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Abstract

We create a novel measure of job search effort starting in 1994 by exploiting the overlap between the Current Population Survey and the American Time Use Survey. We examine the cyclical behavior of aggregate job search effort using time series and cross-state variation and find that it is countercyclical. About half of the countercyclical movement is explained by a cyclical shift in the observable characteristics of the unemployed. Individual responses to labor market conditions and drops in wealth are important in explaining the remaining variation.

Key words: 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 Diamond (1982), 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 major 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 individual and 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-searching activities on a particular day, which is perhaps the most natural quantitative measure of job search effort, 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 to the ATUS, utilizing the fact that both contain the *same questions* on 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

[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.

all CPS respondents. Using individual search effort measures, we compute a monthly 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 margin and the intensive margin. The extensive margin is represented by the number of unemployed workers and the intensive margin is measured as the average search time in minutes that an unemployed worker spends on job search activities. We show that aggregate search effort is countercyclical both at 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 (2013) 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 or in gross state product.

We then examine why aggregate search effort is countercyclical. One possibility is that search effort is countercyclical because individuals change their search effort in response to macroeconomic conditions, such as changes in job availability or wealth shocks. Alternatively, aggregate 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 find that both of these factors play a role in explaining the rise in search effort during recessions. Specifically, our estimates suggest that about half of the observed rise in the search effort of the unemployed during the Great Recession can be explained by changes in the observable characteristics of the unemployed. We find that the individuals' responses to macroeconomic conditions are also quantitatively important, potentially explaining most of the remaining variation.

After exploring the reasons for the countercyclicality of search effort, we analyze the relationship between job search effort and labor market outcomes at both the individual and the aggregate level. We find that search time and becoming employed in near future (within a few months and within a year) are positively correlated. While this finding does not necessarily imply that there is a causal effect of search effort on finding a job, it still implies that search effort is a good predictor of an individual's employment likelihood. We then estimate an augmented matching function which takes into account the variation in the search intensity of workers and show that the intensive margin of search effort is an important determinant of the aggregate hiring process.

Lastly, we explore the relationship between our findings and the extensive literature on the disincentive effects of unemployment insurance (UI) benefits on job search.[2] We also find disincentive effects in our data—individuals who are closer to the expiration of their benefits search harder than otherwise similar individuals who have more time remaining on unemployment insurance. Although UI tends to get extended during recessions, leaving people with more time remaining on benefits, this finding is not necessarily inconsistent with the observed countercyclicality of search effort. It rather suggests that the disincentive effect of UI is dwarfed by individual responses to macroeconomic conditions and compositional changes.

To summarize, 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 show that search effort is a predictor of individual and aggregate labor market outcomes. Fourth, we argue that the widely documented negative disincentive effect of UI benefits on job search—which we also document in our dataset—does not necessarily

[2] See, for example, Shavell and Weiss (1979), Wang and Williamson (1996), Hopenhayn and Nicolini (1997), Chetty (2008), and Krueger and Mueller (2010, 2011).

imply that job search effort should be procylical.

We are adding to a growing empirical literature examining job search effort. Shimer (2004) is an early critic of the way search effort is modeled in typical search-matching models. He uses a measure of job search intensity based on the CPS and shows that aggregate search effort does not appear to be procyclical in the data. We build on his work and generalize his insights by providing a richer measure of search effort that spans a longer time period. In addition, we analyze search effort decisions at the individual level in detail and establish a link between search effort and labor market outcomes. Krueger and Mueller (2010) is a recent paper that uses the ATUS for 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 (2013), which analyzes the change in the allocation of time during the great recession. They find that increases in job search absorbed two to six percent of the foregone work hours. Faberman and Kudlyak (2014) is another paper which uses 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 the 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.[3]

Our main finding that search effort is countercyclical contrasts some of the recent work on modeling labor market fluctuations. For example, in the models of Veracierto (2008), Christiano, Trabandt, and Walentin (2012), and Gomme and Lkhagvasuren (2012), an important

[3]Note that the sample size in the DeLoach and Kurt (2012) is much smaller than ours and Faberman and Kudlyak's (2014). The difference in sample sizes is likely to be the cause of the difference in results. Our main motivation for linking the CPS and the ATUS is to overcome the small and short sample problem.

driving force of labor market fluctuations is that search effort by nonemployed households moves procyclically. Our results imply that this channel is not supported empirically. Rather, the data supports the view that the cyclical behavior of nonemployed individuals' job search effort dampens labor market fluctuations.

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 series and state-level variation. Section 4 explores the reasons behind the countercyclicality of aggregate search effort. Section 5 discusses the link between search effort and labor market outcomes at the individual and aggregate levels. Section 6 discusses the incentive effects of UI benefits extensions on job search effort and reconciles our findings with the existing studies. Section 7 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 interviewed 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 includes a follow-up interview in which respondents are re-asked a subset of the CPS questions. Our sample from the ATUS spans 2003-2011 and we restrict our sample for the CPS from 1994 through 2011 since job-search related questions

Table 1: Definitions of job search activities in ATUS

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)

in the ATUS are consistent with the post-1994 CPS.[4] 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 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.[5] The first category (job search activities) includes contacting employers, sending out resumes, and filling out job applications, among others.[6]

The ATUS has two major shortcomings for our purposes—it has a small sample size (12,000–

[4]Before the 1994 redesign of the CPS, 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 1976–2011 period, it is still possible to construct an internally consistent measure of job search for 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 for results and a brief discussion.

[5]We do not include travel time to interviews in our baseline measure as is done in Aguiar, Hurst, and Karabarbounis (2011). 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.

[6]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.

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 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 methods. Shimer (2004) employed the number of methods used by the worker as a proxy of the search effort. The idea is that if a worker uses six methods in one month, she is likely to be searching more intensely than a worker who uses only one method. 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 questions we utilize contain information about job search behavior over the past month, rather than just one interview day. However, the main shortcoming of this proxy is that it assumes that all methods are equally important and utilized with equal intensity across individuals and over time.

2.2 ATUS summary statistics

We first examine some summary statistics about job search from the ATUS for the 2003–2011 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 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 some subgroups to identify who engages most intensively in job search. The unemployed workers are divided into two categories—“temporary

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

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

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

<table>
<tr><td colspan="5">All Workers
1.9</td></tr>
<tr><td rowspan="3">Employed
0.5</td><td colspan="4">Nonemployed
5.6</td></tr>
<tr><td colspan="2">Unemployed
30.4</td><td colspan="2">Not in the Labor Force
0.6</td></tr>
<tr><td>Temp Layoff
9.5</td><td>Not on Temp Layoff
34.0</td><td>Want a Job
5.2</td><td>Other NILF
0.5</td></tr>
</table>

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.[7]

[7]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

Table 3 reveals large differences in search time among different labor force categories.[8] 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 all unemployed workers as the group who engage in job search activity and treat them as the *extensive margin* of the job search activity. We find this choice natural since the CPS uses a search criterion to distinguish between the unemployed and those not in the labor force.

2.3 Linking the ATUS and the CPS

Ultimately, our goal is to obtain a measure of the monthly average of daily search time for 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, 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.

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reporting that she wants a job.

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

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

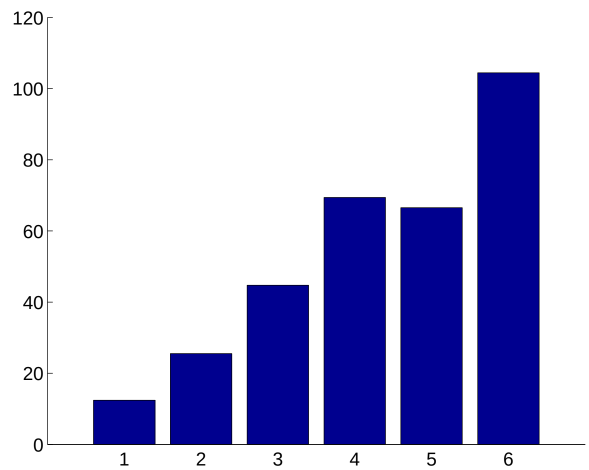


Figure 1 indicates that recorded search time and the number of methods used exhibit a strong positive correlation. This implies that the number of methods contains valuable information on the intensity of job search. Indeed, Shimer (2004) used the number of search methods as a measure of a worker's search effort before the ATUS data were available. However, as we noted earlier, the number of methods does not convey any information on the relative importance of each method in workers' job search activities. In reality, it is likely that workers allocate their search time differently across different methods, considering the effectiveness and time intensiveness of various methods. Workers can also change the time they spend on job search by changing the time they spend on each job search method without changing the total number of methods they use.

This is why we combine the information on job search in the ATUS time diaries with the information on the number of search methods. Since each respondent in the ATUS at the time of the ATUS interview is re-asked in which job search methods they have engaged in the past 4 weeks, we are able to construct a mapping between each reported method 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. This simple approach has some shortcomings. First, the search time variable has a lower bound of zero in the ATUS, but many respondents receive negative imputed minutes.[9] Second, we observe many respondents with zero search time and a positive number of methods since the ATUS asks only about the activities of the day before. Thus the occurrence of zeros may contain separate information from the samples with nonzero minutes.

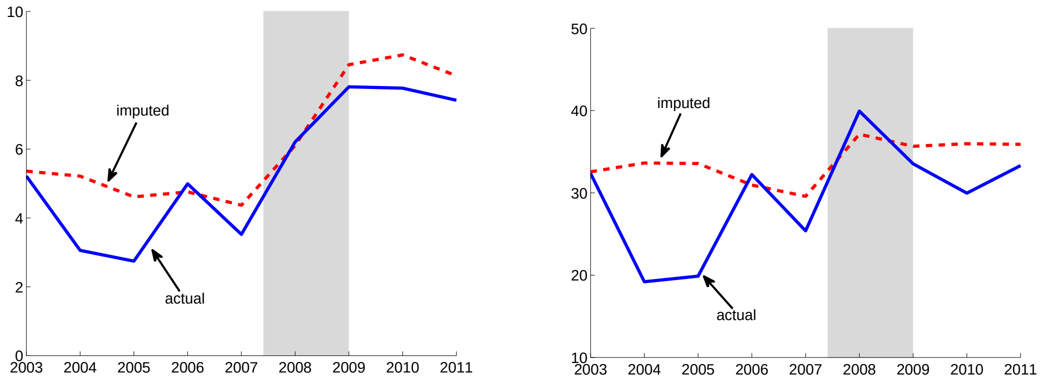
Instead, we take a two-step approach. In the first step, we estimate the probability of observing positive search time in ATUS—if the worker spent many days during the last four weeks actively searching, it is more likely that the ATUS survey day falls onto a day of active search. This is done by running a probit model with dummy variables for each method and worker characteristics on the right-hand side.[10] In the second step, we restrict the ATUS sample to respondents who reported strictly positive search time and run a regression with the logarithm of search time on the left-hand side and dummy variables for each method and worker characteristics on the right-hand side. We conduct the imputation for the CPS sample by using the estimated coefficients to first generate a probability of non-zero search time, then generating an expected search time conditional on observing any search, and then multiply the outcomes.[11] The details of the imputation process and alternate specifications are explored in

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

[10] We include two sets of observable worker characteristics. The first is a set of worker characteristics which may affect the intensity of their job search. We mostly follow Shimer (2004) in the choice of these controls and include a quartic of age, dummies for education levels (high school diploma, some college, and college plus), race, gender, and marital status. We also add the interaction term of female_{it} and married_{it} (for individual i at time t) 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. 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. This is useful and important for capturing aggregate averages in Section 3 but not for exploring individual level effects in Section 4.

[11] For example, if given ones reported search methods, labor market state and demographic characteristics, an individual is estimated to have a 30 percent chance of searching at all and an expected search time of 12 minutes per day if she searchers, we say that individual searched for 4 minutes a day.

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



(a) all nonemployed

(b) unemployed

Appendix A.2.

Figure 2 provides a comparison of the time series of reported minutes and imputed minutes within the ATUS sample. The imputed minutes track the actual minutes closely, with the exception of 2004 and 2005.[12] In the remainder of the paper, we use imputed minutes, which we denote by $\hat{s}_{it}$ for individual i at time t, as our measure of search effort in the CPS sample. This measure is a nontrivial extension of Shimer's measure as 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.[13]

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

[12]The imputed search time is above the actual search time in 2004 and 2005 mostly as a result of the relative behavior of the 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.

[13]Figure A6 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.

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 when search time increases. 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-unemployment ratio (θ)). 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 A5 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 θ are even more cyclical than our baseline measure. Therefore, our baseline specification is a conservative one regarding the cyclicality.

