Essays on Unemployment and Job Search

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Dedication

To my parents, Nila and Rómulo, and siblings, David and Militza, for their support, encouragement, and undying belief in me. In particular, to Nila, for being the inspiration throughout my life. This dissertation is also dedicated to Ivonne, for her love, patience, and endurance.

Abstract

This thesis consists of two chapters. In Chapter 1 I show evidence of job search behavior for the unemployed in the U.S. By using the American Time Use Survey (ATUS) between 2003 and 2014, I document that the unemployed in the U.S. appear to allocate their time to job search regardless of the state of the economy. They increase search intensity only slightly if at all during recessions. While their search intensity depends on a number of factors that change over the business cycle, I primarily argue that a countercyclical value of a job is the most promising explanation to reconcile the evidence with the theory. I show this by providing estimates of the cyclicality of the value of a job in the U.S. To infer the cyclicality of the value of a job, I build on Chodorow-Reich and Karabarbounis (2015), who construct estimates for the opportunity cost of employment. I develop a strategy to gauge an upper bound for the size of job search costs based on the size of the value of non-working time. I discipline these estimates by using an expression for the value of a job that emerges from a search model.

In Chapter 2, I address the role of risk aversion in shaping the job search behavior over the business cycle. I first show that a sufficiently high degree of risk aversion could make the unemployed look for work in a countercyclical fashion, as the data suggests: more intensely in recessions and less intensely in booms. Empirically, I show that such a behavior is inconsistent with the degree of risk aversion used pervasively in the business cycle literature. With the aim of assessing to what extent risk aversion could still play a role, I introduce consumption commitments into an otherwise job search model. As shown by Chetty and Szeidl (2007), commitments in consumption could amplify the degree of risk aversion, the reason being an uneven adjustment in consumption along different spending categories in response to wealth shocks.

Empirically, I find partial support to the insights stemming from the theoretical framework. The results show that the amplification is sensitive to the classification of small and large shocks. I discuss theoretical avenues to improve our understanding on the role of commitments in shaping the job search behavior.

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Chapter 1

Non-procyclical Job Search Intensity

1.1 Introduction

Time allocation and business cycle fluctuations remain in the top of the research agenda in macroeconomics. The profuse research that has gravitated towards the cyclical movements of hours worked, employment, and real wages has shaped our understanding of business cycles. However, little is known about the time allocation of unemployed workers to activities that may contribute to a successful job search, such as sending out resumes and answering ads, and how the time spent in these activities varies with the ups and downs in economic activity.[1]

Still, this allocation decision has important implications for business cycles, and perhaps more notably, for the resilience of the economy in the aftermath of a recession. For instance, discouraged workers could fuel a long-lasting recession. Alternatively, unemployed workers eager or desperate to find a job may increase their odds by searching harder in order to take the yet limited job opportunities, thereby speeding up the recovery.

By using the American Time Use Survey (ATUS) between 2003 and 2014, I document that the unemployed in the U.S. appear to allocate their time to job search regardless

[1] Recent contributions include Shimer (2004), Mukoyama et al. (2013), DeLoach and Kurt (2013) Gomme and Lkhagvasuren (2015), and indirectly Aguiar et al. (2013b).

of the state of the economy. They increase search intensity only slightly if at all during recessions.

It would be odd to interpret this evidence as if the unemployed were unaware of or unaffected by the changing conditions in the labor market. After all, the unemployed remain attached to the labor market and their chances of leaving the pool of unemployment vary with the business cycle. Moreover, their search intensity depends on additional factors that do change with the swings in the business cycle, such as wages, unemployment benefits, and the value of non-working time.

For the sake of exposition, consider the following sketch of the balance of costs and benefits that drives the choice of job search intensity:

$$\underset{\substack{\text{current marginal} \\ \text{costs of searching}}}{\overset{(1)}{}} = \underset{\substack{\text{marginal increase in} \\ \text{the job finding probability}}}{\overset{(2)}{}} \times \underset{\substack{\text{expected} \\ \text{value of a job}}}{\overset{(3)}{}}$$

The left side of the equation represents the foregone leisure time when allocating an additional time unit to the job search. However, this additional effort also brings about benefits. The right side of the equation highlights two motives. Since looking for work is a risky activity, the first motive is the possibility of boosting the chances of finding a job. The second motive is the ultimate payoff of having looked for work in the first place: the value of a job.

The value of a job is the sum of the benefits minus the opportunity costs of being employed. Having a job means receiving a wage in exchange for the hours worked. It also implies avoiding the search costs that could have been incurred had the unemployed failed to find a job and kept looking for work. The opportunity cost of being employed consists of the foregone nonwork-contingent insurance benefits and the foregone value of non-working time.

The evidence I show implies that (1) does not vary over the business cycle under preferences that are separable in search time and consumption. This contrasts with what we know about the right side of the equation. It is well-known that in the U.S., the probability of finding a job tracks closely with the cyclical shifts of the economy (Shimer, 2005 and Shimer, 2012). Hence (2) does vary with the state of the economy. And (3) is predicted to do so in a particular manner. The value of a job is, by construction, strongly procyclical in the Mortensen and Pissarides (1994) search model, which is the workhorse of the macroeconomics of unemployment.[2]

Therefore, if the nearly acyclical allocation of time to job search activities by the unemployed in the U.S. is seen through the lens of above equation, then we have a puzzle.[3]

I discuss two alternative hypotheses aimed to solve this puzzle by addressing (2) and (3) separately. The first one, which focuses on (2), states that the unemployed search for work with an intensity that varies according to the prevalent labor market conditions in a way that makes search intensity more valuable when good job opportunities are lacking. The cyclicality of search intensity will be a direct consequence from assuming a key property in the so-called matching function. This is a rather exogenous way to model the cyclicality of search intensity, yet it has received some attention in the literature (see Mukoyama et al., 2013).

The second hypothesis addresses (3). From the worker's standpoint, a job is more desirable during recessions. The value of a job, which is measured to be higher during recessions, acts as a reward for the search efforts. In a nutshell, the unemployed cannot afford waiting to see how the recession unfolds. They can avoid the future costs of being unemployed by embracing the hassle right away.

Among these, the most promising explanation is that the unemployed place a relatively high value on a job during recessions. I show this by providing estimates of the cyclicality of the value of a job in the U.S. To infer the cyclicality of the value of a job, I build on Chodorow-Reich and Karabarbounis (2015), who construct estimates for the opportunity cost of employment. I develop a strategy to gauge an upper bound for the size of job search costs based on the size of the value of non-working time. I discipline these estimates by using an expression for the value of a job that emerges from a search model.

The estimated value of a job is countercyclical for two reasons. First, having a job during recessions does not hurt much since otherwise workers would have plenty of non-working time. On the contrary, it helps since typically recessions are periods of

[2] This is less so in versions of the model that depart from the Nash bargaining rule or allow for rigid wages in a rather exogenous way. The canonical search model of Mortensen and Pissarides (1994) will also predict that (2) is less procyclical than what it is observed in the data. This counterfactual prediction was first documented by Shimer (2005).

[3] Of course, the puzzle remains if search intensity is countercyclical. Shimer (2004) documents that the average number of search methods used by the unemployed is countercyclical. Mukoyama et al. (2013) construct intensive and extensive margins for search intensity by linking time-use data and number of search methods. They conclude that search intensity is countercyclical.

low consumption. That is, the opportunity cost of being employed is relatively low. Chodorow-Reich and Karabarbounis (2015) report that the time series of this cost is as procyclical as the marginal labor productivity. The second reason is that the opportunity cost of postponing the decision to search for work is relatively high during recessions. The search costs that accumulate over an expected long period of unemployment deter the worker from delaying their efforts.

Chodorow-Reich and Karabarbounis's (2015) estimates would imply that, in a search model with an endogenous search effort, the value of a job is nearly acyclical or slightly countercyclical in the U.S. I show that the puzzle mentioned above could be solved when allowing search costs to play a role as well. Therefore, I argue that both the procyclicality of the opportunity cost of employment and the countercyclicality of future search costs are needed to show that a job is strongly valued during recessions.

How people spend their time to the job search has also implications for our view of business cycles and thereby for policy. To gain some insight, consider a slow economic recovery in retrospection. One view could be that it is the result of people not searching for work hard enough. The alternative view will be that it has occurred despite people making higher efforts to find a job. The culprit is the lack of jobs. Of course, policies aiming at helping the unemployed differ across views.

1.2 Evidence on Time-use in Search Activities

Preliminaries: It was only until recently that time-use data for the U.S. started to be collected in a systematic basis. Since 2003, the American Time Use Survey (ATUS) is the primary source of national representative statistics on how people spend their time in a typical day of the year. The sample is drawn from households that have finished their eighth month of interview in the Current Population Survey (CPS).

Each month, nearly 60,000 households are selected to be part of the CPS sample, which is the nationally representative household survey and source of the most important U.S. labor market statistics, such as unemployment, employment, and hours worked. Members of each participating household aged 15 or over are interviewed once a month for four consecutive months, dropped from the sample for the next eight months, and interviewed again for the final four consecutive months.

The ATUS respondents are usually interviewed two to five months after they leave the CPS sample. The designated person is chosen randomly with equal probability within the household and asked to provide a detailed account of her activities starting at 4 a.m. on the day prior to the interview and ending at 4 a.m. on that day.

Time-use diaries is a rich source of information that throws light on how people allocate their time to a variety of activities including child care, socializing, personal care, and sports. However, some of the peculiarities of how the ATUS is conducted should be considered when judging its suitability as a good measure of time-use in activities that may have implications for the aggregate economy, such as home-production, work, and job search. Next, I dwell on some of these issues.[4]

The first issue rests on the interpretation of the ATUS data, given that questions are about the time-use during the previous day of the interview.[5] Here the concern seems to be justified since my interest is on time allocation over the business cycle, which calls for a rather longer time-use horizon, say, a week or a month.

The previous point touches upon a second issue, which is the substantial fraction of unemployed individuals who report zero minutes spent in search activities.[6] According to Frazis and Stewart (2012) and Stewart (2013), these observations are to be regarded as the influence of day-to-day variation. The decision of whether to look for work in a given day may be conditioned by factors such as sickness, child care responsibilities, and weather conditions. Moreover, the recognition of this source of variation also brings the empirical evidence in consonance with the theoretical framework discussed later, that rules out corner solutions in the allocation of time. These two issues highlight the need to account for non-random day-to-day variation.

Sample size is the third concern. The short time coverage and low frequency of the survey data makes it difficult to interpret the cyclical variation in the time-use extracted using standard filtering methods. Alternative sources of variation may be exploited, based on individual characteristics such as age or education level, or geographical areas,

[4]See Hamermesh et al. (2005) for a review of the ATUS survey and Hurst (2015) for an more recent account of the survey and the challenges in the measure of time-use.

[5]See Frazis and Stewart (2012) for a thorough discussion of the shortcomings that may arise from using short-term time-use data to infer time-use in longer horizons.

[6]The fraction of unemployed workers who report zero minutes spent in search activities is 80%, in average, in the period 2003-2014.

such as U.S. states or regions.[7] Later, I discuss these alternatives.

Previous Findings using ATUS: Previous authors have used alternative measures of search intensity, most prominently, the number of search methods. In a way to categorize unemployed people as accurate as possible, the CPS asks respondents about the things they have done in order to find a job during the 4 weeks previous to the survey week, which includes the nineteenth day of every month.

Although the salient cyclical pattern shown by the average number of search methods is not doubt evidence in favor of a desire to diversify the job search outcomes, it is unclear to which extent the number of methods conveys useful information about the time-use in search activities. Next, I review some of the previous work on the cyclicality of search intensity and the use of alternative measures of search intensity.

Shimer (2004) was the first at documenting the cyclicality of the average number of search methods in the U.S. He uses the number of methods from self-responses of the unemployed people in the CPS. In this paper, I use a direct measure of search intensity based on the time-use in search activities as reported by the ATUS respondents. Mukoyama et al. (2013), in light of the small sample size of ATUS, develop a methodology to infer both extensive and intensive margins in time-use in searching activities. Instead on using directly the raw time-use data from ATUS, they infer the cyclicality in time-use by regressing individual time-use from ATUS on the CPS number of methods. I rely exclusively on the allocation of time to search activities, which is the variable that reflects ultimately the allocation of time among competing alternative.

The following two papers show results in favor of the procyclicality of search intensity. DeLoach and Kurt (2013) report that the time-use in job search is procyclical. This study is perhaps the closest to the present paper. They also are sympathetic to Stewart (2013)'s recommendation on the treatment of zero reported time. They, however, find that individual labor market variables, such as duration of unemployment, are not relevant in shaping the job search behavior. I revisit this finding by including this variable and other related variables. I find that the labor market experience is important in shaping the job search behavior. Gomme and Lkhagvasuren (2015) has a critical view

[7] An example of this latter approach is Aguiar et al. (2013b). They rescale the ATUS weights so as to mimic the unemployment rate at the U.S. state level. ATUS data is only representative at the national level.

on the use of the number of search methods. They show that the statistical association between number of methods and the tightness of the aggregate labor market is weak. On top of that, they claim that the time series pattern in the time-use in search activities — that has a noticeable peak in 2008 — is accounted for by compositional changes related to the hours worked. I control for the type of job the unemployed is looking for (part time vs. full time) and find no evidence in favor of unemployed spending less time looking for work in recessions.

Non-procyclical search intensity: In preparation to the empirical results, I discuss some issues that will be connected to the challenges mentioned before. It is tempting to exploit cross-section variations by grouping variables according to a demographic characteristic or a geographic area in light of the short time coverage of the survey and the low frequency of the data. This approach comes, however, at the expense of discarding individual variation that may be relevant. I settle the issue by estimating the ratio of group variation to the total variation. I perform a covariance-analysis to assess the relative contribution of within-variance in the total variance, using a variety of criteria, such as age, education, U.S. state and region. I show the results from this exercise in Table 1.1.

I find that the contribution is negligible, not enough to lend support to an analysis that rests on the grouping of variables. Interestingly, only two criteria seem to be somewhat important: the U.S. state and the labor force status. Still, the magnitude of their relative contribution is small enough to call for such an analysis. As a result, the following analysis rests upon pooled data.

The small sample makes the incoming results particularly susceptible to day-to-day variation. As another consequence, it is difficult to distinguish between a true absence of association between search intensity and the business cycle or a false one accounted for by the lack of sufficient variation to identify the cyclical pattern. Therefore, I pool all ATUS respondents regardless of their labor force status. I then generate conditional predictions for only the unemployed workers. In Figure 1.1 I plot the time series of time-use across labor force status.

I consider the following regression equation:

$$s_{ijt} = \alpha + \psi \text{ time dummies}_t + \beta \text{ urate}_{jt} + \gamma \text{ demo}_{it} + \phi \text{ day}_{it} + \delta \text{ labor}_{it} + \epsilon_{ijt} \quad (1.1)$$

where s_{ijt} is the time-use in hours per week used by worker i in state j in year t. Next I dwell on the a priori rationale behind the inclusion of the variables in the right side.

Aggregate macroeconomic effects on the choice of search intensity are captured by yearly dummies. Local conditions in the market may affect the job search behavior. The inclusion of URATE is intended to capture issues related to competition for and availability of jobs in the state that differ from the aggregate labor market conditions. A buoyant local labor market may spur the intensity of searching at the individual level. Alternatively, even a depressed local labor market may call for the increase in the intensity in order to exhaust the few job opportunities.

Variables in DEMO include individual characteristics that may influence the job search behavior: age, sex, race, education, marital status. Aguiar et al. (2013a), for instance, show that the allocation of time to the job search changes over the life cycle, with the peak occurring at the end of their prime-age (46-50). The job search behavior may also depend on the presence or support of a partner in the household. In recessionary periods, the pooling of income may help the unemployed insure themselves against unemployment shocks. In addition, women and men may allocate time to search activities differently as part of a specialization of tasks within the household. Race may also account for biases in the economic marketplace. Finally, education may affect the job search behavior in two different ways. On the one hand, higher educated unemployed individuals have more to lose in times when job opportunities are scarce since they are the ones who have accumulated skills. They would be expected to search more intensely. On the other hand, the same group of educated people may have additional means to cushion unemployment shocks. The less educated may be more desperate and, therefore, more willing to search intensely.

The allocation of time as measured by the ATUS is subject to day-to-day variation. With the aim of controlling for systematic variation of this sort, I include a variety of variables ranging from daily factors to seasonal factors. Among the first group, I include the day of the week, whether the day is a holiday or not. To control for seasonal factors affecting the job search, I include the month of interview. As mentioned before, one of the implications of this source of variation in time-use is the high fraction of respondents reporting zero time. This is not only related to daily factors such as sickness or child care responsibilities that may absorb the time that otherwise would have allocated to the job search. It also reflect aggregate and local economic conditions. This observation support, in addition, the inclusion of state-unemployment rate and the yearly dummies.

An account of the job search behavior would be incomplete if individual labor market considerations were left out of the analysis. For ATUS respondents, it is possible to learn what was their labor force status and other information, such as the interrupted duration of unemployment and the reason of unemployment, at the moment of their eighth month of interview in the CPS. The timing, however, is not as neat as one would desire, since the ATUS interview is usually taken 2 to 5 month after the respondents leave the CPS. Thus, these variables are measured with some error. I create a variable that distinguishes between short and long-term spell of unemployment. Those respondents who are unemployed in ATUS but were employed in CPS right before leaving the survey permanently are considered short-term unemployed. Those who were unemployed in CPS are considered long-term unemployed. This variables is less accurate is people gained transitory reemployment during these 2 to 5 months gap. I control for the type of job the unemployed is looking for. It is natural to expect that those who look for part-time jobs have a higher propensity to transit between employment and unemployment. I also control for the attachment to the labor market. From those leaving the CPS, I distinguish workers who were unemployed in the 8th month of interview and reported being out of labor force before. I finally control for the labor force status in ATUS.

I estimate equation (1.1) by Ordinary Least Squares. Previous authors have used censored limited dependent variable models, such as the one suggested by Tobit (1981), motivated by the presence of zero-time observations. However, as Stewart (2013) note, these observation arise, rather as a result of the way the ATUS is conducted, so they should be regarded as the result of day-to-day variation in time-use. The sample comprises civilian people aged between 18 and 65. The sample period is annual data from 2003 to 2014. The estimated coefficients are displayed in Table 1.2. Next, I comment on these results.

Table 1.2 displays four set of results. In column (1), I display the unconditional estimates of the time-series of time-use in search activities. I include the state-unemployment rate in column (2). Interestingly, the associated coefficient is positive and statistically significant. Columns (3) and (4) report estimated coefficients after controlling for demographic variables, individual labor market experience, and day-to-day systematic variation factors. They differ in that the fourth column includes the state-unemployment rate. In this case, the estimated parameter remains positive but no longer statistical significant. Next, I focus on the full specification in column (4).

The relative magnitude of the coefficients associated to the yearly dummies are consistent with spending more time during recessions (2008 and 2009). Interestingly, the state-unemployment rate coefficient is positive, although not statistically significant. The demographic variables affect the job search behavior in the direction it was expected. Education attainment is the exception. According to these results, higher educated people tend to search more intensely, perhaps reflecting the idea that more educated people are those whose stakes are higher in the event of unemployment. Marital status has an interesting effect on the time allocated to the job search. The presence of a partner seems to be an important factor for the intensity of searching. Those who never married, however, search with an intensity comparable to those married. Those widowed and legally separated search with higher intensity. The hump-shaped pattern of search intensity over the life cycle reported by Aguiar et al. (2013b) is confirmed by the results reported here, with the highest search intensity observed between the ages 45-50.

These qualitative findings also apply to the group of unemployed people in particular. Based on regression equations similar to (1.1), I calculate the estimated search intensity by groups according to age, education, and marital status. With the aim of assessing the extent to which this behavior is not restricted to time-use data, I run similar regressions with the number of search methods, from ATUS and CPS.[8] In Figure 1.2, I show that the resemblance of all three measures of search intensity, across a selective set of demographics variables, is impressive. That is reassuring of the way age, education, and marital status affect job search behavior. It is important to mention that this

[8]For the sake of a fair comparison, I consider the same set of covariates when performing the set of regressions based on ATUS (time-use and number of methods) and CPS (number of methods). Thus the set of covariates differ from the set included in equation (1.1). See notes in Figure 1.2 for details.

favorable comparison extends to sex and race. It does not extend, however, to state or region, which is not surprising since ATUS data is not representative at either of these geographical levels.

