Online Appendix for "Intra-Household Risk Sharing and Job Search over the Business Cycle"

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Appendix A. Transitions Between Non-Participation and Unemployment

In the Current Population Survey (CPS), non-employed individuals are classified as unemployed workers or labor force non-participants based on their reported job search activities. Thus, transitions between the two states can reflect changes in the level of job search effort. Here I highlight two observations based on a sample of married individuals in the CPS. First, the transition rates between unemployment and non-participation exhibit cyclical patterns. Second, the transitions are closely associated with spousal labor force status.

Appendix A.1. Cyclicality

Figure A.1 shows that the monthly rates of transitions between unemployment and non-participation are highly cyclical among married individuals.[1] Table A.1 shows the correlation of these transition rates with the unemployment rate and the job-finding rate. Specifically, a higher transition rate from unemployment to non-participation correlates with a tight labor market, characterized by a low unemployment rate and a high job-finding rate, while a high transition rate from non-participation to unemployment correlates with a slack labor market.

I compute the transition rates by exploiting the panel structure of the CPS. For example, the transition rate from non-participation to unemployment is computed as the fraction of non-participants who are unemployed a month later. I apply the de-NUN technique introduced by Elsby et al. (2015) to correct potential mistakes in the recorded labor force status of non-employed individuals, which are known as classification errors.[2]

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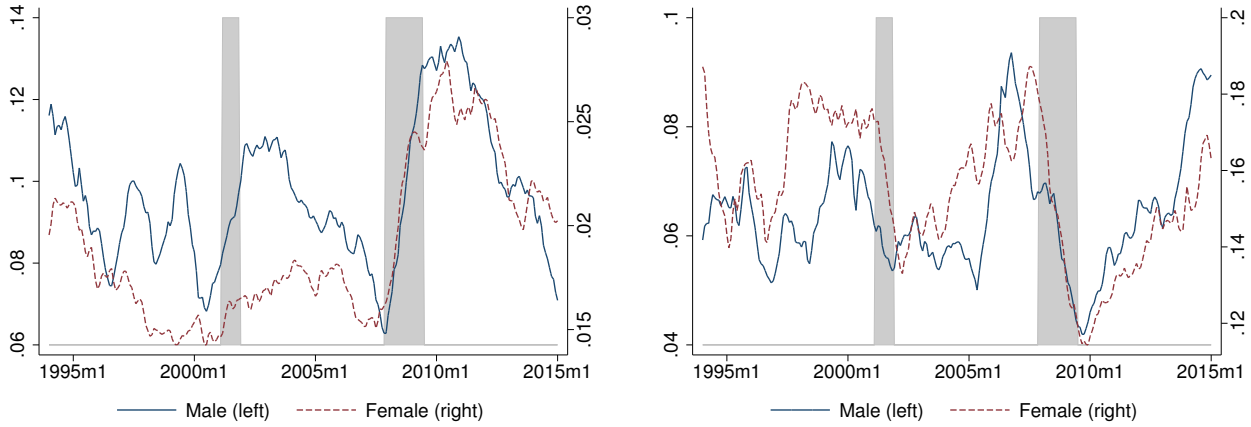
[1] I focus on married individuals in this appendix because they are the population of interest in this paper. The transition rates between unemployment and non-participation of unmarried individuals also exhibit cyclical patterns.

[2] Classification errors can lead to spurious transitions between unemployment and non-participation, resulting in an upward bias in the transition rates in recessions because a non-employment spell is more likely to span multiple survey-rounds. However, Elsby et al. (2015) show that the cyclical patterns of the transition rates are qualitatively robust to classification errors.



(a) Non-Participation to Unemployment

(b) Unemployment to Non-Participation

Figure A.1: Monthly transition rates between unemployment and non-participation of married individuals.

Notes: The graphs show the 12-month moving average of the monthly transition rates computed based on a sample of married individuals age 30-60 with at least high-school education drawn from the matched monthly CPS data from 1994-2014. Shaded areas indicate NBER recessions.

	Married Women		Married Men	
	Unemp. Rate	Unemp. to Emp.	Unemp. Rate	Unemp. to Emp.
Non-Particip. to Unemp.	0.96	-0.89	0.84	-0.75
Unemp. to Non-Particip.	-0.84	0.75	-0.47	0.34

Table A.1: Cyclicality of monthly transition rates.

Notes: The table shows coefficients of correlation. "Non-Particip. to Unemp.", "Unemp. to Non-Particip.", and "Unemp. to Emp." are monthly transition rates from non-participation to unemployment, from unemployment to non-participation, and from unemployment to employment, respectively. The unemployment rate and transition rates are 12-month moving averages computed based on a sample of married individuals age 30-60 with at least high-school education drawn from the matched monthly CPS data from 1994-2014.

Appendix A.2. Spousal Unemployment Effects

For married individuals, transitions between unemployment and non-participation may depend on spousal labor force status. To examine this relationship, I estimate two multinomial logistic regressions, in which the response variables are transitions originating from unemployment ($l_0 = U$) and non-participation ($l_0 = N$), respectively. Let $p_{i,t}(l_0, l_1)$ be the probability that individual i is in the labor force state l_1 in period $t+1$ conditional on being in the state l_0 in period t. For each $l_0 \in \{U, N\}$, let η_{i,t,l_1} denote the log-odds of transitioning to l_1 relative to remaining at l_0 such that:

$$\eta_{i,t,l_1} = \ln\left(\frac{p_{i,t}(l_0, l_1)}{p_{i,t}(l_0, l_0)}\right),$$

and let the regression equation be

$$\begin{aligned}\eta_{i,t,l_1} \quad = \quad & \sum_{l'=U,N} \beta_{l_1}^{SP,l'} \mathbf{1}_{\{l_{i,t}^{sp}=l'\}} + \sum_{l'=U,N} \beta_{l_1}^{SP_0,l'} \mathbf{1}_{\{l_{i,t-12}^{sp}=l'\}} \\ & + \beta_{l_1}^{KID} KID_{i,t} + \sum_{l'=U,N} \beta_{l_1}^{KID,l'} KID_{i,t} \mathbf{1}_{\{l_{i,t}^{sp}=l'\}} + \boldsymbol{\beta}_{\mathbf{l_1}}^{\mathbf{0}} \mathbf{X_i} + \beta_{l_1}^{UR} UR_{st(i),t}\end{aligned} \tag{A.1}$$

In Eq. A.1, $l_{i,t}^{sp}$ and $l_{i,t-12}^{sp}$ are, respectively, the current spousal labor force status and the labor force status a year ago. The parameters of interest are $\beta_{l_1=U}^{SP,U}$ when $l_0 = N$ and $\beta_{l_1=N}^{SP,U}$ when $l_0 = U$; these parameters capture the relationship between labor force transitions and spousal unemployment.[3] $KID_{i,t}$ is an indicator for having at least one child aged 12 or under. The coefficient $\beta_{l_1}^{KID}$ captures the effect of having children on labor market transitions, while $\beta_{l_1}^{KID,U}$ captures the interaction between spousal unemployment and children. $\mathbf{X_i}$ is a vector containing a constant term, age, race, and spouse's education. Finally, $UR_{st(i),t}$ is the unemployment rate in the state of residence.[4]

I estimate the regressions based on a sample of married couples drawn from the matched monthly CPS and consider two education levels, a high-school group consisting of individuals who have completed high school but have not finished college and a college group consisting of individuals with at least a college degree.

Table A.3 shows the estimation results for the regression with $l_0 = N$. For all gender-education groups, a key observation is that $\beta_{l_1=U}^{SP,U}$ is positive and significant, suggesting that non-participants who have an unemployed spouse are more likely to increase their search effort relative to those with an employed spouse. $\beta_{l_1=U}^{SP,N}$, the effect of spousal non-participation relative to spousal employment, is largely insignificant. Since relatively fewer men are non-participants, the small sample size limits the power of the corresponding estimates for

[3] Note that the estimates of $\beta_{l_1=U}^{SP,U}$ and $\beta_{l_1=N}^{SP,U}$ should not be interpreted as indicating a causal effect of spousal unemployment because the spouse's labor force status is likely endogenous.

