Intra-Household Risk Sharing and Job Search over the Business Cycle

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Abstract

Over the business cycle, married households differ from single individuals in two ways: (1) they make joint job search decisions by varying search participation in response to changes in their spouse’s labor force status (2) spouses share cyclical risks with one through joint-search and the fact that they provide separate sources of income. These differences lead to different interpretations of the cyclicality of the unemployment fluctuations for the married population. I consider a dynamic model of unitary households in which the spouses make joint job search and savings decisions and face aggregate shocks in the labor market. The model is estimated using data from the Current Population Survey by the simulated method of moments. I find that married individuals participate in job search more actively when their spouse is unemployed. Because of the counter-cyclicality of spousal unemployment, the joint-search behavior leads to counter-cyclical search participation, and thus counter-cyclical unemployment rate. In addition, marriage diversifies the income shocks each individual faces, and the diversification is further achieved through joint-search. Because of this, married individuals suffer less welfare costs to business cycle fluctuations.

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1 Introduction

The unemployment rate soars during economic downturns and raises great concerns in a society. However, if the unemployment rate is used as an indicator for the wellbeing of the labor market, the hardship caused by a recession may be exaggerated, especially for married individuals who constitute the majority of the working-age population. First, the labor market behaviors of married individuals are affected by their spouse’s employment outcome. Those who are not participating in the labor market may wish to engage in job search when their spouse faces unfavorable employment shocks, a phenomenon known as the added-worker effect. Because of the counter-cyclicality of such employment shocks, the added-worker effect can generate counter-cyclicality in the participation of job-search, giving rise to a higher unemployment rate during recessions. Second, as married spouses make joint consumption and job search decisions, they are able to insure against one another’s employment shocks. This intra-household risk sharing can lower the welfare costs of business cycle fluctuations.

The matched monthly data from the Current Population Survey (CPS) suggests strong added-worker effect. In particular, labor force non-participants are significantly more likely to transition to the state of unemployment if their spouse is unemployed rather than employed. Meanwhile, unemployed workers are less likely to transition out of the labor force if they have an unemployed spouse.\(^1\)

When designing policies that aim to tackle the high unemployment rate in recessions, the cyclicality of the search participation decision is highly relevant. For example, during the recovery from the Great Recession, the unemployment rate stays stagnant while the vacancy rate is improving. As a result, the Beveridge curve - the empirical relationship between the unemployment and vacancy rates - shifts outwards (see Figure 1.1). The shift of the Beveridge curve may be due to permanent reasons such as worsened matches between skills supplied and demanded, or the reduced efficiency in the process that allows workers and firms to meet one another. However, the shift may be also due to cyclical fluctuations in the search participation. The added-worker effect may be strong during the period following the trough of the Great Recession, because the job finding rate remains low and the household financial conditions have not fully recovered.\(^2\)

\(^{1}\)See Table 3.5.
\(^{2}\)Mirroring this view, Davis et al. (2013) argue that the number of vacancies is a poor measure of firms’ recruitment.
Figure 1.1: US Beveridge Curve. The unemployment rate is based on the data from the Current Population Survey, and the vacancy rate is based on data from the Job Openings and Labor Turnover Survey. The figure shows monthly rates over the period of 2000-2014. The unemployment rate is the fraction of unemployed workers in the US civilian labor force consisting of workers age 16 or older. The job openings rate is the fraction of job openings among all filled and unfilled US non-farm jobs. Recession refers to the Great Recession (December 2007 - June 2009). The fitted lines are plotted for pre- and post-June 2009 periods.

In this paper, I construct and estimate a dynamic model of married households in the presence of aggregate shocks in order to understand the contribution of the added-worker effect to the counter-cyclicality in the unemployment rate and the reduction in the cyclical costs due to intra-household risk sharing. In the model, households are unitary and risk-averse, and the financial markets are incomplete. In each period, the spouses jointly determine the household consumption level and the levels of job search effort for each person who is not currently employed. Joint-search implies that the search effort of an individual depend on the labor force status of the spouse. Intra-household risk sharing arises from two factors. First, a two-person household allows for two independent income streams and the diversification of the unemployment risks. Second, when spouses joint-search, they

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The authors contend that firms’ recruitment efforts, in addition to vacancy posting, exhibits a procyclical pattern and helps explain the outward shift of the Beveridge curve.
can increase search efforts when the spouse is not employed, which further reduces the impacts of unemployment shocks.

The model parameters are estimated using the simulated method of moments based on the matched monthly data from the CPS. The estimated model closely matches targeted moments of labor force stock and flow statistics by spouse’s employment status. Consistent with the added-worker effect, the model generates substantially higher transition rate from non-participation to unemployment as well as higher unemployment rate when the spouse is unemployed rather than employed. Outside of the targeted moments, the model generates qualitatively plausible cyclical patterns: the labor force participation rate is a-cyclical to weakly pro-cyclical, and the unemployment rate is counter-cyclical. Nevertheless, the degree of counter-cyclicality in the unemployment is underpredicted, suggesting that the added-worker effect is not the sole explanation for the cyclical fluctuations.

Given the estimated model, I find that, for females, the joint-search mechanism leads to counter-cyclical fluctuations in the unemployment rate via counter-cyclical search participation. With joint-search, fluctuations in search participation gives rise to more counter-cyclical unemployment rate. In counter-factual environments in which individuals cannot vary search decisions based on the spouse’s labor market state, fluctuations in search participation have little effect or lead to less counter-cyclical unemployment rate. On the contrary, joint-search plays little role in males’ unemployment rate.

The household structure has been shown to be a valuable source of insurance against idiosyncratic labor market shocks (Ortigueira and Siassi, 2013; Pistaferri et al., 2014). I find that the household is also very effective in insuring against cyclical shocks. The welfare cost of cyclicality, computed in terms of the consumption equivalent of life-time utility, is 3/4 to 1 percentage point to an average single individual. The cost reduces to 1/8 to 1/2 percentage point for a married household. Focusing on on the lowest 5% of the welfare distribution, the cyclical costs to singles are 2 to 7 percentage points, whereas the cyclical costs to married households are less than 1 percentage point.

The rest of the paper is organized as follows. I review the related literature in Section 2. In Section 3 I present empirical evidence on the cyclicality of search participation and its correlation with spouse’s employment status. I introduce the structural model in Section 4 and explain the method of estimation in Section 5. I discuss the findings of the estimated model in Section 6. Finally, I
conclude in Section 7.

2 Literature Review

This paper lies in the intersection of three strands of literature: the empirical microeconomic literature on the added-worker effect, the macro-labor literature on the volatility of labor force participation and unemployment, and the growing literature on household joint-search.

The added-worker effect has received attention from researchers for decades. Empirical studies have produced mixed results on effects of a spouse’s labor market status on workers’ labor force participation because of the differences in the measurements of added-worker effect and in the specification of the econometric models. Nonetheless, it is a consensus that the presence of uninsured uncertainty in the labor market and liquidity constraints are two necessary factors that generates that a negative income shock of the spouse leads to a positive labor supply response (Mincer, 1962; Lundberg, 1985). Although Cullen and Gruber (2000) argue that unemployment insurance significantly crowds out spousal labor supply as a household self-insurance device, recent studies find that the added-worker effect is still important in today’s labor market (Juhn and Potter, 2007), especially in the Great Recession (Mattingly and Smith, 2010). In this paper, I also find evidence for the added-worker effect in the form that the search participation is correlated with spousal unemployment. More importantly, such added-worker effect plays an important role in the counter-cyclicality of the unemployment rate.

The counter-cyclicality of search participation has been documented by several studies. However, such counter-cyclical pattern has not been fully explained in a theoretical framework (Shimer, 2004; Tripier, 2004; Veracierto, 2008; Shimer, 2013) because the marginal return to search effort is often positively correlated with the aggregate economic conditions. Shimer (2004) and Patterson et al.

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For example, see Heckman and MaCurdy (1982), Lundberg (1985), Maloney (1991), Spletzer (1997), Stephens (2002).

For example, Elsby et al. (2015) note that the participation margin plays an important role in the fluctuations in the unemployment rate. Patterson et al. (2013) show that, in addition to the transitions between unemployment and non-participation, the degree of labor force participation among unemployed workers also exhibits strong counter-cyclicality. Specifically, the authors find that unemployed workers spend more time searching for jobs during recessions than during expansions.
show that countercyclical search intensity can be generated if a model allows for negative correlation between marginal return to search and market conditions. In this paper, I show that the joint-search is an additional mechanism that generates countercyclical search participation.

In the search literature, Burdett and Mortensen (1977) first studied the household decision in a frictional labor market. Recently, there has been an increasing interest on search decisions at the household level. The ability to joint-search with a spouse has been shown to have both theoretical and empirical relevance. Guler et al. (2012) find that joint-search models lead to different equilibrium decisions than single-agent search models. Further, Flabbi and Mabli (2012) estimate a version of Guler et al.'s model and find that the household model yields significantly different estimates than the single-agent model. Mankart and Oikonomou (2015) consider a general equilibrium joint-search framework with real business cycle shocks. They show that calibrated household model with incomplete markets generates plausible cyclical volatility in labor force participation and unemployment. Finally, the model in this paper is closest to that in Haan and Prowse (2015). As their paper focuses on the design of the optimal welfare systems while the household composition is taken into account, their model environment differs from mine in that they do not consider aggregate fluctuations. My contribution to this literature is structurally estimating of a joint-search model with aggregate labor market shocks, and finding that, on one hand, joint-search contributes to the counter-cyclicality of the unemployment rate, and on the other hand, joint-search reduces welfare costs of cyclicity.

3 Empirical Motivations

The search participation decision is defined as the choice between the two non-employment states: unemployment and non-participation. Cyclical fluctuations in the search participaiton decision are associated with the added-worker effect (increased search participation with spousal unemployment) and can lead to cyclical fluctuations in the unemployment rate. In Sec. 3.1 I provide evidence on the cyclical patterns of search participation. In Sec. 3.2 I investigate the relationship between search participation and spouse’s labor force status.
3.1 Search Participation

Figure 3.1 shows the transition rates among the three labor market states: employment (E), unemployment (U), and non-participation (N). While the job finding rate (U-to-E transition rate) is clearly pro-cyclical, the fact that it takes unemployed workers longer to find employment is not the only factor contributing higher unemployment rate in a recession. The movements in and out of the labor force (N-to-U and U-to-N transitions), which I will refer to as the search participation decisions, also fluctuates cyclically.

Table 3.1 shows the correlations between the N-to-U and U-to-N transitions with the unemployment rate (UR) and the job finding rate. For all groups, both the N-to-U and the U-to-N transition rates are highly correlated with the UR and the job finding rate. In particular, a high UR or low job finding rate is associated with higher search participation, i.e. higher N-to-U and lower U-to-N transitions. Consistent with these observations, Elsby et al. (2015) find that the labor force participation margin accounts for a third of unemployment fluctuations.

One explanation for the counter-cyclical search participation is the added-worker effect. Motivated by sharing risks with one another within a married household, added-worker effect entails increasing one’s search participation while his or her spouse is unemployed. Because spousal unemployment is counter-cyclical, the added-worker effect contributes to the counter-cyclical search participation of married individuals.

