Household Search and the Aggregate Labor Market *

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Abstract

Sharing risks is one of the essential economic roles of families. The importance of this role increases in the amount of uncertainty that agents face and the degree of financial market incompleteness. We develop a theory of joint household search in frictional labor markets under incomplete financial markets. Couples households can insure themselves by savings and by timing their labor market participation. We show that this theory can match one aspect of the US data that conventional search models cannot match; that whilst aggregate employment is pro-cyclical and unemployment counter-cyclical their sum, the labor force is acyclical. In our model, and in the US data, when a family member loses her job in a recession the other family member joins the labor force to provide insurance. We also explore other important implications of our theory for the aggregate labor market. Our analysis offers new insights for the cyclical behavior of the labor wedge in models of heterogeneous agents and wealth accumulation.

JEL Classification: E24, E25, E32, J10, J64

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1 Introduction

In March 2009 there were roughly 13 million unemployed workers in the US economy. A large fraction (40%) of these workers were married. Married men accounted for 25% of total unemployment and married women for 15%. 68% of all US workers participated in the labor force; for married women the analogous participation rate was 61%.

Economic decisions such as whether or not to work and whether or not to search for job opportunities in the labor market, are surely made jointly in the family. Moreover when financial markets are incomplete, as they are in the real world, these decisions are influenced by the incentive of households to insure against shocks to their labor income. Unemployment is such a shock and families are an important insurance device against it.

With very few exceptions these features have not been part of the literature of search models of the labor market; nor have they been part of the literature of models of heterogeneous agents and wealth accumulation. Take for instance the baseline model of Krusell & Smith (1998) in the latter literature. In this economy workers face idiosyncratic labor income risks, such as the risk of unemployment, and they can self-insure against them by trading claims on the aggregate capital stock. Much less common is the idea that a considerable amount of employment risk diversification can be provided within the family. Moreover in Mortensen & Pissarides (1994) and in the considerable literature of search and matching models of the labor market, households are also viewed single agents decision units.

We present a theoretical framework where financial markets are incomplete, labor markets are subject to search frictions and households are formed by two members that make labor supply, search and savings decisions jointly. We use this framework to investigate the effects of family self insurance on the aggregate labor market outcomes. In particular we show that our model can match one aspect of the US data that conventional search models cannot match; that whilst aggregate employment is very procyclical and unemployment countercyclical, their sum, the labor force is nearly acyclical. Search models that allow for endogenous participation in the labor force have a hard time in matching these facts. As we explain they typically produce a very procyclical labor force and we argue that what they are missing out on is to assign an important role to family self insurance.

To understand this last point consider the following realistic example: Assume that a couple has one of its members employed and the other member is out of the labor force. This is a pattern of intra-household specialization that we observe very frequently in the data. Usually primary earners in US households are husbands and secondary earners wives. Assume also that the economy is in a recession, when the separation rate is higher and the job finding rate is lower. If the husband loses his job in a recession, household income suffers a big shock. Moverover if financial markets are incomplete, income losses have an impact on consumption; but joint search can provide an important buffer against these risks. The wife can join the labor force, and search actively in the market, to maximize the chances that the household will have at least one of its members employed next period.

In section 2 of our paper we show that similar adjustments of labor supplies at the household level are a feature of the US data. We show that some household members time their flows in and out of the labor market to provide insurance, and once we remove this insurance effect their labor force participation becomes considerably more procyclical. We also draw on several studies that document the magnitude of the added worker effect, the behavioral response of female labor supply to spousal unemployment (for example Lundberg (1985) and Stephens (2002)).

Then we turn to the theory. We construct three general equilibrium models with search frictions in the labor market and shocks in individual (idiosyncratic) labor productivity. There are incomplete financial markets as in Krusell & Smith (1998). We first present a model where households are bachelors. This is a natural starting point that helps us to examine transparently the role of family insurance and to describe the economic environment. Subsequently we present two models where families are couples. In the first one we assume that the two agents that form the family are ex ante identical, meaning that they have the same potential labor income and confront the same frictions in the labor market. In the second we populate each household with a husband and wife, and we calibrate labor market risks and search frictions for males and females separately; we also introduce differences in the gender price of labor, a gender pay gap. We consider these two different structures because the notion that families pool resources and adjust labor supply is central in our theory. When family members have the same potential labor income there is possibly too much insurance relative to the data. When we model households as couples with a husband and a wife we address this concern.

We compare the aggregate labor market allocations in these environments when we introduce business cycle fluctuations. If family self insurance is important in the models as it is in the data, then bachelor households should produce a more procyclical labor force. This is what we find; the three economies share similar cyclical properties for aggregate employment unemployment, but they deliver very different predictions for the cyclical behavior of the labor force. In both couples economies the contemporaneous correlation with GDP is nearly 50% smaller than that of our bachelors households model. The couples economies match the cyclical properties of this statistic as in the US data.

We show that our models are consistent with the data in a number of dimensions. First, all of our economies can match very well the patterns of worker reallocation (worker flows between employment, unemployment and inactivity), and they can account for the idiosyncratic labor market risks that agents face throughout their working lives. Second our couples economies can account for the patterns of household specialization in market work and leisure and the distribution of household members across labor market states.

A large part of the success of our model in matching the US business cycle in the aggregate labor market, is due the assumption that risk sharing in the macro-economy is imperfect. This is the very important difference between our approach and previous work in the literature that studies the cyclicality of labor force participation in search models. For instance Tripier (2004) uses the search and matching model as in Merz (1995) and Veracierto (2008) considers a version of the equilibrium unemployment theory of Lucas & Prescott (1974) with undirected search and endogenous separations. Haefke & Reiter (2009) augment the Mortensen & Pissarides (1994) model with home production, but they assume risk neutrality. All of these models generate a very procyclical labor force, because the notion that families adjust their labor supply to provide insurance is absent. Instead we interpret movements in labor market flows over the business cycle partly as a behavioral response of household members to changes in unemployment risks.

Finally, we explore another important implication of our theory. There is a growing literature that studies the cyclical properties of the wedge derived from the optimality condition that links consumption and hours in real business cycle theory. One strand of this literature views labor market wedges as a by product of aggregation of individual policy rules, in models of heterogeneous agents and wealth accumulation (Chang & Kim (2007)), and another strand as a symptom of the failure of labor markets to clear when there are frictions (see for instance Hall (2009)). Our theory combines both of these features. We find that although incomplete financial markets models can generate cyclical wedges when agents are bachelors they cannot do so when families are larger. Even with as few as two agents in the household the labor wedge has cyclical properties very different from the US data. Instead we argue that labor market frictions are more crucial.

Only very recently a handful of papers highlight the role of family labor supply as an insurance margin against idiosyncratic labor income risks. Chang & Kim (2006) develop a framework where households consist of two members (a male and female) and use it to understand how individual labor supply rules affect the value of the aggregate elasticity of labor supply. Attanasio, Low, & Sanchez-Marcos (2005) quantify the welfare benefits from female labor force participation when income uncertainty increases in a model with incomplete asset markets. Attanasio, Low, & Sanchez-Marcos (2008) and Heathcote, Storesletten, & Violante (2008) analyze the effects of changes in the economic environment (such as changes in gender wage premia or changes in idiosyncratic labor income risks) on the historical trends of female labor supply. The difference from our work is that we emphasize the role of families in circumventing frictions in the labor market, whilst this literature overlooks the importance of frictions. This has the following implication: insurance against any income risk other than unemployment becomes less meaningful since families cannot readily assign the most productive agents to employment. The literature on the added worker effect that we summarize is corroborative to this interpretation of the risk sharing role of families. Finally, Guler, Guvenen, & Violante (2008) explore the implications of joint search on optimal reservation wage policies. They use a stylized search model, while we build a general equilibrium framework with realistic heterogeneity that accounts for the observed labor market flows as well as the effects of shocks in aggregate productivity.

The rest of this paper is organized as follows: Section 2 uses the estimated flows from the CPS to provide evidence that joint insurance and labor supply are key factors that explain the low procyclicality of the US LF participation. In section 3, we develop the bachelor household model and the couple household models. In section 4, we show and discuss the basic results and implications of our theory. Section 5 concludes and the computational details are relegated to the appendix.

2 The US Labor Market

Table (1) summarizes the US labor market business cycle statistics. The data are constructed from the CPS and they correspond to observations spanning the years 1976 to 2005. They are logged and HP filtered and all quantities refer to quarterly aggregates and are expressed relative to a detrended measure of GDP. Unemployment is very counter-cyclical and more than 7 times as volatile as aggregate output. Aggregate employment has two thirds of the volatility of output at business cycle frequencies and is very procyclical. The labor force is not volatile and its contemporaneous correlation with GDP is low (.45).

Table 1: US Business Cycle: Labor Market Statistics

	E	**U**	**LF**	**LF Couples**	**LF Wives**
	Aged 16 and Above			Aged 25 to 55	
$\frac{\sigma_x}{\sigma_y}$	0.62	7.48	0.21	0.17	0.36
$\rho_{x,y}$	0.89	-0.91	0.45	0.26	0.26

Notes: The data are from the CPS and based on the years 1976 to 2005. They are logged and HP filtered and all quantities refer to quarterly aggregates and are expressed relative to a detrended measure of GDP. $\frac{\sigma_x}{\sigma_y}$ is the volatility of variable x relative to the volatility of GDP. $\rho_{x,y}$ is the correlation of variable x with GDP. E is the employment to population ratio, U refers to the unemployment rate (number of unemployed agents over the labor force), and LF is the labor force (number of workers who are either employed or unemployed) over total population. Population is the total number of individuals in the relevant demographic group.

The last columns of Table (1) present a breakdown of the relevant quantities into demographic groups that are of particular interest to us. For married couples aged 25 to 55 in our sample, aggregate statistics are no different than those of the full population (aged 16 and above). The labor force participation for this demographic is even more acyclical (and hence even more puzzling from the point of view of theory) owning to the strong acyclical attachment of males in the sample, but also to the low contemporaneous correlation with GDP of female labor force participation. The volatility of both males (not shown) and females are higher than the aggregate volatility for this demographic group (column 4), because the labor force participation rates of wives and husbands in our sample are negatively correlated.

We note that married couples in the data are an imperfect measure of our notion of couples in the model. Ideally we would like to have duads of agents that are linked with near perfect insurance opportunities within the family, and little insurance between, but the data preclude us from doing so. In the data families are extended beyond the household unit; singles are not really singles and frequently households consist of more than two agents who make labor supply decisions jointly. Despite these caveats, in what follows we will treat the joint search behavior of married couples as an ideal ground to provide evidence for our theory.

2.1 Implications for models: Fixed participation?

The bulk of the literature of search theoretic models of the labor market assumes that agents can be either employed or unemployed at any point in time (see for example Mortensen & Pissarides (1994) and the considerable literature of search and matching models). We view this as a major shortcoming of the theory. In this section we show that flows between activity and inactivity are an important aspect of worker reallocation. We argue that the US data suggest that agents flow readily across labor market states and economic models need to embrace this feature of the data. The moments that we summarize here are also key targets for our models.

In Table (2) we summarize the flows estimated from the CPS. Our sample includes all individuals, married or single, aged 16 and above. This is the population used by the BLS to construct aggregate labor market statistics for the US economy. These flows are the transition probabilities that an agent who is state i in period t will be in state j in period $t+1$ where $\{i, j\} \in \{E, U, I\}$. E is employment, U is unemployment and I is inactivity (out of labor force). In the top panel (A) of the table we report the average transition probabilities for the population in the years 1976 -2005. In panels (B) and (C) we disaggregate our data into populations of males and females.

Each month roughly 7 % of OLF (out of labor force) workers join the labor force (5% directly to employment), and 3 % of employed workers and 22 % of unemployed workers become inactive. Across the two genders, labor market flows seem strikingly similar, although males appear to have somewhat of a stronger labor force attachment than females. The employment population rate for males is 70% in our sample and roughly 50% for females. Aggregate employment population ratio is 60%.

Table 2: Flow rates Bachelors and Couples

	Panel A: All Agents Age $\geq$ 16		
	E	U	I
E	.9558	.0144	.0298
U	.2536	.5226	.2238
I	.0485	.0275	.9240

	Panel B: Males Age $\geq$ 16			Panel C: Females Age $\geq$ 16		
	E	U	I	E	U	I
E	.9621	.0166	.0213	.9485	.0131	.0384
U	.2831	.5448	.1721	.2440	.4835	.2725
I	.0554	.0326	.9120	.0417	.0224	.9359

Notes: The data are drawn from the CPS. These flow rates are averages over the period 1976-2005. They are the monthly transitions from one labor market state in month t (rows) to another labor market state in month $t+1$ (columns). E denotes employment, U unemployment and I inactivity (out of labor force).

Table 3: Flow rates Married Couples

	Males Age 25-55			Females Age 25-55		
	E	U	I	E	U	I
E	.9762	.0131	.0107	.9597	.0104	.0300
U	.2827	.5929	.1244	.2331	.5142	.2527
I	.0669	.0418	.8913	.0510	.0251	.9240

In table 3 we look closer at labor market flows of married couples (males and females) aged between 25 and 55. We do so to dispel the suspicion that the results are driven by demographics; by focusing on this age bracket, we can partially control for schooling and retirement decisions. If anything the estimates in table 3 reinforce our conviction that individuals make frequent transitions between labor market states from one month to the other. The flows from inactivity to either employment or unemployment are even larger in this case (roughly 10% for males and 9% for females vs 7.8 % and 6.5% in table 2). Also 1% of males and 3% of females quit employment each month and exit the labor force. [1]

These numbers are huge. Over our sample period there are more workers flowing from employment to out of the labor force than to unemployment; moreover if 35% of the US population are inactive and roughly 4% unemployed, there are more workers moving from out of the labor force to employment each month (1.7%) than from unemployment (1%). One of the important contributions of this paper is that it offers a framework that can be used to think about the determinants of these transitions. In the next paragraph we show that a large part of these flows is driven by the incentive of families to insure against unemployment.

2.2 How can we use the data to demonstrate our point?

We show in this paragraph that family self insurance is important in the US data. We do two things. The first is that we estimate several limited dependent variable (linear probability) models to gauge the effect of the husband's employment status, on the wife's labor force transition probabilities; this allows us to control for some relevant aspects of heterogeneity. We also provide a summary of numerous attempts in the literature to determine the magnitude of the so called added

[1] There is a large literature that documents similar facts using different micro data sets for the US economy (for instance Blanchard, Diamond, Hall, & Murphy (1990), Nagypal (2005), Davis & Haltiwanger (2006) and Shimer (2007)). We summarize a few relevant findings here. First Nagypal (2005) argues that around 40% of the transitions from employment to out of labor force are followed by a transition to employment in the next month. Some of these workers search for new opportunities on the job, and they obtain a new job but the starting date is postponed by a month. Second, flows from I to E are surely affected by time aggregation, since within a month, which is the interview horizon in the CPS, workers can move from inactivity to employment without having a recorded unemployment spell (e.g. Shimer (2007)). Finally Jones & Riddell (1999) argue that the behavior of passive searchers and marginally attached workers is important; for these groups they demonstrate that they have transition probabilities to employment that are nearly half as large as those of unemployed workers, and hence part of the flows between states U and I can be broadly interpreted as time variation in search intensity for these groups.

These implications have already been explored in the literature; For instance it appears that adjusting the transition probabilities to embrace the idea that marginally attached workers should be treated as unemployed rather than inactive does not make a big difference in the estimated transition matrices, see Krusell, Mukoyama, Rogerson, & Sahin (2009a). In the models we try to match the flow rates as we document them in table 2. What is important is that our economies leave room for individuals to make frequent transitions between employment, unemployment and inactivity, so that the labor force is not fixed. (See also Garibaldi & Wasmer (2005) for a model on worker flows.)

worker effect, the behavioral response of female labor supply to spousal income shocks. Both our own estimates and the related literature seem to be corroborative to our view that family labor supply is an important insurance mechanism against unemployment risks.

Our second piece of evidence is that we use the data from the CPS to provide an answer to the following question: assuming that the employment status of married men does not fluctuate over the business cycle, how would female labor force participation behave? We perform a counterfactual experiment that can partially quantify the contribution of the joint labor supply on the cyclicality of the US labor force.

2.2.1 The Response of Female Labor Supply and Search

We first give a brief summary of a related literature that uses panel data to investigate the effect of unemployment spells experienced by the husband on the spousal supply of labor. Our reading suggests that at least with respect to data and methodology there are two strands in this literature. [2]

First, there are models that use variation in annual hours of work to identify how the husband's recorded unemployment spells affect the wife's labor supply. There does not appear to be a consensus in this empirical work for the magnitude of the AWE. For instance Heckman & MaCurdy (1980) find a small but significant added worker effect, but Pencavel (1982) doesn't. The reason for this is twofold. First there are other sources of insurance (besides joint labor supply) that minimize the loss of income due to an unemployment spell. Cullen & Gruber (2000) show that unemployment benefits have a massive crowding out effect on family self insurance. Second, more recently Stephens (2002) argues that the empirical literature fails to identify unemployment spells that result in substantial earnings losses. He shows, using data from the PSID, that in families of displaced workers there are significant added worker effects.

More related to our story is the subset of studies that use short run transitions across labor market states (employment, unemployment and inactivity). These studies tend to find significant added worker effects. Lundberg (1985) uses monthly employment histories from a sample of the Seattle and Denver Income Maintenance Experiments (SIME DIME) to conclude that if a husband is unemployed then the probability that his wife enters the labor force increases by 25 %, and the probability of her leaving the labor force is 33 % lower, and she is also 28 % less likely to leave employment for unemployment.[3] Further more

[2]There is also a recent set of studies that focus on the responses of spousal labor supply to health shocks, such as Gallipoli & Turner (2008, 2009) for Canada and Coile (2004) for the US. This work documents the complete lack of an added worker effect, although, in the context of health shocks this has an obvious interpretation; since disability shocks entail an intra-household transfer of time, that allows wives to 'care' for the their ill spouses, wives are unable to increase hours in the market to make up for the lost income.

[3]This pattern seem to hold mainly for white families in Lundberg's dataset. For hispanics

SPLETZER (1997) uses a sample from the CPS and estimates limited dependent variable models of the probability that wives join the labor force on demographics and the husbands' employment transitions. His estimates also show that wives increase their labor force participation in response to spousal unemployment.

In table 4 we provide our own estimates; We use data from the CPS over the period 1994-2010, a longer and more recent sample than the one used by SPLETZER (1997). Our sample consists of married couples aged between 25 and 55; the husband is employed at the beginning of the month and the wife is out of the labor force. We estimate the probability that the wife joins the labor force as a function of various demographic characteristics, month effects and the transition of the husband between employment and unemployment, if any.

The results derive from a simple linear probability model; [4] The first column shows that conditional on the husband becoming unemployed, his wife is 9 % more likely to join the labor force in any given period. In column 2 we distinguish between the husband's reason for job separation. [5] In families where the husband looses his job, wives are 5.7 % more likely to enter the labor force, than in those families where the husband quit, and 13.1 % more likely than in families where the husband remains employed. This result is, off course, very much consistent with models of joint labor supply; an unanticipated fall in income is much more likely to induce a powerful added worker effect.

