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 in the labor market and in the degree of incompleteness of financial markets. We develop a theory of joint household search in frictional labor markets under incomplete financial markets. 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, which do not incorporate joint household search, cannot match. In the data, aggregate employment is procyclical and unemployment countercyclical, but their sum, the labor force, is acyclical. In our model, and in the US data, when a family member loses his job in a recession, the other family member joins the labor force to provide insurance.

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1 Introduction

Economic decisions such as whether or not to work and whether or not to search for jobs are made jointly in the family. 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 the labor income. Unemployment is such a shock, and families can be an important insurance device against it.

To see this consider the following example: Assume that a family consists of two members; one of the members is employed and the other member is out of the labor force. This is a pattern that we observe frequently in the US data; typically, primary earners are husbands and secondary earners, wives. Assume further that the economy is in a recession, the separation rate from employment is high and the job finding probability is low. If the husband loses his job during the recession then, household income suffers a big shock. To provide insurance against this shock the wife may join the labor force; she will look for a job (and hence become unemployed) or accept job offers and become employed.

We show that this simple mechanism which the literature calls the 'added worker effect' (AWE) can resolve an extremely persistent puzzle: in the US data, aggregate employment is procyclical but the labor force participation, the fraction of the population that wants to work, is not correlated with aggregate economic activity. This fact is in sharp contradiction with many macroeconomic models of the business cycle. For example, in search theoretic models of the labor market (e.g. Mortensen and Pissarides (1994) , and Pissarides (2000)) the labor force is the sum of the employed and unemployed individuals. These models predict that participation rises sharply during economic expansions (Veracierto (2008) and Tripier (2004)). Moreover, in the 'neoclassical labor supply models' of Hansen (1985) and Rogerson (1988), and more recently Chang and Kim (2006, 2007), Gourio and Noual (2006) and Rogerson and Wallenius (2009), the labor force is all employed individuals; these models also predict a very procyclical participation in the labor market.

The model that we propose in this paper can resolve the puzzle since it acknowledges the importance of joint labor supply decisions within households. We present a general equilibrium framework with search frictions in the labor market, and incomplete insurance markets (as in Aiyagari (1994) and Krusell and Smith (1998)). The novelty of our framework is that we assume that in every household there are two members; therefore, relative to the considerable literature of 'heterogenous agents and wealth accumulation', which typically assumes 'bachelor households', we add a second member to the family.

Following this literature we assume that the household members are ex ante identical; they differ only in terms of their productivity endowments. Idiosyncratic productivity becomes the statistic which determines which household member is the primary earner (the husband) and which is the secondary earner (the wife). The model is very tractable; it abstracts from other forms of heterogeneity which we do not need anyway: with the simple framework that we propose we can match very accurately the intra-household patterns of employment, unemployment and labor force participation.

To generate transitions across labor market states, the model possesses two key mechanisms: First, search frictions, which are modeled by assuming a low probability of receiving a job offer in each period and by assuming that jobs are destroyed exogenously, through separation shocks. These are standard ingredients of search and matching models.

Second, idiosyncratic productivity and household wealth exert an influence on labor supply; when individuals experience a drop in productivity and the family is wealthy, the reservation wage is higher than the actual wage. Then individuals withdraw from employment. This feature of the model follows the standard neoclassical labor supply arguments (e.g. Chang and Kim (2006, 2007), Gourio and Noual (2006)). The model, therefore, combines the two key macroeconomic channels to generate fluctuations in the labor market.

We show that the first channel (the frictions) is relevant mainly for primary earners. These are the most productive individuals that the family wants to keep employed. The secondary earners are mainly the out of the labor force individuals. For them, the frictions are not very relevant, it is reservation wages that determine their participation patterns.

Over the business cycle the frictions shift along with total factor productivity. This makes transitions into unemployment more likely during economic recessions, and the duration of unemployment longer. In response to these shocks there are two main channels that influence the behavior of individuals: First, due to the standard intertemporal substitution effects (see Veracierto (2008)), participation becomes very procyclical. Job opportunities are scarce in recessions and search is costly; therefore, individuals look for jobs in expansions, when expected costs are lower. Second, the family insurance channel: since it is more likely that primary earners become unemployed in recessions, and the expected duration of unemployment is longer, secondary earners wish to flow in the labor force to provide insurance. We show that these two important aspects of intertemporal optimization are balanced over the cycle. Labor force participation becomes acyclical.

We find strong empirical support in favor of the family insurance channel in the data. First, when we look at the micro-data from the Current Population Survey (CPS), there is indeed a substantial response of female labor force participation to spousal unemployment. This is in line with the earlier literature on the AWE (e.g. Lundberg (1985) and Stephens (2002) among others). We illustrate that the response may not only occur right after the unemployment shock, but also with a lag, in the months that follow the shock. This pattern is matched by the model: Since we assume incomplete markets, household wealth is reduced during unemployment. Then, standard wealth effects induce secondary earners to join the labor force when the unemployment shock arrives, but also in the months thereafter.

In the aggregate data we also find strong support in favor of family insurance. We show i) that the labor force participation of married women is negatively correlated with the business cycle, and ii) the employment rate of women is not strongly procyclical and exhibits moderate volatility. The model can match these facts because secondary earners join the labor force and therefore (some of them) become employed during downturns. In contrast, primary earners, exhibit a more procyclical and volatile employment pattern due to the impact of the frictions.

To show clearly that these facts are in sharp contradiction with the existing macroeconomic theories of the business cycle, we compare the performance of our new framework with the bachelor model of incomplete markets and with the complete market model. As is well known, in the bachelor economy, household wealth becomes an important state variable. Indeed a considerable literature has shown that in the presence of idiosyncratic income risks, individuals save for self-insurance purposes. This feature is completely absent when we assume complete financial markets: in this case idiosyncratic risks and household wealth do not exert any influence on allocations.

The couple model we present in this paper is somewhere in between these two extremes. As we show, couples do not want to save as much as bachelors do, because they can utilize joint labor supply as an alternative self-insurance margin. Furthermore, couples allocate their most productive members in the labor force, a standard feature of the complete market allocation. However, because financial markets remain incomplete in the couple model, some families are unlucky in the labor market; and as a consequence their wealth is low. These households typically have both of their members in the labor market, even if one of the members (or both) are unproductive. This is a well know property of the bachelor household model, that in the presence of borrowing restrictions unproductive and poor individuals are part of the labor force because reservation wages drop with wealth.

These observations are crucial to demonstrate that across the models, heterogeneity derives from different sources. Comparing their cyclical properties is therefore interesting also for this reason. Our findings are that both the bachelor and the complete market models, predict a very procyclical and volatile participation rate. Whether wealth is the important state variable which influences the participation margin or idiosyncratic productivity is the important state, does not alter conclusions. However, the resulting composition of effects (between wealth and productivity across models) matter for the cyclical behavior of other quantities, most notably for the behavior of aggregate consumption and wages.