Now, I turn to the variables intended to capture day-to-day systematic variation in the time-use. It is interesting to note that the sign and significance of the associated coefficients agree with sensible a priori explanations. For instance, during holidays, searching for work is not a popular activity and weekdays are the days where more time is spent in looking for work. The signs of the monthly dummies are easy to interpret as well. Apparently, the first months of year are the periods where worker finds more efficient to spend time in the job search.

Finally, the individual labor market experiences seem to condition the job search behavior. For example, long-term unemployed look for work more intensely than the short-term unemployed. At first sight, this finding may seem to contradict a potential discouragement effect in the decision to search when the spell of unemployment is long. However, this apparent contradiction points out the need to be precise about the duration of unemployment.

I compare the shape of search intensity across the duration of unemployment using, again, the number of methods from ATUS and CPS. I link ATUS and CPS data to infer the duration of unemployment of ATUS respondent based on their response during the 8th CPS interview. Unfortunately, I can compare only the truncated distributions since there is a gap of 2 to 5 months when individuals are not followed. Figure 1.2 shows this comparison. The comparison between time-use and number of methods from ATUS is again outstanding. They both capture very well the search intensity behavior over the spell of unemployment. The CPS measure is a little bit off from 60 weeks onwards, but the declining shape of the pattern is also reassuring.

Finally, the labor force status coefficient is consistent with the unconditional degree of time-use. Unemployed workers spend more time looking for work than any other type of worker, followed by those out of the labor force and the employed workers.

All in all, the estimated results are supportive of a meaningful measure of time-allocated to the job search and, most importantly, of its cyclical nature. The evidence shows that in average people spend more time in search activities during recessions.

To see the latter point more clearly, I perform a conditional prediction based on the regression coefficients estimated from (1.1). The time series of the time-use in search activities by the unemployed is displayed in Figure 1.1. Notice the spike occurring in the years 2008 and 2009. The slight increase in search intensity could lead one to interpret this evidence as showing that search intensity if acyclical instead. After all, the increase in time-use during the recession periods is 30 minutes in average. In any case, it is both revealing and reassuring that by no means one would conclude that unemployed people in the U.S. look for work in a procyclical fashion. In this sense, I confirm the conclusions by Shimer (2004) and Mukoyama et al. (2013) in that search intensity is not procyclical, based on evidence that exploits directly time-use in search activities. Interestingly, the puzzle that motivates this paper remains even if search intensity is acyclical.

1.3 Model Economy

I lay out a theoretical framework to evaluate the hypotheses that motivate this paper. I follow the Mortensen and Pissarides (1994) canonical search model in some respects but depart from it in others.

As in the canonical search model, I assume that workers and jobs meet according to a matching technology that captures the role of trading frictions in the labor market and, in particular, recognizes that the activity of searching for work is risky and costly. I depart from the canonical search model in that I ignore the role of firms in the creation of job vacancies. The source of aggregate fluctuations is then the tightness of the labor market.

Following Merz (1995) and Andolfatto (1996), consider a stand-in household with a unit measure of workers and a fraction $u \in (0,1)$ of unemployed workers. Time is discrete. At any given time t, a worker is either unemployed or employed. If unemployed, the worker is endowed the exogenous process $y_t^u(\theta_t)$ that depends on the aggregate state of the economy. Otherwise, the worker is endowed $y_t^n(\theta_t)$, with $y_t^n(\theta_t) > y_t^u(\theta_t)$, for every realization of $\theta_t \in \Theta$. The wealth of the household thus results from pooling the endowments of its members:

$$W_t(u_t, \theta_t) = u_t y_t^u(\theta_t) + (1 - u_t) y_t^n(\theta_t),$$

where θ is the ratio of vacancies to unemployment, i.e., the tightness of the labor market. Here θ is permitted to follow an arbitrary exogenous process; it represents the aggregate shock in the economy which is taken as given by the household. By now, I do not take a stand on how wealth is allocated within the household. Later, I discuss two alternative arrangements.

The household also takes the law of motion of unemployed workers as given. This measure evolves as follows:

$$u_{t+1} = u_t + (1-u_t)\lambda - u_t f(s_t, \bar{s}_t, \theta_t) \equiv \lambda + \alpha(s_t, \bar{s}_t, \theta_t, \lambda)u_t, \tag{1.2}$$

where $\alpha(s, \bar{s}, \theta, \lambda) = 1 - \lambda - f(s, \bar{s}, \theta)$, λ is the job destruction rate, and $f(s, \bar{s}, \theta)$ is the probability of finding a job that depends on the individual search intensity s, the average search intensity $\bar{s}$, and the tightness of the labor market. Function f is strictly increasing in both s and θ, and strictly concave in s. I also leave the complementarity between s and θ $f_{s\theta}$ unrestricted.

It will be important to understand beforehand the role of α. I make two comments. First, labor market flow estimates reported in the literature imply that $\alpha > 0$ (Shimer, 2005). Second, α may be regarded as a persistence coefficient of the law of motion of unemployment. If both λ and f are small then the process of destruction and creation of jobs is weak, in which case the worker would expect to remain in the unemployment pool for a longer time. This is more eloquently shown in the decomposition of the unemployment rate in the steady state:

$$u^{ss} = \frac{\lambda}{\lambda + f(s^{ss}, \theta^{ss})} = \lambda \frac{1}{1 - \alpha(s^{ss}, \theta^{ss}, \lambda)} \equiv \substack{\text{incidence of} \\ \text{unemployment}} \times \substack{\text{duration of} \\ \text{unemployment}}$$

where λ is the incidence of new spells of unemployment and $1/(1-\alpha)$ is the average duration of those out of work.

Finally, the preferences of the household in any arbitrary period t are represented by the following instantaneous utility function[9]

$$\mathcal{U}(c_t^u, c_t^n, s_t) = u_t\big(U(c_t^u) - V(s_t)\big) + (1 - u_t)\big(U(c_t^n) - \gamma\big)$$

where U is the utility function over consumption, V is the disutility over time spent in search activities, and $\gamma > 0$ is the disutility from working. Later, I allow γ to vary with θ. Function U is strictly increasing and strictly concave in c, and V is strictly increasing and weakly convex.

Although this is a partial equilibrium economy, I assume an implicit linkage between θ and a measure of aggregate productivity in the economy p, reflecting the creation of jobs that will show up naturally in a general equilibrium setup when firms face a positive productivity shock.

The representative household seeks to solve

$$\max_{\{c_t^u(\theta^t),\, c_t^n(\theta^t),\, s_t(\theta^t)\}_{t\geq 0}} \sum_{t=0}^{\infty} \sum_{\theta^t} \pi(\theta^t)\beta^t \Big[u_t(\theta^t)\big(U(c_t^u(\theta^t) - V(s_t(\theta^t))\big) + (1 - u_t(\theta^t))\big(U(c_t^n(\theta^t)) - \gamma\big)\Big]$$

subject to

$$\begin{aligned} u_{t+1}(\theta^{t+1}) &= \lambda + \alpha(s_t(\theta^t), \bar{s}_t(\theta^t), \theta_t), \lambda)u_t(\theta^t) \quad \forall t \geq 0 \\ \theta_t & \quad \text{follows a Markov chain} \end{aligned}$$

and taking $\bar{s}_t$ for any t, γ, λ, (u_0, θ_0) and processes for $y_t^n(\theta)$ and $y_t^u(\theta)$ as given. Additional technical constraints guarantee that $s_t \in [0, 1]$ and $u_{t+1} \in [0, 1]$ $\forall t \geq 0$.

I accommodate two alternative arrangements that determine how wealth is allocated within the household, through the additional constraint

$$c^j(\theta^t) = \begin{cases} y^j(\theta^t) & \text{no full insurance} \quad \text{or} \\ W(u_t, \theta_t) & \text{full insurance,} \end{cases}$$

[9] Instead of laying out the problem of the individual worker (see for example, Pissarides (2000), Mortensen and Pissarides (1994), and Shimer (2004)) I adopt the big household interpretation pioneered by Andolfatto (1996) and Merz (1995), and subsequently used by Shimer (2010), Christiano et al. (2013), and Chodorow-Reich and Karabarbounis (2015). There are only gains by proceeding in this way. The preferred framework would allow me to discuss two alternative setups that differ in the possibility of pooling income within the household. In addition, no intuition is lost.

for $j \in \{u, n\}$.

Characterization of the solution: I characterize the optimal choice of search intensity. The Lagrangian function could be written as follows:

$$\begin{aligned}
&\mathcal{L}\big(\{s_t(\theta^t), u_{t+1}(\theta^{t+1})\}_{t\geq 0}^{\infty}\big)= \\
&\sum_{t=0}^{\infty}\sum_{\theta^t}\pi(\theta^t)\beta^t\Bigg\{\Big[u_t(\theta^t)\big(U(c_t^u(\theta^t)-V(s_t(\theta^t))\big)+(1-u_t(\theta^t))\big(U(c_t^n(\theta^t))-\gamma\big)\Big] \\
&+\mu_t(\theta^t)\Big[\lambda+\alpha(s_t(\theta^t),\bar{s}_t(\theta^t),\theta_t),\lambda)u_t(\theta^t)-u_{t+1}(\theta^{t+1})\Big]\Bigg\}.
\end{aligned}$$

The first-order conditions imply that

$$V_s(s_t^\star(\theta^t)) \quad = \quad f_s(s_t^\star(\theta^t),\theta_t)\mu_t^\star(\theta^t) \tag{1.3}$$

and

$$\begin{aligned}
\mu_t^\star(\theta^t)\pi(\theta^t) \quad = \quad & \sum_{\theta^{t+1}}\Big[\pi(\theta^{t+1})\beta\Delta^n\left(s_{t+1}^\star(\theta^{t+1}),u_{t+1}(\theta^{t+1}),y_{t+1}^n(\theta^{t+1}),y_{t+1}^u(\theta^{t+1}),\gamma\right) \\
& + \quad \pi(\theta^{t+1})\beta\alpha\big(s_{t+1}^\star(\theta^{t+1}),\theta_{t+1},\lambda\big)\mu_{t+1}^\star(\theta^{t+1})\Big],
\end{aligned} \tag{1.4}$$

where

$$\Delta^n(s,u,y^n,y^u,\gamma)=\begin{cases} U(y^n(\theta))-U(y^u(\theta))-\gamma+V(s) & \text{or} \\ (y^n(\theta)-y^u(\theta))U_c\left[W(u,\theta)\right]-\gamma+V(s) \end{cases}$$

and the stars denote the solution of the problem. It is understood that Δ^n is independent of u when every worker consumes their own endowment. Notice that in symmetric equilibrium, $s_t = \bar{s}_t$ for every t.

Equation (1.3) is key to understand the optimal choice of search intensity. The left side stands for the marginal cost of searching, purely reflecting the foregone leisure time. The right side highlights two motives behind the action of searching. The first is boosting the odds of finding a job, denoted by $f_s(s,\bar{s},\theta)$. The second motive is captured by the Lagrange multiplier μ. In the subsequent discussion, I construct a case in favor of understanding the role played by the multiplier in shaping the choice of search intensity.

The Lagrange multiplier $\mu_t^\star$ represents the marginal utility of an infinitesimal decrease in the current measure of unemployed workers u_t. Precisely, equation (1.2) reads follows:

$$u_{t+1} \geq \lambda + \alpha(s_t, \bar{s}_t, \theta_t, \lambda) u_t.$$

The direction of the inequality is not arbitrary. To see this, consider the following useful rearrangement:

$$\frac{u_{t+1} - \lambda}{\alpha(s_t, \bar{s}_t, \theta_t, \lambda)} \geq u_t.$$

The latter inequality can be viewed as a budget constraint, where the resource to be allocated is the shock. Suppose the current measure of unemployed workers (the right side) shrinks suddenly by a small amount. The worker thus faces the following dilemma: She could take advantage of the good shock and substitute leisure time for time spent searching for work (reducing s at the expense of an increase in α), or she may keep searching with the same intensity, thereby boosting even more her chances of landing into employment in the next period (reducing u in the next period). A reduction in u_t, in any case, loosens the constraint.

How much is the worker willing to pay to experience such a a good shock? Not surprisingly, the answer is given by the multiplier μ_t. Working out equation (1.4) up to T periods ahead gives[10]

$$\mu_t^\star(\theta^t) = \sum_{i=t+1}^{\infty} \sum_{\theta^{t+1}} \frac{\pi(\theta^i)}{\pi(\theta^t)} \beta^{i-t} \left(\prod_{j=t+1}^{i-1} \alpha(s_j^\star(\theta^j); \bar{s}_j(\theta^j), \lambda, \theta_j) \right) \Delta^n \left(u_i^\star(\theta^i), s_i^\star(\theta^i); y_i^n(\theta^i), y_i^u(\theta^i), \gamma \right) \quad (1.5)$$

The variable μ admits a useful interpretation that will be invoked repeatedly in the remainder of this paper: it is the marginal utility of a decline in u_t. Thus, μ is the price, in units of leisure time, the unemployed worker is willing to pay for such a slightly increase in the share of employed members within the household. In real life, there may

[10]I rule out bubbles in μ, that is, I impose

$$\lim_{T\to\infty} \sum_{\theta^{t+1}} \pi\left(\theta^{s+T}\right) \prod_{j=t+1}^{t+T} \beta\alpha(s_j^\star, \bar{s}_j, \theta_j, \lambda)\mu_{t+T}^\star = 0$$

which establishes that μ does not grow faster than the discount gross rate given by $\left(\prod_{j=t+1}^{\infty} \beta\alpha(s_j^\star, \bar{s}_j, \theta_j, \lambda)\right)^{-1}$ as the future becomes more distant.

be countless reasons to be willing to pay this price. Equation (1.5) highlights three: the discount factor β, the rewards to search effort $\Delta^n(s, u, y^n, y^u, \gamma)$, and the persistence of the unemployment process $\alpha(s, \bar{s}, \theta, \lambda)$. Clearly, μ is simply the present value of the stream of future benefits carried by the decision of searching for work in the present. A higher time preference for the future will directly make searching for work more valuable.

Second, the higher the reward $\Delta^n(s, u, y^n, y^u, \gamma)$, the higher the incentive to substitute time allocated to the job search for leisure time. If y^n is regarded as the reemployment wage, then this component resembles the usual opportunity cost of leisure, highlighted in the real business cycle literature. The disincentive effect of nonwork-contingent insurance benefits is captured by y^u. Notice that although an increase in y^u — say, the unemployment insurance benefit — would make the unemployed exert less effort, the generosity of the benefit is counterbalanced by the associated costs of being unemployed (the future effort costs denoted by $V(s_i)$ with i starting in $t+1$ in the above formula). Think of the unemployed worker who has to provide proof of an active job search in order to remain eligible for the unemployment benefit. That is, even collecting benefits is costly.

Third, if both the creation and destruction of jobs is determined by a rather weak process, meaning that α is high, the stakes of being unemployed for along time will accordingly be higher. This should come with a stronger desire to escape from unemployment, which in turn, should be reflected in a higher price $\mu^\star$.

In a nutshell, μ is the present value of the future marginal benefits $(\Delta^n(s, u, y^n, y^u, \gamma))$ and the marginal contribution of searching today to the *reduction* of future effort costs.

Now, I write the household problem in recursive form for further reference. First let

$$B\left(u_0, \theta_0; y^n, y^u, \bar{s}, \gamma, \lambda\right) \quad = \quad E_0 \sum_{t=0}^{\infty} \beta^t \mathcal{U}(c_t^{u\star}, c_t^{n\star}, s_t^\star) \tag{1.6}$$

be the indirect utility of a household, upon following an optimal strategy for c^u, c^n, and s, that starts with measure of unemployed workers u_0 and shock θ_0, and takes $\bar{s}$, γ, λ, and processes for $y^n(\theta)$ and $y^u(\theta)$ as given. The problem of the household is to solve

$$B(u; y^n, y^u, \bar{s}, \gamma, \theta) = \max_{s,u'} \left\{ \mathcal{U}(c^u, c^n, s) + \beta \int_\Theta B(u'; y^n, y^u, \bar{s}, \gamma, \theta') Q(\theta, d\theta') \right\} \tag{1.7}$$

subject to

$$u' \;=\; \lambda + \alpha(s, \bar{s}, \theta, \lambda)u \tag{1.8}$$

given $y^n(\theta)$, $y^u(\theta)$, $\bar{s}$, γ, λ, u_0 and θ_0, and the transition function Q.

The optimal condition is

$$V_s(h(u,\theta) = \beta f_s(h(u,\theta), \bar{s}, \theta) \int_\Theta -B_u(u', \theta')Q(\theta, d\theta') \tag{1.9}$$

and the envelope condition

$$B_u(u,\theta) = -\Delta^n(h(u,\theta), u, y^n, y^u, \gamma) + \beta\alpha(h(u,\theta); \theta, \bar{s}, \lambda) \int_\Theta B_u(u', \theta')Q(\theta, d\theta') \tag{1.10}$$

where $h(u,\theta)$ is the optimal search intensity as a function of the state of the economy.

From the comparison between the sequential problem and the recursive form problem, it can be seen that

$$\mu^\star = \beta \int_\Theta -B_u(u', \theta')Q(\theta, d\theta') \tag{1.11}$$

That is, as stated above, $\mu^\star$ represents the willingness to pay in units of leisure time for a reduction in the measure of unemployed workers. This has to be equal to the expected value of a job $\left(\int_\Theta -B_u(u', \theta')Q(\theta, d\theta')\right)$, discounted by β, for $s^\star$ to be the optimal choice.

Two Rewards of Searching: Combining the optimal and envelope conditions yields:

$$V_s(s^\star) = f_s(s^\star, \theta)\, \underbrace{\beta \int_\Theta \left\{ \Delta'^n(s'^\star, u', y'^n, y'^u, \gamma) + \alpha\big(s'^\star, \theta', \lambda\big) \frac{V_s(s'^\star)}{f_s(s'^\star, \theta')} \right\} Q(\theta, d\theta')}_{\text{expected value of a job} \,\equiv\, \mu_t^\star} \tag{1.12}$$

According to this equation, the reason the unemployed look for work is threefold. The first is the contribution of the additional search effort to boosting their chances of finding a job in the future $f_s(s^\star, \theta)$. Second, upon finding a job, the worker receives the difference in utility of moving from unemployment to employment $\Delta'^n(s'^\star, u', y'^n, y'^u, \gamma)$, part of which is the marginal utility of consumption. One would expect that in recessions the unemployed would search more intensely as they look forward to smoothing consumption. The third reason is captured by the following expression

$$\alpha\big(s'^{\star}, \theta', \lambda\big)\,\frac{V_s(s'^{\star})}{f_s(s'^{\star}, \theta')}$$

which partly describes the contribution of the current search effort to the reduction of the future search costs — deflated by this effort's contribution to increasing the likelihood of leaving the unemployment pool in the future. Thus, the expression V_s/f_s.

The remaining part accounts for the persistence of the state of unemployment. If this is persistent enough, unemployed workers would expect to stay out of work for a long time, and the future stakes would be weighed so as to tilt the time allocation decision to the job search. In this sense, α in equation (1.12) is a sort of discount factor. The higher α, the more weight is placed on the future search costs. There is, then, a smoothing motive in the allocation of efforts over time.[11]

This taxonomy of the rewards of search intensity motivates the discussion of the following hypotheses.

Substitutability in the matching function

A standard assumption in the literature is that the search effort and the tightness of the labor market are complements in the matching function, that is $f_{s\theta} > 0$ holds. Put it differently, searching for work becomes more valuable in booms than in recessions. Thus, the substitutability between s and θ, that is, $f_{s\theta}$, would seem to be a natural candidate to explain why unemployed workers search for work in a countercyclical fashion.

Substitutability in the matching function may be interpreted in at least two ways. First, from the perspective of the unemployed, it could simply mean that they view searching time as a substitute for the prevalent labor market conditions in the economy. In recessions, they will search more intensely to compensate for the decline in their chances to find work. Conversely, in booms, the unemployed will minimize the hassle and enjoy additional leisure time instead.

