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Job Search Behavior over the Business Cycle[†]

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We create a novel measure of job search effort exploiting the American Time Use and Current Population Surveys. We examine the cyclicality of search effort using time-series, cross-state, and individual variation and find that it is countercyclical. We then set up a search and matching model with endogenous search effort and show that search effort does not amplify labor market fluctuations but rather dampens them. Lastly, we examine the role of search effort in driving recent unemployment dynamics and show that the unemployment rate would have been 0.5 to 1 percentage points higher in the 2008–2014 period had search effort not increased. (*JEL* E24, E32, J22, J64)

Job search effort of job seekers is one of the key determinants of labor market outcomes in the Diamond-Mortensen-Pissarides (DMP) model of frictional labor markets. While aggregate job search effort is typically summarized by the number of unemployed workers, variations in each unemployed worker's search effort can also be important in determining labor market outcomes. While this possibility has been analyzed theoretically in the past, for example, by Hosios (1990) and Pissarides (2000), very little is known about the empirical properties of job search effort. In this paper, we analyze how job search effort varies over the business cycle and examine its implications for aggregate labor market outcomes in the context of the DMP framework.

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

In order to extract as much information as possible, we link the CPS monthly basic survey and the ATUS by utilizing the fact that both contain the same questions on the search methods used during the previous month. We first estimate a relationship between search time and search methods using the ATUS sample, and then use this relationship to impute job search time for all CPS respondents. Using individual search effort measures, we compute a monthly series of aggregate worker search effort starting in 1994.

In an analogy to the labor supply literature, we analyze the cyclical movement in aggregate search intensity along two margins: the extensive and intensive margins. The extensive margin is represented by the number of unemployed searchers relative to the total pool of nonemployed workers and the intensive margin is measured as the average minutes of job search per day that an unemployed worker spends on job search activities. We show that aggregate search effort is countercyclical both along the extensive and intensive margins: during recessions, nonemployed workers are more likely to actively engage in job search (and thus be labeled as unemployed) and are likely to search more 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 or job-finding rate.

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

[1] Before the 1994 redesign of the CPS, the respondents were given 6 job search methods to choose from, while the number of methods increased to 12 after 1994. We discuss the data before 1994 in online Appendix A.3.

responses is interesting and potentially important for understanding the effect of various policies, the aggregate implications for search and matching models depend on the total moments, whether those are driven by composition or individual responses.

After documenting the countercyclicality of search effort, we analyze the role of search effort in accounting for labor market fluctuations in the context of the unemployment volatility puzzle. We first extend the basic DMP model by Pissarides (1985) and Shimer (2005) to include worker search effort and a generalized matching function that is new to the literature. We then calibrate this model and use it to explore the role that search effort and, in particular, countercyclical search effort, plays in explaining labor market dynamics and accounting for the cyclicality of unemployment and vacancies. We show that once endogenous search effort is introduced to the basic model and it is calibrated to match the cyclical responsiveness of search effort in the data, the unemployment volatility puzzle becomes more acute.

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

This paper adds to a growing empirical literature examining job search effort. Shimer (2004) is an early critic of search effort being modeled as procyclical in search-matching models. He uses a measure of job search intensity based on the CPS and finds that the aggregate search effort does not appear to be procyclical in the aggregate data. We build on his insight by providing a richer measure of search effort that spans a longer time period and use additional variation at the state and individual level to establish the countercyclicality of search effort. We also extend his analysis by delving into the reasons behind this pattern and investigate its aggregate implications. More recently, Krueger and Mueller (2010) use the ATUS from 2003–2007 to analyze job search behavior by labor force status, though their focus is not on its cyclical properties. Another recent study based on the ATUS is Aguiar, Hurst, and Karabarbounis (2013), which analyzes the change in the allocation of time during the Great Recession. They find that increasing job search absorbed 2 to 6 percent of the forgone work hours. Faberman and Kudlyak (2016) use the micro data from a job search website to study the relationship between search intensity and search duration. While their dataset is completely different from ours, their results are broadly consistent with our findings in that they find that the number of applications sent by a job seeker per week is significantly higher in metropolitan areas with more slack labor markets. DeLoach and Kurt (2013) analyze the determinants of search time at the individual level using the ATUS for 2003–2009 period. However, contrary to our and Faberman and Kudlyak's (2016) findings, they find evidence for a discouragement effect—that individuals respond negatively to a deteriorating labor market conditions.[2] Our main motivation for linking the CPS

[2] DeLoach and Kurt's (2013) individual regression results are not necessarily inconsistent with aggregate countercyclicality, as their finding on labor market conditions are after controlling for the regional house price index,

and the ATUS is to overcome the small and short sample problem and to exploit the individual variation in job search effort instead of using a small sample of repeated cross-sectional data, such as in DeLoach and Kurt (2013). Since we can observe an individual's search effort repeatedly using the semi-panel structure of the CPS, we are able to control for observed and unobserved heterogeneity at the individual level and isolate the role of labor market conditions in determining job search effort.[3] In addition, our paper complements Davis, Faberman, and Haltiwanger's (2013) recent work which provides a measure of firms' recruiting effort beyond posting vacancies and shows its importance in accounting for the cyclical patterns of hiring.

Our main finding that search effort is countercyclical contrasts some of the recent work modeling labor market fluctuations. For example, in the models of Veracierto (2008); Christiano, Trabandt, and Walentin (2012); and Gomme and Lkhagvasuren (2015) an important driving force of labor market fluctuations is the procyclical search effort of nonemployed households. Our empirical findings rule out this channel. Rather, the data support the view that the countercyclicality of nonemployed individuals' job search effort dampens labor market fluctuations. An important issue to note is that even if part of the countercyclicality of search effort is due to a change in the composition of job seekers, it does not imply that its countercycliality is less relevant for labor market fluctuations. What matters for the matching process in the search and matching framework is the variation in *total* search intensity. When the pool of job seekers shifts toward more attached workers who search harder, the total search input to the economy on the worker side still increases and affects aggregate labor market outcomes.

The main contributions of our paper relative to existing studies are as follows. First we propose a method to link the ATUS and the CPS to obtain a measure of search effort starting in 1994. Second, we document the business cycle properties of aggregate job search effort exploiting time and state-level variation in macroeconomic conditions and explore the determinants of the observed pattern. Third, after establishing the link between search effort and labor market outcomes, we set up a search and matching model with endogenous search effort and a generalized matching function. Our quantitative analysis shows that once its empirical properties are correctly incorporated to the model, endogenous search effort does not amplify labor market fluctuations but rather dampens them.