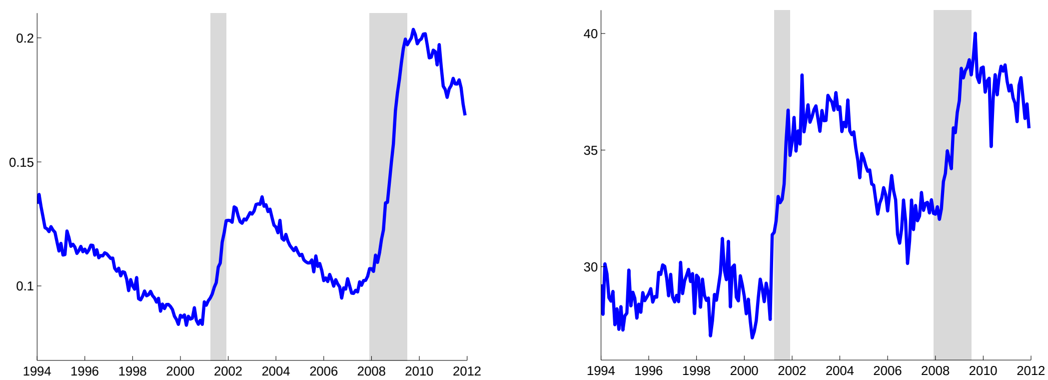
3 Cyclicality of search effort

In this section, we examine how nonemployed workers' search behavior changes over the business cycle. We exploit two distinct types of variation—the time series variation and cross-state variation in the intensity of business cycles.

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. The extensive margin is represented by the number of unemployed workers relative to total nonemployment, and the intensive margin is measured as the average search time in minutes per day that unemployed workers spend on job

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).



search activities.[14] 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).[15] Figure 3 clearly shows that the extensive margin is countercyclical, which is not a surprising observation given that the strong countercyclicality of unemployment has been widely documented.[16]

To measure the intensive margin of search effort, we use the imputed minutes, $\hat{s}_{it}$, calculated in Section 2.3.[17] 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 exhibits 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 the cyclical component of GDP is -0.55.[18]

[14] As discussed in section 2.2, this 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.

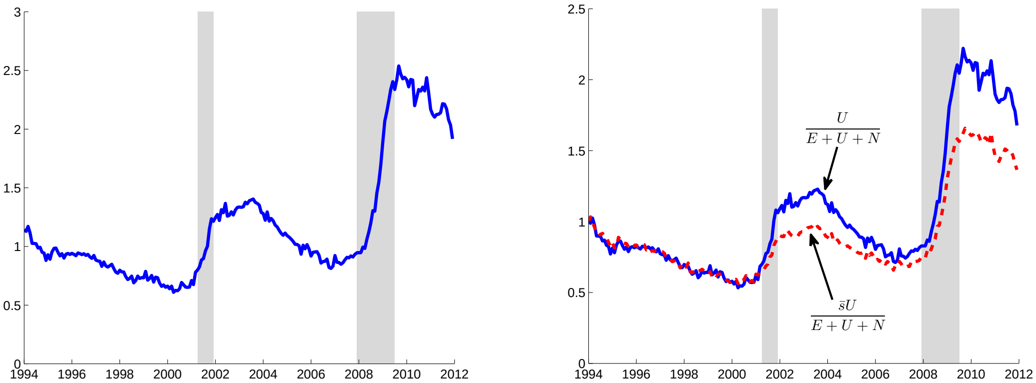
[15] We see the same pattern even when we use an alternative denominator of U plus the nonparticipants who want a job.

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

[17] 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, while we are in the process of getting this fixed, we exclude this month from our analysis.

[18] The pattern is similar if we restrict our sample to only unemployed workers who are not on temporary layoff.

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 $U/(E+U+N)$. In the right panel, both series are normalized to 1 at the beginning of 1994.



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 two sections' results, total search effort in the left panel of Figure 4 also exhibits a countercyclical pattern.

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 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 importance of ignoring the intensive margin. In other words, failing to take into account the variation in the intensive margin of search intensity results in an underestimation of the variation of total search effort in the economy over the business cycle.

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.

3.2 State-level variation

In addition to the time series variation that we exploited above, we employ cross-state variation in the intensity of business cycles to explore the cyclicality of search effort along the intensive margin. Looking across different states provides additional information, as it utilizes a different and potentially richer source of variation. This method of utilizing state-level variation to establish the cyclicality of a series is similar to that in Aguiar, Hurst, and Karabarbounis (2013) and Haltiwanger, Hyatt, and McEntarfer (2014).

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

$$s^c_{st} = \lambda_s + \lambda_t + \beta_1 CYCLE_{st} + \varepsilon_{st}, \tag{1}$$

where s^c_{st} is the cyclical component of average search time in state s in time t, λ_s is a state fixed effect, λ_t is a time control that we explain in detail below, $CYCLE_{st}$ is the measure of the business cycle in state s in time t, and ε_{st} is the error term. We construct two different measures of the business cycle at the state level: HP-filtered state-level unemployment rate and HP-filtered real state level gross product (GSP).[20] The parameter of interest is β_1 which captures the correlation of search time with the business cycle, or more explicitly the correlation of the cyclical component of search time with the cyclical variation of market indicators. State fixed effects capture any static difference in job search behavior across states.

In order to identify the cyclicality of job search effort from cross-state variation, we need to control for variations in search effort over time that are common across states. To this end, we explore two specifications for λ_t. In the first version, we include time fixed effects which control flexibly for any variation that is constant across states but varies over time. The second version adds state-specific linear time trends, which allow for each state to experience a different linear time trend, controlling for time-varying state level policies that may affect trends in job search differentially. We control for the differing seasonality in the cross-state data using two alternate

[20] The state-level unemployment rate is available monthly and HP-filtered with smoothing parameter $\lambda = 6.25$ and state level gross-product is available annually and filtered with smoothing parameter $\lambda = 129,600$.

Table 4: Exploiting state-level variation

	Unemployment Rate				GSP	
Unemployment Rate (NSA)	0.5772***	0.5784**				
	(0.2154)	(0.2162)				
Unemployment Rate (SA)			0.7089***	0.7089***		
			(0.2296)	(0.2301)		
GSP					-0.0080*	-0.0079*
					(0.0041)	(0.0042)
Observations	10965	10965	10965	10965	918	918
R^2	0.191	0.191	0.118	0.118	0.369	0.370
State Month Dummies	X	X				
State Time Trend		X		X		X

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. All coefficients are the result of a weighted least squares regression, where the weights are the average state population over the sample period. All regressions include state and month fixed effects. Standard errors are clustered by state. NSA stands for not seasonally adjusted and SA stands for seasonally adjusted.

methods: state-specific month dummies and seasonally adjusting the data state by state.

Table 4 shows the estimates of β_1 from a series of regressions. The left four columns reveal that across specifications, the coefficient on the unemployment rate is positive and statistically significant, meaning that search effort is above trend when the unemployment rate is above trend. Specifically, these coefficient estimates suggest that if the unemployment rate is 2 percentage point above trend, then workers search an extra minute per day. The right two columns show that results are similar when we use GSP as our cyclical indicator—search effort is above trend when GSP is below trend. These results support our finding that search effort is countercyclical. Recall that this measure of cyclicality exploits only cross state-variation while the results in Section 3.1 utilized only the time series variation and yet both methods demonstrate that search effort is strongly countercyclical.

4 Why is aggregate search effort countercyclical?

In this section, we study the reasons for the countercyclicality of the aggregate search effort. There are several potential reasons for this pattern. It may simply be because individual search effort is countercyclical. An individual worker's search effort can respond to macroeconomic conditions for several reasons. The first potential reason is the presence of strong wealth effects. For example, if the worker loses some of her assets during a recession, she might search harder since it becomes more important for her to find a job to finance her consumption. Second, the worker might increase her search effort to try to compensate for weak labor demand during recessions. In particular, if the *marginal* increase in the job-finding probability due to increase in effort is inversely related to labor demand conditions, the worker would increase her search effort in recessions. However, theoretically, it is not obvious that search effort at the individual level should be countercyclical. Since wages tend to be lower during recessions, the marginal return to search (captured by the re-employment wage) is lower and therefore incentives to search are lower. Additionally, if workers are responsive to the generosity of unemployment benefits, the extension of benefits that usually accompanies recessions is likely to decrease search effort among workers who are eligible for unemployment benefits.

Alternatively, aggregate search effort may be countercyclical if, in recessions, the pool of searchers skews towards the types of people who typically search harder. This compositional shift could occur along both observed and unobserved dimensions. For example, suppose that (i) searchers are heterogeneous in their desire to work; (ii) a worker with a stronger preference for work searches 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 of a desire to work during booms. This channel would lead to countercyclical average search effort through unobserved composition changes. The following subsections disentangle these effects.

4.1 The role of observed heterogeneity

It is well known that there are notable shifts in the observable characteristics of unemployed workers over the business cycle.[21] If the pool of unemployed workers shifts towards types of workers who typically search harder, aggregate search effort can be countercyclical without a cyclical change in the search behavior of individual workers.

In order to explicitly estimate the effect of observed changes in the pool of unemployed on the cyclicality of search effort at the extensive margin, we first estimate a linear probability model of the following form similar to that in Shimer (2004):

$$y_{it} = \delta + \mathbf{x}_{it}'\boldsymbol{\delta_x} + \sum_s \mu_s m_s + \varepsilon_{it}, \tag{2}$$

where y_{it} is 1 if individual i is unemployed and 0 if i is not unemployed, $\mathbf{x}_{it}$ is the same set of controls as in Section 2.3 with the coefficient vector $\boldsymbol{\delta_x}$, m_s is the month dummy that takes 1 if $s = t$ and 0 otherwise, and ε_{it} is the error term. In addition, we run a regression similar to (2) using $\hat{s}_{it}$ as the dependent variable and using only the sample of unemployed workers to examine the effect of observable characteristics at the intensive margin.

Table 5 shows the coefficient estimates from these regressions and shows that search intensity on the intensive and extensive margin varies significantly across demographic characteristics. Women are less likely to search and, conditional on searching at all, search for fewer minutes. This is even more pronounced for married women. Search effort on both the intensive and extensive margin is increasing in education. The coefficients on the occupation categories reveal that workers from non-routine occupations search more than those in routine occupations, with those in cognitive-non-routine occupations searching the most and those in non-cognitive routine occupations searching the least.[22] Appendix Figure B1 displays the quartic age-search effort profile estimated using the above regressions. We see that search effort is relatively

[21] See, for example, Darby, Haltiwanger, and Plant (1986), Baker (1992), Shimer (2004, 2012), and Mueller (2012).

[22] Note that we only include occupation controls in the intensive margin regression since they are not well reported in the CPS for those not in the labor force.

Table 5: Coefficients on control variables in regression (2), using the indicator for being unemployed in the left column and search time in the right column.

Variable	Extensive Margin	Intensive Margin
Age	-0.137^{***}	-5.378^{***}
	(0.003)	(0.704)
Age^2	-0.005^{***}	0.103^{***}
	(0.000)	(0.025)
Age^3	-0.000^{***}	0.000
	(0.000)	(0.000)
Age^4	0.000^{***}	$-.000^{***}$
	(0.000)	(0.000)
Female	-0.067^{***}	-5.908^{***}
	(0.001)	(0.108)
Married	-0.006^{***}	7.687^{***}
	(0.001)	(0.116)
Married×Female	-0.067^{***}	-26.185^{***}
	(0.001)	(0.147)
Black	0.021^{***}	-0.794^{***}
	(0.001)	(0.093)
High School	0.026^{***}	4.591^{***}
	(0.001)	(0.068)
Some College	0.032^{***}	22.141^{***}
	(0.000)	(0.096)
College	0.022^{***}	43.393^{***}
	(0.001)	(0.162)
Cognitive-Routine		-5.056^{***}
		(0.138)
Non-Cognitive-Non-Routine		$-.536^{***}$
		(0.140)
Non-Cognitive-Routine		-9.518^{***}
		(0.139)
Unemployment Duration		1.052^{***}
		(0.016)
(Unemployment Duration)^2		-0.031^{***}
		(0.001)
(Unemployment Duration)^3		0.004^{***}
		(0.000)
(Unemployment Duration)^4		0.000^{***}
		(0.000)

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors. All regressions include month dummies. The excluded category for occupational groups is "Cognitive-Non-Routine" and the excluded category for education groups is "less than high school".

invariant to age until around 50 and then declines. Lastly, for the intensive margin regression, we include a quartic function of unemployment duration following Shimer (2004). Appendix Figure B2 demonstrates that search effort initially rises with unemployment duration and then declines, a finding that is consistent with Shimer (2004). With the quartic specification plotted here, search effort peaks after a year of being unemployed.[23]

How much of the cyclicality can be explained by these observed changes in the composition of the unemployed? To illustrate this, the dashed lines in Figure 5 plot the coefficients on the month dummies μ_s in equation (2).[24] These coefficients provide estimates of how much being in a particular month raises the probability of being unemployed (in the case of extensive margin) or increases search minutes (in the case of intensive margin) *after* controlling for these observed individual characteristics. The blue lines are reproductions of the aggregate estimates from Figure 3, both normalized to zero in the initial period to match the scale of the time dummies. Figure 5 clearly shows that even after controlling for observable characteristics, search effort at both the intensive and extensive margin is still strongly countercyclical. A comparison of the two lines suggests that changes in the unemployed pool across the observables described above explains 45 percent of the rise in the intensive margin in the 2001 recession and 62 percent of the rise in the intensive margin in the 2007-09 recession. Thus, overall, about half of the countercyclical movement of the intensive margin is explained by the shift in observable characteristics.