The alternative interpretation rests upon the firm's side. Recessions will be times when firms post fewer vacancies since the fact that workers are particularly eager to

[11] The presence of this smoothing motive is also recognized by Merz (1995).

take a job will make them easier to fill. In any case, one would observe the unemployed allocating more time to search activities in recessions despite the limited availability of jobs.

Although the substitutability in the matching function is a rather exogenous way to model the cyclicality of search intensity, it has received some attention in the literature (Mukoyama et al., 2013).[12] Below, I extend some previous results in the literature and offer a cautious note on the empirical scope of this hypothesis as it is stated here.[13] For consistency, I omit the underlying mechanisms that may explain how this substitutability arise.

In the remainder of this section, I argue that the procyclicality of search intensity relies exclusively on complementarities in the matching function. Two assumptions are essential. First, I assume each worker within the household consumes their own endowment. Second, I assume that the value of a job is procyclical, to be consistent with the outcome of the canonical general equilibrium search model.

To gain insight on how s and θ are combined, consider the following functional form for the individual probability of finding a job:

$$f(s, \bar{s}, \theta) = s\frac{m(\bar{s}u, \theta)}{\bar{s}u},$$

where

$$m(\bar{s}u, \theta) = \left((\bar{s}u)^{\frac{\sigma-1}{\sigma}} + \theta^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

is the matching function proposed by den Haan et al. (2000). Combining the previous two expressions yields

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

[12]By building on **?**, Shimer (2004) shows that a countercyclical search intensity may show up in a general equilibrium search model as a natural consequence of the discrete time setting. In his model, search intensity, which is approximated by the number of search methods, depends on the job finding probability in a nonlinear fashion. Search intensity is countercyclical for values of the job finding rate exceeding 80%, a lower bound that does not seem to bind in light of the evidence on transition probabilities in the U.S. (see Shimer, 2005 and Shimer, 2012).

[13]That is, ruling out arguments that rest upon microfoundations of the matching function.

The parameter $\sigma \in (0,1)$ is the constant elasticity of substitution between the average search intensity and the labor market tightness. If $\sigma < 1$, it is guaranteed that the job finding probability is well defined (i.e., $f(s,\bar{s},\theta) \leq 1$). For a proof of this, see Appendix B.

In symmetric equilibrium, $s = \bar{s}$, so the probability function reduces to

$$f(s,\theta) = \left(s^{\frac{\sigma-1}{\sigma}} + \theta^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{1.13}$$

The purpose of the next proposition is to establish that it will suffice to assume a complementarity in the matching technology if one wants to show that the unemployed will search more intensely during booms. Interestingly, this statement does not depend on the stochastic nature of θ.

Proposition 5: If $f_{s\theta} > 0$ then $h(u,\theta)$ is strictly increasing in θ regardless of the nature of θ.
Proof: See Appendix B.
Remark: When θ is I.I.D. $f_{s\theta} > 0$ is also a necessary condition.

The latter result resembles Proposition 1 in Mukoyama et al. (2013) when θ is I.I.D. Proposition 5 thus extends their results by finding that the latter property remains sufficient for recessions of any type of persistence.[14]

As decisive as it seems, I argue that the sufficient condition $f_{s\theta} > 0$ cannot be disciplined from the data. The reason is twofold. First, as suggested by the latter proposition, the procyclicality of the optimal search intensity relies exclusively on the complementarities in the matching function, giving the theory little opportunity to fail. Second, it is hard to come up with independent data to judge whether complementarities in s and θ capture how workers and jobs meet in an actual labor market. Such a hypothesis could not be subject to criticism.

I conclude that entertaining the presence or absence of complementarities in the matching function is not a promising candidate to account for the cyclicality of search intensity. Of course, this conclusion does not rule out arguments that find support in

[14] Mukoyama et al. (2013) assume a flexible constant elasticity of substitution (CES) matching function, permitting $f_{s\theta} < 0$.

microfoundations of the matching function. These efforts would raise important avenues for future research.

Broadly speaking, this pessimistic conclusion is not definitive if we consider alternative and perhaps more interesting explanations on why the unemployed may search harder in recessions. Intuitively, risk preferences may play a role for workers who are particularly uneasy about states of low consumption. I elaborate on this next.

Countercyclical Value of a Job

The previous hypothesis relies on the proposition that the value of a job is procyclical, and this proposition, in turn, rests upon a key assumption that lies at the core of old and heated debates in macroeconomics: whether real wages are strongly or mildly procyclical.

While the strong procyclicality of wages is an assumption in a partial equilibrium setup, that cyclicality would be an outcome in a framework that incorporates firms' decisions as well. In particular, it is well-known that in the canonical search model, wages absorb most of the productivity shocks when the former are settled using the Nash bargaining rule (see Shimer, 2005).

As stated before, the procyclicality of wages would make the unemployed search less intensely during recessions. Shimer (2004), for instance, asserts that the value of a job is almost, by definition, procyclical in the canonical search model as a direct consequence of assuming the Nash bargaining rule. He also notes that in accounting for the countercyclicality of search intensity, which he documents using the number of search methods used by the unemployed in the U.S., wages would need to be strongly countercyclical to offset the procyclicality of f_s.

I show that this claim does not necessarily hold true when search intensity is an endogenous variable and the opportunity cost of delaying search efforts plays a role in shaping the value of a job.

In this section, recessions are times when the opportunity cost of postponing the decision to look for work increases. When the recession is persistent enough, the unemployed would expect to remain jobless for a long time. Since the worker will need to give up leisure in every period during the spell of unemployment, the allocation of time in search activities becomes an intertemporal decision: the marginal contribution of the current search is the reduction of future search costs. Other things equal, a strong motive to smooth search costs will make a job highly valuable in recessions.

Using data for the U.S. and estimates on the value of non-working time from Chodorow-Reich and Karabarbounis (2015), I find that the opportunity cost of postponing the decision to look for work is countercyclical.

Unemployment, in the real world, is costly for a variety of reasons, ranging from the wage that is no longer earned to wider psychological implications. In this model, being unemployed is costly because of the foregone wage and the search costs. Certainly, a complete picture of the cost of unemployment will have to allow for the benefits of being out of work, such as nonwork-contingent insurance benefits and the dislike about working.

I begin by invoking the envelope condition, which I rewrite for the sake of exposition

$$B_u(u,\theta) = (y^u(\theta) - y^n(\theta))U_c(c^\star) + \gamma - V(s^\star) + \alpha(s^\star,\theta,\lambda)\int_\Theta B_u(u',\theta')Q(\theta,d\theta')$$

Using the optimal condition for search intensity gives

$$B_u(u,\theta) = (y^u(\theta) - y^n(\theta))U_c(c^\star) + \gamma - V(s^\star) - \alpha(s^\star,\theta,\lambda)\frac{V_s(s^\star)}{f_s(s^\star,\theta)}$$

As in Chodorow-Reich and Karabarbounis (2015), I express this value in consumption units:

$$J(u,\theta) = y^n(\theta) - y^u(\theta) - \frac{\gamma}{U_c(c^\star)} + \frac{V(s^\star)}{U_c(c^\star)} + \alpha(s^\star,\theta,\lambda)\frac{V_s(s^\star)}{U_c(c^\star)}\frac{1}{f_s(s^\star,\theta)}$$

This is the equation that formally portrays the accounting of (marginal) unemployment costs. The first term is the foregone wage minus nonwork-contingent insurance benefits. This is perhaps the cost that has received particular attention in the literature.

Unemployment is less costly if the alternative involves some costs as well. The cost of being employed in units of consumption is denoted by γ/U_c. Chodorow-Reich and Karabarbounis (2015) study how this cost varies over the business cycle in the U.S.

The last term in the equation denotes very broadly the costs of searching. I make a distinction between total and marginal search costs. Although both reflect the leisure foregone, they differ in one important respect. Marginal costs are conditioned to the persistence of the unemployment process. If unemployment becomes highly persistent, that adds value to the only decision that could redound to reemployment: allocating time to the job in the margin.

An interval estimate is obtained by adopting an eclectic approach. Recently, Chodorow-Reich and Karabarbounis (2015) provide estimates of the size of y^u and γ/U_c, relative to the size of a unit of (after-tax) marginal productivity. In addition, I make a sensible assumption on the size of y^n. Finally, I make an inference on the magnitude of total and marginal search costs, based on the assumption that search costs cannot exceed employment costs.

I proceed to describe this approach in detail. In a recently influential paper, Chodorow-Reich and Karabarbounis (2015) argue that the opportunity cost of employment, most prominently the non-working time, is strongly procyclical in the U.S. They show that it is as cyclical as a measure of labor productivity which is usually regarded as the key driving aggregate shock in many business cycle models. Being employed is then less costly during recessions since workers have plenty of non-working time.[15] As a by-product of their methodology, they provide estimates on the size of the value of nonwork-contingent insurance benefits and the value of the cost of employment. I reproduce these estimates here:

$$\frac{\gamma}{pU_c} \in (0.41, 0.9) \quad \text{and} \quad \frac{y^u}{p} = 0.06$$

where these numbers are expressed in units of marginal productivity, which I should call p.

The second piece of information is the size of y^n. I simply assume that the wage is as large as p. There could be more than one reason to speculate that this assumption is not called for. For instance, wages would not entirely reflect gains in labor productivity in the presence of hiring costs.[16] In any case and in light of the size of $\gamma/(pU_c)$, $y^u/p = 1$ does not seem to be an unsound assumption.

[15]They also show that the role of nonwork-contingent insurance benefits is rather minor.

[16]See, for example, Pissarides (2000).

Now, I turn to search costs

$$\frac{V}{U_c} + \alpha \frac{V_s}{U_c} \frac{1}{f_s} \tag{1.14}$$

where I save notation for the sake of clarity. I start by noting that the expression for the marginal search costs could be expressed as a function of total search costs:

$$\alpha \frac{V_s}{f_s} \frac{1}{U_c} = \alpha \varepsilon_{V,s} \frac{s}{f} \frac{V}{s} \frac{1}{U_c}, \quad \text{where} \quad \varepsilon_{V,s} = \frac{dV}{ds} \frac{s}{V} \quad \text{and} \quad f_s = \frac{f}{s} \tag{1.15}$$

Intuitively, $\varepsilon_{V,s}$, which is the ratio of marginal to average search costs, stands for how fast search costs increase when adding an additional time unit to the job search. I now invoke an assumption which is key for what follows. I assume that $V/U_c < \gamma/U_c$, that is, searching costs cannot exceed employment costs, both represented by the foregone leisure time and expressed in terms of consumption. This assumption together with equation (2.6) imply the following inequality

$$\alpha \varepsilon_{V,s} f^{-1} \frac{V}{U_c} < \alpha \varepsilon_{V,s} f^{-1} \frac{\gamma}{U_c}$$

I can now add the remaining component V/U_c to the previous expression to obtain an upper limit for (2.5)

$$\frac{V}{U_c} + \alpha \varepsilon_{V,s} f^{-1} \frac{V}{U_c} < \frac{\gamma}{U_c} + \alpha \varepsilon_{V,s} f^{-1} \frac{\gamma}{U_c} \equiv \left(1 + \alpha \varepsilon_{V,s} f^{-1}\right) \frac{\gamma}{U_c}$$

With the aid of this inequality, I am ready to restrict sensible values for the size of search costs (in terms of p) from above. I make the following conservative assumption

$$V(s) = \chi s, \quad \chi > 0$$

which agrees with the weakly convexity assumption made on V. With this specification, $\varepsilon_{V,s} = 1$. To estimate α, the persistence of unemployment, I rely again on the flow market transition probabilities calculated using Shimer (2012)'s methodology. The probability of transiting from employment to unemployment and the job finding probability are $\lambda = 0.02$ and $f = 0.31$.[17] Thus

[17] These values imply a steady-state unemployment rate of 6.1% in the period 1967.II-2012.IV.

$$\alpha = 0.67 \quad \text{and} \quad f^{-1} = 0.31^{-1} = 3.23$$

To conclude, I find the following inequality holds

$$\frac{V}{pU_c} + \alpha \frac{V_s}{pU_c} \frac{1}{f_s} < 1.30 \tag{1.16}$$

where I have used the more conservative value for $\gamma/(pU_c)$, 0.41, estimated by Chodorow-Reich and Karabarbounis (2015).

For the sake of clarity, I adopt the following notation:

$$\begin{aligned} \text{TSC} &= \frac{V(s^\star)}{U_c(c^\star)} \\ \text{MSC} &= \alpha(s^\star, \theta, \lambda) \frac{V_s(s^\star)}{U_c(c^\star)} \frac{1}{f_s(s^\star, \theta)} \end{aligned}$$

where TSC and MSC stand for total search costs and marginal search costs. To measure how $J(u, \theta)$ varies over the business cycle, I calculate the elasticity of the value of a job with respect to changes in the tightness of the labor market:

$$\varepsilon_{J,\theta} = \varepsilon_{y^n,\theta} \frac{y^n}{J} - \varepsilon_{z,\theta} \frac{z}{J} + \varepsilon_{\text{TSC},\theta} \frac{\text{TSC}}{J} + \varepsilon_{\text{MSC},\theta} \frac{\text{MSC}}{J}$$

where $z = y^u + \gamma/U_c$. Dividing both sides of the equation by $\varepsilon_{J,\theta}$ gives

$$1 = \varepsilon_{y^n,J} \frac{y^n}{J} - \varepsilon_{z,J} \frac{z}{J} + \varepsilon_{\text{TSC},J} \frac{\text{TSC}}{J} + \varepsilon_{\text{MSC},J} \frac{\text{MSC}}{J}$$

For the sake of consistency with estimates available in the literature, I express the elasticities with respect to p. Thus

$$\varepsilon_{J,p} = \varepsilon_{y^n,p} \frac{y^n}{J} - \varepsilon_{z,p} \frac{z}{J} + \varepsilon_{\text{TSC},p} \frac{\text{TSC}}{J} + \varepsilon_{\text{MSC},p} \frac{\text{MSC}}{J} \tag{1.17}$$

I provide lower and upper bounds for the cyclicality of J, captured here by the elasticity $\varepsilon_{J,p}$. As in the previous section, when I measured the size of J relative to the size of p, I will consider the assumption that the foregone leisure time, in units of consumption, is larger for the employed than for the unemployed to generate a lower bound for $\varepsilon_{J,p}$. An upper bound will naturally arise by assuming that search is not needed to find work.

Lower Bound for $\varepsilon_{J,p}$: Results presented in the previous subsection imply that the accounting of unemployment costs looks like

$$\frac{J(u,\theta)}{p} = \underbrace{\frac{y^n}{p}}_{1} - \underbrace{\frac{z}{p}}_{0.47} + \underbrace{\frac{\text{TSC}}{p}}_{0.41} + \underbrace{\frac{\text{MSC}}{p}}_{0.89} = 1.83$$

which means that a job is valued as twice as the marginal productivity of labor. If finding a job were a trivial matter, an average job in the economy will worth p. The excess in value that workers place in a job is the result of the benefits in the avoidance of search costs that having a job brings about.

Hagedorn and Manovskii (2008) and Chodorow-Reich and Karabarbounis (2015) provide estimates on the elasticity of wages and z with respect to a measure of marginal productivity, respectively. They find that

$$\varepsilon_{y^n,p} = 0.449 \quad \text{and} \quad \varepsilon_{z,p} = 1$$

What remains to be determined are the search cost elasticities. I start by simplifying the expression for the total search costs

$$\varepsilon_{\text{TSC},\theta} = \underbrace{\left\{ \frac{V_s}{U_c} h_\theta + \frac{V}{U_c} \frac{\sigma_c \varepsilon_{c,\theta}}{\theta} \right\}}_{\partial\text{TSC}/\partial\theta} \frac{\theta}{\text{TSC}}$$

and for the marginal costs as well

$$\varepsilon_{\text{MSC},\theta} = \left\{ \underbrace{\frac{1}{U_c} \left[\frac{\alpha h_\theta}{f_s} \left(V_{ss} - \frac{V_s f_{ss}}{f_s} \right) - \alpha V_s \frac{f_{s\theta}}{f_s^2} - V_s \left(h_\theta + \frac{f_\theta}{f_s} \right) \right]}_{\partial\text{MSC}/\partial\theta} + \frac{\alpha V_s}{f_s U_c} \frac{\sigma_c \varepsilon_{c,\theta}}{\theta} \right\} \frac{\theta}{\text{MSC}}$$

where $h_\theta(u,\theta)$ denotes the optimal response of search intensity to changes in the aggregate labor market conditions. In section 2, I argue that the unemployed increased their search intensity only slightly if at all during the recent recession, implying that $h_\theta = 0$. Notice that this interpretation of the evidence based on ATUS is conservative. By assuming $h_\theta < 0$ instead, the resulting value of a job would end up being more countercyclical. I use the index on the number of vacancies constructed by Barnichon

(2010) and divide it by the unemployment rate to obtain a measure of θ. Information used so far imply that

$$\begin{aligned}\varepsilon_{\mathrm{TSC},\theta} &= \sigma_c \varepsilon_{c,\theta} \\ &= \sigma_c \rho_{\tilde{c},\tilde{\theta}} \frac{\mathrm{sd}(\tilde{c})}{\mathrm{sd}(\tilde{\theta})} \\ &= 2\left(0.797 \frac{0.870}{24.432}\right) \\ &= 0.06\end{aligned}$$

and

$$\begin{aligned}\varepsilon_{\mathrm{MSC},\theta} &= -\left(\frac{\alpha+f}{\alpha}\right)\varepsilon_{f,\theta} + \sigma_c \varepsilon_{c,\theta} \\ &= -\left(\frac{0.67+0.31}{0.67}\right)\left(0.894 \frac{8.746}{24.432}\right) + 0.06 \\ &= -0.41\end{aligned}$$

where I use $\sigma_c = 2$ as in most business cycle studies. Multiplying these elasticities by the elasticity of θ to p gives

$$\varepsilon_{\mathrm{TSC},p} = 0.224 \quad \text{and} \quad \varepsilon_{\mathrm{MSC},p} = -1.533$$

It should not be surprising to find that the sensitivity of TSC to productivity changes is negligible. In fact, it is reflecting only the relatively smooth cyclical pattern of consumption. The low elasticity is a direct consequence of my conservative assumption about the optimal cyclical movements of search intensity. Perhaps less obvious is to see why, even under this assumption, MSC is strongly countercyclical. Note that per every 1% decrease in labor productivity, the MSC increases in 1.5%.

The unemployed, by definition, spend some time looking for work. As tiny as it may be, this allocation of time to the job search may make a difference in the prospects of finding work. More precisely, even if the worker does not change her search intensity over the business cycle, as my conservative assumption states, her chances of leaving the pool of unemployment and the costs of remaining in that pool do. Put it differently, function matters, not size.

Plugging these numbers into (1.17) gives

$$\varepsilon_{J,p} = -0.67$$

Upper Bound for $\varepsilon_{J,p}$: In the absence of search costs on the side of the unemployed, the accounting of unemployment costs is

$$\frac{J(u,\theta)}{p} = \underbrace{\frac{y^n}{p}}_{1} - \underbrace{\frac{z}{p}}_{0.47} = 0.53$$

I recalculate the elasticity of the value of a job, obtaining

$$\varepsilon_{J,p} = -0.04$$

Thus, Chodorow-Reich and Karabarbounis (2015) estimates would imply that, in a search model with an endogenous search effort, the value of a job is nearly acyclical or slightly countercyclical in the U.S.

The bounds calculated for the cyclicality of $J(u,\theta)$ should be taken in perspective. If finding a job were a frictionless activity, the value of a job would move slightly along the business cycle. In the other extreme, if searching for work were as costly as working, in terms of the foregone leisure time, the value of a job would be highly countercyclical. Per every 1% in increase in the labor productivity, the value of a job would decrease by almost two-thirds.

