Online Appendix

Job Search Behavior over the Business Cycle

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A Data Appendix

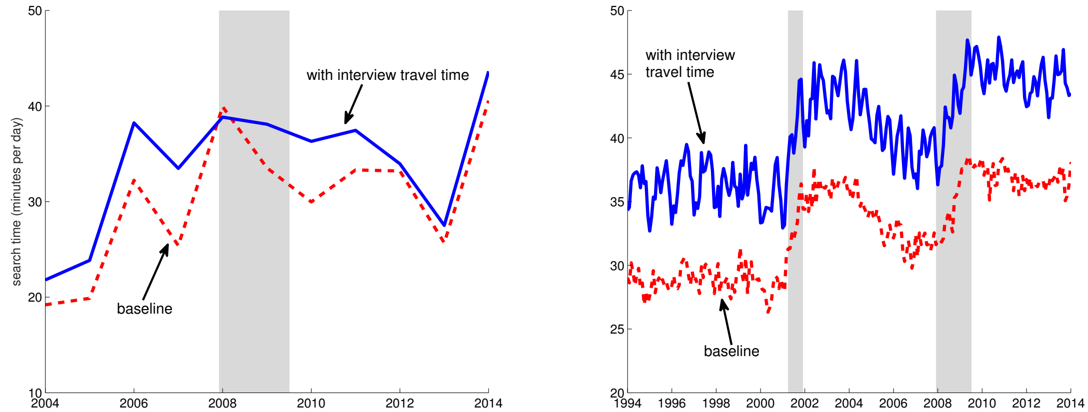
A.1 Data construction

This appendix describes the data sources used in this analysis in greater detail. From the ATUS, we use the Multi-Year microdata files. The advantage to using the multi-year files as opposed to the individual year files is that they provide consistent population weights across years. However, this comes at the cost of slightly less detailed job search categories. As explained in Section 2.1, we define define job search activities to include all search, interviews and time spent at the interview location. Because we use the multi-year files which do not provide data at the full level of disaggregation, we do not include the time spent traveling to interviews (180311) in our job search measure. Figure A1 plots the ATUS time series with and without interview travel time as well as the imputed minutes computed as before but including travel time in measured minutes in the imputation regression.[1] We see that while including this additional category affects the level of search effort, the cyclicality of our series is unaffected. Therefore, we continue the main analysis without travel time included in our search time.

We impose several important sample restrictions on the ATUS data. In order to restrict our sample to people who have completed their education and are still active workers, we restrict our respondents to be those between the ages of 25 and 70. We also drop individuals who report more than 8 hours of search in each day. This excludes only 33 respondents or around 2.5% of the active searchers.[2] Per year, this leaves us with around 2,500 nonemployed respondents,

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

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



(a) reported minutes of search in ATUS

(b) Imputed minutes of search in CPS

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

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 2014. Again, we restrict our sample to include only respondents between 25 and 70 years old. This leaves us with approximately 20,000 nonemployed individuals and on average 2,000 unemployed searchers each month. In order to run the individual-level regressions in Section 3.3, we match our sample across the eight survey months.[3] We are able to match 93% of the sample to at least 1 other month of the survey, 60% of respondents to at least 4 months, and 40% across all 8 survey months.

A.2 Details on linking the ATUS and the CPS

Let Y_{it} be the search time we observe in the ATUS for worker i at time t. We are not interested in Y_{it} per se – Y_{it} contains one day's sample from the search activities in the entire period t (one month), and we are interested in the entire month's activity. Denote the average search time over the month as $E[Y_{it}]$. Let P_{it} be the probability that i searches strictly positive minutes at

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

the ATUS survey date in period t. Let M_{it} be the minutes that i searches at the survey date of time t, conditional on searching strictly positive minutes. Then the average minutes, $E[Y_{it}]$, is

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

from the law of iterated expectations.

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

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

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

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

and we could follow a simple two-step procedure in which we estimate $E_X[P_{it}]$ using a probit regression and $E_X[E[M_{it}]]$ using OLS.[4] However, the assumption that $cov_X(P_{it}, E[M_{it}]) = 0$ is unlikely to hold in our setting, as there is likely to be a positive relationship between the probability that a respondent is observed searching on a given day and how much one search conditional on searching at all.

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

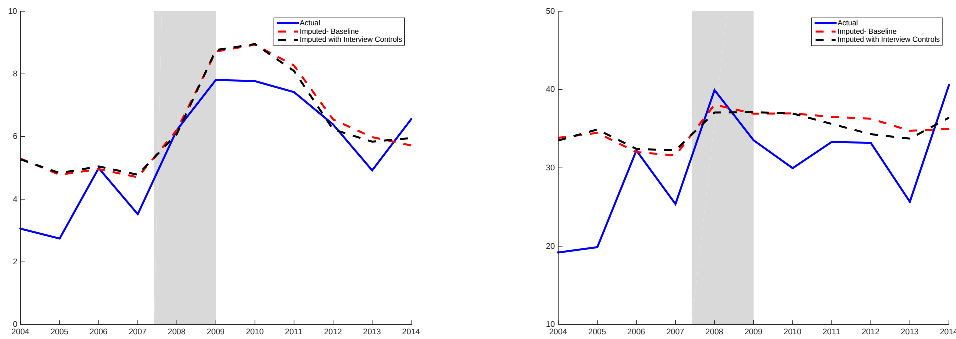
[4]Note that this is the assumption we imposed in a 2014 working paper draft of this paper.

non-negative amount of search time for all non-employed respondents in both the ATUS and CPS.

In this imputation, we include as predictors both dummies for each of the twelve search methods and two sets of observables. The first set of controls includes worker characteristics which may affect the intensity of their job search. We mostly follow Shimer (2004) in the choice of these controls and include a quartic of age, dummies for education levels (high school diploma, some college, college and college plus), race, gender, and marital status. We also add the interaction term of female and married since being married is likely to affect the labor market behavior of men and women differently. The second set of controls are for labor market status. These controls are intended to capture the search time for the respondents who do not answer the CPS question on job search methods but still report positive search time. Here, we include a dummy for being out of the labor force but not wanting a job, being on temporary layoff, and being a out of the labor force but wanting a job.

We also explore the role the measurement error plays in the imputation method. To do this, we included in the ATUS regression dummies for the day of the week of the diary as well as the fraction of time in the day that is unaccounted for in the respondent'a diary. Figure A2 shows the resulting imputation. We find that they make a very small difference in the imputation fit, especially in early years of the sample, where the fit is the lest good.

A much simpler, although likely biased, method for computing imputed search time using the relationship between reported search time and the number of minutes is to run a simple OLS regression using reported time on the left-hand side and dummy variables for each method and other worker characteristics on the right-hand side. Figure A3 shows a comparison of the actual reported minutes, the imputed minutes using the two-step selection procedure and the imputed minutes using the simple OLS regression. Unsurprisingly, we see that the OLS provides a better within-sample fit but is lower than the search time resulting from the Heckman procedure. The two imputation methods produce similar results. Additionally, we also explored a version of



(a) all nonemployed

(b) unemployed

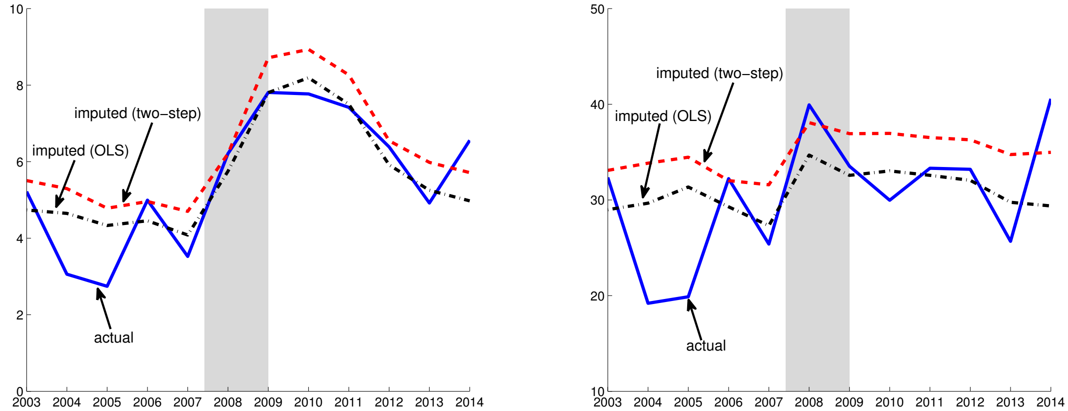
Figure A2: Actual and imputed average search minutes per day for all nonemployed workers and unemployed workers using controls for data quality.

the regression where we allow the relationship between search methods and search time to vary by gender and with age. Figure A4 shows that the resulting cyclicality of the search effort series is very similar with and without these additional interactions.