While I focus only on the married population, most of the patterns are also found among singles. It is beyond the scope of the paper to compare single to married individuals. It should be noted that being married is self-selected and also implies differences in circumstances that affect one’s labor market behavior. Therefore it is difficult to interpret a comparison between the cyclicalities of the two groups’ search participation decisions.
Figure 3.1: Labor Market Transition Rates of Married Individuals. The transitions rate are computed based on matched monthly CPS data between 1976-2014 for married individuals age 30-60 with at least high-school education. The reported labor force state is corrected for classification errors using the de-NUN and de-UNU method in Elsby et al. (2015). The figure show 12-month moving averages of monthly transition probabilities. Vertical bars indicate NBER recessions.
Table 3.1: Correlations and Means. UR = unemployment rate, U-to-E = unemployment to employment transition rate, N-to-U = non-participation to unemployment transition rate, and U-to-N = unemployment to non-participation transition rate. The transitions rate are computed based on matched monthly CPS data for sample individuals age 30-60 with at least high-school education. The reported labor force state is corrected for classification errors using the de-NUN and de-UNU method in Elsby et al. (2015). Statistics are based on 12-month moving averages.

3.2 Added-Worker Effect

To measure the magnitude of the added-worker effect, I regress one’s labor market transitions on the spouse’s labor force status. I consider multinomial logit regressions of labor force transitions where the dependent variable is defined as the log likelihood of a transition from the labor force state \( l_0 \):

\[
\eta_{i,t,l} = \log(P(LFS_{i,t} = l|LFS_{i,t-1} = l_0)/Pr(LFS_{i,t} = l_0|LFS_{i,t-1} = l_0)) \tag{3.1}
\]

where \( LFS_{i,t} \) is the labor force state of individual \( i \) at time \( t \), and \( l \in \{E, U, N\} \). I consider two sets of regressions: in the first set, the dependent variable is transition from unemployment \((l_0 = U)\), and in the second set, the dependent variable is transition from non-participation \((l_0 = N)\). In both sets of regression, the estim equation is as follows:

\[
\eta_{i,t,l} = \beta^0_l + \sum_{l_{sp}=U,N} \beta^{SP,l_{sp}}_l1\{LFSSP_{i,t}=l_{sp}\} + \sum_{l_{sp}=U,N} \beta^{SP_0,l_{sp}}_l1\{LFSSP_{i,t-1}=l_{sp}\} \\
+ \beta^{KID}_{l} KID_{i,t} + \sum_{l_{sp}=U,N} \beta^{KID,l_{sp}}_l KID_{i,t}1\{LFSSP_{i,t}=l_{sp}\} + \beta^X_l X_i + \beta^UR_t UR_t \tag{3.2}
\]

Among the covariates, \( 1\{LFSSP_{i,t-1}=l_{sp}\} \) is an indicator that is equal to 1 if the spouse’s labor force state a year ago is equal to \( l_{sp} \). \( 1\{LFSSP_{i,t}=l_{sp}\} \) is an indicator equal to 1 if the spouse’s labor force
state at time $t$ is equal to $l_{sp}$. $KID_{i,t}$ is an indicator for having kid of age 12 or under. $X_i$ is a vector of demographic variables of $i$ and $i$’s spouse, including age, race, and education of the spouse. I consider three education levels: (1) less than high school, (2) high school or some college (HS), and (3) college or more (COL). Finally, $UR_t$ is the state-level unemployment rate at time $t$. The regression is estimated by gender and by education level (HS or COL). Maloney (1991) points out that estimates of spousal unemployment effects may be biased because of the correlations between spouses due common economic conditions and due to positive assortative matching in marriage formation. By controlling for the local unemployment rate at the state level, spouse’s education level and spouse’s previous labor market experience, I hope to reduce such biases.

Among the coefficients, the main parameter of interest is $\beta^{SP l_{sp}=U}_l$, which captures how one’s labor market transition is associated with spousal unemployment (relative to spousal employment). Also important are the parameters related to children, as having children can greatly influence the parents’ labor force decisions. $\beta^KID_l$ captures the effect of having children on the labor market transitions, and $\beta^{KID l_{sp}}_l$ captures how kids affect the spousal effects. If the estimated value of $\beta^{KID l_{sp}}_l$ is significant, a structural model that studies the added-worker effect must account for the presence of children in the household.

Tables 3.3 shows the results from the first set of regressions where the dependent variable is the transition from the state of non-participation. For all gender-education groups, and particularly for females, the spousal unemployment effect on the N-to-U transition is significantly positive, i.e. relative to having an employed spouse, the non-participants with an unemployed spouse are more likely to transition into the state of unemployment. This is consistent with the added-worker effect. The marginal effects of spousal unemployment are shown in Table 3.5, also shown in the table for comparison are the average N-to-U transition rates. An average non-participating High School educated wife transitions to the state of unemployment with a monthly rate of 0.03; for those with an unemployed husband, the likelihood of such transition increases by 0.05, making them 2.7 times as likelihood to make an N-to-U transition compared to an average person. Similarly for College educated wives, having an unemployed spouse is associated with a N-to-U transition rate that is 2.6 times an average person. The spousal unemployment effect is weaker and less significant for husbands.
Women with kids are less like to transition into either employment or unemployment, while men’s labor market transitions are less significantly responsive to having kids. More interestingly, having kids does not significantly change the spousal unemployment effect in all groups. In other words, kids do not make women or men less likely to increase search participation when their spouse suffers unemployment. Nevertheless, having kids affects the spousal non-participation effect - non-participating men of both education levels and women of college education are more likely to become employed if their spouse is a non-participant. Non-participating women of college education are also more likely to become unemployed when their husband is a non-participant.

The regression results also show a positive correlation between the unemployment rate and the N-to-U transition, despite controlling for spouse’s labor force status. This suggests that there can be other factors responsible for the cyclical fluctuations in the N-to-U transition.

Tables 3.4 shows the results from the second set of regressions where the dependent variable is the transition from the state of unemployment. Here, the spousal unemployment effect on the U-to-N transition is negative, but the significance varies by gender-education group. The marginal effects are summarized also in Table 3.5 which shows the spousal unemployment effect on U-to-N is most significant for college educated men. Compared to the average transition rates, relative to having an employed spouse, having an unemployed spouse lowers the U-to-N transition rate by around 60% for college educated men, and around 1/3 for the other groups.

Kids increase unemployed women’s likelihood to exit the labor force, but they do not significantly affect the spousal unemployment effects. For college educated unemployed men, having kids eliminates the strong spousal unemployment effect on the U-to-N transition that presents in this group. Finally, for all groups, the local unemployment rate is negative correlated with the U-to-N transition rate, which suggests, similar to the previous case, that there exists other factors responsible for the cyclicalities in the U-to-N transitions.

To summarize, the regressions show significantly positive spousal effects on the N-to-U transition for women; the effects are weaker and less significant for men. Spousal effects on the U-to-N transitions are negative but not as significant or strong as in the case of the N-to-U transitions. The results are consistent with the added-worker effects - married individuals, particularly women, increases search
participation when their spouse is unemployed. Having kids significantly discourages women from search participation, but it does little to interfere with the added-worker effect.

4 Model

In this section, I present the structure of the model and the value functions. The model corresponds to the decision problem of a household consisting of a husband and a wife.

**Decision horizon.** Time is discrete. Each period corresponds to a month. The decision horizon spans over two stages of life: a working stage that lasts from age $\tau = 1$ up to $\tau = \tau_{work}$, and a retirement stage that lasts from age $\tau = \tau_{work} + 1$ up to $\tau = \tau_{work} + \tau_{ret}$. $\tau_{work}$ and $\tau_{ret}$ are exogenous.

**Household structure.** A household consists of a heterosexual couple: a husband ($i = h$) and a wife ($i = w$). Both of the spouses can engage in home production, job search, and market production, but their abilities in these activities may differ from one another. The household is a unitary household who maximizes only the household-level net utilities.\(^6\)

\(^6\)The unitary model is a commonly chosen starting point in the joint-search literature (Guler et al. 2012) and is a useful framework to study the household behavior under the full-commitment assumption. Nevertheless, Mazzocco (2007) rejects the unitary household model in an intra-household commitment test. A channel for future research is to develop a collective household model and compare it to the unitary model.
Table 3.3: Multinomial Logit Regression of Transitions from Non-Participation ($l_{t-1} = N$). The regressions are based on matched monthly CPS data for married individuals age 30-45. HS (COL) sample consists of individuals such that their spouse and themselves are high school (college) educated. The reported labor force state is corrected for classification errors using the de-NUN and de-UNU method in Elsby et al. (2015). The regression equation is provided in Section 3.

<table>
<thead>
<tr>
<th></th>
<th>Male, HS</th>
<th>Male, COL</th>
<th>Female, HS</th>
<th>Female, COL</th>
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<tbody>
<tr>
<td>$LFSSP_{t, i} = U$</td>
<td>0.187</td>
<td>0.430</td>
<td>0.240</td>
<td>0.647</td>
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<tr>
<td>$LFSSP_{t, i} = N$</td>
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<td>-0.391</td>
<td>0.067</td>
<td>-0.286</td>
</tr>
<tr>
<td>$KID_{t}^*$</td>
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<td>-0.112</td>
<td>-0.486</td>
<td>-0.698</td>
</tr>
<tr>
<td>$KID_{t} \times {LFSSP_{t, i} = U}$</td>
<td>0.089</td>
<td>-0.286</td>
<td>0.253</td>
<td>-0.238</td>
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<tr>
<td>$KID_{t} \times {LFSSP_{t, i} = N}$</td>
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<td>-0.238</td>
<td>-0.063</td>
<td>-0.240</td>
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<tr>
<td>Age 35-39</td>
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<td>-0.102</td>
<td>0.281</td>
<td>-0.0701</td>
</tr>
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<td>-0.126</td>
<td>0.278</td>
<td>-0.148</td>
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<td>0.0189</td>
<td>-0.273</td>
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<td>-0.127</td>
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<tr>
<td>Constant</td>
<td>-0.616</td>
<td>-0.396**</td>
<td>-0.083**</td>
<td>-0.0806**</td>
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<tr>
<td>Observations</td>
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<td>2272</td>
<td>64730</td>
<td>42194</td>
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<tr>
<td>Pseudo $R^2$</td>
<td>0.028</td>
<td>0.042</td>
<td>0.016</td>
<td>0.021</td>
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</table>