The rest of the paper is organized as follows. Section I describes the data and explains how we combine the information from the two datasets. Section II documents the cyclicality of search effort using time-, state-, and individual-level variation. Section III analyzes the implications of our empirical results for aggregate labor market dynamics. First we set up a search and matching model with search effort choice and analyzes its implications for the unemployment volatility puzzle.

which is another cyclical indicator. In fact, DeLoach and Kurt (2013) observe an increase in the average search time by the unemployed in 2008, which is consistent with our findings.

[3] Gomme and Lkhagvasuren (2015) also examine job search efforts using the ATUS and point out the small sample issue with the ATUS job search measures. They find time spent on job search by short-term unemployed workers to be procyclical while also observing an increase in average search time for the entire population of the unemployed in 2008. Our main focus is the search effort of the entire population of unemployed workers rather than a particular subset of unemployed workers since aggregate search effort is a key input for analyzing labor market fluctuations in a macroeconomic context.

Second, we discuss the implications for labor market dynamics during the Great Recession. Section IV concludes.

I. 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.

A. *Data*

The CPS is a monthly survey conducted by the US Census Bureau for the Bureau of Labor Statistics (BLS). It is a primary source of labor force statistics for the population of the United States. The ATUS is a relatively new survey conducted by the BLS where individuals are drawn from the exiting samples of the CPS. Respondents are contacted 2–5 months after their final CPS interview. Through a daily diary, the ATUS collects detailed information on the amount of time respondents devote to various activities during the day preceding their interview. In addition to the time diaries, the ATUS also asks a subset of the CPS questions again. Our sample from the ATUS spans 2003–2014 and we restrict our sample for the CPS from 1994 through 2014 because job-search related questions in the ATUS are consistent with the post-1994 CPS.[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 search activities. This is a natural measure of job search effort, paralleling hours worked in measuring the labor input for production. We identify job search activities as the ones in Table 1.[5] The first category (job search activities) includes contacting employers, sending out resumes, and filling out job applications, among others.[6]

[4] Before the 1994 redesign of the CPS, the respondents were given only 6 job search methods to choose from, while after the redesign, this number increased to 12. Consequently, it is not straightforward to use our imputation method before 1994, as the method categories are inconsistent across the ATUS and CPS. Even though it is not possible to have a consistent measure of job search for the 1976–2014 period, it is still possible to construct an internally consistent measure of job search for the 1976–1993 period as done by Shimer (2004) by just using the available information on job search methods in the CPS. See online Appendix A.3.1 for results and a brief discussion.

[5] We do not include travel time to interview in our baseline measure as is done in Aguiar, Hurst, and Karabarbounis (2013). This choice was motivated by our use of the multiyear files created by the ATUS. The advantage of using these files is that they include preconstructed 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 online 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 online Appendix A of their paper for details. In the analysis below, we exclude the respondents who report more than eight 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 five hours) except for a small change in the average level.

Table 1—Definitions of Job Search Activities in ATUS

Job search activities includes contacting employer, sending out resumes, etc. (050401)
Interviewing (050403)
Waiting associated with job search interview (050404)
Security procedures related to job search/interviewing (050405)
Job search activities, not elsewhere specified (050499)

Source: American Time Use Survey Documentation

Table 2—Definitions of Job Search Methods in CPS and ATUS

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

Note: The first nine are active, the last three are passive.

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

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

B. *ATUS Summary Statistics*

We first examine overall patterns of job search from the ATUS for the 2003–2014 period. Table 3 reports the average reported time spent on job search activities (in

TABLE 3—AVERAGE SEARCH TIME (*minutes per day*) FROM THE ATUS

All workers				
1.9				
Employed	Nonemployed			
0.5	5.6			
	Unemployed		Not in the labor force	
	31.1		0.7	
	Temp. layoff	Not on temp. layoff	Want a job	Other NILF
	9.0	34.6	4.5	0.7

Notes: Average search time is calculated on the pooled 2003–2014 sample of the ATUS. Observations are weighted by their sample weights.

minutes per day recorded in time diaries). We calculate average search time for respondents in different labor market states separately to identify the labor force categories that are the main drivers of search activity in the economy.

We first group the respondents into three broad categories: employed, unemployed, and not in the labor force (NILF). We also consider several subgroups to identify who engages most intensively in job search. The unemployed workers are divided into two categories: "temporary layoff" and "not on temporary layoff." Workers who are on "temporary layoff" are those waiting to be recalled to a job from which they have 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]

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 unemployed workers as the group who engage in job search activity and therefore define the *extensive margin* of the job search activity as the fraction of nonemployed individuals who are unemployed. We find this choice natural since the CPS uses a search criterion to classify workers as unemployed if they are not on temporary layoff. We also include unemployed workers on temporary layoff since they spend considerable time searching.

[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 4 weeks), in addition to reporting that she wants a job.

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

C. *Linking the ATUS and the CPS*

Ultimately, our goal is to obtain a measure of the monthly average of daily search time of each respondent in the CPS survey. However, we do not observe this directly in either the CPS, where we only observe search methods over the past month, or the ATUS, where we observe search methods over the past month and search time in the previous day. Therefore, 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. Tables 1 and 2 shows that many CPS job search activities overlap with the job search activities recorded in the ATUS time diaries. Therefore, it is likely that similar information is contained in the answers to the methods question in the CPS and in the ATUS time diaries. To see how closely these two measures are related, we first categorize unemployed workers (excluding the ones on temporary layoffs, who do not report search methods) by the number of methods they report using and plot the average minutes per day that each group spends on job search activities.

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

This is why we combine the additional information on job search in the ATUS time diary with the information on search methods in the CPS. Since each respondent of the ATUS is again asked (at the time of the ATUS survey) which job search methods they have engaged in the past four weeks, we are able to construct a mapping between their response on methods and the job search time recorded in their diary from the previous day. The simplest approach would be to run an OLS regression for the ATUS sample with search time as the left-hand side variable and dummy variables for each method used (and various worker characteristics) as right-hand side variables, and then use this estimated equation to compute search time for the CPS sample starting in 1994. However, this approach does not account for the nonlinearities at zero reported minutes of search.[9] Instead, we use the Heckman selection correction procedure, which estimates the probability of observing positive search time and how many minutes one searches conditional on searching. Specifically, we estimate the following two equations:

$$p_i = \beta_0 + \beta_1 D_i + \beta_2 X_i + \varepsilon_i$$

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

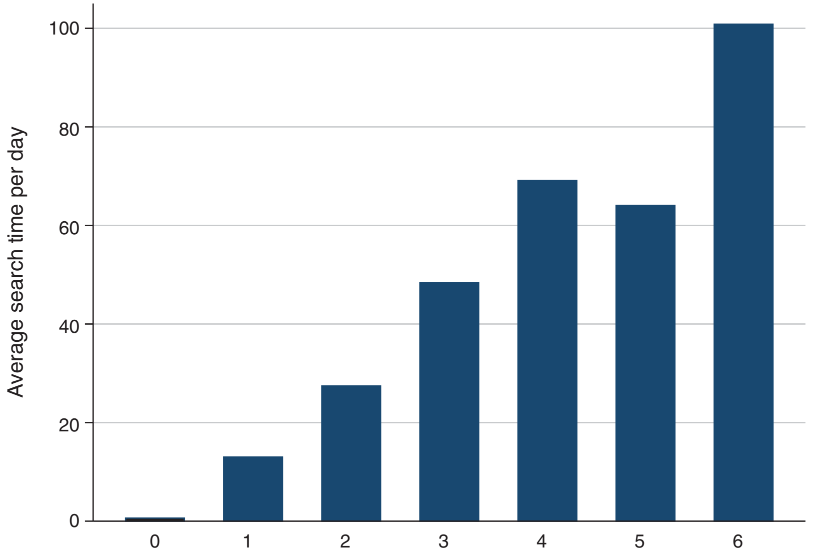

Figure 1. The Average Minutes (*per day*) Spent on Job Search Activities by the Number of Search Methods