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

To explore this possibility, we first include year dummies in the regression.[5] Results in Table

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



(a) all nonemployed

(b) unemployed

Figure A3: Actual and imputed average search minutes per day for all nonemployed workers and unemployed workers using the 2 imputation methods

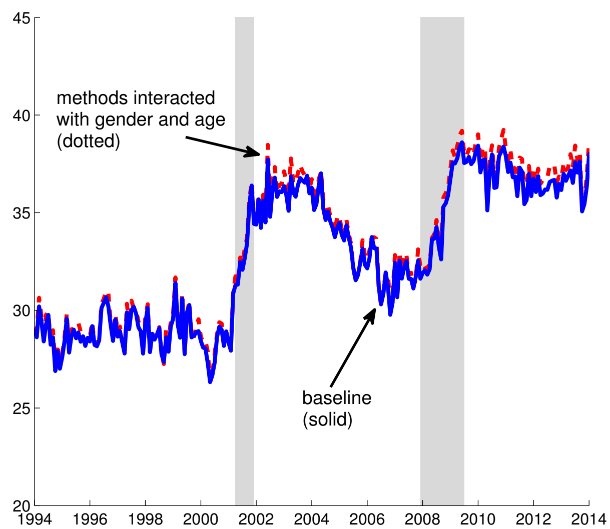


Figure A4: Cyclicality of Search effort allowing for interactions between search methods and demographic controls

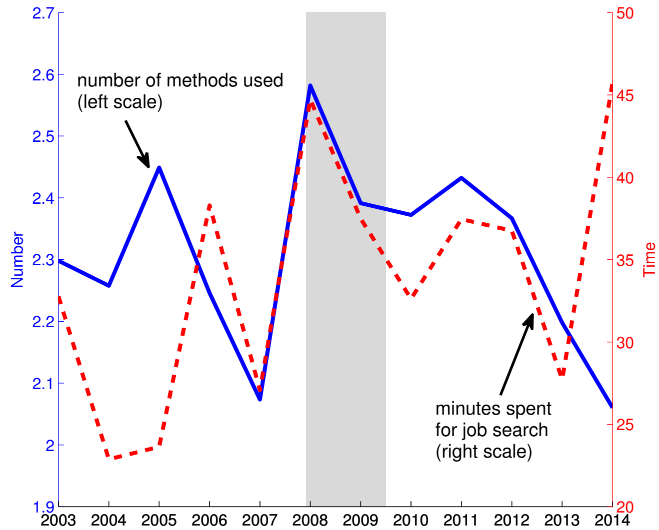


Figure A5: Minutes spent on job search activities and number of search methods in the ATUS sample

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 A5 shows the mechanical reason that the fit of the regression is worst in 2004 and 2005: while reported search time (dashed line, right scale) and number of methods used (solid line, right scale) track each other closely for most of the sample, the relationship breaks down in these two years. In particular, there is a decline in search time in 2004 to 2005 that is not mirrored in the number of methods. As a result of the divergence of these two measures in these years, the imputation method overestimates the total search time in 2004 and 2005.

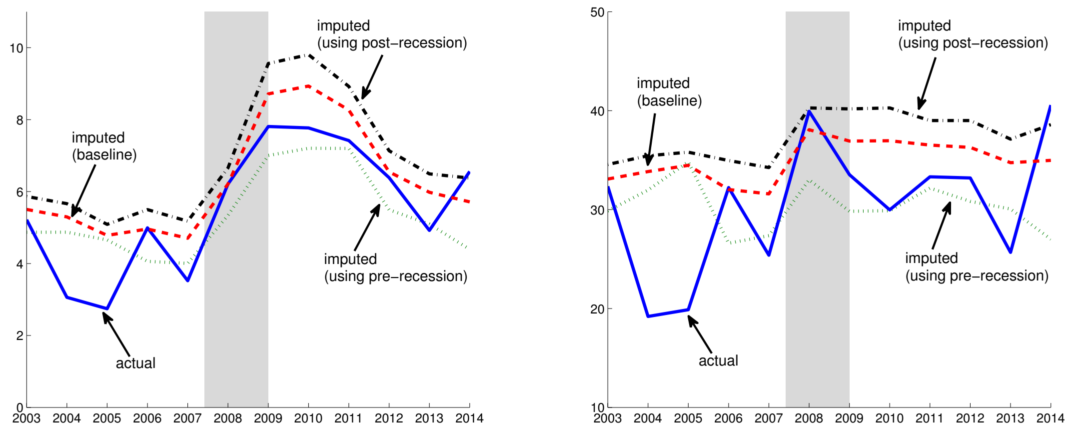
To further explore the possibility that the relationship between search methods and search time varies over time, we break our data into a pre-recession (2003–2007) and a post-recession (2008–2014) sample. We then calculate the imputed minutes for each of the subsamples and explore the in and out of sample fit. Figure A6 shows that the regression using the pre-recession sample slightly underpredicts the reported search time among both the unemployed only and

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

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

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 A5.

Lastly, we explore the effect of including aggregate macro-economic indicators in the imputation procedure. As discussed in Section 2.3, we include each aggregate measure separately and interact with each search method, essentially allowing the relationship between search time and a particular search method to vary over the business cycle. Figure A7 shows the imputed minutes that result from estimates that include either cyclical component of GDP, the unemployment rate, or the vacancy-to-unemployment (θ). The imputation allowing the relationship to vary with either of the labor market indicators is similar to our baseline, but somewhat more cyclical. Thus, our benchmark imputation method is the most conservative one for representing



(a) all nonemployed (b) unemployed

Figure A6: Average search minutes per day for all nonemployed workers and unemployed workers using pre- and post-recession samples of ATUS data.

the cyclicality of search effort.

A.3 Additional results for the cyclicality of search effort

A.3.1 Robustness of time series analysis

In order to examine the robustness of our aggregate results in Section 3, we present a number of additional measures of the intensive and extensive margins. The left panel of Figure A8 shows the time series of the average number of search methods used in the CPS over our sample period. This more simple measure of search effort shows a countercyclical pattern very similar to Figure 3 in the main text. There are two differences between this count measure and our imputed minutes measure. First, our measure weights each search method differently according to the estimated time intensity. Secondly, our minutes measure allows for baseline search effort to vary by demographic characteristics. The right panel of Figure A8 plots our imputed minutes measure with the average number of methods, both normalized to 1 in the initial period to account for differences in scale. The two series have a correlation of 0.94, but we see that the imputed minutes measure of search effort is more volatile than the simple count of the number of methods. This suggests that either individuals shift to more time intensive

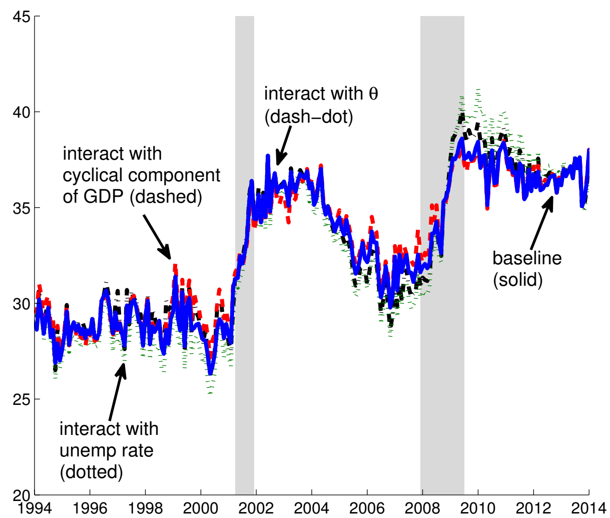
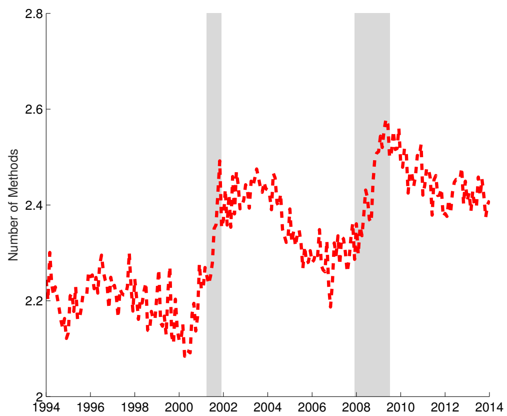


Figure A7: Imputed minutes in the CPS using market aggregates.