In figures 1 and 2 we look at the dynamic response of female labor force participation to spousal unemployment. [6] We estimate the following equation with dynamic panel data:

$$\begin{aligned} \mathit{Transition}_{i,t} &= \sum_{\tau=-2}^{\tau=+2} \alpha_\tau \mathcal{I}\{\text{ Husband Spell in t} + \tau\} + \\ &+ Z_{i,t}\delta + \mathit{Time\ Dummies} + f_i + \epsilon_{i,t} \end{aligned}$$

where $Z_{i,t}$ are demographic characteristics and f_i is a household fixed effect. Moreover we define the dependent (dummy) variable as:

$$Transition = \begin{cases} 1 & \text{if} \quad \mathit{olf} \rightarrow \mathit{lf} \\ 0 & \text{if} \quad \mathit{olf} \rightarrow \mathit{olf} \end{cases}$$

that is it takes the value one if the wife flows from out of the labor force into the labor force and the value zero otherwise. The coefficients α_τ measure the change in the probability that the wife will join the labor force in period $t+1$ if her husband lost his job in period $t+\tau$. These coefficients are the dynamic effects of spousal unemployment on family labor supply that we want to estimate.

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and blacks the added worker effect is not significant or in some cases the flows to unemployment for husbands and out of the labor force for wives are synchronized (mainly for black families). That aside Lunberg's conclusion is that there is still a significant added worker effect.

[4] Probit regressions give similar results. See Appendix for details.

[5] The CPS allows us to distinguish between quits and layoffs.

[6] To the best of our knowledge we are the first to look at the dynamic response of female participation in the context of monthly transitions.

Table 4: Added Worker Effect

Variable	LPM Model 1	LPM model 2
Husband EU	.0917***	.0744***
	(.0066)	(.0078)
Husband Job Loser		.0577***
		(.0104)
Age_f	$-.0011^{***}$	$-.0011^{***}$
	(.0001)	(.0001)
$\text{Age}_f^2/100$	$-1e-5^{***}$	$-1e-5^{***}$
	(2.18e-6)	(2.18e-6)
Age_m	$-.00032^{***}$	$-.00032^{***}$
	(5.6e-5)	(5.6e-6)
Educ_f	.01384***	.01384***
	(.00027)	(.00027)
Educ_m	$-.0077^{***}$	$-.0078^{***}$
	(.00023)	(.00023)
White	.00798***	.00798***
	(.00012)	(.00012)
Black	.03769***	.03737***
	(.0015)	(.0015)
No of Kids	.00025	.00026
	(.00023)	(.00023)
No of Kids ≤ 5	$-.0275^{***}$	$-.0275^{***}$
	(.000417)	(.000417)
Time Dummies	YES	YES
R^2	.1024	.1035

Notes: The data are from the CPS for the years 1994-2010. They are observations for families where at the beginning of month t the wife is out of labor force and the husband is employed. The dependent variable takes the value one if the female spouse becomes part of the labor force (employed or unemployed) in month $t+1$. The estimates are from a linear probability model with household fixed effects. ***Indicates significant at 1 percent level.

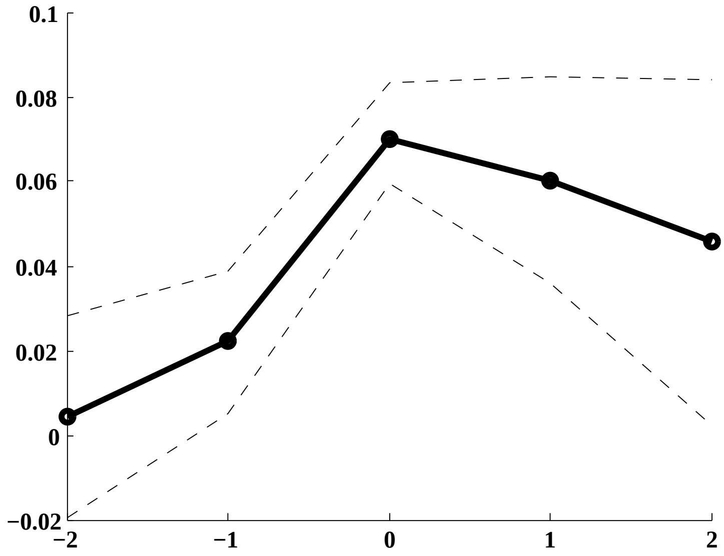

Figure 1: Dynamic Response of Female LF Participation

In figure 1 we plot the α_{tau} coefficients for the entire sample (job losers and leavers). The graph shows that wives increase their participation a month before the unemployment spell occurs and are more likely to join the labor force one or even two months after the spell. The contemporaneous effect is a 7.5% increase in the probability, whereas in the two months following the unemployment spell the rise is 6% and 4.8% respectively. [7] In figure 2 we show the dynamic responses for the sample of job losers (we drop quits so any EU transition is a job loss). The effects are even stronger in this case; the peak occurs at one month before the recorded EU transition and there is an 18% rise in the probability that the female spouse joins the labor force. At all horizons the effects are significant.

Why is it important to look at these dynamic responses? Because the change in the search behavior occurs when the relevant information for the unemployment spell arrives. Just think of a couple where the husband knows with certainty that his job will end in one or two months (if say he is given an advance notice of termination). In that case joint search may be optimal even before the unemployment spell occurs. Similarly the response could be delayed if there are adjustment costs, for example for families with children, or if the couple fails to realize the magnitude of the shock to labor income; in the latter case the husband searches for a new job in the first month and if this search doesn't pay off, then joint search may be optimal.

In the Appendix we take a closer look at these dynamic responses. We explain in some detail our empirical methodology as well as the limitations of analyzing joint insurance with data from the CPS. We also try to decompose how much

[7] See the Appendix for a thorough description of our data selection process a discussion of robustness.

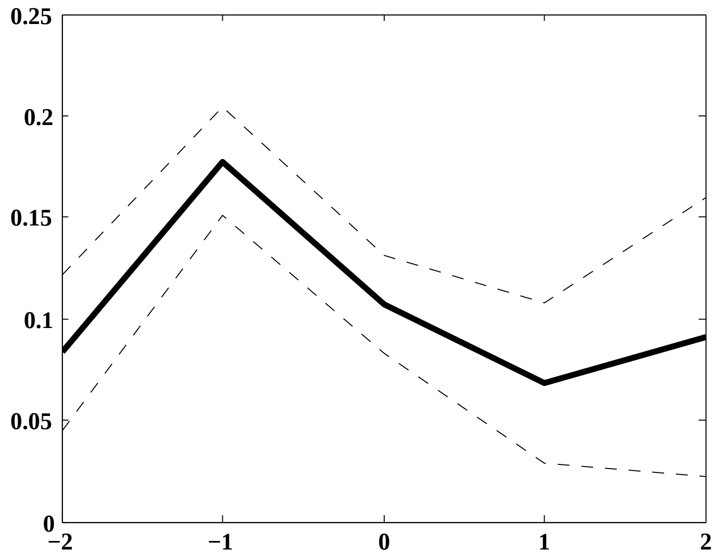

Figure 2: Dynamic Response of Female LF Participation (losers only)

of this added worker effect comes from transitions from out of the labor force to unemployment and how much directly employment (unsurprisingly the first transition dominates). We look at joint insurance from different perspectives (say are wives less likely to drop out of the labor force when their husbands lose their jobs?).

Finally we document the effect of spousal unemployment on search intensity (the number of different search methods employed by individuals to look for jobs). We find that there is a huge effect of male unemployment on female search intensity which we interpret as that family insurance through search in the labor market responds both at the extensive and the intensive margin. This finding is interesting in its own right; points out that search and matching models imply that search intensity is procyclical, a notion that the US (CPS) data seem to contradict. Our empirical results lead us to conclude that the facts can be partly explained by taking more seriously the role of family self insurance in both the data and the models.

We conclude this paragraph by noting two things: First both the relevant literature and our own empirical work confirm that there is a sizable response of female labor supply and search to spousal unemployment. Second, although estimates such as those of table 4 and are useful because they control for observed heterogeneity they cannot quantify the impact of family search insurance in the cyclicality of the US labor force. This is something that we address in the next paragraph.

2.2.2 A counterfactual experiment.

We use our sample from the CPS to provide an answer to the following question: Assuming that the employment status of married men does not fluctuate over the business cycle how would the labor force participation of their wives behave? Recessions are times when husbands are more likely to become unemployed and if so they are less likely to find new job opportunities. If female labor supply acts as a family insurance device, more wives will flow into the labor force during a recession than otherwise expected, making female labor force participation less pro-cyclical. We test the converse: if it were not for the cyclicality in husband's unemployment incidence, female labor force participation would be more pro-cyclical.

For each period t we estimate the transition probability of a wife from state i to state j conditional on her spouse making a transition from state k to l ($p_t^f(i,j|k,l)$), and the unconditional probability for the husband ($p_t^m(k,l)$). Due to data limitations we cannot define these probabilities for all relevant labor market states. For this reason we restrict our attention to $i,j \in \{lf, olf\}$, and $k,l \in \{e,n\}$ meaning that wives can either be in or out of the labor force and husbands either employed or nonemployed. [8]

We let $n_t(i,k)$ be the share of the population of couples with a wife in state i and a husband in state k. With these estimates we construct markov transition matrices over the relevant state space $\{lf, olf\} \times \{e,n\}$. We multiply the initial shares $n_t(i,k)$ with these matrices and we construct distributions of agents over one and three month ahead horizons. We consider two objects; The first, that we label $n_{t+s}^A(i,j)$, is created by the product of $n_t(i,k)$ and a matrix whose typical entry is $p_t^f(i,j,k,l)p_t^m(k,l)$. The second which we label $n_{t+s}^C(i,j)$ is the result of the product of $n_t(i,k)$ with a matrix where we time average the husbands' transition probabilities between employment and non-employment. [9]

The labor force participation of married women is given by $\sum_j n_t^C(lf,j)$ and $\sum_j n_t^A(lf,j)$ under the two measures. We note that if family insurance is important in the data then $\sum_j n_t^C(lf,j)$ should be much more procyclical than $\sum_j n_t^A(lf,j)$. The reason is that under measure $\sum_j n_t^C(lf,j)$ husbands are not more likely to loose their jobs in a recession; and they are not less likely to find new jobs if they become unemployed, in a recession than in a boom. If female labor supply is an important insurance device against unemployment (as the estimates of table 4 suggest) then by time averaging the husband's transitions, we reduce the insurance effect in a recession for US households.

Table 5 summarizes the results from this experiment. We compare the relative standard deviations and contemporaneous correlation with a detrended measure of GDP. The first column refers to the cyclical properties of the labor force

[8] We focus on families where both spouses are between the ages 25 and 55. For this demographic group married agents account for roughly 60 % of the population.

[9] We need both of these objects because small errors that compile over time make the comparison between $n_t^C(i,j)$ and $n_t^A(i,j)$ much more meaningful than between $n_t^C(i,j)$ and $n_t(i,j)$.

Table 5: Experiments

	n_t	n_t^A	n_t^C	n_t^A	n_t^C
		One Month Horizon		**Three Month Horizon**	
$\frac{\sigma_x}{\sigma_y}$	.3604	.3770	.3805	.4294	.4362
$\rho_{x,y}$	.2963	.2988	.3703	.2570	.3216

Notes: The table shows the cyclical component of female labor force participation rates according to two measures: n_t^C corresponds to a markov transition matrix where the husbands' transition probabilities (between employment and non-employment are kept constant; n_t^A allows for changes in the numbers of non-employed male spouses over time.

participation rate of married wives based on the actual population measure n_t. Columns 2 to 3 and 4 to 5 compare the analogous objects based on the measures n_t^A and n_t^C, for one and three months horizons respectively.

The result is both qualitatively and quantitatively encouraging. The cyclical correlation of labor force participation for wives jumps from .2988 to .3703 in columns 2 and 3 and from .257 to .3216 in columns 4 and 5 which roughly corresponds to a 25% increase in cyclicality. We do not interpret this 25% as a target for our models to match; the calculation of this section misses out on several important aspects of family self insurance, for example, that households respond preemptively to increases in unemployment risks in recessions or with a lag, and it doesn't account for the distinction between quits and separations which we showed to be important. Rather we give the following interpretation to our results: if in US households there was no family insurance then the labor force would be substantially more procyclical. We investigate whether our theory is consistent with this implication in section 4.

3 The model

We develop three related models in which households face uninsurable idiosyncratic labor income risk. In section 3.1 a household consists of one agent, the bachelor. In section 3.2 families are formed by two ex ante identical agents. In section 3.3 we add further heterogeneity and we assign a gender (male or female) to each member of the household.

3.1 Bachelor economy

We consider first an economy populated by a unit mass of strictly risk averse bachelor households; these agents are identical in preferences and they get utility from consumption c and disutility from hours working or from looking for job opportunities. We denote the discount factor by β and the period utility from consumption by $u(c)$.

At any point in time an individual can be either employed, unemployed or not part of the labor force. We assume that labor supply decisions are formed at the extensive margin and are subject to the frictions that impede instantaneous transitions across these labor market states. In particular employed agents are matched with firms in production and spend a fraction $\overline{h}$ of their unitary time endowment each period in market activities associated with a utility cost $\Phi(\overline{h})$. Every match operates a technology with constant returns to scale so that without loss of generality we represent the total production in the economy as $Y_t = K_t^{\alpha}(L_t\lambda_t)^{1-\alpha}$. K_t and L_t denote the aggregate capital stock and labor input (per efficiency units); λ_t denotes the level of TFP. We assume that λ_t evolves according to the transition cumulative distribution function $\pi_{\lambda'|\lambda} = Prob(\lambda_{t+1} < \lambda'|\lambda_t = \lambda)$.

For non employed agents we assume that job availability is limited: We endow them with a technology that transforms units of search effort s_t into arrival rates of job opportunities $p(s_t, \lambda_t)$ at a cost $k(s_t)$ per unit of time. As we elaborate below on the basis of these optimal choices, we classify household members as either unemployed (active searchers) or out of labor force workers.

We assume that individuals face idiosyncratic labor productivity risks and we summarize this in two independent stochastic processes; The first one, which we denote by ϵ, is an agent specific process, an own labor productivity component, that is a persistent state variable in the value function independent of her labor market status. We assume that ϵ evolves over time according to the transition cumulative distribution function $\pi_{\epsilon',\epsilon} = Pr(\epsilon_{t+1} < \epsilon', \epsilon_t = \epsilon)$. The second stochastic process is match quality; we assume that shocks arrive to this match quality at rate $\chi(\lambda_t)$ each period. When the shock hits, match productivity is driven to zero, which effectively leads the worker and the firm to separate.

Financial markets are incomplete and agents can self insure by trading non contingent claims on the aggregate capital stock, earning a return R_t each period, subject to an ad hoc borrowing limit $a_t \geq \overline{a} \;\; \forall t$. Wages per efficiency units of labor w_t as well as rental rates R_t are determined in competitive markets where the representative firm aggregates all inputs into the multipurpose final good. Aggregate capital K_t depreciates at rate δ each period. Finally, we let Γ_t denote the density function of agents over the relevant state space (of employment status, productivity and wealth). The law of motion for the distribution of workers is defined as: $\Gamma_{t+1} = \mathcal{T}(\Gamma_t, \lambda_t)$ where $\mathcal{T}$ is the relevant transition operator.

3.1.1 The timing of events

Each period t, and after the resolution of all relevant uncertainty, a non-employed agent chooses optimally the number of search units s_t to exert. Her choice of s_t maps into a probability $p(s_t, \lambda_t)$ of receiving a job offer in the next period. When this opportunity arrives the new values of the idiosyncratic productivity ϵ_{t+1} is sampled and the aggregate state vector $\{\Gamma_{t+1}, \lambda_{t+1}\}$ is revealed and the agent will decide whether she wants to give up search and become employed. Notice that given that all jobs entail a cost $\Phi(\overline{h})$ per period, the realization of the relevant state vector might not be such that the prospective match generates a positive surplus for the worker. In that case the agent continues to search in the labor market.

Employed agents run the risk of loosing their jobs from two sources. First a fraction $\chi(\lambda_t)$ of all exiting matches terminate each period due to the arrival of the match quality shock. Second, the sampling of the new value of ϵ_{t+1} generates the risk of separation. If ϵ_{t+1} is too low the worker may decide that it is not worthwhile to spend $\overline{h}$ of her time working and would rather be not employed next period. We assume that match quality (separation) shocks occur independently of the realization of ϵ.

3.1.2 Value functions

Denote by V^n and V^e the value functions of a non-employed and an employed agent respectively. Also define $Q^e = \max\{V^n, V^e\}$ as the outer envelope over the relevant menu of choices for the non-employed agent conditional on her receiving a job offer next period. Lifetime utility V^n solves the following functional equation:

$$\begin{aligned} V^n(a, \epsilon, \Gamma, \lambda) &= \max_{a' \geq \overline{a}, s} u(c) - k(s) + \beta \int_{\epsilon', \lambda'} \Big[p(s, \lambda) Q^e(a', \epsilon', \Gamma', \lambda')) \\ &+ (1 - p(s, \lambda)) V^n(a', \epsilon', \Gamma', \lambda') \Big] d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda} \end{aligned} \tag{3.1}$$

subject to the constraint set [10]:

$$a' = R_{\lambda,\Gamma} a - c. \tag{3.2}$$

Moreover the lifetime utility of an employed worker is the solution to the following functional equation:

$$\begin{aligned} V^e(a, \epsilon, \Gamma, \lambda) &= \max_{a' \geq \overline{a}} u(c) - \Phi(\overline{h}) + \beta \int_{\epsilon', \lambda'} \Big[(1 - \chi(\lambda)) Q^e(a', \epsilon', \Gamma', \lambda')) \\ &+ \chi(\lambda) V^n(a', \epsilon', \Gamma', \lambda') \Big] d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda} \end{aligned} \tag{3.3}$$

subject to

$$a' = R_{\lambda,\Gamma} a + w_{\lambda,\Gamma} \overline{h} \epsilon x - c \tag{3.4}$$

.

[10]Notice that the distribution Γ becomes a state variable in the worker's value function. In order to forecast prices in the current context and to make optimal savings and labor market search decisions knowledge of Γ' is necessary since this object determines the economy's aggregate capital stock and effective labor in the next period.

A few comments are in order: First note that although the value function V^n in equation 3.1 makes no explicit reference to unemployed or OLF workers, it summarizes both of these labor market states. Our classification criterion is the following:

$$\text{if} \quad s^* \begin{cases} < s_{min} & \text{Worker is OLF} \\ \geq s_{min} & \text{Worker is Unemployed} \end{cases}$$

In words we classify an agent as unemployed if she chooses effort above a given threshold s_{min}, and as out of the labor force otherwise. This mapping is consistent with the notion that inactive agents search less intensively in the labor market. [11]

Furthermore, we normalize the value of income for both unemployed and OLF workers to zero so that their consumption is financed exclusively out of the stock of savings. This assumption is made mainly to avoid the complications of having to talk about eligibility in government insurance schemes as it is not clear how benefits would be distributed across the population. For instance inactive workers in principle should not receive any replacement income but in our model there is a considerable amount of mobility between the two non employment states. Keeping track of benefit histories would add to the computational burden of our exercise.[12] In the Appendix we present the definition of the competitive equilibrium in this economy (see section A.2.1 for details).

3.2 Couples economy: Ex ante Identical Agents

We now study the program of a couple in the same economic environment as described above. In this section a couple consists of two ex ante identical agents who pool their income and make labor supply and search decisions jointly. We adopt the unitary framework for simplicity and we assume that consumption is a public good in the household. We denote the time preference parameter for the household by β.

[11] The CPS classifies non employed workers on the basis of the following algorithm: First a non-employed respondent is asked whether he would like to have a job. Those who reply 'no' are automatically considered as OLF workers. Those who reply 'yes' are then asked to indicate what steps they have taken towards finding employment in the previous month. In particular they are asked to outline their methods of search; there are twelve such methods; for example workers can send out applications, answer job adds, enrol with a government employment agency. Those that have not used either of these methods but also those who search passively, for instance by reading newspaper adds, are classified as OLF workers. See Shimer (2004) for further details.