Notes: Each bin reflects the average search time in minutes per day by the number of search methods that the individual reports using in the previous month. Data is pooled from 2003–2014 and observations are weighted by the individual sample weight.

and

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

the first using a probit and the second using OLS. Here, p_i is the probability that an individual searches on the day of the interview and s_i is the number of minutes they report searching, conditional on searching a positive number of minutes. The term D_i includes dummies for use of each search method, and $\lambda(\hat{p}_i)$ is the inverse Mills ratio evaluated at the predicted value of p_i, $\hat{p}_i$, which corrects for the correlation between error terms across the two equations. The term X_i includes two sets of observable worker characteristics. The first is a set of worker characteristics which may affect the intensity of job search. We mostly follow Shimer (2004) in the choice of these controls and include a quartic of age, dummies for education levels (high school diploma, some college, and college plus), race, gender, and marital status. We also add the interaction term of being female and being married since being married is likely to affect the labor market behavior of men and women differently.[10] 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

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

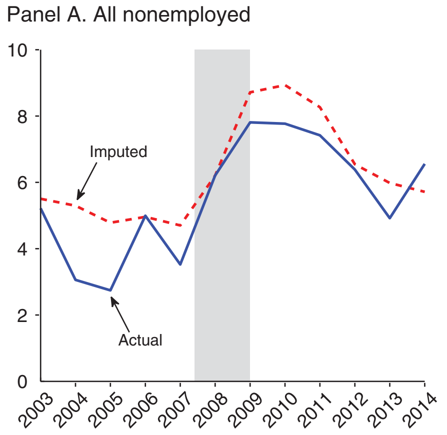

FIGURE 2. ACTUAL AND IMPUTED AVERAGE SEARCH TIME (*minutes per day*) FOR ALL NONEMPLOYED WORKERS (*panel A*) AND UNEMPLOYED WORKERS (*panel B*)

Notes: Regressions are estimated in the ATUS from 2003–2014. While both panels A and B plot the fitted values from the sample regression, panel A plots the actual and imputed search time for all nonemployed, while panel B plots them for just the unemployed. Observations are weighted by their ATUS sample weight.

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.[11] Variables ε_i and ν_i are error terms.

Figure 2 provides a comparison of the time series of the reported minutes and the imputed minutes within the ATUS sample. The imputed minutes track the actual minutes closely, with the exception of 2004 and 2005.[12] Using the coefficients underlying the lines in Figure 2, we impute search time for every individual in the CPS. In the remainder of the paper, we use the imputed minutes, which we denote by $\hat{s}_{it}$ for individual i at time t, as our measure of search effort. This measure is a nontrivial extension of Shimer's (2004) measure since it exploits information on job search from the ATUS. Specifically, our measure weights each search method differently according to the estimated time intensity and allows for baseline search effort to vary by demographic characteristics.[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 increasing the minutes spent on each method

[11] Note that we do not include unemployment duration in this regression, as it is not asked again in the ATUS. We also tried variations where we include controls for data quality, such as indicators for the day of the week or the fraction of time in the individual's diary that is unaccounted for. However, these additional controls had a very small effect on the imputation.

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

[13] Figure A8 in online 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 toward higher search demographics over the business cycle.

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 alternative 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 online Appendix A.2 shows that the year dummies are statistically significant only in 2004 and 2005, suggesting that the relationship between time and methods does not change significantly over the business cycle. We also considered a version of our imputation where we include various measures of aggregate market conditions (cyclical fluctuations in GDP, the unemployment rate, and the vacancy-to-unemployment ratio). We interact each aggregate variable with each search method, thereby allowing the relationship between search methods and search time to vary over the cycle as the market aggregate moves. Figure A7 in online Appendix A.2 shows the resulting imputed minutes in the CPS sample. We see that the versions with methods interacted with the unemployment rate or vacancy-to-unemployment ratio exhibit even stronger countercyclicality than our baseline measure, suggesting that individuals tend to use search methods slightly more intensely when the labor market is weak. Therefore, our baseline specification is a conservative one regarding the overall cyclicality of search effort.

II. Cyclicality of Search Effort

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

A. *Time-Series Variation*

We begin by exploiting the time-series variation in our sample, which covers two recessions. Following the labor supply literature, we analyze variation in search intensity along two margins: the extensive margin and the intensive margin. As we discussed in the previous section in the context of Table 3, we measure the extensive margin with the number of unemployed workers relative to total nonemployment and measure the intensive margin as the average search time in minutes that unemployed workers spend on job search activities per day.[14] The left panel of Figure 3 plots the fraction of nonemployed workers who decide to engage in search, which

[14] As discussed in Section IIB, this definition of the extensive margin does not capture the full extensive margin in our data, as we find evidence in the ATUS of job search among some nonparticipants 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.

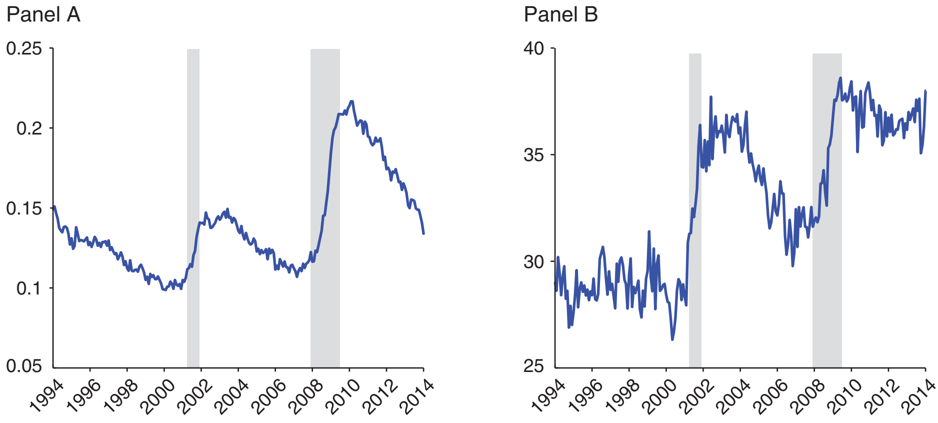

FIGURE 3. THE TIME SERIES OF THE EXTENSIVE MARGIN $(U/(U+N))$ (*panel A*) AND THE INTENSIVE MARGIN (*panel B*), MEASURED BY THE AVERAGE MINUTES OF SEARCH PER DAY FOR UNEMPLOYED WORKERS

Notes: Panel A plots the monthly ratio of the number of unemployed (U) to the total number of unemployed $(U+N)$ in the CPS from 1994–2014. Panel B plots the average minutes of search per day, constructed as described in the text. Each observation is weighted by its CPS sample weight.

