681***	6.624***	6.616***	6.553***
	(0.098)	(0.099)	(0.125)	(0.125)	(0.126)	(0.126)
Some College	27.085***	27.024***	27.706***	27.654***	27.625***	27.570***
	(0.130)	(0.130)	(0.162)	(0.162)	(0.163)	(0.163)
College	49.392***	49.417***	49.211***	49.258***	49.108***	49.127***
	(0.205)	(0.205)	(0.251)	(0.252)	(0.252)	(0.252)
Occupation Groups						
Cognitive Routine	-4.364***	-4.421***	-3.293***	-3.349***	-5.476***	-6.938***
	(0.175)	(0.175)	(0.214)	(0.214)	(0.410)	(0.345)
Manual Non-Routine	-1.025***	-1.051***	-0.394*	-0.423**	-1.584***	-2.385***
	(0.175)	(0.175)	(0.213)	(0.213)	(0.285)	(0.258)
Manual Routine	-6.372***	-6.450***	-5.050***	-5.124***	-7.431***	-9.089***
	(0.179)	(0.179)	(0.220)	(0.220)	(0.444)	(0.372)
Observations	317881	317881	212048	212048	210012	210012

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors. All Regressions include month dummies.

Table 17: Full regression results for table 9. Regression includes aggregate market tightness and wealth.

	JOLTS		HWOL	
log(theta)	-0.577***	-0.924***	-1.476***	-3.574***
	(0.213)	(0.214)	(0.451)	(0.607)
Employed 1 year ago	6.015***	6.029***	5.975***	5.981***
	(0.216)	(0.216)	(0.271)	(0.271)
Unemployed 1 year ago	4.918***	4.821***	4.910***	4.856***
	(0.255)	(0.254)	(0.306)	(0.306)
S & P 500	-0.005***		-0.004***	
	(0.001)		(0.001)	
House Price Index		-0.023***		0.011
		(0.004)		(0.010)
age	-7.565***	-7.422***	-4.388**	-4.375**
	(1.736)	(1.737)	(2.109)	(2.109)
age^2	0.154**	0.149**	0.047	0.047
	(0.060)	(0.060)	(0.073)	(0.073)
age^3	-0.000	0.000	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
age^4	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration	0.573***	0.586***	0.530***	0.533***
	(0.039)	(0.039)	(0.048)	(0.048)
Unemployment $Duration^2$	-0.006***	-0.007***	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Unemployment $Duration^3$	0.000	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment $Duration^4$	-0.000	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
black	-2.437***	-2.453***	-1.933***	-1.934***
	(0.231)	(0.231)	(0.292)	(0.292)
married	11.542***	11.541***	11.220***	11.220***
	(0.282)	(0.282)	(0.342)	(0.342)
female	-5.619***	-5.637***	-5.485***	-5.484***
	(0.263)	(0.264)	(0.324)	(0.324)
married*female	-31.902***	-31.896***	-31.521***	-31.509***
	(0.355)	(0.355)	(0.435)	(0.435)
High School	6.260***	6.234***	6.689***	6.675***
	(0.183)	(0.183)	(0.230)	(0.230)
Some College	26.696***	26.672***	27.534***	27.520***
	(0.234)	(0.234)	(0.290)	(0.290)
College	50.040***	50.020***	49.992***	49.981***
	(0.361)	(0.362)	(0.443)	(0.443)
Occupation Groups				
Cognitive Routine	-3.693***	-3.719***	-2.330***	-2.332***
	(0.315)	(0.315)	(0.385)	(0.385)
Manual Non-Routine	-1.049***	-1.066***	-0.143	-0.148
	(0.308)	(0.309)	(0.376)	(0.376)
Manual Routine	-6.087***	-6.101***	-4.241***	-4.233***
	(0.318)	(0.319)	(0.392)	(0.392)
Observations	103016	103016	68950	68950

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors. All Regressions include month dummies.