4.2 The role of labor market conditions and unobserved heterogeneity

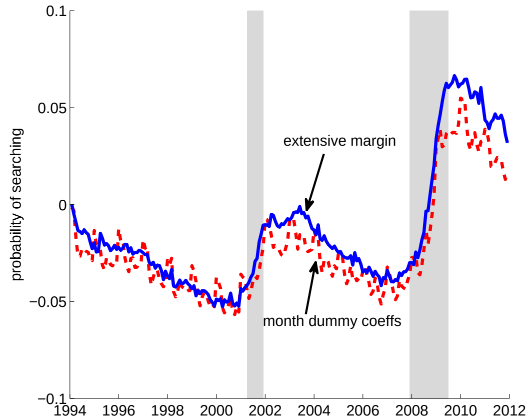
In this section, we examine search effort at the individual level to understand the reasons behind the countercyclicality of the job search effort beyond observable compositional shifts. Here, we focus on the intensive margin. We run variations on a regression of the form

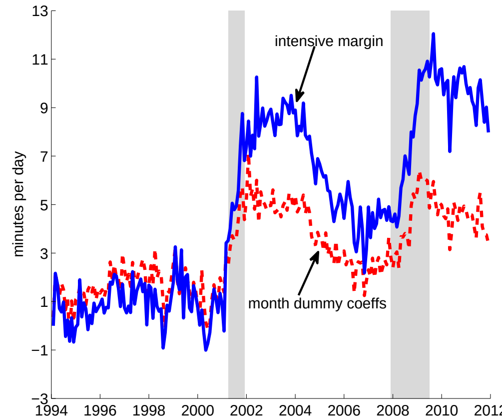
$$\hat{s}_{it} = \delta + \log(\theta_{it})\delta_\theta + w_{it}\delta_w + \mathbf{x}'_{it}\boldsymbol{\delta}_x + \varepsilon_{it}, \tag{3}$$

[23]While the hump-shaped pattern remains, this peak is not robust to cubic or quintic polynomial specification. See Appendix B for further discussion.

[24]The coefficients of month dummies are seasonally adjusted to be comparable with the series from Figure 3.

Figure 5: The month dummy coefficients μ_s for the extensive (left panel) and intensive (right panel) margins. The initial values are normalized to zero.





where θ_{it} is a measure of labor market conditions with δ_θ as the associated coefficient, w_{it} is the wealth variable with the associated coefficient δ_w, $\mathbf{x}_{it}$ is the vector of controls with the associated coefficient vector $\boldsymbol{\delta}_x$, and ε_{it} is the error term. The controls include the demographic controls (a quartic in age, marital status, race, sex, and education), four occupation dummies,[25] and a quartic function of unemployment duration. In the main text, we use the Job Openings and Labor Turnover Survey (JOLTS) data to compute the the aggregate labor market tightness $\theta = v/u$, where v is vacancy and u is unemployment.[26] We use two alternative aggregate measures of wealth—the S&P 500 and the aggregate Core-Logic house price index. A negative δ_w would be consistent with the presence of wealth effects and a negative δ_θ would imply that workers' search effort responds negatively to labor market conditions. The sample for this regression includes only those 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.

[25]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.

[26]The JOLTS survey started in 2001 and therefore covers two recessions. In the Appendix, we report results using the the Conference Board Help Wanted OnLine (HWOL) vacancy series to construct θ, which only begins in 2005.

Recall that by including various covariates, we control for observed changes in the composition of the unemployed. However, if the average desire to work of the unemployed is correlated with labor market conditions because of compositional change in unobservable heterogeneity, estimates of δ_w and δ_θ will be biased. Therefore, we attempt to control for this unobserved heterogeneity in two ways.

We first attempt to explicitly control for the desire to work. One component of the unobserved heterogeneity that can affect the cyclicality of job search effort is an individual's labor market attachment, which is typically hard to observe and affects the individual's desire to work. We attempt to control for labor force attachment by following Elsby, Hobijn, and Şahin (2013) who use prior labor market status of unemployed workers as a proxy for labor force attachment.[27] To do this, we use the CPS microdata matched across all eight survey months.[28] We define their prior status as their labor market status 12 months ago and therefore, we only include people who were unemployed at some point in the 5th to the 8th month in the survey and who we are able to match to their survey exactly one year ago. From this, we construct 3 dummy variables to a capture a prior status of unemployed, employed, or not in the labor force.[29]

Table 6 shows the individual-level regressions on this sample of matched individuals, with and without the respondent's prior status. To separate the effects of observed and unobserved heterogeneity on the estimated responsiveness of individuals to labor market conditions, we estimate three versions of the regression. The first ("Basic") does not include any observable controls; this is to capture a simple correlation with labor market conditions. The second ("Observables") includes observable controls but does not include the labor force attachment variable; this is to isolate the effect of observed heterogeneity. The third ("Full") includes

[27]Elsby, Hobijn, and Şahin (2013) find that the composition of the unemployment pool gets skewed towards workers who are more attached to the labor force during recessions using prior labor force status, as well as demographic characteristics such as age and gender.

[28]Note that there is an eight month break between the fourth survey and the fifth survey.

[29]Note that these variables only contain information on the employment status 12 months before unemployment: we do not control for labor market transitions within this 12 months period.

Table 6: Individual level regression controlling for prior status.

	S&P			House Price		
	Basic	Observables	Full	Basic	Observables	Full
$\log(\theta)$	-1.548***	−0.745***	−0.593***	−2.225***	−1.085***	-0.954***
	(0.266)	(0.216)	(0.216)	(0.275)	(0.220)	(0.220)
Emp 1 year ago			6.435***			6.449***
			(0.219)			(0.219)
Unemp 1 year ago			4.773***			4.674***
			(0.250)			(0.249)
S & P 500	−0.009***	−0.006***	−0.005***			
	(0.001)	(0.001)	(0.001)			
House Price Index				−0.027***	−0.025***	−0.023***
				(0.006)	(0.005)	(0.004)
R^2	0.003	0.419	0.423	0.002	0.419	0.423
Observations	100870	99325	99325	100870	99325	99325

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors in the parenthesis. All regressions include month dummies. Sample includes only those observations that are unemployed and matched to their labor force status 1 year ago. The entire regression results are reported in Appendix B, Table B1.

both observable controls and the labor force attachment variables; this regression illustrates the effect of unobserved heterogeneity.[30] We run two sets of regressions, one for each of the wealth variables. The entire results for these regressions and discussions of individual control variables are in Appendix B.

The first column of Table 6 shows that when we do not include either a proxy for labor force attachment or demographic controls, the coefficient on $\log(\theta)$ is negative and significant, confirming that 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. We also find that even after controlling for labor market conditions, workers search harder in periods where aggregate wealth measures are low, suggesting the presence of wealth effects.

A comparison of the coefficients on $\log(\theta)$ in the first and second columns of Table 6 pro-

[30] In the first regression, we also include the dummies for each month of the year to control for seasonality. See Appendix B for similar regression results using the full unemployed CPS sample.

vides a measure of how important the included observables are in explaining the correlation between θ and job search effort. The results here confirm the finding in Section 4.1 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 half. 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.

Lastly, by examining the difference between the coefficients on market variables in the model with and without controls for prior labor force status (the second and the third column), we can get a sense of the size of the bias induced by changes in the labor force attachment of the unemployed over the business cycle. The third column of Table 6 shows that workers who were nonparticipants a year ago, and thus had the lowest degree of attachment, have the lowest job search effort. Workers who were in the labor force a year ago search harder, with those who were employed a year ago searching more than those who were unemployed. Interpreting the prior employment status as a proxy for labor force attachment, we can conclude that individuals with a higher labor force attachment search more. Additionally, once we include our proxy an individual's desire to work, the effect of market conditions on individual search effort becomes less negative. This suggests that failing to control for unobserved differences in the labor force attachment also biases our estimate of δ_w and δ_θ downward for a reason similar to that for observed composition changes—even after controlling for demographics, the pool of unemployed shifts to higher search effort individuals in recessions. Columns four to six of Table 6 show that results are very similar when we use an alternate measure of wealth (the aggregate Core-Logic house price index).

Next, in order to more explicitly account for potential unobserved heterogeneity, we exploit the full panel structure of the CPS and run regressions with individual fixed effects. Assuming that an individual's unobserved characteristics related to search effort do not change over the

Table 7: Individual level regression including individual fixed effects.

	S&P			House Price		
	Basic	Observables	FE	Basic	Observables	FE
$\log(\theta)$	-2.073***	-0.875***	-0.295	-2.351***	-1.046***	-0.980**
	(0.148)	(0.120)	(0.510)	(0.153)	(0.121)	(0.480)
S & P 500	-0.007***	-0.005***	-0.003***			
	(0.000)	(0.000)	(0.001)			
House Price Index				-0.037***	-0.027***	-0.020
				(0.003)	(0.002)	(0.013)
R^2	0.003	0.410	0.001	0.002	0.410	0.001
Observations	311453	311453	311453	311453	311453	311453

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors. All Regressions include month dummies. Sample includes individuals who are unemployed at least twice over the sample period. Full regression results presented in Appendix Table B2.

sample period, this specification directly controls for all compositional bias. When we control for individual fixed effects, we only use individuals with at least 2 periods of unemployment in the eight months in which they are surveyed. In Table 7, we report regression results on this modified sample (i) without any demographic controls ("Basic"), (ii) with demographic controls ("Observables"), and (iii) with individual fixed effects ("FE"). As before, a comparison of the first and second columns demonstrates that observed changes in the composition of the unemployed is important in explaining the correlation of search effort and labor market conditions. A comparison of the results with and without fixed effects on the same sample suggests that introducing fixed effects tends to make individual search effort less responsive to labor market conditions. In fact, in the specification with the S&P as the measure of aggregate wealth, the coefficient on θ is no longer statistically significant. 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.[31]

[31] See Appendix B for results using more individual-specific measures of labor market tightness. Specifically, we present results using θ at the 4 census regions and at the 4 census regions divided into 4 occupation groups each (thus 16 submarkets). We find that the results are very similar.

4.3 Taking stock

Taken together, these findings suggest that the observed countercyclicality of aggregate job search effort is a consequence of both cyclical shifts in the composition of the unemployed and individual responses to macroeconomic conditions. A useful application of our analysis is to decompose the change in the aggregate search effort that we observed during the Great Recession into different sources. This can be done with a simple back of the envelope calculation using the regression coefficients from column 3 and column 6 of Table 6 and Table 7, which are the versions that control for both observed and unobserved heterogeneity. Specifically, we document in Figure 3 that over that period, search effort went from an average of 32 minutes per day to an average of 38 minutes per day. The coefficients on θ suggest then that the response of individual search effort to weak labor market conditions explains 7–22 percent of the rise in search effort over the recent recession.[32] A similar calculation reveals that wealth as measured Core-Logic house price index[33] explains between 15–17 percent and wealth as measured by the S&P 500 index explains 27–44 percent.[34] Taken together, in each regression, individual responses to labor market conditions explain between 33 and 57 percent of the increase in search effort. The remaining variation can therefore be attributed to shifts in the composition of the unemployed, either observed or unobserved. Although the exact numbers in the above calculation depend on the details of the regression specification, we conclude that individuals' responses to weak macroeconomic conditions and compositional change were both important in explaining the increase in the average search time during the Great Recession.

5 Job search effort and labor market outcomes

In this section, we analyze how search effort affects individual and aggregate labor market outcomes. We first establish the relationship between search effort and job-finding probabilities

[32] Over the 2008 recession, θ, the vacancy-to-unemployment ratio, dropped from an average of 0.64 in 2007 to an average of 0.17 in 2009, an overall drop of 0.47.

[33] The aggregate Core-Logic house price index fell by 45 point from 2007 to 2009.

[34] The S&P 500 index fell by an average of 530 from 2007 to 2009.

at the individual level. We then examine the role of search effort in aggregate matching function specifications.

5.1 Job search effort and individual labor market outcomes

To establish the link between search effort and individual labor market outcomes, we use the CPS microdata matched across all eight survey months, similar to our analysis in Section 4.2. In particular, we start with a set of respondents who report being unemployed at the time of the survey in month t and record their labor market statuses in months $t+1$, $t+2$, $t+3$, $t+12$, $t+13$, $t+14$, and $t+15$.[35] Since we are interested in how search effort affects an individual's job finding prospects, we call a worker "successful at finding a job before n months" if a worker who is unemployed at time t experiences employment before time $t+n$. For example, an individual with a history of $UUEU$ (U for unemployment and E for employment) at time t to $t+3$ is considered unsuccessful in finding a job before one month ahead but considered as successful before two and three months ahead. To isolate the effect of search effort measured at month t, $\hat{s}_{it}$, on successful job finding, we run separate regressions for each n in the form of

$$I^E_{i,t+n} = \hat{s}_{it}\delta_s + \log(\theta_{i,t})\delta_\theta + \theta_t\hat{s}_{it}\delta_{s\theta} + w_{i,t+n}\delta_w + \mathbf{x}'_{i,t+n}\boldsymbol{\delta}_x + \varepsilon_{i,t+n}, \tag{4}$$

where $I^E_{i,t+n}$ is the indicator that takes the value of 1 if individual i reports being employed at least for one month within the next n months. The key parameters of interest are δ_s and $\delta_{s\theta}$, which capture the relationship between the job finding probability and search effort. The term $\theta_t\hat{s}_{it}\delta_{s\theta}$ allows the effect of search effort on finding a job to vary with aggregate labor market conditions summarized by the aggregate labor market tightness, θ_t. The key results are summarized in Table 8. The relationship between search time and being employed in the near future is positive and significant, with the exception of the first month following the measurement of job search effort.[36] Regression results also show that the effect of job search

[35] Note that due to the interview structure of the CPS, respondents are not interviewed between months $t+3$ and $t+12$.