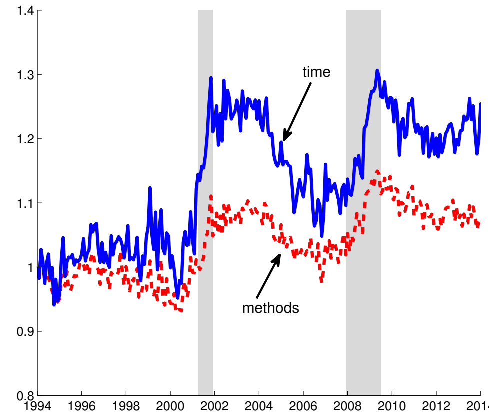
search methods in recessions or that the composition of the unemployed pool shifts towards higher search demographics over the business cycle.

To directly compare the search time information in the ATUS and the CPS, Figure A9 plots search time (left panel) and the average number of search methods (right panel) from the CPS sample and the ATUS sample. As discussed in Section 2.1, the ATUS data is very noisy and therefore we plot the annual average. We see that although the ATUS is more volatile, the two search intensity measures are very similar across the datasets, both showing a sharp peak during the Great Recession.

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

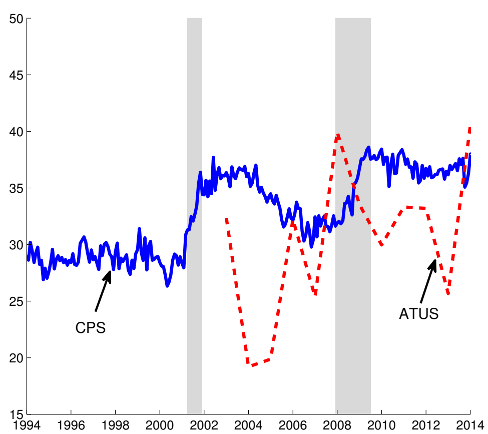


(a) Average number of search methods

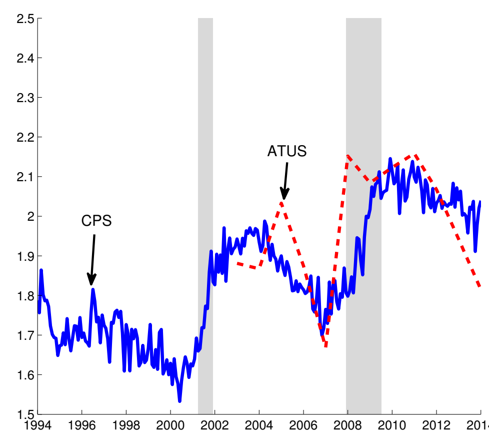


(b) Comparison of the number of search methods (dashed) and search time (solid)

Figure A8: Two measure of the intensive margin of job search.

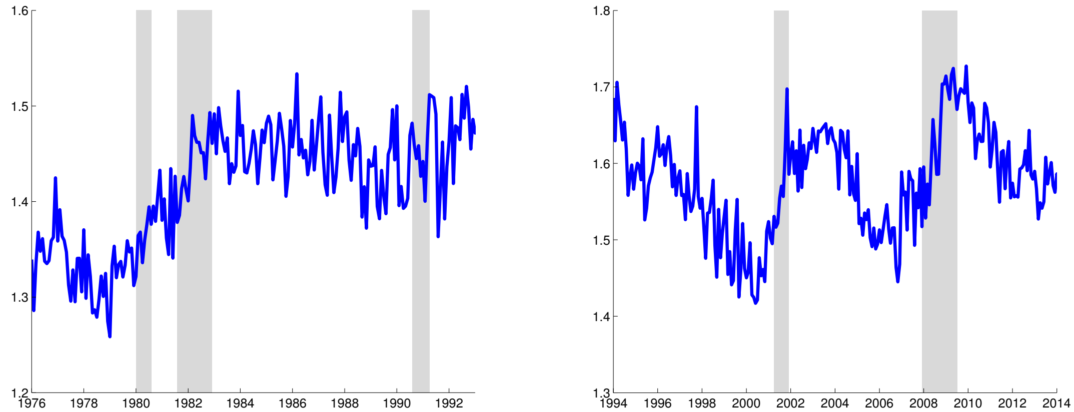


(a) Average minutes of search (per day)



(b) Average number of search methods

Figure A9: Intensive margin measures in the ATUS and the CPS



(a) 1976–1993

(b) 1994–2012

Figure A10: Historical time series of the average number of job search methods (from 5 methods)

in order to create a time series of search intensity that is consistent over the full sample, we restrict our attention to the first five major search methods. Since the additional job 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 A10 shows the time series of the average number of reported search methods, selected from these five possible search methods.[6] The left panel shows the series from 1976–1993 and the right panel shows the series from 1994-2014, shown separately to account for the remaining discontinuity at the 1994 redesign. We see that the countercyclical pattern of job search effort is weaker but also evident in the earlier data as well, with large rises in search effort around the early 1980 recessions.

Lastly, Figure A11 plots the time series of the fraction of the unemployed who are using each search method. The figure shows that each search method shows a slightly different time

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

series, with some, such as "contacting an employer directly" trending down and others, like "contacting friends or relatives" trending up. The figure also shows that the cyclical increase in the number of search methods is more pronounced in some methods than others.

A.3.2 Robustness of individual level analysis

In this section, we present the details of our exploration of the determinants of aggregate search effort. First, we discuss the details of the multiple imputation method that we use to calculate the standard errors in Table 5. Second, we report additional results that demonstrate the robustness of the qualitative results in Table 5. Lastly, we show how the fraction of the unemployed who are eligible for benefits changes over the cycle.