[4] The correlation between a married couple's employment opportunities due to common local markets or assortative mating may bias the estimation of $\left\{\beta_{l_1}^{SP,l'}\right\}_{l'=U,N}$ (Lundberg, 1985). Controlling for spousal education and previous labor market outcomes as well as the unemployment rate can ease such concerns.

men. Although having kids is negatively related to transitions into both employment and unemployment, its interaction with spousal unemployment ($\beta_{l_1}^{KID,U}$) is insignificant.

Table A.4 shows the estimation results for the regression with $l_0 = U$. $\beta_{l_1=N}^{SP,U}$ is negative in all groups and it is significant among college men and high school women. Similar to the first set of regressions, having children affects the transition rates but independently of spousal employment status except for college men.

Table A.5 summarizes the average spousal unemployment effects. Relative to having an employed spouse, having an unemployed spouse is associated with a substantial increase in the non-participation-to-unemployment transition rate and a substantial decrease in the unemployment-to-non-participation transition rate.

Appendix B. Simplified Model of Couples

Here, I analyze a simplified version of the model described in Section 2 in order to disentangle the various mechanisms affecting the cyclicality of the optimal search intensity. In the simplified model, couples are endowed with an initial asset level a and initial labor force statuses l_h and l_w; they face baseline job finding rates λ_h and λ_w. I assume that the life cycle consists of two periods. During the first period, couples make consumption and job search decisions to maximize their joint utility over the two periods. Job search outcomes are realized at the beginning of the second period. Households consume all incomes and savings in the second period because there is no preference for bequests.

For simplicity, I assume a zero interest rate ($r = 0$), no subjective discounting ($\beta = 1$), no non-employment income ($\mu^n = 0$), and no separation from employment ($\delta = 0$). The disutility of search intensity and the utility of consumption are specified in Eq. 2 and 3, respectively. As I explain in Section 2, the optimal consumption decision has $c_h = c_w = c$ where c denotes household consumption. The household utility is

$$U(c) = 2u(c/2)$$

with $U'(c) > 0$ and $U''(c) < 0$ for all $c \geq 0$.

To examine the cyclicality of the optimal search intensity, I first investigate how the optimal search intensity varies with the baseline job finding rate conditional on spousal employment status; then, I study how the optimal search intensity depends on spousal employment status.

In the case that both spouses are non-employed, couples solve the following problem:

$$\max_{a', s_h, s_w} \left\{ U(a - a') - \sum_{i=h,w} \kappa_i(s_i) + \mathbf{E}_{Inc'} U(a' + Inc') \right\} \tag{B.1}$$

	(1) Married Men, HS		(2) Married Men, COL		(3) Married Women, HS		(4) Married Women, COL	
	$l_1 = E$	$l_1 = U$	$l_1 = E$	$l_1 = U$	$l_1 = E$	$l_1 = U$	$l_1 = E$	$l_1 = U$
$\beta_{l_1}^{SP,U}$	0.187	1.194*	0.450	1.276*	0.240	1.294***	0.647	1.408**
	(0.553)	(0.604)	(0.923)	(0.623)	(0.250)	(0.247)	(0.387)	(0.545)
$\beta_{l_1}^{SP,N}$	-0.388	-0.391	0.0637	-0.357	0.486*	-0.272	-0.174	-2.089*
	(0.245)	(0.336)	(0.347)	(0.539)	(0.232)	(0.496)	(0.371)	(1.015)
$\beta_{l_1}^{KID}$	-0.218	-0.102	-0.142	-0.488	-0.296***	-0.480***	-0.698***	-0.856***
	(0.114)	(0.155)	(0.169)	(0.252)	(0.0466)	(0.0841)	(0.0627)	(0.129)
$\beta_{l_1}^{KID,U}$	0.0889	-0.108	0.286	-0.0333	-0.0700	0.259	-0.712	-0.263
	(0.646)	(0.691)	(1.091)	(0.911)	(0.285)	(0.272)	(0.445)	(0.608)
$\beta_{l_1}^{KID,N}$	0.818**	0.112	0.785*	0.847	0.191	0.177	1.172**	3.067**
	(0.265)	(0.374)	(0.369)	(0.597)	(0.271)	(0.578)	(0.406)	(1.096)
Age 35-39	0.0155	-0.230	0.304	0.286	0.111*	0.134	-0.0240	-0.000789
	(0.124)	(0.169)	(0.168)	(0.271)	(0.0460)	(0.0895)	(0.0572)	(0.126)
Age 40-45	0.0102	-0.101	0.281	0.436	0.0807	0.182*	0.0864	0.0141
	(0.116)	(0.153)	(0.160)	(0.250)	(0.0478)	(0.0906)	(0.0560)	(0.123)
Race: Black	0.0466	0.330	0.746**	1.117***	0.391***	0.773***	0.489***	1.068***
	(0.136)	(0.170)	(0.252)	(0.339)	(0.0820)	(0.119)	(0.127)	(0.216)
Non-White, Non-Black	-0.360*	-0.126	-0.278	-0.140	-0.0688	0.108	-0.233**	0.239
	(0.176)	(0.222)	(0.175)	(0.263)	(0.0834)	(0.139)	(0.0779)	(0.145)
Spouse HS	-0.183	-0.273	0.0791	2.364*	0.140	-0.281*	-0.221	0.910
	(0.189)	(0.240)	(0.488)	(1.182)	(0.0792)	(0.122)	(0.261)	(0.842)
Spouse COL	-0.646**	-0.956***	-0.431	1.922	-0.0701	-0.751***	-0.641*	0.365
	(0.207)	(0.270)	(0.477)	(1.175)	(0.0855)	(0.142)	(0.258)	(0.836)
$\beta_{l_1}^{SP_0,U}$	0.414	0.489	-0.0935	-0.662	-0.0514	0.263	0.0740	0.107
	(0.251)	(0.308)	(0.444)	(0.511)	(0.123)	(0.170)	(0.218)	(0.393)
$\beta_{l_1}^{SP_0,N}$	0.655***	0.340	0.118	-0.161	-0.0987	0.680**	-0.288	-0.542
	(0.158)	(0.198)	(0.217)	(0.356)	(0.177)	(0.259)	(0.249)	(0.495)
$\beta_{l_1}^{UR}$	-0.0850***	0.0536	-0.0191	0.129**	-0.0806***	0.0848***	-0.0259*	0.123***
	(0.0227)	(0.0274)	(0.0308)	(0.0460)	(0.00955)	(0.0157)	(0.0114)	(0.0223)
Constant	-0.284	-1.856***	-0.927	-5.280***	-2.065***	-4.024***	-1.331***	-4.938***
	(0.259)	(0.323)	(0.523)	(1.223)	(0.106)	(0.179)	(0.273)	(0.863)
Observations	4727		2272		64730		42419	
Pseudo R^2	0.038		0.042		0.016		0.021	

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Multinomial logistic regression of transitions from non-participation ($l_0 = N$).

Notes: The regressions are based on a sample of married individuals of age 30-45 drawn from the matched monthly CPS data from 1994-2014. "HS" = high school education or some college; and "COL" = college education or more. See Appendix A.2 for the regression model.