Standard errors in parentheses, $^*$, $p < 0.05$, $^{**}$, $p < 0.01$, $^{***}$, $p < 0.001$.
<table>
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<td>Male, COL</td>
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<td>Female, COL</td>
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</tr>
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<td>(LFSSP_{i,t} = U)</td>
<td>-0.294 (-0.266)</td>
<td>-1.216* (-0.590)</td>
<td>-1.389*** (-0.364)</td>
<td>-0.677** (-0.253)</td>
</tr>
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<td>-0.397 (-0.464)</td>
<td>-13.89*** (-0.560)</td>
<td>-0.669* (-0.315)</td>
<td>-0.115 (-0.430)</td>
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<tr>
<td>(LFSSP_{i,t} = N)</td>
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<td>0.624 (0.363)</td>
<td>0.854 (0.558)</td>
<td>0.361 (0.567)</td>
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<td>1.215*** (0.297)</td>
<td>0.654 (0.558)</td>
<td>1.736* (0.518)</td>
<td>0.97 (0.565)</td>
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<td>(KID_i)</td>
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<td>-0.0466 (-0.131)</td>
<td>-0.315 (-0.0819)</td>
<td>0.155 (0.114)</td>
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<td></td>
<td>0.0868 (0.139)</td>
<td>-0.315 (0.241)</td>
<td>-0.0372 (0.0998)</td>
<td>0.359 (0.151)</td>
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<td>(KID_i \times {LFSSP_{i,t} = U})</td>
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<td>1.211 (0.656)</td>
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<td>-0.991** (0.316)</td>
<td>-0.352* (0.649)</td>
<td>-0.609 (0.614)</td>
<td>0.405 (0.850)</td>
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<td>Age 35-39</td>
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<td>-0.0600 (-0.144)</td>
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<td>-0.115 (0.839)</td>
</tr>
<tr>
<td></td>
<td>-0.273 (0.137)</td>
<td>-0.609* (0.248)</td>
<td>-0.0542 (0.614)</td>
<td>0.405 (0.850)</td>
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<td>Age 40-45</td>
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<td>0.0958 (0.111)</td>
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<td>-0.210 (0.147)</td>
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<td>0.131 (0.168)</td>
<td>0.405 (0.850)</td>
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<td>0.580 (0.220)</td>
<td>-0.389* (0.127)</td>
<td>-0.115 (0.839)</td>
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<tr>
<td></td>
<td>0.423** (0.146)</td>
<td>-0.195 (0.333)</td>
<td>-0.0372 (0.146)</td>
<td>0.405 (0.850)</td>
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<tr>
<td>Non-White, Non-Black</td>
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<td>0.223 (0.182)</td>
<td>0.0942 (0.108)</td>
<td>-0.115 (0.839)</td>
</tr>
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<td></td>
<td>0.475* (0.221)</td>
<td>0.0942 (0.108)</td>
<td>0.125 (0.158)</td>
<td>0.405 (0.850)</td>
</tr>
<tr>
<td>Spouse HS</td>
<td>-0.109 (0.134)</td>
<td>0.589 (0.605)</td>
<td>-0.108 (0.126)</td>
<td>-0.115 (0.839)</td>
</tr>
<tr>
<td></td>
<td>0.199 (0.248)</td>
<td>-0.364 (1.086)</td>
<td>-0.389** (0.143)</td>
<td>0.405 (0.850)</td>
</tr>
<tr>
<td>Spouse COL</td>
<td>-0.166 (0.151)</td>
<td>0.548 (0.599)</td>
<td>0.058 (0.151)</td>
<td>-0.115 (0.839)</td>
</tr>
<tr>
<td></td>
<td>0.0628 (0.281)</td>
<td>-0.383 (1.070)</td>
<td>0.127 (0.169)</td>
<td>0.405 (0.850)</td>
</tr>
<tr>
<td>(LFSSP_{i,t_0} = U)</td>
<td>-0.0686 (-0.152)</td>
<td>0.272 (0.277)</td>
<td>0.0369 (0.161)</td>
<td>-0.115 (0.839)</td>
</tr>
<tr>
<td></td>
<td>0.185 (0.244)</td>
<td>0.587 (0.556)</td>
<td>-0.107 (0.193)</td>
<td>0.405 (0.850)</td>
</tr>
<tr>
<td>(LFSSP_{i,t_0} = N)</td>
<td>0.0897 (0.108)</td>
<td>0.0305 (0.177)</td>
<td>-0.382 (0.324)</td>
<td>-0.115 (0.839)</td>
</tr>
<tr>
<td></td>
<td>-0.215 (0.216)</td>
<td>-0.108 (0.435)</td>
<td>0.0577 (0.328)</td>
<td>0.405 (0.850)</td>
</tr>
<tr>
<td>(UR_t)</td>
<td>-0.108*** (-0.0140)</td>
<td>-0.118*** (-0.0261)</td>
<td>-0.0954* (-0.0250)</td>
<td>-0.145*** (-0.0286)</td>
</tr>
<tr>
<td></td>
<td>-0.109*** (-0.0140)</td>
<td>-0.0954* (-0.0250)</td>
<td>-0.145*** (-0.0286)</td>
<td>0.026 (0.0281)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.174 (0.180)</td>
<td>-1.808*** (0.334)</td>
<td>-0.0131 (0.654)</td>
<td>-0.145*** (-0.0286)</td>
</tr>
<tr>
<td></td>
<td>-1.808*** (0.334)</td>
<td>-1.808*** (0.334)</td>
<td>-0.0131 (0.654)</td>
<td>-0.145*** (-0.0286)</td>
</tr>
<tr>
<td>Observations</td>
<td>7690 0.021 0.021 0.021</td>
<td>2625 0.026 0.026 0.026</td>
<td>6620 0.023 0.023 0.023</td>
<td>3212 0.026 0.026 0.026</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* \(p < 0.05\), ** \(p < 0.01\), *** \(p < 0.001\)

Table 3.4: Multinomial Logit Regression of Transitions from Unemployment \((t_{t-1} = U)\). The regressions are based on matched monthly CPS data for married individuals age 30-45. HS (COL) sample consists of individuals such that their spouse and themselves are high school (college) educated. The reported labor force state is corrected for classification errors using the de-NUN and de-UNU method in Elsby et al. (2015). The regression equation is provided in Section 3.
Table 3.5: Spousal Unemployment Effects on Transition Probability. The effects are estimated based on matched monthly CPS data in 1994-2014 for married individuals age 30-45. HS (COL) sample consists of individuals such that their spouse and themselves are high school (college) educated. Spousal unemployment effects are estimated as average marginal effects of “spouse U” on the monthly transition rates, based on regressions in Section 3 (Results are reported in Tables 3.3 and 3.4).

**Choice set.** In each period during the working stage, the choice set contains the search intensities of the spouses \( s_h, s_w \) and household savings \( a' \). An individual is either employed (\( l^i = 1 \)) or non-employed (\( l^i = 0 \)). Only non-employed individuals can find employment, so that the household chooses positive search intensity only for its non-employed members. A non-employed individual who searches at \( s_i > \bar{s} \) is categorized as an unemployed worker by the econometrician; otherwise, the individual is categorized as a non-participant. The search intensity decision thus encompasses the decision between the two non-employment states—unemployment and non-participation. In each period during the retirement stage, the choice set contains only the household savings \( a' \).

**Transitions between labor force states.** In each period during the working stage, a non-employed individual is subject to a transitory \( \eta \)-shock such that \( Pr(\eta_i, \tau = 1) = \pi_\eta \) and \( Pr(\eta_i, \tau = 0) = 1 - \pi_\eta \). The \( \eta \)-shock induces exogenous transitions between unemployment and non-participation, which capture the unexpected incidences such as sickness and family emergency that inevitably pause job search efforts.

---

<table>
<thead>
<tr>
<th>Spousal Unemployment Effect</th>
<th>Average Transition Rate</th>
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</thead>
<tbody>
<tr>
<td><strong>Effects on HS Wives</strong></td>
<td></td>
</tr>
<tr>
<td>N-to-U</td>
<td>0.050*** (0.007)</td>
</tr>
<tr>
<td>U-to-N</td>
<td>-0.043* (0.017)</td>
</tr>
<tr>
<td><strong>Effects on COL Wives</strong></td>
<td></td>
</tr>
<tr>
<td>N-to-U</td>
<td>0.027*** (0.010)</td>
</tr>
<tr>
<td>U-to-N</td>
<td>-0.059* (0.024)</td>
</tr>
<tr>
<td><strong>Effects on HS Husbands</strong></td>
<td></td>
</tr>
<tr>
<td>N-to-U</td>
<td>0.131** (0.045)</td>
</tr>
<tr>
<td>U-to-N</td>
<td>-0.024* (0.010)</td>
</tr>
<tr>
<td><strong>Effects on COL Husbands</strong></td>
<td></td>
</tr>
<tr>
<td>N-to-U</td>
<td>0.095 (0.056)</td>
</tr>
<tr>
<td>U-to-N</td>
<td>-0.038** (0.012)</td>
</tr>
</tbody>
</table>

(1) Standard errors in parentheses. * \( p < 0.05 \), ** \( p < 0.01 \), *** \( p < 0.001 \)
If $\eta_{i,\tau} = 1$, the individual must choose $s_i = 0$. If $\eta_{i,\tau} = 0$, the non-employed individual becomes employed with probability $\lambda$, which is a function in the search intensity and the baseline job finding rate $\lambda_{i, z}$, a parameter that depends on the gender $i$ and the aggregate state of the labor market $z$.

An employed worker becomes non-employed with probability $\delta_{i, z}$, an exogenous parameter that depends on gender and $z$.

**Incomes.** In each period, an employed individual receives wage $w_{i, p^i} > 0$, a non-employed individual receives non-employment income $w_{i, p^i}^n > 0$, and a retiree receives retirement income $w_{i, p^i}^r > 0$. $p^i$ denotes the person-type of individual $i$. For each individual $(i, p^i)$, there is only one type of employment opportunity that offers a wage $w_{i, p^i}$ which is deterministic throughout the individual’s lifetime. Since all jobs that a given individual encounters are identical, I use the terms “job” and “employment” interchangeably in this paper. Because of this assumption, there is no incentive to search on-the-job. In addition, as long as the wage is greater than the non-employment income ($w_{i, p^i} > w_{i, p^i}^n$), individuals always start employment once they find a job, and would not quit a job voluntarily.

**Preferences.** The household derives utility $u(c)$ from household consumption $c$ with $u' > 0$. Since intra-household risk-sharing is important for the counter-cyclicality of the search intensity, I allow for risk-aversion, that is, $u''(c) < 0$.

Searching for employment is costly in utility terms—the household suffers a disutility of $k^i(s_i)$ if spouse $i$ searches at $s_i$. The search disutility increases in $s_i$, and, to ensure that the household does not choose infinite search intensity, it is a convex function. The disutility captures the pecuniary and non-pecuniary costs of carrying out job-search, including the value of foregone leisure and home production. The disutility function is gender-specific to allow for cross-gender differences in carrying out job search.

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*The non-employment income does not correspond to the unemployment benefits; it is positive in order to avoid the situation in which a household faces zero consumption and negative infinite utility. Modeling the unemployment insurance (UI) system is beyond the scope of the paper. I briefly discuss its implications on cyclical behaviors in Section 5.7.3.*

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Moreover, I assume that the disutility from search and utility from consumption are additively separable.

The search disutility function does not depend on the household asset level. Together with the decreasing absolute risk aversion feature of the CRRA utility function and the additive separability between consumption and search, the model is able to give plausible implications that, relative to wealthier households, those from less wealthy households search more intensively. These are consistent with the empirical findings found in Bloemen and Stancanelli (2001) and Alexopoulos and Gladden (2004).