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

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

2. Estimate Equation (1) at the individual level.

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

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

and

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

where

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

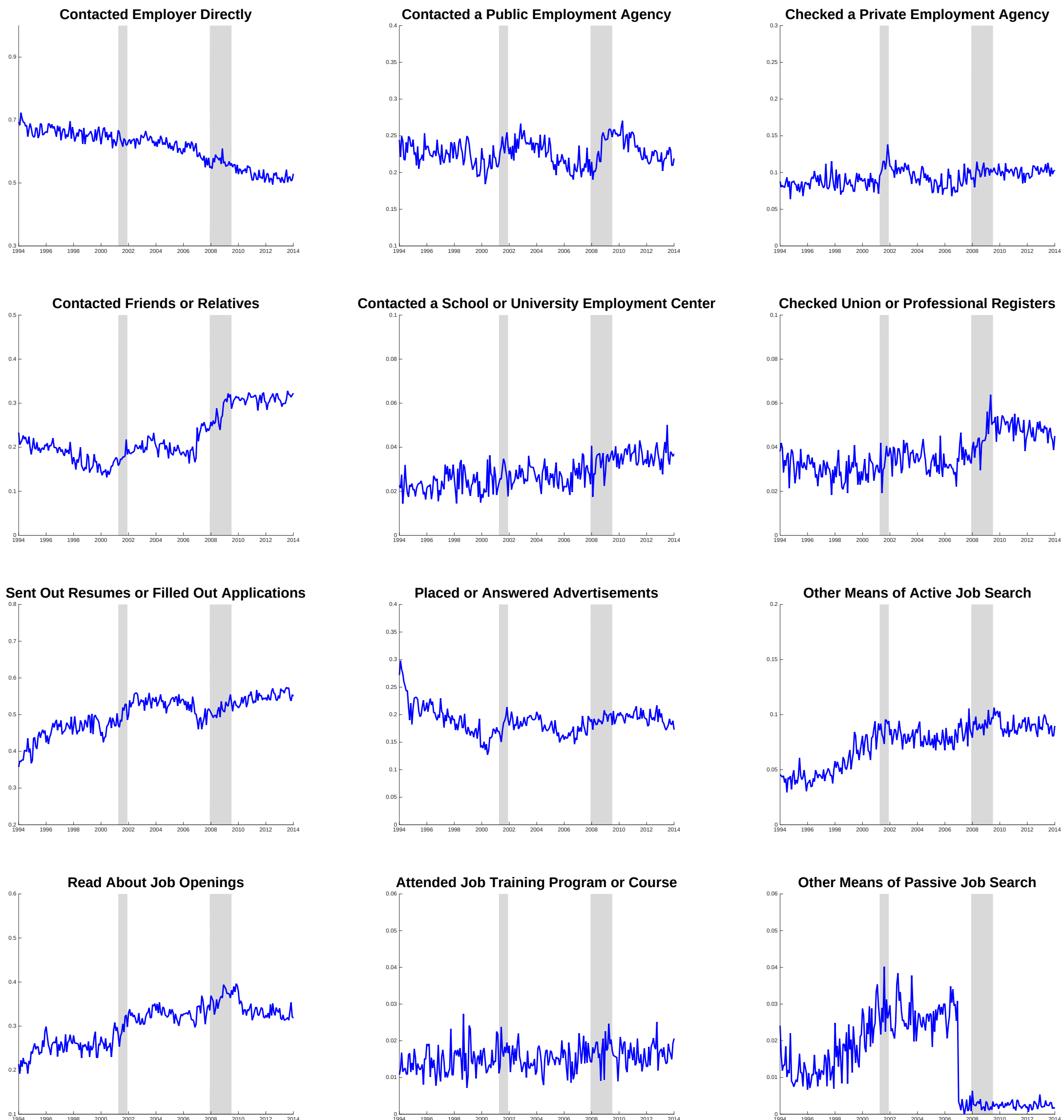


Figure A11: The fraction of unemployed using each search method.

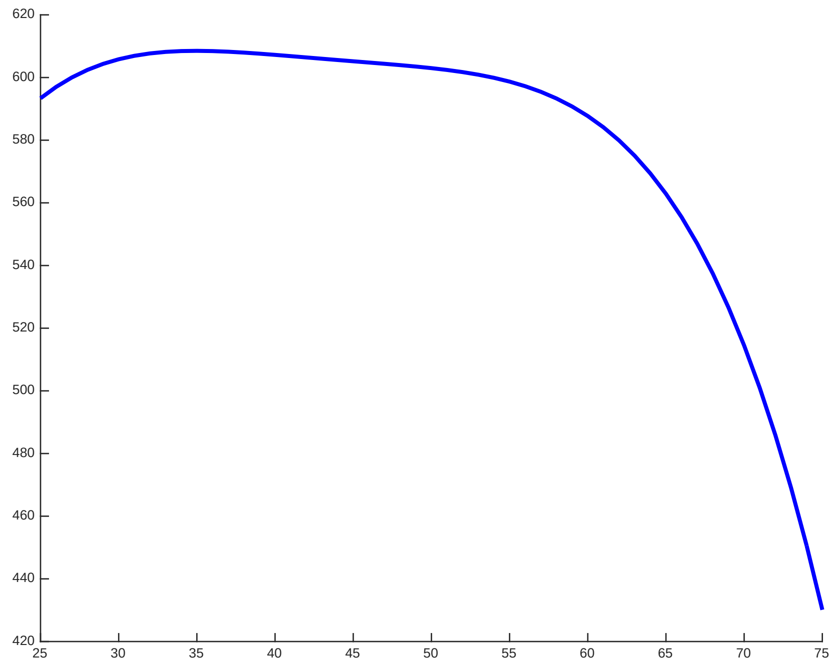


Figure A12: The effect of age on the intensive margin of job search. Quartic polynomial coefficients from regression (1)

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

The following set of results expand on those reported in Table 5. First, Figure A12 shows the age-search effort profile, estimated using a quartic polynomial in regression (1). The intensive margin stays almost flat (increasing slightly) before starting to fall after 50 years of age.

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

Empirical studies that examine the response of job search effort to increasing unemployment duration have mixed results. Krueger and Mueller (2011), for example, find that job search effort declines as the unemployment spell progresses at the individual level. However, at the cross-section, they find that job search effort is similar across workers with different unemployment durations. In our regressions we include a quartic function of unemployment duration following Shimer (2004). Figure A13 plots the response of search intensity to unemployment duration. This result is similar to Shimer's (2004) findings. Search effort initially rises with unemployment duration and then goes down (and slightly goes up). When we change the specification to cubic and quintic polynomials, we find that, while the other coefficients of the regressions are robust to the degree of the polynomial in unemployment duration, the peak of the graph changes. This result is consistent with the result of Shimer (2004).

Table 5 demonstrated the behavior of individual search effort over the business cycle by looking at its correlation with $\theta = v/u$. While this measure is both a good indicator of the labor market and a measure that most directly maps into the search model framework, we can also explore the co-movement of search effort with other cyclical indicators. Table A2 explores the sensitivity of the findings in Section 3.3 to various alternate measures of the business cycle. For compactness, the table only reports the specifications with individual fixed effects, although the results with controls only show similar patterns. Specifically, Column 1 uses state-level

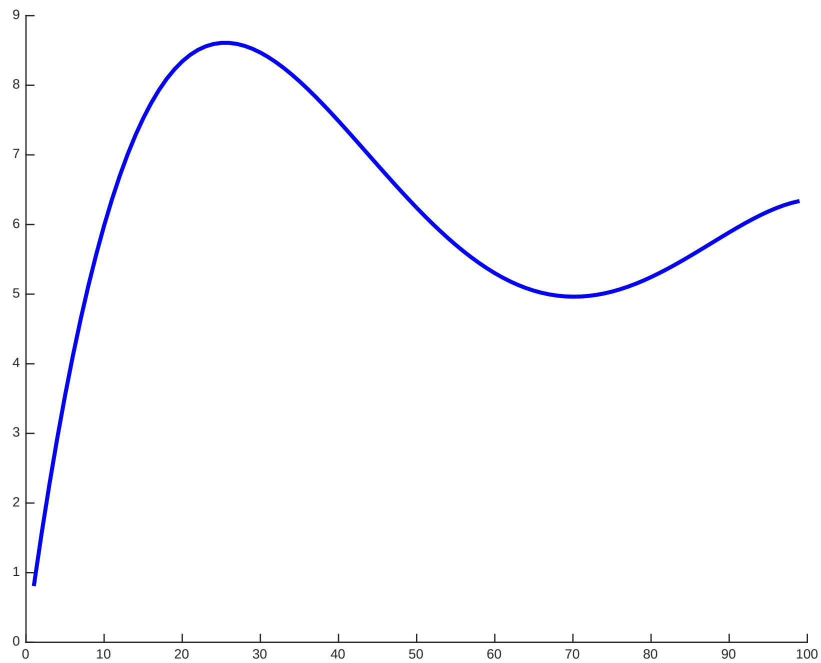


Figure A13: The effect of unemployment duration on the intensive margin of search. Drawn from the quartic polynomial coefficients in regression (1) market tightness, which is only available beginning in May 2005 and Columns 2-4 show the countercyclical relationship with different wealth measures. Overall, we see statistically significant negative relationships between job search effort at the individual level and the business cycle.

	State HWOL	S & P	House Price	State House Price	Payroll Employment
log (Indicator)	−4.048***	−6.967***	−15.334***	−12.701***	−972.742***
	(0.696)	(0.960)	(2.320)	(3.053)	(118.891)
Unemployment Duration	0.123**	0.170***	0.177***	0.178***	0.176***
	(0.051)	(0.039)	(0.039)	(0.045)	(0.039)
Unemployment Duration^2	−0.006***	−0.008***	−0.008***	−0.008***	−0.008***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Unemployment Duration^3	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Duration^4	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. Obs.	302578	528727	528727	528727	528727

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

Table A2: Response of individual search effort to changes in macroeconomic conditions proxied by state level vacancy-to-unemployment ratio, stock price series, aggregate and state-level house prices, and aggregate payroll employment. State level vacancy-to-unemployment ratios come from The Conference Board Help Wanted OnLine Data Series (HWOL).