	(1)		(2)		(3)		(4)	
	Married Men, HS		Married Men, COL		Married Women, HS		Married Women, COL	
	$l_1 = E$	$l_1 = N$	$l_1 = E$	$l_1 = N$	$l_1 = E$	$l_1 = N$	$l_1 = E$	$l_1 = N$
$\beta_{l_1}^{SP,U}$	-0.294	-0.397	-1.216*	-13.89***	-0.677**	-0.669*	-0.115	-0.402
	(0.266)	(0.464)	(0.590)	(0.364)	(0.253)	(0.315)	(0.430)	(0.511)
$\beta_{l_1}^{SP,N}$	0.284	1.215***	0.624	0.854	-0.335	0.361	0.797	1.368*
	(0.193)	(0.297)	(0.363)	(0.558)	(0.567)	(0.518)	(0.565)	(0.691)
$\beta_{l_1}^{KID}$	-0.0646	0.0868	-0.0466	-0.315	0.155	0.359***	0.393***	0.405**
	(0.0782)	(0.139)	(0.131)	(0.241)	(0.0819)	(0.0998)	(0.114)	(0.151)
$\beta_{l_1}^{KID,U}$	-0.0919	-0.348	1.211	12.72***	0.224	0.227	-0.139	-0.472
	(0.306)	(0.560)	(0.656)	(1.089)	(0.297)	(0.364)	(0.503)	(0.660)
$\beta_{l_1}^{KID,N}$	0.0649	-0.991**	-0.391	-0.353	1.073	0.448	-0.827	-0.550
	(0.204)	(0.316)	(0.377)	(0.649)	(0.651)	(0.614)	(0.839)	(0.850)
Age 35-39	-0.0937	-0.273	-0.0600	-0.609*	0.0887	-0.0542	0.0396	-0.0266
	(0.0830)	(0.147)	(0.151)	(0.282)	(0.0958)	(0.111)	(0.131)	(0.168)
Age 40-45	-0.121	-0.210	-0.352*	-0.655**	0.0236	-0.0257	-0.0879	-0.0963
	(0.0784)	(0.137)	(0.144)	(0.248)	(0.0942)	(0.108)	(0.125)	(0.158)
Race Black	-0.359***	0.423**	-0.0311	0.580	-0.389**	-0.195	-0.0372	0.0675
	(0.101)	(0.146)	(0.220)	(0.333)	(0.127)	(0.146)	(0.183)	(0.239)
Non-White, Non-Black	-0.186	0.475*	-0.347	0.223	-0.295	0.210	-0.516**	0.123
	(0.145)	(0.221)	(0.187)	(0.325)	(0.173)	(0.182)	(0.164)	(0.185)
Spouse HS	-0.109	0.199	0.589	-0.364	0.159	-0.127	-0.890	-1.823*
	(0.134)	(0.248)	(0.605)	(1.086)	(0.126)	(0.143)	(0.712)	(0.765)
Spouse COL	-0.166	0.0628	0.548	-0.383	0.328*	0.152	-0.810	-1.420
	(0.151)	(0.281)	(0.599)	(1.070)	(0.151)	(0.169)	(0.711)	(0.764)
$\beta_{l_1}^{SP_0,U}$	-0.0686	0.185	0.272	0.587	0.0369	-0.107	-0.152	0.115
	(0.152)	(0.244)	(0.277)	(0.556)	(0.161)	(0.193)	(0.256)	(0.337)
$\beta_{l_1}^{SP_0,N}$	0.0897	-0.215	0.0305	-0.108	-0.382	0.0577	-0.544	-0.224
	(0.108)	(0.216)	(0.177)	(0.435)	(0.324)	(0.328)	(0.440)	(0.622)
$\beta_{l_1}^{UR}$	-0.108***	-0.109***	-0.118***	-0.0954*	-0.162***	-0.0818***	-0.145***	-0.0999***
	(0.0140)	(0.0261)	(0.0250)	(0.0439)	(0.0170)	(0.0186)	(0.0228)	(0.0281)
Constant	0.174	-1.808***	-0.538	-1.056	-0.0131	-0.899***	0.956	0.476
	(0.180)	(0.334)	(0.654)	(1.117)	(0.183)	(0.206)	(0.742)	(0.803)
Observations	7690		2625		6620		3212	
Pseudo R^2	0.021		0.026		0.023		0.026	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: Multinomial logistic regression of transitions from unemployment ($l_0 = U$).

Notes: See notes in Table A.3.

	Spousal Unemployment Effect	Average Transition Rate
Effects on HS Wives		
N-to-U	0.050*** (0.007)	0.029
U-to-N	-0.043* (0.017)	0.146
Effects on COL Wives		
N-to-U	0.027*** (0.010)	0.017
U-to-N	-0.059* (0.024)	0.125
Effects on HS Husbands		
N-to-U	0.131** (0.045)	0.109
U-to-N	-0.024* (0.010)	0.069
Effects on COL Husbands		
N-to-U	0.095 (0.056)	0.076
U-to-N	-0.038** (0.012)	0.056

Table A.5: Spousal unemployment effects on transition rates between unemployment and non-participation.
*Notes: The effects are estimated based on a sample of married individuals age 30-45 drawn from the matched monthly CPS data in 1994-2014. "HS" = high school education or some college; and "COL" = college education or more. Spousal unemployment effects are estimated average effects of spousal unemployment relative to spousal employment. See Appendix A.2 for the regression model. Full regression results are reported in Tables A.3 and A.4. Standard errors are shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

subject to $0 \leq s_i \leq \frac{1}{\lambda_i}$ for each $i = h, w$, where λ_i is the baseline job finding rate for spouse i and Inc' is the household income in the second period. The expectation term is

$$\begin{aligned}\mathbf{E}_{Inc'}U(a' + Inc') &= (\lambda_h s_h)(\lambda_w s_w)U(a' + w_h + w_w) + (1 - \lambda_h s_h)(1 - \lambda_w s_w)U(a') \\ &\quad +(1 - \lambda_h s_h)(\lambda_w s_w)U(a' + w_w) + (\lambda_h s_h)(1 - \lambda_w s_w)U(a' + w_h)\end{aligned}$$

Let a'_{nn}, $s_{h,nn}$, and $s_{w,nn}$ be policy functions; for brevity, I drop their dependence on initial asset level a and baseline job finding rates λ_h and λ_w. Interior optimal decisions must satisfy the following first order conditions:

$$U'(a - a'_{nn}) = \mathbf{E}_{Inc'}U'(a'_{nn} + Inc') \tag{B.2}$$

$$\begin{aligned}\kappa_i'(s_{i,nn}) &= \lambda_i\{\lambda_j s_{j,nn}[U(a'_{nn} + w_i + w_j) - U(a'_{nn} + w_j)] \\ &\quad +(1 - \lambda_j s_{j,nn})[U(a'_{nn} + w_i) - U(a'_{nn})]\} \text{ for } i, j = h, w; i \neq j\end{aligned} \tag{B.3}$$

Differentiating Eq. B.3 with respect to λ_i gives

$$\begin{aligned}\kappa_i''(s_{i,nn})\frac{\partial s_{i,nn}}{\partial \lambda_i} &= \lambda_j s_{j,nn}[U(a'_{nn} + w_i + w_j) - u(a'_{nn} + w_j)] + (1 - \lambda_j s_{j,nn})[U(a'_{nn} + w_i) - U(a'_{nn})] \\ &\quad +\frac{\partial s_{j,nn}}{\partial \lambda_i}\lambda_i\lambda_j\{[U(a'_{nn} + w_i + w_j) - U(a'_{nn} + w_i)] - [U(a'_{nn} + w_i) - U(a'_{nn})]\} \\ &\quad +\frac{\partial a'_{nn}}{\partial \lambda_i}\lambda_i\{\lambda_j s_{j,nn}[U'(a'_{nn} + w_i + w_j) - U'(a'_{nn} + w_i)] + (1 - \lambda_j s_{j,nn})[U'(a'_{nn} + w_j) - U'(a'_{nn})]\}\end{aligned} \tag{B.4}$$

The sign of $\frac{\partial s_{i,nn}}{\partial \lambda_i}$ is the object of interest. On the left-hand side, $\kappa_i''(s_{i,nn}) > 0$ by the convexity assumption. The first line on the right-hand side captures the direct effect of a marginal increase in λ_i: As i is more likely to earn wage w_i in the second period, the expected utility in the second period is higher due to a higher

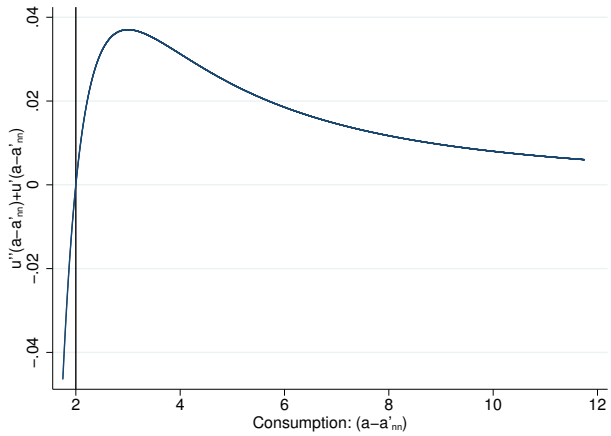


Figure B.1: Denominator of Eq. B.5. $\gamma = 2$ in the utility function. $\frac{\partial a'_{nn}}{\partial \lambda_i} > 0$ to the left of the vertical line, and $\frac{\partial a'_{nn}}{\partial \lambda_i} < 0$ to the right of the vertical line.

household income.