**Aggregate State.** The aggregate state $z$ follows a two-state Markov process. The aggregate state is either Good or bad, i.e. $z \in \{G, B\}$. The aggregate state transition probabilities are given as $Pr(z' = G|z = B) = \pi_{z,B}$ and $Pr(z' = B|z = G) = \pi_{z,G}$. The aggregate state affects the household behavior through the baseline job finding rate $\lambda_{i,z}$ and the employment separation rate $\delta_{i,z}$. A “Good” aggregate state is typically characterized by a high baseline job finding rate and, sometimes, a low employment separation rate.

### 4.1 Value Functions

In the working stage, the household observes the current asset level $a$, the employment status of each spouse $l^i$, the current aggregate state of the labor market $z$, and the realization of $\eta$-shocks $\eta^i$ of each spouse. For all $\tau$ such that $1 \leq \tau \leq \tau_{work}$, the household’s value function is given as follows.

$$V_\tau(a, l^h, l^w, z, \eta^h, \eta^w) = \max_{a', s^h \in S(l^h, \eta^h), s^w \in S(l^w, \eta^w)} \left\{ u(c) - k^h(s^h) - k^w(s^w) + \beta E V_{\tau+1}(a', l'^h, l'^w, z', \eta'^h, \eta'^w) \right\}$$

subject to the budget constraint
\[0 \leq a' \leq (1 + r)a + \sum_{i=h,w} [w_{i,p} l^i + w_{i,p}^h (1 - l^i)] - c\] (4.2)

The expectation in the value function is taken over \(\{l^{h'}, l^{w'}, z', \eta^{h'}, \eta^{w'}\}\). I use the prime notation to denote the next period. The transition probabilities are given as follows.

\[
\begin{align*}
Pr(l^i = 0|l^i = 1) &= \lambda(s, \lambda_i, z) \quad i = h, w; \\
Pr(l^i = 1|l^i = 0) &= \delta_{i,z} \quad i = h, w \\
Pr(z' = G|z = B) &= \pi_{z,B} \\
Pr(z' = B|z = G) &= \pi_{z,G} \\
Pr(\eta^i = 1) &= \pi_{\eta,i} \quad i = h, w
\end{align*}
\]

Only non-employed individuals with \(\eta^i = 0\) are eligible to search for work. They choose a search intensity out of the feasible set \(S(l^i = 0, \eta^i = 0) = S = \{0, 0.4, 0.8, 1.2, 1.6, 2.0\}\). The classification of the non-employed into unemployed workers and non-participants is according to a cut-off rule. Those who do not search or search at an intensity smaller than 1 are classified as labor force non-participants; those who search at an intensity above 1 are classified as unemployed workers. Although this classification has no bearing on the decision making of the model agents, it helps generate statistics that can be compared to the actual data. The household discount the future with a discount factor \(\beta\), and \(r\) is the rate of return on assets.

In the retirement stage, the household can no longer send its members to the labor force; it makes the savings decisions based on solely the current asset level. For \(\tau\) such that \(\tau_{work} + 1 \leq \tau \leq \tau_{work} + \tau_{ret}\), the household value function is given as follows.

\[
V_{\tau}(a, l^h, l^w, z, \eta^h, \eta^w) = V^R_{\tau}(a) = \max_{a'} \left\{ u(c) + \beta V^R_{\tau+1}(a') \right\}
\] (4.3)
subject to the budget constraint

\[ 0 \leq a' \leq (1 + r)a + \sum_{i=h,w} w_{i,p}^r - c \]

At \( \tau = \tau_{\text{work}} + \tau_{\text{ret}} + 1 \), the household’s lifecycle terminates. For \( \tau \geq \tau_{\text{work}} + \tau_{\text{ret}} + 1 \), the household value \( V^{R}_\tau \) is zero.

### 4.2 Model Implications on the Cyclicality of Search Intensity

In Appendix A, I use a simplified version of the model presented here to illustrate the two mechanisms in the model that can generate counter-cyclical search intensity. The first mechanism is the wealth effect resulting from cyclical fluctuations in the expected future incomes. Conditional on both spouses being non-employed, a decrease in one’s own and one’s spouse’s job finding rate lowers expected future incomes of the two, leading to increases in search intensity. Unconditionally, the expected non-employment duration of one’s spouse is longer with lower job finding rate, and the spouse of an non-employed searches more due to wealth effects. This also leads to the observation of higher search intensities in periods of lower job finding rates. The second mechanism comes from the cyclical variations in the comparative advantage. If one’s job finding rate is less cyclical than the spouse’s, the person has greater comparative advantage (or less comparative disadvantage) than the spouse, and thus chooses more counter-cyclical search intensity.

### 5 Estimation

#### 5.1 Simulated Method of Moments

The model in Section 4 can be estimated by the Simulated Method of Moments (SMM). Given a vector of structural parameters \( \theta \), I first solve the model by backward induction for the choice functions. Using the choice functions, I simulate a sample of households and compute a vector of
moments \( \hat{m}(\theta) \), which, for example, may include the average labor force transition probabilities. The SMM estimator is

\[
\hat{\theta}_{SMM} = \arg \min_{\theta} (\hat{m}(\theta) - m_{\text{data}})^T \hat{W}^{-1} (\hat{m}(\theta) - m_{\text{data}})
\]

where \( \hat{W} \) is the weighting matrix which I construct using the sample variances of the moments as diagonal elements and zeros as off-diagonal elements. I obtain the sample variances of data moments by bootstrapping the data sample and computing \( N_{\text{boot}} \) sets of bootstrap data moments. I solve for the SMM estimator using the Nelder-Mead Simplex algorithm.

5.2 The Data

I use the Current Population Survey (CPS) data from 1994 to 2014 to estimate the model. The CPS is a monthly survey that collects detailed information on topics including demographic characteristics and labor force activities, from about 60,000 households that constitute a nationally representative sample. Each household is in the survey for four consecutive months, out of the survey for 8 months, and in for another four months. The survey design allow me to calculate month-to-month transition probabilities between labor force states. The gross flows between non-participation and unemployment is relatively small, especially for married males. The large sample size in the CPS is essential in producing reliable measurements of such flows.

I restrict the sample to civilian couples comprised of household-heads and their spouse such that the labor force and demographic information are available for both spouses. I focus on two groups by the education level of the couples. The first group (hereafter, HS) contains couples both of whom are high-school educated and the second group (hereafter, COL) contains only couples both of whom have some college education or a college degree.

In addition, I drop couple-months if I observe that the couple is becomes married or separated in the enclosing four-month window of consecutive surveys. I also drop couple-months if either spouse reports periods of disability or retirement in the enclosing four-month window.
Finally, I restrict the sample based on age. Specifically, I select couples such that at least one spouse is above age 30 (inclusive) and at least one spouse is below age 45 (inclusive)\(^9\) I choose the 30-45 age range and ignore the older population for two reasons. First, I do not model the retirement decision. The retirement decisions may be correlated with the business cycle\(^10\) and are correlated between spouses. Second, in the model, households save for retirement. Second, the model does not distinguish between savings for retirement purpose and savings for consumption-smoothing purpose. In practice, however, the retirement assets (such as real estate, pension funds) are more illiquid and using them for consumption is more costly. A household with illiquid assets are not as well-insured against income fluctuations than one with liquid asset. As the model households save for retirement, the savings can be used for precautionary purpose without extra cost. As a result, they are overly insured and this affects search decisions, and in particular, the search response to spousal non-employment.

The final sample contains 1,054,667 HS couple-months and 619,890 COL couple-months over the span of 252 months, from January 1994 to December 2014.

### 5.3 Aggregate States of the Labor Market

In the model, the aggregate state \(z\) affects the household decisions in two ways: through the baseline job finding rate \(\lambda_{i,z}\) and through the job separation probability \(\delta_{i,z}\). Shimer (2012) find that the job finding rate accounts for three quarters of the cyclicality fluctuation in the unemployment, whereas the separation rate is largely irrelevant in recent decades. Because of this, I identify the aggregate state of the labor market according to the monthly job-finding probability of workers.

The job finding probability is computed as the monthly unemployment-to-employment transition probability (U-to-E) from the matched CPS monthly data. I approximate the monthly U-to-E with a two state Markov process by maximum likelihood estimation using the CPS data from 1976 to 2014. Months in which the approximated U-to-E takes the higher value are identified as \(z = G\), otherwise, \(z = B\).

---

\(^9\)I select the sample in this fashion (instead of using the average age or restricting both spouses to be between 30-45) because this gives me a relatively large sample size to compute transitions probabilities of less common flows.

\(^{10}\)For example, see Haaga and Johnson (2012), Merkurieva (2013).
Figure 5.1 shows the data and approximated U-to-E transition probabilities. For both HS and COL samples, the probability for an unemployed worker to find employment in a month is around 0.24 in $z = B$, and 0.31 in $z = G$. The aggregate state transition probabilities $\pi_{z,G}$ and $\pi_{z,B}$ are shown in Table 5.1. On average, a bad state lasts for 38 months in both HS and COL samples; and a good state lasts for 40 months in the HS sample, and 56 months in the COL sample.

Given the definitions approximated aggregate states, the separation probabilities $\delta_{i,z}$ are computed directly from the data and shown in Table 5.1.

### 5.4 Wage and Retirement Income

In the model, each individual faces a fixed wage throughout his or her lifetime according to the person-type $p^i$. I assume that there are three person-types for each gender, i.e. $p^i \in \{\text{low, med, high}\}$. The wages $w_{i,p^i}$ are estimated using data on usual weekly earnings from the CPS. I convert the weekly earnings are converted to monthly earnings and adjust for inflations using the consumer price index. I exclude the top and bottom 1% earnings in each sample. I then take the average of the earnings data of each individual, and compute the mean $\bar{\omega}_i$ and the standard deviation $\sigma_{\omega_i}$ of the log individual earnings by gender. I define $w_{i,p^i=M} = \exp \bar{\omega}_i$, $w_{i,p^i=L} = \exp(\bar{\omega}_i - \sigma_{\omega_i})$, and $w_{i,p^i=H} = \exp(\bar{\omega}_i + \sigma_{\omega_i})$.

I also compute the covariance $\sigma_{\omega_i,\omega_j}$ of husbands’ and wives’ earnings. To determine $p^i$ and $p^j$ for each simulated household, I first draw a pair of wages $\hat{\omega}_i, \hat{\omega}_j$ from the bivariate normal distribution specified by $\bar{\omega}_i, \bar{\omega}_j, \sigma_{\omega_i}, \sigma_{\omega_j}$, and $\sigma_{\omega_i,\omega_j}$. $p^i$ and $p^j$ are defined as $\arg\min_{p^i,p^j} [(\hat{\omega}_i - \ln w_{i,p^i})^2 + (\hat{\omega}_j - \ln w_{j,p^j})^2]$.