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

	Composite Help-Wanted Index (1994-2014)		JOLTS (2001-2014)	
	Basic	Observables	Basic	Observables
log (θ)	-7.635^{***}	-4.901^{***}	-4.285^{***}	-2.931^{***}
		(0.256)	(0.258)	(0.225)
Age	.	66.500***	.	70.216***
		(10.388)		(10.747)
Age^2	.	-2.303^{***}	.	-2.431^{***}
		(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	.	-1.034	.	-0.852
		(1.314)		(1.369)
Married	.	4.256***	.	4.333***
		(1.611)		(1.655)
Female	.	-11.701^{***}	.	-11.741^{***}
		(1.586)		(1.630)
Married x Female	.	-25.806^{***}	.	-26.219^{***}
		(2.239)		(2.303)
High School	.	6.046***	.	6.051***
		(1.301)		(1.361)
Some College	.	26.235***	.	26.536***
		(1.620)		(1.671)
College	.	57.380***	.	57.470***
		(2.108)		(2.149)
Cognitive Routine	.	-6.053^{***}	.	-5.710^{***}
		(0.276)		(0.293)
Manual Non-Routine	.	-1.229^{***}	.	-0.961^{***}
		(0.234)		(0.256)
Manual Routine	.	-7.550^{***}	.	-6.992^{***}
		(0.309)		(0.323)
Unemployment Duration	.	0.845***	.	0.816***
		(0.032)		(0.034)
Unemployment Duration^2	.	-0.027^{***}	.	-0.025^{***}
		(0.001)		(0.001)
Unemployment Duration^3	.	0.000	.	0.000
		(0.000)		(0.000)
Unemployment Duration^4	.	-0.000	.	-0.000
		(0.000)		(0.000)
No. Obs.	547315	547315	414843	414843

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

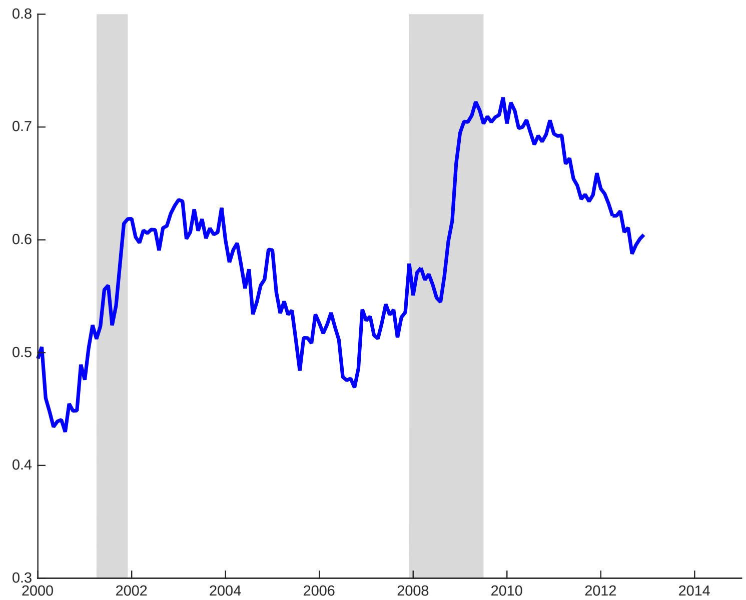


Figure A14: Fraction of the unemployed who are eligible for UI.

Lastly, Figure A14 shows the fraction of the unemployed workers who are eligible for unemployment insurance benefits in each month. The figure shows that in recessions, a higher fraction of the unemployed are eligible for UI benefits, suggesting a substantial change in composition over the cycle along this margin.

A.4 Matching function estimation

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

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

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

provides a useful benchmark.

We consider the formulation

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

where f_t is the job-finding probability, $\theta_t \equiv v_t/u_t$ where v_t is the number of vacancies and u_t is the number of unemployed, $\boldsymbol{\tau_t}$ is the vector of month dummies for each month of a year, and ε_t is the error term. $\bar{s}_t$ is the average value of imputed search minutes for unemployed workers, measured in Section 3. d_t is a dummy variable that takes the value of 1 after July 2009, which is intended to control for a recent large decline in matching efficiency. We use data from the JOLTS and CPS from December 2000 to December 2014 to estimate this relationship.[7]

Table A4 shows the results of a simple OLS regression of the form (A1), with and without the intensive margin, $\log(\bar{s}_t)$. The first column is the conventional matching function estimation, and the result is within the range of the OLS results in the literature. The second column adds our search effort variable estimated from the CPS, $\bar{s}$. The coefficient of $\log(\bar{s})$ is positive and significant at the 1% level, suggesting the importance of the variation in job search effort.

[7]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.

This finding implies that search effect has a positive effect on the job-finding probability at the aggregate level. Of course, this correlation can be the consequence of a shift in the composition of unemployed workers as well as the direct effect of job search on the matching process. Note that since search effort tends to be high when market tightness is low, when search effort is included, the coefficient on market tightness increases.

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

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

While these results suggest that search effort is important in explaining aggregate variations in the job finding rate, as is argued by Borowczyk-Martins, Jolivet, and Postel-Vinay (2013), the OLS estimates are likely biased. In particular, they argue that θ_t is endogenous in the conventional matching function estimation when there are shocks to the matching efficiency. In our formulation, their argument also can be applied to $\bar{s}_t$. They devised a GMM estimation

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

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

method that is immune from this endogeneity bias. In particular, they assume that ϵ_t in (A1) has an ARMA structure and estimate the AR parameters ϵ_t together with the coefficients β_i using the lagged values of $\log(\theta_t)$ as instrumental variables. We extend their method to incorporate another endogenous variable $\log(\bar{s}_t)$. Following their method, we assume that ϵ_t follows ARMA(3,3). We use $\log(\theta_{t-i})$ and $\log(\bar{s}_{t-i})$ where $i = 4, 5, 6, 7, 8, 9$ as the instrumental variables. (Note that here the system is over-identified.) Following Borowczyk-Martins, Jolivet, and Postel-Vinay (2013), we repeat the estimation also with $\log(f_{t-4})$ included in the list of instrumental variables.

Table A6 shows the result. In both cases, the coefficient of $\log(\theta_t)$ is significant at 0.1% significance level and also in line with the estimates in the previous studies (in Borowczyk-Martins, Jolivet, and Postel-Vinay (2013), the corresponding numbers are 0.706 and 0.692). The point estimates of both coefficients are lower than the OLS estimates, as the theory would predict. Unfortunately, the coefficients of $\log(\bar{s})$ have large standard errors and thus cannot provide a conclusive evidence on the effect of $\bar{s}_t$. We also experimented with adding more instruments, including S&P-500 index and nation-wide house price index, but they did not improve the estimates. This is likely to be because (i) the measurement of $\bar{s}_t$ is not as precise

	Lags of $\log(\theta_t)$ and $\log(\bar{s}_t)$ used as IV	$\log(f_t)$ lag also included as IV
$\log(\theta_t)$	0.638^{***}	0.620^{***}
	(0.163)	(0.105)
$\log(\bar{s}_t)$	-0.538	-0.545
	(0.455)	(0.448)

Table A6: Matching function estimation: GMM method based on Borowczyk-Martins, Jolivet, and Postel-Vinay (2013). Standard errors are in the parenthesis. *** indicates being significant at 0.1% level.

as θ_t and (ii) the instruments are not very strong for $\bar{s}_t$, and (iii) the negative externality among workers may wash out the individual effect at the aggregate level. These econometric issues encouraged us to follow a more structural approach outlined in Section 4.

B Theory Appendix

B.1 General setup

We consider an infinite-horizon setting with discrete time. A worker has to be matched with a vacant job to start working. The aggregate number of matches at each period is dictated by the matching function, in which matches are created as a function of the number of vacancies, the number of unemployed workers, and each unemployed worker's search effort. At the individual level, matching is stochastic, and we assume that the probability of worker i finding a job can be expressed as $f(s_{it}, \bar{s}_t, \theta_t)$, where s_{it} is her own search effort, $\bar{s}_t$ is the average search effort of all unemployed workers in the economy, and $\theta_t = v_t/u_t$ is the labor market tightness. We also assume that the probability of a firm finding a worker can be expressed by $q(\bar{s}_t, \theta_t)$. The separation probability of a matched job-worker pair, denoted by σ, is assumed to be constant. The job-worker match produces z_t units of consumption goods in each period, where z_t follows a Markov process. The total population has mass 1, and therefore the number of employed workers is $1 - u_t$.

B.1.1 Value functions

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

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

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

$$V(S_t) = -\kappa + \beta E[q(\bar{s}_t, \theta_t)J(S_{t+1}) + (1 - q(\bar{s}_t, \theta_t))V(S_{t+1})], \tag{B1}$$

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

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

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

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

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

$$c'(s_{it}) = \beta f_1(s_{it}, \bar{s}_t, \theta_t)E[W(S_{t+1}) - U(S_{t+1})]. \tag{B2}$$

This equation specifies that the worker will increase their job search until the point where the marginal cost of job search equals the expected benefit of an additional unit of search, which is given by the relative expected benefit of being employed times the probability that the worker finds a job with that search effort. We denote the optimal search effort that satisfies (B2) by s^*_{it}.

