Job Search Behavior over the Business Cycle*

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Abstract

We create a novel measure of job search effort exploiting the American Time Use and Current Population Surveys. We examine the cyclicality of search effort using time-series, cross-state and individual variation and find that it is countercyclical. We then set up a search and matching model with endogenous search effort. Our model provides strong support for matching function specifications with substitution between search effort and labor-market tightness. We then examine the role of search effort on unemployment fluctuations and show that the unemployment rate would have been 0.5-to-1 percentage points higher in the 2008-2014 period had search effort not increased.

Keywords: job search, time use, business cycles
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1 Introduction

In the basic Diamond-Mortensen-Pissarides model of frictional labor markets, such as Pissarides (1985) and Mortensen and Pissarides (1994), the search effort of unemployed individuals and the recruiting effort of firms (other than posting vacancies) do not play a role in determining the level of aggregate employment. A recent paper by Davis, Faberman, and Haltiwanger (2013) emphasizes the importance of firms' recruiting effort beyond posting vacancies in accounting for the cyclical patterns of hiring. This paper complements Davis, Faberman, and Haltiwanger's (2013) argument and extends their critique to the worker side. In particular, we analyze how nonemployed workers' job search effort varies over the business cycle and examine its implications for aggregate labor market outcomes.

To this end, we construct a measure of search effort by combining information from the American Time Use Survey (ATUS) and the Current Population Survey (CPS). Both the ATUS and the CPS have their own advantages and disadvantages for measuring job search effort. While the ATUS reports the time spent on job-search activities on a particular day, which is perhaps the most natural measure of job search, it has a small sample size and a short sample period (starting in 2003). The CPS does not include direct information on search time but it does include questions on the types and number of search methods used by the respondents. Despite reporting a measure that is harder to interpret, the CPS has the advantage of a larger sample size and questions on job search that are available beginning in 1994.[1]

In order to extract as much information as possible, we link the CPS monthly basic survey and the ATUS by utilizing the fact that both contain the *same questions* on the search methods used during the previous month. We first estimate a relationship between search time and search methods using the ATUS sample, and then use this relationship to impute job search time for all CPS respondents. Using individual search effort measures, we compute a monthly

[1] Before the 1994 redesign of the CPS, the respondents were given six job search methods to choose from, while the number of methods increased to twelve after 1994. We discuss the data before 1994 in Appendix A.3.

series of aggregate worker search effort starting in 1994.

In an analogy to the labor supply literature, we analyze the cyclical movement in aggregate search intensity along two margins: the extensive and intensive margins. The extensive margin is represented by the number of unemployed searchers relative to the total pool of non-employed workers and the intensive margin is measured as the average minutes of job search that an unemployed worker spent on job search activities. We show that aggregate search effort is countercyclical both along the extensive and intensive margins: during recessions, nonemployed workers are more likely to actively engage in job search (and thus be labeled as unemployed) and are likely to search longer conditional on searching. In addition to analyzing time variation in aggregate search effort, we follow Aguiar, Hurst, and Karabarbounis (2012) and exploit cross-state variation in the intensity of business cycles to further explore the cyclicality of search effort along the intensive margin. We find that search effort increased more in states with more severe recessions, as measured by movements in the state unemployment rate.

Additionally, using individual level data, we unpack the mechanisms driving this aggregate cyclicality. Aggregate and state-level search effort could be countercyclical because the composition of the unemployed changes systematically over the cycle. In particular, if, during recessions, the unemployment pool shifts towards workers who typically search more, aggregate search effort can be countercyclical even if individual search effort is invariant to market conditions. We examine search effort at the individual level and control for observable and unobservable heterogeneity by exploiting the semi-panel feature of the CPS. We find that shifts in the composition of the unemployed play a role in explaining the rise in search effort during recessions. Specifically, our estimates suggest that around half of the correlation between labor market conditions and search effort is explained by changes in the composition of the unemployed. Note that while understanding the role of composition and individual responses is interesting and potentially important for understanding the effect of various policies, the aggregate implications for search and matching models depend on the total moments, whether

those are driven by composition or individual responses.

After documenting the countercyclicality of search effort, we analyze the relationship between job search effort and aggregate labor market outcomes by estimating an augmented Cobb-Douglas matching function which takes into account the cyclical variation in the search intensity of workers. We find that the intensive margin of search effort is an important determinant of the aggregate hiring process. While this exercise is informative, in order to relax the Cobb-Douglas assumption and better inform theoretical search and matching models with endogenous search intensity, we develop a general equilibrium search and matching model which explicitly incorporates search effort choice by unemployed workers and allows for a generalized matching function. We then calibrate it to match the standard business cycle targets as well as the new target that we introduce: the cyclical responsiveness of search effort. We find strong support for matching function specifications with substitution between search effort and aggregate labor market conditions and reject commonly used matching function specifications in the literature such as in Christiano, Trabandt, and Walentin (2012) and Gomme and Lkhagvasuren (2015).

Finally, we quantify the importance of search effort in explaining the recent labor market dynamics. We find that the increase in search intensity during and following the Great recession moderated the increase in the unemployment rate. Absent this increase, the unemployment rate would have peaked at around 11 percent and would have been consistently higher by about 0.5 to 1 percentage points during the recovery. Relatedly, our findings imply that variation in the search effort of unemployed workers can not account for the recent decline in the estimated matching efficiency.

This paper adds to a growing empirical literature examining job search effort. Shimer (2004) is an early critic of search effort being modeled as procyclical in search-matching models. He uses a measure of job search intensity based on the CPS and finds that the aggregate search effort does not appear to be procyclical in the aggregate data. We build on his insight by

providing a richer measure of search effort that spans a longer time period and use additional variation at the state and individual level to establish the countercyclicality of search effort. We also extend his analysis by delving into the reasons behind this pattern and investigate its aggregate implications. More recently, Krueger and Mueller (2010) use the ATUS from 2003–2007 to analyze job search behavior by labor force status, though their focus is not on its cyclical properties. Another recent study based on the ATUS is Aguiar, Hurst, and Karabarbounis (2012), which analyzes the change in the allocation of time during the Great Recession. They find that the increase in job search absorbed two to six percent of the foregone work hours. Faberman and Kudlyak (2014) use the micro data from a job search website to study the relationship between search intensity and search duration. While their dataset is completely different from ours, their results are broadly consistent with our findings in that they find that the number of applications sent by a job seeker per week is significantly higher in metropolitan areas with more slack labor markets. DeLoach and Kurt (2013) analyze the determinants of search time at the individual level using the ATUS for the 2003–2009 period. However, contrary to our and Faberman and Kudlyak's (2014) findings, they find evidence for a discouragement effect—that individuals respond negatively to a deteriorating labor market conditions.[2]

Our main finding that search effort is countercyclical contrasts some of the recent work modeling labor market fluctuations. For example, in the models of Veracierto (2008), Christiano, Trabandt, and Walentin (2012) and Gomme and Lkhagvasuren (2015), an important driving force of labor market fluctuations is the procyclicality of nonemployed households search effort. Our empirical findings rule out this channel. Rather, the data support the view that the countercyclicality of nonemployed individuals' job search effort dampens labor market fluctuations.

[2]Our main motivation for linking the CPS and the ATUS is to overcome the small and short sample problem and to exploit the individual variation in job search effort instead of using a small sample of cross-sectional data such as in DeLoach and Kurt (2013). Since we can observe individuals' search effort repeatedly using the semi-panel structure of the CPS thanks to our methodology, we are able to control for observed and unobserved heterogeneity at the individual level and isolate the role of labor market conditions on job search effort.

An important issue to note is that even if part of the countercyclicality of search effort is due to a change in the composition of the job seekers, it does not imply that its countercycliality is less relevant for labor market fluctuations. What matters for the matching process in the search and matching framework is the variation in *total* search intensity. When the pool of job seekers shifts towards more attached workers who search harder, the total search input to the economy on the worker side still increases and affects aggregate labor market outcomes.

The main contributions of our paper relative to existing studies are as follows. First, we propose a method to link the ATUS and the CPS to obtain a measure of search effort starting in 1994. Second, we document the business cycle properties of aggregate job search effort exploiting time and state-level variation in macroeconomic conditions and explore the determinants of the observed pattern. Third, after establishing the link between search effort and labor market outcomes, we set up a search and matching model with endogenous search effort and estimate a generalized matching function within the model. Our model provides strong support for matching function specifications with substitution between search effort and aggregate labor market conditions. We also examine the role of fluctuations in search effort on unemployment rate fluctuations and argue that search effort does not amplify labor market fluctuations but rather dampens them.

The rest of the paper is organized as follows. Section 2 describes the data and explains how we combine the information from the two datasets. Section 3 documents the cyclicality of search effort using time-, state- and individual-level variation. Section 4 sets up a search and matching model with search effort choice and analyzes its implications for aggregate labor market dynamics. Section 5 concludes.

2 Measuring search effort

This section explains how we measure individuals' job search effort by combining information from the CPS and the ATUS. The method we propose in this section allows us to construct a

measure of job search effort for each individual in the CPS sample at a monthly frequency.

2.1 Data

The CPS is a monthly survey conducted by the U.S. Census Bureau 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 a relatively new survey conducted by the BLS where individuals are drawn from the exiting samples of the CPS. Respondents are contacted 2–5 months after their final 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. In addition to the time diaries, the ATUS also re-asks a subset of the CPS questions. Our sample from the ATUS spans 2003-2014 and we restrict our sample for the CPS from 1994 through 2014 because job-search related questions in the ATUS are consistent with the post-1994 CPS.[3] We follow Shimer (2004) and restrict the sample of workers to those over 25 to ensure that most respondents have completed their schooling by the time of the interview. We also truncate our sample at age 70 to avoid issues related to retirement.

The ATUS has the advantage of having a quantifiable measure of job search effort: the number of minutes each nonemployed individual spends on job search activities. This is a natural measure of job search effort, paralleling hours worked in measuring the labor input for production. We identify job search activities as the ones in Table 1.[4] The first category (job search activities) includes contacting employers, sending out resumes, and filling out job

[3]Before the 1994 redesign of the CPS, the respondents were given only six job search methods to choose from, while after the redesign, this number increased to twelve. Consequently, it is not straightforward to use our imputation method before 1994, as the method categories are inconsistent across the ATUS and CPS. Even though it is not possible to have a consistent measure of job search for the 1976-2014 period, it is still possible to construct an internally consistent measure of job search for the 1976-1993 period as done by Shimer (2004) by just using the available information on job search methods in the CPS. See Appendix A.3.1 for results and a brief discussion.

[4]We do not include travel time to interview in our baseline measure as is done in Aguiar, Hurst, and Karabarbounis (2012). This choice was motivated by our use of the multi-year files created by the ATUS. The advantage of using these files is that they include pre-constructed sample weights that are consistent over time. However, the disadvantage is that these files contain only more aggregated time categories, eliminating travel time to interviews as its own category. We explore the importance of this selection in Appendix A.1. Figure A1 shows that while the measured number of minutes per day increases when travel time is added, the cyclicality of the resulting series is unchanged.

Job search activities (050401) includes: contacting employer, sending out resumes, etc.
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

applications, among others.[5]

The ATUS has two major shortcomings for our purposes—it has a 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, as the ATUS only contains information about the day before the interview and therefore there are fewer than 100 observations per day. The short sample is a problem because the U.S. economy has experienced only one recession after 2003, making it difficult to detect a recurring cyclical pattern.

In order to overcome these shortcomings, we also utilize information on job search in the monthly CPS. Conditional on the individual being unemployed and not on temporary layoff, the interviewer asks what kind of search methods the individual has used in the past month. In the question, respondents are allowed to select from nine active search methods and three passive search methods. Table 2 lists all possible reported methods. This measure has many advantages over the ATUS measure. The CPS has a larger sample size (150,000 individuals per month) and a longer sample period (we use the surveys after 1994 redesign). Moreover, the question on search methods in the CPS contains information about job search behavior over the past month, rather than just one interview day.

[5]See Krueger and Mueller's (2010) Table 1 in Appendix A for details. In the analysis below, we exclude the respondents who report more than 8 hours of job search activities in order to avoid the effects of large outliers. The results in this and the next section are not affected by this adjustment (or other cutoffs such as 5 hours) except for a small change in the average level.

Contacting an employer directly or 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)

<table>
<tr><td colspan="5">All Workers
1.9</td></tr>
<tr><td rowspan="3">Employed
0.6</td><td colspan="4">Nonemployed
6.4</td></tr>
<tr><td colspan="2">Unemployed
35.1</td><td colspan="2">Not in the Labor Force
0.7</td></tr>
<tr><td>Temp Layoff
11.8</td><td>Not on Temp Layoff
38.9</td><td>Want a Job
5.8</td><td>Other NILF
0.7</td></tr>
</table>

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

2.2 ATUS summary statistics

We first examine overall patterns of job search from the ATUS for the 2003–2014 period. Table 3 reports the average reported time spent on job search activities (in minutes per day recorded in time diaries). We calculate average search time for respondents in different labor market states separately to identify the labor force categories that are the main drivers of search activity in the economy.

We first group the respondents into three broad categories: employed, unemployed and not in the labor force (NILF). We also consider several subgroups to identify who engages most intensively in job search. The unemployed workers are divided into two categories—"temporary

layoff" and "not on temporary layoff." Workers who are on "temporary layoff" are those waiting to be recalled to a job from which they had been laid off and do not need to have been looking for work to be classified as unemployed. The "not in temporary layoff" workers are the ones who report having conducted some job search activities in the last four weeks and thus are classified as unemployed. In the NILF category, there are two subcategories: "want a job" and "other NILF." The former are the workers who are not in the labor force but who report that they want a job.[6]

Table 3 reveals large differences in search time among different labor force categories.[7] Not surprisingly, unemployed workers spend substantially more time searching for a job than either employed workers or those not in the labor force. Even unemployed workers on temporary layoff spend a significant amount of time searching. As can be expected, nonemployed workers outside the labor force do not spend significant time searching for a job. The same is the case even when we look at the subset of the NILF workers who report wanting a job. Motivated by Table 3, we identify unemployed workers as the group who engage in job search activity and therefore define the *extensive margin* of the job search activity as the fraction of nonemployed individuals who are unemployed. We find this choice natural since the CPS uses a search criterion to classify workers as unemployed if they are not on temporary layoff. We also include unemployed workers on temporary layoff since they spend considerable time searching.

2.3 Linking the ATUS and the CPS

Ultimately, our goal is to obtain a measure of the monthly average of daily search time of each respondent in the CPS survey. However, we do not observe this directly in either the CPS, where we only observe search methods over the past month, or the ATUS, where we observe search methods over the past month and search time in the previous day. Therefore,

[6]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.

[7]The statistics are very similar to those in Krueger and Mueller (2010) who use 2003–2007 data.