This paper brings several new insights to the literature and relates to several strands. First, a very common perception among macroeconomists is that even though insurance through the financial market is limited, assuming complete markets, is a valid simplification because families are typically larger than one individual. For example Robert E. Hall (2009) states the following:

'*I do not believe that in the US economy, consumption during unemployment behaves literally according to the model of full insurance against unemployment risk. But families and friends may provide partial insurance. I view the full insured case as a good and convenient approximation to the more complicated reality...*'

This very common perception is further reinforced by the fact that research in macroeconomics has not produced (to our knowledge) striking differences between the bachelor and the complete market models, at least not in terms of the behavior of the aggregate economy and the business cycle fluctuations.[1] Our results in this paper, are in sharp contrast with this wide-held view. We find that the dual earner model produces vastly different behavior for the labor market, relative to the bachelor and the complete market models, which lead to basically the same predictions. This result highlights that studying explicitly the decisions of families under incomplete markets is important.

A few recent papers have moved towards this direction. Guler, Guvenen and Violante (2012) construct a search theoretic model with dual earner households, to show that joint search presents households with the opportunity to increase income. In their model individuals receive random offers from a wage distribution; employed individuals quit voluntarily into unemployment when their spouse receives a high wage offer. Through taking turns being employed, households can then climb up the wage ladder. These features are not present in our model.[2] Flows in and out of the labor force are not driven by comparative advantage, they are driven by the motive of households to self-insure

[1]It is for example well known that the wealth inequality in heterogeneous agents models does not affect the business cycle properties of aggregate capital, investment and consumption (e.g. Krusell and Smith (1998)). On the other hand, assuming incomplete markets has been shown important for optimal fiscal policy (e.g. Conesa, Kitao and Krueger (2009)).

[2]Guler et al. (2012) show that their mechanism is weakened when households can save.

against the unemployment risk. This means that secondary earners flow in the labor force to provide insurance, not to replace the primary earner in the labor market. In the CPS data we find strong support in favor of the insurance argument whereas we do not find evidence (at least in terms of the monthly flows that we analyze) in favor of a comparative advantage.

Our analysis is intimately related to the recent work of Blundell, Pistaferri and Saporta-Eksten (2014). They estimate, using PSID data, a life cycle model which features couples, idiosyncratic productivity risks, and wealth accumulation. Since their data has an annual frequency, they rightfully leave frictions outside their model. They find that families provide insurance against labor income shocks through adjusting hours worked. Our results are complementary to theirs. We focus on short term unemployment shocks which are precisely identified in the CPS data and document how they can affect desired labor supply and participation patterns more broadly. We show that household search helps households circumvent the frictions in the labor market, whereas Blundell et al. (2014) find that joint hours insulate the household's budget from more persistent productivity shocks. Theirs is a life cycle model, which can be conveniently mapped to the data and used to assess the welfare effects from insurance; ours is an infinite horizon macro-model which explores the business cycle impact of intra-household decisions.

A large literature which studies business cycles in neoclassical models and assumes an extensive margin of labor supply, has identified the importance of 'marginal workers' for aggregate employment fluctuations. Chang and Kim (2006, 2007), Gourio and Noual (2006) and Rogerson and Wallenius (2009) (among many others) follow in this vein. Married women are undeniably an important group of marginal workers and yet the data patterns that we identify go against the view that they contribute much to fluctuations in the labor market.[3] Many papers in this literature, look at different 'marginal worker groups' than we do; for example, they study young and low income individuals. In principle, our theory could become pertinent for other groups, however, our model does not have an elaborate life cycle structure, this matters because young individuals enter in the labor market when wages are low to accumulate human capital, to become economically independent from their parents and so on. These features are for now left outside the model.

Our work is closely related to a recent stream of papers which study search models with three labor market states (employment, unemployment and participation). Noteworthy examples are Garibaldi and Wasmer (2005), Krusell, Mukoyama, Rogerson and Şahin (2011), and Krusell, Mukoyama, Rogerson and Şahin (2012). Garibaldi and Wasmer (2005) present a search and matching model assuming that heterogeneity derives from temporary shocks to preferences. Krusell et al. (2012) use a model similar to ours (with household wealth and idiosyncratic productivity shocks) to analyze business cycle fluctuations, but assume bachelor households. Some of the mechanisms that they highlight are pertinent for the models we study. When we present the results from the bachelor model we explain the differences in terms of the modeling assumptions and how these may affect the conclusions drawn. In contrast to all of these papers, our focus is to analyze the effects of introducing a second member to the household maintaining the assumption that markets are incomplete.

Finally, our conclusions are relevant for the design of tax policies and benefits. First, optimal

[3] A few papers have looked at the impact of tax policies on female labor market participation, sometimes finding sizable effects (see for example Chetty, Guren, Manoli and Weber (2012) and the references therein, see also Guner, Kaygusuz and Ventura (2012)). Our results do not go against these findings, since changes in taxes do not lead to increases in the unemployment rates of primary earners. Our analysis is pertinent for the business cycle.

unemployment insurance policies should be influenced by the insurance margins that households possess. This has been demonstrated for the case of household savings by a series of papers (see for example Hansen and İmrohoroğlu (1992),Wang and Williamson (2002) and Young (2004) among others). Second, many papers have shown that the incentive of households to accumulate precautionary savings exerts a crucial influence on the optimal capital tax (e.g. Domeij and Heathcote (2004) and Conesa et al. (2009)). Since we have shown that precautionary savings are less important for couples households it would be interesting to apply the insights of these literatures to the couple model. Finally, Arseneau and Chugh (2009, 2012) have demonstrated that the tax smoothing result of Aiyagari, Marcet, Sargent and Seppälä (2002) is reversed in the presence of search and matching frictions in the labor market. Their analysis assumes that the labor force is exogenously fixed. As the authors acknowledge, this is crucial to generate excess tax volatility as a Ramsey outcome. The interplay between the optimal tax smoothing model and the forces we identify in this paper remains to be explored.

The paper proceeds as follows: Section 2 presents the empirical analysis. It describes some key aggregate labor market facts from the US and presents the estimates of the AWE using microeconomic data from the CPS. Section 3 presents the model and Section 4 calibrates the model. Section 5 discusses the behavior of the model in the steady state. Section 6 contains the main results. Section 7 reports sensitivity of these results to different parameterizations of the model. A final section concludes.

2 The US Labor Market

2.1 Business Cycles

2.1.1 Aggregate Moments

Table 1 summarizes the US labor market business cycle statistics. The data are constructed from the CPS and correspond to observations spanning the years 1994 (January) to 2014 (October). The unemployment rate (U-rate) is very counter-cyclical and more than 10 times as volatile as aggregate output. The employment population (E-pop) has more than 80 percent of the volatility of output at business cycle frequencies and is very procyclical.[4] The labor force (LF), the sum of all individuals who are either employed or unemployed, is not volatile and its contemporaneous correlation with GDP is low (0.34).

According to the definitions provided by the *Bureau of Labor Statistics*, individuals are employed if they have been working during the month of the CPS survey; unemployed are those individuals who are not working, though they want jobs and search in the labor market to find them. Therefore, according to the *official definitions*, the civilian labor force is all individuals who want to work. The moments presented suggest that the fraction of these individuals over the total US population (older than age 16), hardly varies with the business cycle.

[Table 1 About Here]

[4]More recent observations contributed to an increase in the volatility of aggregate employment, which now accounts for more than two thirds of the volatility of aggregate output.