[36] The negative effect of job search on being employed in the subsequent month is possibly the effect of the delay between finding a job and starting to work. It is likely that unemployed respondents who receive offers

effort on the probability of employment is higher when labor market conditions are better. These findings imply that for a vacancy-unemployment ratio of 0.4,[37] an additional half an hour of job search per day increases the likelihood of being employed within the next year by 3.7 percentage points.[38]

Our analysis implies that unemployed individuals who reported searching for a longer period of time were more likely to report being employed at some point in the next 2, 3, 4, 12, 13, 14, and 15 months. Admittedly, this finding does not necessarily imply that there is a direct effect of search effort on finding a job (that is, spending more time on job search makes it more likely for an unemployed worker to find a job). Alternatively, this positive effect could be the result of unobserved heterogeneity—unemployed workers who search harder may have some unobservable characteristics which make them more likely to find a job. While we establish a positive relationship between job search effort and future employment prospects, available data do not allow us to distinguish rigorously between these two potential explanations. As an additional analysis, in Appendix C we look at the job finding probability within the next 1, 2, or 3 months while controlling for prior labor market status.[39] Results presented in Table C2 in Appendix C show that once we include a control for labor force attachment, the positive relationship between search effort and job finding largely disappears. This suggests that the relationship between job finding and search effort may largely be driven by unobserved heterogeneity (i.e. people who are more employable both search harder and are more likely to transition back to employment within the next 3 months).

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reduce their search effort in the month preceding the start of their employment.

[37]The average value of this ratio for the JOLTS sample period (Dec 2001-April 2014) is 0.41.

[38]Note that since we cannot observe jobs that start and end within the same month, we are likely to underestimate the probability of finding a job. However, as we are most interested in transitions to steady employment, this effect is unlikely to be important.

[39]As individuals are only interviewed 8 times over a 16 month span, we were not able to match individuals to their status both 1 year ago and 1 year in the future.

Table 8: The relationship between search time and the job-finding probability of individuals

The job-finding probability...		S&P	House Price
...1 month ahead	Search time	-0.00025^{***}	-0.00025^{***}
		(0.00006)	(0.00006)
	Search time$\times\log(\theta)$	0.00011^{**}	0.00011^{**}
		(0.00004)	(0.00004)
...2 months ahead	Search time	0.00002	0.00002
		(0.00008)	(0.00008)
	Search time$\times\log(\theta)$	0.00020^{***}	0.00020^{***}
		(0.00006)	(0.00006)
...3 months ahead	Search time	0.00020^{*}	0.00020^{*}
		(0.00012)	(0.00012)
	Search time$\times\log(\theta)$	0.00023^{***}	0.00023^{***}
		(0.00009)	(0.00009)
...12 months ahead	Search time	0.00071^{***}	0.00070^{***}
		(0.00009)	(0.00009)
	Search time$\times\log(\theta)$	0.00020^{***}	0.00019^{***}
		(0.00007)	(0.00007)
...13 months ahead	Search time	0.00063^{***}	0.00062^{***}
		(0.00010)	(0.00010)
	Search time$\times\log(\theta)$	0.00015^{**}	0.00014^{*}
		(0.00008)	(0.00008)
...14 months ahead	Search time	0.00064^{***}	0.00062^{***}
		(0.00011)	(0.00011)
	Search time$\times\log(\theta)$	0.00013	0.00011
		(0.00009)	(0.00009)
...15 months ahead	Search time	0.00063^{***}	0.00061^{***}
		(0.00015)	(0.00015)
	Search time$\times\log(\theta)$	0.00008	0.00007
		(0.00012)	(0.00012)

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. All Regressions include month dummies, a full set of controls, and θ and wealth controls. Full regression results presented in Appendix Table C1.

5.2 Job search effort and aggregate labor market outcomes

The previous section documented the relationship between search effort and job finding at the individual level, suggesting that individuals who search more are more likely to be employed in the future, either because their search effort leads them to find a job or because they are more employable individuals. However, this finding does not necessarily imply that job search effort affects job finding at the aggregate level, because an individual's search effort can reduce the job finding probability of others. This section examines the effect of job search effort on job finding at the aggregate level.

Typical matching function specifications assume that the only search input in the economy on the worker side is the number of unemployed workers.[40] 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.

We consider the formulation

$$\log(f_t) = \delta_0 + \delta_\theta \log(\theta_t) + \delta_s \log(\bar{s}_t) + \delta_d d_t + \boldsymbol{\tau_t}'\boldsymbol{\delta_\tau} + \varepsilon_t, \tag{5}$$

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 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 2011 to estimate this relationship.[41]

Table 9 shows the results of a simple OLS regression of the form (5), with and without the intensive margin, $\log(\bar{s}_t)$. The first column is the conventional matching function estimation,

[40] 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).

[41] 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.

Table 9: Matching function estimation: OLS

	Without $\log(\bar{s}_t)$	With $\log(\bar{s}_t)$
$\log(\theta_t)$	0.746^{***}	0.818^{***}
	(0.022)	(0.037)
$\log(\bar{s}_t)$		0.455^{**}
		(0.169)

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Standard errors are in the parenthesis.

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 percent level, suggesting the importance of the variation in job search effort.[42] Since search effort rises when the labor market is weaker, inclusion of this variable increases the estimated coefficient of $\log(\theta_t)$.

Table 9 demonstrates that search effect has a positive effect on the job-finding probability at the aggregate level. Similar to our interpretation of the positive correlation between search time and individual job finding prospects, 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.

Once again, consider the period of the Great Recession to see the quantitative significance. 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 $0.455 \times (\log(38) - \log(32)) = 0.078$, if θ had stayed the same and only search effort had risen, the job finding probability would have increased to $28 \times \exp(0.078) = 30$ 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

[42]The simple OLS framework may have its own econometric problems—for example, 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. In Appendix C, we apply their methodology to our framework, however we did not obtain a significant estimate likely due to weak instruments.

instead of 17 percent.

6 Unemployment insurance benefit extensions and search effort

The link between job search effort and unemployment insurance has received significant attention in both the labor economics literature and macroeconomics literature. Various theoretical and empirical studies find that a more generous unemployment insurance discourages workers from searching for jobs and causes longer unemployment spells.[43] In this section, we discuss how our finding of countercyclical aggregate job search effort can be reconciled with the disincentive effects of UI benefits at the individual level. In particular, we examine whether workers' search behavior depends on the number of weeks they have left on their benefits, testing the hypothesis that unemployed workers search harder as they get closer to the expiration of UI benefits. Specifically, we estimate the effect of the number of weeks left on UI on job search effort using only the sample of unemployed workers who are eligible for UI benefits. We define eligibility following Rothstein (2011) and assume that unemployed workers who report being job losers or temporary job enders as the eligible worker pool.[44] Table 10 shows that search effort responds negatively to the number of weeks left on UI. In other words, workers who are closer to the expiration of their UI benefits search more minutes per day.

Taken at the individual level, this would imply that the extension of UI benefits during recessions could lead to procyclical job search effort. Specifically, the average number of weeks of benefits remaining among the eligible unemployed was 12 in 2007 and rose to 33 in 2009, suggesting a decline of 0.5 minutes, or 1.5 percent of total search time. This quantitatively small disincentive effect on search effort is likely to be dominated by individual's response to weak market conditions and shifts in the composition of the unemployed, which we analyze next.

[43]See, for example, Shavell and Weiss (1979), Wang and Williamson (1996), Hopenhayn and Nicolini (1997), Chetty (2008), and Krueger and Mueller (2010, 2011).

[44]Due to the availability of benefits data, this regression is estimated using data from January 2004 to March 2011. Additionally, since the number of weeks remaining on UI is a direct function of the individual's unemployment duration, we do not separately control for the unemployment duration in this regression.

Table 10: The disincentive effect of unemployment benefits.

	S&P 500	House Price
$\log(\theta)$	-1.382^{***}	-0.646
	(0.227)	(0.395)
Weeks of Benefits Remaining	-0.022^{***}	-0.026^{***}
	(0.005)	(0.005)
S & P 500	-0.005^{***}	
	(0.001)	
House Price Index		-0.053^{***}
		(0.010)
R^2	0.401	0.401
Observations	132751	132751

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors. All regressions include month dummies. Included in the regression are only eligible workers in the months in which there is benefits information. Full regression results reported in Appendix B Table B8.

Workers who are eligible for UI are likely to be different from other unemployed workers not only in their receipt of benefits but also in their unobservable characteristics, mainly in their labor force attachment.[45] Table 11 presents the results of the regressions from Table 6 in which we also control for unemployment benefit eligibility. We see clearly that even after controlling for other observable characteristics and our proxy for labor force attachment, eligible unemployed workers search more, and this effect is large and statistically significant. It is possible that eligible unemployed search more because workers need to provide some evidence of job search in order to receive benefits. Alternatively, a worker's eligibility for unemployment may be an additional proxy for unobserved characteristics that are not captured in observable characteristics or prior employment status. Appendix Figure B3 shows that the fraction of the unemployed who are eligible for unemployment benefits increases sharply during recessions, from around 0.55 in 2007 to around 0.75 in 2009. The combination of this large increase in the fraction of eligible unemployed and the large coefficient on eligibility in Table 11 suggests that

[45] For example, Figure B3 in Appendix B shows that over our sample, around 70 percent of the eligible workers were employed a year ago, as opposed to only around 40 percent of non-eligible workers.

Table 11: The effect of UI eligibility on search effort.

	S&P	House Price
$\log(\theta)$	0.027	-0.388^{*}
	(0.218)	(0.221)
Employed 1 year ago	4.605^{***}	4.631^{***}
	(0.228)	(0.228)
Unemployed 1 year ago	3.516^{***}	3.423^{***}
	(0.252)	(0.252)
Eligible for UI Benefits	4.979^{***}	4.950^{***}
	(0.193)	(0.193)
S & P 500	-0.006^{***}	
	(0.001)	
House Price Index		-0.021^{***}
		(0.004)
R^2	0.426	0.426
Observations	99325	99325

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors. All regressions include month dummies. Full regression results are reported in Appendix B Table B8.

the changing composition of the unemployed along this dimension dominates the disincentive effects of UI extensions at the individual level.[46] This finding has important implications for policy design, as in some recent studies of optimal unemployment insurance over the business cycle, such as Kroft and Notowidigdo (2014) and Landais, Michaillat, and Saez (2011), moral hazard in worker's search effort (and how it varies over the business cycle) is the central focus in determining the optimal policy.

7 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 showed that this countercyclical pattern is the consequence of cyclical shifts

[46]We also see that once we control for workers UI eligibility, which can be thought of a reduced form way to control for UI benefits, the coefficient on θ shrinks, and in the version where we capture wealth effects using the S&P, it becomes insignificant.

in the composition of the unemployed pool as well as individuals' responses to changes in macroeconomic conditions, such as job availability, stock prices, and house prices. We also established a positive link between job search effort and job finding at the individual and aggregate level. Finally, we showed that the disincentive effects that are typically associated with UI benefits extensions does not contradict our findings. While we also observed a negative effect of UI extensions on job search effort, we found that this disincentive effect is likely dwarfed in the aggregate by a compositional shift towards more attached workers during recessions.

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 procyclicaly to economic conditions. When worker search effort is procyclical, variations in the search decision can generate realistic labor market fluctuations either as the primary source of fluctuations or as an amplifier of other sources of fluctuations.[47] In this class of models, the returns to work, i.e. wages, are lower during recessions. Since in this case the return to search is lower, unemployed workers reduce their search effort, causing an increase in the unemployment rate during recessions. However, we have seen that the opposite is true in the data. Aggregate search intensity of workers increases during recessions, and thus this cannot be the primary driver of the labor market fluctuations over the business cycle. Instead, the decline in labor demand must be sufficiently strong to counteract the increase in worker search effort during recessions. In other words, labor supply is assumed to amplify labor demand fluctuations in this class of models while in reality it dampens the fluctuations in labor demand.