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 the widely documented strong countercyclicality of unemployment.[16]

To measure the intensive margin of search effort, we use the imputed minutes, $\hat{s}_{it}$, calculated in Section IC.[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 market tightness $\theta = v/u$, where v is the vacancy rate[18] and u is unemployment rate, is negative at -0.78.[19]

The total search effort of nonemployed workers in the economy can be calculated as the extensive margin times the intensive margin.[20] As one can infer from the previous figures, total search effort in panel A of Figure 4 also exhibits a strongly countercyclical pattern. Indeed, the correlation of total search effort with θ is -0.89.

[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, we exclude this month from our analysis.

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

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

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

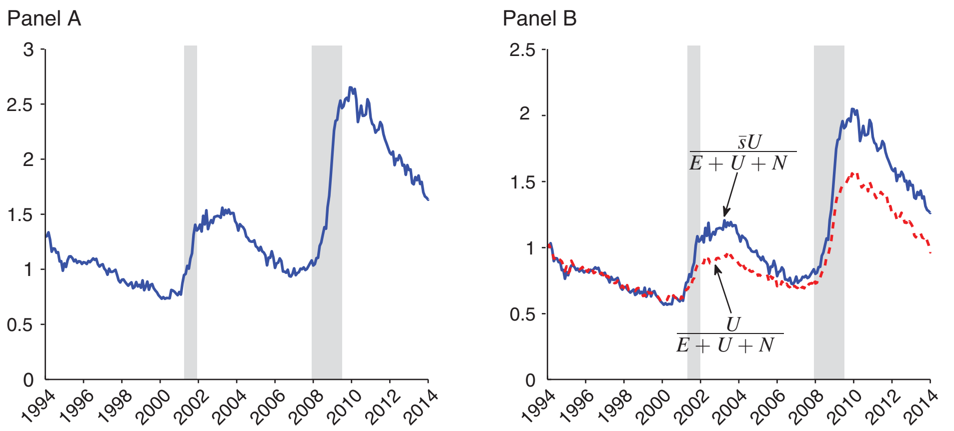

Figure 4. Time Series of Total Search Effort (*panel A*) and Total Search Effort Using the Search Time of Unemployed Workers $(\bar{s}U/(E+U+N))$ versus Using the Number of Unemployed Workers $U/(E+U+N)$ (*panel B*)

Notes: Total search effort is defined as the ([extensive margin] $\times$ [intensive margin]). Each series in panel B is normalized to one in the beginning of 1994.

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

B. *State-Level Variation*

In addition to the time-series variation that we explored in the previous subsection, we also exploit cross-state variation in the intensity of business cycles to establish the cyclical properties of search effort. Looking across different states provides additional information, as it utilizes a different and potentially richer source of variation by answering the question "Did search effort increase more in states where the recessions were relatively more severe?" This method of utilizing state-level variation to establish the cyclicality of a series is similar to that in Aguiar, Hurst, and Karabarbounis (2013) and Haltiwanger, Hyatt, and McEntarfer (2015).

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

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

where s_{jt} is the average search time of unemployed workers in state j in time t, λ_j is a state fixed effect, λ_t is a time control that we explain in detail below, X_{jt} is the cyclical indicator, and ε_{jt} is the error term. We use three different cyclical indicators: changes in the state-level monthly unemployment rate (Δu_{jt}), changes in labor market tightness $\theta = v/u$, and changes in the flow rate from unemployment to employment.[21] For each of these variables, we explore both three-month and six-month changes. The parameter of interest is β, which captures the correlation of search time with the cyclical indicator. The state fixed effects capture any static difference in job search behavior across states and the time fixed effects control flexibly for any variation that is constant across states but varies over time. Therefore, this specification identifies the relationship between unemployment and job search effort using cross-sectional variation across states. In each of these regressions, we also allow the change in job search effort in each state to follow a different linear time trend, controlling for time-varying state level policies that may affect trends in job search differentially.[22]

Table 4 shows the estimates of β from a series of regressions. The left two columns reveal that across specifications, the coefficient on the unemployment rate is positive and statistically significant, implying that in states where the unemployment rate increases were larger, the search effort of the unemployed increased more both in terms of three-month and six-month changes. Specifically, the left two columns suggests that if a state's unemployment rate is 1 percentage point higher, the average worker's search effort is about 1.5 percent higher. The middle two columns reveal that results are similar when we use θ as our cyclical indicator—search effort is higher in states with weaker labor markets. Lastly, the right two columns show that results are similar when we use the unemployment-to-employment flow—search effort is higher in states when the job finding rate of the unemployed is lower. Taken together, these results, which utilize a completely different variation than in Section IIA, further suggest that search effort is countercyclical.

C. *Individual-Level Regressions*

The final source of variation we exploit is the individual level variation in search effort both in the cross section and over time. While the finding above that total search effort is countercyclical are important for aggregate analysis, understanding the individual response is still important for understanding the mechanisms underlying these patterns and for understanding the potential effect of various labor market policies. Even if aggregate search effort and state-level search effort are countercyclical, individual search effort may not covary with labor market conditions in a countercyclical manner. It is possible that aggregate search effort and state-level search effort are countercyclical because in recessions the pool of searchers skews

[21] State-level vacancies come from The Conference Board Help Wanted OnLine Data Series (HWOL) and are available beginning in May 2005, and state-level flow rates from unemployment to employment come from the matched monthly basic CPS and are available from January 1996. While the data are available beginning in 1994, a change in the household identifier makes it difficult to match individuals before 1996.