A reasonable guess would be to place the relative importance of search costs something in between, and therefore, conclude that the value of a job in the U.S. is somewhat countercyclical, with the elasticity being something around one-third. It should be recalled, however, that the procedure followed to arrive at these bounds was, in every stage, conservative. To calculate the relative size of search costs I assumed preferences allowing for search costs that increase linearly as more time is allocated to the job search while it is reasonable to think that costs increase at a faster rate. And in order to calculate the cyclicality of search costs I assumed an optimal search intensity that does not change over the business cycle while the evidence shows that the unemployed increase their effort a little bit during recessions.

1.4 Conclusion

I document that the unemployed in the U.S. appear to allocate their time to job search activities regardless of the business cycle. This finding, when seen through the lens of the Mortensen and Pissarides (1994) search model, represents a puzzle. Among the arguments examined in this paper, I conclude that the countercyclicality of the value of a job is the most promising explanation to reconcile the evidence. Next, I add some other implications for our understanding of business cycles and the design of policy.

First, the more persistent the recession is, the higher the incentives to invest time in searching for work. One broad interpretation is that fears about the consequences of being jobless for a long time provide the impetus to look for work.[18]

The second implication is that wages and unemployment benefits appear to play a relatively minor role in the allocation of time in the search activities of the unemployed over the business cycle. This implication contrasts with the decisive role wages play in the allocation of hours worked in the real business cycle literature. Thus, persistent effects seem to matter more than intertemporal substitution effects (Clark and Summers, 1982).

Third, given that in a recession the cumulative future search costs, expressed in units of consumption, are expected to be relatively high, and in response, the unemployed will choose to give up leisure time to look for work, one may conclude that income effects dominate the substitution effects. Again, this implication clashes with the primary role assigned to a strong intertemporal substitution of leisure and procyclical real wages in generating procyclical responses in the labor supply in the real business cycle literature.[19]

The fourth implication is that the burden of being unemployed should be assigned a specific weight in the balance of costs and benefits of providing unemployment insurance during recessions. The persistence of unemployment by itself also has implications on

[18] Davis and von Wachter (2011) show that workers' anxieties and perceptions about labor market conditions track closely with actual conditions, and that prime-age workers' anxieties are highly correlated to the unemployment rate in the U.S. in the period of 1977-2010.

[19] Mankiw (1989) provides a critical assessment of this mechanism in the real business cycle model. Ramey and Francis (2009)) contradict the real business cycle model, showing that leisure time has witnessed a secular increase over the last century.

the design of the optimal unemployment insurance over the business cycle.

Fifth, if the value of a job varies in a countercyclical way, then the job-to-job turnover in booms may be more important than what we know. The sixth implication, also pointed out by Chodorow-Reich and Karabarbounis (2015), is that if the value of a job is countercyclical, then productivity shocks in the canonical search model will generate still milder fluctuations in the unemployment rate and number of vacancies.

Finally, Davis and von Wachter (2011) recently conclude that in the canonical search model, job loss is a rather inconsequential event for the unemployed. In light of the findings of this paper, the culprit behind such implication of the search model might be the procyclicality of the value of a job. To put it differently, in the canonical search model, unemployment is less costly in recessions which is something that may sound odd for anyone acquainted with the stakes of being unemployed for a long time. I would venture that to make the search model conform to the main findings of this paper, it will require changes that go beyond mere twists on its key underlying mechanisms.

1.5 Appendix A: Tables and Figures

Table 1.1: Covariance Analysis Decomposition

criteria	ATUS sample time-use	ATUS sample number of methods	CPS sample number of methods
U.S. State			
unemployment rate	0.10	0.03	0.03
	(0.06)	(0.01)	(0.00)
constant	2.50	2.09	2.12
	(0.40)	(0.05)	(0.04)
ρ	0.00	0.01	0.02
σ_e	0.00	0.11	0.16
σ_u	9.55	1.20	1.26
Observations	5,714	5,714	501,677
Groups	51	51	51
U.S. Region			
unemployment rate	0.10	0.02	0.03
	(0.04)	(0.01)	(0.01)
constant	2.47	2.11	2.16
	(0.35)	(0.06)	(0.06)
ρ	0.00	0.00	0.00
σ_e	0.24	0.03	0.07
σ_u	9.56	1.20	1.27
Observations	5,714	5,714	501,677
Groups	4	4	4
Age Groups			
unemployment rate	0.08	0.02	0.02
	(0.06)	(0.01)	(0.00)
constant	2.70	2.13	2.18
	(0.42)	(0.12)	(0.06)
ρ	0.01	0.01	0.01
σ_e	0.73	0.11	0.15
σ_u	9.51	1.19	1.26
Observations	5,714	5,714	501,677
Groups	6	6	6
Educational Attainment			
unemployment rate	0.09	0.02	0.02
	(0.03)	(0.00)	(0.00)
constant	2.66	2.12	2.17
	(0.79)	(0.16)	(0.12)
ρ	0.02	0.05	0.01
σ_e	1.44	0.26	0.12
σ_u	9.46	1.18	1.26
Observations	5,714	5,714	501,677
Groups	4	4	4
Marital Status			
unemployment rate	0.10	0.02	0.02
	(0.06)	(0.00)	(0.00)
constant	2.50	2.11	2.16
	(0.43)	(0.07)	(0.06)
ρ	0.00	0.00	0.00
σ_e	0.00	0.00	0.00
σ_u	9.56	1.20	1.27
Observations	5,714	5,714	501,677
Groups	2	2	2

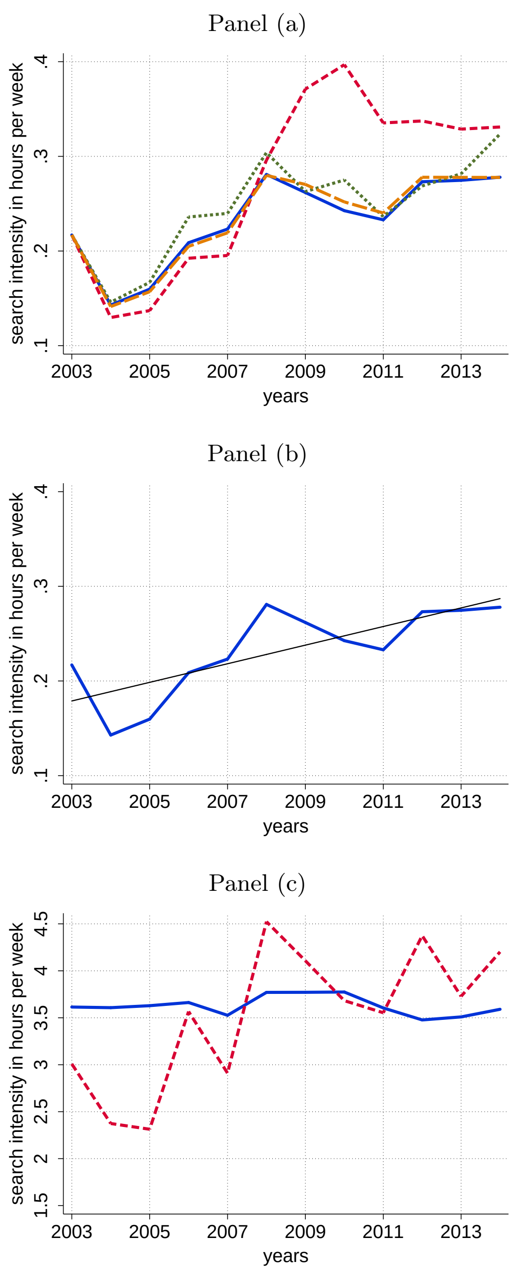
Notes: The unemployment rate is calculated using CPS data. The ratio of group to total variance is denoted by $\rho = \sigma_e/(\sigma_e + \sigma_u)$. The sample includes people unemployed and looking for work, aged between 18 and 65, and the period 2003-2014. ATUS data is annual. CPS annual data is calculated based on quarterly data, which in turn, is constructed appending the monthly CPS microfiles. I only include unemployed people looking for work to make ATUS estimate consistent with CPS estimates.

Table 1.2: Baseline Regression Results for Search Intensity

	OLS estimates (1)	OLS estimates (2)	OLS estimates (3)	OLS estimates (4)
$t = 2004$	−0.09	−0.07	−0.08	−0.07
	(0.03)	(0.03)	(0.03)	(0.03)
$t = 2005$	−0.08	−0.05	−0.06	−0.06
	(0.03)	(0.04)	(0.03)	(0.04)
$t = 2006$	−0.02	0.02	−0.01	−0.01
	(0.04)	(0.04)	(0.04)	(0.04)
$t = 2007$	−0.02	0.02	0.00	0.01
	(0.04)	(0.05)	(0.04)	(0.04)
$t = 2008$	0.08	0.09	0.06	0.06
	(0.05)	(0.05)	(0.05)	(0.05)
$t = 2009$	0.15	0.05	0.05	0.04
	(0.05)	(0.06)	(0.05)	(0.06)
$t = 2010$	0.18	0.06	0.03	0.03
	(0.05)	(0.06)	(0.05)	(0.06)
$t = 2011$	0.12	0.02	0.02	0.02
	(0.05)	(0.05)	(0.05)	(0.05)
$t = 2012$	0.12	0.05	0.06	0.06
	(0.05)	(0.05)	(0.05)	(0.05)
$t = 2013$	0.11	0.06	0.06	0.06
	(0.05)	(0.06)	(0.05)	(0.05)
$t = 2014$	0.11	0.11	0.06	0.06
	(0.06)	(0.06)	(0.05)	(0.05)
unemployment rate		0.03		0.00
		(0.01)		(0.01)
employed (absent)			0.08	0.08
			(0.03)	(0.03)
unemployed (temp. layoff)			−1.42	−1.42
			(0.45)	(0.45)
unemployed (looking)			2.17	2.17
			(0.23)	(0.23)
not in labor force			0.12	0.12
			(0.02)	(0.02)
short-term unemployed			1.85	1.85
			(0.51)	(0.51)
long-term unemployed			2.98	2.98
			(0.46)	(0.46)
part-time short-term unemployed			1.59	1.59
			(0.64)	(0.64)
less attached short-term unemployed			−2.85	−2.85
			(0.55)	(0.55)
constant	0.22	0.03	0.17	0.15
	(0.03)	(0.06)	(0.11)	(0.14)
Observations	125,505	125,505	125,505	125,505
R^2	0.001	0.001	0.103	0.103

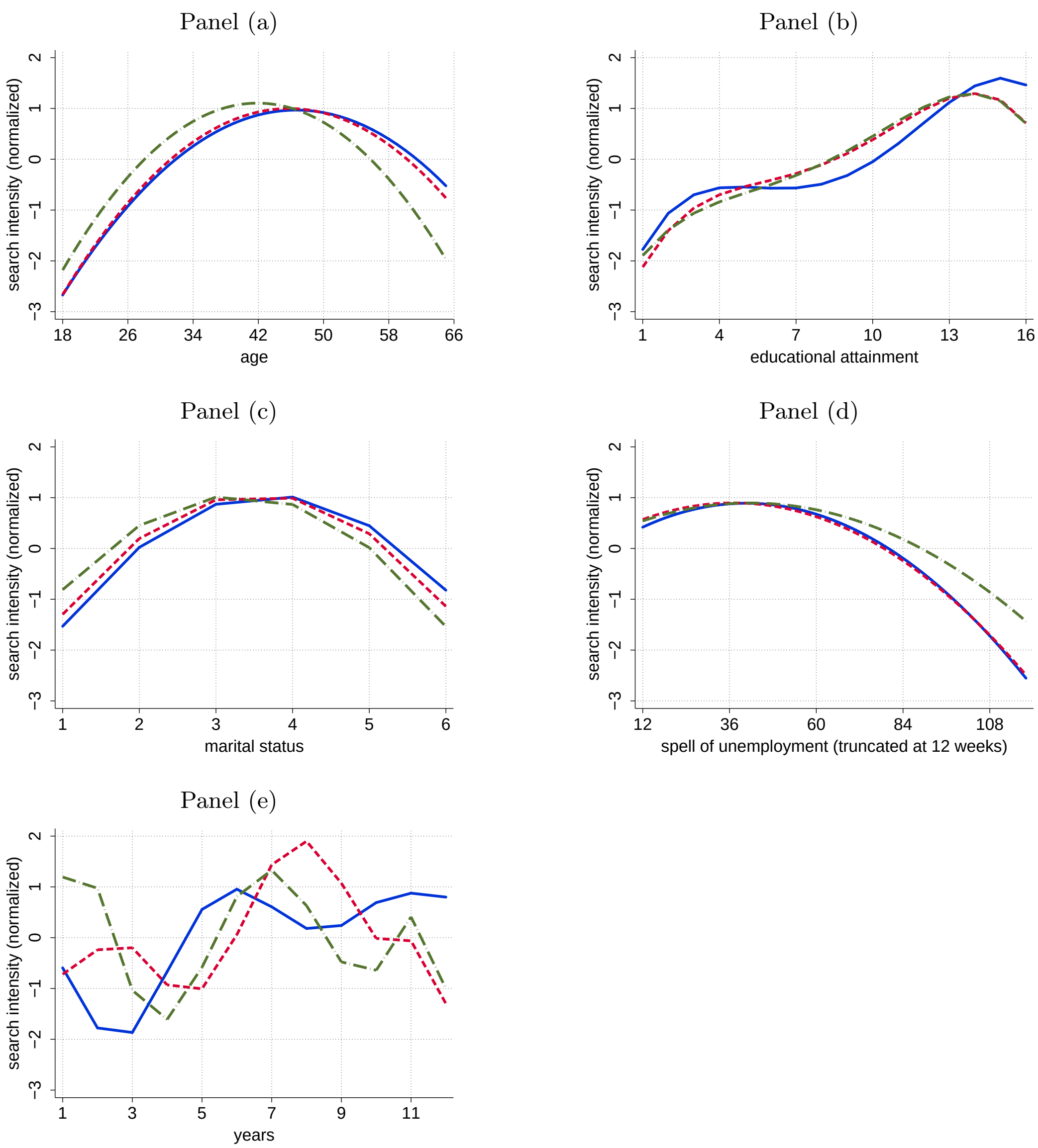
Notes: Details on the variables included in the regression are in text. Robust standard errors are reported in parenthesis. The unemployment rate is calculated using CPS data. The sample includes people aged between 18 and 65, and the period 2003-2014. ATUS data is annual. Column (1) shows unconditional estimates. Column (2) shows estimated coefficients controlling for unemployment rate at the U.S. level. Column (3) controls for covariates shown in the table and the following list (not reported): age, education, sex, race, presence the spouse, age of the youngest child, labor force status of the spouse, replacement ratio, month of interview, day of interview, whether the respondent is enrolled in school, whether the day prior to the interview is a holiday, whether the respondent is latino, and whether the ATUS designated person is the same as the CPS respondent.

Figure 1.1: Time-use in Search Activities



Notes: Panel (a) shows the unconditional time-use in the period 2003-2014 in short-dashed red. It corresponds to Column (1) in Table 1.2. The dotted green line corresponds to Column (2). The long-dashed orange line corresponds to Column (3). The solid blue line corresponds to Column (4) in that table. These time series correspond to the coefficients from $t = 2003$ to $t = 20134$ reported in Table 1.2. Panel (b) reproduces the time series of time-use based on the full specification (Column 4). It shows that time-use in search activities for all workers follows apparently an upward trend. It can be seen that all worker in average spend more time in the 2008-2009. Panel (c) shows the conditional prediction on the time-use by the unemployed workers (on temporary lay-off and those looking for work) along with the unconditional time series of time allocated to the job search.

Figure 1.2: Search Intensity Patterns across Measures and Surveys



Notes: This figure shows the pattern of search intensity across a age, education, marital status, (interrupted) duration of unemployment, and time. Search intensity in ATUS is measured using both time-use and number of methods. In CPS, search intensity is measured as the number of search methods. All patterns are normalized, that is, are obtained by dividing the difference between the actual time-use and the mean by the standard deviation. The solid blue and dashed red lines correspond to time-use and number of methods using ATUS. The long-dashed green line corresponds to the number of methods using CPS. The patterns are calculated using a regression equation with search intensity in the left side and polynomials on the variable of interest, controlling for demographic variables such as age, sex, education, race, and marital status, and U.S. states and yearly dummies, the reason of unemployment, and the U.S. state unemployment rate. The sample comprises people aged between 18 and 65. Coefficient regressions are estimated using OLS. The degree of polynomials is 2 for all cases, except education (4) and time (7). All regressions across surveys share the same covariates. In Panel (b), educational attainment groups are: less than first grade, 7th or 8th grade, 11th grade, some college but no degree, bachelor's degree (BA, AB, BS, etc.), and doctoral degree (PhD, EdD, etc.). To see the complete list check the CPS layouts. In Panel (b), marital status groups are: married, spouse present, married spouse absent, widowed, divorced, separated, and never married . In Panel (e), the period is 2003-2014.

1.6 Appendix B: Proofs

1.6.1 Main Propositions

In this section I present proofs of the propositions that hold when there is full insurance within the household. When pertinent, I remark on the specifics of the proposition with the alternative arrangement discussed in this paper. These latter proofs are omitted since they can be easily inferred from the case of full insurance.

Let the unit interval $[0, 1]$ be the set of possible values for the state u. Let

$$\Gamma(u, \theta; \bar{s}, \lambda) = \left[\lambda + \alpha(1, \bar{s}, \theta, \lambda)u, 1\right]$$

be the feasibility set, which comprises all the possible values that the measure u could take in the next period given that the current state is given by u and θ, and given values for $\bar{s}$ and λ.

Consider the following assumptions:

Assumption 1: $\Gamma(u, \theta; \bar{s}, \lambda)$ is monotone decreasing in u for fixed θ and given $\bar{s}$ and λ; that is, $u^2 > u^1$ implies $\Gamma(u^2, \theta; \bar{s}, \lambda) \subseteq \Gamma(u^1, \theta; \bar{s}, \lambda)$.
Assumption 2: $U(c)$, $V(s)$, and $f(s, \bar{s}, \theta)$ are once-differentiable functions with respect to the first argument. Further $U(c)$ is strictly increasing, $V(s)$ is strictly increasing, and $f(s, \bar{s}, \theta)$ is strictly increasing in s for fixed $\bar{s}$ and θ. Also, $\beta \in (0, 1)$.
Assumption 3: $y^n(\theta) > y^u(\theta)$ for fixed θ and $(y^n(\theta) - y^u(\theta))U_c(c) - \gamma + V(s) > 0$ for fixed u and θ.
Assumption 4: $\alpha(s, \theta; \bar{s}, \lambda) \equiv 1 - \lambda - f(s, \bar{s}, \theta) > 0$ for every λ, s, $\bar{s}$, and θ.

This assumption ensures that the time persistence of u is positive as in the data.

The following Lemma will be useful to prove the subsequent proposition:
Lemma 1: Let U, V, f, y^n, y^u, γ, and λ satisfy Assumptions 2-4. Then $\mathcal{U}(u, u', \theta)$ is strictly decreasing in u for fixed u' and θ.

Proposition 1 (*Strict decreasing monotonicity of $B(u, \theta)$ with respect to u*): Let Γ, U, V, f, y^n, y^u, γ, λ and β satisfy Assumptions 1-4. Then $B(u, \theta)$ is strictly decreasing in

u for fixed θ.

PROOF: I rely on the theory developed by Lucas et al. (1989), Chapter 4. In particular, I invoke Theorem 4.7 (Lucas et al., 1989, p. 80). First, I note that since the set $[0, 1]$ is compact then the boundedness assumption on the return function $\mathcal{U}$ could be easily disregarded for the application of Theorem 4.7.

Continuity of $\mathcal{U}$ is implied by Assumption 2. Lemma 1 establishes that $\mathcal{U}$ is strictly decreasing in u for fixed u' and θ. Indeed, notice that

$$\frac{\partial \mathcal{U}}{\partial u} = (y^u(\theta) - y^n(\theta))U_c + \gamma - V(s) - \alpha(s, \bar{s}, \theta, \lambda)\frac{V_s(s)}{f_s(s, \bar{s}, \theta)} < 0$$

under Assumptions 2-4. In the previous expression, I have benefited from an intermediate result,

$$\frac{\partial s}{\partial u} = \frac{\alpha(s, \bar{s}, \theta, \lambda)}{u f_s(s, \bar{s}, \theta)} > 0$$

which is obtained by applying the Implicit Function Theorem to the law of motion of unemployment and holding u fixed.