The second line captures the indirect effect due to changes in spousal search effort. The term between the curly brackets is negative because of the concavity of the utility function. Thus, the second line is positive if and only if $\frac{\partial s_{j,nn}}{\partial \lambda_i} < 0$. Intuitively, there is substitution between search efforts of the two household members. In practice, λ_i and λ_j are likely to be correlated due to common aggregate shocks. The greater $d\lambda_j/d\lambda_i$ is, the more likely it is to have a positive $\frac{\partial s_{j,nn}}{\partial \lambda_i}$, which in turn makes the second line negative. I refer to this as the comparative advantage effect.

The third line captures the indirect effect from changes in savings. The term between the curly brackets is again negative because of the concavity of the utility function. Therefore, the third line is negative if and only if $\frac{\partial a'_{nn}}{\partial \lambda_i} > 0$. Intuitively, the third line reflects the substitution between higher savings and higher search intensity as both are ways to provide consumption for the second period. To investigate the sign of $\frac{\partial a'_{nn}}{\partial \lambda_i}$, I differentiate Eq. B.2 with respect to λ_i. After rearranging, $\frac{\partial a'_{nn}}{\partial \lambda_i}$ can be expressed as follows:

$$\frac{\partial a'_{nn}}{\partial \lambda_i} = -\frac{s_{i,nn}\lambda_j s_{j,nn}[U(a'_{nn}+w_i+w_j)-U(a'_{nn}+w_j)] + s_{i,nn}(1-\lambda_j s_{j,nn})[U(a'_{nn}+w_i)-U(a'_{nn})]}{U''(a-a'_{nn})+U'(a-a'_{nn})} \tag{B.5}$$

The numerator is positive because of the monotonicity of the utility function. In the denominator, $U''(a - a'_{nn}) < 0$ and $U'(a - a'_{nn}) > 0$. The sign of the denominator, and hence the sign of $\frac{\partial a'_{nn}}{\partial \lambda_i}$, varies with the first period's consumption, $a - a'_{nn}$. As seen in Figure B.1, the denominator is negative if the first-period consumption is small. In other words, a wealth-poor household is more likely to increase search intensity instead of cutting back consumption in a slack labor market. I refer to the effect of λ_i on the household's choice between saving and searching as the wealth effect.

Next, I turn to the effects of spousal employment on the optimal search intensity. Relative to a dual-non-employment household, having an employed spouse is equivalent to an increase in a and an increase in the

baseline job finding rate of the spouse to infinity. Therefore, to understand the spousal employment effect, it suffices to show that the optimal search intensity $s_{i,nn}$ decreases with both a and the spouse's λ_j. To illustrate this, I differentiate Eq. B.3 with respect to a and λ_j in turn and hold the spouse's search intensity $s_{j,nn}$ constant at some fixed level $\hat{s}_j$. This gives:

$$\begin{aligned}
\frac{\partial s_{i,nn}}{\partial a}\kappa_i''(s_{i,nn}) &= \frac{\partial a'_{nn}}{\partial a}\lambda_i\{\lambda_j\hat{s}_j[U'(a'_{nn}+w_i+w_j)-U'(a'_{nn}+w_j)] \\
&\quad +(1-\lambda_j\hat{s}_j)[U'(a'_{nn}+w_i)-U'(a'_{nn})]\} \qquad \text{(B.6)} \\
\frac{\partial s_{i,nn}}{\partial \lambda_j}\kappa_i''(s_{i,nn}) &= \frac{\partial a'_{nn}}{\partial \lambda_j}\lambda_i\{\lambda_j\hat{s}_j[U'(a'_{nn}+w_i+w_j)-U'(a'_{nn}+w_j)] \\
&\quad +(1-\lambda_j\hat{s}_j)[U'(a'_{nn}+w_i)-U'(a'_{nn})]\} \qquad \text{(B.7)} \\
&\quad +\lambda_i\hat{s}_j[U(a'_{nn}+w_i+w_j)-U(a'_{nn}+w_i)]-\lambda_i\hat{s}_j[U(a'_{nn}+w_j)-U(a'_{nn})]
\end{aligned}$$

where $\frac{\partial a'_{nn}}{\partial a}$ and $\frac{\partial a'_{nn}}{\partial \lambda_j}$ can be obtained by differentiating Eq. B.2 with respect to a and λ_j:

$$\begin{aligned}
\frac{\partial a'_{nn}}{\partial a} &= \frac{U''(a-a'_{nn})}{U''(a-a'_{nn})+\mathbf{E}_{Inc'}U''(a'_{nn}+Inc')} \\
\frac{\partial a'_{nn}}{\partial \lambda_j} &= \frac{\lambda_i s_{i,nn}\hat{s}_j[U'(a'_{nn}+w_i+w_j)-U'(a'_{nn}+w_i)]+(1-\lambda_i s_{i,nn})\hat{s}_j[U'(a'_{nn}+w_j)-U'(a'_{nn})]}{U''(a-a'_{nn})+\mathbf{E}_{Inc'}U''(a'_{nn}+Inc')}
\end{aligned}$$

Given the concavity of the utility function, we have $\frac{\partial a'_{nn}}{\partial a}>0$ and $\frac{\partial a'_{nn}}{\partial \lambda_j}>0$. Therefore, we have $\frac{\partial s_{i,nn}}{\partial a}<0$ and $\frac{\partial s_{i,nn}}{\partial \lambda_j}<0$, implying that non-employed individuals would search more intensively if the spouse provides less income in the current period or if the spouse is less likely to become employed in the second period. Therefore, spousal non-employed increases search one's search intensity. In addition, if the likelihood of having a non-employed spouse is counter-cyclical, it can cause one's search intensity to vary counter-cyclically. I refer to this as the added-worker effect.

Appendix C. Data Appendix: the Current Population Survey

Appendix C.1. Job Search Methods by Gender

Table C.6 shows the list of search methods in the CPS, of which (1)-(9) are active search methods and (10)-(12) are passive search methods. Non-employed individuals who reportedly use at least one active method are classified as unemployed workers. As shown in Table C.6, among actively job-seeking unemployed workers, men use a slightly greater number of search methods than women. The most commonly used actives search methods are contacting employer or interviewing and sending resumes or applications.

There are also differences in the usage of specific search methods between men and women. To further investigate these differences, I estimate Probit regressions of the effect of gender on the usage of each search method while controlling for age, unemployment duration, education, race, and year fixed effects. I present the results in Table C.7. Among the most commonly used search methods, women are substantially more

	Job Search Method	Men	Women
(1)	Contact employer or interview	0.62	0.56
(2)	Contact public employment agency	0.26	0.20
(3)	Contact private employment agency	0.11	0.08
(4)	Contact friends or relatives	0.26	0.19
(5)	Contact school employment center	0.03	0.03
(6)	Send resumes or applications	0.51	0.55
(7)	Checked union or professional registers	0.06	0.03
(8)	Placed or answered ads	0.21	0.19
(9)	Other active methods	0.08	0.08
(10)	Looked at ads (passive)	0.31	0.30
(11)	Attended training or courses (passive)	0.01	0.01
(12)	Other passive methods (passive)	0.01	0.01
	Average Number of Methods	2.48	2.24

Table C.6: Job search methods in the CPS.