Table 18: Full regression results for Table 12

	JOLTS		HWOL	
log(theta)	-0.247**	-0.457***	-1.086***	-2.331***
	(0.119)	(0.119)	(0.249)	(0.335)
Eligible for UI Benefits	5.151***	5.135***	4.843***	4.826***
	(0.101)	(0.101)	(0.125)	(0.125)
S and P	-0.004***		-0.003***	
	(0.000)		(0.001)	
House Price Index		-0.023***		0.003
		(0.002)		(0.006)
age	-3.458***	-3.458***	-3.161***	-3.161***
	(0.951)	(0.951)	(1.154)	(1.154)
age^2	0.011	0.012	0.003	0.003
	(0.033)	(0.033)	(0.040)	(0.040)
age^3	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
age^4	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration	0.534***	0.545***	0.510***	0.513***
	(0.021)	(0.021)	(0.026)	(0.026)
Unemployment Duration^2	-0.005***	-0.006***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment Duration^3	0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration^4	-0.000*	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
black	-2.151***	-2.157***	-1.822***	-1.820***
	(0.123)	(0.123)	(0.154)	(0.154)
married	10.897***	10.900***	10.515***	10.516***
	(0.158)	(0.158)	(0.192)	(0.193)
female	-5.813***	-5.825***	-5.663***	-5.666***
	(0.140)	(0.140)	(0.173)	(0.173)
married*female	-30.970***	-30.970***	-30.742***	-30.737***
	(0.199)	(0.199)	(0.244)	(0.244)
High School	6.193***	6.176***	6.468***	6.456***
	(0.099)	(0.099)	(0.125)	(0.125)
Some College	27.055***	27.036***	27.650***	27.635***
	(0.130)	(0.130)	(0.162)	(0.162)
College	49.419***	49.412***	49.223***	49.212***
	(0.204)	(0.204)	(0.251)	(0.251)
Occupation Groups				
Cognitive Routine	-3.830***	-3.840***	-2.878***	-2.889***
	(0.174)	(0.174)	(0.213)	(0.213)
Manaul Non-Routine	-0.864***	-0.865***	-0.253	-0.253
	(0.174)	(0.174)	(0.212)	(0.212)
Manual Routine	-6.384***	-6.385***	-5.080***	-5.075***
	(0.178)	(0.178)	(0.219)	(0.219)
Observations	317881	317881	212048	212048

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors adjusted for clustering by state. All Regressions include month dummies.

Table 19: Regression using aggregate measures of labor market tightness and wealth using the matched CPS sample but without fixed effects.

	JOLTS		HWOL	
log(theta)	-0.927***	-1.090***	-2.151***	-2.882***
	(0.120)	(0.120)	(0.251)	(0.339)
S & P 500	-0.005***		-0.003***	
	(0.000)		(0.001)	
House Price Index		-0.025***		-0.004
		(0.002)		(0.006)
age	-2.626***	-2.635***	-2.486**	-2.491**
	(0.965)	(0.965)	(1.170)	(1.170)
age^2	-0.017	-0.017	-0.020	-0.020
	(0.034)	(0.034)	(0.041)	(0.041)
age^3	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
age^4	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration	0.587***	0.598***	0.548***	0.551***
	(0.022)	(0.022)	(0.027)	(0.027)
Unemployment $Duration^2$	-0.007***	-0.007***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment $Duration^3$	0.000***	0.000***	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment $Duration^4$	-0.000***	-0.000***	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
black	-2.205***	-2.212***	-1.884***	-1.883***
	(0.125)	(0.125)	(0.158)	(0.158)
married	11.127***	11.127***	10.711***	10.712***
	(0.160)	(0.160)	(0.195)	(0.195)
female	-6.299***	-6.309***	-6.108***	-6.110***
	(0.142)	(0.142)	(0.175)	(0.175)
married*female	-31.581***	-31.577***	-31.288***	-31.282***
	(0.202)	(0.202)	(0.248)	(0.248)
High School	6.390***	6.372***	6.634***	6.622***
	(0.100)	(0.100)	(0.126)	(0.126)
Some College	27.104***	27.086***	27.673***	27.657***
	(0.131)	(0.131)	(0.163)	(0.163)
College	49.434***	49.427***	49.188***	49.177***
	(0.207)	(0.207)	(0.254)	(0.254)
Occupation Groups				
Cognitive Routine	-4.370***	-4.373***	-3.283***	-3.291***
	(0.176)	(0.176)	(0.216)	(0.216)
Manual Non-Routine	-1.035***	-1.034***	-0.376*	-0.375*
	(0.176)	(0.176)	(0.214)	(0.214)
Manual Routine	-6.389***	-6.388***	-5.027***	-5.022***
	(0.180)	(0.180)	(0.222)	(0.222)
Observations	312114	312114	208241	208241

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors. All Regressions include month dummies.