Assumption 1 requires that the feasibility set satisfies a monotonicity condition with respect to u. It is straightforward to verify, from the law of motion of unemployment, that $u^2 \geq u^1$ implies $\Gamma(u^2, \theta; \bar{s}, \lambda) \subseteq \Gamma(u^1, \theta; \bar{s}, \lambda)$. That is, $\Gamma(u, \theta; \bar{s}, \lambda)$ is in this sense monotone decreasing in u.

Using Theorem 4.7 in Lucas et al. (1989), I conclude that $B(u, \theta)$ is *strictly decreasing* in u.

REMARK: In the absence of full insurance within the household, $B(u, \theta)$ is also strictly decreasing in u for fixed θ.

ASSUMPTION 5: $U(c)$, $V(s)$, and $f(s, \bar{s}, \theta)$ are twice-differentiable functions with respect to the first argument. $U(c)$ is strictly concave, $V(s)$ is weakly convex and $f(s, \bar{s}, \theta)$ is strictly concave in s for fixed $\bar{s}$ and θ.

The following Lemma and Assumption will be useful to prove the subsequent proposition:

LEMMA 2: Let V and f satisfy Assumptions 2 and 5. Then $\mathcal{U}(u, u', \theta)$ is strictly concave in u and u' for fixed θ.

REMARK: In the absence of full insurance within the household, $\mathcal{U}$ is weakly concave.

ASSUMPTION 6: $\Gamma(u, \theta; \bar{s}, \lambda)$ is convex in u for fixed θ and given $\bar{s}$ and λ.

PROPOSITION 2 (*Strict concavity of $B(u, \theta)$ with respect to u*): Let Γ, U, V, f, y^n, y^u, γ, λ and β satisfy Assumptions 1-6. Then $B(u, \theta)$ is strictly concave in u for fixed θ.

PROOF: I invoke Theorem 4.8 from Lucas et al. (1989), Chapter 4, p. 81. Lemma 2 guarantees that $\mathcal{U}(u, u', \theta)$ is strictly concave with respect to u and u' for fixed θ. I show this by constructing the Hessian matrix. I first compute

$$\begin{aligned} \frac{\partial \mathcal{U}}{\partial u} &= -(y^n - y^u)U_c + \gamma - V - \frac{\alpha V_s}{f_s} \\ \frac{\partial \mathcal{U}}{\partial u'} &= \frac{V_s}{f_s}, \end{aligned}$$

from which I calculate the entries of the Hessian matrix

$$\begin{aligned} \frac{\partial^2 \mathcal{U}}{\partial u^2} &= (y^n - y^u)^2 U_{cc} + \frac{\alpha^2}{u f_s^2}\left[\frac{V_s f_{ss}}{f_s} - V_{ss}\right] \\ \frac{\partial^2 \mathcal{U}}{\partial u'^2} &= \frac{1}{u f_s^2}\left[\frac{V_s f_{ss}}{f_s} - V_{ss}\right] \\ \frac{\partial^2 \mathcal{U}}{\partial u' \partial u} &= \frac{-\alpha}{u f_s^2}\left[\frac{V_s f_{ss}}{f_s} - V_{ss}\right] \end{aligned}$$

Assumptions 2 and 5 ensure that $\frac{\partial^2 \mathcal{U}}{\partial u^2} < 0$. In addition, notice that $\frac{\partial^2 \mathcal{U}}{\partial u^2}\frac{\partial^2 \mathcal{U}}{\partial u'^2} - \left(\frac{\partial^2 \mathcal{U}}{\partial u' \partial u}\right)^2 = \frac{(y^n - y^u)^2 U_{cc}\psi}{u f_s^2} > 0$, where $\psi = \frac{V_s f_{ss}}{f_s} - V_{ss} < 0$, under those assumptions. Thus, the Hessian matrix is negative definite. I conclude that $\mathcal{U}(u, u', \theta)$ is strictly concave in u and u' for fixed θ.

Finally, $\Gamma(u, \theta; \bar{s}, \lambda)$ is convex in the sense that if $u' \in \Gamma(u, \theta; \bar{s}, \lambda)$ and $w' \in \Gamma(w, \theta; \bar{s}, \lambda)$ then $\phi u' + (1 - \phi)w' \in \Gamma(\phi u + (1 - \phi)w, \theta; \bar{s}, \lambda)$ for any $\phi \in (0, 1)$. Hence Assumption 6 is verified.

Using Theorem 4.8 in Lucas et al. (1989), I conclude that $B(u, \theta)$ is *strictly concave* in u for fixed θ.

REMARK: In the absence of full insurance within the household, $B(u, \theta)$ is linear in u for fixed θ. I use the equivalence (1.11) highlighted earlier in the paper. By using equations (1.5) and (1.11), it is easy to see that B_u is a constant.

Next, I make an assumption that will ensure the interiority and uniqueness of the optimal search intensity even under the linearity of the value function.

ASSUMPTION 7: $f(s, \bar{s}, \theta)$ satisfies the Inada's conditions with respect to s.
NOTE: Two of the conditions are implied by Assumptions 2 and 5. It remains to require that

$$\lim_{s \to 0} f_s(s, \bar{s}, \theta) = \infty$$

NOTE: Even if $B(\cdot, \theta)$ and $V(s)$ are linear, Assumption 7 guarantees a unique interior solution. To see this recall equation (1.9). The intuition is simply that a little bit of effort is highly valuable. That is, the unemployed worker would be better-off if exerting a minimal positive level of effort.

The following assumption is crucial to prove the subsequent proposition:

ASSUMPTION 8: Let the value function $B(u, \theta)$ be a smooth function with respect to u and θ.

Let $l(u, \theta)$ denote the next period's optimal measure of unemployed workers as a function of the state (u, θ). The policy function $l(u, \theta)$ is, of course, linked to the optimal search intensity $h(u, \theta)$ through the law of motion of unemployment:

$$l(u, \theta) = \lambda + \alpha \left(h(u, \theta), \bar{s}, \theta, \lambda \right) u$$

PROPOSITION 3 (*Strict monotonicity of* $h(u, \theta)$ *with respect to* u): Let B, Γ, U, V, f, y^n, y^u, γ, λ and β satisfy Assumptions 1-8. Then the optimal search intensity is a strictly increasing function of u for fixed θ.
PROOF: I use the optimal condition for search intensity and apply the Implicit Function

Theorem to obtain:

$$h_u(u,\theta)\Big[\underbrace{V_{ss}(h(u,\theta))}_{\geq 0}+\underbrace{\beta}_{+}\underbrace{f_{ss}(h(u,\theta),\bar{s},\theta)}_{-}\underbrace{B_u(u',\theta')}_{-}-\underbrace{\beta}_{+}\underbrace{u}_{+}\underbrace{f_s(h(u,\theta),\bar{s},\theta)^2}_{+}\underbrace{B_{uu}(u',\theta')}_{-}\Big]=$$
$$-\underbrace{\beta}_{+}\underbrace{f_s(h(u,\theta),\bar{s},\theta)}_{+}\underbrace{B_{uu}(u',\theta')}_{-}\underbrace{\alpha(h(u,\theta),\bar{s},\theta,\lambda)}_{+}$$

The assumptions made on the primitive functions U, V, and f lead to the conclusion that $h(u,\theta)$ is strictly increasing in u for fixed θ.
REMARK: In the absence of full insurance within the household, $h(u,\theta)$ is constant in u for fixed θ. The reason why the optimal search intensity does not depend on u is twofold. Neither do the marginal costs nor the marginal benefits of searching depend on the state. The latter is a direct consequence of the absence of full insurance within the household.

Two of the hypotheses entertained in the paper use the procyclicality of the value of a job as an assumption. Next, I provide conditions that guarantee this to happen. I rely on supermodularity techniques developed by Topkis's (1998). To use his theorems, I express the objective function as dependent of n', n, and θ, where $n = 1-u$ is the measure of *employed* workers. Let

$$\tilde{H}(n,n',\theta) = \tilde{\mathcal{U}}(n,n',\theta) + \int_{\Theta} \tilde{B}(n',\theta')Q(\theta,d\theta')$$

be the objective function (the right side of the Bellman equation), where the tilde denotes that the problem is restated in terms of the measure of employed workers.
Consider the following assumptions:

ASSUMPTION 9: f is strictly increasing in θ.
ASSUMPTION 10: The transition probability Q is monotone increasing.
ASSUMPTION 11: $f(s,\theta)$ has strictly increasing differences in s and θ, i.e., $f_{s\theta} > 0$.
ASSUMPTION 12: $f(s,\theta)$ has strictly decreasing differences in s and θ, i.e., $f_{s\theta} < 0$.

ASSUMPTION 13:

$$\frac{\partial \tilde{\mathcal{U}}(n, n', \theta)}{\partial n \partial \theta} = \frac{y^n(\theta)}{\partial \theta} - \frac{y^u(\theta)}{\partial \theta} - \frac{\partial \gamma}{\partial \theta} + \frac{\partial V}{\partial \theta} + \frac{\partial (\alpha V_s / f_s)}{\partial \theta} > 0$$

where

$$\frac{\partial V}{\partial \theta} + \frac{\partial (\alpha V_s / f_s)}{\partial \theta} = -\frac{V_s f_\theta}{f_s} + \alpha \left(\frac{f_\theta}{f_s^2} \left[\frac{V_s f_{ss}}{f_s} - V_{ss} \right] - \frac{V_s f_{s\theta}}{f_s^2} \right)$$

Then under Assumption 13, wages minus unemployment benefits are more procyclical than the value of non-working time when moving from unemployment to employment. The next proposition asserts than with the aid of the latter assumptions the value of a job is procyclical, as in the canonical general equilibrium search model.

PROPOSITION 4 (*Strict increasing monotonicity of* $\tilde{B}_n(n, \theta)$): Let Q, U, V, f, and λ satisfy Assumptions 2, 4, 5, 9, 10, and 11. Then $\tilde{B}(n, \theta)$ is supermodular in n and θ, i.e., $\tilde{B}_{n,\theta} > 0$.

PROOF: First I prove that $\tilde{\mathcal{U}}(n, n', \theta)$ is strictly supermodular in (n, θ) and has strictly increasing differences in (n', n) and (n', θ). Notice that

$$\begin{aligned} \frac{\partial^2 \tilde{\mathcal{U}}}{\partial n' \partial n} &= -\frac{\alpha}{u f_s^2} \left[\frac{V_s f_{ss}}{f_s} - V_{ss} \right] > 0 \\ \frac{\partial^2 \tilde{\mathcal{U}}}{\partial n' \partial \theta} &= -\frac{f_\theta}{f_s^2} \left[\frac{V_s f_{ss}}{f_s} - V_{ss} \right] + \frac{V_s f_{s\theta}}{f_s^2} > 0 \end{aligned}$$

establishes that $\tilde{\mathcal{U}}$ has strict increasing differences in (n', n) and (n', θ), respectively. The sign of the following expression

$$\frac{\partial^2 \tilde{\mathcal{U}}}{\partial n \partial \theta} = \frac{\partial \Delta U(\theta)}{\partial \theta} - \alpha \left(-\frac{f_\theta}{f_s^2} \left[\frac{V_s f_{ss}}{f_s} - V_{ss} \right] + \frac{V_s f_{s\theta}}{f_s^2} \right) - \frac{V_s f_\theta}{f_s},$$

where $\Delta^n(\theta) \equiv (y^n - y^u) U_c + V(s(\theta)) - \gamma$ or $\Delta^n(\theta) \equiv U(y^n(\theta)) - U(y^u(\theta)) + V(s(\theta)) - \gamma$ (depending on whether full insurance within the household is possible), is not clear. Under Assumption 13, the first term in the above equation outweighs the remaining term so that $\tilde{\mathcal{U}}$ is supermodular in (n, θ). Finally, by Proposition 2 in Hopenhayn and Prescott (1992), it follows that $\tilde{B}(n, \theta)$ is supermodular in (n, θ).

Now, I am ready to state the main propositions concerning the choice of search intensity in response to changes in θ.

PROPOSITION 5 (*Strict increasing monotonicity of* $h(u,\theta)$ *with respect to* θ): Let Q, B, Γ, U, V, f, λ, γ, and β satisfy Assumptions 1-10. Further let θ be either I.I.D. or correlated. Then $h(u,\theta)$ is strictly increasing in θ if $f_{s\theta} > 0$ in the absence of full-insurance within the household.

PROOF: The optimal condition reads as follows

$$V_s(h(u,\theta)) = -\beta f_s(h(u,\theta),\theta)\int_\Theta B_u(u',\theta')Q(\theta,d\theta')$$

where $u' = \lambda + \alpha(s,\bar{s},\theta,\lambda)u$.

Taking derivatives with respect to θ gives:

$$V_{ss}h_\theta = -\beta(f_{ss}h_\theta + f_{s\theta})\int_\Theta B_u(u',\theta')Q(\theta,d\theta') - \beta f_s \frac{\partial \int_\Theta B_u(u',\theta')Q(\theta,d\theta')}{\partial\theta}$$

or

$$h_\theta\left[\underbrace{V_{ss}}_{\geq 0} + \underbrace{\beta}_{+}\underbrace{f_{ss}}_{-}\underbrace{\int_\Theta B_u(u',\theta')Q(\theta,d\theta')}_{-} - \underbrace{\beta}_{+}\underbrace{u}_{+}\underbrace{f_s^2}_{+}\underbrace{\int_\Theta B_{uu}(u',\theta')Q(\theta,d\theta')}_{0}\right] =$$

$$-\underbrace{\beta}_{+}\left[\underbrace{f_{s\theta}}_{+}\underbrace{\int_\Theta B_u(u',\theta')Q(\theta,d\theta')}_{-}\right.$$

$$\left. - \underbrace{u}_{+}\underbrace{f_s}_{+}\underbrace{f_\theta}_{+}\underbrace{\int_\Theta B_{uu}(u',\theta')Q(\theta,d\theta')}_{0} + \underbrace{f_s}_{+}\underbrace{Q'(\theta)}_{+}\underbrace{\frac{\partial \int_\Theta B_u(u',\theta')Q(\theta,d\theta')}{\partial\theta'}}_{-}\right]$$

where the signs are added in light of the assumptions previously made and the results proved so far. Recall that, in the absence of full insurance within the household, $B(u,\theta)$ is linear in u for fixed θ. With the value of moving from unemployment to employment procyclical (i.e., $\tilde{B}_{n\theta}(n,\theta) > 0$ or $B_{u\theta}(u,\theta) < 0$), the procyclicality of search intensity

depends almost exclusively on the procyclicality of the marginal return of searching f_s.
REMARK: When θ is I.I.D. $f_{s\theta} > 0$ is also a necessary condition.
NOTE: The sufficiency and necessity of $f_{s\theta} > 0$ for the deterministic case is shown by Mukoyama et al. (2013) in their Proposition 1.

PROPOSITION 6 (*Strict increasing monotonicity of $h(u, \theta)$ with respect to θ*): Let Q, B, Γ, U, V, f, λ, γ, and β satisfy Assumptions 1-10. Further let θ be either I.I.D. or correlated. Then $h(u, \theta)$ is strictly increasing in θ if $f_{s\theta} > 0$ and

$$\frac{f_{s\theta}}{f_s f_\theta} > \frac{u \int_\Theta B_{uu}(u', \theta')Q(\theta, d\theta')}{\int_\Theta B_u(u', \theta')Q(\theta, d\theta')}$$

in the presence of full insurance within the household.
PROOF: The optimal condition reads as follows

$$V_s(h(u, \theta)) = -\beta f_s(h(u, \theta), \theta) \int_\Theta B_u(u', \theta')Q(\theta, d\theta')$$

where $u' = \lambda + \alpha(s, \bar{s}, \theta, \lambda)u$.
Taking derivatives with respect to θ gives:

$$V_{ss}h_\theta = -\beta(f_{ss}h_\theta + f_{s\theta}) \int_\Theta B_u(u', \theta')Q(\theta, d\theta') - \beta f_s \frac{\partial \int_\Theta B_u(u', \theta')Q(\theta, d\theta')}{\partial \theta}$$

or

$$h_\theta \left[\underbrace{V_{ss}}_{\geq 0} + \underbrace{\beta}_{+} \underbrace{f_{ss}}_{-} \underbrace{\int_\Theta B_u(u', \theta')Q(\theta, d\theta')}_{-} - \underbrace{\beta}_{+} \underbrace{u}_{+} \underbrace{f_s^2}_{+} \underbrace{\int_\Theta B_{uu}(u', \theta')Q(\theta, d\theta')}_{-} \right] =$$

$$- \underbrace{\beta}_{+} \Bigg[\underbrace{f_{s\theta}}_{+} \underbrace{\int_\Theta B_u(u', \theta')Q(\theta, d\theta')}_{-}$$

$$- \underbrace{u}_{+} \underbrace{f_s}_{+} \underbrace{f_\theta}_{+} \underbrace{\int_\Theta B_{uu}(u', \theta')Q(\theta, d\theta')}_{-} + \underbrace{f_s}_{+} \underbrace{Q'(\theta)}_{+} \underbrace{\frac{\partial \int_\Theta B_u(u', \theta')Q(\theta, d\theta')}{\partial \theta'}}_{-} \Bigg]$$

where the signs are added in light of the assumptions previously made and the results proved so far and just discussed.

Remark: When θ is I.I.D. the latter condition is also a necessary condition.

1.6.2 Ancillary Proofs

Proposition 7: Consider the following expression for the probability of finding a job of an individual unemployed worker under symmetric equilibrium ($s = \bar{s}$):

$$f(s, \bar{s}, \theta)|_{s=\bar{s}} = \left(\bar{s}^{\frac{\sigma-1}{\sigma}} + \theta^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

If $\sigma < 1$ then $f \leq 1$.

Proof: First, I note that f can be alternatively expressed as follows:

$$f(s, \bar{s}, \theta) = \frac{\bar{s}\theta}{\bar{s}^{\frac{1-\sigma}{\sigma}} + \theta^{\frac{1-\sigma}{\sigma}}},$$

which is the matching function proposed by den Haan et al. (2000). With this observation, the proof is straightforward. Suppose, by using an argument by contradiction, that $f > 1$. This implies that

$$\bar{s}\theta > \left(\bar{s}^{\frac{1-\sigma}{\sigma}} + \theta^{\frac{1-\sigma}{\sigma}}\right)^{\frac{\sigma}{1-\sigma}}.$$

Now define $\tilde{s} = \bar{s}^{\frac{1-\sigma}{\sigma}}$ and $\tilde{\theta} = \theta^{\frac{1-\sigma}{\sigma}}$ and notice that the right side of the inequality could be written as

$$\bar{s}\theta = (\tilde{s}\tilde{\theta})^{\frac{\sigma}{1-\sigma}}.$$

Take logs to the right side of the inequality and invoke the Jensen inequality to conclude that

$$\frac{\sigma}{1-\sigma}(\ln \tilde{s} + \ln \tilde{\theta}) \leq \frac{\sigma}{1-\sigma} \ln (\tilde{s} + \tilde{\theta})$$

where I have used $\sigma < 1$. By taking exponentials to both sides of the latter inequality

$$(\tilde{s}\tilde{\theta})^{\frac{\sigma}{1-\sigma}} \leq \left(\tilde{s} + \tilde{\theta}\right)^{\frac{\sigma}{1-\sigma}}$$

we reach a contradiction.

NOTE: It can be verified that this function is of the constant returns to scale type and increasing in both arguments as noted by den Haan et al. (2000). It also exhibits decreasing returns to each argument. Desirable properties of the CES function have also been pointed out by Menzio and Shi (2010).

Chapter 2

Job Search and Commitments

2.1 Introduction

Recent evidence suggests that in the U.S. unemployed workers search for work more intensely during recessions, in sheer contradiction to the prediction of the canonical Mortensen and Pissarides (1994) model.[1] However, a recession may not precisely be regarded as a timely period to look for work. Firms are less reluctant to open job vacancies and there is an ever-increasing number of unemployed workers as the recession unfolds. Shimer (2005) and Shimer (2012) show that the probability of finding a job is as cyclical as the unemployment rate in the U.S., falling sharply during recessions. Why do the unemployed workers search more intensely in times when all odds are against them?