In the 4th column of the table we document the behavior of an alternative and more broadly defined measure of labor force participation. It includes the so called 'non-searchers' (also known as 'marginal attached individuals'); these are individuals who state in the CPS interviews that they want to work, however they do not look for jobs. Because they do not search, or they search too little, they are considered in official statistics in the US as out of the labor force. As the moments illustrate, the quantity LF+NS is also acyclical in the US data. Its contemporaneous correlation with GDP is even lower, and essentially equal to 0.

Though it is unusual to include the non-searchers in the pool of labor force participants we have added the last column in Table 1 to show that the precise definition of participation is not important for our conclusions. In our analysis we will follow official definitions; we will assume that the labor force consists of employed and unemployed individuals. This is also the convention followed by the considerable literature of search and matching models (e.g. Mortensen and Pissarides (1994)).[5]

2.1.2 Primary and Secondary Earners

In Table 2 we document the cyclical behavior of employment, unemployment and participation for various demographic groups. We begin by documenting the cyclical patterns for married men and women. From the table we see the following: First, the labor force participation of married women is counter-cyclical; the contemporaneous correlation with GDP is -0.23. Second, participation is more volatile for women than for men. The ratio of standard deviations ($\frac{\sigma_{LF}}{\sigma_Y}$) equals 0.42 for women vs. 0.19 for men. Finally, the employment rate of women is weakly correlated with aggregate economic activity (0.45).

Panel 3 of the table looks at the business cycle moments for 'household heads'. These include married men, but also individuals that are not married, either living on their own, or with other individuals in the household (for example, single men/women with children in the household).[6] As the table shows the business cycle patterns for household heads are very similar to the analogous moments for married men. The contemporaneous correlation of participation with GDP is 0.27 (vs. 0.12 for married men) and the relative standard deviation is 0.22 (vs. 0.21).

It is typical to interpret the 'bachelor household model' under incomplete markets, as a model that is suitable to study the behavior of household heads. Therefore, the moments reported in the third panel of the table represent the targets for this model. On the other hand, the couple model that this paper studies adds another member to the household. Therefore, the data counterpart are married men and women who are shown in panels A and B.

In the last panel of Table 2 we study the behavior of a broader group of 'secondary earners', including children along with married women. We now see that, in terms of the business cycle moments, the behavior of this group, differs somewhat from the behavior of married women alone. Though participation remains acyclical, employment becomes more procyclical and volatile. This fact is well known (see for example Jaimovich and Siu (2009) and Jaimovich, Pruitt and Siu (2013));

[5]Two exceptions are Hall (2005) and Krusell et al. (2011). These papers consider non-searchers as part of unemployment. Jones and Riddell (1999) have shown that non-searchers in Canada have roughly half the probability of flowing to employment, than unemployed individuals do. In the CPS data we found that the monthly transition to employment for non-searchers is 14.5% (vs. 26% for unemployed individuals).

[6]56% of 'household heads' are married men. A small fraction (16.5% of the US population older than age 16) are singles, not married and living with no other relatives in the household. These include retirees, divorcees with children living outside the household, widowers with children and grandchildren, college students etc.

younger individuals have more volatile employment and hours patterns. This explains the larger variability we now see in the data. As discussed previously, we will leave children outside the model. Though, we could (hypothetically) extend the family insurance argument to children[7], our model abstracts from schooling and does not contain an elaborate life cycle structure.

[Table 2 About Here]

2.2 Labor Market Flows

In order to deal with the acyclicality of labor force participation, search theoretic models of the labor market have built on the assumption that the labor force is fixed. This assumption is at odds with the substantial flows from employment (E) and unemployment (U) to out of the labor force (O) and the flows from O into the labor force. This fact is well known, here we look at the transitions of individuals across labor market states in a more recent sample.

In Table 3 we report the average transition probabilities for the population in the years 1994 -2014. Each month roughly 7% of all individuals who are O, join the labor force, and roughly 2.8% of all employed individuals (and 23.5% of unemployed individuals) become inactive.[8] These numbers are obviously substantial. Over our sample period there are more workers flowing from E to O than to U and more workers moving from O to E each month, than from U to E. Therefore, assuming a fixed labor force is a poor approximation of the US labor market data.

[Table 3 About Here]

In Table 4 we look at married men and women. We show that married men typically have higher flow rates from E to U and lower rates from E to O. Married women, on the other hand, have substantially larger flows than men from E to O (3.1% v.s. 1.5%) and from U to O (27% v.s. 14.8%). Overall, married men are more attached to the labor force.

It has been argued (see for example Clark and Summers (1979), Krusell et al. (2011)), that flows from U to O are temporary. This could mean that they reflect temporary shocks (for example to preferences) which induce individuals to flow to out of the labor force and subsequently flow back

[7] For example, we could claim that college students receiving transfers from their parents (e.g. Keane and Wolpin (2001)) are affected by unemployment shocks in the family. It would be interesting to know whether they begin to work partime in response to the shocks. This, however, is probably difficult to test: We suspect that in the CPS the participation status of college students is very imprecisely measured. In this example, students are simultaneously employed and out of the labor force; it is questionable whether the structure of the CPS survey can accurately identify both.

Moreover, young individuals work even when wages are low to accumulate human capital, become economically independent, become more attractive in the marriage market and so on. It is not clear that we can think of them as secondary earners in their current household. From the aggregate data we can see that their employment rates are very procyclical and volatile.

[8] Arguably, part of the OE flow could reflect a time aggregation bias; within the month individuals may first flow from O to U and subsequently to E, but the CPS does not observe the unemployment spell. Moreover, Nagypál (2005) argues that around 40% of the transitions from E to O result in a flow directly to employment in the next month. Some of these workers, have searched for a job while employed, obtained an offer but the new job starts in one month. In the online data appendix we verified that the CPS data is consistent with this interpretation. In particular, when we looked at the behavior of prime aged married men who flow from E to O, we found that roughly half of them move back to employment one or two months after the transition. We can infer that Nagypal's findings are relevant in our data set.

in.[9] Since our theory will built on shocks to idiosyncratic productivity solely, which is persistent in the data, it will be difficult to match this probability, the same problem is identified by Krusell et al. (2011).

However, through documenting the transition probabilities separately for married men and women, we can identify an important economic force beyond temporary innovations to preferences, explaining why these flows are substantial: they are influenced by intra-household decisions.

[Table 4 About Here]

In the appendix we show that the above patterns also hold for individuals aged 25-55. This means that the flow rates documented in Tables 3 and 4 are not driven by retirees or by new entrants in the labor market. The business cycle patterns documented in Tables 1 and 2 also do not change.

2.3 Joint Search in US Households

In this section we provide evidence of joint search in US households. We use the data from the CPS to estimate the impact of the husband's unemployment spell on the wife's search and labor force participation. Following the literature on the AWE (see Lundberg (1985) and Stephens (2002) among others) we focus on the behavior husbands and wives. We ask whether an unemployment spell suffered by the husband influences the labor supply of the wife, and in particular, whether it influences the probability that she joins the labor force, flowing either to employment or to unemployment.