[12] Arguably the unemployment insurance in the current context would crowd out family self-insurance, see Cullen & Gruber (2000), but it would also crowd out the precautionary role of assets, see Engen & Gruber (2001). Further more, although empirically one effect may not make up for the other it seems to be the case for the incomplete market model that we use here. For instance Young (2004) finds that the optimal level of benefits in an economy with frictions is always zero. The reason is that in general equilibrium, wealth accumulation minimizes the utility costs from the lack of government insurance. In the context of our model it seems likely that introducing benefits would only shift the regions in the state space where all the action takes place without any significant impact on the main conclusions.

3.2.1 Value functions.

We adopt the convention that the array (k, l) $k, l \in \{E, N\}$ denotes a household whose first and second member are in states k and l respectively. Also it will prove useful to define the following objects beforehand:

$$
\begin{aligned}
Q^{en} &= \max\{V^{nn}, V^{en}\} && (3.5) \\
Q^{ne} &= \max\{V^{nn}, V^{ne}\} && (3.6) \\
Q^{ee} &= \max\{Q^{en}, Q^{ne}, V^{ee}\} && (3.7)
\end{aligned}
$$

These objects are the upper envelopes of the value functions and define the relevant menu of choices for our households. A household with one employed member can in any given period decide to withdraw her from the labor market and allocate both agents to search. This option is described in equation (3.5). Analogously, in (3.7) a household in which both members are employed, can withdraw both of them to non-employment, or keep one working or both.

Each agent has her own idiosyncratic productivity and consequently household members differ in their productive endowments. But to conserve on the notation we denote by ϵ the vector of productivities of the members of a household. With these definitions we can represent the dynamic program of a household with two non-employed members as:

$$
\begin{aligned}
V^{nn}(a, \epsilon, \lambda, \Gamma) &= \max_{a' \geq \bar{a}, s_1, s_2} \quad u(c_t) - \sum_i k(s_i) \\
+ \quad & \beta \int_{\epsilon', \lambda'} \Big[p(s_1, \lambda) p(s_2, \lambda) Q^{ee}(a', \epsilon', \lambda', \Gamma') \\
+ \quad & p(s_1, \lambda)(1 - p(s_2, \lambda)) Q^{en}(a', \epsilon', \lambda', \Gamma') \\
+ \quad & p(s_2, \lambda)(1 - p(s_1, \lambda)) Q^{ne}(a', \epsilon', \lambda', \Gamma') \\
+ \quad & (1 - p(s_2, \lambda))(1 - p(s_1, \lambda)) V^{nn}(a', \epsilon', \lambda', \Gamma') \Big] d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda}) \qquad (3.8)
\end{aligned}
$$

subject to:

$$
a' = R_{\lambda, \Gamma} a - c. \qquad (3.9)
$$

Optimal choices consist of current consumption and a pair of search intensity levels. Note that nothing precludes household members from setting $s_i \neq s_j$ although with standard convexity arguments this can only be the case if the productivity endowments ϵ_i and ϵ_j are unequal. Given s_1 and s_2 the household can anticipate that both of its members will receive a job offer next period with probability $p(s_1, \lambda) p(s_2, \lambda)$ (in which case the envelope Q^{ee} applies) and that with probability $1 - (1 - p(s_1, \lambda))(1 - p(s_1, \lambda))$ either one or both of its members will encounter a job opportunity in the market.

The lifetime utility for a household with the first member employed solves the following functional equation:

$$
\begin{aligned}
V^{en}(a,\epsilon,\lambda,\Gamma) = \max_{a'\geq \overline{a}, s_2} \quad & u(c_t) - k(s_2) - \Phi(\overline{h}) \\
+ \quad & \beta \int_{\epsilon',\lambda'} \Big[(p(s_2,\lambda)(1-\chi(\lambda))\; Q^{ee}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & p(s_2,\lambda)\; \chi(\lambda)\; Q^{ne}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & (1-p(s_2,\lambda))\;(1-\chi(\lambda))\; Q^{en}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & (1-p(s_2,\lambda))\chi(\lambda)\; V^{nn}(a',\epsilon',\lambda',\Gamma') \Big] d\pi_{\epsilon'|\epsilon}\; d\pi_{\lambda'|\lambda}) \qquad (3.10)
\end{aligned}
$$

subject to

$$
a' = R_{\lambda,\Gamma} a + w_{\lambda,\Gamma} \overline{h} \epsilon_1 - c. \qquad (3.11)
$$

Given the level of search intensity s_2 with a probability $p(s_2,\lambda)(1-\chi(\lambda))$ the family will have both members employed next period. Moreover, with a probability $p(s_2)\chi(\lambda)$ the family members will alternate roles in the labor market and the second agent will be allocated to market work (if he takes up on the offer). For the sake of brevity we omit the object V^{ne} since the recursive representation is similar to that of equation (3.10). Finally, the lifetime utility for a household with both members employed solves the functional equation:

$$
\begin{aligned}
V^{ee}(a,\epsilon,\lambda,\Gamma) = \max_{a'\geq \overline{a}} \quad & u(c_t) - \sum_i \Phi(\overline{h}) \qquad (3.12) \\
+ \quad & \beta \int_{\epsilon',\lambda'} \Big[(1-\chi(\lambda))^2\; Q^{ee}(a',\epsilon',\lambda',\Gamma') + \chi(\lambda)^2\; Q^{nn}(a',\epsilon'\lambda',\Gamma') \\
+ \quad & (1-\chi(\lambda))\; \chi(\lambda)(Q^{en}(a',\epsilon',\lambda',\Gamma') + Q^{ne}(a',\epsilon',\lambda',\Gamma')) \Big] d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda}
\end{aligned}
$$

$$
a' = R_{\lambda,\Gamma} a + w_{\lambda,\Gamma} \overline{h} \sum_i \epsilon_i - c \qquad (3.13)
$$

3.2.2 Competitive Equilibrium

The definition is similar to that of section 3.1 and for the sake of brevity we relegate it to the appendix.

3.3 Couples economy: Husbands and Wives

The model of this section introduces further heterogeneity. We populate our economy with males and females of equal measure and we assume that each household consists of a husband and a wife. As in the model of the previous section we assume that there is an aggregate (household) period utility function for consumption of the form $u(c)$ but here we assume that household members can differ in terms of their search technologies, separation probabilities and the value of leisure. In particular, we distinguish between $p_m(s)$ and $p_f(s)$, $k_m(s)$ and $k_f(s)$, $\Phi_m(\bar{h})$ and $\Phi_f(\bar{h})$ and $\chi_m(\lambda)$ and $\chi_f(\lambda)$. Subscripts m and f denote male and female spouses respectively.

We also introduce differences in the earnings potential of household members; first we allow the idiosyncratic labor income processes to differ between males and females. We denote the productive endowments of the male and female spouse by ϵ_m and by ϵ_f respectively. Second, we assume that there are differences in the relative prices of male and female labor inputs, i.e. that there is a gender wage premium. Female wages are a fraction $\mu_f < 1$ of male wages for any given level of idiosyncratic productivity.

These features are important for two reasons. First, in the data, see section 2, the labor force attachment of males and females is significantly different. 70% of the male population and 50% of the female population are employed and hence with these additions we can go a lot further in matching patterns of intra-household specialization that we see in the data. Second, by introducing differences in potential labor income between spouses we hope to get a more realistic account for the role of family self insurance than in the previous model with ex ante identical agents.

The value functions for the model of this section are similar to equations (3.8), (3.10) and (3.12) in the previous section and for the sake of brevity we omit them (see section A.1 of the Appendix for details).

3.4 Discussion

Our model builds on Chang & Kim (2007) and Gomes, Greenwood, & Rebelo (2001) who assess the labor market implications of models with heterogeneous agents and aggregate uncertainty. There, as well as here, the distribution of match (job) rents is governed by the idiosyncratic productivity endowments. And, according to their realizations agents adjust their labor market status in each period. Our model goes beyond this by adding the following features: we introduce both own productivity shocks ϵ and match quality (separation) shocks $\chi(\lambda)$. And we assume that search in the labor market is subject to a technology that maps search effort s into arrival rates of job offers $p(s, \lambda)$.

Why do we need a rich structure of shocks? Without these shocks we would not be able to match the worker flows which we summarize in Tables 2 and 3. In particular, without the match specific shock ($\chi(\lambda)$)our model would not be able to match the observed flows from employment to non-employment, and without the labor productivity shock ϵ we would not be able to target the flows between inactivity and unemployment.

To see this consider an economy where only $\chi(\lambda)$ shocks matter. Search intensity would be increasing over time. In this environment because agents run down their stock of wealth during non-employment, and flows from unemployment to inactivity would be zero. If, however, the only shock in our economy was an ϵ shock then existing matches would only dissolve when the agent's own productivity has fallen. In that case it would only be coincidental if our model matched both the observed EU and EI flows. Put differently $\chi(\lambda)$ shocks add a valuable degree of freedom to our calibration that allows us to force productive agents from employment to unemployment and let those agents whose ϵ has fallen over the life on the job, match the observed employment to out of the labor force pattern.[13]

The search technology. We adopt a parsimonious representation of the search technology. In particular we assume that there two levels of search intensity that a worker can exert $s \in \{s_I, s_U\}$ where the subscripts I and U stand for inactive (out of labor force) and unemployment (active searchers) respectively. Associated with these choices are the following probabilities of receiving a job offer next period:

$$p(s,\lambda) = \begin{cases} p_I(\lambda) & \text{if} \quad s = s_I \\ p_U(\lambda) & \text{if} \quad s = s_U \end{cases}$$

Further on the search costs are assumed to be of the form:

$$k(s) = \begin{cases} 0 & \text{if} \quad s = s_I \\ k & \text{if} \quad s = s_U \end{cases}$$

These discrete choices are enough to capture our division between workers that search actively, and hence are counted as unemployed, and those whose optimal choice of search does not translate into a large enough contact rate with potential employers and hence are considered out of the labor force workers.

We give the following interpretation to our technology: $p_U(\lambda)$ and $p_I(\lambda)$ are treated as technological upper bounds to the number of matches that are possible each period from states U and I, respectively. When we increase the values of these parameters we also have to increase the variance of the ϵ shocks to keep the transition rates close to the data, since standard arguments imply that a mean preserving spread in the distribution of ϵ should make searchers more selective.

Why do the probabilities change over the business cycle? The idea here is to have frictions in the background as in Mortensen & Pissarides (1994) without making their micro-foundations explicit. By changing $p_U(\lambda)$ and $p_I(\lambda)$ we replicate the behavior of aggregate labor market conditions, i.e. the availability of job opportunities, over the business cycle. Similarly, when we shift

[13]With couples search intensity is a function of the productivity and employment status of the spouse. We show below that this is one of the reasons couples models perform much better in matching the worker flows.

$\chi(\lambda)$ we try to match the cyclical patterns for job separations that we observe in the data.

We opt for this simpler formulation for two reasons: first it would be extremely hard to solve the bargaining problem between a worker and a firm under aggregate uncertainty and to keep track of the worker's outside option when the latter is determined by the family's resources (both the own and the partner's productivity) as well as the partner's employment status.[14] Second, even if the computation was manageable, such a model would still have to confront the reality that the search and matching framework has a hard time in matching the volatility of the aggregate labor market over the business cycle, see for example Shimer (2005) and Mortensen & Nagypal (2007). Moreover we note that the cyclical properties of labor force participation in a model with matching would be no different from ours; Tripier (2004) and Haefke & Reiter (2009) use this framework and they get a very procyclical labor force. Put it differently search and matching models generate a very procyclical search intensity, so agents flow from inactivity to unemployment in expansions.

4 Calibration and Baseline Results

4.1 Parametrization

Technology and Preferences. We briefly discuss our choice of parameters and functional forms: For all three models we adopt a period utility function of the form:

$$u(c_t) = \log(c_t)$$

Given that the model's horizon is one month, we set the depreciation rate δ to .0083. The capital share α equals 0.36 and we assume that the employed agents spend roughly a third of their time endowment in market work (hence we set $\overline{h} = 0.33$). Moreover, the values for the time preference parameter β is chosen for each model to yield an equilibrium steady state interest rate, $R = 1 + r - \delta$, of 1.0041 (an annual interest rate of 5%). The estimated values are 0.992 for the model with bachelor agents, 0.994 for the model of couples with ex ante identical agents, and 0.994 for couples with husbands and wives. This process ensures that in the steady state our economies have identical capital labor ratios, thus making their business cycle properties more readily comparable. Finally, for the aggregate TFP process λ_t we follow Chang & Kim (2007) and calibrate it so that the quarterly first order autocorrelation is $\rho_\lambda = 0.95$ and the conditional standard deviation $\sigma_\lambda = 0.007$. The corresponding monthly values are 0.9830 and 0.0041 respectively.

Disutility of labor and search technologies. We set the disutility from

[14] See Krusell, Mukoyama, & Sahin (2009b) and Oikonomou (2009) amongst others for modeling strategies of joint asset and labor market frictions with bachelor agents.

working $\Phi(\overline{h})$ equal to the function $B\frac{\overline{h}^{1+\gamma}}{1+\gamma}$ and we normalize the value of γ to unity. For the models in sections 3.1 and 3.2 we choose the value of B to target the average employment population ratio of 60 % in the data. For the model in section 3.3 where we distinguish between B_m and B_f, we choose numbers for these parameters to match and employment population ratio of 70% for males and 50% for females.[15]

Our approach for choosing the search technology parameters is similar. We assign values to $p_U(\overline{\lambda})$, $p_I(\overline{\lambda})$ and $\chi(\overline{\lambda})$ in the steady state ($\overline{\lambda}$ denotes the mean of aggregate TFP) in order to match the average worker flows in the US economy. We also calibrate the values $p_U^m(\overline{\lambda})$, $p_I^m(\overline{\lambda})$, $\chi_m(\overline{\lambda})$ and $p_U^f(\overline{\lambda})$, $p_I^f(\overline{\lambda})$, $\chi_f(\overline{\lambda})$ to match the worker flows for males and females separately in the population. The cost of search parameters for unemployed workers k, k_m and k_f are chosen to target an unemployment rate of 6 % for both males and females and in the aggregate.

In Table 7 we summarize our estimates of the search frictions and the separation probabilities in the three models. We note the following two implications: first a separation rate of 2.5% implies that 73.8% of constant productivity, i.e. constant ϵ, jobs survive at an annual horizon. This value is somewhat lower than the 3.4% usually used in calibration of search models, see for example Shimer (2005) and Hall (2005), but in our model job separations derive also from changes in idiosyncratic productivity. We show in section 4.2 that all of our economies can match the total outflow from employment as well as the division between flows to unemployment and flows to out of the labor force. Second the arrival rate of job offers for out of labor force agents is nearly as high as that for active searchers but again the reservation wage policy rules and the endogenous distribution across ϵ and labor market status in the models, make it possible to match the flows from out of the labor force to employment.[16] [17]

When we introduce aggregate fluctuations, both, the arrival rates of job offers and the separation probabilities are assumed to change with the aggregate state. Our approach is to choose the values for these objects in recessions and expansions

[15] According to the empirical literature (e.g. MaCurdy (1981)) a more appropriate value for γ (the inverse of the Frisch elasticity) is around 2. But with labor supply decisions formed at the extensive margin these choices are somewhat irrelevant. For instance if we were to set $\gamma > 1$ then employment costs would be larger, and we would have to adjust B (B_m and B_f) downwards to ensure that our steady state calibration meets the targets. See also Chang & Kim (2006) for a discussion of the empirical value of the elasticity in this class of models.

[16] Krusell et al. (2009a) calibrate a model with bachelor agents that can be employed, unemployed or out of the labor force at any point in time. They set $p_U(\overline{\lambda}) = p_I(\overline{\lambda})$ so that the job offer arrival rates are identical for unemployed and inactive agents and use the policy rules to distinguish between states U and I. Out of labor force are those workers who at the current conditions (productivity) would not work even if a job was available. We get a similar property out of our model.

[17] We think of this feature as one of the strong points of our model. The mechanism that we propose in this paper is that marginal workers flow into the labor force in recession to help circumvent the frictions in the labor market. The larger the difference between $p_U(\overline{\lambda})$ and $p_I(\overline{\lambda})$ the larger the scope and the benefit of this adjustment and hence the less procyclical the labor force. This is something that we verify by running different versions of the model.

to mimic the patterns of worker flows that we see in the US data and the volatility of aggregate employment and unemployment. We describe these choices in some detail in the section of the paper that contains our main results.

Table 6: The model parameters (monthly values)

Parameter	**Symbol**	**Value**	**Target**
	Technology and Preferences		
TFP shock	σ_λ	.0041	
	ρ_λ	0.983	**US DATA**
Capital Share	α	0.33	
Depreciation	δ	.0083	
Time Working	$\overline{h}$	0.33	**Normalization**
Discount Factor	β		**R-1 =.41%**
Labor Disutility	$B,\ B_f,\ B_m$		**E/pop , Urate**
Search Cost	$k,\ k_f,\ k_m$		
	Labor Productivity		
Moments ϵ_m	$\sigma_{\epsilon,m},\ \rho_{\epsilon,m}$	.107, .979	Chang & Kim (2006)
Moments ϵ_f	$\sigma_{\epsilon,f},\ \rho_{\epsilon,f}$	.113, .973	
Gender Gap	μ_f	.65	Heathcote et al (2008a)

Idiosyncratic productivity. The idiosyncratic labor productivity processes are of the following form:

$$\log(\epsilon_t) = \rho_\epsilon \log(\epsilon_{t-1}) + v_{\epsilon,t}$$

These choices are guided by the relevant literature that uses similar representations of the stochastic process of labor income, see for example Heathcote et al. (2008). Further on, we assume that the innovations are iid with mean zero and constant variance (i.e. $v_{\epsilon,t} \sim \mathcal{N}(0, \sigma_\epsilon)$).

We calibrate ρ_ϵ and σ_ϵ following Chang & Kim (2006) who estimate, a model that accounts for selection effects. They find $\rho_{\epsilon,m} = 0.781$ and $\sigma_{\epsilon,m} = 0.331$, for males in their sample, and $\rho_{\epsilon,f} = 0.724$ and $\sigma_{\epsilon,f} = 0.341$, for females. When we calibrate the models with ex ante identical agents (couples and bachelors) we use the estimates for the male population consistent with the notion that household members are household heads in these cases. We convert the annual moments into their corresponding monthly values. Finally, for the relative price of female labor, μ_f, we follow Heathcote et al. (2008) who report an average value of the gender wage premium of 0.65 in their PSID sample (1968-2003). Table 6 summarizes these choices.

Table 7: Search Frictions (monthly values)

Parameter	Symbol	Value	Target
		Frictions	
		Bachelors	
Offer Rates	$p_I(\bar{\lambda})$	.18	
	$p_U(\bar{\lambda})$	.26	**Worker Flows**
Separation Rate	$\chi(\bar{\lambda})$	.025	
		Couples: EAI	
Offer Rates	$p_I(\bar{\lambda})$	.23	
	$p_U(\bar{\lambda})$	.26	**Worker Flows**
Separation Rate	$\chi(\bar{\lambda})$	.025	
		Couples: H W	
Offer Rates	$p_{I,m}(\bar{\lambda}),\ p_{I,f}(\bar{\lambda})$	.24, .20	
	$p_{U,m}(\bar{\lambda}),\ p_{U,f}(\bar{\lambda})$	.29, .25	**Worker Flows**
Separation Rate	$\chi_m(\bar{\lambda})\ ,\chi_f(\bar{\lambda})$	.028, .028	

Notes: The table shows the estimates of arrival rates of job offers and separation rates that make the steady flow rates in the models consistent with the CPS targets in table 2. $\bar{\lambda}$ denotes the mean steady state value of TFP.