Risk aversion over consumption offers a reason. Consider the outset of a recession, when a stand-in household's consumption is expected to decline since more members are expected to fall into unemployment. The more risk averse the household is, the higher the motivation to smooth consumption over time. In the absence of assets, the fall in consumption will lead to higher efforts by the unemployed members in order to escape from unemployment and smooth household consumption over time, albeit imperfectly. How sensitive search effort is in response to anticipated consumption drops will depend ultimately in the degree of risk aversion over consumption.

[1] See Shimer (2004) and Mukoyama et al. (2013) for this recent evidence. Merz (1995) shows that a search model with investment decisions, calibrated for the U.S. economy, predicts a procyclical search intensity.

I address the role of risk aversion in shaping the job search behavior over the business cycle. I first show that a sufficiently high degree of risk aversion could make the unemployed look for work in a countercyclical fashion, as the data suggests: more intensely in recessions and less intensely in booms. Empirically, I show that such a behavior is inconsistent with the degree of risk aversion used pervasively in the business cycle literature.

It may be argued that the presence of commitments in consumption may pose additional reasons to look for work even in times when it is less probable to find it. For instance, in the event of unemployment, a homeowner may feel the urge to keep paying the utility bills and mortgage loans since the avoidance of these commitments may be too costly. Stop paying for mortgage loans may result in home foreclosure with all the associated costs it entails.

With the aim of assessing to what extent risk aversion could still play a role, I introduce consumption commitments into an otherwise job search model. As shown by Chetty and Szeidl (2007), commitments in consumption could amplify the degree of risk aversion, the reason being an uneven adjustment in consumption along different spending categories in response to wealth shocks.

I lay out a model in the spirit of Merz (1995) and Andolfatto (1996), which offers a framework suitable to study the role of risk aversion and consumption commitments on the job search behavior. I show that the theoretical insights of Chetty and Szeidl (2007) applies naturally to my framework. Hence consumption commitments may amplify the degree of risk aversion, depending on the size of the wealth shocks and the magnitude of the adjustment cost.

Empirically, I exploit recently released PSID data on consumption expenditures in a variety of categories such as food, housing, transportation, education, child care, and health to calculate consumption drops in the event of unemployment. As pointed out by Chetty and Szeidl (2007), these event studies provide with a natural classification of spending categories into flexible and commitment consumption based on their response to wealth shocks.

The idea of consumption commitments is not new. The interplay between the uneven adjustment of spending categories and job search behavior in response to unemployment shocks is the contribution of this paper.

2.2 The Role of Risk Aversion

Consider the outset of a recession, when a stand-in household's consumption is expected to decline since more members are expected to fall into unemployment. The more risk averse the household is, the higher the motivation to smooth consumption over time. In the absence of assets, the fall in consumption will lead to higher efforts by the unemployed members in order to escape from unemployment and smooth household consumption over time, albeit imperfectly. How sensitive search effort is in response to anticipated consumption drops will depend ultimately in the degree of risk aversion over consumption.

I address the role of risk aversion in shaping the job search behavior over the business cycle. I show that a sufficiently high degree of risk aversion could make the unemployed look for work in a countercyclical fashion, as the data suggests: more intensely in recessions and less intensely in booms. Empirically, however, I show that such a behavior is inconsistent with the degree of risk aversion used pervasively in the business cycle literature.

The theoretical framework is the same as the one presented in the previous chapter. I discuss a theoretical result that balances out a measure of complementarity in the matching function and a measure of risk aversion over unemployment fluctuations. Interestingly, this result holds regardless of the nature of the recession, whether it is temporary or highly persistent. Three assumptions will prove to be crucial. I assume that the value of a job moves in the same direction as the business cycle. The pooling of endowments within the household that provide full insurance to its members is also an important assumption. Finally, I assume $f_{s\theta} > 0$ as is customary in the literature.

In preparation for the next proposition, consider a change in θ, which is the driver of aggregate fluctuations. This shock will have two clashing effects on the choice of search intensity. If the complementarity between s and θ in the probability of finding a job is sufficiently high, then a reduction in θ would bring the marginal return of search downwards and would call for a reduction in s. That is, s would be procyclical. On the other hand, workers that particularly dislike states of low consumption will ponder heavily the effect of the current drop in θ on the decline of future consumption. When the marginal utility of consumption is sufficiently elastic, a minimal decline in consumption will boost the worker's search intensity. Proposition 6 below illustrates this tension.

To gain insight on how s and θ are combined, consider the following functional form for the individual probability of finding a job:

$$f(s, \bar{s}, \theta) = s\frac{m(\bar{s}u, \theta)}{\bar{s}u},$$

where

$$m(\bar{s}u, \theta) = \left((\bar{s}u)^{\frac{\sigma-1}{\sigma}} + \theta^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

is the matching function proposed by den Haan et al. (2000). Combining the previous two expressions yields

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

The parameter $\sigma \in (0, 1)$ is the constant elasticity of substitution between the average search intensity and the labor market tightness. If $\sigma < 1$, it is guaranteed that the job finding probability is well defined (i.e., $f(s, \bar{s}, \theta) \leq 1$). In symmetric equilibrium, $s = \bar{s}$, so the probability function reduces to

$$f(s, \theta) = \left(s^{\frac{\sigma-1}{\sigma}} + \theta^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{2.1}$$

Proposition 6: $h(u, \theta)$ is strictly increasing in θ if $f_{s\theta} > 0$ and

$$\frac{f_{s\theta}}{f_s f_\theta} > \frac{u\int_\Theta B_{uu}(u', \theta')Q(\theta, d\theta')}{\int_\Theta B_u(u', \theta')Q(\theta, d\theta')}, \tag{2.2}$$

regardless of the nature of θ.

Proof: See Appendix B.

Remark: When θ is I.I.D. the latter condition is also necessary.

Proposition 6 offers a condition that could be judged even when $f_{s\theta} > 0$.[2] The left

[2] Interestingly, the tension between complementarity in the matching function and risk preferences mimics the tension between complementarity in the aggregate technology and risk preferences which guarantees that optimal investment is procyclical in the one-sector growth model when the productivity shock is correlated. See Hopenhayn and Prescott (1992).

side of the inequality depends entirely on the functional form of the matching function. The right side looks convoluted but familiar as well. At first sight, it is a degree of risk aversion over fluctuations in the labor force composition of the household. Below, I show that this degree of aversion could be readily linked to the more familiar degree of risk aversion over consumption.

In working against this hypothesis, I regard the left side of the inequality as a lower bound for the degree of risk aversion. Thus, workers will need to be risk averse in a degree that is at least as large as this bound to be suspicious about the procyclicality of s. Next, I describe the procedure that makes this test operational.

Computation of the Bound: Using equation (2.1) the bound has a simple form:

$$\frac{f_{s\theta}}{f_s f_\theta} = \frac{1}{f}$$

To compute this bound in the steady state, I construct a time series of the probability of finding a job following Shimer (2012)'s methodology. I use CPS labor market data for the period 1967.II-2012.IV to compute transition probabilities among the states of employment, unemployment, and out of labor force. Based on this information, I obtain the following numbers

$$f = 0.31 \quad \text{and} \quad \tfrac{1}{f} = 3.23$$

Degree of Risk Aversion over u: I turn now to the right side of inequality (2.2). I show that, in the steady state, risk preferences over the labor force composition of the household has a direct bearing on the degree of risk aversion over consumption. To see this, I start by defining

$$\sigma_u = \frac{uB_{uu}(u,\theta)}{B_u(u,\theta)}$$

as the relative risk aversion over fluctuations in the employment status of the members of the household.[3] Next, I invoke the envelope condition to derive

$$B_{uu}(u,\theta) = (y^u(\theta) - y^n(\theta))U_{cc}(c^\star)\frac{\partial c^\star}{\partial u}$$

I assume that preferences over consumption are of the constant relative risk aversion type. Under some convenient rearrangements, the envelope condition could be alternatively written as

$$\frac{uB_{uu}(u,\theta)}{B_u(u,\theta)} = \frac{\partial c^\star}{\partial u}\frac{u}{c^\star}(y^n(\theta) - y^u(\theta))\sigma_c\frac{U_c(c^\star)}{B_u(u,\theta)},$$

where

$$\sigma_c = -c\frac{U_{cc}(c)}{U_c(c)}$$

is the relative risk aversion over consumption. Finally,

$$\sigma_u = \sigma_c\,|\varepsilon_{c,u}|\,\frac{y^n(\theta) - y^u(\theta)}{J(u,\theta)} \tag{2.3}$$

where

$$J(u,\theta) = -B_u(u,\theta)/U_c(c^\star)$$

is the marginal cost of unemployment or alternatively, the value of a job. The term accompanying σ_c acts as a dampening or amplifying effect. The intuition of this equation is as follows. The first component of this effect is the elasticity of consumption to changes in the measure of unemployed workers $\varepsilon_{c,u} < 0$, whose presence is a direct consequence of assuming full insurance within the household. If more members in the household are expected to fall into unemployment, all will suffer the consequences of a lower consumption. The higher this elasticity, the greater the dislike about unemployment fluctuations.

The second component stands for how important foregone consumption $(y^n - y^u)$ is in the accounting of the costs of being unemployed (measured in consumption units).

[3] It could also be regarded as the risk aversion over wealth shocks driven by (idiosyncratic) unemployment shocks, as opposed to aggregate shocks θ.

Unemployment is costly not only because of the foregone wage (minus the nonwork-contingent insurance benefits and the cost of employment), but also because of the leisure time that has to be given up as long as the worker keeps looking for work along the spell of unemployment. Notice that if both searching and employment costs are ignored, we have

$$\frac{y^n(\theta) - y^u(\theta)}{J(u,\theta)} = 1$$

Hence, neglecting these costs will portray an incomplete picture of how unemployment shocks affect risk preferences.

In what follows, I painstakingly describe the procedure to parameterize the amplification or dampening effect in (2.3). I start with the elasticity of consumption to unemployment shocks. The relative size of the foregone wage requires a lengthier discussion which is addressed subsequently.

Degree of Risk Aversion over u: Elasticity. This elasticity could be calculated by using

$$\varepsilon_{c,u} = \rho_{\tilde{c},\tilde{u}} \frac{\mathrm{sd}(\tilde{c})}{\mathrm{sd}(\tilde{u})},$$

where $\tilde{x}$ denotes the deviation of $x = \{c, u\}$ from its steady state, ρ is the correlation coefficient, and $\mathrm{sd}(\tilde{x})$ stands for the standard deviation of $\tilde{x}$. I construct a quarterly series of real private consumption (excluding durables) based on NIPA tables 1.1.5 (nominal consumption) and 1.1.4 (price indexes). The quarterly series for unemployment rate, for people aged 16 and over, is taken directly from the BLS. To extract the cyclical component of both series, I use the Hodrick-Prescott filter with smoothing parameter 1600. The sample period is 1967.II-2012.IV. I conclude that

$$\varepsilon_{c,u} = -0.78 \frac{0.87}{12.47} = -0.05$$

This elasticity has been calculated using time-series data for private consumption and under the assumption of full insurance within the household. Alternatively, I can calculate this elasticity in the absence of full insurance within the household. In this case, the elasticity is expected to be greater. To be precise, I would need estimates of both the consumption drop in the event of unemployment and the annual average percentage increase in the unemployment rate during the recent recession. First, I construct a panel using PSID data from 2003 to 2013 to compute the (food) consumption annual drops in the event of unemployment.[4] This drop is measured at 4.5% as compared with the level of consumption when employed.[5] Second, the spike in unemployment between 2007 and 2012 corresponds to an annual average increase of 34%. Thus, the elasticity of consumption to unemployment shocks is 0.13, almost the double of the previous number. Qualitatively speaking, however, the main conclusion, regarding the degree of risk aversion needed to make sense of the empirical evidence on search intensity, does not change. Next, I focus on the second component of (2.3).

Degree of Risk Aversion over u: Accounting of the Costs of Unemployment. Unemployment, in the real world, is costly for a variety of reasons, ranging from the wage that is no longer earned to wider psychological implications. In this model, being unemployed is costly because of the foregone wage and the search costs. Certainly, a complete picture of the cost of unemployment will have to allow for the benefits of being out of work, such as nonwork-contingent insurance benefits and the dislike about working. In this subsection, I develop a strategy to gauge the relative size of the foregone wage minus the nonwork-contingent insurance benefits

$$\frac{y^n(\theta) - y^u(\theta)}{J(u,\theta)} \tag{2.4}$$

Again, I begin by invoking the envelope condition, which I rewrite for the sake of exposition

$$B_u(u,\theta) = (y^u(\theta) - y^n(\theta))U_c(c^\star) + \gamma - V(s^\star) + \alpha(s^\star,\theta,\lambda)\int_\Theta B_u(u',\theta')Q(\theta,d\theta')$$

[4] Food consumption includes the value of food stamps.

[5] PSID data in the period 2003-2013 is released every other year. The figure 4.5% is the one-year drop equivalent.

Using the optimal condition for search intensity gives

$$B_u(u,\theta) = (y^u(\theta) - y^n(\theta))U_c(c^\star) + \gamma - V(s^\star) - \alpha(s^\star,\theta,\lambda)\frac{V_s(s^\star)}{f_s(s^\star,\theta)}$$

As in Chodorow-Reich and Karabarbounis (2015), I express this value in consumption units:

$$J(u,\theta) = y^n(\theta) - y^u(\theta) - \frac{\gamma}{U_c(c^\star)} + \frac{V(s^\star)}{U_c(c^\star)} + \alpha(s^\star,\theta,\lambda)\frac{V_s(s^\star)}{U_c(c^\star)}\frac{1}{f_s(s^\star,\theta)}$$

This is the equation that formally portrays the accounting of unemployment costs. The first term is the foregone wage minus nonwork-contingent insurance benefits. This is perhaps the cost that has received particular attention in the literature.

Unemployment is less costly if the alternative involves some costs as well. The cost of being employed in units of consumption is denoted by γ/U_c. Chodorow-Reich and Karabarbounis (2015) study how this cost varies over the business cycle in the U.S.

The last term in the equation denotes very broadly the costs of searching. I make a distinction between total and marginal search costs. Although both reflect the leisure foregone, they differ in one important respect. Marginal costs are conditioned to the persistence of the unemployment process. If unemployment becomes highly persistent, that adds value to the only decision that could redound to reemployment: allocating time to the job in the margin.

Instead of providing a point estimate of (2.4), I construct lower and upper bounds. An interval estimate is obtained by adopting an eclectic approach. Recently, Chodorow-Reich and Karabarbounis (2015) provide estimates of the size of y^u and γ/U_c, relative to the size of a unit of (after-tax) marginal productivity. In addition, I make a sensible assumption on the size of y^n. Finally, I make an inference on the magnitude of total and marginal search costs, based on the assumption that search costs cannot exceed employment costs.

I proceed to describe this approach in detail. In a recently influential paper, Chodorow-Reich and Karabarbounis (2015) argue that the opportunity cost of employment, most prominently the non-working time, is strongly procyclical in the U.S. They show that it is as cyclical as a measure of labor productivity which is usually regarded as the key driving aggregate shock in many business cycle models. Being employed is then less costly during recessions since workers have plenty of non-working time.[6] As a by-product of their methodology, they provide estimates on the size of the value of nonwork-contingent insurance benefits and the value of the cost of employment. I reproduce these estimates here:

$$\frac{\gamma}{pU_c} \in (0.41, 0.9) \quad \text{and} \quad \frac{y^u}{p} = 0.06$$

where these numbers are expressed in units of marginal productivity, which I should call p.

The second piece of information is the size of y^n. I simply assume that the wage is as large as p. There could be more than one reason to speculate that this assumption is not called for. For instance, wages would not entirely reflect gains in labor productivity in the presence of hiring costs.[7] In any case and in light of the size of $\gamma/(pU_c)$, $y^u/p = 1$ does not seem to be an unsound assumption.

Now, I turn to search costs

$$\frac{V}{U_c} + \alpha \frac{V_s}{U_c} \frac{1}{f_s} \tag{2.5}$$

where I save notation for the sake of clarity. I start by noting that the expression for the marginal search costs could be expressed as a function of total search costs:

$$\alpha \frac{V_s}{f_s} \frac{1}{U_c} = \alpha \varepsilon_{V,s} \frac{s}{f} \frac{V}{s} \frac{1}{U_c}, \quad \text{where} \quad \varepsilon_{V,s} = \frac{dV}{ds} \frac{s}{V} \quad \text{and} \quad f_s = \frac{f}{s} \tag{2.6}$$

Intuitively, $\varepsilon_{V,s}$, which is the ratio of marginal to average search costs, stands for how fast search costs increase when adding an additional time unit to the job search. I now invoke an assumption which is key for what follows. I assume that $V/U_c < \gamma/U_c$, that is, searching costs cannot exceed employment costs, both represented by the foregone leisure time and expressed in terms of consumption. This assumption together with equation (2.6) imply the following inequality

$$\alpha \varepsilon_{V,s} f^{-1} \frac{V}{U_c} < \alpha \varepsilon_{V,s} f^{-1} \frac{\gamma}{U_c}$$

[6] They also show that the role of nonwork-contingent insurance benefits is rather minor.

[7] See, for example, Pissarides (2000).

I can now add the remaining component V/U_c to the previous expression to obtain an upper limit for (2.5)

$$\frac{V}{U_c} + \alpha\varepsilon_{V,s} f^{-1} \frac{V}{U_c} < \frac{\gamma}{U_c} + \alpha\varepsilon_{V,s} f^{-1} \frac{\gamma}{U_c} \equiv \left(1 + \alpha\varepsilon_{V,s} f^{-1}\right) \frac{\gamma}{U_c}$$

With the aid of this inequality, I am ready to restrict sensible values for the size of search costs (in terms of p) from above. I make the following conservative assumption

$$V(s) = \chi s, \quad \chi > 0$$

which agrees with the weakly convexity assumption made on V. With this specification, $\varepsilon_{V,s} = 1$. To estimate α, the persistence of unemployment, I rely again on the flow market transition probabilities calculated using Shimer (2012)'s methodology. The probability of transiting from employment to unemployment and the job finding probability are $\lambda = 0.02$ and $f = 0.31$.[8] Thus

$$\alpha = 0.67 \quad \text{and} \quad f^{-1} = 0.31^{-1} = 3.23$$

To conclude, I find the following inequality holds

$$\frac{V}{pU_c} + \alpha \frac{V_s}{pU_c} \frac{1}{f_s} < 1.30 \tag{2.7}$$

where I have used the more conservative value for $\gamma/(pU_c)$, 0.41, estimated by Chodorow-Reich and Karabarbounis (2015).

I end this discussion by returning to the equation of interest

$$\frac{y^n(\theta) - y^u(\theta)}{J(u, \theta)}$$

and obtaining lower and upper bounds for the relative size of the foregone wage (minus the nonwork-contingent insurance benefits). I mentioned earlier that search costs is an additional factor that makes unemployment unbearable. The larger these costs, the less important the foregone wage becomes in the accounting of unemployment costs. The value for the size that search costs could take at most thus is used to compute the lower

[8] These values imply a steady-state unemployment rate of 6.1% in the period 1967.II-2012.IV.

bound of (2.4). The upper bound is obtained by assuming that search frictions on the side of the unemployed are meaningless (i.e., $s = 0$). Finally, I can conclude that

$$\frac{y^n(\theta) - y^u(\theta)}{J(u, \theta)} \in [0.51, 1.77]$$

Interestingly, the case that ignores search and employment costs is located at the middle of this interval.

Degree of Risk Aversion over u: Summary. By bringing the two pieces together I obtain

$$\frac{\sigma_u}{\sigma_c} \in [3\%, 9\%]$$

Therefore, risk aversion over the labor force composition of the household represents a tiny fraction of the degree of risk aversion over consumption, the reason being the little impact unemployment shocks have on household consumption.