[47] See, for example, Veracierto (2008), Christiano, Trabandt, and Walentin (2012), and Gomme and Lkhagvasuren (2012)

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For Online Publication

A Data Appendix

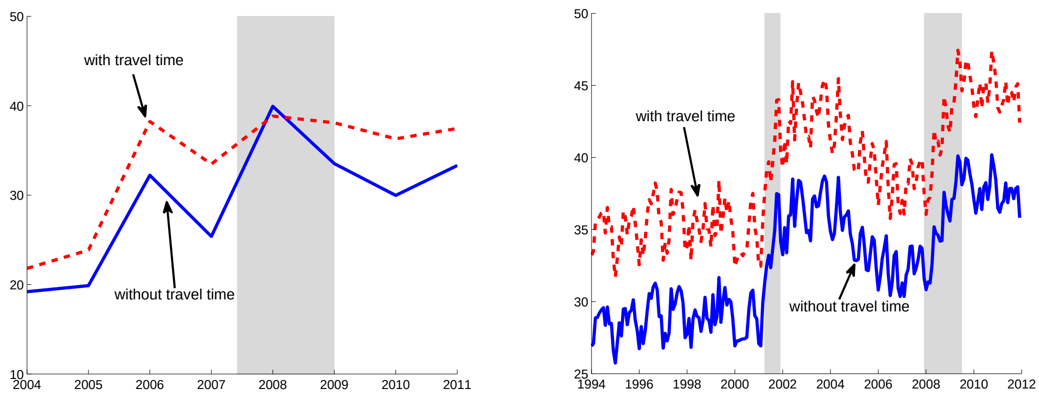
A.1 Data description

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 it provides consistent population weights across years. However, it comes at the cost of slightly less detailed job search categories. As explained in Section 2.1, we 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. We see that while it 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. 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 age of 25 and 70. We also drop individuals who report more than 8 hours of search in each day. This excludes only 33 respondents or around 2.5 percent of the active searchers.[48] 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.

From the CPS, we use monthly basic samples from January 1994 through December 2011. 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 4.2, we match

[48]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.

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



(a) reported minutes of search in ATUS (b) Imputed minutes of search in CPS

our sample across the eight survey months.[49] We are able to match 93 percent of the sample to at least 1 other month of the survey, 60 percent of respondents to at least 4 months and 40 percent across all 8 survey months.

A.2 Details on how we link between 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, $E[Y_{it}]$, 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.

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

Our purpose 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 she reports using. We estimate $E[Y_{it}]$ based on the characteristics X_{it} (denote the estimate as $E_X[E[Y_{it}]]$). From the above equation,

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

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

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

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

1. Obtaining $E_X[P_{it}]$ for the CPS sample:

    (a) Generate $\{0, 1\}$ indicator variable (call y_{it}) for whether or not the individual reported positive search minutes in the ATUS time diary (zero if minutes are zero, one if strictly positive).

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

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

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

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

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

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

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

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

for the ATUS sample, where ϵ is assumed to be normally distributed mean zero and variance σ^2.

(b) For the CPS sample, obtain

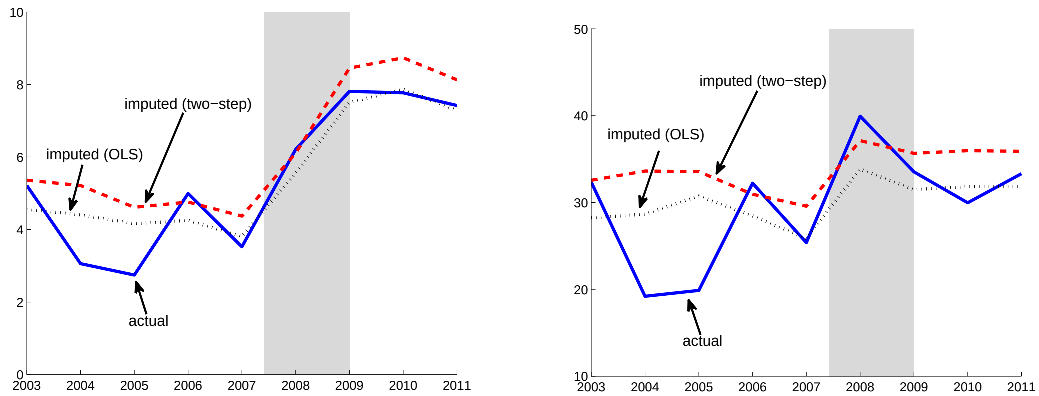
$$E_X[E[M_{it}]] = \exp\left(\gamma_0 + \gamma_1 X_{1,it} + ... + \gamma_n X_{n,it} + \frac{\hat{\sigma}^2}{2}\right)$$

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

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

Through this method, we are able to impute a strictly non-negative amount of search time for all non-employed in both the ATUS and CPS given their reported search methods and observables. Importantly, in addition to including dummies for each of the twelve search methods, x_{it} contains two sets of observables. The first is a set of worker characteristics which may affect the intensity of their job search. We mostly follow Shimer (2004) in the choice of these controls and include a quartic of age, 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 out of the labor force but wanting a job.

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

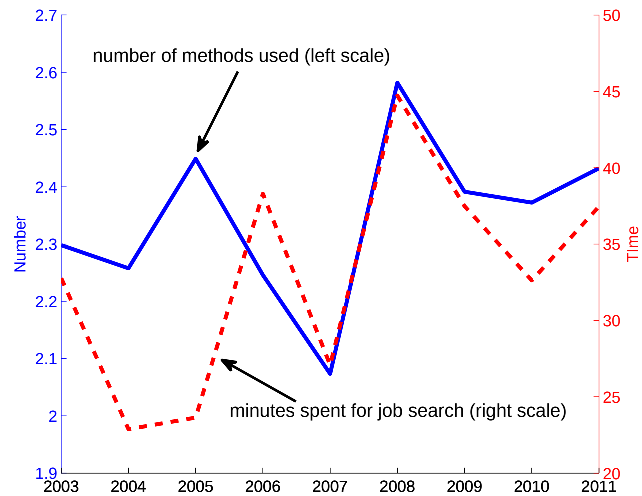


(a) all nonemployed (b) unemployed

As mentioned before, a much simpler 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 method described above and the imputed minutes using the simple OLS regression. The two imputation methods produce similar results.

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 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 percent in both the ATUS and CPS sample and therefore it is

Figure A3: Minutes spent on job search activities and number of search methods in the ATUS sample



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.[50] 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 A3 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

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

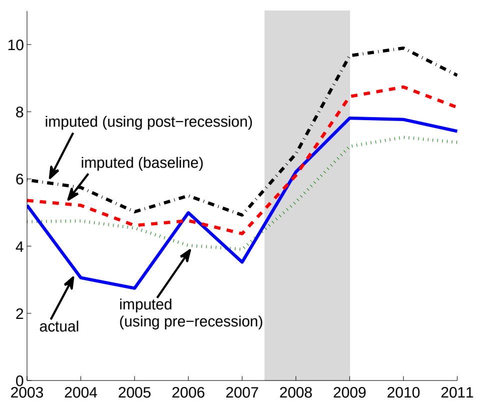
Table A1: Time dummy estimates from OLS regression of reported search time on search methods.

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

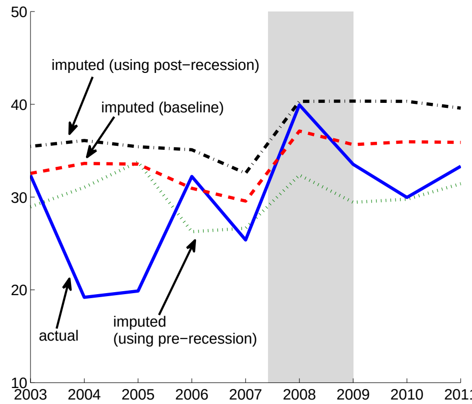
time varies over time, we break our data into a pre-recession (2003-2007) and a post-recession (2008-2011) sample. We then calculate the imputed minutes for each of the subsamples and explore the in and out of sample fit. Figure A4 shows that the regression using the pre-recession sample slightly underpredicts 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 A3.

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 interacted with each search method, essentially allowing the relationship between search time and a particular search method to vary over the business cycle. Figure A5 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

Figure A4: Average search minutes per day for all nonemployed workers and unemployed workers using pre- and post-recession samples of ATUS data.



(a) all nonemployed



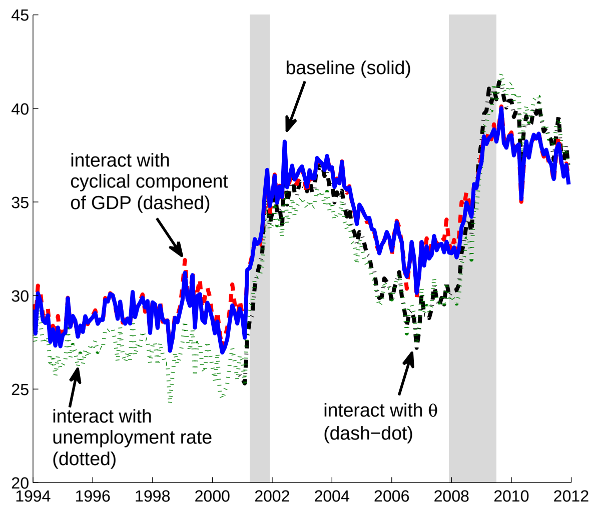
(b) unemployed

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 a conservative one in terms of representing the cyclicality of search effort.

A.3 Additional results for the cyclicality of search effort

In order to examine the robustness of our aggregate results, we present a number of additional measures of the intensive and extensive margins. The left panel of figure A6 shows the time series of the average number of search methods used in the CPS sample over our sample period. This more simple measure of search effort shows a countercyclical pattern very similar to Figure 3. 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 A6 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

Figure A5: Imputed minutes in the CPS using market aggregates.

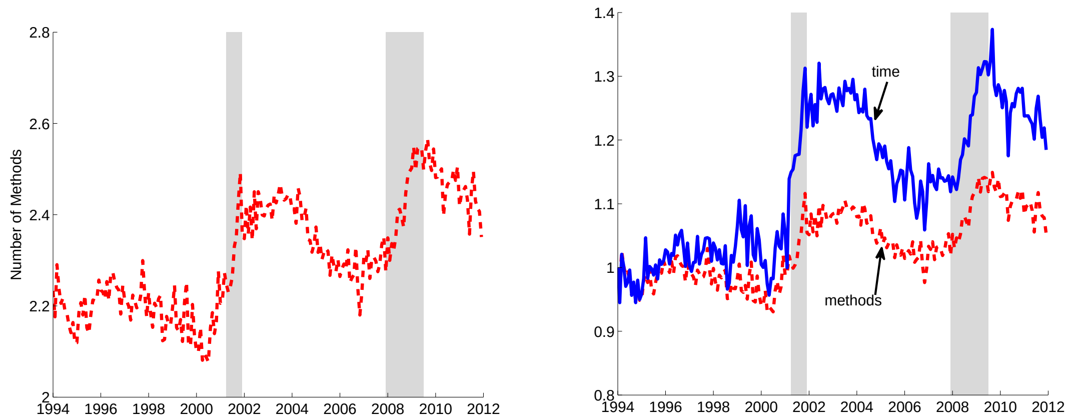


methods. This suggests that either individuals shift to more time intensive search methods in recessions or that the composition of the unemployed pool shifts towards higher search demographics over the business cycle.

In order to directly compare the search time information in the ATUS and the CPS, Figure A7 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 in 2009.

Lastly, although our main analysis begins 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

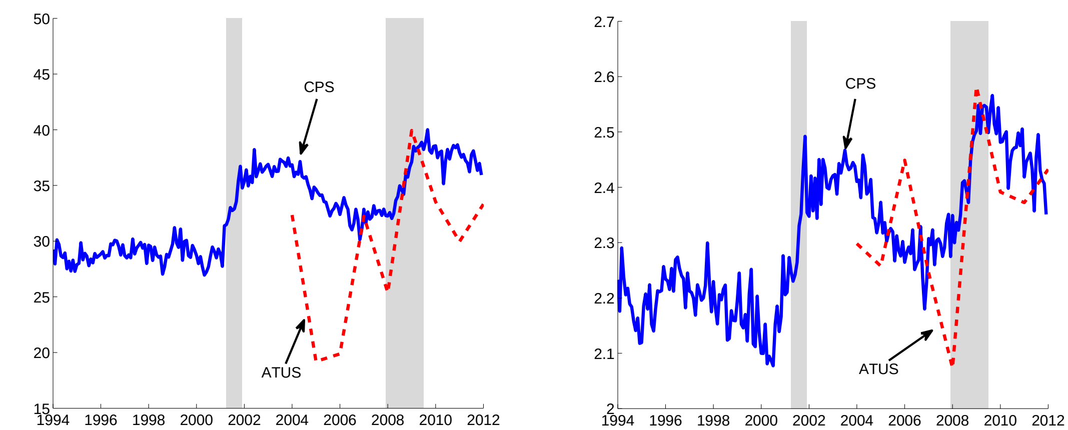
Figure A6: Two measure of the intensive margin of job search.