4.2 Steady State Findings

4.2.1 Labor market flows

In this section we evaluate the model in a number of relevant dimensions. Table 8 summarizes the estimated worker flows from the bachelor model (Panel A), the couples economy with ex ante identical agents (Panel B) and the couples economy with husbands and wives (Panel C). Our targets are the analogous statistics in the US data for all agents, aged 16 and above, independent of their marital status (Table 2).[18]

These steady state values are consistent with an employment population ratio of 60% (70% for males and 50% for females), an unemployment rate to 6%, a job finding probability of roughly 26% (28% and 25% for males and females, respectively) and a total outflow from employment (EU + EI) of 4.5% which is what we find in the data.

There are two features that stand out. First, whilst the couples models match both the total outflow from employment and the composition between EU and EI, with single agents the division between the number of workers who leave their jobs to search intensively (unemployed) and those who leave their jobs but do not

[18]The reason that we do not try to target flows for other relevant demographic groups, for example the population of married agents, is that we do not have measures of aggregate output for these groups. Hence, we cannot assess easily their business cycle properties.

Table 8: Steady State Labor Market Flows

	Bachelors			Couples Ex Ante Identical		
	E	**U**	**I**	**E**	**U**	**I**
E	.9538	.0106	.0356	.9544	.0148	.0308
U	.2600	.7017	.0383	.2590	.6548	.0862
I	.0485	.0140	.9375	.0452	.0120	.9428

	Couples Husbands and Wives					
	E	**U**	**I**	**E**	**U**	**I**
E	.9621	.0163	.0228	.9544	.0121	.0391
U	.289	.5448	.0829	.2490	.6548	.1268
I	.0575	.0204	.9120	.0382	.0127	.9428

Notes: The flow rates are estimated from the steady state of the models. They represent the probability that a generic agent in labor market state i in period t will be in labor market state j in period $t+1$, where $i, j \in \{E, U, I\}$.

search intensively is off targets. In particular in the data the EU rate is around 1.49% on average and the EI is 2.98% whereas the bachelor household economy yields average flows of 1.06% and 3.56%, respectively.

Second, the couples models are also able to match better (but not perfectly) the average flows between unemployment and inactivity. In particular, the UI flow rate is 8.6% in the couples model with ex ante identical agents, whilst it is only 3.83% with bachelor agents. In the data this quantity is in the order of 22%. Analogously, the model with husbands and wives produces a male UI flow of 8.2% (compared to 17% in the data) and a female flow rate of 12% (27% in the data).

Both of these features are at the center of our notion of joint insurance here that makes the choice of search intensity affected by both the agent's own productivity and the productivity and employment status of her partner. In the steady state there is a large fraction of families where one member is employed and the other not and also a significant number of families were both members are unemployed. Changes in household income in the first case (changes in the productivity of the employed agent) entail a wealth effect on the labor supply of non employed spouse which could induce them to drop out of the labor force. Similarly, when both members of a household are unemployed and one of them receives a job offer and becomes employed, there is an analogous wealth effect on the labor supply of the other family member. These effects are quantitatively important in the model with couples but do not occur, by definition, in the bachelor model.

Moreover, the differences between EU and EI reflect the opportunities that families that are populated by more than one agent have, to specialize in market hours and leisure. To some extent families assign their most productive members in the market (there are, of course, obvious limitations due to frictions). When these agents loose their jobs due to a separation shock, their potential income is still higher than that of their spouses, and it is optimal for them to become unemployed. Again, such specialization in terms of family resources is absent in an economy with bachelors.

We conclude this paragraph by noting that although our model compiles labor income risks from many sources it is yet too parsimonious to match some aspects of the data. In particular, we cannot match the flows between unemployment and inactivity; in order to do so we would need to include more shocks in our model but it is not so clear whether a more complicated structure would add much to the business cycle dynamics which are the main focus of our study. What is critical is that our model economies leave ample room for agents to make transitions in and out of the labor force and clearly they do so.

4.2.2 Family Self Insurance

Our models generate large added worker effects. We estimate the conditional probability that an OLF spouse flows into the LF when the family's employed member experiences a transition from E to U. We contrast this with the corresponding unconditional probability, i.e. a flow into the LF when the employed member either remains employed or becomes unemployed next period). In the model with husbands and wives, section 3.3, we restrict our attention to families where the husband is employed and the wife is out of the labor force.

The values for these quantities are as follows: With ex ante identical agents the conditional probability is 9% and the unconditional is 5.1% and with males and females they are 8.1% and 4.2% respectively. These results are consistent with US data, as shown in section 2. The estimates from the linear probability model in Table 4 implied a 5% increase in this probability when the husband became unemployed. This effect was even stronger when husbands lost their jobs (as opposed to have quit to unemployment) and conditional on that event we found that the likelihood that the wife flowed into the LF was 8% larger than if her husband remained employed. In our model the difference between job losers and job quitters is not so clear and hence we drop this consideration from our calculations.

We mentioned earlier that a large strand in the literature of the behavioral responses of female labor supply to spousal unemployment, estimates the added worker effect in regressions of the wife's annual hours on observables and the husband's spell duration. We perform this exercise here using the model of section 3.3. In particular, we use simulated data from the steady state (a population of

10000 families and 25 annual observations) to run the following regression:

$$h_{f,t} = \alpha_0 + \alpha_1 w_{f,t} + \alpha_2 D^U_{m,t} + \alpha_3 D^*_{m,t} + u_t \tag{4.1}$$

where $h_{f,t}$ denotes female hours and $D^U_{m,t}$ is the number of periods that the husband has remained non employed in any given year.[19] The variable $D^*_{m,t}$ is a dummy that takes the value one if the male spouse's hours in the labor market fall short of his desired hours, and hence is an index of whether the husband is hours constrained. The way we back out desired hours is to use the optimality condition from a model that features an intensive margin and no frictions. Given our parameterization of the household utility function the definition of $D^*_{m,t}$ becomes:

$$D^*_{m,t} = \begin{cases} 1 & \text{if} \quad (\frac{w_{m,t}}{c_t B_m})^{\frac{1}{\gamma}} > h_{m,t} \\ 0 & \text{otherwise} \end{cases}$$

The idea here is that whilst the duration of the husband's unemployment may be an important determinant of the wife's labor supply, equally important are restrictions that do not allow male spouses to work as much as they want.[20] This type of friction also produces an added worker effect and in equation 4.1 we study the impact of both of these two factors jointly.

Table 9 summarizes our estimates of equation 4.1. Column (1) shows the results without the dummy $D^*_{m,t}$ as a regressor, whereas column (2) includes this dummy. We restrict our attention to male spouses in the sample who spend less than a quarter of their time in non-employment (roughly 75% of the simulated population).

When $D^*_{m,t}$ is not a regressor the added worker effect, the response of female hours to the husband's duration in unemployment, is statistically insignificant. This point was first raised by Maloney (1987) who argues that omitting hours restrictions is likely to bias the coefficient α_2 to zero and demonstrates this effect using PSID data.[21] Column (3) replaces the dependent variable $h_{f,t}$ (annual female hours) with the wife's desired hours in the market $h^*_{f,t}$, again based on the optimality condition in a model with an intensive margin and no frictions, and repeats the regression of column (1). The results show that the influence of male unemployment on optimal female labor supply is even stronger in this case: the coefficient α_2 doubles and becomes statistically significant. Notice also that the model fit is better in this case.

[19] We pool unemployment and non-participation in one variable following the bulk of the literature.

[20] Such a constraint in hours exists in the model because each month agents can spend a fraction $\overline{h}$ of their time endowment working.

[21] The results are not readily comparable because Maloney (1987) uses different econometric techniques that allow him to deal with censoring of female hours in the PSID data and account for selection effects. There is not enough variation in our model in terms of observables to apply this approach here.

Table 9: Added Worker Effect in the Model

	Benchmark			**No Frictions**		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	$h_{f,t}$	$h_{f,t}$	$h^*_{f,t}$	$h_{f,t}$	$h_{f,t}$	$h^*_{f,t}$
$w_{f,t}$	.0677***	.0663***	.063***	.0675***	.0661***	.062***
	($8.0e^{-4}$)	($8.0e^{-4}$)	($3.6e^{-4}$)	($8.0e^{-4}$)	($8.0e^{-4}$)	($3.1e^{-4}$)
$D^U_{m,t}$	$1.7e^{-3}$	$5.3e^{-3}$***	$3.1e^{-3}$***	.0149	.0103***	.0108***
	($1.3e^{-3}$)	($8.0e^{-4}$)	($6.1e^{-4}$)	($2.0e^{-3}$)	($9.0e^{-4}$)	($8.1e^{-4}$)
$D^*_{m,t}$		.0336***			.0404***	
		(.0029)			(.0031)	
R^2	.592	.600	.879	.620	.641	.883

Notes: OLS estimates of equation (4.1) based on time-averaged simulated data from the steady state of the model with husbands and wives. Standard errors in parentheses. ***Significant at 1 percent level.

We interpret this result as indicating that whilst in our model economy there is ample scope for family self insurance, labor market frictions and hours constraints (the fact that hours are restricted to be $\overline{h}$ each period) pose a serious impediment to it, because females cannot adjust both at the extensive and the intensive margins readily when the male spouse experiences some time in non-employment.

Finally, in columns (4) -(6) we repeat these regressions for a model without search frictions. We set the arrival rates of job offers equal to unity (for all workers) and the separation rates equal to zero. In this environment families can assign their most productive members to the market without having to search for job opportunities, and the bulk of insurance in this case comes against changes in the idiosyncratic component of wages ϵ. We find that the coefficients on $D^U_{m,t}$ (duration of unemployment of the male spouse) increase a lot and they are everywhere statistically significant. This implies that labor market frictions and not hours constraints are the most important obstacle for family self insurance in the model.

Household Heads. How frequently do household members alternate roles as primary and secondary earners in the model and in the data? The answer to this question gives an indication of whether our economies exaggerate the importance of joint labor supply adjustments within the family. Our measures are the persistence of income and hours over time in a sample of 10000 households simulated from the steady state distribution. For each period we assume that a family's primary earner is the agent that had the highest recorded annual labor income or the highest recorded hours respectively. We refer to this agent here, somewhat abusing the term, as the household head.

To uncover the persistence we estimate the Markov transition matrix between primary and secondary earner roles in the family, i.e. the probability that the identity of the household head changes from one year to the next. Roughly 21%

our families alternate roles in the model with ex ante identical agents when we use income as our index. When we use the number of hours as our index, and drop productivity from the calculations, we find that this rate increases to 22%. In the PSID data these numbers are roughly 15% based on income and 12 % based on hours. We get a slightly better result in the couples economy with males and females. The persistence in the identity of the primary earner is 81% in this model. When males (females) have the highest labor income in the family in one year, they still have the highest income with a probability of 86% (72%) in the following year. In the data these conditional probabilities are 90% for husbands and 52% for wives.

Table 10: Persistence of Household Heads

		Benchmark		
Measure		**EAI**	**H & W**	**US DATA**
Hours	Total	.78	.81	.85
	Males		.86	.90
	Females		.72	.52
Income	Total	.79	.81	.88
	Males		.86	.91
	Females		.69	.50

Notes: The persistence of household heads based on time aggregated simulated data from the two models with couples. The top (bottom) three rows show a measure based on hours (income). We calculate the probability that the identity of the family's primary earner in one year doesn't change in the next year. Columns (1) and (2) show these moments for the benchmark calibration. The data column (3) are drawn from the PSID 1993 survey.

We conclude that our economies provide a good approximation of the role of families as an insurance mechanism against labor market risks. There is some excess insurance in the model with ex ante identical agents. When we assign gender to the household member and calibrate the productivity processes, the search costs and frictions for males and females realistically we do better. We do not fully match the data because our models still miss several aspects that affect intra-household decisions such as children, marital sorting, human capital accumulation and specialization in household production etc. [22]

Distributions of Labor Market Status. In this section we investigate the distribution of labor market states within the family. Table 11 shows, for an

[22] See Mazzocco (2007) for a model, with several of these ingredients, that matches hours of married couples and singles in the US.

agent that is unemployed or out of the labor force, the conditional probabilities that she lives in a household where the other member is employed, unemployed or out of the labor force, in both the models and the data. The data are drawn from the CPS and they correspond to married couples for two age groups; aged 16 and older and aged between 16 and 65.

With ex ante identical agents in the household roughly 25% of all OLF agents in the economy live in households where both members are inactive and the remaining 75% percent are in families where one member is either unemployed or employed. In the husbands and wives model the analogous fractions are 21% and 79% respectively. The model produces numbers for these statistics that are very close to the US data. In our sample from the CPS (married couples) these fractions are 24% and 76% respectively, for a population aged between 16 and 65, and 50% for ages 16 and above. Clearly demographics play a significant role here, and without a detailed life cycle structure our model cannot match the behavior of older couples.

Table 11: Decompositions of Unemployment and Inactivity

OLF	**II**	**UI**	**IE**
Couples: EAI	.25	.05	.70
Couples: H+ W	.21	.05	.74
US Data: Ages 16-65	.24	.03	.73
US Data: Ages >16	.5	.02	.48
Unemployed	**UU**	**UI**	**UE**
Couples: EAI	.06	.41	.52
Couples: H + W	.06	.45	.49
US Data: Ages 16-65	.07	.19	.74
US Data: Ages >16	.1	.22	.68

Notes: The table shows the probability that an individual that is in state $i \in \{U, I\}$ lives in a household where the other member is in state $j \in \{E, U, I\}$. Data are drawn from the CPS and they are averaged over the period 1976-2005.

Both economies match the fraction of households where both agents are unemployed to the population aged 16 to 65 in the US data. The models produce a value of 6% with the data counterpart being 7%. However, they overestimate the fraction of those households where one agent is unemployed and the other is OLF. Despite this discrepancy we conclude that our models do a good job in matching the distributions of employment, unemployment and inactivity within the family.

In the Appendix (section A.3) we expand on the results of this section; we discuss how well the models capture the wealth and earnings distributions relative to the data, and we estimate the implied process of wages from a panel of households from the steady state. We show that in the steady state all three economies approximate the US data reasonably well.

4.3 Cyclical properties

4.3.1 Solution method

We solve the model with aggregate uncertainty using the bounded rationality approach whereby agents forecast future factor prices using a finite set of moments of the distribution Γ_t. As in KRUSELL & SMITH (1998) we find that the first moments (means) are sufficient for accurate forecasts in our context, i.e. approximate aggregation holds. A detailed description of the algorithm is relegated to the appendix.

4.3.2 Aggregate Labor Market

In the models the arrival rates of job offers $p_U(\lambda)$, $p_I(\lambda)$ and the separation probabilities $\chi(\lambda)$ change over the business cycle. In recessions (expansions) $p_U(\lambda)$ and $p_I(\lambda)$ fall (rise) and separation shocks $\chi(\lambda)$ rise (fall). We adjust the values for these rates to match the cyclical properties of the quarterly flow rates EU, EI, UE, and UI. In particular, we start with an initial guess for the cyclical behavior of these fundamental parameters. We solve the model and estimate the average labor market flows. We take logs and remove non-cyclical components and compute the relative volatility and the cyclical correlation with aggregate output. Then, we compare these moments with the US data.

This procedure leads to the following values for the parameters: with bachelor agents we estimate that separation shocks $\chi(\lambda)$ are 16% higher (lower) in recessions (expansions) than in the steady state; $p_U(\lambda)$ and $p_I(\lambda)$, both, shift by 13%, relative to the steady state. In the couples model with ex ante identical agents separations shocks change by 11% and arrival rates of job offers by 10%. Finally, in the model with husbands and wives,[23] $p_{U,m}(\lambda)$ and $p_{I,m}(\lambda)$ shift by 12%, $p_{U,f}(\lambda)$ and $p_{I,f}(\lambda)$ by 11%, $\chi_m(\lambda)$ and $\chi_f(\lambda)$ by 13% and 11%,respectively.

Table 12 presents the results from our benchmark calibrations for three different economies. We restrict attention here to key labor market statistics and all quantities are expressed relative to a detrended measure of GDP.[24] The data are quarterly aggregates of the simulated aggregate paths from the three models.[25]

[23]For this model we target the cyclical properties of labor market flows for males and females separately.

[24]They are logged and HP filtered with a parameter $\lambda = 1600$.

[25]The differences in the statistics are not the result of sampling variation; in the appendix we outline an algorithm due to YOUNG (2010) that computes the equilibrium in the economy by working with the histogram instead of simulating panels of a finite number of agents. There is no sampling variation here due to the Law of Large Numbers.

Table 12: Fluctuations in the Labor Market

Model	Moment	**U**	**E**	**LF**
Bachelors	$\rho_{x,y}$	-0.97	0.89	0.80
	$\frac{\sigma_x}{\sigma_y}$	7.37	0.90	0.46
Couples: EAI	$\rho_{x,y}$	-0.96	0.91	0.44
	$\frac{\sigma_x}{\sigma_y}$	7.38	0.70	0.22
Couples: H & W	$\rho_{x,y}$	-0.97	0.92	0.49
	$\frac{\sigma_x}{\sigma_y}$	7.60	0.77	0.30

Notes: The statistics are based on quarterly (time aggregated) data from the three models. $\rho_{x,y}$ denotes the correlation of variable x with y (GDP). $\frac{\sigma_x}{\sigma_y}$ is the relative standard deviations. The analogous moments for the US economy are summarized in table 1.

Our main result is that couples economies produce a much less procyclical labor force than the model with bachelor households. The contemporaneous correlation of the labor force with aggregate output is 0.44 in the couples model with ex ante identical agents and 0.49 in the couples model with husbands and wives but 0.80 in the singles model. The couples economies are strikingly close to the US data. In the data labor force participation has a correlation with GDP equal to .45; our couples models match completely the cyclical properties of this statistic.

In section 2 we showed that once we removed (partially) the influence of the added worker effect from the data we got a more procyclical labor force for the US economy. This is precisely what we get out of our models. In the model with ex ante identical agents, we preserve as much as possible the structure of the bachelor household economy. The only difference is the introduction of a second member to the household. This simple addition is enough to engineer a fall in the cyclical correlation of the labor force of roughly 50%. In the more realistic structure of families that we pursue in section 3.3, spouses no longer have the same potential income or confront the same frictions in the labor market. In this case, the importance of family self insurance against unemployment is somewhat smaller but the properties of the aggregate labor market in this case are still remarkably close to those of the US economy. Thus, we conclude that joint search is important in both the data and the models.

In terms of other moments, all models generate very similar cyclical properties for aggregate unemployment. The relative volatility is 7.37, 7.38 and 7.6 in the three models; it is 7.48 in the US data. The contemporaneous correlation of unemployment with GDP is around -.97 in all models. Aggregate employment is slightly more procyclical and more volatile in the models than in the data, but changes in our measure of employed workers partly reflect changes in hours; because we time aggregate our simulated data it could be that in expansions the typical worker works more months supplying $\overline{h}$ hours each month. Aggregate hours in the US have a relative standard deviation with detrended output of 0.85 so it could be that our models strike a balance between the two. Moreover, with bachelors households there is considerably more volatility in aggregate employment. We investigate later on whether this implication derives from our calibration of the behavior of $p_U(\lambda)$, $p_I(\lambda)$ and $\chi(\lambda)$ over the business cycle in the three models.

Finally the labor force is less volatile in the two economies with couples in the household; They match the analogous object in the data where the ratio of standard deviations of labor force participation to GDP is .22. We do not emphasize this as a relative success of the model for the following two reasons: our theory suggests that the labor force is less procyclical because couples time their flows in and out of the labor market to provide insurance. There is nothing in this proposition that guides us to believe that these movements will somehow sum up to a lower volatility. This however turns out to be the case in the three models. Second in the experiment of section 2 where we partially removed the added worker effect we found only a small increase in volatility of female labor force participation. We highlighted there that our empirical analysis missed out on many important aspects of family self insurance that are present in both the models and the data (such as that families may respond preemptively to news about unemployment or that the distinction between quits and separations are important). Whether these aspects in the data would change the cyclical behavior of the labor force by increasing its volatility is a question that we leave for future work.