The theory and evidence shown before suggest that a sufficiently high risk aversion over unemployment fluctuations could be the reason to observe a countercyclical search intensity. Recall the tension which is at the heart of Proposition 6:

$$\frac{f_{s\theta}}{f_s f_\theta} > \frac{u \int_\Theta B_{uu}(u', \theta') Q(\theta, d\theta')}{\int_\Theta B_u(u', \theta') Q(\theta, d\theta')}$$

As can be seen from the previous discussion, σ_u/σ_c is much lower than $1/f = 3.23$. Based on the interval estimated for σ_u/σ_c, σ_c would need to range between 34 and 117, which are values even larger than those contemplated by Mehra and Prescott (1985), in their account of the equity premium puzzle.

As a conclusion to this section, I state that although a natural candidate, risk aversion over u is not empirically relevant to understand why the unemployed search more intensely during recessions.[9]

[9] An alternative interpretation is that these results constitute another type of evidence, based on labor market theory and data, consistent with the equity premium puzzle.

2.3 Job Search and Commitments

With the aim of assessing to what extent risk aversion could still play a role, I introduce consumption commitments into an otherwise job search model, as the one described in the previous chapter. The reduction in household consumption in response to earning losses may be uneven across different spending items due to the presence of adjustment costs. After losing a job, a worker with a house loan may be reluctant to cut mortgage payments and instead concentrate most of the reduction on flexible spending such as food and clothes. Mortgage payments may be difficult to adjust because of the costs associated with the event of foreclosure, including the loss of equity in the house, moving expenses, and possibly some legal fees.

This uneven adjustment across different spending categories may amplify the household's degree of risk aversion over consumption, depending on the magnitude of the wealth shock and the size of the adjustment cost. To continue with the previous example, if foreclosure looks imminent or moving costs are so high, the household would be forced to make a deep cut in food consumption. A higher risk aversion will in turn make the worker's search effort more sensitive to changes in consumption. In a moderate recession, for instance, the presence of consumption commitments may be sufficient to induce higher efforts to escape from unemployment, from workers who are particularly uneasy about facing states of low consumption.

In this section I incorporate this linkage between adjustment costs and job search into an otherwise standard job search model. Following Merz (1995) and Andolfatto (1996), consider a stand-in household with a unit measure of workers and a fraction $u \in (0, 1)$ of unemployed workers. Time is discrete. At any given time t, a worker is either unemployed or employed. If unemployed, the worker is endowed the exogenous process $y_t^u(\theta_t)$ that depends on the aggregate shock of the economy. Otherwise, the worker is endowed $y_t^n(\theta_t)$, with $y_t^n(\theta_t) > y_t^u(\theta_t)$, for every realization of $\theta_t \in \Theta$. Household wealth thus results from pooling the endowments of its members

$$W_t(u_t, \theta_t) = u_t y_t^u(\theta_t) + (1 - u_t) y_t^n(\theta_t)$$

where θ is the ratio of vacancies to unemployment, i.e., the tightness of the labor market. Here θ is permitted to follow an arbitrary exogenous process; it represents the aggregate shock in the economy which is taken as given by the household. I assume the household allocates wealth among its members regardless of their employment status. Hence

$$c_t + h_t + \kappa h_{t-1}\mathbf{1}(h_t \neq h_{t-1}) = W_t(u_t, \theta_t)$$

There are two types of consumption goods, c and h. The adjustment in h involves a cost $\kappa > 0$ while the adjustment in c does not. The uneven nature in the adjustment of c and h reflects the presence of previous commitments made on h. For simplicity, I will call h the commitment good and c the flexible good. The discussion around the notion of commitments rests on Chetty and Szeidl (2007).

The household also takes the law of motion of unemployed workers as given. This measure evolves as follows

$$u_{t+1} = u_t + (1 - u_t)\lambda - u_t f(s_t, \bar{s}_t, \theta_t)$$

where λ is the job destruction rate, and $f(s, \bar{s}, \theta)$ is the probability of finding a job that depends on the individual search intensity s, the average search intensity $\bar{s}$, and the tightness of the labor market. Function f is strictly increasing in both s and θ, and strictly concave in s. I also assume that s and θ are complements in the probability of finding a job, that is, $f_{s\theta} > 0$.

Finally, the preferences of the household in any arbitrary period t are represented by the following instantaneous utility function

$$\mathcal{U}(c_t^u, h_t^u, c_t^n, h_t^n, s_t) = u_t\big(U(c_t^u, h_t^u) - V(s_t)\big) + (1 - u_t)\big(U(c_t^n, h_t^n) - \gamma\big)$$

where U is the utility function over consumption, V is the disutility over time spent in search activities, and $\gamma > 0$ is the disutility from working. Function U is strictly increasing and strictly concave in c and h, and V is strictly increasing and weakly convex. I leave the complementarity between flexible and commitments spending U_{ch} unrestricted. Full insurance in consumption within the household implies that

$$\mathcal{U}(c_t, h_t, s_t) = U(c_t, h_t) - u_t V(s_t) - (1 - u_t)\gamma$$

The household lives forever and discounts the future with $\beta \in (0,1]$. Its problem, in recursive form, is to solve

$$\max_{s,u',c,c',h'} \left\{ U(c,h) - uV(s) - (1-u)\gamma + \beta \int_{\Theta} \Big[U(c',h') - u'V(s') - (1-u')\gamma \Big] Q(\theta, d\theta') \right\}$$

subject to

$$\begin{aligned} c + h &= (1-u)y^n(\theta) + uy^u(\theta) \\ c' + h' + \kappa h \mathbf{1}(h' \neq h) &= (1-u')y'^n(\theta') + u'y'^u(\theta') \\ u' &= \lambda + (1 - \lambda - f(s, \bar{s}, \theta))u \\ u & \text{ is given} \\ h & \text{ is given} \quad \text{(commitment)} \end{aligned}$$

where Q is a monotone increasing transition function.

Recall the tension that relied on the cyclicality of search intensity:

$$\frac{f_{s\theta}}{f_s f_\theta} > \frac{u \int_\Theta B_{uu}(u', \theta') Q(\theta, d\theta')}{\int_\Theta B_u(u', \theta') Q(\theta, d\theta')}$$

An alternative interpretation of this inequality is that workers will search in a countercyclical fashion provided that unemployment shocks are more important than aggregate shocks in the determination of their optimal search intensity. Previously, I showed that a countercyclical search intensity would be consistent with a degree of risk aversion that is well-above the one used pervasively in the business cycle literature, casting doubts on the relative importance of (idiosyncratic) unemployment shocks.

In the remainder of this paper, I explore both theoretically and empirically whether this result goes through when adding commitments in consumption. Although simple in nature, this allocation friction brings home the idea of how unwarranted could delaying search efforts be when the household has to afford ineludible expenses, like utility bills and mortgage payments.

2.4 Consumption Commitments and Risk Aversion

In this section, I argue that consumption commitments may be relevant in shaping the job search behavior of the worker. I proceed in a number of steps. First, I characterize the optimal decision plans for c and h. I show that there exists a region of inaction where it is optimal for the household not to adjust commitment spending. Next, I turn to the implications of facing consumption commitments for the job search behavior. I show that in the region of inaction, the household is more risk averse over unemployment fluctuations than in the case where it faces no adjustment costs, and consequently, has more incentives to look for work in the event of a consumption drop.

Existence of a Wealth Region of Inaction: Wealth of the household is driven by the two states of the economy, u and θ. For reasons that will be clear later, I abstract from variation in wealth induced by the aggregate shock θ. In the subsequent discussion, wealth shocks are meant to capture (idiosyncratic) unemployment shocks only.

The cost κ that has to be paid whenever the household adjusts h introduces nonlinearities in the optimal consumption plans. At the core of these nonlinearities is the tension between the magnitude of the adjustment cost and the desire to allocate current wealth between flexible and commitment spending optimally (as dictated by relative prices only). The larger the shock, either good or bad, the more bearable the cost will be and adjustment in commitment spending will follow.

Proposition 8 states that there exists unemployment levels that define a region where the household does not adjust the commitment spending. It requires mild assumptions on preferences.

Proposition 8 (Chetty and Szeidl (2007)): There exists a region of inaction.

The optimal time allocated to job search is characterized by

$$V_s(s) = \beta f_s(s, \bar{s}, \theta) \int_{\Theta} \Delta^n(u', s'; y'^n, y'^u, \gamma) Q(\theta, d\theta') \tag{2.8}$$

where $\Delta^n(u, s; y^n, y^u, \gamma) \equiv (y^n - y^u)U_c[(1-u)y^n + uy^u - h', h'] + V(s) - \gamma$ is the net gain reaped if moving from unemployment to employment. Equation (2.8) holds regardless of the level of wealth as a direct consequence of the separation between wealth and time allocation, in turn implied by the presence of full insurance within the household.

Amplification of Risk Aversion: In the region of inaction, the risk aversion over wealth of the household is amplified with respect to the degree prevalent in the absence of such costs. To gain intuition on this result, I derive an expression for the ratio of curvatures with and without adjustment costs for a specific level of wealth.

Let $B(u, \theta)$ be the indirect utility of the household contingent on following optimal plans for consumption and job search. I start by defining

$$\sigma_u = \frac{uB_{uu}(u, \theta)}{B_u(u, \theta)}$$

as the relative risk aversion over fluctuations in the employment status of the members of the household. I invoke the envelope condition

$$B_u(u, \theta) = -\Delta^n(s^\star, u, y^n, y^u, \gamma) + \beta\alpha(s^\star; \theta, \bar{s}, \lambda) \int_\Theta B_u(u', \theta')Q(\theta, d\theta')$$

to derive

$$B_{uu}(u, \theta) = (y^u(\theta) - y^n(\theta)) \left(U_{cc} \frac{\partial c^\star}{\partial u} + U_{ch} \frac{\partial h^\star}{\partial u} \right),$$

which, under some convenient rearrangements and in the absence of adjustment costs, could be alternatively written as

$$\sigma_u^{nc}(u, \theta) = \left(\sigma_c^{nc} \left|\varepsilon_{c,u}^{nc}\right| - \varepsilon_{U_c,h}^{nc} \left|\varepsilon_{h,u}^{nc}\right|\right) \left(\frac{y^u - y^n}{B_u^{nc}/U_c^{nc}} \right) \tag{2.9}$$

where θ is fixed, $\varepsilon_{c,u}$ and $\varepsilon_{h,u}$ are the elasticities of flexible and commitment spending to unemployment shocks. Analogously, in the presence of commitments we have

$$\sigma_u^{cc}(u, \theta) = \sigma_c^{cc} \left|\varepsilon_{c,u}^{cc}\right| \left(\frac{y^u - y^n}{B_u^{cc}/U_c^{nc}} \right) \tag{2.10}$$

since, in this case h is not adjusted. In general, equation (2.9) and (2.10) are not comparable since allocations will differ under the presence or absence of consumption commitments. However, at an unemployment rate $\bar{u}$ such that $h^{nc}(\bar{u},\theta) = h^{cc}$, the amplification of risk aversion could be expressed as follows

$$\frac{\sigma_u^{cc}(\bar{u},\theta)}{\sigma_u^{nc}(\bar{u},\theta)} = \frac{\sigma_c^{cc}\left|\varepsilon_{c,u}^{cc}\right|}{\sigma_c^{nc}\left|\varepsilon_{c,u}^{nc}\right| - \varepsilon_{U_c,h}^{nc}\left|\varepsilon_{h,u}^{nc}\right|}$$

Alternatively, this could be written as

$$\frac{\sigma_u^{cc}(\bar{u},\theta)}{\sigma_u^{nc}(\bar{u},\theta)} = \frac{\sigma_c^{cc}\left|\varepsilon_{c,W}^{cc}\right|}{\sigma_c^{nc}\left|\varepsilon_{c,W}^{nc}\right| - \varepsilon_{U_c,h}^{nc}\left|\varepsilon_{h,W}^{nc}\right|}$$

since the effect of unemployment shocks on wealth is the same regardless of the presence of commitments. Adjustment costs in h warrants this ratio to be greater than one since in this case the household will concentrate the adjustment in total spending in c, making flexible spending more sensitive to changes in wealth than in the case where there are no such costs. The second reason is the complementarity between c and h.

Under specific preferences, I can proceed one step further and obtain close-form expressions for the ratio of curvature with and without adjustment costs.

Separable Utility: Consider the following utility function used by Chetty and Szeidl (2007):

$$U(c,h) = \frac{c^{1-\sigma_c}}{1-\sigma_c} + \mu\frac{h^{1-\sigma_h}}{1-\sigma_h}, \quad \mu > 0$$

with the restriction that $\sigma_c \geq \sigma_h > 0$. Chetty and Szeidl (2007) show that in this case the ratio of curvatures has the following form:

$$\frac{\sigma_u^{cc}(\bar{u},\theta)}{\sigma_u^{nc}(\bar{u},\theta)} = 1 + \frac{h}{c}\frac{\sigma_c}{\sigma_h} \tag{2.11}$$

Nonseparable Utility with Homogeneity of Degree $1-\sigma$: Consider the following utility function

$$U = \frac{\tilde{U}^{1-\sigma}}{1-\sigma}, \quad \sigma > 0$$

where $\tilde{U}$ has the CES form

$$\tilde{U} = \left(\alpha c^{\frac{\gamma-1}{\gamma}} + (1-\alpha)h^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}},$$

where $\gamma > 0$ is the elasticity of substitution between c and h, and $\sigma > 0$ is the degree of risk aversion over wealth in the absence of adjustment costs. In the appendix, I show that[10]

$$\frac{\sigma_u^{cc}(\bar{u},\theta)}{\sigma_u^{nc}(\bar{u},\theta)} = 1 + \frac{h}{c}\frac{1}{\gamma\sigma} \tag{2.12}$$

In any case, expressions (2.11) and (2.12) reassure the intuition provided before. The next proposition states that the amplification of risk aversion holds for any level of wealth in the region of inaction.

Proposition 9 (Chetty and Szeidl (2007)): Amplification of risk aversion in the region of inaction

The requirement that $U_{ch} > 0$ deserves some discussion. Chetty and Szeidl (2007) requires $U_{ch} > 0$ which rules out the cases $\gamma > 1$ and $\sigma > 1$ in (2.12). In the appendix, I show that even in these two latter cases, the amplification effect still holds. That is, at least for the class of CES preferences, $U_{ch} \geq 0$, although sufficient, is not necessary. In (2.12), it can be seen that the amplification effect is decreasing in both γ and σ since the higher each of these parameters is, the less complements c and h become. Between the two, the more problematic parameter is γ. A value for the relative risk aversion σ could be set according to the literature of business cycles. Little is known, however, with respect to the complementarity between commitment and flexible spending.

Notice that as a result of the absence of a savings technology, the share of commitment spending is time-dependent. Thus, the amplification will respond to changes in the commitment share instantly, implying that the household decision to whether adjust or not the commitment spending depends solely on the information available at the current period.

It is instructive to evaluate this latter result under alternative environments discussed

[10]I thank Job Boerma for suggesting the idea of working out this case.

in the literature. Chetty and Szeidl (2007) show that the household will adjust commitment spending (housing) only once over its lifetime. In their framework, the discount factor is the inverse of the gross interest rate which implies that the household smooths consumption perfectly and if moving, it does so right after making the commitment. Vereshchagina (2014) shows that assuming a zero net interest rate, as Chetty and Szeidl (2007) does, may be quite restrictive. With a positive interest rate, adjustment in commitment spending may be delayed with non-trivial implications for risk preferences. In this case, it is possible that the presence of commitments may even make the individual a risk seeker. Of course, in my setup such a concern is ruled out since consumption decisions are taken in a period-to-period basis.

2.5 Empirical Strategy

In this section, I examine the empirical scope of the theoretical insights discussed in the previous section. I construct a panel of observations at the family-level using the PSID data for the period 1999-2013. Using this sample, I allow for earnings shocks and the share of commitment spending to play a role in the allocation of search effort in the event of unemployment.

Three variables will be key in the subsequent discussion. The measure of consumption drops, the definition of earnings shocks, and the measure of search intensity. Later, I discuss the empirical strategy in itself that combines these three pieces. I start with the share of commitment spending.

Consumption Drops: I use PSID expenditure data, which covers nearly 72% of total household spending, to calculate the share of commitment spending at the family level. To do this, I need to determine beforehand whether a specific expenditure item (food or housing, for instance) is a commitment or flexible spending. I follow Chetty and Szeidl (2007) in categorizing spending items by measuring aggregate consumption drops in the event of unemployment. I exploit recently released PSID consistent data on consumption expenditures in a variety of categories such as food, housing, transportation, education, child care, and health. The methodology used to gauge consumption drops is inspired by Chetty and Szeidl (2007), Stephens (2001), and Aguiar and Hurst (2005).

The previous section pointed out the need to measure the consumption responses to unemployment shocks for both flexible and commitment spending. PSID data is suitable for these purposes for the following two reasons. First, its panel structure permits a more accurate description of consumption drops in the event of unemployment. Second, since 1999 the PSID asks respondents about expenditures on consumption categories other than food, such as housing, transportation, education, child care, and health, with the advantage of having a comprehensive picture of consumption adjustment along different margins.

Li et al. (2010) report that with this expanded coverage the PSID consumption data compares favorably to the Consumption Expenditure Survey (CE) data, accounting for 72% of total spending across all CE categories. In 2005 the expansion of the coverage went even further by including additional housing expenditures, such as home repairs and household furnishings, and other categories such as clothing, trips, vacations, and other recreation activities. Currently, the PSID data comprises almost all spending categories from CE (Andreski et al., 2014).

I use recently released PSID data on consumption expenditures with needed imputations.[11] I construct real figures for consumption expenditures in food, housing, transportation, education, child care, and health by using the corresponding consumer price indices from the BLS.[12] Food consumption includes the value of food stamps. Housing spending includes expenditures in mortgages, rent, property taxes, insurance premiums, and utilities (electricity, heat, and water).

The final sample is created after making the following adjustments. First, I keep families whose head of the household experience only one spell of unemployment along the entire panel (1999-2013). Second, the sample comprises individuals aged between 25 and 65. Third, I discard observations with changes in family size to get rid of variation in consumption attributed to changes in the number of family members. Fourth, I exclude observations for individuals who report no ownership status (renting or owning a house).

I measure consumption drops in the event of unemployment along different spending categories separately. As Chetty and Szeidl (2007) argue, this could lead to a natural classification of expenditures into flexible and commitment categories, according to the

[11] See Andreski et al. (2015) for details on the methodology. Data is available here `http://simba.isr.umich.edu/Zips/ZipMain.aspx`. I thank Geng Li for making me aware of this dataset.

[12] I use the CPI-All Urban Consumers index available here `http://www.bls.gov/cpi/data.htm`.

extent of their adjustment in response to wealth shocks.

I construct a panel by merging the individual and family PSID files for the period 1999-2013 (every other year since 1999). The sample size ranges from 634 (child care) to 5011 (housing) observations. I report the results from this exercise in Figure 2.1.

It is observed that the degree of downward adjustment in consumption differs among the spending categories. They differ both in depth and duration after the event of unemployment. In particular, the study of events of unemployment reveals the long-lasting effects on consumption drops induced by negative earning shocks. This is perhaps, more noticeable in the case of food and housing spending. Although these findings may be surprising, it is worth noting that these long-run effects are in line with Stephens (2001) for food spending.

It is important to address the distinction between expenditure and consumption data. Aguiar and Hurst (2005) show that this distinction matters in the event of retirement. In the event of unemployment, however, the comparison between expenditure and consumption data leads to fairly similar conclusions about the fall in consumption.

By relying on the significance of the consumption drops, I conclude that education, health, and housing spending could be regarded as commitment spending while categories such as food, child care, and transportation as could be regarded as flexible spending.

Earning Shocks: In the model laid out before, earnings shocks affect the allocation of income in a nonlinear fashion. Only shocks that are either small or large enough would call for an adjustment in the commitment spending. Risk preferences are affected only in the case of moderate earnings shocks. I calculate family earnings as the sum of the labor income of the head of the household and wife, deflated by the CPI-All Urban Consumer price index. To distinguish between small and large shocks, I use percentiles of the distribution of changes in earnings.

Search Intensity: I use the number of search methods as a measure of search intensity. Although it is unclear to which extent the number of methods conveys useful information about the time-use in search activities, the use of more search methods in times when the odds of finding a job are not that favorable, is indicative of a desire of escaping unemployment by diversifying the job search outcomes.