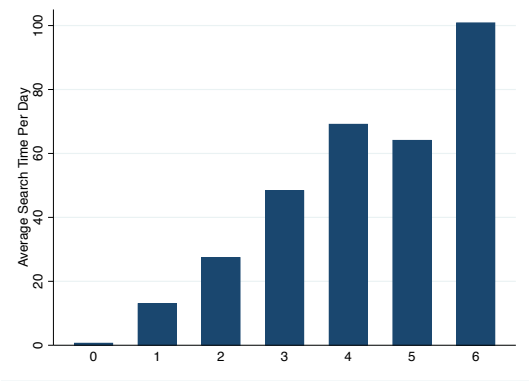


Figure 1: The average minutes (per day) spent on job search activities by the number of search methods.

we estimate the relationship between daily search time and search methods in the ATUS and use this relationship to construct an *imputed job search time* for every respondent in the CPS. Table 2 shows that many CPS job search activities overlap with the job search activities recorded in the ATUS time diaries. Therefore, it is likely that similar information is contained in the answers to the methods question in the CPS and in the ATUS time diaries. To see how closely these two measures are related, we first categorize unemployed workers (excluding the ones on temporary layoffs, who do not report search methods) by the number of methods they report using and plot the average minutes per day that each group spends on job search activities.

Figure 1 indicates that recorded search time and the number of methods used exhibit a strong positive correlation. This implies that the number of methods contains valuable information on the intensity of job search. Indeed, Shimer (2004) used the number of search methods as a measure of a worker's search effort before the ATUS data were available. However, the number of methods does not convey any information on the relative importance of each method in workers' job search activities since the assumption is that all methods are equally important and utilized with equal intensity across individuals and over time. In reality, it is likely that workers allocate their search time differently across different methods, considering the effectiveness and time intensiveness of various methods.

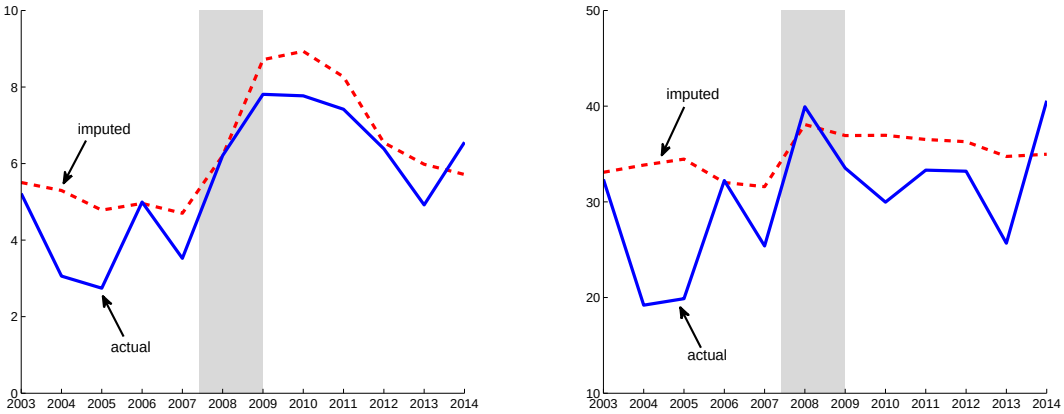
This is why we combine the additional information on job search in the ATUS time diary with the information on search methods in the CPS. Since each respondent in the ATUS at the time of the ATUS survey is re-asked in which job search methods they have engaged in the past 4 weeks, we are able to construct a mapping between their response on methods and the job search time recorded in their diary from the previous day. The simplest approach would be to run an OLS regression for the ATUS sample with search time as the left-hand side variable and dummy variables for each method used (and various worker characteristics) as right-hand side variables, and then use this estimated equation to compute search time for the CPS sample starting in 1994. However, this approach does not account for the nonlinearities at zero reported minutes of search.[8] Instead, we use the Heckman selection correction procedure, which estimates the probability of observing positive search time and how many minutes one searches conditional on searching. Specifically, we estimate the following two equations,

$$p_i = \beta_0 + \beta_1 D_i + \beta_2 X_i + \epsilon_i \tag{1}$$

$$s_i = \gamma_0 + \gamma_1 D_i + \gamma_2 X_i + \gamma_3 \lambda(\hat{p}_i) + \nu_i \tag{2}$$

the first using a probit and the second using OLS where p_i is the probability that an individual searches on the day of the interview and s_i is the number of minutes they report searching, conditional on searching a positive number of minutes. D_i includes dummies for use of each search method, and $\lambda(\hat{p}_i)$ is the inverse mills ratio evaluated at $\hat{p}_i$, which corrects for the correlation between error terms across the two equations. X_i includes two sets of observable worker characteristics. The first is a set of worker characteristics which may affect the intensity of job search. We mostly follow Shimer (2004) in the choice of these controls and include a quartic of age, dummies for education levels (high school diploma, some college, and college plus), race, gender, and marital status. We also add the interaction term of being female and

[8] Only around 20% of the unemployed searchers reported positive search time on the day of the diary. See Appendix A.2 for imputation results using this simple OLS regression.



(a) all nonemployed

(b) unemployed

Figure 2: Actual and imputed average search time (minutes per day) for all nonemployed workers and unemployed workers.

being married since being married is likely to affect the labor market behavior of men and women differently.[9] The second set of 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. We include a dummy for being out of the labor force but not wanting a job, being on temporary layoff, and being a out of the labor force but wanting a job.[10]

Figure 2 provides a comparison of the time series of the 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.[11] Note that the selection model is not intended to minimize the mean-square error, but rather to recover unbiased relationships between characteristics and search times. The fact that the imputed minutes are above the actual minutes suggests that individuals who we observe searching are slightly negatively selected. Using the coefficients

[9] In Appendix A.2, we also explored a version where each search method is interacted with gender and age to allow the relationship between methods and search time to vary by demographics. We find that these additional interactions do not affect the cyclicality of the time series.

[10] Note that we do not include unemployment duration in this regression as it is not re-asked in the ATUS.

[11] The imputed search time is above the actual search time in 2004 and 2005 mostly as a result of the relative behavior of total number of methods and search time in those years. While these two alternative measures track each other very closely in the rest of the sample, they deviate in 2004 and 2005 as shown in the Appendix A.2.

underlying the lines in Figure 2, we impute search time for every individual in the CPS. In the remainder of the paper, we use the imputed minutes, which we denote by $\hat{s}_{it}$ for individual i at time t, as our measure of search effort. This measure is a nontrivial extension of Shimer's (2004) measure since it exploits information on job search from the ATUS. Specifically, our measure weights each search method differently according to the estimated time intensity and allows for baseline search effort to vary by demographic characteristics.[12]

One critical assumption embedded in this imputation method is that the relationship between the methods used and the number of search minutes is constant over time. It is plausible that since the number of search methods are limited, searchers increase their search effort by increasing the minutes spent on each method rather than trying additional methods. Our imputation method would fail to capture this effect. To check the importance of this assumption, we have explored several alternate specifications. First, while including year dummies is not possible for our exercise, it is informative in checking the stability of our estimates over time. Table A1 in Appendix A.2 shows that the year dummies are only statistically significant in 2004 and 2005, suggesting that the relationship between time and methods does not change significantly over the business cycle. We also considered a version of our imputation where we include various measures of aggregate market conditions (cyclical fluctuations in GDP, the unemployment rate, and the vacancy-to-unemployment ratio). We interact each aggregate variable with each search method, thereby allowing the relationship between search methods and search time to vary over the cycle as the market aggregate moves. Figure A6 in Appendix A.2 shows the resulting imputed minutes in the CPS sample. We see that the versions with methods interacted with the unemployment rate or vacancy-to-unemployment ratio exhibit even stronger countercyclicality than our baseline measure, suggesting that individuals tend

[12]Figure A7 in Appendix A.3 plots our imputed minutes measure with the average number of methods, both normalized to 1 in the initial period to account for differences in scale. The two series have a correlation of 0.94, but the imputed minutes measure of search effort is more cyclical than the simple count of the number of methods. This suggests that either individuals shift to more time intensive search methods in recessions or that the composition of the unemployed pool shifts towards higher search demographics over the business cycle.

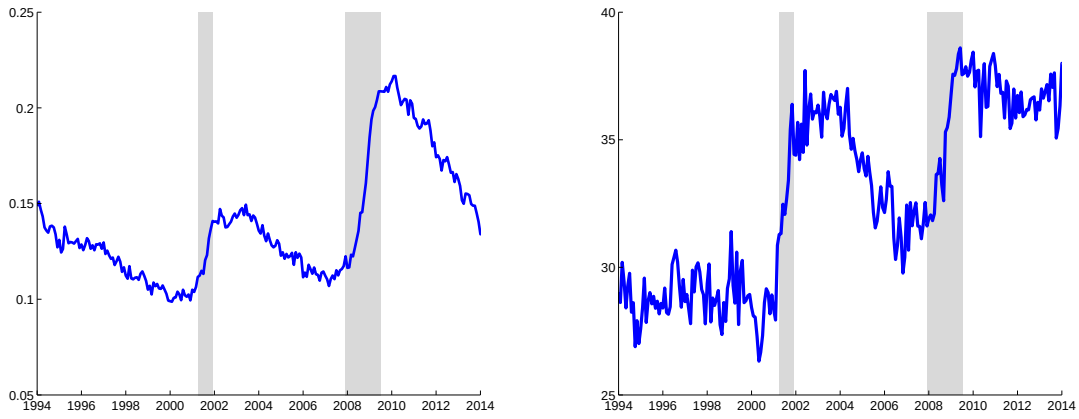


Figure 3: Left panel: the time series of the extensive margin ($U/(U+N)$). Right panel: the intensive margin (average minutes of search per day for unemployed workers).

to use search methods slightly more intensely when the labor market is weak. Therefore, our baseline specification is a conservative one regarding the overall cyclicality of search effort.

3 Cyclicality of search effort

In this section, we use our constructed search time measures to examine how nonemployed workers' search behavior changes over the business cycle. We exploit three distinct types of variation: time-series variation, cross-state variation in the intensity of business cycles, and individual-level variation. We find that aggregate search effort is countercyclical due to a combination of two effects. First, the composition of unemployed shifts in recessions towards workers with higher average search intensity. Second, unemployed workers respond to weak labor market conditions by increasing their search effort. Both these factors reinforce each other and generate a countercyclical pattern for the aggregate search effort.

3.1 Time-series variation

We begin by exploiting the time-series variation in our sample, which covers two recessions. Following the labor supply literature, we analyze variation in search intensity along two margins: the extensive margin and the intensive margin. As we discussed in the previous section in the

context of Table 3, we measure the extensive margin with the number of unemployed workers relative to total nonemployment and measure the intensive margin as the average search time in minutes that unemployed workers spend on job search activities per day.[13] The left panel of Figure 3 plots the fraction of nonworkers who decide to engage in search, which we calculate as the ratio of unemployed workers (U) to all nonemployed workers ($U+N$, where N is the number of the NILF workers).[14] Figure 3 clearly shows that the extensive margin is countercyclical, which is not a surprising observation given the widely documented strong countercyclicality of unemployment.[15]

To measure the intensive margin of search effort, we use the imputed minutes, $\hat{s}_{it}$, calculated in Section 2.3.[16] The right panel of Figure 3 plots the evolution of the average minutes per day that an unemployed worker spends on search activities. This time series also exhibit a countercyclical pattern, meaning that conditional on searching for a job, workers on average spend more time searching during recessionary periods. Indeed, as one could expect from the figure, the correlation with market tightness $\theta = v/u$, where v is the vacancy rate[17] and u is unemployment rate, is negative at -0.78.[18]

The total search effort of nonemployed workers in the economy can be calculated as the extensive margin times the intensive margin.[19] As one can infer from the previous figures, total search effort in the left panel of Figure 4 also exhibits a strongly countercyclical pattern.

[13] As discussed in Section 2.2, this definition of the extensive margin does not capture the full extensive margin in our data, as we find evidence in the ATUS of job search among some non-participants and employed. However, the unemployed not only engage in the most job search in the ATUS sample but they are also identified as such precisely because they are actively searching.

[14] We see the same pattern even when we use an alternative denominator of [U plus the nonparticipants who want a job].

[15] All aggregate search effort series are seasonally adjusted.

[16] Due to a data problem within the Census Bureau extraction tool ("Dataferret"), half of the states are missing job-search information in January 1997. Therefore we exclude this month from our analysis.

[17] We use the Composite Help-Wanted Index constructed in Barnichon (2010) as the measure of vacancies.

[18] The pattern is similar if we restrict our sample to only unemployed workers who are not on temporary layoff. See Appendix A.3 for the time series of the intensive margin measured by the number of methods used, as well as a comparison of the intensive margin in the CPS to the intensive margin in the ATUS.

[19] This calculation assumes that nonparticipants do not spend any time searching. Since some nonparticipants report positive search minutes, our computed measure is slightly different from the total search effort of nonemployed workers that is directly measured. The results are very similar if we include the search minutes of the NILF workers.

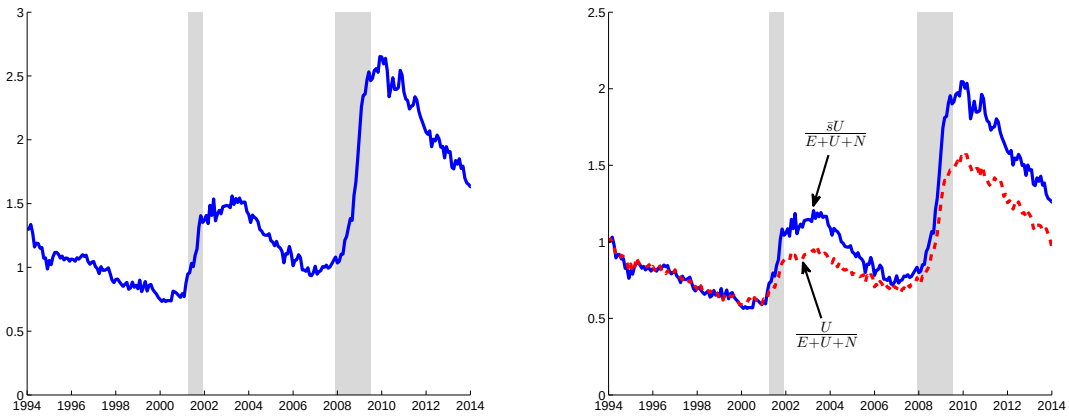


Figure 4: Left panel: Time series of total search effort ([extensive margin] × [intensive margin]). Right panel: Total search effort using the search time of unemployed workers ($\bar{s}U/(E+U+N)$) versus using the number of unemployed workers $U/(E+U+N)$; normalized to 1 at the beginning of 1994.