I assume that $w_{i,p^i}^{\text{ret}} = 0.02 w_{i,p^i}$. The retirement income $w_{i,p^i}^{\text{ret}}$ is determined roughly following the Primary Insurance Amount (PIA) computed by the Social Security. While the actual PIA is computed using the average indexed monthly earnings (AIME), which averages individual indexed earnings

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11 The usual weekly earnings data represent earnings before taxes and other reductions, and includes overtime pays. The data is collected from out-going rotations, so that each individual is asked about the earnings at most twice.
Figure 5.1: U-to-E transition probability for married individuals between age 25 and 60. HS sample contains high school educated married couples, and COL sample contains married couples who have some college education or a college degree. Data is drawn from the matched CPS monthly data, 1976-2014.
in up to 35 best working years, I simply use the model wages \( w_{i,p} \) as the basis for computing the retirement income. Following the computation of the PIA, the retirement income is the sum of the following: 90% of \( w_{i,p} \) under point 1, 32% of \( w_{i,p} \) between points 1 and 2, and 15% of \( w_{i,p} \) in excess of point 2. I use bend points for year 2014 as \( w_{i,p} \) is in 2014 dollars. The two bend points are 816 and 4,917\(^{12}\).

Table 5.1 shows the values of \( w_{i,p} \) and \( w_{i,p}^r \).

5.5 Parametric Specifications

**Utility Function** \(^{12}\)I adopt the widely-used constant-relative-risk-aversion (CRRA) formulation.

\[
 u(c) = \begin{cases} 
 c^{(1-\gamma)} & \gamma > 0, \gamma \neq 1 \\
 \ln(c) & \gamma = 1 
\end{cases}
\] (5.1)

I do not attempt to estimate the coefficient of risk-aversion, \( \gamma \), because of the lack of strong identification. Flabbi and Mabli (2012) argue that the correlation between one’s labor market decisions and one’s spouse’s labor force status identifies the risk-aversion parameter. However, this correlation is to a great extend generated by the wealth effects of spousal income shocks, and the magnitude of the wealth effects depends crucially on the household asset level. Unfortunately, the CPS does not contain information on household assets. In estimating the model, I choose \( \gamma = 2 \), following the common practice in the literature.

**Search Disutility Function** \(^{12}\)I assume that the search disutility function takes the following form

\[
 k^i(s^i) = \kappa_0^i s^i & \kappa_1^i > 0, \kappa_1^i > 1
\] (5.2)

The job-finding probability \( \lambda \) is parametrized as follows.

\(^{12}\)http://www.ssa.gov/oact/cola/bendpoints.html
\[ \lambda(s, \lambda_{i,z}) = \min\{1, s\lambda_{i,z}\} \quad \lambda_{i,z} \geq 0; i = h, w \quad (5.3) \]

Note that \( \kappa_{i,0}, \lambda_{i,z} \) and \( \bar{s} \) (the threshold search intensity above which a non-employed worker is classified as unemployed) cannot be jointly identified. I therefore normalize \( \bar{s} = 1 \).

**\( \eta \)-Shock** The \( \eta \)-shock captures the unexpected incidences that forces individuals to pause job search. I assume that the \( \eta \)-shock only hits women because, in the data, men are rarely non-participants and the U-to-N transitions are less likely (Figure 3.1). Moreover, I set \( \pi_{\eta,w} = 0.15 \), i.e. a 15\% chance that a non-employed wife being hit by the \( \eta \)-shock and pause job-search every month. The value allows the model to better match the levels of the transitions between non-participation and unemployment.

**Interest Rate and Subjective Discount Factor** I set the monthly subjective discount factor \( \beta = 0.9957 \), which corresponds to a commonly used annual discount factor of 0.95, a value commonly assumed in the literature. As I do not model the capital market, the interest rate is exogenously given. I set the monthly interest rate \( r = 0.002 \), which corresponds to an annual interest rate of 0.024. The interest rate is intentionally set to be lower than what is implied by \( \beta(1 + r) = 1 \). Although in a life-cycle model, an interest rate close to the subjective discount rate \( (1/\beta - 1) \) would not lead to arbitrarily high levels of savings as argued by Aiyagari (1994), such an interest can nevertheless lead to excessively high savings which in turn bias the job search outcomes.

The reason for the lower interest rate is that the asset accumulation is two-fold. First, similar to Aiyagari (1994), households in the model face uninsurable risks and a borrowing constraint. They necessarily save more than those who face no uncertainty (or have access to complete markets). Second, households save for life-cycle as well as precautionary purposes. Household accumulate assets as they approach retirement, resulting in higher levels of assets than those in an infinite-time horizon model.

One may argue that making the interest rate \( r \) smaller than the subjective discount rate \( (1/\beta - 1) \) suppress asset accumulation, which in turn causes the model households to overreact to labor market
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate State Transition Rate</td>
<td>$\pi_{z,\text{Good}}$ 0.025 $\pi_{z,\text{Bad}}$ 0.026</td>
<td>CPS, see Sec. 5.3</td>
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<tr>
<td>Employment Separation Rate</td>
<td>$\delta_{h,z=\text{good}}$ 0.014 $\delta_{h,z=\text{bad}}$ 0.018</td>
<td>[ \delta_{i,e^i,z} ]</td>
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<tr>
<td></td>
<td>$\delta_{w,z=\text{good}}$ 0.032 $\delta_{w,z=\text{bad}}$ 0.031</td>
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</tr>
<tr>
<td>Monthly Wage ($w_{i,e^i,p^i}$)</td>
<td>$w_{h,p^h=\text{high}}$ 10003 $w_{h,p^h=\text{med}}$ 3680 $w_{h,p^h=\text{low}}$ 1354 $w_{w,p^w=\text{high}}$ 6118 $w_{w,p^w=\text{med}}$ 2251 $w_{w,p^w=\text{low}}$ 828</td>
<td>CPS, see Sec. 5.4</td>
</tr>
<tr>
<td>Monthly Retirement Income ($w_{i,e^i,p^i}$)</td>
<td>$w_{r,h,p^h=\text{high}}$ 2810 $w_{r,h,p^h=\text{med}}$ 1651 $w_{r,h,p^h=\text{low}}$ 906 $w_{r,w,p^w=\text{high}}$ 2227 $w_{r,w,p^w=\text{med}}$ 1193 $w_{r,w,p^w=\text{low}}$ 738</td>
<td></td>
</tr>
<tr>
<td>non-employment income</td>
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</tr>
<tr>
<td>Coefficient of Risk Aversion $\gamma$</td>
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<td>Wives’ $\eta$-Shock Arrival Rate $\pi_{i=w,\eta}$</td>
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<tr>
<td>monthly interest rate $r$</td>
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<td>See Sec. 5.5</td>
</tr>
<tr>
<td>monthly discount factor $\beta$</td>
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<td></td>
</tr>
</tbody>
</table>

Table 5.1: Parameters Determined Outside of the Model.

risks compared to actual households. However, it should be noted that assets in the model differ from those in reality. In the real world, households set aside the assets for retirement by, for example, investing in pension accounts or real estate. The retirement assets are likely to have high return but are relatively illiquid. Consumption assets such as an ordinary savings account, in contrast, are highly liquid but yields lower returns. In the model, however, there is no distinction between retirement and consumption assets. As a result, the total level of assets possessed by survey households overestimates their ability to smooth consumption, and the rate of return on non-consumption assets does not correspond to the interest rate in the model.
5.6 Moments and Identification

In the SMM estimation, I use a set of moments, listed in Table 5.2, by gender and spousal labor force status (employed or unemployed). In particular, I estimate the structural parameters by matching the labor market stocks - labor force participation rate and unemployment rate, and flows - unemployment to employment transitions, non-participation to employment transitions, and non-participation to unemployment transitions. I estimate 8 parameters from the 40 moments using SMM. The parameters are the baseline job finding probabilities $\lambda_{i,z}$, and the search disutility parameters $\kappa^i_0$ and $\kappa^i_1$. Because of the complicated mapping from the structural parameters to the moments, a rigorous analysis of identification cannot be provided. In the rest of this subsection, I explain the moments that mainly identify each parameter.

Given that the utility function is fixed, $\kappa^i_0$ determines the level of search disutility relative to the utility from consumption. $\kappa^i_0$ plays an important role in determining the average level of search intensity, a trade of leisure for future consumption opportunities. The labor force participation rate and the unemployment rate together give ratio of unemployment to non-participation, which corresponds to the ratio of high-intensity searchers to low-intensity searchers.

The curvature of the disutility function $\kappa^i_1$ influences the correlation between search intensity and spousal employment status. With a linear search disutility, the household would always choose the highest search intensity for the primary earner before engaging the secondary earner in job search. With a more convex search disutility, the marginal cost of primary earner’s search intensity is increasing, and thus whenever the primary earner becomes non-employed, the secondary earner is more likely to engage in job search. As a result, the variations in the labor force participation rate, unemployment rate, and the N-to-U transition rate across spousal labor force status helps identify $\kappa^i_1$.

The transition probabilities from unemployment and non-participation to employment are products of the baseline job finding rate $\lambda_{i,z}$ and the average search intensity of the respective non-employment states. $\lambda_{i,z}$ are mainly identified by these transition probabilities. $\lambda_{i,z}$ is the key driver of the

\textsuperscript{13}Primary earner is defined as the spouse with the higher marginal return to search relative to the marginal cost of search.
Table 5.2: Moments Used in SMM Estimation. All moments are by aggregate state, gender and spouse’s labor force status (employed or unemployed).

aggregate state fluctuations. If \( \lambda_{i,B} = \lambda_{i,G} \) for both genders, there would be little variation in the simulated moments across aggregate states.

5.7 Estimation Results

5.7.1 Parameter Estimates

Table 5.3 presents structural parameter estimates with standard errors. The standard errors are obtained using the formula provided by Gourieroux et al. (1993). A key parameter is the exponent parameter in the search cost function, \( \kappa_{i}^{1} \) which plays an important role in determining the joint-search pattern. In both High School and the College samples, \( \kappa_{i}^{1} \) is considerably higher for husbands than wives, meaning that husbands' marginal cost of search increases much more rapidly than wives'. Although in most households the husband has higher wage and higher baseline job finding rate, the wife’s participation in job search becomes necessary when it is too costly for the husband to further increase his search intensity. A low \( \kappa_{w}^{1} \) leads to higher elasticity in wives’ search intensity in response to the husband’s employment status and household asset level.

Moreover, it is worth noting that, for both samples, the cyclical variations in the baseline job finding rate is smaller for wives than for husbands, i.e. \( \lambda_{h,z=Good} - \lambda_{h,z=Bad} > \lambda_{w,z=Good} - \lambda_{w,z=Bad} \). This implies that, ceteris paribus, the husband has a smaller comparative advantage in the labor market in a Bad aggregates state than in the Good one.
Table 5.3: Structural Parameter Estimates and Standard Errors. The HS (COL) sample consists of married households in which both spouses are high school (college) educated.