I use the number of search methods reported by the head of the household. In the PSID, respondents are asked about the things they have done to look for work during the previous 4 weeks. These questions have changed throughout the years since the inception of the PSID in 1968. Fortunately, from 1999 to 2011, questions about the use of search methods were asked in a consistent basis.[13] This measure has been used before as a proxy of search intensity by Yoon (1981) in the case of PSID and Shimer (2004) in the case of CPS. To investigate whether the time series of search methods is capturing anything of interest, in Figure 2.2 I plot the time average along with its CPS counterpart. The resemblance lends support to the use of the number of search methods from PSID as a proxy of search intensity.

Consumption commitments and search intensity: Once consumption expenditures has been categorized, I can calculate the share of commitment spending at the family level. To measure the sensitivity of search intensity to this share and earnings shocks, I run the following regression

$$s_{it} = \alpha + \gamma \left(h/c\right)_{it} + \beta X_{it} + \psi \epsilon_{it} + \upsilon_{it} \tag{2.13}$$

where s_{it} is the number of methods used by the head of household in family i in period t, $(h/c)_{it}$ is the share of commitment spending, X_{it} is a set of covariates such as, age, educational level, marital status of the head of household, and time spent (in weeks) looking for work. Finally, W stands for real family earnings. I estimate equation (2.13) by Ordinary Least Squaresf. Results are reported in Table 2.1.

I construct two set of samples. Sample 1 includes workers who get reemployed or leave the labor force in the period following the event of unemployment. In addition to this sample of individuals, sample 2 includes workers who remain jobless and looking for work in the period following the first unemployment episode.

Next, I proceed to comment some salient features from the estimation of equation (2.13). Among the most important results that deserve some comments are the following. Unemployed workers tend to search more intensely in response to a higher share of

[13]These questions bear a resemblance to the CPS questions on methods used since 1997.

commitment spending, and more so if the unemployment event occurs in a recession period. The times dummies, meant to capture aggregate effects, are consistent with search intensity being countercyclical in the aggregate. Another important variable is the drop in earnings at the event of job loss. I split earnings drops into small, moderate, and large shocks. The cutoffs used to distinguish among shocks depending on their size are no doubt a problematic choice. With no information of the size of the adjustment cost κ, I adopt a rather eclectic approach. Hence I use percentiles on the lower side of the distribution of earnings shocks, measured as change in real earnings.

The inclusion of demographic variables is meant to capture potential compositional bias across unemployment events in different periods. Finally, the number of family members and of kids (aged less than 18) may be important to capture particular needs within the household in shaping the use of more or less search methods.

All in all, the main takeaways of the regression results are as follows. The effect of the share of commitment spending on search intensity is as expected from the model. The coefficients and significance of the time dummies are consistent with workers, in average, using a higher number of methods during recessions. Most importantly, I find partial support to the insights stemming from the theoretical framework. Not surprisingly, the results show that the amplification is sensitive to the classification of small and large shocks. This is still an open question. To be definitive, I would need to parameterize either σ_h and σ_c or the parameters of the CES preferences (γ and σ). In the latter case, γ would be the more contentious parameter. I leave these issues for the future.

2.6 Concluding Remarks

I introduce consumption commitments into an otherwise standard job search model. I show that the theoretical insights of Chetty and Szeidl (2007) follows naturally from my framework. The absence of assets and the assumption of full insurance within the household are key to obtain these results. Hence consumption commitments may amplify the degree of risk aversion, depending on the size of the wealth shocks and the magnitude of the adjustment cost.

Empirically, I find partial support to the insights stemming from the theoretical framework. The results show that the amplification is sensitive to the classification of small and large shocks. This is still an open question. To be definitive I would need to parameterize either σ_h and σ_c or the parameters of the CES preferences (γ and σ). In the latter case, γ is the more contentious parameter. I leave these issues for future research.

The framework discussed in this paper was intentionally one of partial equilibrium. The implication of a higher degree of risk aversion for aggregate fluctuations may impose some challenges that are left for future research as well. Hopenhayn and Prescott (1992), for instance, show that a sufficiently high degree of risk aversion implies investment moving in a countercyclical fashion over the business cycle. Further empirical work is needed to gauge the degree of risk aversion.

This paper has been silent about the consumption smoothing benefits of unemployment, pointed out by Gruber (1997) and Chetty (2008), and its apparent role in downplaying the relevance of consumption commitments. Consumption commitments and unemployment insurance, however, may interact in a rather complex way. The interplay between the uneven adjustment of expenditures among consumption categories and risk aversion begs the questions whether the unemployment insurance is used to smooth flexible consumption, such as food, or honor previous commitments made on categories such as education, health care, and housing. This distinction matters because the allocation of the unemployment insurance to either flexible or commitment consumption has different implications for the amplification of risk aversion through its impact on the commitment spending share.

Government policies may affect job search behavior through its direct effect on risk preferences. A more recent episode provides a vivid example on how policies may affect risk preferences and, in turn, job search behavior in a rather unconventional way. Herkenhoff and Ohanian (2015) document a significant foreclosure delay around the recent recession. The time required to initiate and complete a home foreclosure rose from 9 months prior to the 2007-2009 recession to 15 months during the recessions and afterwards. Another reason how this policy could deter people from looking for work could be the effect of the delay on the mortgage payments in the mitigation of risk aversion. The delay in mortgage payments may have reduced the share of commitment spending, reducing thereby the need to look for work as the model laid out before demonstrates.

Appendix

Derivation of equation (2.11): The ratio of curvatures with and without commitments is

$$\frac{\sigma_u^{cc}}{\sigma_u^{nc}} = \frac{\varepsilon_{c,W}^{cc}}{\varepsilon_{c,W}^{nc}} \tag{2.14}$$

In the region of inaction, commitment spending is not adjusted, implying that

$$\varepsilon_{c,W}^{cc} = \frac{W}{c} = 1 + \frac{h}{c} \tag{2.15}$$

In the case without adjustment costs we have

$$\frac{c}{W}\varepsilon_{c,W}^{nc} + \frac{h}{W}\varepsilon_{h,W}^{nc} = 1 \tag{2.16}$$

It can be shown that at optimum, in the case without adjustment costs:

$$\varepsilon_{c,W}^{nc} = \frac{\sigma_h}{\sigma_c}\varepsilon_{h,W}^{nc} \tag{2.17}$$

Combining equations (2.16) and (2.17) yields

$$\varepsilon_{c,W}^{nc} \quad = \quad \frac{1}{1 + \frac{h}{W}\left(\frac{\sigma_c}{\sigma_h} - 1\right)} \tag{2.18}$$

Combining equations (2.18) and (2.15) in (2.14) yields

$$\begin{aligned}
\frac{\sigma_u^{cc}}{\sigma_u^{nc}} &= \frac{\varepsilon_{c,W}^{cc}}{\varepsilon_{c,W}^{nc}} \\
&= \left(1 + \frac{h}{W}\left(\frac{\sigma_c}{\sigma_h} - 1\right)\right)\left(\frac{c+h}{c}\right) \\
&= \frac{c+h}{c} + \frac{h}{c}\left(\frac{\sigma_c}{\sigma_h} - 1\right) \\
&= 1 + \frac{h}{c} + \frac{h}{c}\frac{\sigma_c}{\sigma_h} - \frac{h}{c} \\
&= 1 + \frac{h}{c}\frac{\sigma_c}{\sigma_h}
\end{aligned}$$

Derivation of equation (2.12): The following intermediate results will prove useful. Notation follows that in the text.

$$
\begin{aligned}
U_c &= \tilde{U}^{-\gamma}\tilde{U}_c \\
U_h &= \tilde{U}^{-\gamma}\tilde{U}_h \\
\tilde{U}_c &= \alpha\left(\frac{\tilde{U}}{c}\right)^{\frac{1}{\gamma}} \\
\tilde{U}_h &= (1-\alpha)\left(\frac{\tilde{U}}{h}\right)^{\frac{1}{\gamma}} \\
U_{cc} &= \sigma\alpha^2\tilde{U}^{-\sigma-1}\left(\frac{\tilde{U}}{c}\right)^{\frac{2}{\gamma}} + \frac{\alpha^2}{\gamma}\frac{\tilde{U}^{-\sigma}}{c}\left(\frac{\tilde{U}}{c}\right)^{\frac{2}{\gamma}-1} - \frac{\alpha}{\gamma}\frac{\tilde{U}^{-\sigma}}{c}\left(\frac{\tilde{U}}{c}\right)^{\frac{1}{\gamma}} \\
U_{ch} &= \tilde{U}^{-\sigma-1}\alpha(1-\alpha)\left(\frac{\tilde{U}}{c}\right)^{\frac{1}{\gamma}}\left(\frac{\tilde{U}}{h}\right)^{\frac{1}{\gamma}}\left(\frac{1-\sigma\gamma}{\gamma}\right)
\end{aligned}
$$

The necessary first-order condition implies

$$\frac{h}{c} = \left(\frac{1-\alpha}{\alpha}\right)^{\gamma}$$

The ratio of curvature with and without adjustment costs is

$$\frac{\sigma_u^{cc}}{\sigma_u^{nc}} = \frac{\sigma_c\varepsilon_{c,W}^{cc}}{\sigma_c\varepsilon_{c,W}^{nc} - \varepsilon_{U_c,h}^{nc}\varepsilon_{h,W}^{nc}} \tag{2.19}$$

Given that the U is homothetic, $\varepsilon_{c,W}^{nc} = 1$. Equation (2.19) could be alternatively expressed as follows:

$$\frac{\sigma_u^{cc}}{\sigma_u^{nc}} = \left(\frac{\sigma_c}{\sigma_c - \varepsilon_{U_c,h}}\right)\left(1 + \frac{h}{c}\right) \tag{2.20}$$

where, as before, $\varepsilon_{c,W}^{cc} = 1 + \frac{h}{c}$. Using the intermediate results, it can be seen that

$$\sigma_c \equiv -\frac{cU_{cc}}{U_c} = \alpha\sigma\left(\frac{\tilde{U}}{f}\right)^{\frac{1-\gamma}{\gamma}} - \frac{\alpha}{\gamma}\left(\frac{\tilde{U}}{c}\right)^{\frac{1-\gamma}{\gamma}} + \frac{1}{\gamma}$$

and

$$\varepsilon_{U_c,h} \equiv \frac{xU_{fx}}{U_f} = (1-\alpha)\left(\frac{1-\gamma\sigma}{\gamma}\right)\left(\frac{\tilde{U}}{h}\right)^{\frac{1-\gamma}{\gamma}}$$

and since

$$\sigma_c - \varepsilon_{U_c,h} = \frac{\sigma\gamma - 1}{\gamma} + \frac{1}{\gamma} = \sigma,$$

the first term in (2.20) is

$$\frac{\sigma_c}{\sigma_c - \varepsilon_{U_c,h}} = \frac{\alpha(\tilde{U}/c)^{\frac{1-\gamma}{\gamma}}(\gamma\sigma - 1) + 1}{\gamma\sigma}$$

Let

$$\epsilon = \frac{MU_c}{AU_c} = \alpha(\tilde{U}/c)^{\frac{1-\gamma}{\gamma}}$$

where MU_c is the marginal utility and AU_c is the average utility. Since the utility function is strictly concave, the elasticity ϵ is less than one. Further, one can show that

$$\epsilon = \frac{1}{1 + \left(\frac{1-\alpha}{\alpha}\right)^{\gamma}} = \frac{1}{1 + \frac{h}{c}}$$

by using the first-order condition obtained before. Thus, I can further simplify equation (2.20) to finally obtain

$$\begin{aligned}
\frac{\sigma_u^{cc}}{\sigma_u^{nc}} &= \left(\frac{\epsilon(\gamma\sigma - 1) + 1}{\gamma\sigma}\right)\left(1 + \frac{h}{c}\right) \\
&= \left(\frac{\gamma\sigma - 1}{\gamma\sigma}\right) + \frac{1}{\gamma\sigma}\left(1 + \frac{h}{c}\right) \\
&= 1 + \frac{h}{c}\frac{1}{\gamma\sigma}
\end{aligned}$$

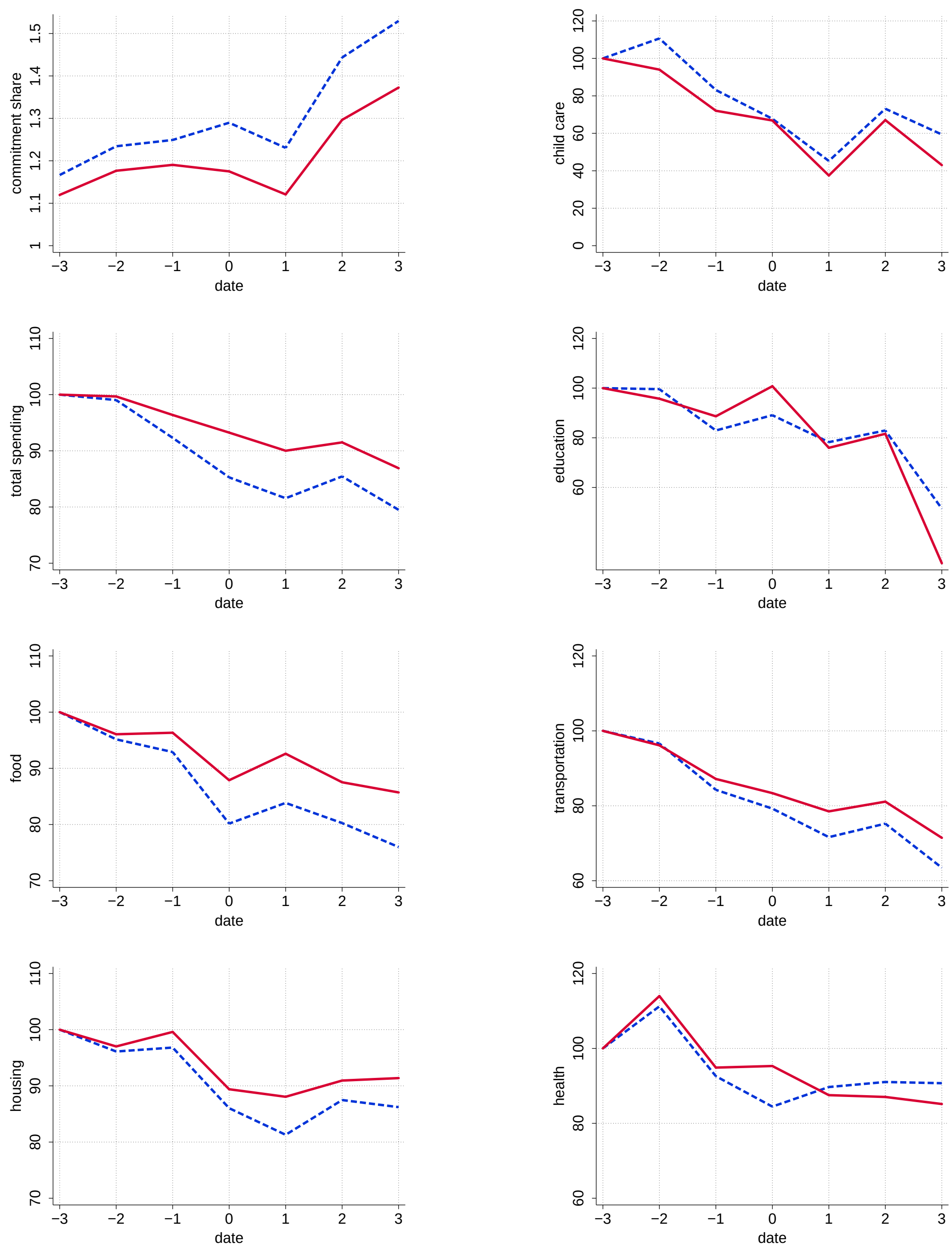
2.7 Appendix A: Tables and Figures

Table 2.1: Baseline Regression Results on Search Intensity and Consumption Commitments

	OLS estimates sample 1	OLS estimates sample 1	OLS estimates sample 2	OLS estimates sample 2
$\frac{h}{c}$	0.02	0.06	0.02	0.06
	(0.04)	(0.04)	(0.04)	(0.04)
$t = 2003$	0.17	0.26	0.17	0.26
	(0.05)	(0.05)	(0.05)	(0.05)
$t = 2005$	0.19	0.25	0.20	0.25
	(0.06)	(0.05)	(0.06)	(0.05)
$t = 2007$	0.24	0.32	0.24	0.32
	(0.06)	(0.05)	(0.06)	(0.05)
$t = 2009$	0.38	0.36	0.38	0.36
	(0.05)	(0.05)	(0.05)	(0.05)
$t = 2011$	0.19	0.24	0.19	0.24
	(0.06)	(0.06)	(0.06)	(0.06)
$\Delta\epsilon_{t-1}$	−0.21	−0.26	−0.20	−0.26
	(0.05)	(0.05)	(0.05)	(0.05)
ϵ_{small}	0.03	0.01	0.03	0.00
	(0.04)	(0.03)	(0.04)	(0.03)
$\epsilon_{\text{moderate}}$	0.15	0.12	0.11	0.09
	(0.04)	(0.04)	(0.04)	(0.04)
ϵ_{large}	−0.04	−0.06		
	(0.06)	(0.06)		
constant	0.47	0.50	0.46	0.49
	(0.12)	(0.11)	(0.12)	(0.11)
Observations	4,738	5,597	4,738	5,597
R^2	0.310	0.313	0.309	0.312

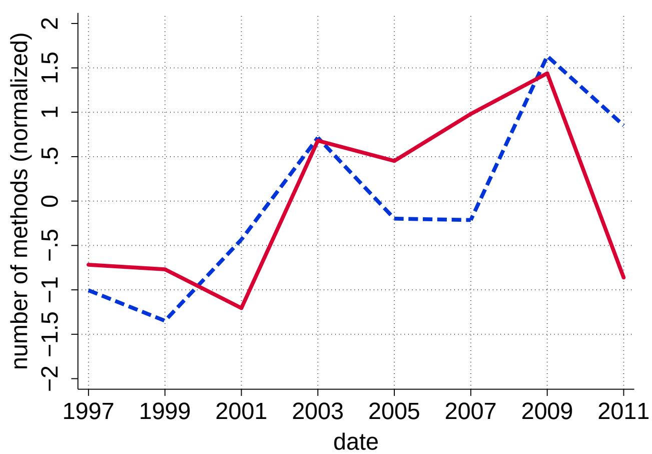
Notes: Number of observations stands for number of families-unemployment events. Sample 1 includes unemployed who either get reemployed or leave the labor force after the unemployment event. Sample 2 includes sample 1 plus unemployed who remain unemployed after the first event takes place. Each column shows OLS estimates that control for age, education, marital status, and time spent looking for work (in weeks) of head of the household. Robust standard errors are reported in parenthesis. The magnitude of the earning shocks is defined as percentiles of the earnings drops distribution. Thus large (negative) shocks are defined as the lower 5% percentile, moderate shocks are defined between the 5% and 25% percentiles, and small shocks acoount for the remaining part of the distribution of negative shocks

Figure 2.1: Consumption Drops in the Event of Unemployment



Notes: The first panel shows the ratio of commitment to flexible spending $\frac{h}{c}$. The remaining figures show the consumption drops along different spending categories such as food, housing, transportation, education, child care, and health. Consumption drops are shown relative to the date of unemployment ($t = 0$). Real spending figures are normalized to 100 in $t = -3$ (6 years before the event of unemployment). The dashed lines represent the consumption patterns without controlling for observables. The solid lines represent consumption patterns after controlling for age of the household, marital status of the head, family size, number of children aged less than 18 years, ownership status of the household, fixed effects, and time effects. Variance is clustered at the family level. Estimation of the panel data model is weighted with constant weights at the family level for workers aged 18 and older.

Figure 2.2: Number of Search Methods in CPS and PSID



Notes: This figure displays the average number of methods used by people unemployed and looking for work aged 18 and older using CPS (in dashed blue) and PSID (in solid red). CPS weighted estimates are calculated using the Composited Final Weight (lines 846-855 in the CPS record layout). Annual estimates based on quarterly figures. PSID estimates are calculated using the family weights. PSID estimates correspond to every other year. Normalization consists on dividing the difference between the raw series and its mean.

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