Indeed, the correlation of total search effort with θ is -0.89.

Lastly, the right panel of Figure 4 plots total search effort measured using only the extensive margin ($U/(E+U+N)$, where E is employment) against a measure that takes into account the variation at the intensive margin as well ($\bar{s}U/(E+U+N)$, where $\bar{s}$ is the average of the intensive margin), normalizing the initial levels to one. As the figure shows, these two measures can diverge significantly, illuminating the potential importance of ignoring the intensive margin. In other words, failing to take into account the variation along the intensive margin of search intensity results in an underestimation of the variation of total search effort in the economy over the business cycle. We will return to the quantitative significance of ignoring the variation along the intensive margin of search effort in Section 4.

3.2 State-level variation

In addition to the time-series variation that we explored in the previous subsection, we also exploit cross-state variation in the intensity of business cycles to establish the cyclical properties of search effort. Looking across different states provides additional information, as it utilizes a

different and potentially richer source of variation by answering the question "Did search effort increase more in states where the recessions were relatively more severe?" This method of utilizing state-level variation to establish the cyclicality of a series is similar to that in Aguiar, Hurst, and Karabarbounis (2012) and Haltiwanger, Hyatt, and McEntarfer (2014).

We examine cyclicality at the state-level by running variants on the following regression:

$$\Delta \log s_{jt} = \lambda_j + \lambda_t + \beta \Delta X_{jt} + \varepsilon_{jt}, \tag{3}$$

where s_{jt} is the average search time of unemployed workers in state j in time t, λ_j is a state fixed effect, λ_t is a time control that we explain in detail below, X_{jt} is the cyclical indicator, and ε_{jt} is the error term. We use two different cyclical indicators: changes in the state-level monthly unemployment rate (Δu_{jt}), and changes in labor market tightness $\theta = v/u$.[20] For each of those variables, we explore both three-month and six-month changes. The parameter of interest is β, which captures the correlation of search time with the cyclical indicator. State-fixed effects capture any static difference in job search behavior across states and the time-fixed effects control flexibly for any variation that is constant across states but varies over time. Therefore, this specification identifies the relationship between unemployment and job search effort using cross-sectional variation across states. In each of these regressions, we also allow the change in job search effort in each state to follow a different linear time trend, controlling for time-varying state level policies that may affect trends in job search differentially.[21]

Table 4 shows the estimates of β from a series of regressions. The left two columns reveal that across specifications, the coefficient on the unemployment rate is positive and statistically significant, implying that in states where the unemployment rate increases were larger, the search effort of the unemployed increased more both in terms of three-month and six-month changes. Specifically, the left two columns suggests that if a state's unemployment rate is one

[20] State level vacancies come from Conference Board Help Wanted OnLine (HWOL) and are available beginning in May 2005.

[21] We also seasonally adjust each state-level series to control for month-to-month fluctuations that differ across states.

percentage point higher, the average worker's search effort is about 1.5% higher. The right two columns reveal that results are similar when we use θ as our cyclical indicator – search effort is higher in states with weaker labor markets. Taken together, these results, which utilize a completely different variation than in Section 3.1, further suggest that search effort is countercyclical.

	3-Month Change	6-Month Change	3-Month Change	6-Month Change
Δunemployment rate	0.0155***	0.0160***		
	(0.0052)	(0.0050)		
Δmarket tightness($\frac{v}{u}$)			-0.1268	-0.1341*
			(0.0760)	(0.0769)
Years	1994-2014	1994-2014	2005-2014	2005-2014
Observations	12495	12189	5763	5610
R-Squared	0.092	0.120	0.113	0.143

Table 4: Estimates of responsiveness of search effort to labor market conditions exploiting state-level variation.

3.3 Individual-level regressions

The final source of variation we exploit is the individual level variation in search effort both in the cross section and over time. While the findings above that total search effort is countercyclical are important for aggregate analysis, understanding the individual response is still important for understanding the mechanisms underlying these patterns and for understanding the potential effect of various labor market policies. Even if aggregate search effort and state-level search effort are countercyclical, individual search effort may not co-vary with labor market conditions in a countercyclical manner. It is possible that aggregate search effort and state-level search effort are countercyclical because in recessions the pool of searchers skews towards the types of people who search harder.[22] This compositional shift could occur along both observed and unobserved dimensions. For example, suppose that (i) searchers are hetero-

[22]This would be consistent with the findings of Mueller (2015) and Elsby, Hobijn, and Şahin (2015) who find strong evidence that the composition of the unemployed shifts toward workers who are more attached to the labor market.

geneous in their desire to work; (ii) workers with a strong preference for work search harder; and (iii) this effort results in a quicker transition to employment. The "high-search type" workers find jobs easily in booms, and therefore these workers disappear from the unemployment pool more quickly during booms. As a result, the unemployment pool would be dominated by workers with less desire to work during booms. This channel would lead to countercyclical average search effort through unobserved composition changes. Note that even if countercyclical search effort is entirely driven by compositional shifts over the business cycle, it can still have important aggregate implications since what matters for the matching process in the search and matching framework is the variation in the total search intensity.

In order to explore the responsiveness of search effort to labor market conditions at the individual level net of these composition changes, we exploit the semi-panel structure of the CPS and look at variation within an individual over time. To do this, we only use individuals with at least two periods of unemployment in the eight months in which they are surveyed. Assuming that an individual's unobserved characteristics related to search effort do not change over the sample period, including an individual fixed effect will directly control for all compositional bias.

Specifically, we run variations on a regression of the form

$$\hat{s}_{it} = \delta + \alpha_i + \delta_\theta \log(\theta_{it}) + \mathbf{x}'_{it}\boldsymbol{\delta}_x + \alpha_i + \varepsilon_{it}, \tag{4}$$

where $\hat{s}_{it}$ is individual i's search effort at time t, θ_{it} is a measure of labor market conditions, $\mathbf{x}_{it}$ is the vector of observable controls, α_i is an individual fixed effect, and ε_{it} is the error term. The controls $\mathbf{x}_{it}$ include the demographic controls (a quartic in age, marital status, race, sex, and education), four occupation dummies,[23] and a quartic function of unemployment duration. The parameter of interest is δ_θ, which captures how job search effort co-moves with the business cycle after controlling for demographic changes. For the cyclical indicator, we use the aggregate

[23] 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.

labor market tightness $\theta = v/u$, computed using Barnichon's (2010) Composite Help-Wanted Index, which is available for the 1951–2014 period. We also repeat the same exercise using job openings data from the Job Openings and Labor Turnover Survey (JOLTS) which started in 2001.[24] Note that the sample for this regression includes only the unemployed who are not on temporary layoff. This is because the search methods are the main time-varying factors in creating the imputed search time and we do not observe the search methods for the workers on temporary layoff. Thus "unemployed workers" this section refers to only this subset of all unemployed workers. In order to account for the fact that our measure of search effort is imputed, we use a multiple imputation method to calculate the standard errors in Table 5. See Appendix A.3.2 for details.

The first column of Table 5 confirms the findings of Section 3.1 and shows that, on average, search effort is low when aggregate labor market conditions are favorable (that is, when θ_t is high). This finding is consistent with Faberman and Kudlyak (2014), who find that the number of applications sent by a job seeker per week is significantly higher in metropolitan areas with more slack labor markets.

A comparison of the coefficients on $\log(\theta)$ in the first and second columns of Table 5 provides a measure of how important the included observables are in explaining the correlation between θ and job search effort. The results demonstrate that shifts in the demographic composition of the unemployed contribute meaningfully to the cyclicality of aggregate search effort, decreasing the estimated individual sensitivity to labor market conditions by about a third. The downward bias in the coefficient on $\log(\theta)$ in the first column comes from the fact that in periods when θ is low (in recessions), the unemployed pool is composed of individuals who are ex-ante high searching types. As the coefficients in Table 5 show, there is significant variation in search effort across demographic groups. On average, search effort is increasing in education, is higher for men than women, is higher for workers who are in cognitive nonroutine occupations, and is

[24] In the Appendix, we also report results using the HWOL vacancy series to construct θ, which only begins in 2005, as well as aggregate house price, stock market series, and payroll employment.

	Composite Help-Wanted Index(1994-2014)			JOLTS (2001-2014)		
	Basic	Observables	FE	Basic	Observables	FE
log (θ)	-7.440^{***}	-5.231^{***}	-3.841^{***}	-4.422^{***}	-3.349^{***}	-3.529^{***}
	(0.683)	(1.094)	(1.034)	(0.928)	(0.901)	(0.794)
Age	.	42.484^{***}	.	.	45.721^{***}	.
		(6.621)			(6.879)	
Age^2	.	-1.391^{***}	.	.	-1.499^{***}	.
		(0.254)			(0.265)	
Age^3	.	0.020^{***}	.	.	0.022^{***}	.
		(0.004)			(0.004)	
Age^4	.	-0.000	.	.	-0.000	.
		(0.000)			(0.000)	
Black	.	-0.023	.	.	0.270	.
		(8.015)			(8.200)	
Married	.	5.290	.	.	5.313	.
		(9.690)			(9.805)	
Female	.	-10.803^{***}	.	.	-10.690^{***}	.
		(1.498)			(1.526)	
Married x Female	.	-25.307^{***}	.	.	-25.541^{***}	.
		(6.233)			(6.106)	
High School	.	5.160	.	.	5.151	.
		(6.843)			(6.993)	
Some College	.	30.683^{***}	.	.	30.964^{***}	.
		(7.334)			(7.507)	
College	.	52.004^{***}	.	.	52.012^{***}	.
		(7.078)			(7.429)	
Cognitive Routine	.	-6.205^{***}	.	.	-5.816^{***}	.
		(1.793)			(1.755)	
Manual Non-Routine	.	-1.064^{*}	.	.	-0.764	.
		(0.612)			(0.650)	
Manual Routine	.	-7.075^{***}	.	.	-6.437^{***}	.
		(1.732)			(1.603)	
Unemployment Duration	.	0.862^{***}	0.154^{***}	.	0.827^{***}	0.123^{***}
		(0.158)	(0.049)		(0.154)	(0.054)
Unemployment Duration^2	.	-0.027^{***}	-0.008^{***}	.	-0.025^{***}	-0.006^{***}
		(0.005)	(0.002)		(0.005)	(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)
No. Obs.	528726	528726	528726	406172	406172	406172

Table 5: The response of individual job search effort, $\hat{s}_{it}$ to variation in labor market conditions.

lower for married female workers. In addition to differences in demographic characteristics, the coefficients in Column 2 suggest that search effort also depends on unemployment duration, rising initially and and then falling at longer durations. When we change the specification to cubic and quintic polynomials, we find that, while the other coefficients of the regressions are robust to the degree of the polynomial in unemployment duration, the peak of the graph changes.[25] See Appendix A.3.2 for a more thorough discussion of the role of unemployment duration.[26]

Lastly, in the third column of Table 5, we report regression results with individual fixed effects ("FE") which control for unobserved differences across individuals and compares the search effort of an individual in months when the labor market is tighter to the same individual in months with a weaker labor market. A comparison of columns 2 and 3 shows that when unobserved heterogeneity is taken into account, individual search effort is less responsive to labor market conditions but that the correlation of search effort with labor market tightness is still significantly negative. This method of controlling for unobserved heterogeneity in the pool of unemployed also suggests that shifts in unobserved heterogeneity among the unemployed over the business cycle play a role in explaining the observed countercyclicality of search effort but that individuals search effort still co-moves negatively with labor market conditions. To see this, consider what these estimates imply for a one standard deviation decrease in θ. The coefficient in column 1 implies that when θ decreases by 1 standard deviation (i.e. 0.38), search effort increases by 2.8 minutes per day. Once we control for observable changes, the implied change falls to 2.0 and when we include controls for unobservable changes, this falls further to 1.5 minutes. Together, this implies that compositional shifts in the pool of unemployed explain 48% of the correlation between θ and overall search effort and that individual-level changes explain the rest.

[25] This result is consistent with the result of Shimer (2004).

[26] A 2014 working paper version of this paper included an analysis of how search effort varies with unemployment insurance benefits.

4 Job search effort and aggregate labor market outcomes

We have shown that search effort co-moves with macroeconomic conditions both along the extensive and intensive margins. This finding potentially has important theoretical implications since typical matching function specifications assume that the only search input in the economy on the worker side is the number of unemployed workers. One method to illustrate the importance of the intensive margin of search intensity on aggregate labor market outcomes would be to estimate the matching function including our measure of search intensity.[27] To illustrate the importance of the intensive margin of search intensity on aggregate labor market outcomes, we first consider a simple linear regression under the constant returns to scale assumption using the average search intensity measure in Figure 3 as a dependent variable in addition to unemployment. We find that the coefficient of $\log(\bar{s})$ is positive and significant at the 1 percent level, suggesting the importance of the variation in job search effort in accounting for the behavior of the job-finding rate.[28] However, while the simple exercise suggests that search effort is important for aggregate job-finding rates, this approach is subject to both theoretical and econometric challenges. First of all, while Cobb-Douglas specification is accepted to provide a good description of the behavior of the aggregate job-finding rate, it is not clear whether this specification should still be used once the search intensity margin is taken into account. Moreover, since we find evidence that s and θ are correlated, we do not want to estimate a model that restricts the complementarity of these two inputs. In addition, even under this specification, Borowczyk-Martins, Jolivet, and Postel-Vinay (2013) argue that due to the endogeneity of vacancies, estimating the matching function using an OLS regression might lead to biased estimates.[29]

Instead of imposing a tight restriction on the structure of the matching function and trying

[27] 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).

[28] The results of this exercise are reported and discussed in appendix A.4.

[29] In Appendix A.4, we apply their methodology to our framework. However, we did not obtain a significant estimate likely due to weak instruments.

to estimate it, we set up a general equilibrium search and matching model with a generalized matching function. We then use this framework to isolate the class of matching functions that are consistent with our empirical findings in Section 3 as well as other important macroeconomic targets. Our goal in this exercise is twofold—first, rather than empirically estimating a matching function, we use the structure of a model to isolate the matching function that best summarizes the data. Second, we explore the performance of our model in explaining fluctuations in the job-finding rate and demonstrate the role of the intensive margin of search effort in accounting for recent labor market dynamics.

4.1 General setup

Our model extends the basic Diamond-Mortensen-Pissarides (DMP) model by Pissarides (1985) and Shimer (2005), used throughout the literature, by incorporating the search effort choice of workers and allowing for a generalized matching function. We consider an infinite-horizon setting with discrete time. A worker has to be matched with a vacant job to start working. 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 by unemployed workers in the economy, v_t is the number of vacancies, 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 her own search effort and $\theta_t = v_t/u_t$ is the labor market tightness. The probability of a firm finding a worker is denoted by $q(\bar{s}_t, \theta_t)$. We assume that the separation probability of a matched job-worker pair (σ) is constant. We also assume that the job-worker match produces z_t units of consumption goods in each period, where z_t follows a Markov process.