<table>
<thead>
<tr>
<th></th>
<th>HS Sample</th>
<th></th>
<th>COL Sample</th>
<th></th>
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</thead>
<tbody>
<tr>
<td>Search cost function: $k^i(s_i) = \kappa_0^i s_i^\kappa_1^i$</td>
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</tr>
<tr>
<td>$\kappa_0^h$</td>
<td>4.00E-5</td>
<td>9.21E-7</td>
<td>1.47E-5</td>
<td>6.35E-7</td>
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<td>$\kappa_1^h$</td>
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<td>2.43E-2</td>
<td>5.89</td>
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<td>$\kappa_0^w$</td>
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<td>1.18E-6</td>
<td>1.39E-4</td>
<td>1.06E-6</td>
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<tr>
<td>$\kappa_1^w$</td>
<td>1.86</td>
<td>9.13E-3</td>
<td>1.39</td>
<td>1.06E-2</td>
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<tr>
<td>Baseline job finding probability: $\min{1, s\lambda_{i,z}}$</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$\lambda_{h,z=G}$</td>
<td>0.309</td>
<td>3.63E-3</td>
<td>0.246</td>
<td>8.65E-3</td>
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<tr>
<td>$\lambda_{h,z=B}$</td>
<td>0.236</td>
<td>1.03E-3</td>
<td>0.204</td>
<td>6.88E-3</td>
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<tr>
<td>$\lambda_{w,z=G}$</td>
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<td>1.48E-4</td>
<td>0.245</td>
<td>4.72E-3</td>
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<td>$\lambda_{w,z=B}$</td>
<td>0.179</td>
<td>3.58E-4</td>
<td>0.230</td>
<td>3.34E-3</td>
</tr>
</tbody>
</table>

5.7.2 Goodness of Fit

Tables 5.4 shows the fit of the moments. In both the High School and the College samples, the model closely matches several patterns displayed in the data. I first examine the patterns in the moments across spouse’s employment status, conditional on the aggregate state. For both wives and husbands, the unemployment rate conditional on spousal unemployment is substantially higher than that conditional on spousal employment. For wives, the labor force participation rate is also higher when the husband is unemployed. The patterns in the unemployment and labor force participation rates can be explained by the N-to-U transitions. The N-to-U transition rate is higher under spousal unemployment than spousal employment. One reason for this pattern is an increase in the optimal search intensity in reaction to spousal job loss. To illustrate this, I show wife’s optimal search decision by husband’s employment status in Figures 5.2a and 5.2b. The optimal search intensity is (weakly) higher when the individual has a spouse who is non-employed. If the household asset level falls within the two vertical lines, the spouse’s employment separation induces an increase in search intensity from $s < \bar{s}$ to $s > \bar{s}$ ($\bar{s} = 1$), which is recorded as an N-to-U transition. Another reason for the higher N-to-U transition rate under spousal unemployment is that households with
two non-employed spouses have lower household asset levels. Figure 5.2b shows that a double-non-
employment household dis-saves more, and the asset level drops faster. A drop in the asset level
leads an individual to increase search intensity (Figure 5.2a), and if the increase in search intensity
crosses $\bar{s}$, an N-to-U transition is recorded.

Next, I examine the patterns in the moments across the aggregate state $z$, conditional on spousal
employment status. In both the data and the model, while the unemployment rate is higher in $z = B$, the change across $z$ is much smaller compared to the change across spousal employment
status. The reasons can be seen from Figures 5.2c and 5.2d. Controling for spousal employment
status, the difference in optimal search intensity by aggregate state is less noticeable. When $z$
switches from Good to Bad, the set of asset levels such that an individual would increase search
intensity from $s < \bar{s}$ to $s > \bar{s}$ is extremely small (indicated by the region between the pair of vertical
lines in Figure 5.2c). Moreover, the saving (or, dis-saving) behavior does not differ significantly by
aggregate state (Figure 5.2d) once the spousal employment status is controlled. As a result, the
aggregate state alone does little to affect the search intensity decision, and thus the unemployment
rate.

5.7.3 Cyclicality

Tables 5.5 shows how the stock and flow statistics vary across aggregate states, unconditional on
spouse’s employment status. The unconditional statistics are not targeted in the SMM estimation.
Qualitatively, the model captures most of the cyclical patterns presented in the data.

The labor force participation rate matches well to the data: it is weakly pro-cyclical in the High
School sample, and a-cyclical in the College sample. The model also generates counter-cyclical
unemployment rates, but the counter-cyclicalty is weaker compared to the data, especially among
Table 5.4: Fit of Moments. Data moments are computed based on the matched monthly CPS data. A description of the sample can be found in Section 5.2. Model moments are computed based on the data simulated from the estimated model. LFPR = labor force participation rate, UR = Unemployment Rate; U-to-E = Unemployment to Employment transition rate, N-to-E = Non-Participation to Employment transition rate, and N-to-U = Non-Participation to Unemployment transition rate. \( z \) = aggregate state of the labor market. Spouse E (U) = spouse’s labor force state is employed (unemployed).
Figure 5.2: Optimal Household Decisions by Spousal Employment Status and Aggregate State. This illustration is based on the HS model with estimated parameter specifications. I show wife’s optimal search intensity and household savings decisions by husband’s employment status at age=30, \( z = B \), \( p^w = p^h = 2 \). In 5.2a and 5.2b, \( z = Bad \); in 5.2c and 5.2d, \( t^h = 0 \).
College wives. This results from the fact that the simulated women’s job finding rate from unemployment (U-to-E) is not pro-cyclical enough, and the transition rate from non-participation to unemployment (N-to-U) is not counter-cyclical enough.

These discrepancies suggest that there are other factors contributing to the countercyclicality of the unemployment rate that the model has not captured. One of such factors may be cyclical shifts in the composition of non-employed workers, a view supported by Elsby et al. (2015). Individuals are heterogeneous in their degree of labor force attachment due to differences in ability or taste. In recessions, the pool of unemployed workers is saturated with highly attached workers. These workers are less likely to exit the labor force even if likelihood of finding a job is lower, and thus giving rise to higher unemployment rate. In my model, however, these dimensions of heterogeneity are missing.

Another factor that may cause counter-cyclicality in the unemployment rate is the extensions of unemployment insurance (UI) benefits during recessions. As a requirement for claiming the benefits, the recipient is required to engage in active job search. Because of this, individuals are encouraged to stay unemployed rather than dropping out of the labor force during recessions. This is supported by Rothstein (2011) who finds that UI extensions lowers the labor force exit rate during the Great Recession. However, Cullen and Gruber (2000) argue that UI crowds out spousal labor supply as a household self-insurance device, which implies a less counter-cyclical N-to-U transition rate and thus a less counter-cyclical unemployment rate. Overall, the effects of the UI system on the cyclicality of the unemployment rate is ambiguous.

6 Discussion

6.1 Countercyclical Unemployment Rate

The estimated model generates cyclical fluctuations in search intensity that contributes the countercyclicality of the unemployment rate. The counter-cyclicality in search intensity owes to the countercyclical variations in spousal employment status, as well as the changes in the comparative advantage
Table 5.5: Unconditional Moments. Data moments are computed from the matched monthly CPS data. A description of the sample can be found in Section 5.2. Model moments are simulated from the estimated model. LFPR = labor force participation rate, UR = Unemployment Rate; U-to-E = Unemployment to Employment transition rate, NP-to-E = Non-Participation to Employment transition rate, and NP-to-U = Non-Participation to Unemployment transition rate. z = aggregate state of the labor market.
within the household\textsuperscript{14} In other words, the unemployment rate is more counter-cyclical as a result of the fact that the job search decisions are jointly made by spouses in a married household. In this subsection, I investigate how much of the counter-cyclicality in the unemployment rate is unique to individuals in a married household. To this end, I look at the effects of fluctuations in search intensity on the unemployment rate, and then compare the effects by assumptions on joint-search. I explain the two steps below.

In the first step, I compare the baseline unemployment rate to the unemployment rate computed while ignoring variations in individuals’ search intensity over time. The latter unemployment rate is labeled as “s-constant”. In the s-constant case, each individual’s search intensity is fixed at a level that is randomly drawn from the individual’s “s-distribution” which formed by pooling all search intensity the individual had chosen in periods in which he or she is non-employed and eligible to search (i.e., \( l = 0 \) and \( \eta = 0 \)). Rather than taking the average life-time search intensity, this way of computing the s-constant unemployment rate ensures that the resulting unemployment rate is on average similar to the baseline.

In the next step, in order to understand the role of joint-search in causing counter-cyclicality in \( s \), I conduct the previous exercise in two counterfactual environments in which search decisions are not jointly made with a household. In the first counterfactual environment, labeled as CF1, individuals make their own decisions independent of their spouse. Specifically, an individual of gender \( i \) and person-type \( p^i \) faces the following value function in the working stage:

\[
V_{t}^{i,p^i}(a, l, z, \eta) = \max_{a',s\in S(l,\eta)} \left\{ u^i(c) - k^i(s) + \beta \mathbb{E}V_{t+1}^{i,p^i}(a', l', z', \eta') \right\}
\]

subject to the budget constraint

\[
0 \leq a' \leq (1 + r)a + [w_{i,p^i}l + w_{i,p^i}(1 - l)] - c
\]

\textsuperscript{14}Appendix A explains the mechanisms that generates counter-cyclical search intensity in a simplified household model.
In the retirement stage, the value function that the individual \((i,p^t)\) faces is

\[
V_{i,p^t}(a,l,z,\eta) = \max_{a'} \left\{ u^i(c) + \beta V_{i,p^{t+1}}(a') \right\}
\]  

(subject to the budget constraint

\[
0 \leq a' \leq (1 + r)a + w_{i,p^t} - c
\]

In the baseline model, I assume that a household chooses a household consumption without specifying the individual utility functions or how the household consumption is allocated between the two spouses. In the CF1 environment, I assume that an individual of gender \(i\) has the following utility function

\[
u^i(c^i) = \alpha^i u\left(\frac{c^i}{\alpha^i}\right)
\]

where \(c^i\) is the consumption level of \(i\) and \(u(\cdot)\) is the household utility function in the baseline model. This utility function has close ties with the household utility function. In a baseline household, if the two spouses have identical individual utility functions, and if \(\alpha^h\) and \(\alpha^w\) are the weights on husband’s and wife’s utility function respectively, the optimal allocation of the household consumption would be \(\{c^h, c^w\}\) such that \(c^h/c^w = \alpha^h/\alpha^w\). At the optimum, the utility of each spouse is exactly \(\alpha^i u(c^i/\alpha^i)\).

In order for the average unemployment rate to match that of the baseline, I choose \(\alpha^h = 3/4\) and \(\alpha^w = 1/4\).

Whereas individuals in CF1 behave as if they are singles and base their search decision only on their own income stream, in the second counterfactual environment (labeled as CF2), I maintain that there are two income streams based on which search decisions are made. However, within each household, I focus on the search decision of one individual while holding his or her spouse’s search intensity at a constant level of \(s = 1\) and eliminating any cyclical fluctuations in the baseline job finding rate or the separation rate that the spouse may face. In this way, the search intensity of the individual of interest does not fluctuate cyclically in response to the spouse’s labor force status.
The results from the baseline and the two counterfactual environments are summarized in their respective columns in Table 6.1. In addition, I define the cyclicity of a variable \( x \) as 
\[
\overline{x}_{z}^{Good} - \overline{x}_{z}^{Bad}
\]
where \( \overline{x}_{z} \) is the average level of \( x \) in aggregate state \( z \); a negative sign indicates counter-cyclicity.