Notes: The table shows a list of job search methods and the share of unemployed workers using each method based on the CPS from 1994-2014. (1)-(9) are active search methods and (10)-(12) are passive search methods. The sample contains unemployed workers who reportedly use at least one active search method drawn from married individuals of age 30-45.

likely to send resumes and applications but less likely to contact employer or interview. The differences across genders are potentially driven by preferences or the opportunity cost of the job search activities, or the fact that men and women look for different jobs.

Appendix C.2. Labor Force Measures

The CPS collects information on employment, availability for work, and job search methods; the labor force status is determined by the responses to these questions. According to the US Bureau of Labor Statistics (BLS), non-employed individuals who are not available for work and have searched for work using at least one active job search method are classified as unemployed workers.[5] Individuals who are neither employed nor unemployed are non-participants. Using the CPS, I compute the labor force participation rate as the fraction of individuals in the sample who are employed or unemployed, while the unemployment rate is the fraction of labor force participants who are unemployed.

As I explain in Section 3.1, I obtain my final sample from the CPS after a series of sample restrictions. Table C.8 shows how the labor force participation rate and the unemployment rate vary with each sample selection criterion. Relative to the broader initial sample, men in my final sample have a higher labor force participation rate, while both genders in my final sample have a lower unemployment rate.

I compute labor force transition rates by exploiting the panel structure of the CPS. Given the rotating panel design of the CPS, I am able to match up to three-quarters of the sample households from one month to the

[5]Individuals who are temporarily laid-off and expecting to be recalled are also classified as unemployed workers.

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.072***	-0.060***	-0.028***	-0.064***	0.001	0.041***
Age	-0.007	0.005	-0.005	0.001	-0.003	-0.011
Age Sq.	0.000	-0.000	0.000	0.000	0.000	0.000
U. Dur.	0.000	0.001***	0.000***	0.001***	0.000	0.002***
U. Dur. Sq.	-0.000**	-0.000***	-0.000***	-0.000***	-0.000	-0.000***
Ddu: HS	-0.004	0.032***	0.021***	-0.060***	0.011***	0.124***
Ddu: COL	0.026***	-0.019***	0.080***	-0.029***	0.040***	0.200***
Race: Black	0.003	0.059***	0.005	-0.020***	0.000	-0.004
Race: Other	-0.030***	-0.020***	0.002	0.013*	-0.001	-0.020**
Observations	103970	103970	103970	103970	103970	103970
Pseudo R^2	0.016	0.014	0.019	0.027	0.028	0.018

	(7)	(8)	(9)	(10)	(11)	(12)
Female	-0.033***	-0.018***	0.001	-0.010**	-0.001	0.001
Age	0.000	0.006	0.005	-0.012	0.003	-0.001
Age Sq.	0.000	-0.000	-0.000	0.000	-0.000	0.000
U. Dur.	0.000	0.001***	-0.000	0.002***	0.000	0.000**
U. Dur. Sq.	-0.000	-0.000***	-0.000	-0.000***	-0.000	-0.000*
Ddu: HS	0.016***	0.069***	0.033***	0.060***	0.005***	0.006***
Ddu: COL	0.035***	0.094***	0.075***	0.034***	0.008***	0.011***
Race: Black	-0.019***	-0.017***	-0.019***	-0.013**	0.001	-0.000
Race: Other	-0.011***	-0.020***	-0.006	0.010	0.001	-0.001
Observations	103970	103970	103970	103970	103970	103970
Pseudo R^2	0.038	0.010	0.025	0.012	0.006	0.126

Table C.7: Marginal effects on the usage of job search methods based on Probit regressions

Notes: Based on a sample of married individuals of age 30-45 drawn from the monthly CPS data from 1994-2014. The sample contains unemployed workers who reportedly use at least one active search method. Year fixed effects are included in the regression model. Columns (1)-(9) are active search methods, and Columns (10)-(12) are passive search methods. See Table C.6 for the list of search methods.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	LFPR		UR	
Sample Restriction	Men	Women	Men	Women
(a) Age 30-45	0.939	0.762	0.041	0.047
(b) Age 30-45, Married	0.953	0.734	0.033	0.037
(c) Age 30-45, Married, HS or COL	0.958	0.752	0.030	0.034
(d) Age 30-45, married, HS or COL, Not Disabled or Retired	0.977	0.767	0.030	0.034
(e) Final Sample	0.980	0.763	0.030	0.033

Table C.8: Labor force participation rate and unemployment rate by sample restriction.

Notes: Based on data from matched monthly CPS from 1994-2014. LFPR is the labor force participation rate, and UR is the unemployment rate. See Section 3.1 for details on the sample restriction criteria.

		HS-HS		COL-COL		COL-HS		HS-COL	
		Data	Model	Data	Model	Data	Model	Data	Model
1	Mean, Women	7.72	7.72	8.24	8.28	7.77	7.83	8.18	8.18
2	St. Dev., Women	0.56	0.44	0.66	0.51	0.62	0.47	0.57	0.45
3	Mean, Men	8.21	8.21	8.65	8.65	8.53	8.53	8.29	8.29
4	St. Dev., Men	0.46	0.36	0.51	0.40	0.50	0.39	0.48	0.38
5	Correlation	0.12	0.11	0.12	0.11	0.06	0.06	0.11	0.09

Table D.9: Moments of the joint distribution of log monthly earnings of married couples.
Notes: The table shows the mean, standard deviation, and coefficient of correlation of the joint distribution of log monthly wages of married couples. "Data" refers to monthly wages computed from the "usual weekly earnings" variable in the CPS from 1994-2014. "Model" refers to observed wages in the simulated data.

next.[6] For example, the transition rate from the labor force state S to the labor force state S' in period t is computed as the fraction of individuals in state S in period $t-1$ who are in state S' in period t.

Appendix D. Calibration

Appendix D.1. Wage Levels and Household-Type Distribution

I choose wage levels $\{w_i(p_i)\}_{i\in\{h,w\};p_i\in\{L,M,H\}}$ and the distribution of (p_h, p_w) based on the "usual weekly earnings" variable in the CPS. The variable records before-tax wages including overtime pay; it is observed in out-going rotations, which are the fourth and the eight interviews of each survey cohort, implying that there are at most two observations per individual.

I take the average of each individual's wage observations and exclude individuals at the top and bottom 1% in each education group in order to eliminate extreme values due to potential measurement errors. I convert the weekly variable into monthly wages and adjust for inflation using the Consumer Price Index so that all measures are in 2014 dollars.

For $i = h, w$ of each of the four household groups, I compute the mean and the standard deviation of log wages, denoted by $\bar{\omega}_i$ and σ_i. I choose wage levels to be $w_i(p_i = L) = \exp(\bar{\omega}_i - \sigma_i)$, $w_i(p_i = M) = \exp\bar{\omega}_i$, and $w_i(p_i = H) = \exp(\bar{\omega}_i + \sigma_i)$. Finally, I choose the distribution of (p_h, p_w) so that the means, the standard deviations, and the correlation of the simulated joint distribution of log wages are similar to those in the CPS. As shown in Table D.9, the model matches the wage distribution moments well.

[6] Between 1994 and 2014, the exceptions are May to September 1995, during which households cannot be matched across survey rounds.

Appendix D.2. Retirement Incomes

I assume that, in the model, the retirement income w_i^r of an individual who faces wage w_i is calculated as follows:

$$w_i^r = \begin{cases} 0.9 w_i & \text{if } w_i \leq 816 \\ 0.9 \times 816 + 0.32\,(w_i - 816) & \text{if } 816 < w_i \leq 4917 \\ 0.9 \times 816 + 0.32 \times (4917 - 816) + 0.15\,(w_i - 4917) & \text{if } w_i > 4917 \end{cases}$$

The function is continuous and piecewise linear; its slopes and bend points are the same as those used by the Social Security Agency in calculating retirement income levels for individuals who retire at the normal retirement age in 2014.[7] In my model, each individual faces a time-invariant degenerate wage distribution, implying that the retirement income level is deterministic.