4.1.1 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:

$$J(S_t) = z_t - w(S_t) + \beta E[(1-\sigma)J(S_{t+1}) + \sigma V(S_{t+1})], \tag{5}$$

where $V(S_t)$ is the value of vacancy and $w(S_t)$ is the wage paid to the worker, and β is the discount rate. The expectation $E[\cdot]$ is taken with the knowledge of S_t. The value of a vacancy, $V(S_t)$, is

$$V(S_t) = -\kappa + \beta E[q(\bar{s}_t, \theta_t)J(S_{t+1}) + (1 - q(\bar{s}_t, \theta_t))V(S_{t+1})], \tag{6}$$

where κ is the vacancy creation cost. On the worker side, the value of being employed, $W(S_t)$, is given by

$$W(S_t) = w(S_t) + \beta E[(1 - \sigma)W(S_{t+1}) + \sigma U(S_{t+1})], \tag{7}$$

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

$$U(S_t) = \max_{s_{it}} \{b - c(s_{it}) + \beta E[f(s_{it}, \bar{s}_t, \theta_t)W(S_{t+1}) + (1 - f(s_{it}, \bar{s}_t, \theta_t))U(S_{t+1})]\} \tag{8}$$

where b is the income while unemployed and $c(\cdot)$ is the cost of job search. We assume that cost of job search is increasing and convex and define $c(s) = \phi s^{\omega}/\omega$, where $\omega > 1$. This formulation is consistent with the cost of search function in Pissarides (2000). The worker's first order condition is given by

$$c'(s_{it}) = \beta f_1(s_{it}, \bar{s}_t, \theta_t)E[W(S_{t+1}) - U(S_{t+1})]. \tag{9}$$

This equation specifies that the worker will increase their job search until the point where the marginal cost of job search equals the expected benefit of an additional unit of search, which is given by the relative expected benefit of being employed times the probability that the worker finds a job with that search effort. We denote the optimal search effort that satisfies (9) by s^*_{it}.

4.1.2 Wage determination

We assume that the equilibrium wage is determined by the generalized Nash bargaining. 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

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

denote the surplus to the firm and worker, respectively, from a match in state S_t. Then, the Nash bargained wage w solves

$$(1-\gamma)(\tilde{W}(w;S_t)-U(S_t))=\gamma(\tilde{J}(w;S_t)-V(S_t)). \tag{10}$$

$\gamma \in (0,1)$ represents the bargaining power of the worker.

4.1.3 Free entry and equilibrium

Lastly, to close the model, we assume free entry to vacancy posting, meaning that the value of a vacancy will go to zero. Using this and the firm's value functions, we can derive an expression for the value of a job to a firm:

$$J(S_t)=z_t-w(S_t)+\frac{(1-\sigma)\kappa}{q(\bar{s}_t,\theta_t)}. \tag{11}$$

This equation shows that the value of a match to a firm is increasing in their productivity, but decreasing in the wage and the ease with which they can hire other worker ($q(\bar{s}_t,\theta_t)$). Turning to the worker side, we can combine the worker's value functions to arrive at an expression for the wage in terms of the relative value to the worker of being employed, $W(S_t)-U(S_t)$:

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

Combining this with the Nash bargaining condition from (10) and the free entry condition that $V(S_t)=0$, we arrive at an expression for the expected wage which is given by:

$$E[w(S_{t+1})]=\frac{\gamma}{1-\gamma}\frac{\kappa}{\beta q(\bar{s}_t,\theta_t)}+b-E[c(s^*_{i,t+1})]-\frac{\gamma}{1-\gamma}E\left[\frac{(1-\sigma-f(s^*_{i,t+1},\bar{s}_{t+1},\theta_{t+1}))\kappa}{q(\bar{s}_{t+1},\theta_{t+1})}\right]. \tag{12}$$

Let us impose the equilibrium condition and denote $s_t=s^*_{it}=\bar{s}_t$. Then, combining (4.1.3) and (12), we solve out the wages and obtain the following equation in terms of s_t and θ_t

$$\frac{\kappa}{1-\gamma}=\beta q(s_t,\theta_t)E\left[z_{t+1}-b+c(s_{t+1})+\frac{1-\sigma-\gamma f(s_{t+1},s_{t+1},\theta_{t+1})}{1-\gamma}\frac{\kappa}{q(s_{t+1},\theta_{t+1})}\right]. \tag{13}$$

Lastly, Equation (9) can be rewritten as

$$c'(s_t) = f_1(s_t, s_t, \theta_t)\frac{\gamma}{1-\gamma}\frac{\kappa}{q(s_t, \theta_t)}. \tag{14}$$

Equations (13) and (14) determine the dynamics of θ_t and s_t. Note that the stock of unemployed, u_t, does not appear in either (13) or (14). This implies that the dynamics of θ_t and s_t, which are both jump variables, are not influenced by u_t and only determined by one state variable z_t.[30] The implication of this is that once we characterize the dynamics of θ_t and s_t from (13) and (14), we can determine the evolution of unemployment using

$$u_{t+1} = \sigma(1-u_t) + (1 - f(s_{it}, \bar{s}_t, \theta_t))u_t, \tag{15}$$

with the total population normalized to 1 and the number of employed workers given by $1-u_t$.

4.2 A generalized matching function

The key component in the specification of our model is the matching function. Recall that the goal of this exercise is to consider a general parameterized formulation of the matching function and use our empirical findings within the search and matching framework to determine the class of matching functions consistent with the data. The tight connection between our empirical findings in Section 3 and the form of the matching function is captured in Equation (14). Log-linearizing (14) around the steady state yields

$$\hat{s}_t = \Phi\hat{\theta}_t, \tag{16}$$

where "hat" ($\hat{}$) denotes the log deviation from the steady state. The coefficient Φ can be expressed as

$$\Phi = \frac{f_{13}\tilde{\theta}/f_1 - q_2\tilde{\theta}/q}{c''\tilde{s}/c' - (f_{11}+f_{12})\tilde{s}/f_1 + q_1\tilde{s}/q},$$

where "tilde" ($\tilde{}$) denotes the value at the steady state. The values of f_i, f_{ij}, q, and q_i are evaluated at the steady state, where the subscripts denote partial derivatives and double-subscripts denote cross derivatives. This expression shows that the sign of Φ, which captures

[30] Note that θ_t depends on u as it is defined as v_t/u_t but is a jump variable because v_t is a jump variable.

whether search effort responds negatively or positively to θ and is what we estimated in our empirical analysis, depends crucially on the form of the matching function.

Quantitatively, we start from a *generalized matching function* where the job-finding rate is given by:

$$f(s, \bar{s}, \theta) = \chi \left(\alpha s^{\psi} + (1 - \alpha) \left(\frac{s}{\bar{s}} \right)^{\xi} \theta^{\psi} \right)^{\eta}. \tag{17}$$

This corresponds to the matching function

$$M(\bar{s}, u, v) = \chi \left(\alpha \bar{s}^{\psi} + (1 - \alpha) \left(\frac{v}{u} \right)^{\psi} \right)^{\eta} u. \tag{18}$$

with $\chi > 0$ and $\alpha \in [0, 1]$. Note that this formulation is a departure from the Pissarides' (2000, Chapter 5) assumption that $f(s, \bar{s}, \theta)$ is proportional to s. In addition, this specification nests some important special cases:

1. When $\xi = \alpha = 0$ and $\psi\eta \in (0, 1)$, (18) reduces to the standard DMP matching function in Cobb-Douglas form, without workers' search effort. We refer to this specification as the *basic Cobb-Douglas case*.

2. 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 $\chi(\bar{s}u)^{\alpha} v^{1-\alpha}$. This is a Cobb-Douglas special case of Pissarides (2000, Chapter 5). We refer to this specification as the *Cobb-Douglas case with search effort*. Note that in this case, the job-finding probability is proportional to the intensive margin of search effort s. It is easy to see that it is always the case that $f_{13} > 0$ with this formulation. That is, s and θ are *complementary* inputs, and Φ is always positive.

3. When $\alpha = 1$ and $\psi\eta = 1$, the job-finding probability is linear in s, as in Christiano, Trabandt, and Walentin (2012). We refer to this specification as the *linear case*.

In all cases, this generalized form of the matching function should satisfy some restrictions on parameter values to ensure that these functions exhibit regular properties, namely that

$f(s, \bar{s}, \theta)$ is increasing in s and θ and $q(\bar{s}, \theta)$ is increasing in $\bar{s}$ and decreasing in θ. First, in order for the matching function to be increasing in $\bar{s}$ and v, ψ and η have to have the same sign. Second, the matching function has to be increasing in u. We assume that $\psi\eta < 1/(1-\alpha)$ holds in order to satisfy this property around $s = 1$ and $\theta = 1$.

4.3 Log linearization

Plugging the assumed functional forms for both the matching function and the cost of search into (14) and log linearizing around the steady state, we obtain a simplified version of Equation (16) [31]

$$\hat{s}_t = \Phi\hat{\theta}_t = \frac{\alpha\tilde{s}^{\psi} - (\psi-1)(1-\alpha)\tilde{\theta}^{\psi}}{\omega\alpha\tilde{s}^{\psi} + (\omega-\psi)(1-\alpha)\tilde{\theta}^{\psi}}\hat{\theta}_t. \tag{19}$$

Evaluating this expression at the steady state $\tilde{s} = 1$ and $\tilde{\theta} = 1$, we can simplify this equation to:

$$\Phi = \frac{1-\psi(1-\alpha)}{\omega-\psi(1-\alpha)}. \tag{20}$$

We are going to assume that ω is sufficiently large so that denominator is always positive. Then, Equation (20) implies that Φ is negative if and only if $\psi > 1/(1-\alpha)$. This equation defined the relationship between θ_t and s_t. Log-linearizing (13) and using (19), we obtain the equation defining the relationship between θ_t and z_t:

$$\mathcal{A}\hat{\theta}_t = E[\tilde{z}\hat{z}_{t+1} + \mathcal{B}\hat{\theta}_{t+1}], \tag{21}$$

where

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

and

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

[31] 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

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

Since we 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 $\tilde{z} = 1$), the equilibrium $\hat{\theta}$ has to take the form

$$\hat{\theta}_t = \Omega\hat{z}_t, \tag{22}$$

The method of undetermined coefficients implies that

$$\Omega = \frac{\rho}{\mathcal{A} - \rho\mathcal{B}}. \tag{23}$$

Equations (20) and (23) determine the equilibrium dynamics of θ_t and s_t.

4.4 Quantitative exercises

4.4.1 Calibration

We start our quantitative exercise by calibrating a subset of parameters to standard values common in the literature. We assume that a period in the model is a month, and thus, following Cooley and Prescott (1995), we set $\beta = 0.987^{\frac{1}{3}}$ and $\rho = 0.95^{\frac{1}{3}}$. Following Shimer (2005), we set the bargaining power of the worker to $\gamma = 0.72$ and the exogenous separation probability to $\sigma = 0.034$. Following the preferred specification in Yashiv (2000), we set the convexity of the search cost function to $\omega = 2$. We set $\tilde{\theta} = 1$ and $\tilde{s} = 1$ in the steady state and choose χ so that the steady-state job-finding rate $\chi(\alpha\tilde{s}^{\psi} + (1-\alpha)\tilde{\theta}^{\psi})^{\eta} = \chi(0.1+0.9)^{0.3} = 0.49$. Thus $\chi = 0.49$.

A new calibration target specific to our setting is the cyclical responsiveness of aggregate search effort, which we denoted as Φ in $\hat{s}_t = \Phi\hat{\theta}_t$. Our empirical evidence strongly suggests that aggregate search effort is countercyclical and therefore Φ is negative. Specifically, we estimate Φ by running a regression of the cyclical component of $\log\theta$ on the cyclical component of $\log s$, which yields an elasticity of $\Phi = -0.15$.[32] We add this additional target to our calibration and compute the set of matching function specifications consistent with this moment.

What does this imply for the parametrization of the matching function? Equation (20) shows that the *sign* of Φ is determined only by the values of α and ψ, which are the non-

[32] The cyclical components of market tightness and search effort are plotted in Appendix B.2.

Calibrated Parameters	Value	Source
β	0.996	Cooley and Prescott (1995)
ρ	0.983	Cooley and Prescott (1995)
γ	0.72	Shimer (2005)
σ	0.034	Shimer (2005)
ω	2	Yashiv (2000)
χ	0.49	Job-finding rate
α	See Table 7	
ψ	See Table 7	
b	0.7	Hall and Milgrom (2008)
Implied Parameters		
η	See Table 7	$\eta = 1/\psi$
κ		Equation (13) and (14)
ϕ		Equation (13) and (14)

Table 6: Calibrated parameters.

standard parameters in our matching function.[33] Figure (5) depicts the combinations of the (α, ψ) values that gives rise to $\Phi < 0$, from Equation (20). As we see analytically from (16), the necessary condition for $\Phi < 0$ is $f_{13} < 0$. Figure 5 shows that this condition corresponds to the set of α and ψ in the shaded region above the black line. The property $f_{13} < 0$ implies that s and θ are *substitutes* as inputs of the job-finding process. In other words, the marginal product of individual search is lower when θ is high. Intuitively, this corresponds to a situation where a favorable labor market conditions for a worker (a high θ) means that the search effort of the worker is less effective in generating a job offer (although the *level* of job-finding probability is high for a given s since θ is high). In booms, job opportunities are abundant, but spending an additional unit of job search effort affects the the number of job offers the workers receive less than it affects in recessions.

Importantly, the purple line shows the set of α and ϕ that are consistent with our estimated $\Phi = -0.15$. Lastly, the orange and blue lines represent the parameters that correspond to the special cases we discussed above—the Cobb Douglas case with search effort and the linear case. Within the structure of this model, both of these cases are inconsistent with our empirical

[33]Note that for a given ψ and α, η has to be set in order to satisfy $\psi\eta < 1/(1-\alpha)$. We set $\eta = 1/\psi$ in order to satisfy this inequality for any value of α.

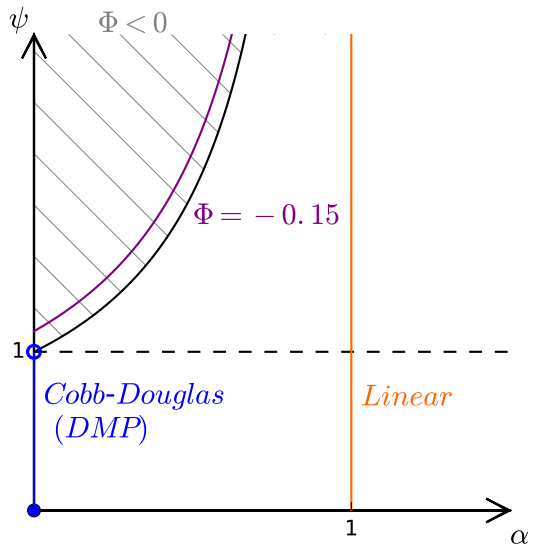


Figure 5: Set of parameters consistent with $\Phi = -0.15$

finding that search effort and θ are negatively related.