We close this section by showing that the couples models can match the US data in one more important dimension; they can match the joint movements of employment population and unemployment population ratios. In figure 3 we plot these movements for the US economy over the period 1960 to 2005. The data are filtered so that a very low frequency trend is removed (HP filter with a parameter $\lambda = 100$). [26] Changes in the two ratios are strongly correlated. In many quarters a one percent increase in the employment population ratio translates into a 1% fall in unemployment, another way of phrasing that the labor force is nearly acyclical. [27]

In figures 4 and 5 we show the analogous movements in the bachelor economy

[26] Figure 3 is taken from Shimer (2009).

[27] The patterns are very similar in the current US recession. In 2008 and 2009 the US labor force has been remarkably stable. In 2010 there has been a 2% fall in the employment population ration which translated into a 1% increase in the unemployment population and a 1% fall in labor force participation. As figure 3 shows similar adjustments have occurred in US data. Moreover in the current recession labor force participation of married women has been extremely stable. These adjustments reflect a fall in the participation of men.

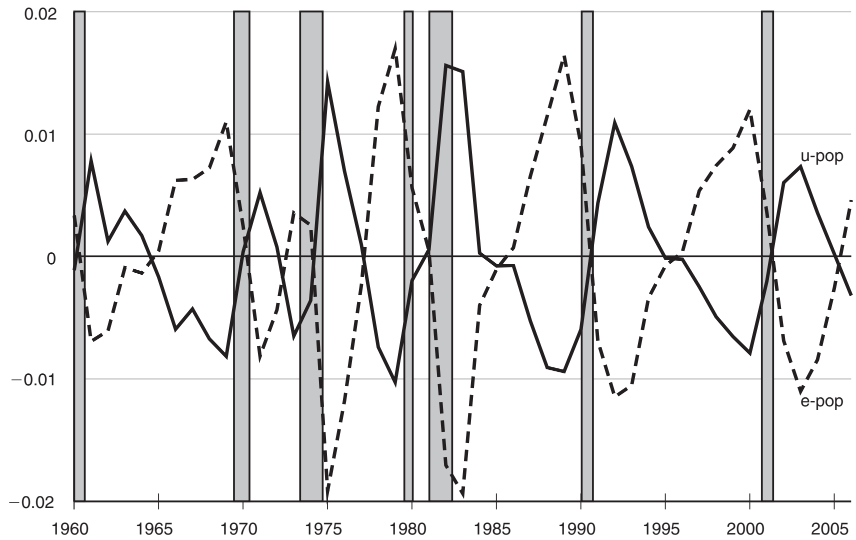

Figure 3: Employment and Unemployment Population

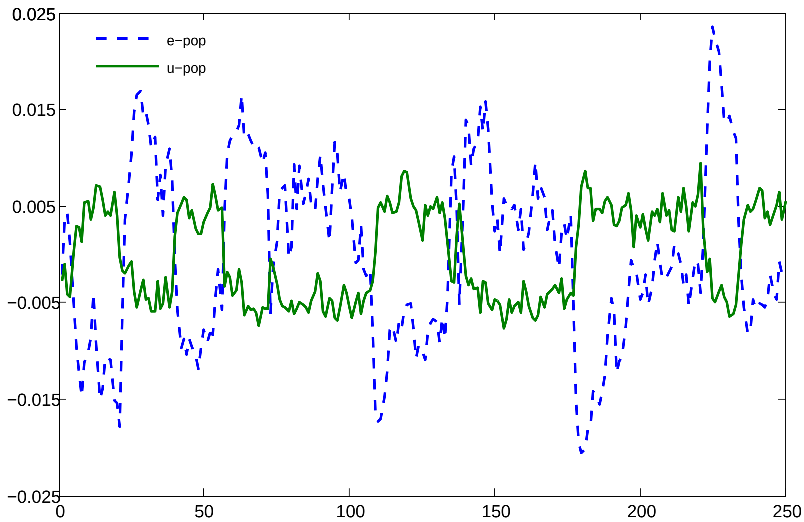

Figure 4: Employment and Unemployment Population Ratios: Bachelors

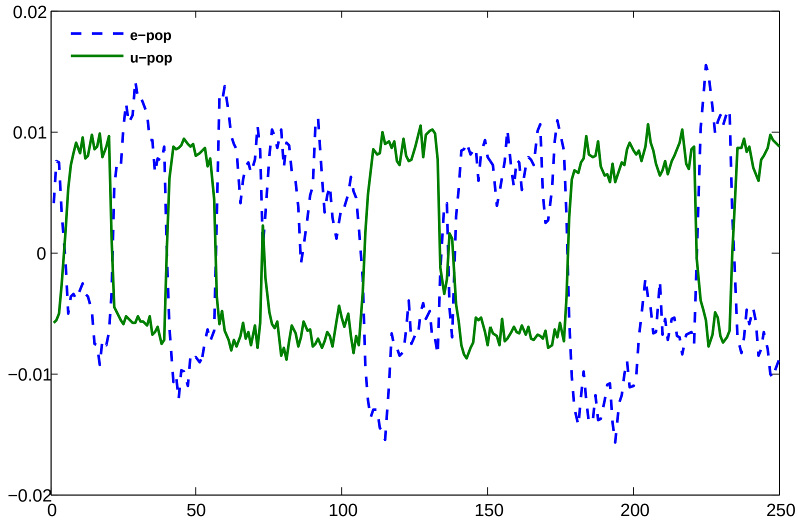

FIGURE 5: EMPLOYMENT AND UNEMPLOYMENT POPULATION RATIOS: COUPLES

and the couples economy with identical agents. With bachelor households changes in the e-pop ratio are not matched by changes in the u-pop ratio with a similar order of magnitude; the e-pop ratio fluctuates between -2% and +2% whilst the u-pop ratio responds with very small movements (between .5% and -.5 %). The gap is filled by workers who join the labor force in expansions and abandon it in recessions. The labor force in the sample is very procyclical (its contemporaneous correlation with output is .89) .

With couples (figure 5) we get a very different prediction. There it is evident that changes in the employment population ratio are compensated with large changes in the unemployment population ratio. In some periods these movements are one for one and clearly very similar to their empirical counterparts in figure 3. In the sample the correlation of employment and labor force participation is .51 (note that these statistics are different from business cycle correlations). The results are similar in the couples model with husbands and wives.

4.3.3 Other calibrations

In this section we evaluate the robustness our results. First, we build a model with bachelor agents where the frictions and the separation probabilities are set to fluctuate by a similar order of magnitude as our model with ex ante identical agents. $p_U(\lambda)$ and $p_I(\lambda)$ shift relative to the steady state by 10% and separations shocks $\chi(\lambda)$ by 11%. We use this version to address whether the excess volatility we found previously with bachelor households is due to our calibration of aggregate uncertainty in the labor market. This model indeed produces a less volatile aggregate labor market (the cyclical correlations are roughly the same); aggregate unemployment is only 6 times as volatile as GDP, it is 7.4 in the data, and the analogous ratio for aggregate employment is 0.8. This is still higher than with ex ante identical agents. However, the cyclical properties of the labor force are the same: the relative standard deviation is 0.42 and the correlation with GDP is 0.77, thus virtually unchanged. This implies that the parametrization of aggregate labor market uncertainty is not too important for the main result of our paper.

Second, we build a model that features bachelor agents that can be either male or female. That is half the population in this economy is male and the other half female. We investigate whether this leads to different properties for the aggregate labor market. We take the calibration of the model of section 3.3 and simply split the couples. We find that the cyclical correlation of the labor force with GDP is 0.79. This is very similar to the results of the benchmark bachelors economy and significantly higher than the 0.49 that we get when households are populated by both males and females.

Finally, we run a number of different versions where we do not recalibrate the frictions between the three environments, i.e. we fix the steady state probabilities $p_U(\overline{\lambda})$, $p_I(\overline{\lambda})$ and $\chi(\overline{\lambda})$ to be the same in the three model, and versions where the discount rates are the same.[28]. None of these variations changes our main result that family self insurance produces a less cyclical labor force. In all the versions the correlation of the labor force with GDP was at least 30% lower in a model with couples.

4.3.4 Other models.

In this section we discuss several extensions of the theory and some important features of our numerical results. We explain why we model labor market frictions they way we do and why we need the arrival rates of job offers and the separation probabilities to fluctuate over the cycle. We also address the generality of our results in other setups where families do not necessarily pool resources to insure against earnings shocks and in setups where insurance is difficult because productivity and unemployment risks are correlated in the household.

How important is to have $p_U(\lambda)$, $p_I(\lambda)$ and $\chi(\lambda)$ change (exogenously) over the business cycle? There are two alternatives of parameterizing uncertainty in the aggregate labor market, whilst remaining within the literature of heterogeneous agents and wealth accumulation. The first is to include a matching technology and firms that make hiring and firing decisions as in Krusell et al. (2009b). We already explained that this is a non-trivial extension of the model, since bargaining between firms and workers involves keeping track of the agents' outside options, which in turn depend on their own productivity and the productivity and employment status of their partners and their wealth. We also emphasized that the cyclical properties in such a model would be no different, because search models of the labor market generate procyclical search intensity, and hence procyclical labor force participation. Such a model would not match

[28]In this case, we adjust the interest rates to clear the savings market.

the volatility of aggregate unemployment and vacancies, see Shimer (2005) and Krusell et al. (2009b).

The second alternative is to keep the frictions constant, for example by using a value of $p_U(\overline{\lambda})$ equal to 0.5 or 1 and to rely on reservation wage policies to match the observed worker flows. This formulation would be more in line with the equilibrium unemployment theory of Gomes et al. (2001). In a previous version of this paper we explored the implications of such a model. We had two independent productivity shocks: one was an own productivity shock (the ϵ shock in this paper) and another represented a match quality shock (call it θ). The match quality shock was drawn when the agent received a job offer, and it evolved stochastically according to a first order markov process. Separations occurred when the values of θ and ϵ were too low to sustain the job match.

Unfortunately the properties of this model for the aggregate labor market were very different from the ones in this paper. There were only small gains in the cyclicality of the labor force. The reason is that this model featured too many choices to assign an important role to family self insurance because agents could effectively choose when to separate, and because frictions were not too tight for unemployment to have an impact on family consumption. We conclude that an important part of our success is that we include both exogenous separation shocks and frictions that make joint search important.

Correlated shocks and non-unitary models. Pooling resources and making search decisions jointly are central in our model; Anything that disturbs the risk sharing arrangement within the family, should in principle infringe on our results. We think of two important features of the data as candidates. The first is that household member productivity and wages are correlated in the US data. For instance, Hyslop (2001) estimates from the PSID the covariance structure of wages of household members and he finds a correlation coefficient of 0.57 in fixed effects and 0.15 in transitory (but persistent) components. In our models there are no fixed effects, we summarize them in the AR(1) process for ϵ, and we set the correlation for the innovations in productivity equal to zero. Does this mean that the insurance role of joint labor supply adjustments is less important in the data than in the models? This might be the case for some families. We think of correlated shocks as having the implication that some couples use the family self insurance margin much more readily than others. But in section 2 we showed that those marginal couples are the ones who explain the low procyclicality of the US labor force. So in principle if we were to include these features into our models we should get similar results. We thus find it appropriate to think of our theory as a theory of marginal couples.

The second important feature is that whilst in the model risk sharing within the household is perfect (agents pool their resources to insure) the data seem to refute this notion (see for example Thomas (1990); Duflo (2003) and the considerable literature on the intrahousehold allocation). Models that incorporate some departure from complete insurance within the family are abundant in the literature, and the collective framework of Chiappori (1988, 1992); Browning

& CHIAPPORI (1998) would be ideal to examine the impact of such effects. [29] The mechanism in these models is as follows: each household member has her own utility function and aggregate welfare can be represented as a weighted average of the payoffs to each member. Intrahousehold allocations are a solution to a Pareto problem where the weights are influenced by distribution factors, i.e. the outside options of each agent. Wealth, productivity, gender specific frictions and aggregate conditions are variables that potentially affect these weights in the current context.[30] The higher the weight of a spouse the higher her consumption and the lower her desired labor supply. This would impact on our results if, for some reason, main earners in the family loose bargaining power in recessions and secondary earners gain relative bargaining power. This is a non-trivial problem and we will investigate this important question in future research.

4.4 Labor Wedges

In this section we discuss the cyclical properties of the wedge derived from the optimality condition for the intra-temporal choice of consumption and hours worked. As is known, in an equilibrium real business cycle model with complete markets the co-movement of these quantities follows the familiar condition that sets the marginal benefit of an extra unit of labor equal to its marginal cost.

$$\text{MRS} = \alpha \frac{Y}{H} \rightarrow BH^{\gamma} \frac{1}{C^{-1}} = \alpha \frac{Y}{H} \tag{4.2}$$

We assume that labor supply is set at the intensive margin as in LUCAS & RAPPING (1969) or KYDLAND & PRESCOTT (1982). B denotes the disutility of labor and γ is the inverse of the Frisch elasticity of labor supply.

In figure 6 we plot the business cycle components of the time series for total hours and the ratio of labor productivity (output over total hours) to consumption. [31] Often hours and the ratio of labor productivity to consumption move in opposite directions suggesting a departure from a stable labor supply schedule. Put it differently equation 4.2 does not hold in the US data; instead there is a time varying residual, the labor wedge.

$$\ln \text{Wedge} = \ln \text{MRS} - \ln \frac{Y}{H} = \ln BH^{\gamma} \frac{1}{C^{-1}} - \ln \frac{Y}{H} \tag{4.3}$$

In figure 7 we plot the time series of the business cycle component of the wedge along with aggregate hours; we assume a value of γ equal to one. The two

[29]Fortunately, the recent work of BLUNDELL, CHIAPPORI, MAGNAC, & MEGHIR (2007) extends the non-unitary model to allow household members to make discrete choices over hours. Also, MAZZOCCO (2007); GALLIPOLI & TURNER (2008) have introduced intertemporal aspects to this framework using the tools of the limited commitment literature based on LIGON, THOMAS, & WORRALL (2000); MARCET & MARIMON (1994).

[30]We have in mind the Nash bargaining model of MCELROY & HORNEY (1981).

[31]Figures 6 and 7 are taken from CHANG & KIM (2007); output and hours worked represent the non-agricultural private sector. Consumption reflects expenditure of non-durable goods and services.

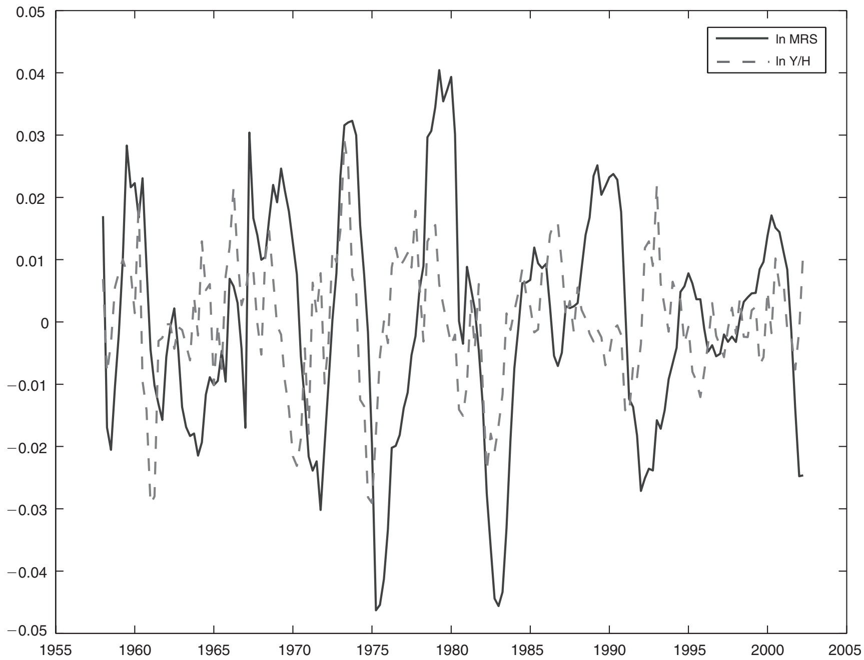

FIGURE 6: LABOR MARKET WEDGE

series are highly correlated and equally volatile; the contemporaneous correlation between them is .92. Moreover the labor wedge has a correlation with detrended GDP equal to .64.

These movements are really important for the US data; in HALL (1997) and in CHARI, KEHOE, & MCGRATTAN (2007) they explain nearly 50% of the US business cycle and there is a growing literature that seeks to understand them. We use our framework to evaluate the relative importance of two recent contributions in this literature. The first one interprets the wedge as an indication that labor markets are not efficient; if there are frictions then condition 4.2 does not hold, and movements in aggregate hours are driven by the demand for jobs over the business cycle (see for example HALL (2009) and GALI, GERTLER, & LOPEZ-SALIDO (2007)). The second contribution views the wedges as a symptom of heterogeneity in the macroeconomy when financial markets are incomplete. In this case condition 4.2 need not hold at the household level and CHANG & KIM (2007) use a model with bachelor households to show that aggregation of individual labor supply rules gives rise to a wedge with similar properties as in the US data.

Models Without Frictions. We first study an economy where labor market frictions are absent and labor supply decisions are set at the extensive margin. This is the model of section 3 of this paper but when $p_U(\lambda) = p_I(\lambda) = 1$ and $\chi(\lambda) = 0$. We assume that each agent in the economy can work $\overline{h}$ hours when employed at a utility cost of $B\frac{\overline{h}^{1+\gamma}}{1+\gamma}$. When families are large enough this economy is similar to the complete market model ROGERSON (1988) but with

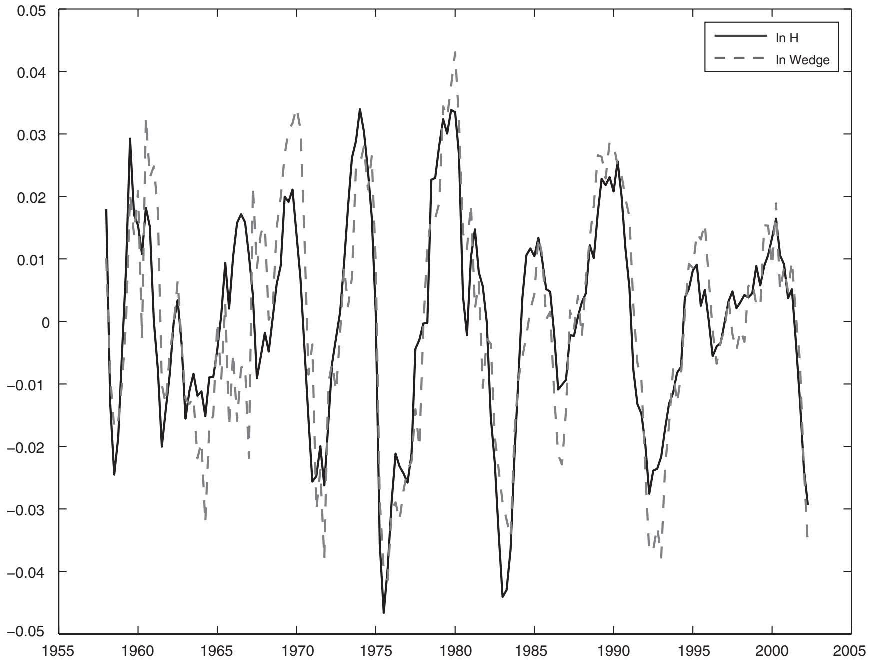

Figure 7: Hours and Labor Wedge

heterogeneous agents. Intra-period optimality requires:

$$B\frac{\overline{h}^{1+\gamma}}{1+\gamma} = \alpha\frac{Y}{L}\epsilon^{*}\overline{h}\frac{1}{C} \tag{4.4}$$

L is hours measured in efficiency units and ϵ^{*} is the cutoff productivity below which workers in this economy are non-employed.