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

Table 4—Response of Search Effort to Changes in Labor Market Conditions Proxied by Changes in the State-Level Unemployment Rate, Labor Market Tightness, and the Job-Finding Rate

	3-month change	6-month change	3-month change	6-month change	3-month change	6-month change
Δunemployment rate	0.0155	0.0160				
	(0.0052)	(0.0050)				
$\Delta \frac{v}{u}$			−0.1268	−0.1341		
			(0.0760)	(0.0769)		
ΔU-to-E rate					−0.1995	−0.2516
					(0.0663)	(0.0705)
Years	1994–2014	1994–2014	2005–2014	2005–2014	1996–2014	1996–2014
Observations	12,495	12,189	5,763	5,610	11,271	10,965
R^2	0.092	0.120	0.113	0.143	0.104	0.137

Notes: All regressions include year fixed effects, state fixed effects, and state-specific linear time trends. Observations are weighted by the state's average population from 1994–2014 and standard errors are clustered at the state level. Search effort is defined for all unemployed, and is smoothed with an HP filter ($\lambda = 10$). Columns 1 and 2 are estimated using monthly data from 1994–2014. State-level unemployment rates are calculated within the CPS. Columns 3 and 4 are estimated using monthly data from 2005–2014. Vacancy data comes from Help Wanted Online (HWOL). Columns 5 and 6 are estimated on data from 1996–2014. Unemployment-to-Employment transition rates are calculated using the semi-panel structure of the monthly basic CPS. All state-level time series are seasonally adjusted using monthly dummies.

towards the types of people who search harder.[23] 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) workers with a strong preference for work search harder; and (iii) this effort results in a quicker transition to employment. The "high-search type" workers find jobs easily in booms, and therefore these workers disappear from the unemployment pool more quickly during booms. As a result, the unemployment pool would be dominated by workers with less desire to work during booms. This channel would lead to countercyclical average search effort through unobserved composition changes. Note that even if countercyclical search effort is entirely driven by compositional shifts over the business cycle, it can still have important aggregate implications since what matters for the matching process in the search and matching framework is the variation in the total search intensity.

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

Specifically, we run variations on a regression of the form

$$\hat{s}_{it} = \delta + \delta_\theta \log(\theta_{it}) + \delta_x X_{it} + \alpha_i + \varepsilon_{it}, \tag{1}$$

[23] This would be consistent with the findings of Mueller (2017) and Elsby, Hobijn, and Şahin (2015), who find strong evidence that the composition of the unemployed shifts toward workers who are more attached to the labor market during recessions.

where $\hat{s}_{it}$ is individual i's search effort at time t, θ_{it} is a measure of labor market conditions, X_{it} is the vector of potentially time-varying observable controls, α_i is an individual fixed effect, and ε_{it} is the error term. The controls X_{it} include the demographic controls (a quartic in age, marital status, race, sex, and education), four occupation dummies,[24] and a quartic function of unemployment duration. In specifications without individual fixed effects, we include all these controls. In specifications with individual fixed effects, we include only a quartic function of unemployment duration, which is the only control that varies month to month. The parameter of interest in (1) is δ_θ, which captures how job search effort co-moves with the business cycle after controlling for demographic changes. For the cyclical indicator, we use the aggregate labor market tightness $\theta = v/u$, computed using Barnichon's (2010) Composite Help-Wanted Index, which is available for the 1951–2014 period. We also repeat the same exercise using job openings data from the Job Openings and Labor Turnover Survey (JOLTS), which started in 2001. In online Appendix Table A2, we also report results using the state-level HWOL (The Conference Board Help Wanted OnLine Data Series) to construct θ, which only begins in 2005, as well as aggregate house price, stock market series, and payroll employment. Note that the sample for these regressions includes only the unemployed who are not on temporary layoff. This is because the search methods are the main time-varying factors in creating the imputed search time and we do not observe the search methods for the workers on temporary layoff. Thus "unemployed workers" in this section refers to only this subset of all unemployed workers. In order to account for the fact that our measure of search effort is imputed, we use a multiple imputation method to calculate the standard errors in Table 5. See online Appendix A.3.2 for details.

The first column of Table 5, which includes no individual-level controls, confirms the findings of Section IIA and shows that, on average, search effort is low when aggregate labor market conditions are favorable (that is, when θ_t is high). This finding is consistent with Faberman and Kudlyak (2016), who find that the number of applications sent by a job seeker per week is significantly higher in metropolitan areas with more slack labor markets.

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

[24] We use the occupation categorization in Acemoglu and Autor (2011), in which occupations are divided into four categories: cognitive/nonroutine, cognitive/routine, manual/nonroutine, and manual/routine. For the unemployed, these refer to the occupation of the previous job, and we exclude unemployed with missing occupation information.

TABLE 5—THE RESPONSE OF INDIVIDUAL JOB SEARCH EFFORT, $\hat{s}_{it}$, TO VARIATION IN LABOR MARKET CONDITIONS

	Composite help wanted index (1994–2014)			JOLTS (2001–2014)		
	Basic	Observables	FE	Basic	Observables	FE
log(θ)	−7.550	−4.860	−3.476	−4.248	−2.933	−3.231
	(0.297)	(0.256)	(0.636)	(0.261)	(0.227)	(0.612)
Age		66.504			69.956	
		(10.410)			(10.765)	
Age^2		−2.304			−2.423	
		(0.352)			(0.364)	
Age^3		0.035			0.037	
		(0.005)			(0.005)	
Age^4		−0.000			−0.000	
		(0.000)			(0.000)	
Black		−0.975			−0.806	
		(1.317)			(1.371)	
Married		4.245			4.343	
		(1.615)			(1.656)	
Female		−11.742			−11.719	
		(1.592)			(1.634)	
Married × Female		−25.856			−26.300	
		(2.244)			(2.307)	
High school		6.017			6.036	
		(1.302)			(1.360)	
Some college		26.218			26.528	
		(1.620)			(1.669)	
College		57.391			57.514	
		(2.111)			(2.150)	
Cognitive routine		−6.093			−5.733	
		(0.279)			(0.295)	
Manual nonroutine		−1.249			−0.974	
		(0.237)			(0.258)	
Manual routine		−7.593			−7.008	
		(0.312)			(0.324)	
Unemployment duration		0.843	0.169		0.817	0.141
		(0.032)	(0.039)		(0.035)	(0.044)
Unemployment duration^2		−0.027	−0.008		−0.025	−0.007
		(0.001)	(0.001)		(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)
Observations	528,727	528,727	528,727	406,171	406,171	406,171

Notes: All regressions include month fixed effects and columns 3 and 6 include individual fixed effects. In each column, the sample includes individuals in the CPS who are linked to at least one additional survey and who are unemployed and not on temporary layoff in at least two of those months. Standard errors are adjusted to account for imputed search effort (see online Appendix A.3.2 for details). Columns 1–3 are estimated on the pooled 1994–2014 sample and columns 4–6 are estimated on the pooled 2001–2014 sample.