Given the previously calibrated parameters, the steady-state versions of (13) and (14) determine the values of κ and ϕ. Finally, we need to calibrate the value of b. This is directly linked to the value of nonemployment, $b - \phi\tilde{s}^{\omega}/\omega = b - \phi/\omega$. We set the value of nonemployment to be 0.7, following Hall and Milgrom (2008). The parameter values are summarized in Table 6.

From the set of parameters identified by the purple line in 5, we select the ones that minimize the distance between the implied job-finding rate and the actual job-finding rate observed in the data. Specifically, we compute the job-finding rate implied by (18) for all combinations of parameters α and ψ feeding in the realized time series for θ and $\bar{s}$ and pick the parameters with the best fit. The resulting parameters are summarized in Table 7. Figure 6 plots the time series for the job-finding rate, calculated following Shimer (2005), against the time series for the job-finding rate that is implied by the model with the best-fit parameters. As the figure shows, the generalized matching function captures the behavior of the job-finding very well in the early part of the sample, underestimates it in the mid 2000s and slightly overestimates it

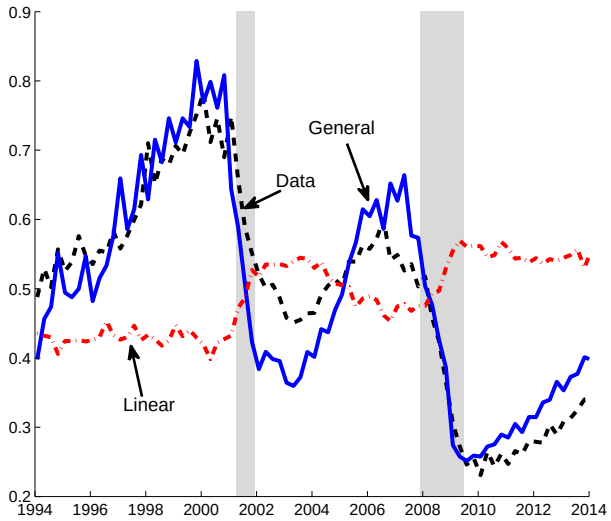


Figure 6: The job-finding rate implied by the generalized and linear matching specifications and the data. Data and model outcomes are plotted as quarterly averages of monthly observations.

	Matching Function	Full Sample Parameters			Pre-Recession Parameters		
		χ	α	ψ	χ	α	ψ
General	$\chi\left(\alpha\bar{s}^{\psi}+(1-\alpha)\left(\frac{v}{u}\right)^{\psi}\right)^{\frac{1}{\psi}}u$	0.49	0.15	1.33	0.49	0.37	1.18
Linear	χsu	0.49	–	–	0.49	–	–

Table 7: Parameters of the generalized and linear matching function specifications plotted in Figure 6.

in the later part of the sample.

The red line in Figure 6 plots the job-finding rate implied by the best fitted linear specification, χsu, which is used by Christiano, Trabandt, and Walentin (2012). This specification fails in two important dimensions: the implied job-finding rate is countercyclical and its fluctuations are much smaller than in the data. This findings suggest that the linear matching function specification—when calibrated to match the time series evidence on search intensity—fails to capture the behavior of the job-finding rate.

4.4.2 Implications for recent labor market dynamics

In this section we explore the role that job search effort played in the labor market movements during the Great Recession, and specifically the much discussed decline in the efficiency of the matching process.[34] The main indication of such a shift was a job-finding rate that was substantially lower than what would be suggested by the matching function relationship observed over the pre-Great recession period. While the generalized matching function fitted to match the job-finding rate in the 1994-2014 period captures the evolution of the job-finding rate well, it overestimates the rate in the later part of the sample, an indication of the decline in the efficiency parameter, χ.

Various explanations have been offered for this decline including skill and geographic mismatch, decline in the search effort of the employers (recruiting intensity), and decline in the search intensity of job seekers. To be able to isolate the contribution of search intensity to changes in match efficiency, we now focus on the pre-recession period and estimate the parameters of our generalized matching function using data up to 2008. We then allow for the efficiency parameter (χ) to vary over time, and solve for the values of χ that would be needed to perfectly match our implied job-finding series to the actual job-finding rate series. We do this exercise using two different generalized matching functions: first, we feed in the time series for $\bar{s}$ and use the best-fit pre-recession parameters from Table 6; second, we shut down variation in $\bar{s}$ and instead impose that $\bar{s} = 1$ and continue to use the same pre-recession best-fit parameters. These two implied series for $\chi_t^{\bar{s}}$ and $\chi_t^{\bar{s}=1}$ are plotted in the left panel of Figure 7. The figure shows that this generalized matching function implies that there was about a 20 percent decline in $\chi_t^{\bar{s}=1}$ from 2009 to 2010 compared to an about 30 percent decline in $\chi_t^{\bar{s}}$. Since search effort rose during this time period and is substitutable with market conditions in the matching function, it moderated the decline in matching efficiency. Indeed, not only does the variation in search effort not explain the decline in matching efficiency, it also makes the drop bigger.

[34] See for example, Elsby, Hobijn, and Şahin (2010), Barnichon and Figura (2015), and Davis, Faberman and Haltiwanger (2012, 2013).

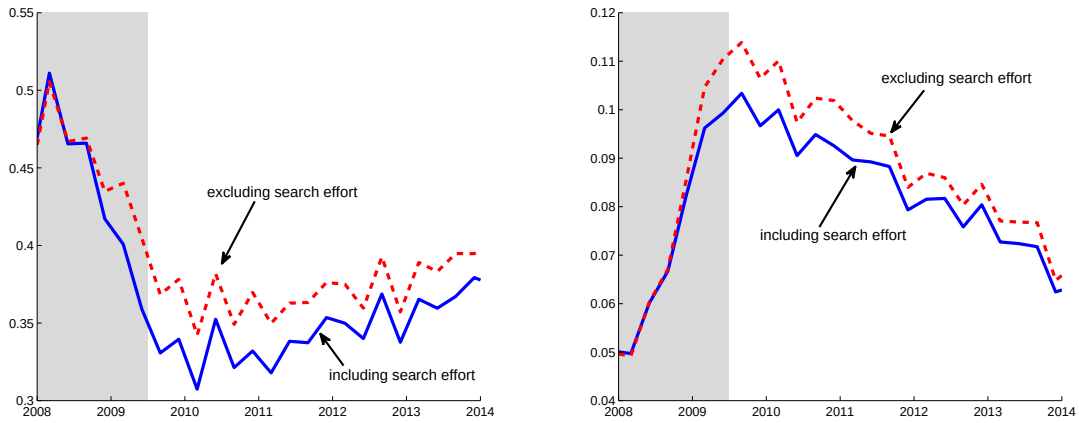


Figure 7: Left panel: $\chi_t^{\bar{s}}$ and $\chi_t^{\bar{s}=1}$; Right panel: The flow steady-state unemployment rate with and without variation in search intensity, quarterly averages of monthly observations.

This is in line with the discussion in Elsby, Michaels, and Ratner (2015) who examine whether the decline in search intensity could explain the *outward* shift in the Beveridge curve. Similar to us, they also conclude that the increase in search intensity during and after the recession would contribute to an *inward* shift in the Beveridge curve, since as workers search harder fewer vacancies are needed to maintain the same level of the unemployment rate, the opposite of the pattern in the post Great recession period.

Finally, in a similar exercise, we quantify how the unemployment rate would have evolved absent the rise in search effort among unemployed workers. We do this by calculating the flow steady-state unemployment rate using the job-finding rate implied by the generalized matching function, $\chi_t^{\bar{s}}(\alpha\bar{s}^{\psi} + (1-\alpha)\theta^{\psi})^{\eta}$, and the job-separation rate observed in the data. We calculate this both assuming $\bar{s}$ moves as in the data and, separately, assuming that $\bar{s}$ is constant at 1.[35] As the right panel of Figure 7 shows, the increase in search intensity during and following the Great recession moderated the increase in the unemployment rate. Absent this increase, the unemployment rate would have peaked at around 11 percent (instead of 10 percent) and would have been consistently higher by about 0.5 to 1 percentage points during the recovery.

[35]Note that flow steady-state unemployment is calculated as $s_t/(s_t + f_t)$ where s_t is the separation rate and f_t is the job-finding rate. Details of this calculations follow Shimer (2005).

These quantitative exercises suggest three important takeaways. First, any search model that includes the intensive margin of search effort should include a matching function that features *substitutability* between the search effort and market tightness. Second, search effort does not act as an amplifier of labor market fluctuations once its empirical behavior is correctly incorporated into the search and matching framework. Third, fluctuations in search intensity do not account for the decline in the measured matching efficiency during and after the Great Recession. If anything, increasing search intensity moderated the rise in the unemployment rate and contributed to its decline.

5 Conclusion

In this paper, we examined the cyclical pattern of job search effort and found that aggregate job search effort by nonemployed workers is countercyclical, along both the extensive and intensive margins. We have shown that this countercyclical pattern is the consequence of the cyclical shifts in the composition of the unemployed pool as well as individuals' responses to changes in macroeconomic conditions.

Our result that the aggregate search effort of nonemployed workers is countercyclical has several important implications for theoretical analyses of labor markets. While most business cycle models abstract from modeling workers' search effort, there are some exceptions which allow for variation in search intensity. In these models, workers' search effort responds procyclically to economic conditions. When worker search effort is procyclical, variations in the search decisions can generate realistic labor market fluctuations either as the primary source of fluctuations or as an amplifier of other sources of fluctuations.[36] In these models, the returns to work, i.e. wages, are lower during recessions. Since in this case return to search is lower, unemployed workers reduce their search effort, causing an increase in the unemployment rate during recessions. However, we have shown that the opposite is true in the data. Aggregate

[36]See, for example, Veracierto (2012) and Christiano, Trabandt, and Walentin (2012), Gomme and Lkhagvasuren (2015).

search intensity of workers increases during recessions, and thus cannot be the primary driver of the labor market fluctuations over the business cycle. Instead, the increase in worker search effort during recessions dampens the fluctuations in labor demand.

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Appendix Not For Publication

A Data Appendix

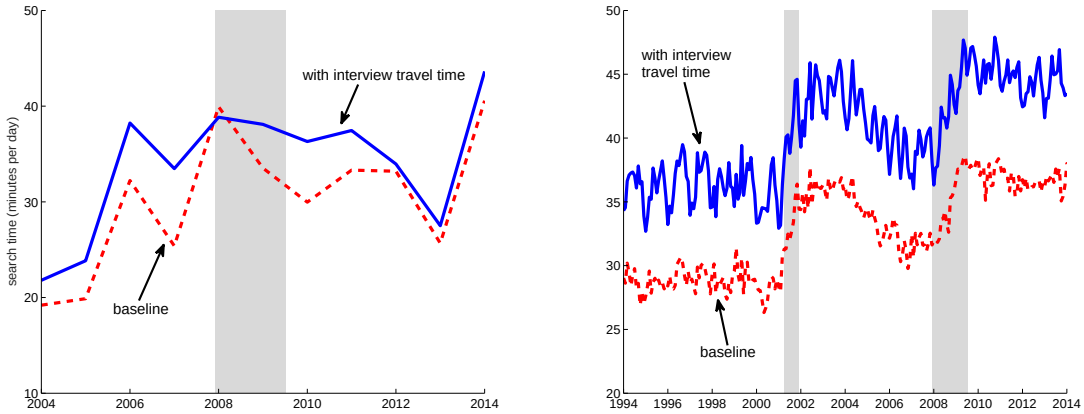
A.1 Data construction

This appendix describes the data sources used in this analysis in greater detail. From the ATUS, we use the Multi-Year microdata files. The advantage to using the multi-year files as opposed to the individual year files is that they provide consistent population weights across years. However, this comes at the cost of slightly less detailed job search categories. As explained in Section 2.1, we define define job search activities to include all search, interviews and time spent 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 traveling to interviews (180311) in our job search measure. Figure A1 plots the ATUS time series with and without interview travel time as well as the imputed minutes computed as before but including travel time in measured minutes in the imputation regression.[37] We see that while including this additional category affects the level of search effort, the cyclicality of our series is unaffected. Therefore, we continue the main analysis without travel time included in our search time.

We impose several important sample restrictions on the ATUS data. In order to restrict our sample to people who have completed their education and are still active workers, we restrict our respondents to be those between the ages 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.[38] Per year, this leaves us with around 2,500 nonemployed respondents, around 400 classified unemployed active searchers and 130 respondents who report positive search time.

[37] Note that search time including interview travel time is not strictly greater than the series without interview travel time because of the way we drop outliers. We drop any obervation that implies more than 8 hours a day of job search. If adding interview travel time to the observation puts the individual above 8 hours, that individual is then dropped from the sample with interview travel time but is not excluded from the sample without travel time.

[38] Our results are not sensitive to this assumption. We repeated our analysis about aggregate search effort using the the full sample including all reported search time and found qualitatively similar results.



(a) reported minutes of search in ATUS

(b) Imputed minutes of search in CPS

Figure A1: Reported and imputed search time with and without travel to interviews included as search time.

From the CPS, we use monthly basic samples from January 1994 through December 2014. Again, we restrict our 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 3.3, we match our sample across the eight survey months.[39] 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.

A.2 Details on linking the ATUS and the CPS

Let Y_{it} be the search time we observe in the ATUS for worker i at time t. We are not interested in Y_{it} per se – Y_{it} contains one day's sample from the search activities in the 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, $E[Y_{it}]$,

[39] 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 of their first month in the survey (mis).

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 aim is to obtain $E[Y_{it}]$ for every respondent. Since we do not observe it directly, we estimate it from the observed characteristics and the search methods the respondent reports using. We first estimate $E[Y_{it}]$ based on the characteristics X_{it} (denote the estimate as $E_X[E[Y_{it}]]$). From the above equation,

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

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

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

and we could follow a simple two-step procedure in which we estimate $E_X[P_{it}]$ using a probit regression and $E_X[E[M_{it}]]$ using OLS.[40] However, the assumption that $cov_X(P_{it}, E[M_{it}]) = 0$ is unlikely to hold in our setting, as there is likely to be a positive relationship between the probability that a respondent is observed searching on a given day and how much one search conditional on searching at all.