2.3.1 Response of Female Participation to Spousal Unemployment

The first column of Table 5 show the results from a linear probability model. We estimate the following equation:

$$\text{Transition}_{i,t} = \alpha EU_m + Z_{t,i}\zeta + \text{Time Dummies} + \chi_{i,t} \tag{1}$$

The variable $\text{Transition}_{i,t}$ is a dummy variable which takes the value 1 if the wife joins the labor force in t (conditional on not being in the labor force in $t-1$) and zero otherwise. EU_m is a dummy which equals 1 if the husband becomes unemployed in t. $Z_{t,i}$ is a set of demographic variables (age, education, race etc). Our data refers to families where both the husband and the wife are older than age 24 and younger than 56 (to eliminate retirement, and new entrants in the labor market). We further, restrict our sample to consider husbands who are employed in a given month $t-1$ and either employed or unemployed in month t; wives are out of the labor force in $t-1$ and may remain O in t or join the labor force (flow to E or U).

[Table 5 About Here]

According to the results shown in Column (1) of the table, when the husband becomes unemployed the wife is 7.8% more likely to flow in the labor force. This effect is measured by the coefficient on

[9] Another possibility is that U to O flows are large if it takes time for job applications to become successful. Consider the following example: In month t individual i is unemployed, she has just send applications to vacancies. If these applications are not answered by $t+1$, it may be optimal to postpone further search. It is also plausible that the individual has found a job, but her employment begins in (for example) two months. The large UO rates in this case are consistent with the findings of Nagypál (2005) previously mentioned.

the variable EU_m. Since, in the sample considered, the overall probability that wives flow into the labor force is in the order of 9.5%, spousal unemployment nearly doubles the entry rate of married women.

Column (2) decomposes the husband's unemployment spell into three sources: the variable "Loss" represents unemployment spells that are due to permanent job losses, the variable "Quit" is spells initiated when the husband quits his job, and "Layoff" represents spells in which the work is suspended for a given period, but the husband expects (with some positive probability) a call back from his previous employer. The results suggest that losses lead to a 10.3% rise in the probability that the wife joins the labor force, quits to a 9% and layoffs to a 3.9% increase, relative to a couple where the husband remains employed in both months.

These numbers could seem surprising if one thinks of quits as being initiated on the worker's side and losses or layoffs on the firm's side. Workers that quit must, all else equal, be better placed to deal with separations than workers that get fired, this should attenuate substantially the AWE. One explanation for why quits and losses lead to a response is that, in most cases, job losers claim unemployment benefits from the government and/or are given severance compensation by their employers.[10] Put differently, workers that are eligible for unemployment insurance in the US, are job losers and not job quitters. Moreover, severance payments (in principle) are given after a termination that is initiated by the firm, this corresponds more accurately to the case the job is lost than to the case the worker quits. To the extent that these payments mitigate the effect unemployment on the household's budget, they also mitigate the AWE to the wife's desired labor supply.[11]

To explain why layoffs lead to a substantially smaller AWE the following channels have to be considered: i) A layoff is often a temporary termination of the match and therefore it does not represent an important shock to the family's resources. ii) Layoffs are more more likely to be anticipated because of an advance notice (see for example Ruhm (1990)). In this case, female labor force participation could be frontloaded and the smaller effect we observe would be due to the fact that wives have already joined the labor force before the husband's EU transition. [12] We will return to test the relevance of ii) in the next subsection.

2.3.2 Dynamic response of female labor force participation

Looking at the instantaneous response of female participation (as we have thus far) may be incomplete for several reasons: First, because the change in the desired labor supply occurs when the household receives information about the unemployment spell, this need not coincide with the month we observe the spell. Just think of the case where the husband is given an advance notice of termination, that his job will be lost in 2-3 months. Second, some families may be slow to react to the unemployment

[10] Benefits and severance compensation are not substitutes. In many US states unemployment benefits are not reduced when the worker has received a severance package (see for example Oikonomou (2014)).

[11] See for example Engen and Gruber (2001) for evidence on the importance of this channel. Another explanation for why quits lead to a substantial AWE is that job terminations no matter where they originate, derive from the same principle; that the surplus of the match is negative and that the productivity of the worker is higher elsewhere. (See for example Borjas and Rosen (1980)).

[12] Relative to quits layoffs lead to small AWE also because laid off workers claim unemployment benefits. The structure of our data set does not allow us to test this directly, however, layoffs and loses are typically seen in empirical studies as proxies for 'claiming unemployment benefits' (see for example Mukoyama, Patterson and Sahin (2014) and the references therein). Hence, we are fairly confident that this effect shows up in our estimates.

Moreover, Fujita and Moscarini (2013) illustrated that a substantial fraction of laid off workers get call backs from their previous employers. This proves that i) also holds.

shock. This can, for example, be due to labor supply adjustment costs (e.g. in the presence of small children); it can also be because agents fail to realize the magnitude of the shock to labor income, or (consistent with the model mechanism) because family wealth is run down during the unemployment spell. In all of these cases, we may observe an AWE in the months that follow the husband's *EU* transition.

We now use our data set to detect whether the AWE can start before the month the unemployment spell is realized, or it can extend beyond the month. In Table 6 we document the dynamic responses of female labor force participation to spousal unemployment; we estimate the following equation with dynamic panel data:

$$\text{Transition}_{i,t} = \sum_{\tau=-2}^{\tau=+2} \alpha_\tau I(\text{Husband Becomes } U \text{ in } \ t-\tau) + Z_{t,i}\zeta + \text{Time Dummies} + \chi_{i,t} \tag{2}$$

where Z is again a matrix of demographic characteristics which includes, age, education, race, number of children and so on, and $\chi_{i,t}$ is the error term.

The idea behind equation (2), is that the α_τ coefficients capture the conditional probability that a wife which has not joined the labor force $\tau - 1$ periods after (before if $\tau \leq 0$) the husband's unemployment spell, will join in the τth period.[13]

[Table 6 About Here]

According to the results shown in the first column of the table, there is an AWE that increases the probability of joining the labor force one month and two months after the unemployment spell. There is also an effect one month before the spell, and smaller, yet significant, effect two months prior to the spell. The contemporaneous effect is 7.8%, similar to our previous estimate. The coefficient α_{+1} (one month after) is 5.1% and the analogous value for α_{+2} is 3.9%. The lagged terms are 3.15% and 1.9% (α_{-1} and α_{-2} respectively).

Columns 2-4 in the table show separately these dynamic AWEs for layoffs, loses and quits. The patterns which emerge are consistent with our previous findings; quits and loses yield larger responses than layoffs. There is however, the following noteworthy feature: the estimates show that quits yield a substantial response one month after after the spell. For quits we get $\alpha_{+1} = 12.2\%$ whereas for loses and layoffs α_{+1} equals 5.3% and 3.6% respectively. Any of the channels outlined previously to explain why why we observe a lagged AWE in the data, can also explain why the lagged response in the case of quits is larger. [14]

Another noteworthy feature is that we do not observe significant differences in the coefficients α_{-1} and α_{-2} across the three unemployment categories. This suggests that households, two months

[13] Since the CPS tracks individuals for 4 consecutive months, the survey is interrupted for 8 months and then another four monthly observations are collected, we study transitions ranging from $\tau = -2$ up until $\tau = +2$. We only look at consecutive observations, to avoid having to deal with censoring issues. Moreover, since in our data for some households we only have one data point (we drop the household when the wife joins the labor force) we did not include any fixed effect in our estimation. In the online data appendix we explain in detail how we constructed the sample to estimate equation 2.