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

Lastly, in the third column of Table 5, we report regression results with individual fixed effects ("FE"), which control for unobserved differences across individuals, and compare the search effort of an individual in months when the labor market is tighter to the same individual in months with a weaker labor market. A comparison of columns 2 and 3 shows that when unobserved heterogeneity is taken into account, individual search effort is less responsive to labor market conditions, but that the correlation of search effort with labor market tightness is still significantly negative. This method of controlling for unobserved heterogeneity in the pool of unemployed also suggests that shifts in unobserved heterogeneity among the unemployed over the business cycle play a role in explaining the observed countercyclicality of search effort, but that individuals search effort still co-moves negatively with labor market conditions. To see this, consider what these estimates imply for a 1 standard deviation decrease in θ. The coefficient in column 1 implies that when θ decreases by 1 standard deviation (i.e., 0.38), search effort increases by 2.9 minutes per day. Once we control for observable changes, the implied change falls to 1.9; and when we include controls for unobservable changes, this falls further to 1.3 minutes. Together, this implies that compositional shifts in the pool of unemployed explain 54 percent of the correlation between θ and overall search effort and that individual-level changes explain the rest.

Discussion: The Role of Unemployment Insurance Benefits.—The link between job search effort and unemployment insurance (UI) has received significant attention in both the labor economics literature and macroeconomics literature. Various theoretical and empirical studies find that more generous unemployment insurance discourages workers from searching for jobs and causes longer unemployment spells.[26] 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 are the eligible worker pool.[27] The first column of Table 6 shows that, among the eligible population, search effort responds negatively to the number of weeks left on UI, even after controlling for the average unemployment duration and state-level fixed effects. In other words, even

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

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

[27] Due to the availability of benefits data, this regression is estimated using data from January 2004 to March 2011.

TABLE 6—THE RESPONSE OF INDIVIDUAL JOB SEARCH EFFORT, $\hat{s}_{it}$, TO VARIATION IN LABOR MARKET CONDITIONS, UI ELIGIBILITY, AND WEEKS REMAINING IN UI

	Weeks remaining	Eligibility
log(θ)	−4.321	−2.510
	(0.364)	(0.231)
Eligible for UI		7.150
		(0.297)
Weeks of benefits remaining	−0.042	
	(0.011)	
Unemployment duration	−0.002	0.790
	(0.006)	(0.045)
Unemployment duration^2		−0.026
		(0.002)
Unemployment duration^3		0.000
		(0.000)
Unemployment duration^4		−0.000
		(0.000)
Observations	132,751	212,731

Notes: All regressions include month fixed effects. Column 1 also includes state fixed effects. The sample in column 1 is restricted to the unemployed, who report being job losers or temporary job enders from January 2004–March 2011. Column 2 includes all unemployed searchers from January 2004–March 2011. Standard errors are adjusted to account for imputed search effort (see online Appendix A.3.2 for details).

for a given level of unemployment duration, workers who are closer to the expiration of their UI benefits search more minutes per day. This finding is consistent with the findings of a recent study by Marinescu (2017), which shows, using data from CareerBuilder.com, that a 10 percent increase in benefit duration decreased state-level job applications by 1 percent. 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 approximately 1 minute, or 3 percent of total search time.

At first glance, this finding seems to be at odds with our finding of countercyclical search effort. However, we find that this quantitatively small disincentive effect on search effort is dominated by shifts in the composition of the unemployed, thereby resulting in the observed countercyclicality of search effort. 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, such as labor force attachment. The second column of Table 6 repeats the regression analysis in the fifth column of Table 5 controlling for UI eligibility for the 2004–2011 period. We see clearly that even after controlling for other observable characteristics, eligible unemployed workers search more, and this effect is large and statistically significant. It is possible that UI 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. Online Appendix Figure A14 shows that the fraction of the unemployed who are eligible for unemployment benefits increases sharply during recessions.[28] The combination of this large increase in the fraction of eligible unemployed and the large coefficient on eligibility in Table 6 suggests that the changing composition of the unemployed along this dimension dominates the disincentive effects of UI extensions at the individual level. Even though the widely documented disincentive effects of UI are still operative in our data, the changing composition of the unemployed pool results in a rise in the average job search effort of the unemployed. 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 (2016) and Landais, Michaillat, and Saez (2010), moral hazard in worker's search effort (and how it varies over the business cycle) is the central focus in determining the optimal policy.

III. Implications for Search-Matching Models and the Great Recession

We have shown that search effort co-moves with macroeconomic conditions both along the extensive and intensive margins. This finding potentially has important implications for the analysis of labor markets. In this section, we first extend the basic Diamond-Mortensen-Pissarides (DMP) model to include worker search effort and a generalized matching function. We use it to explore the role that countercyclical search effort plays in explaining labor market dynamics, and accounting for the cyclicality of unemployment and vacancies. Second, we discuss the implications of countercyclical search effort for the decline in matching efficiency during the Great Recession period.

A. *Job Search Effort and Unemployment Volatility in Search and Matching Models*

Our model is an extension of Pissarides (1985) and Shimer (2005) in a discrete-time setting. Given that the model is well known, we leave the detailed exposition to online Appendix B and outline the main departures from the standard model here. The most important departure from the standard model is that we explicitly incorporate the search effort of unemployed workers. Let s_{it} be the search effort of unemployed worker i at period t. The probability that she finds a job at the beginning of period $t+1$ is expressed as $f(s_{it}, \overline{s}_t, \theta_t)$, where $\overline{s}_t$ is the average search effort of all unemployed workers in the economy and θ_t is labor market tightness, the vacancy (v_t) to unemployment (u_t) ratio. The job-finding probability is increasing in s_{it}, but the worker has to incur a search cost which is increasing in s_{it}.

We assume that the job-finding probability is based on a matching function. In particular, we consider a *generalized matching function*, where the job-finding rate is given by (we omit the subscripts i and t)

$$f(s, \overline{s}, \theta) \equiv \chi\left(\alpha s^{\psi} + (1-\alpha)\left(\frac{s}{\overline{s}}\right)^{\xi}\theta^{\psi}\right)^{\eta},$$

[28] It increased from around 0.50 in 2000 to around 0.70 in 2002 and around 0.55 in 2007 to around 0.75 in 2009.

with $\chi > 0$ and $\alpha \in [0,1]$. When workers are homogeneous (that is, $s = \overline{s}$ in equilibrium), this corresponds to the matching function[29]

$$(2) \qquad M(\overline{s},u,v) \equiv \chi\left(\alpha\,\overline{s}^{\psi} + (1-\alpha)\left(\frac{v}{u}\right)^{\psi}\right)^{\eta} u.$$

Let $q(\overline{s},\theta) \equiv f(\overline{s},\overline{s},\theta)/\theta$ be the probability that a vacancy gets filled by a worker.