(a) Average number of search methods

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

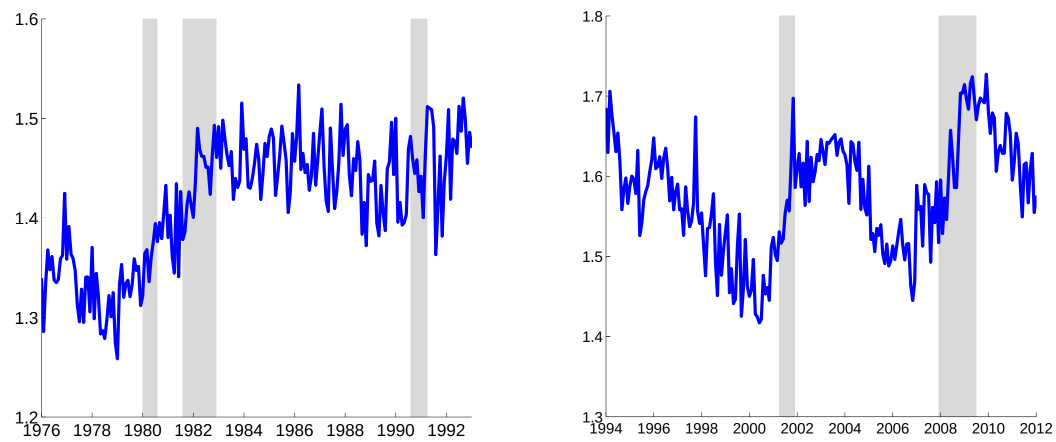
Figure A7: Intensive margin measures in the ATUS and the CPS



(a) Average minutes of search (per day)

(b) Average number of search methods

Figure A8: Historical time series of the average number of job search methods (from 5 methods)



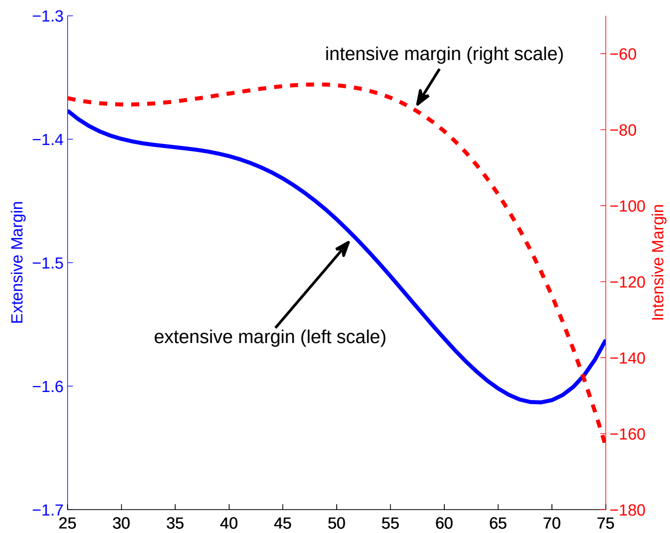
(a) 1976–1993

(b) 1994–2012

five of these search methods were also options after the 1994 redesign as well, therefore 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 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 A8 shows the time series of the average number of reported search methods, selected from these five possible search methods.[51] The left panel shows the series from 1976-1993 and the right panel shows the series from 1994-2012, 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.

[51]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.

Figure B1: The effect of age on the intensive and extensive margins of job search. Quartic polynomial coefficients from regression 2



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B Additional results for determinants of aggregate search effort

In this section, we present the details of our exploration of the determinants of aggregate search effort. Section 4.1 discussed the role of observed heterogeneity. Table 5 in the main text shows the coefficients from the regressions that produced the time dummies in Figure 5, capturing the cyclicality of job search that remains after controlling for unobserved heterogeneity.

Figure B1 shows the age-search effort profile, estimated using a quartic polynomial in regression 2. The extensive margin falls over the most of the life, while the intensive margin stays almost flat (increasing slightly) before starting to fall after 50 years of age.

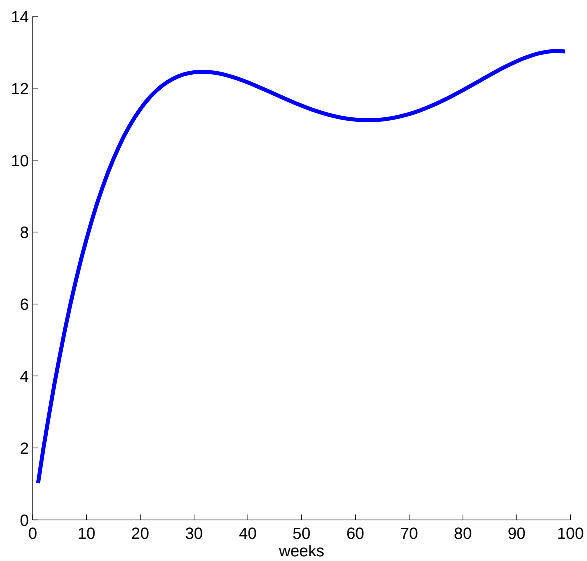
The duration of unemployment is often considered an important determinant of job search effort. In many models, agents' search effort responds to their unemployment duration but the direction of the change varies from model to model. One possibility is that as the unemployment spell progresses, an unemployed worker's savings become depleted, leading the worker to search harder. However, various other forces can move job search 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, in 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 B2 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).

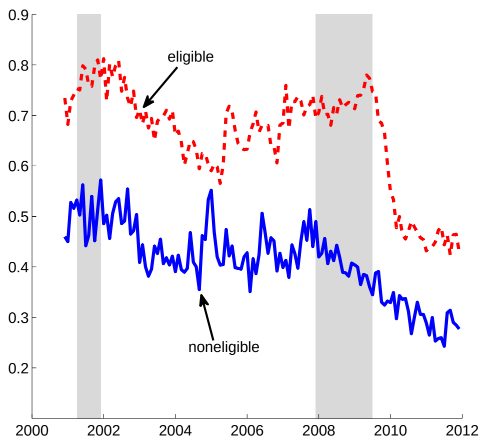
In the following tables, we present the full regression results for all of the regression tables presented in Section 4.2. We also include versions of the regressions using the HWOL vacancy series to construct θ. This restricts the sample to begin in 2005 and therefore covers only one recession. However, we find that the results are very similar qualitatively to those using the JOLTS vacancy series. The magnitude of the coefficients on θ across all specifications tend to be larger (i.e. more negative) using HWOL than using JOLTS, which is likely because it is estimated on a portion of the sample where search time moves more dramatically. In each of

Figure B2: The effect of unemployment duration on the intensive and extensive margins of search. Drawn from the quartic polynomial coefficients in regression (2)

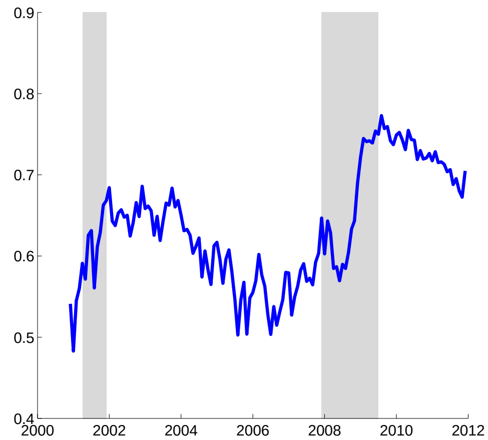


the regressions without individual fixed effects, we present the results controlling for various demographic characteristics that generally affect the labor market behavior of individuals. An examination of the coefficients across specifications reveals that the effects of these characteristics on search intensity are robust to various specifications and are similar to those discussed in Section 4.1. We find that women in general search less than men and this effect is more pronounced for married women. For men, it is the opposite, with married men searching more than single men. Another interesting finding is that search effort increases by education and that workers in non-routine occupations tend to search more than workers in routine occupations. Table 10 reveals additionally that changes in the unemployment benefit eligibility played an important role in explaining job search, with eligible workers searching more than similar workers who are not eligible. Figure B3 reveals that one explanation for this finding is that eligible workers may be more attached to the labor force. In the left panel, we see that during the Great Recession, around 70 percent of the eligible unemployed was employed 1 year ago, as compared with only around 40 percent of the noneligible unemployed. If we interpret one's

Figure B3: Changes in the composition of the unemployed



(a) Fraction of eligible (dashed) and noneligible (solid) workers who were employed 1 year ago



(b) Fraction of the unemployed who are eligible for UI

labor force status 1 year ago as a proxy for her labor force attachment, this suggests that eligible workers are more strongly attached to the labor force than those who are not eligible. We also see in the right panel of Figure B3 that the fraction the unemployed that is eligible for UI increases significantly during recessions, providing a countercyclical force for aggregate search effort.

Additionally, Table B3 and B4 display the results for the regressions with various control variables using the full unemployed sample from the CPS. Recall that in controlling for either prior labor force status or individual fixed effects, we selected the sample to include only those individuals who we were able to match to the survey 1 year ago or who we observed to be unemployed for at least 2 periods, respectively. We see that the results of the regression on the full CPS sample closely match the similarly specified results presented in the main text in Table 6 and 7. Most importantly, the coefficients on θ and the wealth variables have the same sign, significance level, and very similar magnitudes. This suggests that the sample selection induced by the data limitations is not driving our results.

While looking at aggregate labor market conditions is informative, one can argue that aggregate measures of wealth and market tightness are not what most workers take into account when they decide on how much to search. Ideally, one wants to control for the labor market conditions that an individual faces in her job search and her current level of wealth. Unfortunately, it is impossible to observe the labor market conditions that an individual is actually facing in her job search for two reasons: (i) there is no information about the market in which the unemployed are searching in currently available data sources; (ii) computing labor market tightness requires knowing the number of unemployed in very small markets. Due to the small sample size of the CPS, unemployment counts become unreliable for small labor markets making it impossible to compute labor market tightness. In addition, available data sources do not provide us good information on individuals' wealth.

Since we don't have individual measures of labor market conditions and wealth, we run the regression (3) using more disaggregated measures of labor market conditions and wealth. In particular, we use market tightness at the census region in order to capture more individual-specific labor markets and a state-level house price index to get closer to personal wealth. In addition, we also try the interaction of occupations and locations as the definition of the individual's labor market—specifically, we define $4 \times 4 = 16$ labor markets which are the interaction of four occupation categories and four Census regions.[52] We run the regressions in Table 6 and 7 of the main text using these various refinements of the labor market and report results in Table B6 and Table B5, respectively. For compactness, we report only the specification using the state-level house price index as our measure of wealth but results are similar using the S&P 500. Again, we see a general pattern that the coefficient on θ decreases when we include some control for the unobserved characteristics of the workers.

Taken together, this analysis continues to imply that the countercyclicality of aggregate search effort is the consequence of both individual search effort responding negatively to aggregate market conditions as well as both observed and unobserved changes in the composition of

[52] The occupation categories are the same as in the footnote 25. Since we need information on vacancies within occupation, this series uses vacancy data from HWOL and therefore begins in 2005.

the unemployed over the business cycle.

Table B1: Full regression results for Table 6

	JOLTS				HWOL			
	S&P		House Price		S&P		House Price	
	Observables	Full	Observables	Full	Observables	Full	Observables	Full
$\log(\theta)$	-0.745***	-0.593***	-1.085***	-0.954***	-1.635***	-1.335***	-3.889***	-3.523***
	(0.216)	(0.216)	(0.220)	(0.220)	(0.462)	(0.462)	(0.614)	(0.614)
Employed 1 year ago		6.435***		6.449***		6.351***		6.356***
		(0.219)		(0.219)		(0.271)		(0.271)
Unemployed 1 year ago		4.773***		4.674***		4.820***		4.756***
		(0.250)		(0.249)		(0.297)		(0.297)
S&P 500	-0.006***	-0.005***			-0.005***	-0.005***		
	(0.001)	(0.001)			(0.001)	(0.001)		
House Price Index			-0.025***	-0.023***			0.012	0.010
			(0.005)	(0.004)			(0.010)	(0.010)
Age	-10.969***	-11.678***	-10.800***	-11.510***	-8.292***	-8.846***	-8.279***	-8.826***
	(1.996)	(1.991)	(1.997)	(1.992)	(2.418)	(2.415)	(2.418)	(2.415)
Age^2	0.266***	0.291***	0.260***	0.286***	0.174**	0.195**	0.174**	0.194**
	(0.068)	(0.068)	(0.068)	(0.068)	(0.082)	(0.082)	(0.082)	(0.082)
Age^3	-0.002	-0.002**	-0.002	-0.002*	-0.000	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age^4	-0.000	-0.000	-0.000	-0.000	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration	0.679***	0.610***	0.695***	0.623***	0.635***	0.561***	0.638***	0.564***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.049)	(0.049)	(0.049)	(0.049)
$(\text{Unemployment Duration})^2$	-0.022***	-0.019***	-0.022***	-0.020***	-0.020***	-0.018***	-0.021***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$(\text{Unemployment Duration})^3$	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$(\text{Unemployment Duration})^4$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	-2.428***	-2.253***	-2.448***	-2.268***	-1.929***	-1.754***	-1.933***	-1.756***
	(0.234)	(0.234)	(0.234)	(0.234)	(0.291)	(0.292)	(0.291)	(0.292)
Married	11.443***	11.089***	11.442***	11.084***	11.022***	10.680***	11.023***	10.678***
	(0.287)	(0.286)	(0.287)	(0.286)	(0.345)	(0.344)	(0.345)	(0.345)
Female	-6.474***	-6.190***	-6.496***	-6.214***	-6.330***	-6.060***	-6.331***	-6.063***
	(0.271)	(0.271)	(0.271)	(0.271)	(0.330)	(0.329)	(0.330)	(0.329)
Married×Female	-31.867***	-31.226***	-31.854***	-31.213***	-31.217***	-30.571***	-31.199***	-30.553***
	(0.362)	(0.361)	(0.362)	(0.361)	(0.439)	(0.438)	(0.439)	(0.438)
High School	6.312***	5.982***	6.292***	5.958***	6.655***	6.368***	6.641***	6.353***
	(0.184)	(0.184)	(0.184)	(0.184)	(0.229)	(0.230)	(0.229)	(0.230)
Some College	25.923***	25.561***	25.906***	25.541***	26.438***	26.126***	26.423***	26.110***
	(0.236)	(0.236)	(0.236)	(0.236)	(0.291)	(0.290)	(0.291)	(0.290)
College	49.168***	48.779***	49.159***	48.764***	48.703***	48.354***	48.695***	48.342***
	(0.368)	(0.367)	(0.369)	(0.367)	(0.448)	(0.446)	(0.448)	(0.446)
Occupation Groups								
Cognitive Routine	-4.105***	-3.768***	-4.132***	-3.797***	-2.682***	-2.404***	-2.686***	-2.408***
	(0.321)	(0.320)	(0.321)	(0.320)	(0.391)	(0.390)	(0.391)	(0.390)
Non-Cognitive Non-Routine	-1.250***	-1.164***	-1.268***	-1.182***	-0.341	-0.267	-0.348	-0.275
	(0.315)	(0.314)	(0.315)	(0.314)	(0.380)	(0.379)	(0.380)	(0.379)
Non-Cognitive Routine	-6.435***	-6.252***	-6.451***	-6.266***	-4.561***	-4.416***	-4.556***	-4.410***
	(0.324)	(0.323)	(0.324)	(0.323)	(0.395)	(0.394)	(0.395)	(0.394)
Observations	99325	99325	99325	99325	66676	66676	66676	66676

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors. All regressions include month dummies. Sample includes only those observations that are unemployed and matched to their labor force status 1 year ago.