Appendix D.3. Aggregate States of the Labor Market

In the model, the aggregate state z follows a two-state Markov process; it affects the baseline job finding rate and the separation rate. I calibrate the Markov process using the observed monthly job finding rate of unemployed workers.[8] Specifically, I approximate the observed monthly job finding rate with a two-state Markov process using the maximum likelihood method such that the Good state ($z = G$) is associated with the higher approximated job finding rate while the Bad state ($z = B$) is associated with the lower approximated job finding rate. Based on the matched monthly CPS data, the job finding rate is computed for a sample of married individuals as the 12-month moving average of the transition rate from unemployment to employment. In order to better estimate the aggregate state transition rates, I use a sample that covers a longer time span and a wider age range than the sample used in estimating the structural parameters of the model. Figure D.1 shows the approximation result. The aggregate state transition rates ($\pi_{z'|z'}$) are shown in Table 1. On average, a Bad state lasts for 3.7 years and a Good state lasts for 6 years.

Appendix E. Numerical Procedure

For each type of households characterized by the education group EDU_h-EDU_w and the household type (p_h, p_w), I solve the model presented in Section 2 by backward induction from the terminal period $\tau = \tau_{work} + \tau_{ret}$. The approach is standard. In each period τ, I solve for the optimal decisions given the state

[7] See https://www.ssa.gov/oact/COLA/piaformula.html.

[8] Compared to the job finding rate, the separation rate affects the cyclicality of the unemployment rate to a lesser extent (Shimer, 2012).

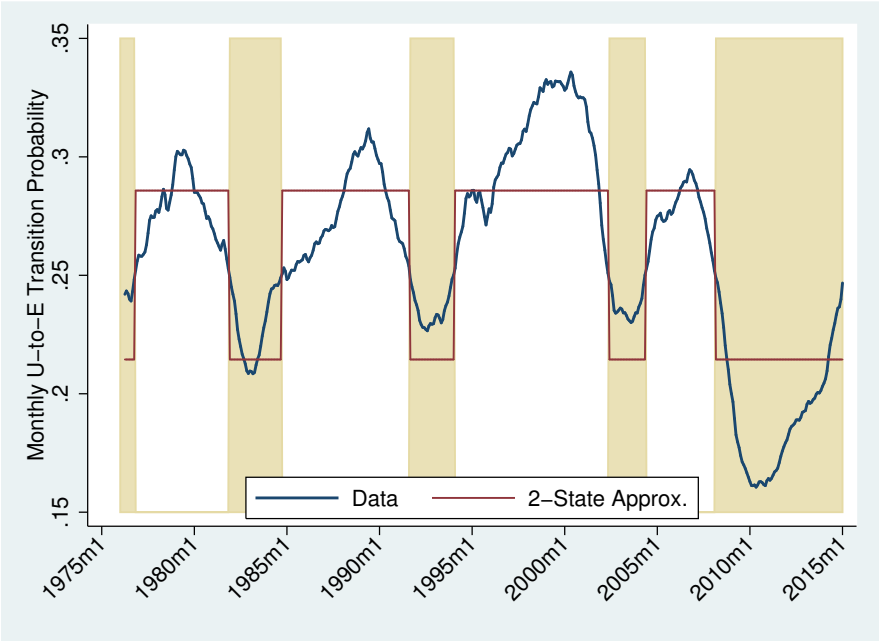


Figure D.1: Monthly job finding rate in the CPS and in the two-state Markov approximation.
Notes: "Data" refers to 12-month moving average of the unemployment-to-employment transition rate computed from the matched monthly CPS data from 1976 to 2014. The sample includes individuals between age 25 and 60 with at least a high-school degree. "2-State Approx." refers to the unemployment-to-employment transition rate in the approximated two-state Markov process. Shaded areas indicate the Bad state ($z = B$).

variables and next period's value function. If $\tau \geq \tau_{work} + 1$, there are only savings decisions; if $t \leq \tau_{work}$, there are both savings and job search decisions.

I discretize the asset space with $N_a = 97$ grid points. The grid is uneven, with more grid points distributed at low asset levels. For $\tau \geq \tau_{work} + 1$, I linearly interpolate the next period's value function and use the Golden-section search technique to find the optimal savings level.

For $\tau \leq \tau_{work}$, I first solve for the optimal asset level given each combination of search intensity levels $(s_h, s_w) \in S(l_h, \eta_h) \times S(l_w, \eta_w)$ via linear interpolation and the Golden-section search technique. The budget constraint holds with equality and the consumption level of each household member is simply half of the household consumption level, which can be computed from the budget constraint. After the optimal asset level is found for each search intensity combination (s_h, s_w), I solve for the optimal search intensity decisions. This is trivial when both spouses are employed or under the η-shock. Otherwise, the search intensity vector (s_h, s_w) that maximizes the present value given the optimal asset level is the optimal search decision.

In the retirement stage, the value function is always increasing and concave in asset level. In the working stage, however, the value function is increasing in asset level a but not necessarily concave.[9] As discussed

[9]See Lentz and Tranaes (2005) for a discussion of this problem.

in the Online Appendix of Low et al. (2010), uncertainties in the model can smooth local convexities. The problem of non-concavity in the value function is not present in the numerical procedure.

Appendix F. Objective Function

Figure F.1 shows the simulated objective function of the SMM estimation around the estimated parameter values for the HS-HS group; the parameter estimates are shown in Table 2. I vary one parameter at a time while holding the others constant at the estimated values. The figure shows that the objective function achieves a minimum at the estimated values, consistent with the fact that the parameters are well identified. The same conclusion is drawn for the other three groups of households.