[14] In particular, it may be that households now realize that unemployment is a more important shock to their intertemporal budgets than what they thought one month ago, when the husband quit. Second, these responses are also consistent with the view that workers that quit do not receive unemployment benefits, therefore household wealth is run down faster during unemployment. Finally, it could be that husbands quit when they known that their wives can easily join the labor force; in this case the responses we see, reveal that quits become more likely in families where wives can provide insurance (because they face low labor supply adjustment costs etc).

before the spell occurs, are not sure that the husband will be without a job soon. They only know that unemployment is likely because the conditions on the job have become worse.

One possible reason for the smaller static AWE in Table 5 in the case of lay-offs was advance notice and therefore a frontloaded adjustment of female labor market entry. The results in Table 6 do not support this view since the estimates for α_{-1} and α_{-2} for lay-offs are not significantly larger than for job losses or quits.[15]

2.3.3 Comparative Advantage

In equation 2 we have included forward variables to explain female labor market transitions. One may criticize the estimates of α_{-1} and α_{-2} on the grounds that they are potentially fraught with simultaneity bias; if husbands become unemployed because wives have decided to join the labor force, then the AWE is not driven by the insurance motive we claim, it is rather driven by a comparative advantage (the family wants to make the wife its main earner and so on).

In the appendix we have taken several steps to rule out this possibility. In particular, we looked at the employment and labor force participation distributions of husbands and wives one year after we record an AWE. We do not find any evidence suggesting that there is a change in the identity of the household's primary earner. Husbands continue having substantially higher employment and labor force participation rates than their wives. Thus the comparative advantage effect is unlikely; this suggests that our estimation does not suffer from any bias in this respect.

As we will later illustrate, our theoretical model will not yield any effect of future spousal unemployment on current participation. Therefore, we will not rely at all on these estimates. The empirical findings in this and the previous subsection are new to the literature.

3 The model

3.1 Economic Environment

Our benchmark model is a heterogeneous household economy, with incomplete financial markets, labor market frictions, and aggregate uncertainty. It can been seen as a variant of the models Krusell and Smith (1998), Krusell et al. (2011) and Krusell et al. (2012); the key difference between our framework and the previous papers, is that we add a second member to the household. In this section we present this new framework.

3.1.1 Population and Preferences

We consider an economy with a unit mass of households, each household is inhabited by two individuals. We assume that preferences are identical across individuals and households. All agents in the economy discount future utility at rate β. Therefore, this rate also applies at the household level. Individuals have preferences of the form $u(c_t^i, l_t^i)$ where $i = 1, 2$ is an index denoting a household member. c_t^i is consumption of individual i at t and l_t^i denotes leisure. At the household level we can represent preferences as: $\sum_{i=1}^{2} u(c_t^i, l_t^i)$ within the period. We assume $u_c > 0, u_l > 0$ and $u_{c,l} \geq 0$.

[15] We cannot definitely reject a frontloaded adjustment since we do not have data on further lags which would be necessary to rule out even earlier adjustments.

3.1.2 Employment Opportunities

At any point in time a household can be economically active or retired. We model retirement as an exogenous event. In every period there is a (time invariant) probability ϕ_R that the household retires. If the retirement event is realized the household has to wait for another shock $\phi_A \neq \phi_R$ in order to become active in the labor market.[16] Retired households are out of the labor force. Non-retired households can choose, separately for each member, a labor market state (S_t^i). There are three states : employment $(S_t^i = E)$, unemployment $(S_t^i = U)$ and out of the labor force $(S_t^i = O)$. $S_t = (S_t^1, S_t^2)$ denotes the joint labor market status of the household members.

There are frictions in the labor market so that agents who are not employed but who want a job are not guaranteed to find one next period. In order to find a job, they have to engage in a costly search activity. A higher search effort leads to a higher job finding probability. Specifically, s_t^i denotes the level of search intensity exerted by individual i in t. We assume that s_t^i can take on two different values $\underline{s}$ and $\overline{s} > \underline{s}$. We classify the individual as either unemployed or out of labor force based on his search effort s_t^i . In particular, we assume that:

$$\text{If} \quad s_t^i = \begin{cases} \underline{s} & \text{then} \quad S_t^i = O \\ \\ \overline{s} & \text{then} \quad S_t^i = U \end{cases}$$

In words, individual i is out of the labor force if their search intensity is low and is unemployed otherwise.[17]

Given search intensity s_t^i, a job opportunity arrives at rate $p(s_t^i, \lambda_t)$ where λ_t denotes total factor productivity. First, we assume that $0 \leq p(\underline{s}, \lambda_t) < p(\overline{s}, \lambda_t) < 1$, meaning that jobs arrive at a higher rate when search intensity increases. Second, these probabilities also satisfy: $p_\lambda(s_t^i, \lambda_t) > 0$. Higher values of λ_t shift the probabilities upwards effectively leading to higher arrival rates of job opportunities in good times.

Search costs are denoted by $\kappa(s_t^i)$ and measured in units of foregone leisure. Therefore, we write: $l_t^i = 1 - \kappa(s_t^i)$, i.e. leisure is the unitary time endowment less the time cost of search if the individual is either unemployed or out of the labor force. Finally, employed individuals spend a fixed fraction $\overline{h}$ of their time endowment working so that their leisure is $l_t^i = 1 - \overline{h}$. Thus, labor supply is formed at the extensive margin only.

3.1.3 Labor Income Risks

Individuals face idiosyncratic uncertainty in the labor market which derives from several sources: The first source of risk, which we denote by ϵ_t^i, is a stochastic, agent specific, persistent labor productivity process. $\epsilon_t = \{\epsilon_t^1, \epsilon_t^2\}$ denotes the (vector of) productivity at the household level.

The second source of uncertainty in the model is a match quality shock. We assume that an individual loses exogenously his job and is forced to become non-employed at a rate $\chi(\lambda_t)$ each period.

[16]Equivalently, the household dies with probability ϕ_A and is subsequently replaced by another household in the model which inherits the state variables. This simplistic life cycle structure is the similar to Castaneda, Díaz-Giménez and Ríos-Rull (2003) and Cagetti and De Nardi (2006).

[17] This classification follows closely the analogous criterion of the CPS, whereby individuals are considered unemployed if the utilize at least one of the nine methods considered as 'Active Search'. See the online data appendix B and Shimer (2004) for further details.

The third type of risk is the search friction summarized in the probabilities $p(s_t^i, \lambda_t)$. Individuals who are not employed will face the possibility of remaining jobless for many periods. Since we assume that non-employed individuals earn zero income, search frictions impart a significant risk to the household's budget.

Along with these risks, individuals and households will have a set of choices. As discussed previously, the probabilities $p(s_t^i, \lambda_t)$ are determined endogenously. In every period, each household member draws a new value of ϵ_t^i, these draws (along with other state variables) will determine whether or not it is worthwhile to exert high search effort. Moreover, since labor supply decisions in our model are formulated at the extensive margin, some matches will be terminated voluntarily, without the arrival of the $\chi(\lambda_t)$ shock. For example, if idiosyncratic productivity ϵ_t^i falls, the individual may decide to quit her job and become non-employed. Similarly, when a non employed individual receives a job offer she chooses whether she wants to work, or whether she wants to give up on the offer and wait for a higher productivity draw and a new job opportunity in the future.