B.1.2 Wage determination

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

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

and

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

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

$$(1-\gamma)(\tilde{W}(w; S_t) - U(S_t)) = \gamma(\tilde{J}(w; S_t) - V(S_t)), \tag{B3}$$

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

B.1.3 Free entry and equilibrium

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

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

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

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

Combining this with the Nash bargaining condition from (B3) and the free entry condition that $V(S_t) = 0$, we arrive at an expression for the expected wage which is given by:

$$E[w(S_{t+1})] = \frac{\gamma}{1-\gamma}\frac{\kappa}{\beta q(\bar{s}_t, \theta_t)} + b - E[c(s^*_{i,t+1})] - \frac{\gamma}{1-\gamma}E\left[\frac{(1-\sigma - f(s^*_{i,t+1}, \bar{s}_{t+1}, \theta_{t+1}))\kappa}{q(\bar{s}_{t+1}, \theta_{t+1})}\right]. \tag{B4}$$

Let us impose the equilibrium condition and denote $s_t = s_{it}^* = \bar{s}_t$. Then, combining (B1) and (B4), we solve out the wages and obtain the following equation in terms of s_t and θ_t:

$$\frac{\kappa}{1-\gamma} = \beta q(s_t, \theta_t) E\left[z_{t+1} - b + c(s_{t+1}) + \frac{1-\sigma-\gamma f(s_{t+1}, s_{t+1}, \theta_{t+1})}{1-\gamma} \frac{\kappa}{q(s_{t+1}, \theta_{t+1})}\right]. \quad \text{(B5)}$$

Lastly, Equation (B2) can be rewritten as

$$c'(s_t) = f_1(s_t, s_t, \theta_t) \frac{\gamma}{1-\gamma} \frac{\kappa}{q(s_t, \theta_t)}. \quad \text{(B6)}$$

Equations (B5) and (B6) determine the dynamics of θ_t and s_t. Note that the stock of unemployed, u_t, does not appear in either (B5) or (B6). This implies that the dynamics of θ_t and s_t, which are both jump variables, are not influenced by u_t and only determined by one state variable z_t.[8] The implication of this is that once we characterize the dynamics of θ_t and s_t from (B5) and (B6), we can determine the evolution of unemployment using

$$u_{t+1} = \sigma(1-u_t) + (1 - f(s_{it}, \bar{s}_t, \theta_t))u_t, \quad \text{(B7)}$$

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

B.2 A generalized matching function

The key component in the specification of our model is the matching function. Recall that the goal of this exercise is to consider a general parameterized formulation of the matching function and use our empirical findings within the search and matching framework to determine the class of matching functions consistent with the data. The tight connection between our empirical findings in Section 3 and the form of the matching function is captured in Equation (B6). Log-linearizing (B6) around the steady state yields

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

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

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

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

where "tilde" ($\tilde{}$) denotes the value at the steady state. The values of f_i, f_{ij}, q, and q_i are evaluated at the steady state, where the subscripts denote partial derivatives and double-subscripts denote cross derivatives. This expression shows that the sign of Φ, which captures whether search effort responds negatively or positively to θ and is what we estimated in our empirical analysis, depends crucially on the form of the matching function.

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

$$f(s, \bar{s}, \theta) = \chi \left(\alpha s^{\psi} + (1 - \alpha) \left(\frac{s}{\bar{s}} \right)^{\xi} \theta^{\psi} \right)^{\eta}, \tag{B8}$$

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

$$M(\bar{s}, u, v) = \chi \left(\alpha \bar{s}^{\psi} + (1 - \alpha) \left(\frac{v}{u} \right)^{\psi} \right)^{\eta} u. \tag{B9}$$

This implies that the probability that a firm finds a worker, $q(\bar{s}, \theta)$, can be expressed by $f(\bar{s}, \bar{s}, \theta)/\theta$. Note that the formulation (B8) is a departure from the Pissarides (2000, Chapter 5) assumption that $f(s, \bar{s}, \theta)$ is proportional to s. In addition, this specification nests some important special cases:

1. When $\xi = \alpha = 0$ and $\psi\eta \in (0, 1)$, (B9) reduces to the standard DMP matching function in Cobb-Douglas form, without workers' search effort. We refer to this specification as the *basic Cobb-Douglas case*.

2. If we first set $\xi = \psi = 1/\eta$ and take a limit of $1/\eta \to 0$, $f(s, \bar{s}, \theta)$ becomes $s\chi(\theta/\bar{s})^{1-\alpha}$ and $M(\bar{s}, u, v)$ becomes $\chi(\bar{s}u)^{\alpha}v^{1-\alpha}$.[9] This is a Cobb-Douglas special case of Pissarides

[9] In Appendix A.4, we estimate using OLS a simple linear regression under the constant returns to scale assumption using the average search intensity measure in Figure 3 as a dependent variable in addition to

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

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

In all cases, this generalized form of the matching function should satisfy some restrictions on parameter values to ensure that these functions exhibit regular properties, namely that $f(s, \bar{s}, \theta)$ is increasing in s and θ and $q(\bar{s}, \theta)$ is increasing in $\bar{s}$ and decreasing in θ. First, in order for the matching function to be increasing in $\bar{s}$ and v, ψ, and η have to have the same sign. Second, the matching function has to be increasing in u. We assume that $\psi\eta < 1/(1-\alpha)$ holds in order to satisfy this property around $s = 1$ and $\theta = 1$. We also assume that $\xi = 0$ and $\eta = 1/\psi$. The reason for setting $\xi = 0$ is because it is very difficult to estimate the value of ξ from our limited information about the search effort's influence on the individual match. $\eta = 1/\psi$ is assumed based on the fact that in the special cases above, the both cases that include endogenous search effort satisfy this restriction.

B.3 Characterizing three special cases

B.3.1 The standard DMP model with no effort choice

A special case is when s_t is constant, which boils down to the standard Pissarides (1985) model. This case is easy to analyze. Assume that $f(\theta) = \chi\theta^{1-\lambda}$ and $q(\theta) = \chi\theta^{-\lambda}$, where $\chi > 0$ and $\lambda \in (0, 1)$. Then, log-linearizing (B5) around the steady-state yields (the "tilde" ($\tilde{}$) denotes the value at the steady state and the "hat" ($\hat{}$) denotes the log deviation from the steady state)

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

unemployment. We find that the coefficient of $\log(\bar{s})$ is positive and significant at the 1 percent level, suggesting the importance of the variation in job search effort in accounting for the behavior of the job-finding rate. However, the specification imposes strong restrictions on the interaction between s and θ and therefore we use an alternative calibration method, described in the main text.

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

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

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

using the method of undetermined coefficients,

$$\mathcal{C} = \frac{\rho}{\mathcal{A} - \rho\mathcal{B}} = \frac{1-\gamma}{\kappa\tilde{\theta}^{\lambda}\left(\left[\frac{1}{\rho\beta} - (1-\sigma)\right]\frac{\lambda}{\chi} + \gamma\tilde{\theta}^{1-\lambda}\right)}. \tag{B10}$$

This makes it clear that, for example, for given $\tilde{\theta}$ the amplification ($\mathcal{C}$) is large when κ is small. This is the background of Hagedorn and Manovskii's (2008) main result. (In order to keep $\tilde{\theta}$ and other parameters constant, a small κ requires a large value of b.)

B.3.2 Pissarides (2000, Ch 5) model

Now, let's go back to the original model, with (B5) and (B6). Assume that $c(s) = \phi s^{\omega}/\omega$, where $\omega > 1$. As in Pissarides (2000, Ch 5), assume that the matching function takes the form of $M(\bar{s}u, v)$ and the worker's job finding rate is $f(s, \bar{s}, \theta) = sM(1, \theta/\bar{s})$. In particular, assume a Cobb-Douglas function for the matching function:

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

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

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

The probability of a vacancy finding a worker is

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

The equation (B5) is now

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

Rearranging, this can be rewritten as

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

Log-linearizing this yields

$$\frac{\kappa\tilde{s}^{-\alpha}\tilde{\theta}^{\alpha}\alpha}{(1-\gamma)\beta\chi}(\hat{\theta}_t - \hat{s}_t) = E\left[\tilde{z}\hat{z}_{t+1} + \phi\tilde{s}^{\omega}\hat{s}_{t+1} + \frac{(1-\sigma)\kappa\tilde{s}^{-\alpha}\tilde{\theta}^{\alpha}\alpha}{(1-\gamma)\chi}(\hat{\theta}_{t+1} - \hat{s}_{t+1}) - \frac{\gamma\kappa\tilde{\theta}}{1-\gamma}\hat{\theta}_{t+1}\right]. \tag{B11}$$

The equation (B6) can be rewritten as

$$\phi s_t^{\omega-1} = \frac{\gamma\kappa}{1-\gamma}\frac{\theta_t}{s_t}. \tag{B12}$$

This can be solved as

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

Log-linearizing,

$$\hat{s}_t = \frac{1}{\omega}\hat{\theta}_t. \tag{B13}$$

This makes it clear that s_t responds *positively* to θ_t. The job finding probability is complementary between s and θ, which makes s move in the same direction as θ. It responds less when the curvature of the effort cost function (ω) is larger.