Table 20: Regression controlling for weeks remaining on benefits. Included in the regression are only eligible workers in the months in which there is benefits information. Aggregate measures of markets conditions and wealth

	JOLTS	HWOL
log(theta)	-8.978***	-6.417***
	(0.376)	(0.232)
Weeks of Benefits Remaining	-0.119***	-0.148***
	(0.006)	(0.006)
S and P	0.003***	0.001
	(0.001)	(0.001)
House Price Index		
age	-0.703	-0.934
	(1.750)	(1.628)
age^2	-0.100	-0.092
	(0.061)	(0.057)
age^3	0.004***	0.004***
	(0.001)	(0.001)
age^4	-0.000***	-0.000***
	(0.000)	(0.000)
black	-2.037***	-2.326***
	(0.227)	(0.207)
married	10.935***	11.178***
	(0.252)	(0.235)
female	-5.616***	-5.566***
	(0.255)	(0.234)
married*female	-32.440***	-32.698***
	(0.348)	(0.322)
High School	7.615***	7.383***
	(0.181)	(0.166)
Some College	29.977***	29.698***
	(0.241)	(0.222)
College	54.004***	54.024***
	(0.373)	(0.344)
Occupation Groups		
Cognitive Routine	-4.873***	-5.281***
	(0.322)	(0.298)
Manaul Non-Routine	-1.330***	-1.576***
	(0.314)	(0.292)
Manual Routine	-6.664***	-7.167***
	(0.315)	(0.291)
Observations	114494	132751

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors adjusted for clustering by state. All Regressions include month dummies.

F.2 Duration of Unemployment

The duration of unemployment is often considered an important determinant of job search effort. In many models, agents' search effort respond to their unemployment duration but the direction of the change varies from model to model. One possibility is that as the unemployment spell progresses, an unemployed worker's savings become depleted, leading the worker to search harder. However, various other forces can reverse this effect and move job search time in the opposite direction over the unemployment spell. One example is human capital depreciation. As modeled by Ljungqvist and Sargent (1998), skill depreciation during unemployment could cause a decline in reemployment wages. Consequently, the value of a job to the unemployed worker falls, inducing a decline in job search effort as unemployment duration gets longer. Another possible rationale for declining search effort can be found in stock-flow matching models of the labor market. In that class of models, newly unemployed workers face a pool of job vacancies for which they can apply. Those who exhaust this initial stock of job openings without finding a job then start to monitor the flow of new openings. This stock-flow nature of matching causes a decline in job search time as unemployment duration grows.

Empirical studies that examine the response of job search effort to increasing unemployment duration have mixed results. Krueger and Mueller (2011), for example, find that job search effort declines as the unemployment spell progresses at the individual level. However, at the cross-section, they find that job search effort is similar across workers with different unemployment durations.

In our regressions we include a quartic function of unemployment duration following Shimer (2004). Figure 15 shows that the response of search intensity to unemployment duration in hump shaped, similar to Shimer's findings. Search effort initially rises with unemployment duration and then goes down. With the quartic specification, search effort peaks after a year. We also try cubic and quintic polynomials and find that, while the other coefficients of the regressions are robust to the degree of the polynomial in unemployment

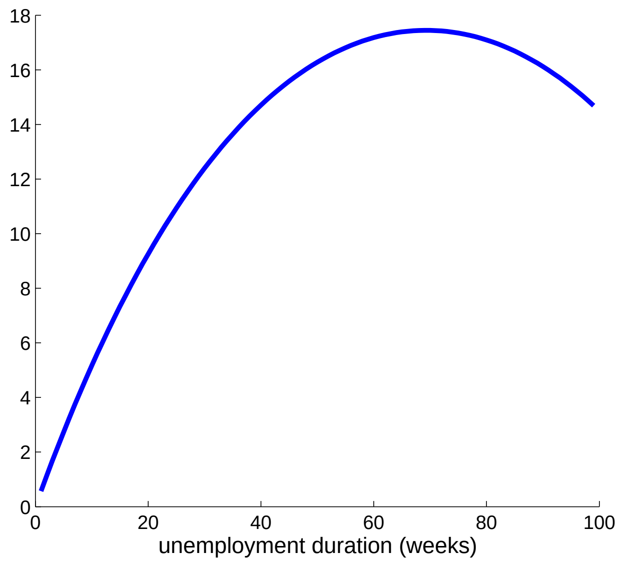


Figure 15: The effect of unemployment duration (in weeks) on search time. These estimates from the regression in Table 7 column 1.

duration, the peak of the polynomial changes, consistent with Shimer (2004).

Additional References for Appendix

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