3.1.4 Technology and Markets

Every match, operates a technology with constant returns to scale and so, without loss of generality, we can aggregate and represent 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 the aggregate labor input (per efficiency units) respectively. We assume that λ_t evolves according to the transition cumulative density function $\pi_{\lambda'|\lambda} = Prob(\lambda_{t+1} < \lambda'|\lambda_t = \lambda)$. Aggregate capital K_t depreciates at rate δ each period. Moreover, wages per efficiency units of labor (w_t) and net interest rates (r_t) are determined in a competitive market. Hence w_t is equal to the marginal productivity of labor and analogously $r_t + \delta$ equals the marginal product of capital in every period.

Financial markets in the economy are incomplete: We assume that households can self-insure through trading claims on the aggregate capital stock subject to an ad hoc borrowing limit. We denote household wealth by a_t. We also assume that $a_t \in \mathcal{A}$ (a compact set). In our model households cannot borrow. Thus, the lower bound of $\mathcal{A}$ is zero.[18] The interest earned on savings is r_t.

Finally, since agents have to forecast future factor prices, they have to know the current distribution of agents across the state space. We denote this cumulative density function by Γ_t. Γ_t is a further state variable in the household's program. The law of motion for this distribution is given by: $\Gamma_{t+1} = \mathcal{T}(\Gamma_t, \lambda_t)$ where $\mathcal{T}$ gives the transition from the current Γ_t and λ_t to the next period's distribution.

3.2 Value Functions

We now describe the household's problem recursively. Following Mazzocco and Yamaguchi (2007), Cubeddu and Ríos-Rull (2003), Regalia, Rios-Rull and Short (1999), we assume that assets are a commonly held resource in the household.[19] In addition to wealth, a household's state vector

[18] Since earning zero income is possible in the model, the no borrowing constraint coincides with the natural borrowing limit. The upper bound of $\mathcal{A}$ will arise endogenously in equilibrium. Because the (average) interest rate is lower than the households' time preference parameter savings will not diverge to infinity (see for example Aiyagari (1994)).

[19] This assumption is used to simplify the household's program. It reduces the number of state variables by one, and ensures that there is one Euler equation for the entire household. Mazzocco and Yamaguchi (2007) show that this

includes the productivity levels ϵ_t, the distribution Γ_t and the aggregate TFP λ_t. We summarize the realizations of these variables with $X_t = \{a_t, \epsilon_t, \Gamma_t, \lambda_t\}$.

Because of the presence of search frictions, the employment status of the each household member also has to be introduced as a state variable to the value function. We have that $S_t^i \in \{O, U, E\}$ and so the joint status $S_t \equiv (S_t^1, S_t^2)$ may take nine possible values. However, there are no frictions between the states O and U. Thus agents can flow freely across these two states, we can use the search intensity choices of individuals to keep track of their labor market status. This implies that the status of an individual can be summarized by two realizations of a (random) state variable: n and e. n corresponds to the case where the individual does not have a job offer (and therefore she can choose between O and U) and e applies when a job offer is available (the choice is then between E, O and U). The joint employment status of the two household members is then summarized into a state variable which takes the following values: $\{nn, en, ne, ee\}$. nn applies to the case the household has both members non-employed; en (ne) when the first (second) member is employed and the second (first) non-employed and finally, when both members are employed we have ee. We denote lifetime utilities as $V^{i,j}(X), i, j \in \{n, e\}$. For retired households we use the symbol R to denote the state.

Consider now a household which has both of its members non-employed. Assume that agent 1 gets a job offer in the next period. When this opportunity arrives, and the new values of the idiosyncratic productivity ϵ_{t+1} are sampled and the aggregate state vector $\{\Gamma_{t+1}, \lambda_{t+1}\}$ is revealed, the household will decide whether agent 1 will go to work. This choice is expressed by: $Q^{en}(X_{t+1}) = \max\{V^{nn}(X_{t+1}), V^{en}(X_{t+1})\}$. Analogously, $Q^{ne}(X_{t+1}) = \max\{V^{nn}(X_{t+1}), V^{ne}(X_{t+1})\}$ defines the choice over keeping agent 2 non employed or allocating her to work.

Finally, $Q^{ee}(X_{t+1}) = \max\{V^{nn}(X_{t+1}), V^{en}(X_{t+1}), V^{ne}(X_{t+1}), V^{ee}(X_{t+1})\}$ defines the options conditional on both individuals receiving job offers in $t+1$.

We represent recursively the program of the household in state nn as:

$$
\begin{aligned}
(3)\quad V^{nn}(X) = \max_{a' \geq \bar{a}, s^i \in \{\underline{s}, \bar{s}\}} \sum_{i=1}^{2} u(c^i, l^i) + \beta \Big[\int_{\epsilon', \lambda'} \phi_R V^R(X') + (1-\phi_R)[p(s^1,\lambda)(1-p(s^2,\lambda))Q^{en}(X') \\
+ p(s^2,\lambda)(1-p(s^1,\lambda))Q^{ne}(X') + \Pi_{i=1}^2 p(s^i,\lambda)Q^{ee}(X') + (1-\Pi_{i=1}^2 p(s^i,\lambda))V^{nn}(X')] d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda} \Big] ;
\end{aligned}
$$

subject to:

$$
a' = (1 + r_{\lambda,\Gamma})a - \sum_{i=1}^{2} c^i, \quad \Gamma' = \mathcal{T}(\Gamma, \lambda) \text{ and } \quad l_i = 1 - \kappa(s^i).
$$

The household chooses consumption c^i and search intensity $s^i, i = 1, 2$ for each individual. Given the search intensity levels there is a probability $\Pi_{i=1}^2 p(s^i, \lambda) \equiv p(s^1, \lambda)p(s^2, \lambda)$ that both members will receive an offer in the next period. The envelope $Q^{ee}(X')$ applies in this case. Similarly, $1 - \Pi_{i=1}^2 p(s^i, \lambda)$ is the probability that no household member receives an offer.

The value function of a household that has one of its members employed (without loss of generality

assumption is realistic and consistent with the U.S. data.

the first one) and the other member non employed is:

$$(4) \qquad V^{en}(X) = \max_{a' \geq \overline{a}, s^2} \sum_{i=1}^{2} u(c^i, l^i) + \beta[\int_{\epsilon', \lambda'} \phi_R V^R(X') + (1-\phi_R)[p(s^2,\lambda)(1-\chi(\lambda))Q^{ee}(X')$$

$$+p(s^2,\lambda)\chi(\lambda)Q^{ne}(X') + (1-p(s^2,\lambda))(1-\chi(\lambda))Q^{en}(X') + (1-p(s^2,\lambda))\chi(\lambda)V^{nn}(X')]] \;\; d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda};$$

subject to:

$$a' = (1+r_{\lambda,\Gamma})a + w_{(\Gamma,\lambda)}\overline{h}\epsilon^1 - \sum_{i=1}^{2} c^i \quad \Gamma' = \mathcal{T}(\Gamma,\lambda) \text{ and } \quad l^1 = 1-\overline{h}, \;\; l^2 = 1-\kappa(s_2),$$

where $\chi(\lambda)$ is the probability that the employed individual loses his job.