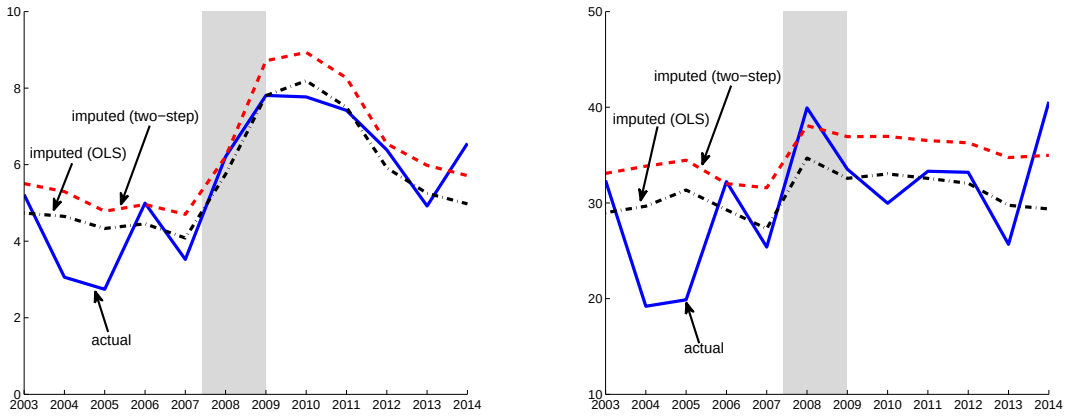
Therefore, we need to take into account that $cov_X(P_{it}, E[M_{it}]) \neq 0$ in our estimation. The procedure for doing this is the Heckman two-step selection procedure. Note that since we do not have an instrument that shifts the probability that we observe positive search time but not how much they search conditional on positive search time, this covariance is estimated using the functional form assumptions embedded in the probit estimation of the selection equation. Through this method, we are able to impute a strictly non-negative amount of search time for all non-employed respondents in both the ATUS and CPS.

[40] Note that this is the assumption we imposed in a 2014 working paper draft of this paper.

In this imputation, we include as predictors both dummies for each of the twelve search methods and two sets of observables. The first set of controls includes 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, dummies for education levels (high school diploma, some college, college and college plus), race, gender, and marital status. We also add the interaction term of female and married since being married is likely to affect the labor market behavior of men and women differently. The second set of 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, being on temporary layoff, and being a out of the labor force but wanting a job.

A much simpler, although likely biased, method 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 A2 shows a comparison of the actual reported minutes, the imputed minutes using the two-step selection procedure and the imputed minutes using the simple OLS regression. Unsurprisingly, we see that the OLS provides a better within-sample fit but is lower than the search time resulting from the Heckman procedure. The two imputation methods produce similar results. Additionally, we also explored a version of the regression where we allow the relationship between search methods and search time to vary by gender and with age. Figure A3 shows that the resulting cyclicality of the search effort series is very similar with and without these additional interactions.

As mentioned above, in each of these imputation methods, we assume that the search time (or the log of 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



(a) all nonemployed

(b) unemployed

Figure A2: Actual and imputed average search minutes per day for all nonemployed workers and unemployed workers using the 2 imputation methods

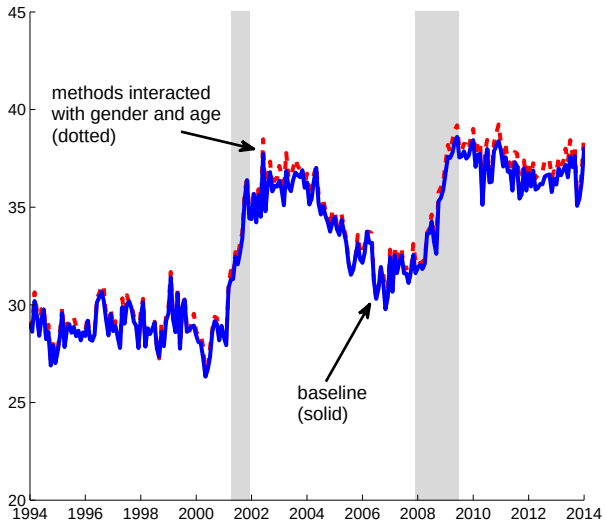


Figure A3: Cyclicality of Search effort allowing for interactions between search methods and demographic controls

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

To explore this possibility, we first include year dummies in the regression.[41] Results in Table A1 show that the only statistically significant coefficients are in 2004 and 2005 and therefore there is no strong evidence that the intensity with which people use various methods changes during the recession. Figure A4 shows the mechanical reason that the fit of the regression is worst in 2004 and 2005: while reported search time (dashed line, right scale) and number of methods used (solid line, right scale) track each other closely for most of the sample, the relationship breaks down in these two years. In particular, there is a decline in search time in 2004 to 2005 that is not mirrored in the number of methods. As a result of the divergence of these two measures in these years, the imputation method overestimates the total search time in 2004 and 2005.

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 (2008–2014) sample. We then calculate the imputed minutes for each of the subsamples and explore the in and out of sample fit. Figure A5 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. This is likely the result of the relationship between minutes and time in 2004–2005 showcased in Figure A4.

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

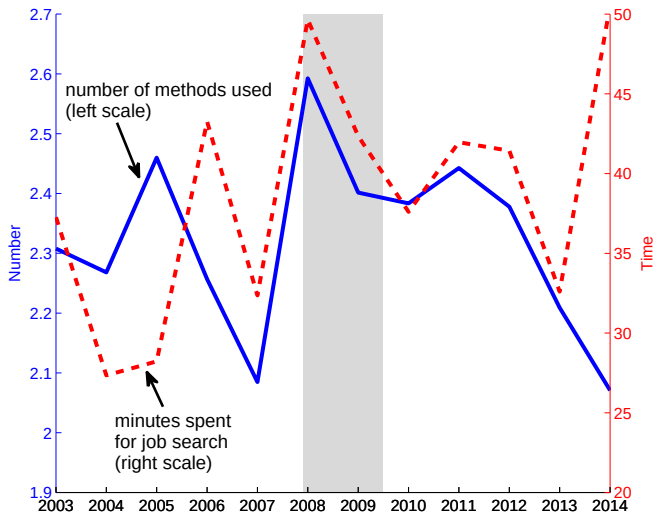
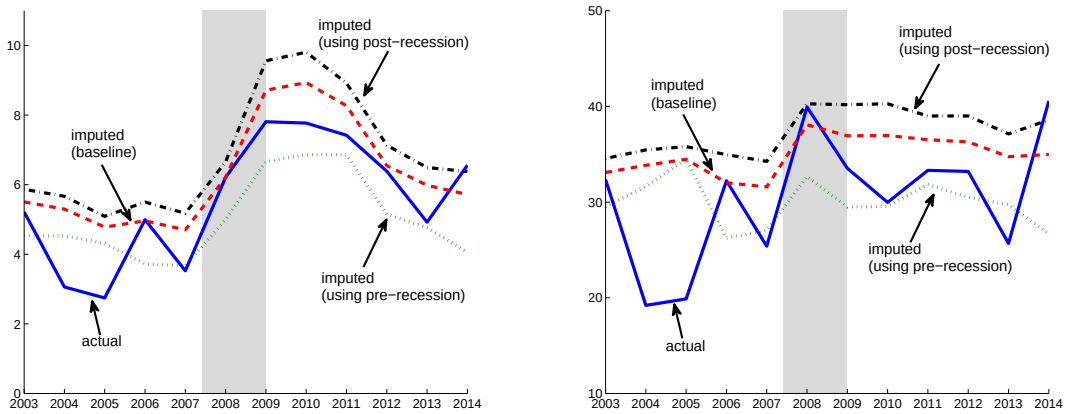


Figure A4: Minutes spent on job search activities and number of search methods in the ATUS sample



(a) all nonemployed

(b) unemployed

Figure A5: Average search minutes per day for all nonemployed workers and unemployed workers using pre- and post-recession samples of ATUS data.

	Search Time
2004	-2.02^{**}
	(0.82)
2005	-2.05^{**}
	(0.82)
2006	0.09
	(1.07)
2007	-1.04
	(0.94)
2008	0.06
	(1.23)
2009	-0.33
	(1.10)
2010	-0.70
	(1.12)
2011	-0.52
	(1.05)
2012	0.05
	(1.06)
2013	-0.79
	(0.98)
2014	1.13
	(1.41)

Table A1: Time dummy estimates from OLS regression of reported search time on search methods.

Lastly, we explore the effect of including aggregate macro-economic indicators in the imputation procedure. As discussed in Section 2.3, we include each aggregate measure separately and interact with each search method, essentially allowing the relationship between search time and a particular search method to vary over the business cycle. Figure A6 shows the imputed minutes that result from estimates that include either cyclical component of GDP, the unemployment rate, or the vacancy-to-unemployment (θ). The imputation allowing the relationship to vary with either of the labor market indicators is similar to our baseline, but somewhat more cyclical. Thus, our benchmark imputation method is the most conservative one for representing the cyclicality of search effort.

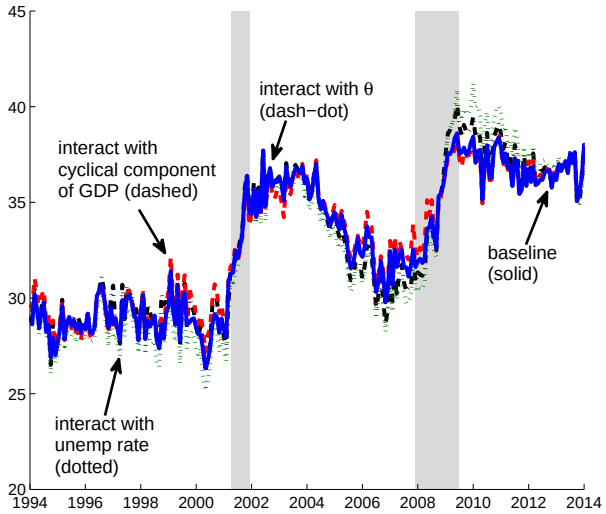
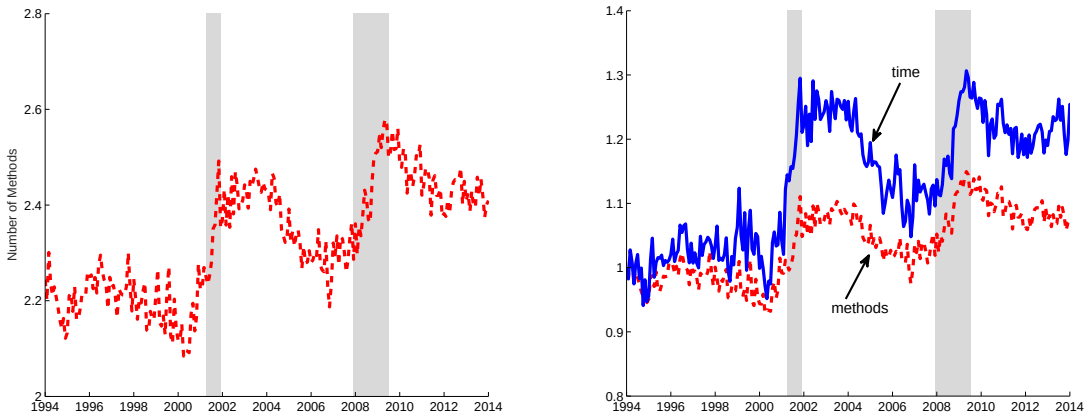


Figure A6: Imputed minutes in the CPS using market aggregates.

A.3 Additional results for the cyclicality of search effort

A.3.1 Robustness of time series analysis

In order to examine the robustness of our aggregate results in Section 3, we present a number of additional measures of the intensive and extensive margins. The left panel of Figure A7 shows the time series of the average number of search methods used in the CPS over our sample period. This more simple measure of search effort shows a countercyclical pattern very similar to Figure 3 in the main text. There are two differences between this count measure and our imputed minutes measure. First, our measure weights each search method differently according to the estimated time intensity. Secondly, our minutes measure allows for baseline search effort to vary by demographic characteristics. The right panel of Figure A7 plots our imputed minutes measure with the average number of methods, both normalized to 1 in the initial period to account for differences in scale. The two series have a correlation of 0.94, but we see that the imputed minutes measure of search effort is more volatile than the simple count of the number of methods. This suggests that either individuals shift to more time intensive search methods in recessions or that the composition of the unemployed pool shifts towards



(a) Average number of search methods

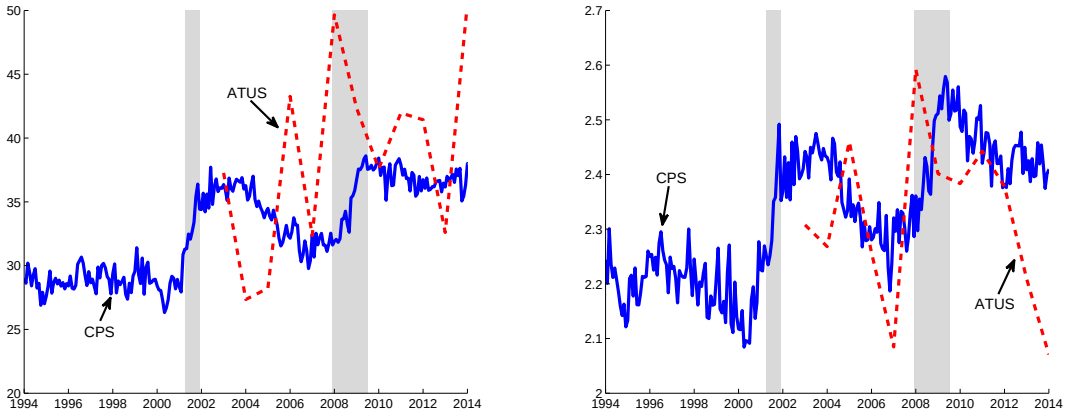
(b) Comparison of the number of search methods (dashed) and search time (solid)

Figure A7: Two measure of the intensive margin of job search.

higher search demographics over the business cycle.

To directly compare the search time information in the ATUS and the CPS, Figure A8 plots search time (left panel) and the average number of search methods (right panel) from the CPS sample and the ATUS sample. As discussed in Section 2.1, 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 during the Great Recession.