The analytical characterization of the model is described in online Appendix B. The key result is that, after log-linearizing, the equilibrium job search effort takes the form of $\hat{s}_t = \Phi\hat{\theta}_t$, where "hat" ($\hat{}$) denotes the log deviation from steady state. The coefficient Φ is

$$(3) \qquad \Phi = \frac{f_{13}\tilde{\theta}/f_1 - q_2\tilde{\theta}/q}{c''\tilde{s}/c' - (f_{11}+f_{12})\tilde{s}/f_1 + q_1\tilde{s}/q},$$

where "tilde" ($\tilde{}$) denotes the value at steady state. The values of f_i, f_{ij}, q, and q_i are evaluated at steady state, where the subscripts denote partial derivatives and double subscripts denote cross derivatives. This shows that the sign of Φ, which captures whether search effort responds negatively or positively to θ and is what we estimated in our empirical analysis, depends crucially on the form of the matching function. Note that $f_{13} < 0$ is necessary for $\Phi < 0$.[30] This means that s and θ are substitutes, rather than complements, as inputs for job matching.

We calibrate a subset of parameters to standard values based on Shimer (2005) and commonly used values in the literature. This calibration strategy allows us to isolate the role of job search effort in the unemployment volatility puzzle since, calibrated in this manner, the basic job search model fails to account for the volatility of unemployment and vacancies in the data. We also consider a calibration strategy following Hagedorn and Manovskii (2008) which matches the volatility of these variables.

A new calibration target specific to our setting is the cyclical responsiveness of aggregate search effort, which we denoted as Φ in $\hat{s}_t = \Phi\hat{\theta}_t$. Our empirical evidence strongly suggests that aggregate search effort is countercyclical and therefore Φ is negative. Specifically, we estimate Φ by running a regression of the cyclical component of $\log\theta$ on the cyclical component of $\log s$, which yields an elasticity of $\Phi = -0.15$.[31] We add this additional target to our calibration and compute the set of matching function specifications consistent with this moment.[32] We solve the model by log-linearly approximating around the steady state.[33]

[29] In online Appendix B, we show that this specification nests several important special cases. This is also a departure from Pissarides (2000, chapter 5), who analyzes a formulation with endogenous search effort. In particular, he assumes that $f(s,\overline{s},\theta)$ is proportional to s.

[30] By assuming linear utility, here we abstract from other potential reasons for countercyclical search effort, such as a wealth effect.

[31] The cyclical components of market tightness and search effort are plotted in online Appendix C.3.

[32] See online Appendix C for the details of the our calibration strategy.

[33] Online Appendix B describes the log-linearized solutions in detail.

Table 7—Unemployment Volatility with Different Specifications

		$\Phi = \frac{d\hat{s}}{d\hat{\theta}}$	$\mathcal{C} = \frac{d\hat{\theta}}{d\hat{z}}$	std$(u) \times 100$
I. Data		-0.15	19.9	12.5
II. Shimer specification	DMP model ($s = 1$)		1.77	1.76
	Endogenous s and θ	-0.15	1.73	1.67
III. HM specification	DMP model ($s = 1$)		35.50	29.04
	Endogenous s and θ	-0.15	33.27	27.03

Notes: In Panels II and III, the matching function is calibrated as in online Appendix C: $\alpha = 0.15$ and $\psi = 1.33$. std(u) is calculated after being logged and HP-filtered with parameter 1,600 in quarterly frequency.

Table 7 displays the results of this quantitative exercise.[34] Panel I shows the actual unemployment volatility in the data. Panel II shows the unemployment volatility in the estimated model under the Shimer-style parametrization where search effort matches the observed cyclicality of search effort, and panel III shows the same statistics under the Hagedorn-Manovskii specification, where $\hat{z}$ denotes the log deviation of the labor productivity from the steady state and std(u) is the standard devidation of the unemployment rate.

Consider first the basic experiment in which search effort is fixed and constant at its steady state value of 1.[35] Unsurprisingly, given the widely discussed unemployment volatility puzzle inherent in this type of calibration (Shimer 2005), the model substantially understates both the elasticity of θ with respect to productivity (1.77 in the model compared with 19.9 in the data) and the volatility of unemployment (standard deviation of 1.76 in the model compared with 12.5 in the data). We consider the role of search effort in determining the cyclicality of unemployment by comparing these estimates to those that result from an extension of the same model in which search effort is endogenous and countercyclical. The results of this parametrization are reported in the second row of panel II. We find that when search effort is countercyclical, the model exhibits even less volatility, both in terms of the elasticity of θ with respect to productivity (1.73) and the volatility of unemployment (1.67). The dampening effect of search effort comes from two effects: (i) the direct effect of search effort on unemployment through the matching function; and (ii) a general equilibrium effect on firm vacancy posting behavior. Take first the direct effect. For a given θ, the job-finding rate is higher when s is higher. Since s is countercyclical, the job-finding rate for a given θ is higher in recessions and therefore unemployment rises by less. However, endogenous search effort also affects θ, since firms take into account worker search effort when posting vacancies. In recessions, when workers are searching harder, the probability of filling a vacancy increases,

[34] We aggregate the monthly model-generated data to quarters, take logs, and HP-filter in the same manner as with the actual data. The data value for $d\hat{\theta}/d\hat{z}$ is calculated as the ratio of the standard deviation of the logged (and HP-filtered) θ relative to the standard deviation of the logged (and HP-filtered) labor productivity in the US data, presented in Hagedorn and Manovskii (2008). Pissarides (2009) argues that the appropriate target should multiply the correlation coefficient between these two variables. With that correction, the target value would become 7.8.

[35] This corresponds to the standard DMP model, with the specification the matching function $M(u, v) = \chi\left(\alpha u^{\psi} + (1-\alpha) v^{\psi}\right)^{1/\psi}$, where α and ψ are calibrated as described in online Appendix C. Note that $\psi \to 0$ gives us the commonly-used Cobb-Douglas form.

and thus the firm has an incentive to post more vacancies, everything else equal. This additional incentive effect dampens the cyclicality of vacancies, and thus θ. We obtain qualitatively similar patterns when we follow the Hagedorn and Manovskii (2008) calibration strategy in panel III.[36]

To summarize, the unemployment rate increases less during recessions with endogenous and countercyclical search effort since both workers' higher search effort and firms' response to higher search effort dampen the drop in the job-finding rate.[37] To conclude, once the true cyclical properties of search effort are properly taken into account, endogenous search effort dampens labor market fluctuations in the DMP framework and cannot alleviate the unemployment volatility puzzle.[38]

B. *Implications for the Great Recession*

In this section, we explore the role that job search effort played in labor market movements during the Great Recession, and specifically the much discussed decline in the efficiency of the matching process.[39] The main indication of such a shift was a job-finding rate that was substantially lower than what would be suggested by the matching function relationship observed over the pre-Great Recession period. While the generalized matching function fitted to match the job-finding rate in the 1994–2014 period captures the evolution of the job-finding rate well, it overestimates the rate in the later part of the sample, an indication of the decline in the efficiency parameter, χ, in (2).