Table B2: Full regression results for Table 7.

	JOLTS				HWOL			
	S&P		House Price		S&P		House Price	
	Observables	FE	Observables	FE	Observables	FE	Observables	FE
$\log(\theta)$	-0.875***	-0.295	-1.046***	-0.980**	-1.955***	-1.362*	-2.863***	-4.346***
	(0.120)	(0.510)	(0.121)	(0.480)	(0.253)	(0.718)	(0.338)	(0.676)
S & P 500	-0.005***	-0.003***			-0.003***	-0.002**		
	(0.000)	(0.001)			(0.001)	(0.001)		
House Price Index			-0.027***	-0.020			-0.004	0.094***
			(0.002)	(0.013)			(0.006)	(0.020)
Unemployment Duration	0.625***	0.142***	0.637***	0.146***	0.574***	0.115***	0.577***	0.115***
	(0.022)	(0.033)	(0.022)	(0.033)	(0.027)	(0.040)	(0.027)	(0.040)
Unemployment Duration^2	-0.020***	-0.007***	-0.020***	-0.007***	-0.018***	-0.006***	-0.019***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(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)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration^4	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-2.422**		-2.429**		-2.186*		-2.191*	
	(0.969)		(0.969)		(1.165)		(1.165)	
Age^2	-0.018		-0.018		-0.025		-0.024	
	(0.034)		(0.034)		(0.040)		(0.040)	
Age^3	0.002***		0.002***		0.003***		0.003***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Age^4	-0.000***		-0.000***		-0.000***		-0.000***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Black	-2.036***		-2.043***		-1.718***		-1.717***	
	(0.124)		(0.124)		(0.154)		(0.154)	
Married	10.685***		10.685***		10.191***		10.192***	
	(0.161)		(0.161)		(0.195)		(0.195)	
Female	-6.992***		-7.003***		-6.752***		-6.754***	
	(0.143)		(0.143)		(0.174)		(0.174)	
Married*Female	-30.881***		-30.876***		-30.357***		-30.350***	
	(0.202)		(0.202)		(0.246)		(0.246)	
High School	6.126***		6.107***		6.339***		6.324***	
	(0.099)		(0.099)		(0.124)		(0.124)	
Some College	26.160***		26.141***		26.490***		26.471***	
	(0.130)		(0.130)		(0.161)		(0.161)	
College	48.427***		48.420***		47.815***		47.802***	
	(0.208)		(0.208)		(0.253)		(0.253)	
Occupation Groups								
Cognitive Routine	-4.375***		-4.378***		-3.257***		-3.267***	
	(0.177)		(0.177)		(0.215)		(0.215)	
Non-Cognitive Non-Routine	-0.986***		-0.984***		-0.302		-0.301	
	(0.177)		(0.177)		(0.214)		(0.214)	
Non-Cognitive Routine	-6.452***		-6.452***		-5.055***		-5.050***	
	(0.181)		(0.181)		(0.221)		(0.221)	
R^2	0.410	0.001	0.410	0.001	0.395	0.001	0.395	0.001
Observations	311453	311453	311453	311453	207852	207852	207852	207852

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors. All regressions include month dummies. Sample includes individuals who are unemployed at least twice over the sample period.

Table B3: Baseline regression using the full CPS sample and aggregate measures of labor market tightness and wealth

	JOLTS		HWOL	
	S&P	House Price	S&P	House Price
$\log(\theta)$	-0.872***	-1.050***	-1.939***	-2.843***
	(0.118)	(0.120)	(0.250)	(0.334)
S&P 500	-0.005***		-0.003***	
	(0.000)		(0.001)	
House Price Index		-0.026***		-0.004
		(0.002)		(0.006)
Age	-2.237**	-2.246**	-1.861	-1.866
	(0.955)	(0.956)	(1.149)	(1.149)
Age^2	-0.024	-0.023	-0.035	-0.035
	(0.033)	(0.033)	(0.040)	(0.040)
Age^3	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.001)	(0.001)
Age^4	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration	0.625***	0.636***	0.577***	0.580***
	(0.022)	(0.022)	(0.026)	(0.026)
$(\text{Unemployment Duration})^2$	-0.020***	-0.020***	-0.018***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
$(\text{Unemployment Duration})^3$	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$(\text{Unemployment Duration})^4$	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Black	-2.043***	-2.050***	-1.727***	-1.725***
	(0.122)	(0.122)	(0.152)	(0.152)
Married	10.671***	10.672***	10.193***	10.194***
	(0.160)	(0.160)	(0.193)	(0.193)
Female	-6.997***	-7.007***	-6.769***	-6.771***
	(0.141)	(0.141)	(0.171)	(0.171)
Married×Female	-30.811***	-30.808***	-30.283***	-30.276***
	(0.200)	(0.200)	(0.244)	(0.243)
High School	6.139***	6.121***	6.367***	6.351***
	(0.097)	(0.097)	(0.122)	(0.122)
Some College	26.179***	26.159***	26.502***	26.483***
	(0.129)	(0.129)	(0.159)	(0.159)
College	48.416***	48.410***	47.819***	47.806***
	(0.206)	(0.206)	(0.251)	(0.251)
Occupation Groups				
Cognitive Routine	-4.355***	-4.359***	-3.256***	-3.266***
	(0.175)	(0.175)	(0.213)	(0.213)
Non-Cognitive Non-Routine	-0.972***	-0.971***	-0.306	-0.305
	(0.176)	(0.176)	(0.212)	(0.212)
Non-Cognitive Routine	-6.427***	-6.426***	-5.049***	-5.043***
	(0.179)	(0.179)	(0.219)	(0.219)
Observations	317881	317881	212048	212048

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

Table B4: Baseline regression using the full CPS sample and disaggregated measures of labor market tightness and wealth

	Census Region		Occupation×Region	
	S&P	House Price	S&P	House Price
$\log(\theta)$	-1.070**	-1.473**	-0.963***	-1.828***
	(0.325)	(0.290)	(0.321)	(0.279)
S&P 500	-0.005*		-0.005***	
	(0.002)		(0.001)	
State House Price Index		-0.018		-0.015***
		(0.010)		(0.005)
Age	-2.277	-2.294	-1.689	-1.694
	(1.685)	(1.688)	(1.617)	(1.630)
Age^2	-0.022	-0.021	-0.041	-0.041
	(0.063)	(0.063)	(0.058)	(0.059)
Age^3	0.003*	0.002*	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Age^4	-0.000**	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration	0.624***	0.635***	0.582***	0.591***
	(0.033)	(0.035)	(0.055)	(0.055)
(Unemployment Duration)^2	-0.020***	-0.020***	-0.018***	-0.019***
	(0.001)	(0.001)	(0.002)	(0.002)
(Unemployment Duration)^3	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
(Unemployment Duration)^4	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Black	-1.995**	-1.942**	-1.809***	-1.818***
	(0.419)	(0.433)	(0.398)	(0.393)
Married	10.670***	10.651***	10.203***	10.180***
	(0.296)	(0.304)	(0.965)	(0.970)
Female	-6.992***	-7.026***	-6.806***	-6.845***
	(0.209)	(0.211)	(0.382)	(0.377)
Married×Female	-30.808***	-30.787***	-30.363***	-30.339***
	(0.812)	(0.817)	(2.212)	(2.218)
High School	6.129***	6.068***	6.324***	6.259***
	(0.153)	(0.128)	(0.299)	(0.294)
Some College	26.158***	26.095***	26.451***	26.395***
	(0.472)	(0.463)	(0.650)	(0.642)
College	48.406***	48.431***	47.756***	47.775***
	(0.249)	(0.248)	(0.767)	(0.767)
Occupation Groups				
Cognitive Routine	-4.366***	-4.426***	-5.134***	-6.839***
	(0.397)	(0.395)	(0.798)	(0.775)
Non-Cognitive Non-Routine	-0.974***	-1.001***	-1.339*	-2.274***
	(0.127)	(0.124)	(0.631)	(0.600)
Non-Cognitive Routine	-6.437***	-6.518***	-7.108***	-9.035***
	(0.480)	(0.483)	(1.016)	(1.103)
Observations	317881	317881	210012	210012

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

Table B5: Full regression results for prior-status regressions using market-specific measures of labor market tightness and the state house price index

	Census Region		Occupation×Region	
	Observables	Full	Observables	Full
$\log(\theta)$	-1.441**	-1.303**	-2.295***	-2.085***
	(0.333)	(0.350)	(0.277)	(0.280)
Employed 1 year ago		6.443***		6.381***
		(0.338)		(0.716)
Unemployed 1 year ago		4.634***		4.729***
		(0.313)		(0.639)
State House Price Index	-0.018	-0.016	-0.014*	-0.013*
	(0.012)	(0.012)	(0.007)	(0.007)
Age	-10.864**	-11.569**	-7.891**	-8.485**
	(2.188)	(2.094)	(3.301)	(3.308)
Age^2	0.263**	0.288**	0.160	0.182
	(0.076)	(0.072)	(0.116)	(0.116)
Age^3	-0.002	-0.002	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)
Age^4	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration	0.694***	0.621***	0.653***	0.576***
	(0.065)	(0.071)	(0.083)	(0.080)
(Unemployment Duration)^2	-0.022***	-0.020***	-0.021***	-0.018***
	(0.002)	(0.002)	(0.003)	(0.003)
(Unemployment Duration)^3	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
(Unemployment Duration)^4	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Black	-2.318**	-2.147**	-2.043***	-1.857***
	(0.418)	(0.384)	(0.523)	(0.535)
Married	11.421***	11.063***	10.987***	10.643***
	(0.641)	(0.666)	(0.969)	(0.960)
Female	-6.506***	-6.223***	-6.410***	-6.148***
	(0.265)	(0.262)	(0.438)	(0.427)
Married*Female	-31.858***	-31.217***	-31.220***	-30.573***
	(0.917)	(0.963)	(2.193)	(2.124)
High School	6.221***	5.893***	6.554***	6.273***
	(0.185)	(0.186)	(0.393)	(0.394)
Some College	25.814***	25.454***	26.322***	26.011***
	(0.601)	(0.617)	(0.895)	(0.943)
College	49.141***	48.746***	48.607***	48.255***
	(0.443)	(0.443)	(0.970)	(1.012)
Occupation Groups				
Cognitive Routine	-4.196***	-3.856***	-7.167***	-6.480***
	(0.492)	(0.493)	(0.918)	(0.948)
Non-Cognitive Non-Routine	-1.295*	-1.207*	-2.828***	-2.527***
	(0.455)	(0.460)	(0.623)	(0.632)
Non-Cognitive Routine	-6.551***	-6.358***	-9.587***	-8.992***
	(0.584)	(0.593)	(1.321)	(1.335)
R^2	0.419	0.423	0.404	0.408
Observations	99325	99325	66042	66042

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors adjusted for clustering by specific market. All regressions include month dummies. Sample includes only those observations that are unemployed and matched to their labor force status 1 year ago.