In figure 8 we plot a sample of 50 quarters of the labor wedge along with aggregate hours when households are formed by bachelor agents. There is a very volatile and pro-cyclical wedge in this model. Its contemporaneous correlation with GDP is 0.59 and the analogous correlation with hours 0.92. The ratio of standard deviations with GDP is 0.85 and with aggregate hours 1.06, remarkably close to the US data. The result confirms the findings of Chang & Kim (2007).

In figure 9 we plot the same series from a model where households are couples and family members are ex ante identical. In contrast to bachelors the properties of the labor wedge in this case are not close to the US data. Often aggregate hours and the wedge move in opposite directions. The overall correlation between these two quantities is 0.42 in the model; the correlation of the wedge with de-trended output is .23 nearly a third of what it is in the US data. Moreover, the ratio of standard deviations is 0.27 with output and 0.35 with hours.

The key difference between these two models is that when families are couples a version of equation 4.4 holds in the household, or at least aggregation of family members labor supplies does not give rise to a wedge as in the US data. With as few as two agents in the household the model is close to an economy with

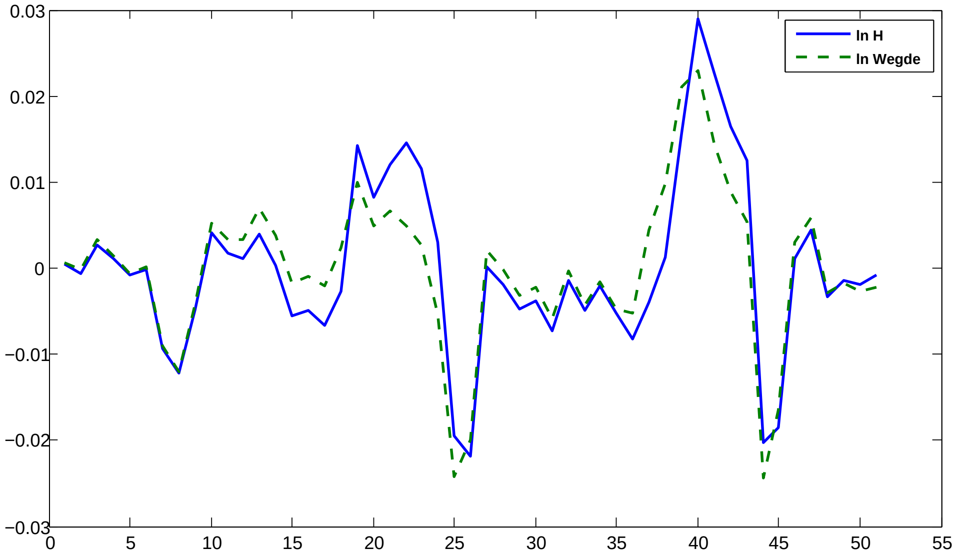

Figure 8: Hours and Labor Market Wedge: Bachelors no Frictions

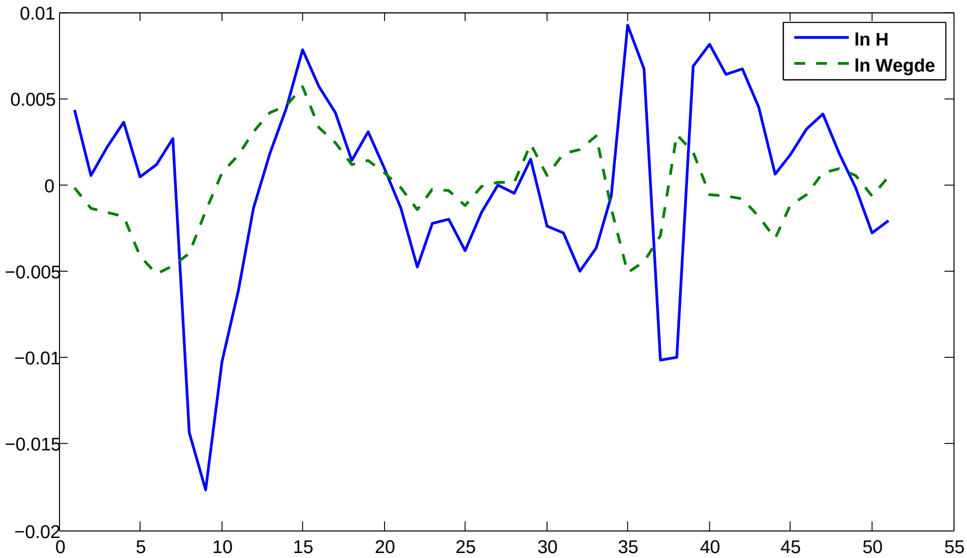

Figure 9: Hours and Labor Market Wedge: Couples no Frictions

complete markets where families are infinitely large. In both cases there is a value of γ that sets the wedge equal to zero. In the couples model with identical agents this value is .43 (corresponding to Frisch elasticity of aggregate labor supply equal to 2.32). [32] Finally, we evaluate whether this result is sensitive to preference heterogeneity and the degree of insurance within the family; it seems not; We get strikingly similar implications out of the model with husbands and wives; the correlation of the wedge with hours is 0.45 and with GDP 0.26 in this model. The volatility ratios are 0.39 and 0.29 respectively.

Models with Frictions. When there are frictions the labor market does not clear. In a recession agents loose their jobs at a faster pace but they are unable to find a news jobs because firms are not recruiting; agents spend more time out of work. In a search and matching model large wedges arise if wages are fixed (the same requirement for these models to produce large fluctuations in aggregate employment and unemployment, e.g. Hall (2009) and Hall (2005). In our model heterogeneity gives rise to acyclical labor productivity and wages as in Solon, Barsky, & Parker (1994).

We find that frictions restore the cyclical properties of labor market wedges as in the US data. In figures 10 and 11 we show the time series for these objects in our bachelors and couples economies. The correlation with aggregate hours is .99 for all models (including for the model with husbands and wives that is not shown) and wedges and hours have the same volatility. Moreover in both cases there is no value of the elasticity of labor supply that eliminates the wedge completely.

Whilst our results isolate labor market frictions as the most important factor, we view them as preliminary; The reason is that our models do not have a micro-foundation for changes in labor demand as in Mortensen & Pissarides (1994); rather frictions change exogenously over the business cycle. In current work we take stock from the results of this section and we construct a model with heterogeneous households (some are bachelors and some couples) and we add frictions as in the canonical search and matching model. We also study more closely the aggregation properties of economies with heterogeneous agents and wealth accumulation, and we evaluate how far the allocations are in these economies from the equilibrium with complete financial markets.

[32] We solve for the equilibrium under complete financial markets by parameterizing expectations (see Den Haan & Marcet (1990) for details). We find that when γ equals .49 in this model the labor wedge is is zero.

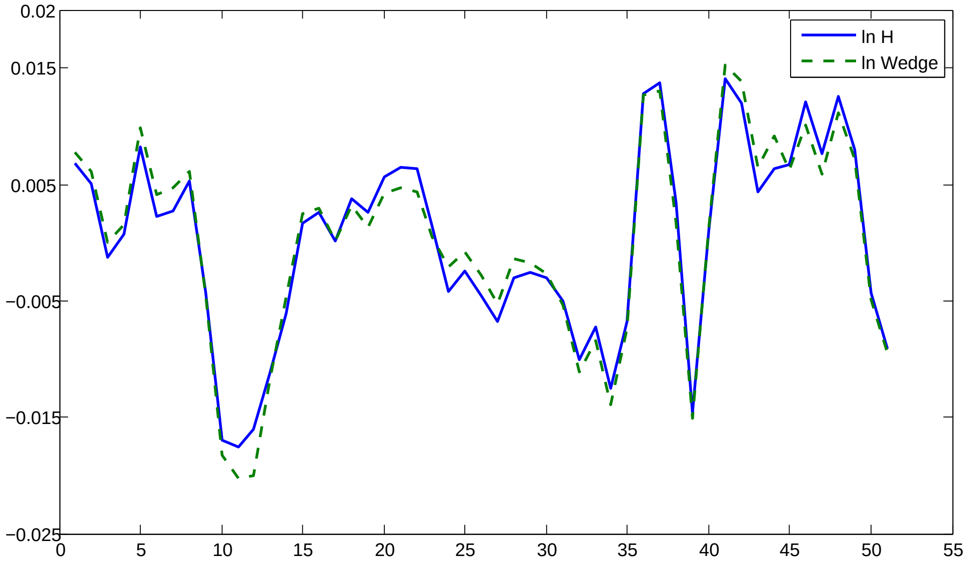

FIGURE 10: HOURS AND LABOR MARKET WEDGE: BACHELORS WITH FRICTIONS

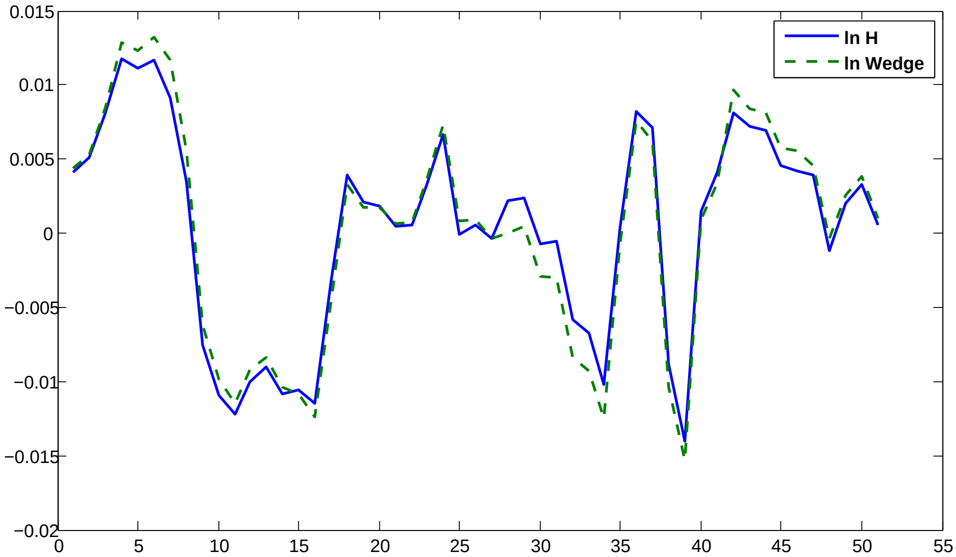

FIGURE 11: HOURS AND LABOR MARKET WEDGE: COUPLES WITH FRICTIONS

5 Conclusion

In this paper we show the importance of family self insurance in matching the business cycle properties of the aggregate labor market in the US. We construct a theory of heterogeneous agents and wealth accumulation when there are frictions in labor markets. Households consist of two members who search jointly for jobs and joint search can help families circumvent the frictions and insure against unemployment risks.

Our theory explains a feature of the US data that search models cannot match; that whilst aggregate employment and unemployment are very volatile and cyclical their sum (the labor force) is not. We argue that what conventional search models miss out on is to embrace the idea that economic decisions such as labor force participation are made jointly in the household. We show that in the US data agents time their flows in and out of the labor market to provide insurance; when a household member loses her job in a recession other household members search for job opportunities with her. Subsequently we show that the theory captures this aspect of the data. Our theoretical model matches the business cycle of not only aggregate employment and unemployment but also of labor force participation.

We also use the model to study the cyclical properties of the wedge derived from the optimality condition that links consumption and hours in real business cycle theory. One strand of the literature views labor market wedges as a by product of aggregation of individual policy rules, in models of heterogeneous agents and wealth accumulation (Chang & Kim (2007)), and another strand as a symptom of the failure of labor markets to clear when there are frictions (see for instance Hall (2009)). Our theory combines both of these features. We find that aggregation of individual policies is not enough to engineer labor market wedges with similar properties as in the US data. When we introduce another member in the household the aggregate labor wedge has no longer a strong negative correlation with aggregate hours. Search frictions are shown to be more crucial and they restore the cyclical properties of this statistic.

One of the main contributions of this paper is to put these ingredients (search, incomplete financial markets and families) in a unified framework. Both search models and models of heterogeneous agents have rightly gained in importance in quantitative macroeconomics over the past decade. Our results demonstrate that search theories are incomplete if they don't embrace the idea that search in the labor market is a family affair, guided by the incentive to insure against unemployment and other labor income shocks. Heterogeneous agents models are also incomplete if they ignore family self insurance.

We think of this work as a step towards an important research agenda. There is much to be said about the role of families in macroeconomics especially since there is a considerable literature on intra-household allocations (for instance Chiappori (1988, 1992); Browning & Chiappori (1998)). In our model we adopt the simple unitary framework whereby household members pool their resources to finance consumption. Extending to a collective model is not a trivial task. Yet a recent paper by Mazzocco, Ruiz, & Yamaguchi (2007) takes up on it. Another important question is to assess how far outcomes in models with heterogeneous agents and large families lie from the complete market benchmark. Some of the results we present in this paper suggest that they are not very far.

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A Model Appendix

A.1 Value Functions

In this section we describe the value functions from the couples model of section 3.3. We adopt the convention that the array (k,l) $k,l \in \{E,N\}$ denotes a couple where the male spouse is in state k and the female spouse in state l. We use the option values Q^{en},Q^{ne}, Q^{ee} to denote the envelope utilities over the relevant menu of choices.

The lifetime utility of a family where both the male and female spouse are non-employed is denoted by V^{nn} and solves the following functional equation:

$$
\begin{aligned}
V^{nn}(a,\epsilon,\lambda,\Gamma) = &\max_{a' \geq \bar{a}, s_m, s_f} \quad u(c_t) - \sum_g k_g(s_g) \\
+ \quad & \beta_C \int_{\epsilon',\lambda'} [p_m(s_m,\lambda) p_f(s_f,\lambda) Q^{ee}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & p_m(s_m,\lambda)(1-p_f(s_f,\lambda)) Q^{en}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & p_f(s_f,\lambda)(1-p_m(s_m,\lambda)) Q^{ne}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & (1-p_f(s_f,\lambda))(1-p_m(s_m,\lambda)) Q^{nn}(a',\epsilon',\lambda',\Gamma')] d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda})
\end{aligned}
\tag{A.1}
$$

subject to:

$$
a' = R_{\lambda,\Gamma} a - c \tag{A.2}
$$

The program of a family where only the husband is employed in the current period can be represented recursively as:

$$
\begin{aligned}
V^{en}(a,\epsilon,\lambda,\Gamma) = &\max_{a' \geq \bar{a}, s_f} \quad u(c_t) - k_f(s_f) - \Phi_m(\bar{h}) \\
+ \quad & \beta_C \int_{\epsilon',\lambda'} [(p_f(s_f,\lambda)\ (1-\chi_m(\lambda))\ Q^{ee}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & p_f(s_f,\lambda)\ \chi_m(\lambda)\ Q^{ne}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & (1-p_f(s_f,\lambda))\ (1-\chi_m(\lambda))\ Q^{en}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & (1-p_f(s_f,\lambda))\ \chi_m(\lambda)\ Q^{nn}(a',\epsilon',\lambda',\Gamma')] d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda})
\end{aligned}
\tag{A.3}
$$

$$
a' = R_{\lambda,\Gamma} a + w_{\lambda,\Gamma} \bar{h} \epsilon_m - c \tag{A.4}
$$

Similarly when only the wife is employed, the family's lifetime utility is given by:

$$
\begin{aligned}
V^{ne}(a,\epsilon,\lambda,\Gamma) = &\max_{a' \geq \bar{a}, s_m} \quad u(c_t) - k_f(s_m) - \Phi_f(\bar{h}) \\
+ \quad & \beta_C \int_{\epsilon',\lambda'} [(p_m(s_m,\lambda)(1-\chi_f(\lambda))\ Q^{ee}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & p_m(s_m,\lambda)\ \chi_f(\lambda)\ Q^{en}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & (1-p_m(s_m,\lambda))\ (1-\chi_f(\lambda))\ Q^{ne}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & (1-p_m(s_m,\lambda))\chi_f(\lambda) Q^{nn}(a',\epsilon',\lambda',\Gamma')] d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda})
\end{aligned}
\tag{A.5}
$$

$$a' = R_{\lambda,\Gamma}a + w_{\lambda,\Gamma}\overline{h}\epsilon_f\mu_f - c \tag{A.6}$$

Finally when both spouses are employed we can write:

$$\begin{aligned}
V^{ee}(a,\epsilon,\lambda,\Gamma) = \max_{a'\geq\overline{a}} \quad & u(c_t) - \sum_g \Phi_g(\overline{h}) \\
+ \quad & \beta_C \int_{\epsilon',\lambda'} \left[(1-\chi_m(\lambda))\,(1-\chi_f(\lambda))\,Q^{ee}(a',\epsilon',\lambda',\Gamma')\right. \\
+ \quad & \chi_m(\lambda)\,\chi_f(\lambda)\,Q^{nn}(a',\epsilon'\lambda',\Gamma') \\
+ \quad & (1-\chi_m(\lambda))\,\chi_f(\lambda)\,Q^{en}(a',\epsilon',\lambda',\Gamma') \\
+ \quad & \left.(1-\chi_f(\lambda))\,\chi_m(\lambda)\,Q^{ne}(a',\epsilon',\lambda',\Gamma'))\right]d\pi_{\epsilon'|\epsilon}d\pi_{\lambda'|\lambda})
\end{aligned} \tag{A.7}$$

$$a' = R_{\lambda,\Gamma}a + w_{\lambda,\Gamma}\overline{h}(\epsilon_m + \epsilon_f\mu_f) - c \tag{A.8}$$

A.2 Competitive Equilibria

A.2.1 Competitive Equilibrium with Bachelors

In this section we define a competitive equilibrium in an economy with bachelor households. The equilibrium consists of a set of value functions $\{V^n, V^e\}$, and a set of decision rules for consumption, asset holdings $a'(a,\epsilon,\lambda,\Gamma)$ ($a'_e(a,\epsilon,\lambda,\Gamma)$, $a'_n(a,\epsilon,\lambda,\Gamma)$ for employed and non-employed agents), search ($s(a,\epsilon,\lambda,\Gamma)$), and labor supply ($h(a,\epsilon,\lambda,\Gamma)$). It also consists of a collection of quantities $\{K_t, L_t\}$ and prices $\{w_t, R_t\}$ and a law of motion of the distribution $\Gamma_{t+1} = T(\Gamma_t, \lambda_t)$[33] such that:

- Given prices households solve the maximization program in 3.1 and 3.3 and optimal policies derive.