Appendix G. Robustness Check: Wage Cyclicality

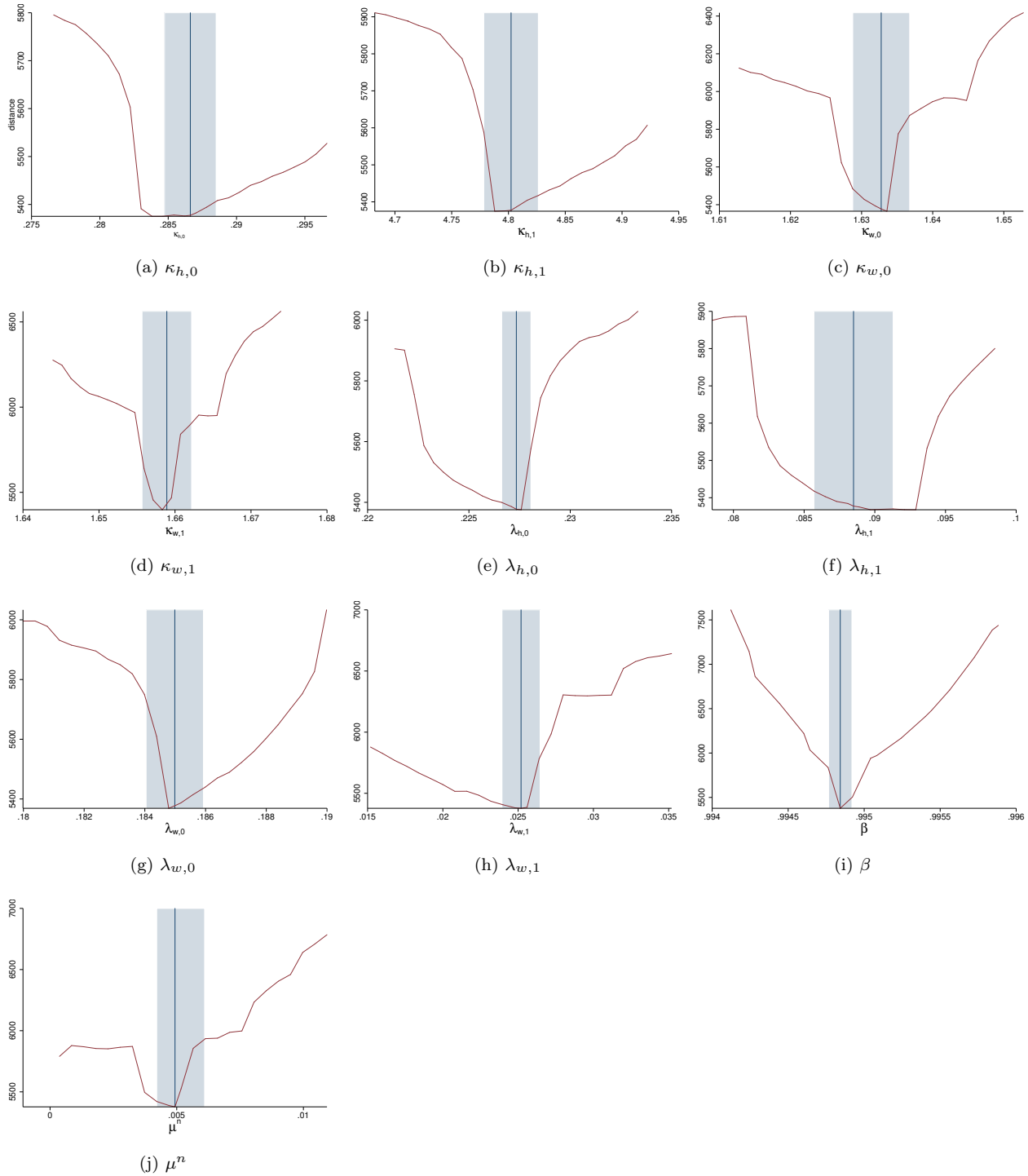
In the baseline model presented in Section 2, I assume that wages $\{w_i\}_{i=h,w}$ do not vary over the business cycle. Elsby et al. (2016) find real wages to be pro-cyclical, while Biddle and Hamermesh (2013) find that the gender wage gap increases in the unemployment rate.

Although the cyclicality of real wages remains an open empirical question in the literature, one may worry about the robustness of the conclusions drawn in this paper when wages are pro-cyclical and the gender wage gap is counter-cyclical. In macroeconomic models with endogenous labor force participation decisions, allowing wages to vary pro-cyclically often leads to counterfactual predictions about the cyclical volatility in unemployment and labor force participation (Shimer, 2013). In my model, counter-cyclical fluctuations in the gender wage gap may attenuate the added-worker effect and the comparative advantage effect.

To demonstrate the robustness of the conclusions, I consider a variation of the baseline model in which there exists wage cyclicality. Specifically, I let $w_{w,z=G} = 1.03w_w$, $w_{w,z=B} = 0.97w_w$, $w_{h,z=G} = 1.02w_h$ and $w_{h,z=B} = 0.98w_h$; the magnitudes of wage fluctuations are plausible given the empirical findings in the literature. I assume that wages are automatically adjusted for employed workers over the business cycle and estimate the model using the method outlined in Section 3 based on HS-HS households.[10] The parameter estimates are shown in Table G.10.

In the baseline model, the fact that the gender gap in the baseline job finding rate is cyclical gives rise to the comparative advantage effect. In the current model, there is additionally the cyclical gender wage gap, which also influences the comparative advantage effect. The two types of gender gap counteract one another:

[10]The assumption that wages are automatically adjusted is consistent with a real business cycle model in which wages are equal to the value of the marginal product of labor.



(a) $\kappa_{h,0}$ (b) $\kappa_{h,1}$ (c) $\kappa_{w,0}$

(d) $\kappa_{w,1}$ (e) $\lambda_{h,0}$ (f) $\lambda_{h,1}$

(g) $\lambda_{w,0}$ (h) $\lambda_{w,1}$ (i) β

(j) μ^n

Figure F.1: Simulated objective function at estimated parameter values.

Notes: The graphs are based on simulations from the HS-HS model. Vertical lines indicate the estimated parameter values. Shaded bands indicate the 95% confidence interval.

κ_0^h	0.272	κ_0^w	1.630	$\lambda_{h,0}$	0.214	$\lambda_{w,0}$	0.181	μ_w	0.005
κ_1^h	4.823	κ_1^w	1.655	$\lambda_{h,1}$	0.109	$\lambda_{w,1}$	0.025	β	0.995

Table G.10: Estimated parameter values in the model with wage cyclicality

The estimation result that $\lambda_{h,1} > \lambda_{w,1}$ suggests that women have counter-cyclical comparative advantage in the labor market, whereas the counter-cyclical gender wage gap suggests the opposite.

As shown in Table G.10, the estimated $\lambda_{h,1} - \lambda_{w,1}$ is higher than that found in the baseline model, implying that the overall comparative advantage effect remains unchanged despite the counter-cyclical gender wage gap. The fitted moments are shown in Table G.11, which closely follow those of the baseline model shown in Table 3.

I repeat the exercises carried out in Section 5 to examine the role of joint decision-making on the cyclicality of the unemployment rate and on the welfare cost of cyclical fluctuations. Table G.12 is constructed in the same fashion as Table 6a, which compares the counter-cyclicality of the unemployment rate between the baseline married-couple model and the counterfactual individualist model. The result that joint decision-making contributes to the counter-cyclicality of women's unemployment rate still holds.

Table G.13 is created in the same fashion as Table 7a, which compares the welfare costs of cyclicality experienced by baseline married-couple households to those experienced by counterfactual individualist households. The conclusions drawn from Table 7a carry over. Married couples experience lower welfare costs of cyclicality, and the benefit of being in a married-couple household is the greatest for those at the bottom of the welfare distribution. Overall, plausible cyclical fluctuations in wages and in the gender wage gap do not alter the conclusions drawn in the paper.

Appendix H. Binary Job Search Decisions

In this Appendix, I consider a version of the baseline model in which there exist only binary job search decisions. Specifically, I assume that $\boldsymbol{S}_i = S_i\left(l_i = 0, \eta_i = 0\right) = \{s_{i,1}, s_{i,2}\}$. Non-employed individuals searching with intensity $s_{i,1}$ are classified as non-participants and those searching with intensity $s_{i,2}$ are classified as unemployed workers. I normalize $s_{i,2} = 1$ for $i = h, w$ and set $s_{i,1}$'s to the ratio of the average non-participation-to-employment transition rate to the average unemployment-to-employment transition rate; for HS-HS of households, $s_{w,1}$ and $s_{h,1}$ are 0.25 and 0.8, respectively.

I estimate the model using the method outlined in Section 3 and focus on HS-HS households. The estimated parameter values are presented in Table H.14a. Columns "Bi-Srch" in Table H.15 present the simulated labor

		Model (Wage Cyc.)	
		Women	Men
LFPR:	$z = G$, sp. Emp.	0.781	0.985
	$z = G$, sp. Unemp.	0.791	0.993
	$z = B$, sp. Emp.	0.771	0.975
	$z = B$, sp. Unemp.	0.816	0.992
UR:	$z = G$, sp. Emp.	0.028	0.024
	$z = G$, sp. Unemp.	0.088	0.076
	$z = B$, sp. Emp.	0.034	0.047
	$z = B$, sp. Unemp.	0.118	0.158
U-to-E:	$z = G$, sp. Emp.	0.219	0.390
	$z = G$, sp. Unemp.	0.221	0.232
	$z = B$, sp. Emp.	0.192	0.258
	$z = B$, sp. Unemp.	0.214	0.129
N-to-E:	$z = G$, sp. Emp.	0.085	0.259
	$z = G$, sp. Unemp.	0.073	0.171
	$z = B$, sp. Emp.	0.073	0.171
	$z = B$, sp. Unemp.	0.062	0.128
N-to-U:	$z = G$, sp. Emp.	0.025	0.029
	$z = G$, sp. Unemp.	0.126	0.280
	$z = B$, sp. Emp.	0.026	0.037
	$z = B$, sp. Unemp.	0.173	0.333
Drop in Consumption:		0.087	
Inc.-Wealth Ratio:		2.044	

Table G.11: Simulated moments in the model with wage cyclicality

Notes: The table shows moments computed from data simulated from the model with wage cyclicality for HS-HS households. See Appendix G for details on wage cyclicality. Labor force moments are conditional on the aggregate state and the spouse's labor force status (employed or unemployed). "Inc.-Wealth Ratio" is the median ratio of lifetime average annual income to lifetime average wealth. "Drop in Consumption" is the rate of drop in consumption at the onset of non-employment.