Although our main analysis begin in 1994 (when the CPS began allowing individuals select from up to 12 possible search methods), we can still present a modified historical analysis beginning in 1976. Prior to 1994, the CPS basic monthly survey allowed respondents to report up to six job search methods from a list of six possible methods. These were limited to: contacting a public employment agency, contacting a private employment agency, contacting employers directly, asking friends or relatives, placing or responding to ads, and other. The first five of these search methods were also options after the 1994 redesign as well. Therefore, in order to create a time series of search intensity that is consistent over the full sample, we restrict our attention to the first five major search methods. Since the additional job



(a) Average minutes of search (per day)

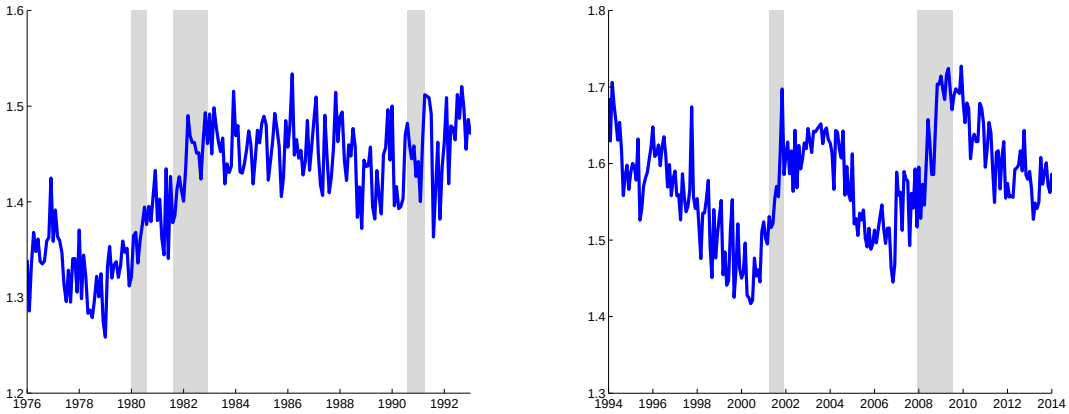
(b) Average number of search methods

Figure A8: Intensive margin measures in the ATUS and the CPS

search categories created in the 1994 re-design are essentially an expansion of the catch-all category "other," the average number of methods is likely to increase post-1994 if having additional options encourages them to distinguish between various activities that they would have otherwise grouped under the same heading. Figure A9 shows the time series of the average number of reported search methods, selected from these five possible search methods.[42] The left panel shows the series from 1976–1993 and the right panel shows the series from 1994-2014, shown separately to account for the remaining discontinuity at the 1994 redesign. We see that the countercyclical pattern of job search effort is weaker but also evident in the earlier data as well, with large rises in search effort around the early 1980 recessions.

Lastly, Figure A10 plots the time series of the fraction of the unemployed who are using each search method. The figure shows that each search method shows a slightly different time series, with some, such as "contacting an employer directly" trending down and others, like "contacting friends or relatives" trending up. The figure also shows that the cyclical increase in the number of search methods is more pronounced in some methods than others.

[42]The sample of individuals who were asked the job search methods question also changed after the 1994 redesign. While the job-search methods were only asked to those who were unemployed and actively looking for a job post-1994, the question was asked to anyone who was looking for work prior to 1993. Because of this change, the ATUS imputation regression does not control for labor force status and is only run on those who have non-missing search methods information.



(a) 1976–1993

(b) 1994–2012

Figure A9: Historical time series of the average number of job search methods (from 5 methods)

A.3.2 Robustness of individual level analysis

In this section, we present the details of our exploration of the determinants of aggregate search effort. First, we discuss the details of the multiple imputation method that we use to calculate the standard errors in Table 5. Second, we report additional results that demonstrate the robustness of the qualitative results in Table 5.

Using a standard regression in Table 5 would overstate the confidence in the estimates as it does not take into account the fact that search effort itself is imputed and therefore is estimated with error. In order to take this into account, we follow the following multiple imputation procedure:

1. Draw a sample of size N in the ATUS with replacement. Use this sample to impute $\hat{s}_{it}$ in the CPS using the Heckman two-step selection correction procedure.

2. Estimate Equation 4 at the individual level.

3. Repeat step 1 and 2 m times and calculate the coefficients and standard errors using the following formulas (Rubin 1987):

$$\beta_{mi} = \frac{1}{m} \sum_{i=1}^{m} \beta_i$$

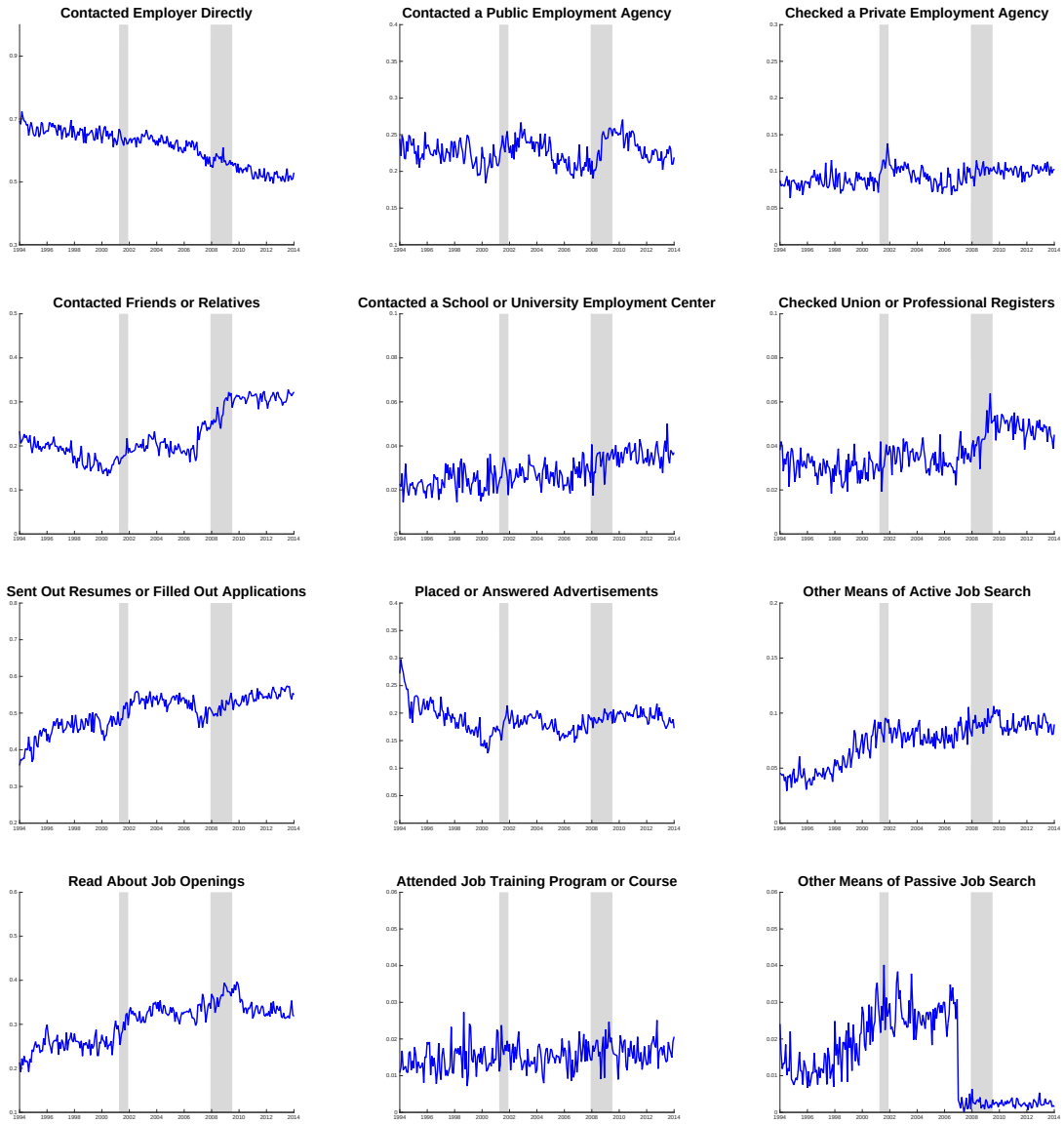


Figure A10: The fraction of unemployed using each search method.

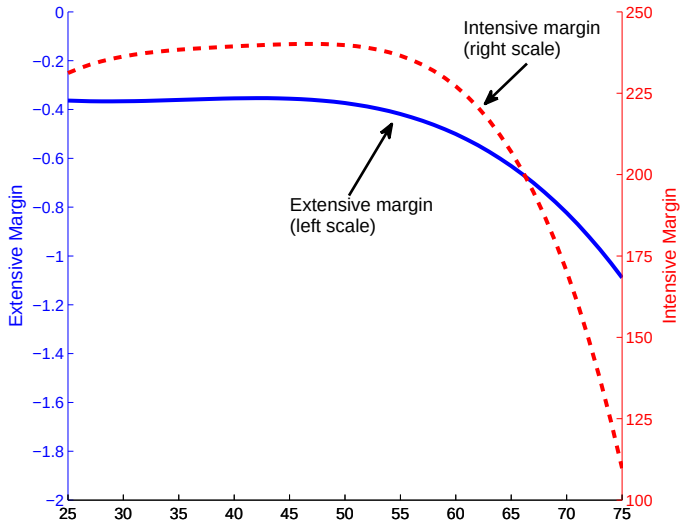


Figure A11: The effect of age on the intensive and extensive margins of job search. Quartic polynomial coefficients from regression 4

.

and

$$\text{s.e.}\beta_{mi} = \frac{1}{m}\sum_{i=1}^{m}\text{s.e.}\beta_i + \left(1+\frac{1}{m}\right)B$$

where

$$B = \frac{1}{m-1}\sum_{i=1}^{m}\left(\text{Var}(\beta_i) - \frac{1}{m}\sum_{i=1}^{m}\text{Var}(\beta_i)\right)$$

The point estimate is the average across the simulations while the standard error is a combination of the average within-imputation variance plus the between-imputation variance.

The following set of results expand on those reported in Table 5. First, Figure A11 shows the age-search effort profile, estimated using a quartic polynomial in regression 4. The extensive margin falls over the most of the lifecycle, while the intensive margin stays almost flat (increasing slightly) before starting to fall after 50 years of age.

The duration of unemployment is often considered an important determinant of job search effort. In many models, agents' search effort responds 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 job search time in the opposite direction over the unemployment spell. Human capital depreciation is one of these. 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 reason 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.

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 A12 plots the response of search intensity to unemployment duration. This result is similar to Shimer's (2004) findings. Search effort initially rises with unemployment duration and then goes down (and slightly goes up). When we change the specification to cubic and quintic polynomials, we find that, while the other coefficients of the regressions are robust to the degree of the polynomial in unemployment duration, the peak of the graph changes. This result is consistent with the result of Shimer (2004).

Table 5 demonstrated the behavior of individual search effort over the business cycle by looking at its correlation with $\theta = v/u$. While this measure is both a good indicator of the labor market and a measure that most directly maps into the search model framework, we

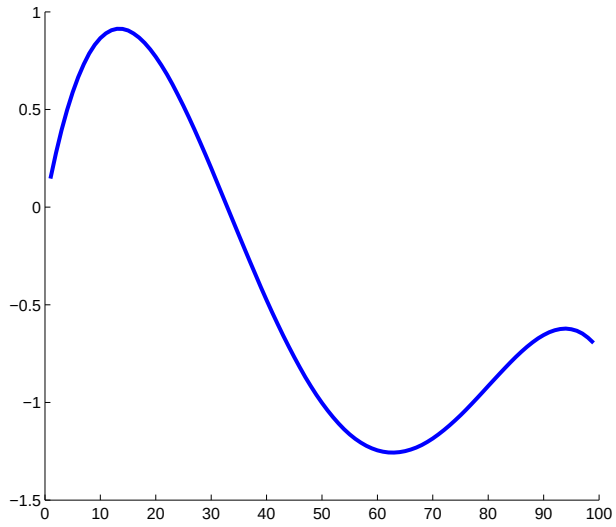


Figure A12: The effect of unemployment duration on the extensive margin of search. Drawn from the quartic polynomial coefficients in regression (4)

can also explore the co-movement of search effort with other cyclical indicators. Table A2 explores the sensitivity of the findings in Section 3.3 to various alternate measures of the business cycle. For compactness, the table only reports the specifications with individual fixed effects, although the results with controls only show similar patterns. Specifically, Column 1 uses state-level market tightness, which is only available beginning in May 2005 and Columns 2–4 show the countercyclical relationship with different wealth measures. Overall, we see statistically significant negative relationships between job search effort at the individual level and the business cycle.

Lastly, Table A3 explores the sensitivity of our estimates to the sample selection induced by the semi-panel structure of the CPS. Specifically, in using fixed effects, we restrict the sample to individuals who are unemployed for 2 or more months in our sample. While we cannot use the fixed-effects specification on any larger sample, Table A3 reports the specifications with and without observable controls for the full CPS sample. We see that for these specifications, the patterns are very similar in that adding controls decreases the coefficient on the cyclical parameter. This suggests that the sample selection induced by the panel structure is minimal.

	State HWOL	S & P	House Price	State House Price	Payroll Employment
log (Indicator)	-4.356	-7.411	-17.305	-14.147	-1066.019
	(0.985)	2.055	5.059	4.881	294.813
Unemployment Duration	0.113	0.154	0.163	0.164	0.161
	(0.052)	0.049	0.050	0.050	0.050
Unemployment Duration^2	-0.005	-0.008	-0.008	-0.008	-0.008
	(0.002)	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	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
No. Obs.	302578	528726	528726	528726	528726

All regressions include individual fixed effects. Coefficients and standard errors are calculated using multiple imputation methods described in detail in Appendix A.3.2. Column 1 includes data from May 2005-Dec 2014, and columns 2-4 include data from Jan 1994-Dec 2014.

Table A2: The relationship between individual search effort and various business cyclical variables.

A.4 Matching function estimation

We begin this section by estimating the aggregate matching function including our measure of search effort. Typical matching function specifications assume that the only search input in the economy on the worker side is the number of unemployed workers. To illustrate the importance of the intensive margin of search intensity on aggregate labor market outcomes, we consider simple linear regressions under the constant returns to scale assumption with alternative measures of search effort. Note that the analysis in Section 4 suggests that the Cobb-Douglas assumption is not supported in the data. However, this empirical specification provides a useful benchmark.