Table B6: Full regression results for individual fixed effect regressions using market-specific measures of labor market tightness and the state-level house price index

	Census Region		OccXRegion	
	Observables	FE	Observables	FE
$\log(\theta)$	-1.470**	-0.721	-1.861***	0.091
	(0.307)	(0.339)	(0.315)	(0.267)
State House Price Index	-0.018	-0.025	-0.015**	-0.012
	(0.010)	(0.013)	(0.007)	(0.016)
Unemployment Duration	0.636***	0.147*	0.587***	0.121**
	(0.033)	(0.054)	(0.034)	(0.054)
Unemployment Duration^2	-0.020***	-0.008**	-0.019***	-0.006***
	(0.001)	(0.002)	(0.001)	(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)
Age	-2.478		-2.061	
	(1.725)		(1.931)	
Age^2	-0.016		-0.029	
	(0.064)		(0.068)	
Age^3	0.002*		0.003**	
	(0.001)		(0.001)	
Age^4	-0.000**		-0.000***	
	(0.000)		(0.000)	
Black	-1.936**		-1.810***	
	(0.426)		(0.527)	
Married	10.664***		10.182***	
	(0.314)		(0.312)	
Female	-7.022***		-6.828***	
	(0.220)		(0.201)	
Married*Female	-30.857***		-30.417***	
	(0.808)		(0.479)	
High School	6.053***		6.230***	
	(0.125)		(0.234)	
Some College	26.075***		26.379***	
	(0.469)		(0.327)	
College	48.439***		47.768***	
	(0.265)		(0.426)	
Occupation Groups				
Cognitive Routine	-4.445***		-6.903***	
	(0.396)		(0.670)	
Non-Cognitive Non-Routine	-1.015***		-2.306***	
	(0.119)		(0.419)	
Non-Cognitive Routine	-6.544***		-9.115***	
	(0.482)		(0.759)	
R^2	0.410	0.001	0.394	0.001
Observations	311453	311453	205870	205870

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. Robust standard errors adjusted for clustering by specific market. All regressions include month dummies. Sample includes individuals who are unemployed at least twice over the sample period.

Table B7: Full regression results for Table 10

	JOLTS		HWOL	
$\log(\theta)$	-1.382***	-0.646	-2.070***	-2.661***
	(0.227)	(0.395)	(0.372)	(0.523)
Weeks of Benefits Remaining	-0.022***	-0.026***	-0.011*	-0.015***
	(0.005)	(0.005)	(0.006)	(0.006)
S&P 500	-0.005***		-0.004***	
	(0.001)		(0.001)	
House Price Index		-0.053***		-0.019**
		(0.010)		(0.010)
Age	-0.934	-0.887	-0.888	-0.886
	(1.613)	(1.613)	(1.730)	(1.731)
Age^2	-0.086	-0.087	-0.087	-0.087
	(0.056)	(0.056)	(0.060)	(0.060)
Age^3	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Age^4	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Black	-2.336***	-2.350***	-2.087***	-2.099***
	(0.204)	(0.204)	(0.223)	(0.223)
Married	10.791***	10.807***	10.551***	10.564***
	(0.232)	(0.232)	(0.250)	(0.250)
Female	-6.150***	-6.141***	-6.200***	-6.190***
	(0.231)	(0.231)	(0.250)	(0.250)
Married×Female	-31.839***	-31.852***	-31.540***	-31.550***
	(0.317)	(0.317)	(0.342)	(0.342)
High School	7.061***	7.041***	7.235***	7.215***
	(0.162)	(0.162)	(0.176)	(0.176)
Some College	28.618***	28.610***	28.788***	28.777***
	(0.218)	(0.218)	(0.236)	(0.236)
College	52.932***	52.931***	52.846***	52.846***
	(0.341)	(0.341)	(0.370)	(0.370)
Occupation Groups				
Cognitive Routine	-5.055***	-5.074***	-4.628***	-4.644***
	(0.295)	(0.295)	(0.318)	(0.318)
Non-Cognitive Non-Routine	-1.447***	-1.458***	-1.189***	-1.196***
	(0.289)	(0.290)	(0.311)	(0.312)
Non-Cognitive Routine	-7.095***	-7.092***	-6.594***	-6.593***
	(0.287)	(0.287)	(0.310)	(0.310)
R^2	0.401	0.401	0.396	0.395
Observations	132751	132751	114494	114494

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

Table B8: Full regression results for Table 11

	JOLTS		HWOL	
	S&P	House Price	S&P	House Price
$\log(\theta)$	0.027	-0.388*	-0.414	-3.142***
	(0.218)	(0.221)	(0.464)	(0.612)
Employed 1 year ago	4.605***	4.631***	4.655***	4.666***
	(0.228)	(0.228)	(0.284)	(0.284)
Unemployed 1 year ago	3.516***	3.423***	3.655***	3.598***
	(0.252)	(0.252)	(0.301)	(0.301)
Eligible for UI Benefits	4.979***	4.950***	4.531***	4.507***
	(0.193)	(0.193)	(0.238)	(0.239)
S&P 500	-0.006***		-0.005***	
	(0.001)		(0.001)	
House Price Index		-0.021***		0.017*
		(0.004)		(0.010)
Age	-12.483***	-12.303***	-9.351***	-9.330***
	(1.987)	(1.988)	(2.411)	(2.412)
Age^2	0.318***	0.312***	0.212***	0.211***
	(0.068)	(0.068)	(0.082)	(0.082)
Age^3	-0.002**	-0.002**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Age^4	-0.000	-0.000	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration	0.575***	0.588***	0.542***	0.544***
	(0.040)	(0.040)	(0.049)	(0.049)
$(\text{Unemployment Duration})^2$	-0.018***	-0.019***	-0.017***	-0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
$(\text{Unemployment Duration})^3$	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$(\text{Unemployment Duration})^4$	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Black	-2.235***	-2.250***	-1.717***	-1.719***
	(0.234)	(0.234)	(0.291)	(0.291)
Married	10.981***	10.978***	10.590***	10.590***
	(0.286)	(0.286)	(0.344)	(0.344)
Female	-5.815***	-5.840***	-5.694***	-5.697***
	(0.270)	(0.271)	(0.329)	(0.329)
Married×Female	-30.903***	-30.894***	-30.327***	-30.311***
	(0.360)	(0.360)	(0.436)	(0.436)
High School	5.881***	5.857***	6.246***	6.233***
	(0.185)	(0.185)	(0.230)	(0.230)
Some College	25.610***	25.587***	26.185***	26.169***
	(0.236)	(0.236)	(0.291)	(0.291)
College	48.828***	48.811***	48.442***	48.433***
	(0.366)	(0.366)	(0.446)	(0.446)
Occupation Groups				
Cognitive Routine	-3.434***	-3.470***	-2.155***	-2.159***
	(0.320)	(0.320)	(0.389)	(0.389)
Non-Cognitive Non-Routine	-1.056***	-1.078***	-0.200	-0.208
	(0.312)	(0.313)	(0.377)	(0.378)
Non-Cognitive Routine	-6.308***	-6.322***	-4.476***	-4.469***
	(0.322)	(0.322)	(0.393)	(0.393)
Observations	99325	99325	66676	66676

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

C Additional results for job search effort and labor market outcomes

In this section, we present the full regression results for the job finding regressions in Table 8. We also present a version of the regressions in Table 8 that includes the individual's prior labor market status. We see that the positive effect on job finding is now reversed and we find that once we control for one's labor force attachment, there is no significant effect of job search effort on an individual's job-finding rate. This finding suggests that the strong positive relationship between job finding and search effort largely reflects the unobserved hetorogeneity in the individual's type.

At the aggregate level, we also present additional results for the estimation of the matching function. As is argued by Borowczyk-Martins, Jolivet, and Postel-Vinay (2013), the OLS estimate is likely biased. In particular, they argue that θ_t is endogenous in the conventional matching function estimation when there are shocks to 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 (5) 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 C3 shows the result. In both cases, the coefficient of $\log(\theta_t)$ is significant at 1 percent 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

Table C1: Full regression results for Table 8

	1 month	2 month	3 month	12 month	13 month	14 month	15 month
Search Time	-0.00025***	0.00002	0.00020*	0.00071***	0.00063***	0.00064***	0.00063***
	(0.00006)	(0.00008)	(0.00012)	(0.00009)	(0.00010)	(0.00011)	(0.00015)
Search Time * log(θ)	0.00011**	0.00020***	0.00023***	0.00020***	0.00015**	0.00013	0.00008
	(0.00004)	(0.00006)	(0.00009)	(0.00007)	(0.00008)	(0.00009)	(0.00012)
log(θ)	0.05135***	0.07456***	0.08739***	0.07199***	0.08243***	0.08637***	0.09008***
	(0.00244)	(0.00350)	(0.00522)	(0.00382)	(0.00444)	(0.00539)	(0.00757)
S&P 500	0.00000	-0.00000	-0.00002*	-0.00002***	-0.00003***	-0.00004***	-0.00005***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00002)
Age	-0.03086**	-0.03659*	-0.06888**	-0.08740***	-0.10030***	-0.11238***	-0.14742***
	(0.01486)	(0.02122)	(0.03174)	(0.02270)	(0.02649)	(0.03239)	(0.04574)
Age^2	0.00097*	0.00116	0.00230**	0.00307***	0.00347***	0.00384***	0.00504***
	(0.00051)	(0.00073)	(0.00110)	(0.00078)	(0.00091)	(0.00112)	(0.00158)
Age^3	-0.00001*	-0.00002	-0.00003**	-0.00004***	-0.00005***	-0.00005***	-0.00007***
	(0.00001)	(0.00001)	(0.00002)	(0.00001)	(0.00001)	(0.00002)	(0.00002)
Age^4	0.00000	0.00000	0.00000*	0.00000***	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Unemployment Duration	-0.01169***	-0.01166***	-0.00976***	-0.00763***	-0.00843***	-0.00727***	-0.00547***
	(0.00035)	(0.00048)	(0.00071)	(0.00052)	(0.00060)	(0.00073)	(0.00101)
(Unemployment Duration)^2	0.00032***	0.00029***	0.00022***	0.00014***	0.00017***	0.00014***	0.00008**
	(0.00001)	(0.00002)	(0.00003)	(0.00002)	(0.00002)	(0.00003)	(0.00004)
(Unemployment Duration)^3	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
(Unemployment Duration)^4	0.00000***	0.00000***	0.00000***	0.00000***	0.00000***	0.00000***	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Black	-0.03540***	-0.05289***	-0.06596***	-0.06917***	-0.07068***	-0.07311***	-0.07518***
	(0.00193)	(0.00280)	(0.00423)	(0.00310)	(0.00364)	(0.00446)	(0.00631)
Married	0.03707***	0.05068***	0.06186***	0.08872***	0.09409***	0.09850***	0.09899***
	(0.00221)	(0.00313)	(0.00466)	(0.00338)	(0.00390)	(0.00473)	(0.00665)
Female	-0.01035***	-0.01346***	-0.01033**	0.00045	-0.00183	-0.00131	0.00342
	(0.00217)	(0.00312)	(0.00468)	(0.00340)	(0.00396)	(0.00483)	(0.00680)
Married×Female	-0.04247***	-0.05103***	-0.05934***	-0.05422***	-0.06429***	-0.06784***	-0.06867***
	(0.00319)	(0.00455)	(0.00680)	(0.00495)	(0.00573)	(0.00697)	(0.00979)
High School	0.00631***	0.01487***	0.01723***	0.03962***	0.03845***	0.03945***	0.03561***
	(0.00230)	(0.00326)	(0.00488)	(0.00354)	(0.00415)	(0.00505)	(0.00712)
Some College	0.02337***	0.03393***	0.03768***	0.06687***	0.06827***	0.06898***	0.06345***
	(0.00256)	(0.00363)	(0.00544)	(0.00396)	(0.00461)	(0.00561)	(0.00792)
College	0.04358***	0.06203***	0.06870***	0.08767***	0.09202***	0.09289***	0.09025***
	(0.00322)	(0.00458)	(0.00682)	(0.00491)	(0.00569)	(0.00692)	(0.00969)
Cognitive Routine	0.00182	-0.00200	-0.00553	-0.04730***	-0.04421***	-0.03716***	-0.03768***
	(0.00267)	(0.00380)	(0.00568)	(0.00413)	(0.00479)	(0.00583)	(0.00821)
Non-Cognitive Non-Routine	-0.00888***	-0.01127***	-0.01196**	-0.02267***	-0.02409***	-0.01875***	-0.02329***
	(0.00232)	(0.00333)	(0.00500)	(0.00363)	(0.00417)	(0.00505)	(0.00708)
Non-Cognitive Routine	0.00360	0.00536	0.00685	-0.02747***	-0.02076***	-0.01408***	-0.01209
	(0.00247)	(0.00353)	(0.00528)	(0.00384)	(0.00443)	(0.00538)	(0.00754)
R^2	0.040	0.052	0.057	0.057	0.063	0.065	0.065
Observations	240338	161949	81424	164828	125001	84434	42504

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. All regressions include month dummies.

predict. Unfortunately, the coefficients of $\log(\bar{s})$ have large standard errors and thus cannot provide 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. Further exploration of this issue and precisely identifying the sign and the magnitude of $\bar{s}_t$ coefficient is left for future research.

Table C2: The effect of search time on the job-finding probability of individuals, controlling for prior labor market status.

The job-finding probability...			S&P	House Price
	1 month ahead	Search time	-0.00047***	-0.00047***
			(0.00010)	(0.00010)
		Search time$\times$ log(θ)	0.00002	0.00002
			(0.00007)	(0.00007)
	2 months ahead	Search time	-0.00023	-0.00023
			(0.00015)	(0.00015)
		Search time$\times$ log(θ)	0.00010	0.00010
			(0.00011)	(0.00011)
	3 months ahead	Search time	-0.00015	-0.00015
			(0.00021)	(0.00021)
		Search time$\times$ log(θ)	0.00010	0.00010
			(0.00015)	(0.00015)

*, **, ***: significant at the 10, 5, and 1 percent level, respectively. All regressions include month dummies, a full set of controls, and θ and wealth controls.

Table C3: 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.

	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)

Additional References for Appendix

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