Using (B13), (B11) can be rewritten as

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

using the same assumption on $\tilde{z}$ as before and following the same steps (we used the fact that (B12) also holds in the steady state), we obtain

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

where

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

This is remarkably similar to (B10). The only differences are (i) χ is now replaced by $\chi\tilde{s}^{\alpha}$, since now this is the "effective" match efficiency on average, and (ii) the term $\omega/(\omega-1)$ is multiplied in front, since the movement of s influences the cyclical movement of the probability of a vacancy finding a worker, changing the incentive for vacancy posting. There is a "magnification" (when $\chi\tilde{s}^{\alpha}$ is replaced by χ), since $\omega/(\omega-1) > 1$. This was observed by Merz (1995) and Gomme and Lkhagvasuren (2015) in numerically-solved models and the analytical comparison of steady states.

B.3.3 The generalized matching function

Now assume that

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

and

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

where $\chi > 0$, $\alpha \in (0,1)$, $\eta \in (0,1)$, $\psi > 0$, and $\psi\eta < 1$. These are special cases of (B8) and (B9), and slightly more general than the specification we used for the quantitative work. It follows that

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

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

The equation (B5) can be rearranged to

$$\begin{aligned} &\frac{\kappa}{(1-\gamma)\beta\chi}(\alpha s_t^{\psi} + (1-\alpha)\theta_t^{\psi})^{-\eta}\theta_t \\ &\qquad = E\left[z_{t+1} - b + \frac{\phi}{\omega}s_{t+1}^{\omega} + \frac{(1-\sigma)\kappa}{(1-\gamma)\chi}(\alpha s_{t+1}^{\psi} + (1-\alpha)\theta_{t+1}^{\psi})^{-\eta}\theta_{t+1} - \frac{\gamma\kappa}{1-\gamma}\theta_{t+1}\right] \quad \text{(B14)} \end{aligned}$$

and the equation (B6) is[10]

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

Rearranging and log-linearizing, we obtain

$$\hat{s}_t = \frac{\alpha\tilde{s}^{\psi} - (\psi-1)(1-\alpha)\tilde{\theta}^{\psi}}{\omega\alpha\tilde{s}^{\psi} + (\omega-\psi)(1-\alpha)\tilde{\theta}^{\psi}}\hat{\theta}_t. \tag{B15}$$

Denoting the right-hand side as $\Phi\hat{\theta}_t$, this corresponds to the equation (**??**) in the main text. Similarly to (B13), the absolute value of Φ is small when ω is large. In contrast to (B13), here $\hat{s}$ can react *negatively* to $\hat{\theta}$ (i.e. $\Phi > 0$) if ψ is sufficiently large (or α is sufficiently small). Note that $f_{13} < 0$ is not sufficient for this because the effect from wage still exists.

Log-linearizing (B14) and using (B15), we obtain the equation

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

where

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

and

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

As before, this can be solved as

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

C Calibration and Additional Results

C.1 Baseline Calibaration

We start our quantitative exercise by calibrating a subset of parameters to standard values based on Shimer (2005) and commonly-used values in the literature. This calibration strategy allows

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

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

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. Since Shimer's influential paper, a considerable literature developed trying to address the unemployment-volatility puzzle. Prominent examples are Hall (2005) or Blanchard and Galí (2010) who argued that a more realistic wage determination scheme is the key to the puzzle. We also consider a calibration strategy following Hagedorn and Manovskii (2008) which matches the volatility of these variables. We find that, regardless of the calibration strategy we follow, search effort dampens unemployment fluctuations. See Appendix C.2 for the details of the Hagedorn and Manovskii (2008) calibration.

We assume that a period in the model is a month, and thus, following Shimer (2005), we set $\beta = 0.988^{\frac{1}{3}}$. Also following Shimer (2005), we set the bargaining power of the worker to $\gamma = 0.72$ and the exogenous separation probability to $\sigma = 0.034$. Following the preferred specification in Yashiv (2000), we set the convexity of the search cost function to $\omega = 2$. We set $\tilde{\theta} = 1$ and $\tilde{s} = 1$ in the steady state and choose χ so that the steady-state job-finding rate $\chi(\alpha \tilde{s}^{\psi} + (1-\alpha)\tilde{\theta}^{\psi})^{\eta} = \chi(0.1+0.9)^{0.3} = 0.49$. Thus $\chi = 0.49$. We assume that the stochastic process for z_t is

$$\log(z_{t+1}) = \rho \log(z_t) + \varepsilon_{t+1},$$

where $\varepsilon_{t+1} \sim N(0, \sigma_{\varepsilon}^2)$. Hagedorn and Manovskii (2008) measure that the quarterly autocorrelation of log of the labor productivity to be 0.765 and the unconditional standard deviation to be 0.013. The corresponding monthly values of ρ and σ_{ε}, calculated through Monte Carlo simulations, are 0.949 and 0.0065.

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 $\log s$,

Calibrated Parameters	Value	Source
β	0.996	Shimer (2005)
ρ	0.949	Hagedorn and Manovskii (2008)
σ_ϵ	0.0065	Hagedorn and Manovskii (2008)
σ	0.034	Shimer (2005)
ω	2	Yashiv (2000)
χ	0.49	Job-finding rate
α	0.15	
ψ	1.33	
$b - \phi/\omega$	0.4	Shimer (2005)
γ	0.72	Shimer (2005)
Implied Parameters		
κ	0.21	Equations (B5) and (B6)
ϕ	0.082	Equations (B5) and (B6)

Table C1: Parameters for Shimer Calibration.

which yields an elasticity of $\Phi = -0.15$.[11] We add this additional target to our calibration and compute the set of matching function specifications consistent with this moment.

What does this imply for the parametrization of the matching function? Equation (3) shows that the *sign* of Φ is determined only by the values of α and ψ, which are the non-standard parameters in our matching function.[12] Figure C1 depicts the combinations of the (α, ψ) values that gives rise to $\Phi < 0$, from Equation (3). As we see analytically from (3), the necessary condition for $\Phi < 0$ is $f_{13} < 0$. Figure C1 shows that this condition corresponds to the set of α and ψ in the shaded region above the black line. The property $f_{13} < 0$ implies that s and θ are *substitutes* as inputs of the job-finding process. In other words, the marginal product of individual search is lower when θ is high. Intuitively, this corresponds to a situation where favorable labor market conditions for a worker (a high θ) mean that the search effort of the worker is less effective in generating a job offer (although the *level* of job-finding probability is high for a given s since θ is high). In booms, job opportunities are abundant, but spending an additional unit of job search effort affects the the number of job offers the workers receive less than it affects in recessions.

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

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

Importantly, the purple line shows the set of α and ϕ that are consistent with our estimated $\Phi = -0.15$. Lastly, the orange and blue lines represent the parameters that correspond to the special cases we discussed above—the Cobb Douglas case with search effort and the linear case. Within the structure of this model, both of these cases are inconsistent with our empirical finding that search effort and θ are negatively related. From the set of parameters identified by the purple line in Figure C1, we select the ones that minimize the distance between the implied job-finding rate and the actual job-finding rate observed in the data. Specifically, we compute the job-finding rate implied by (B9) for all combinations of parameters α and ψ feeding in the realized time series for θ and $\bar{s}$ and pick the parameters with the best fit.[13]

Given the previously calibrated parameters, the steady-state versions of (B5) and (B6) determine the values of κ and ϕ. Finally, we need to calibrate the value of b. This is directly linked to the value of nonemployment, $b - \phi\tilde{s}^{\omega}/\omega = b - \phi/\omega$. We set the value of nonemployment to be 0.4, following Shimer (2005). The resulting parameter values are summarized in Table C1.