[33] The law of motion of the measure Γ can be represented as follows:

$$\begin{aligned}
\Gamma'_e(\mathcal{A},\mathcal{E}) \quad = \quad & \int_{a'_e\in\mathcal{A},\epsilon'\in\mathcal{E}} \mathcal{I}(h(a',\epsilon',\Gamma',\lambda') = \overline{h})(1-\chi(\lambda))\;\; d\pi_{\epsilon'|\epsilon}d\Gamma_e \\
+ \quad & \int_{a'_n\in\mathcal{A},\epsilon'\in\mathcal{E}} \mathcal{I}(h(a',\epsilon',\Gamma',\lambda') = \overline{h})\;\; p(s(a,\epsilon,\Gamma,\lambda),\lambda)\; d\pi_{\epsilon'|\epsilon}\; d\Gamma_n
\end{aligned}$$

$$\begin{aligned}
\Gamma'_n(\mathcal{A},\mathcal{E}) \quad = \quad & \int_{a'_e\in\mathcal{A},\epsilon'\in\mathcal{E}} \mathcal{I}(h(a',\epsilon',\Gamma',\lambda') = 0)(1-\chi(\lambda)) + \chi(\lambda)\;\; d\pi_{\epsilon'|\epsilon}d\Gamma_e \\
+ \quad & \int_{a'_n\in\mathcal{A},\epsilon'\in\mathcal{E}} \mathcal{I}(h(a',\epsilon',\Gamma',\lambda') = 0)\;\; p(s(a,\epsilon,\Gamma,\lambda),\lambda)d\pi_{\epsilon'|\epsilon}d\Gamma_n \\
+ \quad & \int_{a'_n\in\mathcal{A},\epsilon'\in\mathcal{E}} \mathcal{I}(h(a',\epsilon',\Gamma',\lambda') = 0)\;\; (1-p(s(a,\epsilon,\Gamma,\lambda)))d\pi_{\epsilon'|\epsilon}d\Gamma_n
\end{aligned}$$

Where Γ_n and Γ_e denote the marginal cdfs for non-employed and employed workers respectively and $\mathcal{A}$, $\mathcal{E}$ are subsets of the relevant state space. Indicator function $\mathcal{I}(h(a',\epsilon',\Gamma',\lambda') = \overline{h})$ takes the value one if the agent's desired labor supply is $\overline{h}$ and takes the value 0 otherwise. The definition of $\mathcal{I}(h(a',\epsilon',\Gamma',\lambda') = 0)$ is similar.

- The final goods firm maximizes its profits:

$$w_t = (1-\alpha)K_t^{\alpha}{\lambda_t}^{1-\alpha}L_t^{-\alpha} \quad \text{and} \quad r_t = \alpha K_t^{-\alpha}{\lambda_t}^{1-\alpha}L_t^{1-\alpha} - \delta$$

- Goods and factor markets clear:

Resource Constraint

$$Y_t + (1-\delta)K_t = \int (a'(a,\epsilon,\Gamma_t,\lambda_t) + c(a,\epsilon,\Gamma_t,\lambda_t))d\Gamma_t$$

Labor Market

$$L_t = \int \epsilon h_{a,\epsilon,\lambda,\Gamma}\mathcal{I}((h_{a,\epsilon,\lambda,\Gamma} = \overline{h})) \;\; d\Gamma_t$$

Savings Market

$$K_t = \int a_t \;\; d\Gamma_t$$

- Individual behavior is consistent with the aggregate behavior.

A.2.2 Competitive Equilibria with Couples.

In this section we define a competitive equilibrium in an economy with couples. For the sake of brevity we only include the definition for the model of section 3.2. In keeping with the notation of the text we let ϵ be the vector of idiosyncratic productivities of family members and ϵ_1 and ϵ_2 its first and second entries. Γ is the distribution of agents over assets, productivity and employment status. Also we define the marginal cdfs $\Gamma^{i,j}$ where $i,j \in \{e,n\}$. The law of motion of Γ is given by $\Gamma' = \mathcal{T}(\Gamma)$.

The equilibrium in this economy consists of a set of value functions $\{V^{nn}, V^{en}, V^{ne}, V^{ee}\}$ and a set of decision rules for asset holdings, search intensity and labor supply. We define the asset accumulation policy functions and consumption functions as $a'_{ij}(a,\epsilon,\lambda,\Gamma)$ $c'_{ij}(a,\epsilon,\lambda,\Gamma)$ for $i,j \in \{e,n\}$ respectively; the search rules are denoted by $s_k(a,\epsilon,\lambda,\Gamma,ij)$ for $ij \in \{nn,en,ne\}$ $k \in \{1,2\}$ and the labor supply functions as $h_k(a,\epsilon,\lambda,\Gamma,ij)$ for $ij \in \{en,ne,ee\}$ $k \in \{1,2\}$. [34]

Quantities $\{K_t, L_t\}$ (capital and labor input in efficiency units) and prices w_t, r_t (wages and interest rates) are such that:

- Given prices households solve the maximization program in equations 3.8 to 3.12 and optimal policies derive.

- The final goods firm maximizes its profits:

$$w_t = K_t^{\alpha}{\lambda_t}^{1-\alpha}L_t^{-\alpha} \quad \text{and} \quad r_t = K_t^{-\alpha}{\lambda_t}^{1-\alpha}L_t^{1-\alpha} - \delta$$

- Goods and factor markets clear:

[34] Note that the search and labor supply rules can take the value zero if appropriate. For instance $s_k(a,\epsilon,\lambda,\Gamma,ij) = 0$ for $ij \in \{en\}$ $k \in \{1\}$ since in this family the first agent is employed.

Resource Constraint

$$Y_t + (1-\delta)K_t = \int (a'_{i,j}(a_t,\epsilon_t,\Gamma_t,\lambda_t) + c_{i,j}(a_t,\epsilon_t,\Gamma_t,\lambda_t))d\Gamma_t \quad \textbf{R. C.}$$

Labor Market

$$\begin{aligned} L_t &= \int \epsilon_1 h_1(a,\epsilon,\lambda,\Gamma,en)\mathcal{I}_{(h_1(a,\epsilon,\lambda,\Gamma,en)=\overline{h})} \; d\Gamma_t^{e,n} \\ &+ \int \epsilon_2 h_2(a,\epsilon,\lambda,\Gamma,ne)\mathcal{I}_{(h_2(a,\epsilon,\lambda,\Gamma,ne)=\overline{h})} \; d\Gamma_t^{n,e} \\ &+ \int \sum_i \epsilon_i h_i(a,\epsilon,\lambda,\Gamma,ee)\mathcal{I}_{(h_i(a,\epsilon,\lambda,\Gamma,ee)=\overline{h})} \; d\Gamma_t^{e,e} \end{aligned}$$

Savings Market

$$K_t = \int a \;\; d\Gamma_t$$

- Individual behavior is consistent with the aggregate behavior. [35]

A.3 Wealth and Earnings Distributions.

Table 13 summarizes the steady state distributions of wealth and earnings in the models and the analogous statistics in the US data. We look at key moments for quintile groups in the distribution and we calculate the wealth shares, the ratios of group average to economy-wide average, and the earnings shares. The wealth data are from the Panel Study of Income Dynamics (PSID) 1994 survey, and the 1993 topical modules of the Survey of Income and Program Participation and the (SIPP).[36]Our measures of wealth from both sources reflect family net worth; the earnings data reflect household heads earnings.

[35] We can represent the law of motion of the measure Γ_t with similar equations as those in footnote 13 in the main text. For instance the measure of families where both agents are employed evolves according to the following recursion.

$$\begin{aligned} \Gamma_{t+1}^{ee}(\mathcal{A},\mathcal{E}) &= \int_{a'_{ee}\in\mathcal{A},\epsilon'\in\mathcal{E}} \Pi_k \mathcal{I}_{h_k(a',\epsilon',\Gamma',\lambda',ee)=\overline{h}}(1-\chi(\lambda))^2 \;\; d\pi_{\epsilon'|\epsilon} d\Gamma_t^{ee} \\ &+ \int_{a'_{en}\in\mathcal{A},\epsilon'\in\mathcal{E}} \Pi_k \mathcal{I}_{h_k(a',\epsilon',\Gamma',\lambda',ee)=\overline{h}} \; p(s_2(a,\epsilon,\Gamma,\lambda,en),\lambda)(1-\chi(\lambda)) \; d\pi_{\epsilon'|\epsilon} \; d\Gamma_t^{en} \\ &+ \int_{a'_{ne}\in\mathcal{A},\epsilon'\in\mathcal{E}} \Pi_k \mathcal{I}_{h_k(a',\epsilon',\Gamma',\lambda',ee)=\overline{h}} \, p(s_1(a,\epsilon,\Gamma,\lambda,ne),\lambda)(1-\chi(\lambda)) \; d\pi_{\epsilon'|\epsilon} \; d\Gamma_t^{ne} \\ &+ \int_{a'_{nn}\in\mathcal{A},\epsilon'\in\mathcal{E}} \Pi_{k=1}^2 \mathcal{I}_{h_k(a',\epsilon',\Gamma',\lambda',ee)=\overline{h}} \; p(s_k(a,\epsilon,\Gamma,\lambda,nn),\lambda) \; d\pi_{\epsilon'|\epsilon} \; d\Gamma_t^{en} \end{aligned}$$

The laws of motion of $\Gamma^{en},\Gamma^{ne},\Gamma^{nn}$ can be described in a similar way. As in the text $\mathcal{A}$, $\mathcal{E}$ are subsets of the relevant state space. Indicator function $\mathcal{I}(h_k(a',\epsilon',\Gamma',\lambda',ij)=\overline{h})$ takes the value one if the agent $k\in\{1,2\}$ in a family that is in state $ij\in\{en,ne,ee\}$ has a desired labor supply of $\overline{h}$ and takes the value 0 otherwise.

[36] The SIPP is a more unusual source of wealth data but we include it because it contains very detailed information of households' members employment status.

Table 13: Wealth and Earnings Distributions: Models and Data.

		Quintiles				
US DATA		1st	2nd	3rd	4th	5th
Wealth (PSID)	Group Averages	-.061	.044	.250	.736	4.03
	Shares	-.012	.008	.050	.146	.806
Wealth (SIPP)	Group Averages	-.041	.109	.421	1.04	3.45
	Shares	-.008	.021	.083	.209	.691
Earnings (PSID)	Shares	.056	.125	.175	.233	.409
Bachelor Households						
Wealth	Group Averages	.051	.220	.630	1.21	2.90
	Shares	.009	.071	.131	.220	.569
Earnings	Shares	.000	.068	.162	.282	.485
Couples Ex Ante Identical Agents						
Wealth	Group Averages	.060	.241	.652	1.24	2.84
	Shares	.009	.081	.141	.227	.552
Earnings	Shares	.000	.051	.173	.298	.476
Couples: Husbands and Wives						
Wealth	Group Averages	.060	.250	.650	1.23	2.85
	Shares	.010	.071	.141	.239	.549
Earnings	Shares Males	.010	.010	.188	.270	.421
	Shares Females	.000	.021	.166	.313	.498

Notes: Data are from the PSID 1994 survey and the SIPP 1993 survey. They represent family wealth and earnings.

There are several noteworthy features. The first is a well known feature of dynamic models of incomplete markets Castaneda, Díaz-Giménez, & Ríos-Rull (2003, see), that these models cannot account simultaneously for wealth and earnings distributions. Our model economies generate too little wealth concentration at the top quintile. The share of wealth of the top 20% in the distribution over total wealth in the economy is roughly 55% in the three models and the group to population average is around 2.9, whereas in the data these numbers are 80% and 4.03 respectively. The wealth Gini coefficients (not shown) are 0.54 for our bachelor economy and 0.52 for our two couples models, whilst it is 0.71 for our PSID sample. Since the natural borrowing limit in our models is equal to zero,[37] we cannot match the fact that for the first quintile of the wealth distribution average net worth is negative.

Our economies do a good job in matching the earnings distribution although they generate slightly more concentration than in the US data. The earnings Gini coefficient is found roughly equal to 0.47 in the models, while it is 0.41 in the data. Males have slightly less dispersed distributions of earnings than females.

We conclude that given that our focus is not to match moments of the wealth and earnings distributions our models generate sufficient heterogeneity. Reassuringly, both, the bachelors and the couples economies generate similar numbers in terms of these statistics.

The implied process of wages. Since in our models idiosyncratic labor income confounds risks from various sources (search frictions, separations shocks and the stochastic process of productivity), we evaluate how realistic the implied processes are by estimating the following equation of the logarithm of annual (time aggregated) wages:

$$\ln w_t = \phi \ln w_{t-1} + v_t$$

For each model we use a sample of 10000 individuals over 20 years to estimate with OLS the implied values for ϕ and the variance of the shock σ_v. We summarize the results in Table 14.[38]

Our reference estimates in the US data are those of Chang & Kim (2006) who estimate this process using data from the PSID over the period 1979-1992. It is precisely the estimates that we feed as primary processes for idiosyncratic risk in our model.[39]

The models slightly overstate the persistence of wages (ϕ) and understates the standard deviation of the innovation (σ_v). For instance, in the economy where households are formed by single agents the model produces a value for ϕ equal 0.82 whereas the data counterpart is 0.78.[40] With two ex ante identical agents in the family we get very close to the data, but when we distinguish between males and females in the family the model estimates of ϕ are too large, 0.83 and 0.78 in the model but only 0.78 and 0.72 in the data. The converse holds for our estimates of the variance of the innovation v_t.

[37] The search friction in our model implies that there is a positive probability that an agent will never find a job, therefore, he cannot guarantee to pay back any amount of debt.

[38] With ex ante identical agents we pool the two household members in the sample.

[39] These values are the annual analogues of the monthly counterparts that we summarized in Table 6

[40] In both models of sections 3.1 and 3.2 the idiosyncratic labor productivity process is set to match the analogous object for household heads (males) in the data

TABLE 14: ESTIMATES OF WAGE PROCESSES

	Model		ϕ	σ_v
Benchmark	**Bachelors**		.826	.276
	Couples: EAI	.	.789	.296
	Couples: H + W	Males	.836	.241
		Females	.782	.241
	US DATA (CK 2006)	Males	.781	.333
		Females	.724	.341
No Frictions	**Bachelors**		.859	.257
	Couples: EAI	.	.792	.284
	Couples: H + W	Males	.839	.228
		Females	.760	.230

Notes: OLS estimates of coefficients for the AR(1) wage process. The model data are simulated from the steady state in the three models. The data are estimates by CHANG & KIM (2006).

These small discrepancies are due to the following fact: whereas CHANG & KIM (2006) estimate a model that accounts for selection effects our OLS estimates in Table 14 correspond to the truncated distribution of idiosyncratic productivity conditional on participation.[41] Interestingly, CHANG & KIM (2006) report the value of persistence from a simple OLS model in their sample; they find ϕ equal to 0.82 for males and 0.78 for females. These values are strikingly similar to ours. We conclude that the stochastic processes of wages in our model economies are very close to the US data.

The bottom rows of Table 14 report the two moments for the model economies where frictions are absent. This isolates the effect of separations and search on the overall risk in the labor market. We find that frictions have a very small effect on these statistics. There is a small increase in the coefficient ϕ and a small reduction in the standard deviation of the shock σ_v in most cases. These differences reflect the fact that job availability in the economy changes the optimal policy rules for quits and hence they change the composition of the economy's workforce in terms of ϵ. With frictions agents remain employed with lower idiosyncratic productivity ϵ because once they quit it is relatively harder to get job opportunities.

B Data Appendix

B.1 Data Description and Variables

CPS: The CPS is a monthly survey of about 60,000 households (56,000 prior to 1996 and 50,000 prior to 2001), conducted by the Bureau of the Census for the Bureau

[41]There is not enough variation in observables in our model to include non-random selection terms.

of Labor Statistics. The sample is selected to represent the civilian non-institutional population and is the primary source of information on the labor force characteristics of the US population. Respondents are interviewed to obtain information about the employment status of each member of the household 16 years of age and older. Survey questions cover employment, unemployment, earnings, hours of work, and other and a variety of demographic characteristics such as age, sex, race, marital status, and educational attainment.

Although the CPS is not an explicit panel survey, it does have a longitudinal component that allows us to construct the monthly labor market transitions used in section 2 of the paper. Specifically, the design of the survey is such that the sample unit is interviewed for four consecutive months and then, after an eight-month rest period, interviewed again for the same four months one year later. Households in the sample are replaced on a rotating basis, with one-eighth of the households introduced to the sample each month.

Given the structure of the survey we can match roughly three-quarters of the records across months.[42] Using these matched records, we calculate the gross worker flows that we report in section 2.[43] Our sample covers the period 1976-2005. The flows are estimates of a Markov transition matrix (as in Tables 2 and 3) where the three states are employment, unemployment and inactivity (out of the labor force).

We use the CPS classification rule to assign each member of a household to a labor market state. This rule is as follows: employed agents are those who did any work for either pay or profit during the survey week.[44] Unemployed are those who do not have a job, have actively looked for work in the month before the survey, and are currently available for work; 'Actively looking' means that respondents have used one or more of the nine search methods considered by the CPS (6 methods prior to 1994) such as sending out resumes, answering adds, contacting a public or private employment agency etc.[45] Workers who search passively by attending a job training program or simply looking at adds are not considered as unemployed because these methods do not result in potential job offers. Finally, out of labor force are all agents who are neither employed nor unemployed, based on these definitions.

Given the classification, we calculate the conditional probability that an agent who was in state i in the previous month (interview date) is in state j this month, where $i, j \in \{E, U, I\}$. We use the household weights provided by the CPS so that these objects are representative of the US population and we remove seasonal effects using a ratio to moving average procedure. The entries in Tables 2 and 3 are the averages of the gross worker flows that we obtain over the sample period.

[42] Unfortunately, there is some sample attrition from individuals who abandon the survey.

[43] In our investigation we use the public micro-data files from the NBER web site. Our approach is similar to that used by Robert Shimer. For additional details, see Shimer (2007) and his web page.

[44] This includes all part-time and temporary work, as well as regular full-time, year-round employment.

[45] Workers on temporary layoff who expect to be recalled are counted as unemployed no matter if they search actively.

B.2 Female Labor Force Participation.

We explain our sample selection and methodology for the empirical model of section 2. In Table 15 we show the data points that we consider for the estimation of the dynamic equation B.1 which for completeness we repeat here.

There are two types of households; those that start with an EE transition meaning that the male spouse is employed in both the first and the second month, and those that have an EU transition in the first period. We drop all households where the male spouse flows out of the labor force at any point in time. This is not at all restrictive; since the population is for married couples aged 25-55 there are only about 40000 such observations out of total of 2 million in the CPS between 1994 and 2010.

$$\begin{aligned} Transition_{i,t} &= \sum_{\tau=-2}^{\tau=+2} \alpha_\tau \mathcal{I}\{ \text{ Husband Spell in t} + \tau\} + \\ &+ Z_{i,t}\delta + Time\ Dummies + f_i + \epsilon_{i,t} \end{aligned} \tag{B.1}$$

$$Transition = \begin{cases} 1 & \text{if} \quad olf \rightarrow lf \\ \\ 0 & \text{if} \quad olf \rightarrow olf \end{cases}$$

The variable $\mathcal{I}\{ \text{ Husband Spell in t} + \tau\}$ takes the value one if an EU transition occurred between in period $t+\tau$. To understand how we define these variables consider first a family that starts with an EE transition. If the husband remains employed in all of the months of the sample we treat this family as a reference group. Theoretically in this household the probability that the joins the labor force should be lower. A family with a sequence EE, EE, EU defines the following dummy variables: 2 months before, 1 month before and spell month (the relevant coefficients are α_{-2}, α_{-1}, and α_0). Analogously the sequence EE, EU, UU defines the a one month before a spell month and a one month after. Finally from the sequence EE, EU, UE we drop the observation for the UE transition and we define a month before and a month after. The reason is that a transition from unemployment to employment confounds our estimates with the effect finding a job on female labor supply and search.

Households in the CPS can be matched over 8 months in total. There are 4 consecutive months in one year and another 4 in the next, but we are only interested in estimating the dynamic responses in the range minus, plus 2 months from the unemployment spell [46] . In the estimates however we link those observations by including household specific fixed effects. After all selection criteria are accounted for (and we drop all transitions that begin with the wife being in the labor force) we have a sample of nearly 400.000 observations to work with.