I first focus on wives from the High School sample. Based on statistics reported in Table 5.5a, the CPS unemployment rate is 0.47 countercyclical. In the simulated data under the baseline environment, the unemployment rate is 0.013 more counter-cyclical than the \( s \)-constant unemployment rate. In other words, fluctuations in search intensity account for 1/10th of the simulated countercyclicity in the unemployment rate. In contrast to this, in both counterfactual environments CF1 and CF2, the \( s \)-constant unemployment rate becomes significantly more counter-cyclical: without the “joint” nature of the search decisions, fluctuations in search intensity lead to a unemployment rate that is around 0.08 less counter-cyclical. Overall, joint-search increases the counter-cyclicity of the unemployment rate by around 0.09, indicating that almost 19% of the counter-cyclicity in CPS unemployment rate is explained by the joint-search.

For wives in the College sample, the CPS unemployment rate is 0.51 counter-cyclical based on Table 5.5b. In the simulation under the baseline environment, the unemployment rate is 0.02 more countercyclical than the \( s \)-constant rate - the counter-cyclicity in the unemployment rate is almost entirely due to fluctuations in search intensity. Results from the two counterfactual environment differ slightly, but both suggest moderate effects of search intensity fluctuations. In the CF1 environment, the cyclicity of the unemployment rate is nearly unchanged, and in the CF2 environment, the unemployment rate is 0.02 more pro-cyclical with fluctuations in search intensity. From these results, it can be concluded that joint-search increases the counter-cyclicity of the unemployment rate by 0.02-0.04, or 4%-8% of the counter-cyclicity in the data unemployment rate.

Comparing the two samples, joint-search is more important for the unemployment rate fluctuations among High School wives than among College wives, which is anticipated given the differences in their wage distributions. This High School workers receive lower wages, and thus accumulate less wealth. As a result, spousal unemployment leads to stronger wealth effects and greater reaction in terms of search intensity.

Turning to the husbands from the two samples, the results suggest that joint-search does not play
a role in generating counter-cyclicality in the unemployment rate. In the baseline environment, fluctuations in search intensity make the unemployment less counter-cyclic. The similar patterns are found in the counterfactual environments, suggesting that joint-search does not cause fluctuations in search intensity that lead to counter-cyclicality in the unemployment rate.

6.2 Cost of Cyclical Fluctuations

The previous subsection shows that women’s unemployment rate is made more counter-cyclic as a result of joint-search behavior. This subsection will show that married households face lower welfare cost of cyclical fluctuations. Here, I measure the difference in the welfare cost of cyclicity between baseline households and individuals in the CF1 environment as described in Section 6.1, whom I refer to as “singles”.

There are two intra-household risk sharing mechanisms that allows married households lower cyclical welfare costs. First, a married household has two independent income sources that help diversify the labor market risks. Second, the joint-search mechanism, which entails varying search intensity depending on spouse’s employment status, further allows household to manage the cyclical risk.

I measure the welfare level of a married household by the monthly consumption-equivalent of a household’s lifetime utility, \( \bar{c} \), defined as follows:

\[
\bar{c} = u^{-1} \left( \frac{\sum_{\tau=1}^{\tau_{work}+\tau_{ret}} [u(c_{\tau}) - \kappa^{h}(s_{\tau}^{h}) - \kappa^{w}(s_{\tau}^{w})]}{\tau_{work} + \tau_{ret}} \right)
\]  

(6.5)

where \( c_{\tau}, s_{\tau}^{h}, \) and \( s_{\tau}^{w} \) are the simulated household consumption level and search intensities at age \( \tau \). Similarly, the consumption-equivalent of lifetime utility \( \bar{c}^i \) of a single individual of gender \( i \) is defined as follows:

\[
\bar{c}^i = (u^i)^{-1} \left( \frac{\sum_{\tau=1}^{\tau_{work}+\tau_{ret}} [u^i(c_{\tau}^i) - \kappa^i(s_{\tau}^i)]}{\tau_{work} + \tau_{ret}} \right)
\]  

(6.6)
Table 6.1: Cyclicality of the Unemployment Rate. Cyclicality of a variable $x$ is defined as $\bar{x}_{z=\text{Good}} - \bar{x}_{z=\text{Bad}}$ where $\bar{x}_z$ is the average level of $x$ in aggregate state $z$; a negative sign indicates counter-cyclicality. UR = unemployment rate. Unemployment rates computed under “s constant” ignores variations in each individual’s search intensity. CF1 is the counterfactual environment in which each individual make decisions independent of his or her spouse. CF2 is the counterfactual environment in which the spouse of each individual is restricted to a fixed search intensity and does not experience cyclicality. More details are provided in Section 6.1.

### (a) High School Sample

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>CF1</th>
<th>CF2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wives</td>
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<td></td>
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</tr>
<tr>
<td></td>
<td>$z = \text{Good}$</td>
<td>$z = \text{Bad}$</td>
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<tr>
<td></td>
<td>$\times 10^{-2}$</td>
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<td>$\times 10^{-2}$</td>
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<tr>
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<td>$\times 10^{-2}$</td>
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<td>$\times 10^{-2}$</td>
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<td></td>
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</table>

### (b) College Sample

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<th>CF1</th>
<th>CF2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wives</td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td>$z = \text{Good}$</td>
<td>$z = \text{Bad}$</td>
<td>$z = \text{Good}$</td>
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<td></td>
<td>$\times 10^{-2}$</td>
<td>cyclicality</td>
<td>$\times 10^{-2}$</td>
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<tr>
<td>Baseline s constant</td>
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<table>
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<th>Baseline</th>
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<tr>
<td>Wives</td>
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<td></td>
<td>$\times 10^{-2}$</td>
<td>cyclicality</td>
<td>$\times 10^{-2}$</td>
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<tr>
<td>Baseline s constant</td>
<td>1.588</td>
<td>2.152</td>
<td>-35.5</td>
</tr>
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</table>
For each married household or single individual, the cyclical cost is computed as the difference in consumption-equivalent in the a-cyclical environment \((\bar{c}_{a.c.} \text{ or } \bar{c}'_{a.c.})\) and that in the baseline environment \((\bar{c}_{base} \text{ or } \bar{c}'_{base})\), i.e. \(\bar{c}_{a.c.} - \bar{c}_{base} \text{ or } \bar{c}'_{a.c.} - \bar{c}'_{base}\). The percentage cost of cyclicality is defined as \(\frac{\bar{c}_{a.c.} - \bar{c}_{base}}{\bar{c}_{base}} \text{ or } \frac{\bar{c}'_{a.c.} - \bar{c}'_{base}}{\bar{c}'_{base}}\). In the a-cyclical environment, the baseline job finding rate and the separation rate are held at an average level over the sample period. In the simulations, the strings of random draws are the same in the baseline and the a-cyclical environments. Finally, I compare the costs borne by couples to those borne by singles.

Table 6.2 shows the results of the welfare cost comparisons for the High School and the College samples respectively. I present the welfare costs by the welfare percentile groups based on the baseline environment as well as the overall average. For both High School and College samples, the average percentage cost of cyclicality is higher for single individuals than for married households. In the High School sample, married couples face an average of 0.47% welfare cost due to cyclicality, whereas single females and males face 0.75% and 0.92% welfare costs respectively. In the College sample, the difference between couples and singles is more pronounced. Married couples face an average of 0.13% welfare cost due to cyclicality, whereas single females and males face 1.07% and 0.76% welfare costs respectively.

While the overall average cyclical costs borne by model agents are rather moderate, the cyclicality cost is unevenly distributed. Agents with lower life-time welfare levels face higher costs of cyclicality. This is because these households or individuals experience more unfavorable idiosyncratic shocks, and such shocks lower their ability to accumulate assets and thus affect their ability to smooth consumption over the business cycle. I divide each sample into four groups according to the welfare percentile in the baseline environment. In the High School sample, married couples in the lowest 5 percentiles face an 1% welfare cost, whereas single females and males in the same group face substantially higher welfare costs of 4.9% and 2.7% respectively. This pattern is stronger in the College sample. Married couples face only less than a 0.4% welfare cost, whereas single females and males face welfare costs as high as 6.5% and 2.2% respectively.

The results in this subsection indicate that married household is very effective in shielding cyclical risks. The intra-household risk sharing is particularly important for lowering the cyclical costs in households who face more unfavorable idiosyncratic labor market shocks.
<table>
<thead>
<tr>
<th>Welfare Percentile</th>
<th>Married Couples (1)</th>
<th>Married Couples (2)</th>
<th>Single Females (1)</th>
<th>Single Females (2)</th>
<th>Single Males (1)</th>
<th>Single Males (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>lowest 5%</td>
<td>1.03%</td>
<td>2059</td>
<td>4.85%</td>
<td>328</td>
<td>2.71%</td>
<td>1125</td>
</tr>
<tr>
<td>5% to 20%</td>
<td>0.75%</td>
<td>3260</td>
<td>1.01%</td>
<td>538</td>
<td>1.19%</td>
<td>1679</td>
</tr>
<tr>
<td>20% to 50%</td>
<td>0.42%</td>
<td>4286</td>
<td>2.05%</td>
<td>946</td>
<td>0.64%</td>
<td>2981</td>
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<tr>
<td>50% and above</td>
<td>0.01%</td>
<td>6818</td>
<td>-0.72%</td>
<td>1844</td>
<td>0.18%</td>
<td>4608</td>
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<tr>
<td>overall</td>
<td>0.47%</td>
<td>5257</td>
<td>0.75%</td>
<td>1299</td>
<td>0.92%</td>
<td>3496</td>
</tr>
</tbody>
</table>

(a) High School Sample

<table>
<thead>
<tr>
<th>Welfare Percentile</th>
<th>Married Couples (1)</th>
<th>Married Couples (2)</th>
<th>Single Females (1)</th>
<th>Single Females (2)</th>
<th>Single Males (1)</th>
<th>Single Males (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>lowest 5%</td>
<td>0.36%</td>
<td>3023</td>
<td>6.50%</td>
<td>513</td>
<td>2.19%</td>
<td>1793</td>
</tr>
<tr>
<td>5% to 20%</td>
<td>0.36%</td>
<td>4971</td>
<td>1.60%</td>
<td>825</td>
<td>0.78%</td>
<td>2399</td>
</tr>
<tr>
<td>20% to 50%</td>
<td>0.23%</td>
<td>6556</td>
<td>2.29%</td>
<td>1415</td>
<td>0.54%</td>
<td>4671</td>
</tr>
<tr>
<td>50% and above</td>
<td>0.13%</td>
<td>11038</td>
<td>-0.55%</td>
<td>3000</td>
<td>0.31%</td>
<td>7750</td>
</tr>
<tr>
<td>overall</td>
<td>0.13%</td>
<td>8385</td>
<td>1.07%</td>
<td>2069</td>
<td>0.76%</td>
<td>5675</td>
</tr>
</tbody>
</table>

(b) College Sample

Table 6.2: Cost of Cyclical Fluctuations in Consumption-Equivalent of life-time utility. Columns (1): average percentage cost of cyclicality; (2) average monthly consumption-equivalent of lifetime welfare. More details are provided in Section 6.2

7 Conclusion

As previous literature such as Guler et al. (2012) has pointed out, when couples are risk averse and imperfectly insured, the interactions between spouses lead to labor market behaviors that are significantly different from those of singles. In this paper, I find that the household joint-search behavior have implications for cyclicality in the unemployment rate and welfare cost due to cyclical fluctuations.