The value function of a household with two employed members is given by:

$$(5) \qquad V^{ee}(X) = \max_{a' \geq \overline{a}} \sum_{i} u(c^i, l^i) + \beta[\int_{\epsilon', \lambda'} \phi_R V^R(X') + (1-\phi_R)[(1-\chi(\lambda))^2 Q^{ee}(X')$$

$$+(1-\chi(\lambda))\chi(\lambda)(Q^{en}(X') + Q^{ne}(X')) + \chi(\lambda)^2 V^{nn}(X')] \;\; d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda}));$$

subject to:

$$a' = (1+r_{\lambda,\Gamma})a + \sum_{i=1}^{2} \left(w_{(\Gamma,\lambda)}\overline{h}\epsilon^i - c^i\right) \quad \Gamma' = \mathcal{T}(\Gamma,\lambda) \text{ and } \quad l^i = 1-\overline{h}.$$

Finally, the value function of a retired household is:

$$V^R(X) = \max_{a' \geq 0} \sum_{i=1}^{2} u(c^i, l^i) + \beta[\int_{\epsilon', \lambda'} \phi_A V^{nn}(X') + (1-\phi_A)V^R(X') \;\; d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda}));$$

subject to:

$$(6) \qquad a' = (1+r_{\lambda,\Gamma})a - \sum^{i} c^i \quad \Gamma' = \mathcal{T}(\Gamma,\lambda) \text{ and } \quad l^i = 1.$$

3.3 Competitive Equilibrium

The competitive equilibrium consists of a set of value functions V^{ij}, $i,j \in \{e,n\}$ and V^R, and a set of decision rules for consumption ($c^k_{ij}(X)$ and $c^k_R(X)$), asset holdings ($a'_{ij}(X)$ and $a'_R(X)$), search intensity ($s^k_{ij}(X) \in \{\underline{s}, \overline{s}\}$), and labor supply ($h^k_{ij}(X) \in \{0, \overline{h}\}$[20]) for individual $k \in \{1,2\}$. 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 $\Gamma' = T(\Gamma,\lambda)$ such that:

1. Given prices, households optimize and the optimal policies solve the Bellman equations defined previously.

[20] $h^k_{ij}(X)$ reflects desired hours. For example, we have $h^k_{ij}(X) = 0$ if $i = n$ and $k = 1$ (or $j = n$ and $k = 2$). However, we may also have that $h^k_{ij}(X) = 0$ with $i = e$ and $k = 1$, if agent 1 has an offer and decides not to work.

2. Firms maximize profit

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

3. Markets clear

$$Y_t + (1-\delta)K_t = \widetilde{\phi}\sum_{i,j}\int (a'_{ij}(X) + \sum_{k=1,2} c^k_{ij}(X))d\Gamma_t^{ij} + (1-\widetilde{\phi})\int (a'_R(X) + c_R(X)) \ d\Gamma_t^R$$

$$L_t = \sum_{i,j}\int \sum_{k=1,2} \epsilon^k \overline{h}\mathcal{I}(h^k_{i,j}(X) = \overline{h}) \ d\Gamma_t^{i,j} \quad \text{and} \quad K_t = \int_{\mathcal{A}} a \ d\Gamma_t$$

where Γ_t^{ij} and Γ_t^R denote the conditional cdfs for households in states $i, j \in \{e, n\}$ and R respectively and $\widetilde{\phi} = \frac{\phi_A}{\phi_R + \phi_A}$.

4. Individual behavior is consistent with aggregate behavior.

Let us define $\omega^{kl}_{ij}(X)$ the probability (given X) of a transition from the joint state ij to kl where $i, j, k, l \in \{e, n\}$. For example, $\omega^{ee}_{ee} \equiv (1-\chi(\lambda_t))^2$ is the probability that a family in ee in t, remains in ee at the beginning of $t+1$. Analogously, $\omega^{ee}_{nn} \equiv \Pi_{k=1,2}p(s^k_{nn}(X), \lambda_t)$ is the probability that both household members receive a job offer. The law of motion of the measure Γ can be represented as follows:

$$\Gamma^{ee}_{t+1}(\widetilde{\mathcal{A}}, \mathcal{E}) = (1-\phi_R)\sum_{i,j\in\{e,n\}}(\int_{a'_{ij}\in\widetilde{\mathcal{A}}, \epsilon'\in\mathcal{E}} \mathcal{I}(h^1_{ee}(X) = \overline{h} \cap h^2_{ee}(X) = \overline{h})\omega^{ee}_{i,j} \ d\pi_{\epsilon'|\epsilon} \ d\Gamma_t^{i,j}$$

where ω^{ee}_{ij} are the probabilities defined before.

$$\Gamma^{en}_{t+1}(\widetilde{\mathcal{A}}, \mathcal{E}) = (1-\phi_R)\sum_{i,j\in\{e,n\}}\sum_{(kl)\in\{ee,en\}}\int_{a'_{ij}\in\widetilde{\mathcal{A}}, \epsilon'\in\mathcal{E}} \mathcal{I}(h^1_{kl}(X) = \overline{h} \cap h^2_{kl}(X) = 0)\omega^{kl}_{ij}d\pi_{\epsilon'|\epsilon}d\Gamma_t^{ij}$$

The law of motion of Γ_t^{ne} is similarly defined.

$$\Gamma^{nn}_{t+1}(\widetilde{\mathcal{A}}, \mathcal{E}) = (1-\phi_R)\sum_{i,j\in\{e,n\}}\sum_{k,l\in\{e,n\}}\int_{a'_{ij}\in\widetilde{\mathcal{A}}, \epsilon'\in\mathcal{E}} \mathcal{I}(h^1_{kl}(X) = 0 \cap h^2_{kl}(X) = 0)\omega^{kl}_{ij}(X)d\pi_{\epsilon'|\epsilon}d\Gamma_t^{ij}$$
$$+\phi_A\int_{a'_R(X)\in\widetilde{\mathcal{A}}, \epsilon'\in\mathcal{E}} d\pi_{\epsilon'|\epsilon}d\Gamma_t^R$$

Finally,

$$\Gamma^{R}_{t+1}(\widetilde{\mathcal{A}}, \mathcal{E}) = \phi_R\sum_{i,j\in\{e,n\}}\int_{a'_{i,j}\in\mathcal{A}, \epsilon'\in\mathcal{E}} d\pi_{\epsilon'|\epsilon}d\Gamma_t^{i,j} + (1-\phi_A)\int_{a'_R\in\widetilde{\mathcal{A}}, \epsilon'\in\mathcal{E}} d\pi_{\epsilon'|\epsilon}d\Gamma_t^R$$

Where $\widetilde{\mathcal{A}} \subset \mathcal{A}$ and $\mathcal{E} \subset \{\epsilon^1_1, \epsilon^1_2, ..., \epsilon^1_n\} \times \{\epsilon^2_1, \epsilon^2_2, ..., \epsilon^2_n\}$ are subsets of the relevant state space. $\mathcal{I}(x)$ is an indicator function, it takes the value 1 if statement x is true and 0 otherwise.

3.4 Single Agents and Complete Markets

Our model brings together several approaches of the heterogeneous agents literature and extends them through modeling a two earner household. When we set $p(\underline{s}, \lambda_t) = p(\overline{s}, \lambda_t) < 1$ we have a model where individuals are either employed or unemployed and where the relative fractions vary over the cycle. If we further eliminate idiosyncratic productivity (ϵ) risks, the framework considered is essentially that of Krusell and Smith (1998). When the frictions are removed, so $p(\underline{s}, \lambda_t) = p(\overline{s}, \lambda_t) = 1$, we end up with the framework of Chang and Kim (2006, 2007). Krusell et al. (2011, 2012) utilize a model similar to ours, however, they assume bachelor households, and leave costly search outside their model.