Various explanations have been offered for this decline including skill and geographic mismatch, decline in the search effort of the employers (recruiting intensity), and decline in the search intensity of job seekers. To be able to isolate the contribution of search intensity to changes in match efficiency, we now focus on the pre-recession period and estimate the parameters of our generalized matching function using data up to 2008 in the spirit of Davis (2011). Note that this exercise bypasses the unemployment volatility puzzle since it takes the vacancy-unemployment ratio and the job-finding rate in the data as given. We then allow for the efficiency parameter (χ) to vary over time, and solve for the values of χ that would be needed to perfectly match our implied job-finding series to the actual job-finding rate series. We do this exercise using two different generalized matching functions. First, we feed in the time series for $\overline{s}$ and use the best-fit, prerecession

[36] While the baseline volatility in the Shimer (2005) and Hagedorn and Manovskii (2008) calibrations differs greatly, countercyclical search effort dampens labor market fluctuations in both specifications.

[37] In order to isolate the role of the direct and general equilibrium effect, we conduct a third exercise (not shown in the table) in which we allow search effort to vary but fix θ to the value that firms would have chosen had search effort been exogenous (i.e., the time series for θ resulting from constant s experiment). We find that about 45 percent of the dampening effect of search effort comes from the direct effect on the matching function, and the rest from the general equilibrium effect of firm behavior.

[38] The third panel of Table C3 in the online Appendix repeats the two exercises in panel II of Table 7, but with a calibration of the matching function that now matches a *counterfactual* target for the elasticity of θ with respect to the search effort at 0.45. We see that, in this case, search effort has the opposite effect, and now amplifies both the co-movement of θ and z, as well as the volatility of u, even though the model still falls short of matching the fluctuations in the data. In this case, search effort and θ are complements in the matching function, implying that if search effort is low in recessions, firms post fewer vacancies, amplifying the fluctuations of the labor market.

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

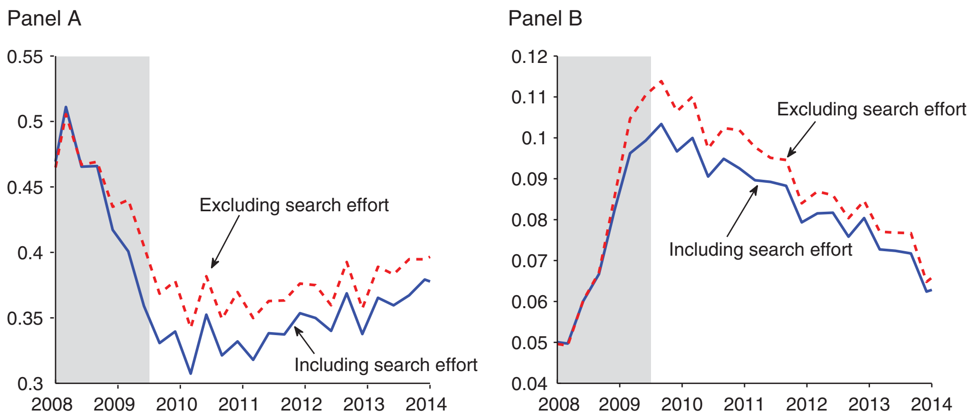

FIGURE 5. MATCHING EFFICIENCY (*panel A*) AND UNEMPLOYMENT RATE (*panel B*) WITH AND WITHOUT THE CHANGE IN SEARCH EFFORT

Notes: Panel A: $\chi_t^{\overline{s}}$ (*including search effort*) and $\chi_t^{\overline{s}=1}$ (*excluding search effort*); panel B: the flow steady-state unemployment rate with and without variation in search intensity, quarterly averages of monthly observations.

parameters from Table C1 in the online Appendix. Second, we shut down variation in $\overline{s}$ and instead impose that $\overline{s} = 1$, and continue to use the same prerecession best-fit parameters. These two implied series for $\chi_t^{\overline{s}}$ and $\chi_t^{\overline{s}=1}$ are plotted in the left panel of Figure 5. The figure shows that this generalized matching function implies that there was about a 20 percent decline in $\chi_t^{\overline{s}=1}$ from 2009 to 2010 compared to about a 30 percent decline in $\chi_t^{\overline{s}}$. Since search effort rose during this time period and is substitutable with market conditions in the matching function, it moderated the decline in matching efficiency. Indeed, not only does the variation in search effort not explain the decline in matching efficiency, it also makes the drop bigger. This is in line with the discussion in Elsby, Michaels, and Ratner (2015) who examine whether the decline in search intensity could explain the *outward* shift in the Beveridge curve. Similar to us, they also conclude that the increase in search intensity during and after the recession would contribute to an *inward* shift in the Beveridge curve, since as workers search harder, fewer vacancies are needed to maintain the same level of the unemployment rate, the opposite of the pattern in the post Great Recession period.

Finally, in a similar exercise, we quantify how the unemployment rate would have evolved absent the rise in search effort among unemployed workers. We do this by calculating the flow steady-state unemployment rate using the job-finding rate implied by the generalized matching function (calibrated as in the previous section), $\chi_t^{\overline{s}}(\alpha\overline{s}^{\psi} + (1-\alpha)\theta^{\psi})^{\eta}$, and the separation rate observed in the data. We calculate this both assuming $\overline{s}$ moves as in the data and, separately, assuming that $\overline{s}$ is constant at 1.[40] As the right panel of Figure 5 shows, the increase in search intensity during and following the Great Recession moderated the increase in the unemployment rate. Absent this increase, the unemployment rate would have peaked at

[40]Note that flow steady-state unemployment rate is calculated as $s_t/(s_t+f_t)$, where s_t is the separation rate and f_t is the job-finding rate. Details of these calculations follow Shimer (2005) and Elsby, Hobijn, and Sahin (2010).

around 11 percent (instead of 10 percent) and would have been consistently higher by about 0.5 to 1 percentage points during the recovery.

IV. Conclusion

In this paper, we examined the cyclical pattern of job search effort and found that aggregate job search effort by nonemployed workers is countercyclical, along both the extensive and intensive margins. We have shown that this countercyclical pattern is the consequence of the cyclical shifts in the composition of the unemployed pool as well as individuals' responses to changes in macroeconomic conditions. Additionally, our quantitative exercises suggest three important takeaways. First, any search model that includes the intensive margin of search effort should include a matching function that features substitutability between the search effort and market tightness. Second, search effort does not act as an amplifier of labor market fluctuations once its empirical behavior is correctly incorporated into the search and matching framework. Third, fluctuations in search intensity do not account for the decline in the measured matching efficiency during and after the Great Recession. If anything, increasing search intensity moderated the rise in the unemployment rate and contributed to its decline.

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