In table 16 we report the linear probability model estimates which we showed in figures 1 and 2 in the main text. In column (1) we report the estimated coefficients for the full sample (job losers and quitters) and in column (2) we keep only those spells

[46] We don't make use of duration variables to extend these estimates backwards. The reason is that we don't observe the history of states for males and females.

Table 15: Relevant Transitions for the Dynamic Model

$$
\begin{tikzcd}
 & & \mathbf{EE} \\
 & \mathbf{EE} \arrow[ur] \arrow[r] & \mathbf{EU} \\
\mathbf{EE} \arrow[ur] \arrow[dr] & & \\
 & \mathbf{EU} \arrow[r] \arrow[dr] & \mathrm{UE} \\
 & & \mathbf{UU}
\end{tikzcd}
$$

$$
\begin{tikzcd}
 & & \mathbf{EE} \\
 & \mathrm{UE} \arrow[ur] \arrow[r] & \mathbf{EU} \\
\mathbf{EU} \arrow[ur] \arrow[dr] & & \\
 & \mathbf{UU} \arrow[r] \arrow[dr] & \mathrm{UE} \\
 & & \mathbf{UU}
\end{tikzcd}
$$

Table 16: Estimates from the Dynamic Model

	LPM		**Probit**	
Variable	(1)	(2)	(3)	(4)
α_{-2}	.022**	.085***	.021**	.106***
	(.011)	(.016)	(.011)	(.023)
α_{-1}	.023***	.173***	.023***	.163***
	(.007)	(.011)	(.008)	(.017)
α_0	.076***	.10***	.074***	.098***
	(.006)	(.010)	(.011)	(.014)
α_1	.061***	.072***	.053***	.051***
	(.0110)	(.0175)	(.013)	(.012)
α_2	.051***	.081***	.033*	.046**
	(.010)	(.029)	(.011)	(.015)
...+Controls				
R^2	.01	.012		
Log Likelihood			-96908.925	-98063.915

Notes: Data are from the CPS 1994-2010. Columns (1) and (2) are estimates from the linear probability model with fixed (household) effects. Columns (3) and (4) are estimates from a probit model with random effects. Columns (1) and (3) are the whole sample (job losers and job quitters) whereas columns (2) and (4) are from a sample of job losers. The estimated equation is B.1

Table 17: Disentangling the Effects

	I to U		I to E	
Variable	(1)	(2)	(3)	(4)
α_{-2}	.029**	.075***	−.003	.052***
	(.006)	(.009)	(.010)	(.015)
α_{-1}	.030***	.098***	−.004	.079***
	(.004)	(.006)	(.007)	(.010)
α_0	.063***	.078***	.024***	.038***
	(.003)	(.005)	(.011)	(.009)
α_1	.053***	.046***	−.004	.001
	(.006)	(.009)	(.013)	(.0161)
α_2	.064***	.078***	−.002	−.024
	(.011)	(.015)	(.018)	(.027)
...+Controls				
R^2	.011	.012	.007	.008

Notes: Data are from the CPS 1994-2010. In columns (1) and (2) joining the LF means a transition to unemployment for the full sample and for a sample of male job losers respectively; in Columns (3) and (4) the relevant transition is to employment. The estimates are from a linear probability model.

that emanate from a job loss. For clarity we suppress demographic variables (such as race, education and age). Columns (3) and (4) in the table report the marginal effects from the probit model (which accounts for random effects). The estimates are similar with those of the linear model, reinforcing our conviction that the effects are present.

More importantly in table 17 we attempt a breakdown of the flows into the labor force by looking separately at the estimates for transitions from I to U (columns (1) and (2)) and from transitions from I to E (columns(3) and (4)). For the entire sample (columns (1) and (3)) the bulk of the added worker effect comes from wives flowing from out of the labor force to unemployment (in the transition for employment only the contemporaneous effect is significant). In the sample with job losers (columns (2) and (4)) both transitions contribute to the aggregate. These results are not surprising; since to move to employment the worker needs to overcome the frictions in the labor market, the effect of insurance on hours is likely to show at longer horizons (from when the information of a potential job loss arrives).

Other transitions. In our estimates we focus on one interpretation of the added worker effect. The marginal worker (wife in our sample) flows into the LF (to either employment or unemployment) to provide insurance. There are other relevant possibilities. For instance wives should be less willing to drop out of the labor force in the event of spousal unemployment or should be more likely to leave the LF when their husband finds a job. We report here briefly our findings for these transitions.

We first run the probability that she drops out of the LF when her husband moves from employment to unemployment. There is only weak evidence in our samples that this effect is relevant (for both loser and quitters). We do find however strong support that she is less likely to leave unemployment to drop out of the labor force when we account for these transitions. In this regression she is 6% less likely in the month of the spell, 6% less likely one month before the spell, 8% less likely one month after and 13 % less likely 2 months after. All of these coefficients are statistically significant.

When we run the probability that she joins when the husband finds a job the only coefficient that is significant is α_2. We interpret this as evidence that what is relevant for these decisions is for the husbands new job to be stable (survive at least for two months in the sample).

Selection and Other Potential Biases. We report several difficulties with our empirical methodology. First we address the problem that we don't observe the husbands employment status continuously in our sample. For instance a recorded UU transition may in fact mean that the male spouse was unemployed at the interview date of month t and at month $t+1$ but was employed (and lost his job) between these dates. Luckily we can control for that, by using information on unemployment duration (equivalently duration of job search). In the example we can match search in between the two interview dates to have lasted 4 weeks then we are certain that there is no intervening employment spell. Reassuringly when we drop the observations with unmatched records we get very similar results. Another difficulty comes from unobserved unemployment spells in between two months that the husband has been recorded as employed. There we don't have a good instrument so that our estimates could be downward biased if there are many of these couples.

B.2.1 Search Intensity

We report in this section the response of the number of search methods for married women to a spousal unemployment spell. An increase in search intensity is essentially a transition from out of the labor force to unemployment. In our sample in the CPS from 1994 to 2010 there are 12 methods of search. We construct an index of search intensity for each individual by adding the number of different search methods that she uses.

We follow a similar methodology as described above and estimate the following equation with dynamic panel data.

$$\begin{aligned} Search_{i,t} &= \sum_{\tau=-2}^{\tau=+2} \alpha_\tau \mathcal{I}\{ \text{ Husband Spell in t} + \tau\} + \\ &+ \; Z_{i,t}\delta + Time\ Dummies + f_i + \epsilon_{i,t} \end{aligned} \tag{B.2}$$

where $Search_{i,t}$ is the index of search intensity and takes values from 0 to 12 (we pool non-searchers together with searchers).

In Table 18 we report the results from the static version of B.2. The results suggest that if the husband experiences a transition from employment to unemployment the wife increases her search intensity by on average 1.34 methods. In column (2) we disentangle the effect of job leavers and job losers. In the husband loses his jobs the response is an increase of roughly 2.5 search methods (the sample average is .2).

Table 18: Response of the Number of Search Methods.

Variable	(1)	(2)
Husband EU	1.34***	.859***
	(.0027)	(.0028)
Husband Job Loser		1.68***
		(.005)
R^2	.421	.541

Notes: Data CPS 1994-2010. Estimates are from a linear probability model that controls for household fixed effects. The regressions include demographic controls (e.g. age of household members, race, education, number of children) and time dummies. ***Indicates significant at 1 percent level.

In Table 19 we estimate the α_τ coefficients from the dynamic model. There are no significant effects before the spell occurs and hence we drop these arguments from the table. [47]. However there are powerful effects both in the period and in the two months after the spell. Moreover we find that a large part of total variation in the number of search methods is explained by the husband unemployment variables. When we

[47]Notice that we don't estimate a transition here. The results from table 19 don't have the same interpretation as those of the previous paragraph because here in the first month the agent could be either unemployed or OLF. Moreover if she finds a job we drop her from the sample

TABLE 19: RESPONSE OF THE NUMBER OF SEARCH METHODS.

Variable	(1)	(2)
α_0	1.32***	2.64***
	(.0037)	(.0032)
α_1	1.64***	2.86***
	(.0062)	(.0049)
α_2	1.68***	.2.69***
	(.01)	(.0081)
...+Controls		
R^2	.521	.641

Notes: Data CPS 1994-2010. Estimates are from a linear probability model of the equation B.2

drop these variables the regression (which includes demographics and time effects) can explain only 5% of total variation in the number of search methods.

We think that these results are particularly interesting. For instance SHIMER (2004) reports that contrary to the implications of search and matching models, the data from the CPS show that search intensity is not procyclical. Part of this reflects that in recessions more active searchers flow to unemployment from employment, but given our results we anticipate that a large part of these outcomes can be explained through the lenses of out model. This is something that we leave for future research.

B.3 Cyclicality of Female LF Participation

In the experiment of section 2 we compute the probabilities $p_t^f(i,j,k,l)$ and $p_t^m(k,l)$ by applying similar steps. The difference here is that due to data limitations we do not have sufficient observations to estimate the transition probabilities over a state space that includes employment, unemployment and inactivity. The difficulty is that for the conditional probability $p_t^f(i,j,k,l)$ (that the wife flows from i to j when her husband flows from k to l) there are nine elements in the state space if both $i,j \in \{E,U,I\}$ and $k,l \in \{E,U,I\}$ and the Markov matrix would contain 81 entries for each month (this is possible in some months). Inevitably, we restrict attention to $i,j \in \{olf, lf\}$, i.e. the wife is either out of the labor force or in the labor force and $k,l \in \{e,n\}$, i.e. the husband is either employed or not.

We construct the populations shares in the following manner: Let $n_t(i,k)$ be the share of couples in our sample where the husband is employed and the wife out of the labor force in period t. We use again the weights from the CPS to make these shares representative of the US population. Let $p_t^f(i,olf,k,e)$ be the conditional probability of the wife flowing to state olf next period when the husband flows to state E. Also, let $p_t^m(e,l)$ be the unconditional probability for the husband's transition. Then, in the next period the fraction of families in state olf,e that were previously i,k is given by $n_t(i,k)p_t^f(i,olf,k,e)p_t^m(k,e)$. More generally, the total number of agents (if populations are normalized to one) in state olf, e next period is given by the following equation:

$$n_{t+1}^{A}(olf,e) = \sum_{i \,\in\, \{olf,lf\} \quad,\, k \,\in\, \{e,n\}} n_t(i,k) p_t^f(i,olf,k,e) p_t^m(k,e) \tag{B.3}$$

We denote the resulting shares for next period by $\tilde{n}_{t+1}(olf,e)$ to make clear that this object is not necessarily equal to the actual population share in the data $n_{t+1}(olf,e)$. Using variations of equation B.3 we construct the populations for the counterfactual experiment in section 2. In one case we average the job finding probabilities for males which we denote by $\overline{p}_t^m(k,e)$ and equation B.3 becomes:

$$n_{t+1}^{C}(NLF,e) = \sum_{i \,\in\, \{olf,lf\} \quad,\, k \,\in\, \{e,n\}} n_t(i,k) p_t^f(i,olf,k,e) \overline{p}_t^m(k,e) \tag{B.4}$$

For a three month ahead population equations B.3 and B.4 need to account for the fact that agents can be in any state in periods t+1 and t+2 in before they end up in olf, e.

B.4 Income and Wealth Data

Our source for wealth and income data in section are the Panel Study of Income Dynamics (PSID) and the Survey of Income and Program Participation (SIPP). Since these data sets are used extensively in quantitative research in macroeconomics, we describe them only briefly.

The SIPP is a longitudinal survey of about 40,000 households that are interviewed every four months. The information collected covers a wide range of demographic characteristics, labor force participation (there is detailed record of weekly employment history), amounts and types of earned and unearned income received, non-cash benefits from various programs, asset ownership, and private health insurance. This information is organized in two categories: core and topical; The core content includes questions asked at every interview whilst the topical modules probe in greater detail about particular social and economic characteristics such as assets and liabilities, school enrollment, marital history, fertility, migration, disability etc.

We use the 1993 topical module files to obtain the wealth data. Wealth is defined as the sum of net worth of all family members resulting from the aggregation of the following components: house (main home), other real estate, vehicles, farms and businesses, stocks, bonds, cash accounts, and other assets net of liabilities. We use this variable to construct the statistics (shares and group averages for each quintile) that we report in table 13. Our data from the PSID reflect a similar definition of net worth. They are derived from the 1994 survey dataset. The moments for household earnings that we report reflect earnings of household heads.

C Computational strategy

In this section, we describe our computational strategy first for the steady state calibrations and second for the model with aggregate uncertainty.

C.1 Computational strategy for steady-state equilibrium

In steady state, factor prices are constant and the distribution of agents over the relevant state space Γ is time invariant. The calibration consists of three nested loops. The outer loop is the estimation loop where we set the endogenous parameters $\{B, k, p_I(\overline{\lambda}), p_U(\overline{\lambda}), \chi(\overline{\lambda})\}$. Then, we solve the model and check whether the generated moments (labor market flows) are close enough to their empirical counterparts. If not, we try a new set of parameters.

The middle loop is the market clearing loop. We guess a value for the discount factor β (β_S for the bachelor household model and β_C for the couples economies) [48] Using the discount factor, we solve the agent's program and we obtain the steady state distribution Γ). The steady sate distribution yields an aggregate savings supply. If the implied marginal product of capital net of depreciation is equal to the calibrated value for the interest rate, we found the equilibrium. If not, we update our guess for the discount factor β. We use a simple bisection algorithm to minimize the number of iterations.

The inner loop is the value function iteration. Details are as follows:

1. We choose an unevenly spaced grid for asset holdings (a) (with more nodes near the borrowing constraint) and a grid for individual productivities ϵ. We experiment with different number of nodes for the asset grid, usually between $N_a = 101$ and $N_a = 161$. The number of nodes for the idiosyncratic labor market productivity is $N_\epsilon = 5$; they are equally spaced and the transition matrix of shocks is obtained by the discretization procedure described by Adda & Cooper (2003).

2. Given the interest rate, the discount factor and the wage rate $w(\overline{\lambda})$ (the latter follows from the production technology), we solve the family's optimal program via value function iteration by working recursively on the objects V^n, V^e in the bachelor model, and $V^{nn}, V^{en}, V^{ne}, V^{ee}$ in the couples models until they converge. Therefore, we start with an initial guess for the lifetime utilities. We approximate numerically the optimal policies (for savings and labor supply) and we update the guess. Values outside the grid are interpolated with cubic splines. We use a golden section search method to solve for optimal savings. Once the value functions have converged we recover the optimal policy functions of the form $a'(a,\epsilon)$ (savings), $s(a,\epsilon)$ (search) and $h(a,\epsilon)$ (employment).

3. The final step is to obtain the invariant measure Γ over the relevant state space (asset, productivities and employment status).

    (a) We first approximate the optimal policy rules on a finer grid which $N_{a_{BIG}} = 2000$ nodes and we initialize our measure Γ_0.

    (b) We update it and obtain a new measure Γ_1

    (c) The invariant measure is found when the maximum difference between Γ_0 and Γ_1 is smaller than a pre-specified tolerance level.

[48] As explained in the main text, we keep the interest rate constant across all models in order to obtain identical capital labor ratios. We set $R(\overline{\lambda}) - 1$, equal to 0.41% (a quarterly analogue of 1.24%).

(d) By using the invariant measure, we compute aggregate labor supply and asset supply. This implies a new marginal product of capital which we then compare to our initial guess.

C.2 Computational strategy for equilibrium with aggregate fluctuations

Aggregate shocks imply that factor prices are time varying. When solving their optimization program agents have to predict future factor prices. Therefore, they have to predict all the individual policy decisions in all possible future states. This requires agents to keep track of every other agent. Thus, in order to approximate the equilibrium in the presence of aggregate shocks, one has to keep track of the measure of all groups of agents over time. Since Γ is an infinite dimensional object it is impossible to do this directly. We therefore follow Krusell & Smith (1998) and assume that agents are boundedly rational and use only the mean of wealth and aggregate productivity to forecast future capital K and factor prices w and R.

Compared to the steady-state algorithm we now have two additional state variables that we must add in the list of the existing state variables in the inner loop: aggregate productivity λ and aggregate capital K. We use the steady state values for the endogenous parameters. But, we still have four nested loops. In the outer loop we set the level of fluctuations in the arrival rates of job offers $p_U(\lambda)$, $p_I(\lambda)$ and the separation probabilities $\chi(\lambda)$. We do this by increasing (decreasing) $p_U(\lambda)$ and $p_I(\lambda)$ proportionally and decreasing (increasing) $\chi(\lambda)$ in a boom (recession) in order to match the cyclical properties of the quarterly flow rates EU, EI, UE, and UI. The next loop is the iteration on the forecasting equations for aggregate capital and factor prices. The details are as follows:

1. We approximate the aggregate productivity process with 2 nodes and use again the methodology of Adda & Cooper (2003) to obtain the values and transition probabilities. We choose a capital grid around the steady state level of capital K^{ss}, particularly we use $N_k = 6$ equally spaced nodes to form a grid with range $[0.95 * K^{ss}; 1.05K^{ss}]$.

2. We set the level of fluctuations in the arrival rates of job offers $p_U(\lambda)$, $p_I(\lambda)$ and the separation probabilities $\chi(\lambda)$.

3. As already mentioned, we choose the means of aggregate capital and aggregate productivity as explanatory variables in the forecasting equations. We use a log-linear form

$$ln\,K_{t+1} = \kappa_0^0 + \kappa_1^0 ln\,K_t + \kappa_2^0 ln\,\lambda_t \quad (C.1)$$
$$ln\,w_t = \omega_0^0 + \omega_1^0 ln\,K_t + \omega_2^0 ln\,\lambda_t \quad (C.2)$$
$$ln\,R_t = \varrho_0^0 + \varrho_1^0 ln\,K_t + \varrho_2^0 ln\,\lambda_t \quad (C.3)$$

4. We initialize the coefficients so that K_{t+1}, w, R are equal to their steady state values.

5. Given equations C.1 to C.3, we solve the value function problems as before, just that now the state vector is four-dimensional. Values that are not on the asset grid are interpolated using cubic splines. Values that are not on the aggregate capital grid are interpolated linearly.

6. Instead of simulating the economy with a large finite number of agents we use the procedure of Young (2010) and simulate a continuum of agents. This procedure has the advantage of avoiding cross-sectional sampling variation. We simulate the economy for 10,000 periods and discard the first 2,000. In each period we get an observation for K, w and R. We use the simulated data to run OLS regressions on equations C.1 to C.3 which yield new coefficient estimates κ^1's, ω^1's, ϱ^1's. If these coefficients are close to the previous ones we stop, otherwise we update equations C.1 to C.3 with the new coefficients and solve the problem again.

The convergent solutions for the forecasting equations of our models are as follows:

Table 20: Bachelor Agents.

Equation	Constant	$\ln(K_t)$	$\ln(\lambda_t)$	R^2
$\ln(K_{t+1})$	.07115	.98175	.02802	.99997
$\ln(w_t)$	-.32154	.39338	.60769	.99636
$\ln(R_t)$	.04485	-.01026	.01023	.98717

Table 21: Couples Ex Ante Identical Agents.

Equation	Constant	$\ln(K_t)$	$\ln(\lambda_t)$	R^2
$\ln(K_{t+1})$	.05427	.98317	.04203	. 99996
$\ln(w_t)$	-.16841	.39621	.55531	.99627
$\ln(R_t)$	.04858	-.01355	.01546	.99108

Table 22: Couples: Husbands and Wives.

Equation	Constant	$\ln(K_t)$	$\ln(\lambda_t)$	R^2
$\ln(K_{t+1})$	.06117	.98221	.03501	. 99997
$\ln(w_t)$	-.2184	.39011	.56834	.99598
$\ln(R_t)$	.04766	-.01145	.01342	.99101