We solve the model by log-linearly approximating around the steady state. The log-linearized system results in a simple relationship

$$\hat{\theta}_t = \mathcal{C}\hat{z}_t, \tag{C1}$$

where $\mathcal{C}$ is a constant that depends on parameters (the explicit expression is presented in Appendix B). Thus the model can easily be simulated by first obtaining the series of z_t, calculating θ_t from (C1), and then solving u_t forward by (B7).[14]

[13] Appendix Figure C3 plots the time series for the job-finding rate, calculated following Shimer (2005), against the time series for the job-finding rate that is implied by the model with the best-fit parameters. As the figure shows, the generalized matching function captures the behavior of the job-finding rate very well in the early part of the sample, underestimates it in the mid 2000s and slightly overestimates it in the later part of the sample.

[14] Note that the restriction of both the job-finding probability and the worker-finding probability being less than one implies that the job-finding probability is less than $\min\{1, 1/\theta\}$, and this restriction is imposed when (B7) is used.

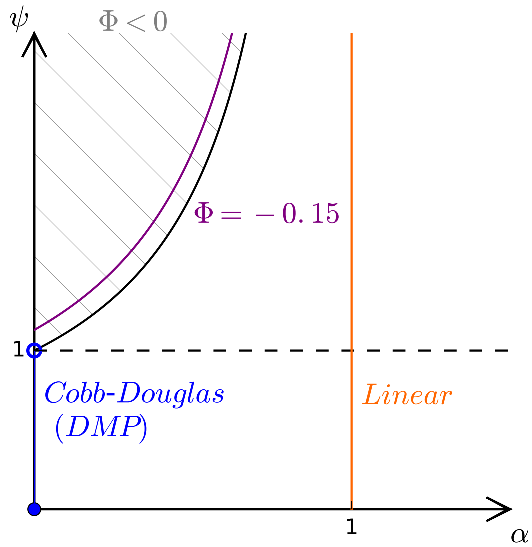


Figure C1: Set of parameters consistent with $\Phi = -0.15$

C.2 Hagedorn and Manovskii (2008) calibration

In Table C2, we report the parameters that are calibrated as in Hagerdon and Manovskii (2008). As expected, this calibration yields much more unemployment volatility when search effort is assumed to be constant. However, adding countercyclical search effort to this calibration dampens these fluctuations. While the baseline result of this calibration is very different from the Shimer (2005) exercises discussed in the main text, search effort plays a similar dampening role with both calibrations.

C.3 Cyclical components of θ and s

Figure C2 below displays the data underlying the target $\Phi = -0.15$. The figure plots the cyclical component of $\ln \theta$ and $\ln \bar{s}$. While the correlation between the two series is large and negative, θ is more volatile than search effort, leading to the target of -0.15.

Calibrated Parameters	Value	Source
β	0.996	Shimer (2005)
ρ	0.949	Hagedorn and Manovskii (2008)
σ_ε	0.00645	Hagedorn and Manovskii (2008)
σ	0.034	Shimer (2005)
ω	2	Yashiv (2000)
χ	0.49	Job-finding rate
α	0.15	
ψ	1.33	
$b - \phi/\omega$	0.955	Hagedorn and Manovskii (2008)
γ	0.052	Hagedorn and Manovskii (2008)
Implied Parameters		
κ	0.33	Equations (B5) and (B6)
ϕ	0.0028	Equations (B5) and (B6)

Table C2: Parameters for Hagedorn-Manovskii Calibration: generalized matching function

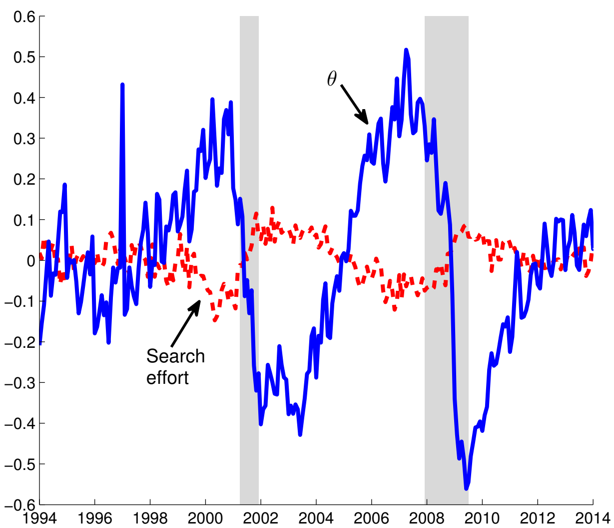


Figure C2: The correlation between the intensive margin of search and market tightness.

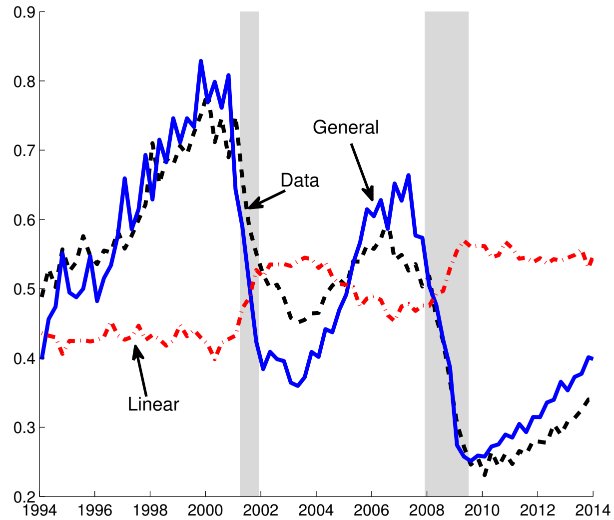


Figure C3: The job-finding rate implied by the generalized and linear matching specifications and the data. Data and model outcomes are plotted as quarterly averages of monthly observations.

C.4 Additional Quantitative Results

We repeat the exercises described in the main text, but with a calibration of the matching function that now matches a *counterfactual* target for the elasticity of search effort and θ of 0.45. The results of this exercise using the Shimer calibration are reported in panel III of Table C3. 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.[15] 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. This finding is consistent with the findings of Veracierto (2008), Christiano, Trabandt, and Walentin (2012) and Gomme and Lkhagvasuren (2015) who get amplification using procyclical search effort. However, our analysis earlier in the paper shows that the assumption of procyclical search effort is not empirically supported

[15]The elasticity of θ with respect to productivity goes up from 1.75 to 1.96 and the standard deviation of the unemployment rate goes up from 1.63 to 2.03 as Panel III of Table 7 shows.

		$\Phi = \frac{d\hat{s}}{d\hat{\theta}}$	$\mathcal{C} = \frac{d\hat{\theta}}{d\hat{z}}$	$Std(u) \times 100$
I. Data		-0.15	19.9	12.5
II. Shimer specification with countercyclical s	DMP Model ($s = 1$)		1.77	1.76
	Endogenous s and θ	-0.15	1.73	1.67
III. Counterfactual with procyclical s	DMP Model ($s = 1$)		1.75	1.63
	Endogenous s and θ	0.45	1.96	2.03

Table C3: Unemployment volatility with different specifications. In Panel II, the matching function is calibrated as in Appendix C and $\alpha = 0.15$ and $\psi = 1.33$. In Panel III, the matching function is calibrated using the method from Appendix C to hit the counterfactual target of $\Phi = 0.45$. The resulting parameter values are $\alpha = 0.2$ and $\psi = 0.23$. $Std(u)$ is calculated after being logged and HP-filtered with parameter 1,600 in quarterly frequency.

and once its true cyclical properties are properly taken into account, endogenous search effort dampens labor market fluctuations in the DMP framework.

Additional References for Appendix

[1] Blanchard, O. and J. Galí (2010). "Labor Markets and Monetary Policy: A New Keynesian Model with Unemployment," *American Economic Journal: Macroeconomics* 2, 1–30.

[2] Borowczyk-Martins, D., G. Jolivet, and F. Postel-Binay (2013). "Accounting for Endogeneity in Matching Function Estimation," *Review of Economic Dynamics* 16, 440–451.

[3] Hall, R. E. (2005). "Employment Fluctuations with Equilibrium Wage Stickiness," *American Economic Review* 95, 50–65.

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

[5] Merz, M. (1995). "Search in the Labor Market and the Real Business Cycle," *Journal of Monetary Economics* 36, 269-300.

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

[7] Yashiv, E. (2000). "The Determinants of Equilibrium Unemployment," *American Economic Review* 90, 1297–1322.