		(1) UR_G	(2) UR_B	(3) $UR_B - UR_G$	(4) $(UR_B - UR_G)/UR_G$
Women	Married	0.030	0.038	0.008	27.0%
	Individualist	0.086	0.087	0.001	1.2%
Men	Married	0.026	0.049	0.023	91.1%
	Individualist	0.019	0.038	0.019	103.1%

Table G.12: Cyclicality of the unemployment rate in the model with wage cyclicality

Notes: The table is based on simulated data of HS-HS households. Married women and men are simulated individuals from the married-couple model with wage cyclicality; individualist women and men are simulated individuals from the counterfactual individualist model with wage cyclicality. See Appendix G for details on wage cyclicality. Columns (1) and (2) show the unemployment rate each aggregate state. Columns (3) and (4) show, respectively, absolute and percentage increases in the unemployment rate from the Good state to the Bad state.

Welfare Percentile	Married-Couple Households		Individualist Households	
	$\bar{c}_{cyc}$	Cost of Cyc.	$\bar{c}_{cyc}$	Cost of Cyc.
Bottom 10%	2493	2.4%	1787	3.4%
10-50%	3971	1.3%	3534	2.4%
Top 50%	6064	0.5%	5745	1.1%
Overall	4995	0.9%	4465	1.8%

Table G.13: Simulated welfare cost of cyclical fluctuations in the model with wage cyclicality

Notes: The tables show the simulated welfare level and the simulated welfare cost of cyclical fluctuations. based on HS-HS households. Married-couple households are simulated households from the married-couple model with wage cyclicality; individualist households are simulated households from the counterfactual individualist model with wage cyclicality. See Appendix G for details on wage cyclicality. "$\bar{c}_{cyc}$" is the average consumption-equivalent of lifetime utility in the baseline (cyclical) environment, defined in Eq. 8. "Cost of Cyc." is the percentage increase in consumption-equivalent compared to a counterfactual environment in which there are no cyclical fluctuations. Welfare percentiles are based on the distribution of $\bar{c}_{cyc}$.

κ_0^h	2.198	κ_0^w	3.206	$\lambda_{h,0}$	0.282	$\lambda_{w,0}$	0.363	μ_w	0.005
κ_1^h	4.187	κ_1^w	1.745	$\lambda_{h,1}$	0.103	$\lambda_{w,1}$	0.017	β	0.996

(a) Model with binary search intensity

κ_0	1.366	λ_0	0.048	$\mu^n_{h,z=G}$	0.005	$\mu^n_{w,z=G}$	0.005	β	0.995
κ_1	1.817	λ_1	0.180	$\mu^n_{h,z=B}$	0.005	$\mu^n_{w,z=B}$	0.007		

(b) Model with gender-neutral search parameters

Table H.14: Estimated parameter values in alternative models

Notes: See Appendix H for the model with binary search decision. See Appendix I for the model with gender-neutral search parameters.

force moments by aggregate state z, which show that the labor force participation rate is counterfactually counter-cyclical.

As I explain in Section 4.3, when job search decisions are multi-level, the optimal search intensity of women varies counter-cyclically among intensive job searchers and pro-cyclically among mild job searchers. The counter-cyclical labor force participation generated in the binary-search model can be explained by the fact that mild job searchers cannot vary their search intensity pro-cyclically. This can be observed from the fact that the simulated transition rate from non-participation to employment is less pro-cyclical than that in the baseline model.

In contrast, men's optimal search intensity in the baseline model is relatively unresponsive to changes in the aggregate state. Consequently, whether the search decision is binary or multi-level does not significantly affect the model's performance in fitting the cyclical patterns in men's labor force moments.

		Women				Men			
		Data	Baseline	Bi-Srch	Gen-Neu	Data	Baseline	Bi-Srch	Gen-Neu
LFPR	$z = G$	0.794	0.789	0.767	0.814	0.985	0.987	0.989	0.981
	$z = B$	0.784	0.778	0.775	0.784	0.978	0.978	0.978	0.967
UR	$z = G$	0.029	0.031	0.031	0.031	0.025	0.026	0.026	0.031
	$z = B$	0.045	0.035	0.037	0.035	0.047	0.045	0.051	0.046
U-to-E	$z = G$	0.305	0.224	0.312	0.241	0.350	0.384	0.377	0.311
	$z = B$	0.205	0.201	0.291	0.192	0.251	0.277	0.238	0.250
N-to-E	$z = G$	0.079	0.087	0.067	0.100	0.270	0.254	0.302	0.182
	$z = B$	0.067	0.075	0.062	0.076	0.209	0.182	0.191	0.145
N-to-U	$z = G$	0.021	0.029	0.030	0.034	0.103	0.048	0.042	0.056
	$z = B$	0.025	0.032	0.036	0.032	0.121	0.055	0.050	0.057

Table H.15: Labor force moments by aggregate state in alternative models

Notes: The table is based on simulated HS-HS households. "Data" columns show moments computed from a sample of married couples drawn from the matched monthly CPS data. "Baseline" columns show simulated moments computed from the baseline model (Section 2). "Bi-Srch" columns show simulated moments computed from the model with binary search decision (Appendix H). "Gen-Neu" columns show simulated moments computed from the model with gender-neutral search parameters (Appendix I).

Appendix I. Gender-Neutral Search Parameters

Differences in wages and non-employment incomes alone are not sufficient to explain the observed gender-asymmetry in labor force moments. To demonstrate this, I consider a version of the baseline model in which the search disutility function and the baseline job finding rate are gender-neutral, while the non-employment income ratio is gender-specific. In other words, I let $\kappa_{i,0} = \kappa_0$, $\kappa_{i,1} = \kappa_1$, $\lambda_{i,0} = \lambda_0$, and $\lambda_{i,1} = \lambda_1$ for $i = h, w$, and let $\mu^n_{i,z}$ be the non-employment income ratio of household member i in the aggregate state z.

I estimate the model using the method outlined in Section 3 and focus on HS-HS households. The estimated parameter values are presented in Table H.14b, and the simulated labor force moments by aggregate state z are shown in Columns "Gen-Neu" of Table H.15.

Overall, the model with gender-neutral search parameters fit the labor force moments poorly. In the model, women's labor force participation rate is too high whereas men's is too low; both are too pro-cyclical. Without gender-specific κ_0 and λ_0, the current model is not able to match the differences in the level and the cyclicality of search intensity across genders. Due to the assumption that couples are unitary decision-makers who pool their incomes, the non-employment income of one spouse inevitably affects both spouses' search decisions in similar ways as a result of the wealth effect. Thus, having gender-specific non-employment incomes has limited ability in helping the model to match the differences in the labor force participation rate across genders.

Another observation is that the current model over-estimates the difference between the unemployment-to-employment transition rate and the non-participation-to-employment transition rate for men. The parameter

κ_1 disciplines the dispersion in search intensity, which in turn influences the difference between the two job finding rates. Under the current specification, κ_1 is gender-neutral, and its estimated value is smaller than the estimated $\kappa_{h,1}$ in the baseline model. As non-employment incomes do not influence the dispersion in search intensity, the current model generates the counterfactually large dispersion in the two job finding rates of men.

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