I consider a dynamic model of unitary households in which spouses make joint job search and savings decision. The households are risk-averse and face aggregate labor market fluctuations. The joint-search structure gives rise to additional mechanisms that drive the search intensity counter-cyclical,
and consequently lead to more counter-cyclical unemployment rate. The first mechanism is the wealth effect resulting from cyclical fluctuations in the expected future household incomes. Spouse’s counter-cyclical unemployment spells strengthens the wealth effect. The second mechanism comes from the cyclical variations in the comparative advantage. If one’s job finding rate is less cyclical than the spouse’s, the person has greater comparative advantage (or less comparative disadvantage) than the spouse, and thus chooses more counter-cyclical search intensity.

The model is estimated by the simulated method of moments. The estimated model matches many patterns in the data across spouse’s employment states. In particular, unemployment rate is substantially higher when the spouse is unemployed rather than employed, while wives’ labor force participation rate is slightly higher when the husband is unemployed. Given the estimated model, I compare couples to counterfactual singles (individuals who are identical to the married individuals in the baseline model except for the lack of joint decision making between spouses). The results show that variations in married women’s search intensity lead to more counter-cyclical unemployment rate, but variations in single women’s search intensity lead to more pro-cyclical unemployment rate. In addition, I also find that a married household also provides insurance against cyclical fluctuations. By comparing simulated married households to singles, I find that married households only experience 2/3 to 1/8 of the welfare losses that single individuals experience due to cyclical fluctuations.

Because of the household structure, the adverse impact of a negative labor market shock is not as severe as how the unemployment rate describes for married people. This calls for policy makers to react to labor market cyclical fluctuations and design government programs differently for the married population.

References


Appendix

A Added-Worker Effect in a Simplified Household Model

In this Section, I analyze a simplified version of the full model of married household introduced in Section 4 in order to better understand the mechanisms behind counter-cyclicality in the search intensity.

In a household model, there are two mechanisms that drive counter-cyclical search intensity. The first mechanism is the wealth effect resulting from cyclical fluctuations in the expected future incomes. Conditional on both spouses being non-employed, a decrease in one’s own and one’s spouse’s job finding rate lowers expected future incomes of the two, leading to increases in search intensity. Unconditionally, the expected non-employment duration of one’s spouse is longer with lower job finding rate, and the spouse of an non-employed searches more due to wealth effects. This also leads to the observation of higher search intensities in periods of lower job finding rates. The second mechanism comes from the cyclical variations in the comparative advantage. If one’s job finding rate is less cyclical than the spouse’s, the person has greater comparative advantage (or less comparative disadvantage) than the spouse, and thus chooses more counter-cyclical search intensity.

In this Section, I assume that the household lives for two periods. In the first period, the household makes the same set of decisions: savings and search intensities of the husband and the wife. For brevity of the presentation, I assume zero interest rate, no subjective discounting, zero home production value, no separation, no expectation for aggregate fluctuation, and zero continuation value after the second period. Similar to the full model, I assume that the utility function is strictly concave and exhibits constant relative risk aversion (CRRA), and the search disutility function is strictly convex.

First, consider the household’s problem when both the husband and the wife are non-employed.

\[
\max_{a', 0 \leq s^i \leq \frac{1}{X_i}, i=h, w} \left\{ u(a - a') - \sum_{i=h, w} \kappa^i(s^i) + E_I u(a' + I) \right\}
\]
where \( \mathbf{E}_I u(a' + I) = \prod_{i=h,w} \lambda^i s^i u(a' + w^i + w^j) + \sum_{i,j=h,w; j \neq i}(1 - \lambda^i s^i) \lambda^j s^j u(a' + w^i) + \prod_{i=h,w}(1 - \lambda^i s^i) u(a') \).

I use the subscript \( nn \) to denote the optimal decision when both spouses are non-employed. The first order conditions for interior solutions are as follows.

\[
\begin{align*}
    u'(a - a'_{nn}) &= \mathbf{E}_I u'(a'_{nn} + I) \quad \text{(A.1)} \\
\kappa^i(s^i_{nn}) &= \lambda^i \{ \lambda^j s^j_{nn}[u(a'_{nn} + w^i + w^j) - u(a'_{nn} + w^j)] \\
    &\quad + (1 - \lambda^j s^j_{nn})[u(a'_{nn} + w^i) - u(a'_{nn})] \}
\end{align*}
\]

First, focus on spouse \( i \)'s search decision in response changes in his or her job finding rate. Differentiate Eq. (A.2) with respect to \( \lambda^i \) gives:

\[
\begin{align*}
    \kappa''(s^i_{nn}) \frac{\partial s^i_{nn}}{\partial \lambda^i} &= \lambda^i \{ \lambda^j s^j_{nn}[u(a'_{nn} + w^i + w^j) - u(a'_{nn} + w^j)] + (1 - \lambda^j s^j_{nn})[u(a'_{nn} + w^i) - u(a'_{nn})] \\
    &\quad + \frac{\partial a'_{nn}}{\partial \lambda^i} \lambda^j \{ [u(a'_{nn} + w^i + w^j) - u(a'_{nn} + w^j)] - [u(a'_{nn} + w^i) - u(a'_{nn})] \}
    \\
    &\quad + \frac{\partial a'_{nn}}{\partial \lambda^i} \lambda^j \{ [u(a'_{nn} + w^i + w^j) - u'(a'_{nn} + w^j)] + (1 - \lambda^j s^j_{nn})[u'(a'_{nn} + w^i) - u'(a'_{nn})] \}
\end{align*}
\]

The first line of Eq. (A.3) shows that, while holding other decisions constant, a higher job finding rate increases the return to search and thus increases spouse \( i \)'s search intensity. This is consistent with the “substitution effect” between leisure and consumption. Here, spouse \( i \) increases search intensity, which can be viewed as a reduction of leisure, in exchange for higher expected consumption in the next period.

In the second line, the term inside the curly brackets is negative, meaning that, if spouse \( j \) lowers the search intensity when spouse \( i \)'s job finding rate goes up, spouse \( i \) is even more willing to search. This is consistent with the fact that spouse \( i \) gains greater comparative advantage in job search, and thus there is a change in the roles of the two spouses.
In the third line, the term inside the curly brackets is negative. The partial derivative of savings with respect to $\lambda^i$ is given by

$$\frac{\partial a'_nn}{\partial \lambda^i} = -s^i_{nn}\lambda^j s^j_{nn}\left[u(a'_nn + w^i + w^j) - u(a'_nn + w^j)\right] + s^i_{nn}(1 - \lambda^j s^j_{nn})[u(a'_nn + w^i) - u(a'_nn)]$$

$$u''(a - a'_nn) + u'(a - a'_nn)$$

If the utility function is CRRA, then $\frac{\partial a'_nn}{\partial \lambda^i} \geq 0$ if $a - a'_nn$ is sufficiently small and $\frac{\partial a'_nn}{\partial \lambda^i} < 0$ otherwise.

When the household’s initial wealth endowment is low (i.e. $a$ is small), the household increases consumption when it becomes easier to find a job. This is consistent with the “wealth effect”. The wealth effect disappears as $a$ and $a - a'_nn$ increase.

Overall, conditional on both spouses being non-employed and holding spouse $j$’s job finding rate constant, $\frac{\partial s^i_{nn}}{\partial \lambda^i} < 0$ only if the wealth effect is strong enough to make $\frac{\partial a'_nn}{\partial \lambda^i}$ sufficiently positive. Moreover, the convexity of the search cost function, $\kappa''(s^i_{nn})$, affects how much search intensity would adjust, and thus how counter-cyclical the search intensity is.

Next, I focus on spouse $i$’s search decision in response changes spouse $j$’s job finding rate. Differentiate Eq. A.2 with respect to $\lambda^j$ gives:

$$\kappa''(s^i_{nn}) \frac{\partial s^i_{nn}}{\partial \lambda^j} = \lambda^j s^j_{nn}\left([u(a'_nn + w^i + w^j) - u(a'_nn + w^j)] - [u(a'_nn + w^i) - u(a'_nn)]\right)$$

$$+ \frac{\partial s^j_{nn}}{\partial \lambda^j} \lambda^j s^j_{nn}\left([u(a'_nn + w^i + w^j) - u(a'_nn + w^j)] - [u(a'_nn + w^i) - u(a'_nn)]\right)$$

$$+ \frac{\partial a'_nn}{\partial \lambda^j} \lambda^j s^j_{nn}\left[u'(a'_nn + w^i + w^j) - u'(a'_nn + w^j)\right] + (1 - \lambda^j s^j_{nn})[u'(a'_nn + w^j) - u'(a'_nn)]$$

The first line of Eq. A.4 is negative, and represents the effects due to the change in comparative advantage. When spouse $j$ becomes more efficient in job search spouse $i$ reduces his or her search intensity. The second line represents the substitution between the two spouses’ search intensities. If $\frac{\partial s^i_{nn}}{\partial \lambda^i} < 0$, the second line is positive. Similar to Eq. A.3, the third line is again the “wealth effect”. When the household is relatively poor, the wealth effect is strong and the third line is be negative.

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Next, suppose that spouse $i$ is non-employed and $j$ is employed, the household solves the following.

\[
\max_{a', 0 \leq s^i \leq \frac{\lambda_i}{\lambda'}} \left\{ u(a + w^j - a') - \kappa^i(s^i) + \mathbb{E}_I[u(a' + w^j + I^i)] \right\}
\]

where $\mathbb{E}_I[u(a' + w^j + I^i)] = \lambda^i s^j u(a' + w^j + w^i) + (1 - \lambda^i s^j) u(a' + w^j)$. I use the subscript $ne$ to denote the optimal decisions when only one of the two spouses is non-employed. The first order conditions for interior solutions are as follows.

\[
u'(a + w^j - a'_{ne}) = \mathbb{E}_I u'(a'_{ne} + w^j + I^i) \quad \text{(A.5)}
\]

\[
\kappa'(s^i_{ne}) = \lambda^i [u(a'_{ne} + w^j + w^i) - u(a'_{ne} + w^j)] \quad \text{(A.6)}
\]

Without make parametric assumptions on the utility function, I make a heuristic argument that the search intensity is higher when one’s spouse is non-employed than when the spouse is employed. Suppose that $a'_{nn} \leq a'_{ne}$, subtracting Eq. A.6 from Eq. A.2 gives $\kappa'(s^i_{nn}) - \kappa'(s^i_{ne}) \geq \lambda^i(1 - \lambda^j s^j_{nn})[u(a'_{nn} + w^j) - u(a'_{nn})]$. Since the right hand side of this inequality is positive, it must be true that $s^i_{nn} > s^i_{ne}$. Given that $s^i_{nn} > s^i_{ne}$, comparing Eq. A.1 to Eq. A.5 shows that it must be the case that $a'_{nn} < a'_{ne}$.