We consider the formulation

$$\log(f_t) = \delta_0 + \delta_\theta \log(\theta_t) + \delta_s \log(\bar{s}_t) + \delta_d d_t + \boldsymbol{\tau_t}'\boldsymbol{\delta_\tau} + \varepsilon_t, \tag{A1}$$

where f_t is the job-finding probability, $\theta_t \equiv v_t/u_t$ where v_t is the number of vacancies and u_t is the number of unemployed, $\boldsymbol{\tau_t}$ is the vector of month dummies for each month of a year, and

	Composite Help-Wanted Index (1994-2014)		JOLTS (2001-2014)	
	Basic	Observables	Basic	Observables
log (θ)	-7.519^{***}	-5.264^{***}	-4.459^{***}	-3.343^{***}
	(0.668)	(1.091)	(0.915)	(0.893)
Age	.	42.402^{***}	.	45.888^{***}
		(6.790)	.	(6.982)
Age^2	.	-1.388^{***}	.	-1.504^{***}
		(0.260)	.	(0.268)
Age^3	.	0.020^{***}	.	0.022^{***}
		(0.004)	.	(0.004)
Age^4	.	-0.000	.	-0.000
		(0.000)	.	(0.000)
Black	.	-0.099	.	0.215
		(7.984)	.	(8.185)
Married	.	5.296	.	5.297
		(9.665)	.	(9.797)
Female	.	-10.776^{***}	.	-10.726^{***}
		(1.482)	.	(1.523)
Married x Female	.	-25.254^{***}	.	-25.452^{***}
		(6.233)	.	(6.112)
High School	.	5.190	.	5.161
		(6.838)	.	(7.004)
Some College	.	30.701^{***}	.	30.973^{***}
		(7.329)	.	(7.514)
College	.	52.005^{***}	.	51.965^{***}
		(7.083)	.	(7.460)
Cognitive Routine	.	-6.159^{***}	.	-5.789^{***}
		(1.790)	.	(1.765)
Manual Non-Routine	.	-1.034^{*}	.	-0.741
		(0.609)	.	(0.662)
Manual Routine	.	-7.023^{***}	.	-6.419^{***}
		(1.725)	.	(1.614)
Unemployment Duration	.	0.866^{***}	.	0.828^{***}
		(0.158)	.	(0.154)
Unemployment Duration^2	.	-0.027^{***}	.	-0.025^{***}
		(0.005)	.	(0.005)
Unemployment Duration^3	.	0.000	.	0.000
		(0.000)	.	(0.000)
Unemployment Duration^4	.	-0.000	.	-0.000
		(0.000)	.	(0.000)
No. Obs.	547315	547315	414843	414843

Table A3: The response of individual job search effort, $\hat{s}_{it}$ to variation in labor market conditions using the full CPS sample.

	Basic	Dummy	Search	Search Dummy	Search Dummy
log $\frac{v_t}{u_t}$	0.943***	0.573***	1.009***	0.585***	0.778***
	(0.019)	(0.037)	(0.035)	(0.052)	(0.056)
log $\frac{h_t}{u_t}$ × Recession Dummy		0.260***		0.258***	0.004
		(0.020)		(0.022)	(0.057)
log $\bar{s}_t$			0.524**	0.070	0.389**
			(0.214)	(0.168)	(0.181)
log $\bar{s}_t$ × Recession Dummy					-0.070***
					(0.016)
R^2	0.923	0.964	0.926	0.964	0.970
Observations	168	168	168	168	168

Table A4: Estimated coefficients for the Cobb-Douglas matching function using aggregate time series data. *, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors.

ε_t is the error term. $\bar{s}_t$ is the average value of imputed search minutes for unemployed workers, measured in Section 3. d_t is a dummy variable that takes the value of 1 after July 2009, which is intended to control for a recent large decline in matching efficiency. We use data from the JOLTS and CPS from December 2000 to December 2014 to estimate this relationship.[43]

Table A4 shows the results of a simple OLS regression of the form (A1), with and without the intensive margin, $\log(\bar{s}_t)$. The first column is the conventional matching function estimation, and the result is within the range of the OLS results in the literature. The second column adds our search effort variable estimated from the CPS, $\bar{s}$. The coefficient of $\log(\bar{s})$ is positive and significant at the 1% level, suggesting the importance of the variation in job search effort. This finding implies that search effect has a positive effect on the job-finding probability at the aggregate level. Of course, this correlation can be the consequence of a shift in the composition of unemployed workers as well as the direct effect of job search on the matching process. Note that since search effort tends to be high when market tightness is low, when search effort is included, the coefficient on market tightness increases.

[43]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 JOLTS by the number of unemployed in the CPS.

	Basic	Dummy	Search	Search Dummy	Search Dummy
log $\frac{v_t}{u_t}$	0.935***	0.806***	0.747***	0.660***	0.661***
	(0.100)	(0.102)	(0.032)	(0.034)	(0.034)
log $\frac{h_t}{u_t}$ × Recession Dummy		0.276***		0.187***	0.188***
		(0.083)		(0.028)	(0.027)
log $\bar{s}_t$			0.997***	0.996***	0.991***
			(0.007)	(0.007)	(0.015)
log $\bar{s}_t$ × Recession Dummy					0.007
					(0.016)
R^2	0.390	0.393	0.957	0.959	0.959
Observations	1895	1895	1895	1895	1895

Table A5: Estimated coefficients for the Cobb-Douglas matching function using state-level time series data.*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Regressions include quarter, year, and state fixed effects. Robust standard errors.

To see the quantitative significance of this, consider the period of the Great Recession. The job-finding probability went down from an average of 28 percent in 2007 to 17 percent in 2009. During the same time period, search effort went up from an average of 32 minutes per day in 2007 to an average of 38 minutes per day in 2009. Since $0.524 \times (\log(38) - \log(32)) = 0.090$, if θ had stayed the same and only search effort had risen, the job finding probability would have increased to $28 \times \exp(0.090) = 30.6$ percent. That is, the search effort's contribution during this period was to increase the job-finding probability by 2 percentage points, meaning that without the increase in search effort, the job finding probability would have been 15 percent instead of 17 percent.

Table A5 shows the same regressions as in Table A4 but using state-level variation. Note that the table also feature a different sample period, as state-level vacancies are only available beginning in May 2005. Because we include state and time fixed effects, identification in this regression is coming from differential patterns across states. Despite these differences, Table A5 shows that the results are very similar – search effort in the aggregate has a positive relationship with aggregate job finding rates. In a given quarter, for a given level of market tightness, states that have higher average search effort have a higher job finding rate.

While these results suggest that search effort is important in explaining aggregate variations in the job finding rate, as is argued by Borowczyk-Martins, Jolivet, and Postel-Vinay (2013), the OLS estimates are 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 (A1) has an ARMA structure and estimate the AR parameters ϵ_t together with the coefficients β_i using the lagged values of $\log(\theta_t)$ as instrumental variables. We extend their method to incorporate another endogenous variable $\log(\bar{s}_t)$. Following their method, we assume that ϵ_t follows ARMA(3,3). We use $\log(\theta_{t-i})$ and $\log(\bar{s}_{t-i})$ 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 $\log(f_{t-4})$ included in the list of instrumental variables.

Table A6 shows the result. In both cases, the coefficient of $\log(\theta_t)$ 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 $\log(\bar{s})$ 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 likely to be 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. These econometric issues encouraged us to follow a more structural approach outlined in Section 4.

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

Table A6: 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.

B Theory Appendix

B.1 Detained derivation of equations (20) and (23)

B.1.1 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:

$$J(S_t) = z_t - w(S_t) + \beta E[(1-\sigma)J(S_{t+1}) + \sigma V(S_{t+1})], \tag{B1}$$

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

$$V(S_t) = -\kappa + \beta E[q(\bar{s}_t, \theta_t)J(S_{t+1}) + (1 - q(\bar{s}_t, \theta_t))V(S_{t+1})], \tag{B2}$$

where κ is the vacancy creation cost. The value of being employed for the worker, $W(S_t)$, is

$$W(S_t) = w(S_t) + \beta E[(1-\sigma)W(S_{t+1}) + \sigma U(S_{t+1})], \tag{B3}$$

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

$$U(S_t) = \max_{s_{it}} \{b - c(s_{it}) + \beta E[f(s_{it}, \bar{s}_t, \theta_t)W(S_{t+1}) + (1 - f(s_{it}, \bar{s}_t, \theta_t))U(S_{t+1})]\} \tag{B4}$$

where b is the return while unemployed and $c(\cdot)$ is the cost of job search with $c'(\cdot) > 0$ and $c''(\cdot) \geq 0$. The workers choose their search intensity to maximize the presented discounted value of their income during search according to the first order condition

$$c'(s_{it}) = \beta f_1(s_{it}, \bar{s}_t, \theta_t)E[W(S_{t+1}) - U(S_{t+1})]. \tag{B5}$$

We denote the optimal search effort s_{it} that satisfies (B5) by s^*_{it}.

B.1.2 Wage determination

The equilibrium wage is determined by the generalized Nash bargaining. 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

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

Then w solves

$$(1-\gamma)(\tilde{W}(w; S_t) - U(S_t)) = \gamma(\tilde{J}(w; S_t) - V(S_t)). \tag{B6}$$

$\gamma \in (0, 1)$ represents the bargaining power of the worker.

B.1.3 Free entry and equilibrium

We assume free entry to vacancy posting, $V(S_t) = 0$. From (B2),

$$\kappa = \beta q(\bar{s}_t, \theta_t) E[J(S_{t+1})] \tag{B7}$$

holds, and (B1) 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 (B7) yields

$$\kappa = \beta q(\bar{s}_t, \theta_t) E\left[z_{t+1} - w(S_{t+1}) + \frac{(1-\sigma)\kappa}{q(\bar{s}_{t+1}, \theta_{t+1})}\right]. \tag{B8}$$

From (B3) and (B4),

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

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 (B6),

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

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 (B7),

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

Forwarding one period, taking expectation, and using (B7) once again,

$$E[w(S_{t+1})] = \frac{\gamma}{1-\gamma} \frac{\kappa}{\beta q(\bar{s}_t, \theta_t)} + b - E[c(s_{i,t+1}^*)] - \frac{\gamma}{1-\gamma} E\left[\frac{(1 - \sigma - f(s_{i,t+1}^*, \bar{s}_{t+1}, \theta_{t+1}))\kappa}{q(\bar{s}_{t+1}, \theta_{t+1})}\right]. \tag{B9}$$

Let us impose the equilibrium condition and denote $s_t = s_{it}^* = \bar{s}_t$. Then combining (B8) and (B9) we obtain

$$\frac{\kappa}{1-\gamma} = \beta q(s_t, \theta_t) E\left[z_{t+1} - b + c(s_{t+1}) + \frac{1 - \sigma - \gamma f(s_{t+1}, s_{t+1}, \theta_{t+1})}{1-\gamma} \frac{\kappa}{q(s_{t+1}, \theta_{t+1})}\right]. \tag{B10}$$

Equation (B5) can be rewritten as

$$c'(s_t) = f_1(s_t, s_t, \theta_t) \frac{\gamma}{1-\gamma} \frac{\kappa}{q(s_t, \theta_t)}. \tag{B11}$$

Equations (B10) and (B11) determine the dynamics of θ_t and s_t. Log-linearizing (B11) yields

$$\hat{s}_t = \Phi \hat{\theta}_t, \tag{B12}$$

where "hat" ($\hat{}$) denotes the log deviation from the steady state. The coefficient Φ can be expressed as

$$\Phi = \frac{f_{13}\tilde{\theta}/f_1 - q_2\tilde{\theta}/q}{c''\tilde{s}/c' - (f_{11} + f_{12})\tilde{s}/f_1 + q_1\tilde{s}/q},$$

where "tilde" ($\tilde{}$) denotes the value at the steady state. The values of f_i, f_{ij}, q, and q_i are evaluated at the steady state, where the subscripts denote partial derivatives and double-subscripts denote cross derivatives. Imposing our generalized matching function in Equation

18 and assuming that cost of job search is increasing and convex and given by $c(s) = \phi s^{\omega}/\omega$, where $\omega > 1$, Equation (B10) rearranges to

$$\frac{\kappa}{(1-\gamma)\beta\chi}(\alpha s_t^{\psi} + (1-\alpha)\theta_t^{\psi})^{-\eta}\theta_t$$
$$= E\left[z_{t+1} - b + \frac{\phi}{\omega}s_{t+1}^{\omega} + \frac{(1-\sigma)\kappa}{(1-\gamma)\chi}(\alpha s_{t+1}^{\psi} + (1-\alpha)\theta_{t+1}^{\psi})^{-\eta}\theta_{t+1} - \frac{\gamma\kappa}{1-\gamma}\theta_{t+1}\right] \quad \text{(B13)}$$

and the Equation (B11) is[44]

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

Rearranging and log-linearizing, we obtain

$$\hat{s}_t = \frac{\alpha\tilde{s}^{\psi} - (\psi-1)(1-\alpha)\tilde{\theta}^{\psi}}{\omega\alpha\tilde{s}^{\psi} + (\omega-\psi)(1-\alpha)\tilde{\theta}^{\psi}}\hat{\theta}_t. \quad \text{(B14)}$$

The right-hand side is $\Phi\hat{\theta}_t$ in (B12). Evaluated at $\tilde{s} = 1$ and $\tilde{\theta} = 1$,

$$\Phi = \frac{1-\psi(1-\alpha)}{\omega-\psi(1-\alpha)}. \quad \text{(B15)}$$

We assume that ω is sufficiently large so that denominator is always positive. Then Φ is negative if and only if $\psi > 1/(1-\alpha)$.

Log-linearizing (B13) and using (B14), we obtain the equation

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

where

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

and

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

[44] 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

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

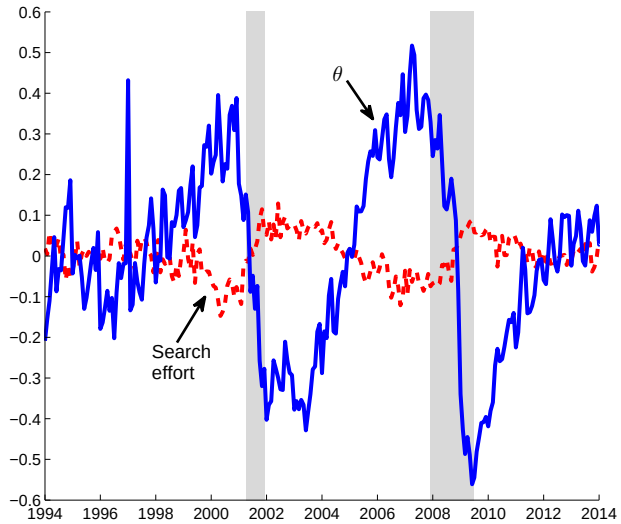


Figure B1: The correlation between the intensive margin of search and market tightness.

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

$$\hat{\theta}_t = \Omega\hat{z}_t,$$

using the method of undetermined coefficients,

$$\Omega = \frac{\rho}{\mathcal{A} - \rho\mathcal{B}}. \tag{B16}$$

B.2 Cyclical components of θ and s

Figure B1 below displays the data underlying the target $\Phi = -0.15$. The figure plots the cyclical component of $\ln\theta$ and $\ln\bar{s}$. While the correlation between the two series is large and negative, θ is more volatile than search effort, leading to the target of -0.15.

Additional References for Appendix

[1] Ljungqvist, L. and T. Sargent (1998). "The European Unemployment Dilemma," *Journal of Political Economy* 106, 514-550.

[2] Rubin, D.B. (1987). "Multiple Imputation for Nonresponse in Surveys". New York: Wiley