As discussed previously, in order to better highlight our model's properties, we will contrast it with the two workhorse macro-models: the bachelor household model of incomplete markets and the complete markets framework.

In the case of the bachelor household model optimal choices are found through the following value functions.

$$V_B^e(X) = \max_{a' \geq 0} \; u(c, 1 - \overline{h}) + \beta \left[\int_{\epsilon', \lambda'} \phi_R V_B^R(X') + (1 - \phi_R) \left[(1 - \chi(\lambda)) Q_B^e(X') + \chi(\lambda) V_B^n(X') \right] d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda} \right].$$
$$\text{subject to} \quad a' = (1 + r_{(\Gamma,\lambda)})a + w_{(\Gamma,\lambda)}\overline{h}\epsilon - c \;\; \text{and} \;\; \Gamma' = \mathcal{T}(\Gamma, \lambda);$$

$$V_B^n(X) = \max_{a' \geq 0, s \in \{\underline{s}, \overline{s}\}} u(c, 1 - \kappa(s)) + \beta \left[\int_{\epsilon', \lambda'} \phi_R V_B^R(X') \right.$$
$$\left. + (1 - \phi_R)[p(s, \lambda) Q_S^e(X') + (1 - p(s, \lambda)) V_B^n(X)] d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda} \right];$$

$$V_R^n(X) = \max_{a' \geq 0} u(c, 1) + \beta \left[\int_{\epsilon', \lambda'} (1 - \phi_A) V_B^R(X') + \phi_A V_B^n(X) d\pi_{\epsilon'|\epsilon} d\pi_{\lambda'|\lambda} \right]$$
$$\text{subject to} \quad a' = (1 + r_{\Gamma,\lambda})a - c \;\; \text{and} \;\; \Gamma' = \mathcal{T}(\Gamma, \lambda),$$

where now ϵ denotes the level of idiosyncratic productivity of the agent, $X \equiv \{a, \epsilon, \Gamma, \lambda\}$, c and l denote as usual aggregate consumption and leisure in the household.

In the case of the complete market model all individuals in the economy are part of one family. Idiosyncratic risks are completely eliminated and individual wealth becomes irrelevant (only aggregate wealth matters). As is well known the optimal allocation in this case is the solution to a planning program. To conserve space we state this program formally in the appendix.

4 Calibration

4.1 Preferences and Technology

In this section we describe the choice of parameters and functional forms. As our baseline we adopt a period utility function for household consumption of the following form:

$$u(c^i, l^i) = \frac{((c^i)^\eta (l^i)^{1-\eta})^{1-\gamma} - 1}{1 - \gamma}$$

We follow the empirical evidence provided by Attanasio and Weber (1995) and Meghir and Weber (1996) and assume that consumption and hours are complements in utility. We set $\gamma = 2$ as our benchmark. Later on, we will show that our results also hold for alternative specifications. Given γ we choose the value of η equal to 0.44 in order to target an employment population ratio of 62% (the CPS average for the years 1994 to 2014) in the deterministic steady state. These choices give us a value of the intertemporal elasticity of substitution $(1-\eta(1-\gamma))^{-1}$ roughly equal to 0.69.

Given that the model's horizon is one month we fix the depreciation rate δ to 0.0083, this corresponds to a quarterly analogue of 2.5%. We set the capital share in final output α to 0.33 and we assume that employed individuals spend a third of their time endowment in market work; hence we set $\overline{h} = \frac{1}{3}$. We choose the value for the time preference parameter β equal to 0.9916 so that the steady state interest rate r is 0.0041. This corresponds to an annual analogue of 5%. For the aggregate TFP process λ_t, we follow Chang and Kim (2006, 2007) and calibrate it so that the quarterly first order autocorrelation is $\rho_\lambda = 0.95$ and the conditional standard deviation is $\sigma_\lambda = 0.007$. We convert these numbers to their monthly analogues and use the technique of Adda and Cooper (2003) to discretize the process into a four state Markov chain.

4.2 Idiosyncratic productivity

The idiosyncratic labor productivity process is parameterized as follows: First, we use the standard AR(1) specification (see for example Heathcote, Storesletten and Violante (2009))

$$\log(\epsilon_t^i) = \rho_\epsilon \log(\epsilon_{t-1}^i) + v_{\epsilon,t}^i \tag{7}$$

with innovations $v_{\epsilon,t}^i \sim \mathcal{N}(0, \sigma_\epsilon)$, $i = 1, 2$. To calibrate ρ_ϵ and σ_ϵ we need to find estimates from the literature which account explicitly for selection effects: Since in the model individuals will quit their jobs in response to a low realization of $v_{\epsilon,t}^i$, it is obvious that focusing only on a group of continuously employed individuals will give us biased estimates. Chang and Kim (2006) have utilized the PSID data to estimate (7) removing the influence of selection effects. They obtain $\rho_\epsilon = 0.781$ and $\sigma_\epsilon = 0.331$.[21]

One important parameter in the calibration of the model is the correlation of shocks inside the household. First, a stronger correlation gives a stronger AWE, since in response to an unemployment shock of, say, agent 1 the insurance value of an increase in the labor supply of agent 2 is greater if ϵ^2 is close to ϵ^1. Second, since agents in the model are ex ante identical, a correlation coefficient below unity gives us a gap in household member productivities. This implies that each household has a primary and a secondary earner. We set the correlation coefficient equal to 0.3 following the empirical evidence presented in Hyslop (2001).[22]

[21] These parameter values derive from a sample of household heads. For married women they estimate $\rho_\epsilon = 0.724$ and $\sigma_\epsilon = 0.341$. Because these values are close and also because our model assumes that individuals are ex ante identical, we use the estimates for the male population. We treat these values as our benchmark. Later on, we how that our results are robust towards different values for these parameters.

[22] The value of 0.3 applies to the raw data of Hyslop's PSID sample. He then estimates that the intra-household correlation of fixed effects is 0.5 and the correlation of temporary shocks is 0.15. Since the ϵ process summarizes both of these random variables it is preferable to use the average correlation coefficient.

4.3 Retirement

According to the CPS the monthly probability that an individual becomes retired is 0.0095. We therefore set of ϕ_R equal to this number. We further choose the value of $\phi_A = 0.0507$ in order to match the fraction of the US population which is retired which is 15.78% in the CPS.[23]

4.4 Search Technology and Separations

4.4.1 Search frictions

Let λ_s be the steady state of TFP. We set $p(\overline{s}, \lambda_s) = 0.26$, $p(\underline{s}, \lambda_s) = 0.16$ and $\chi(\lambda_s) = 0.02$. These choices are explained through the following considerations: First, the average UE rate in the CPS data is equal to 0.25. As we shall see, the equilibrium of the model will give us a selection of productive individuals into unemployment; these individuals will almost always accept job offers. To match the UE rate as in the data we need to assume a tight friction.

Second, out of the labor force individuals will be relatively unproductive; they will reject Offers with a large probability. Over a wide range of values for $p(\underline{s}, \lambda_s)$ the OE rate does not change significantly, and the model produces a value close to the data counterpart. To determine the appropriate value we compute from the US data the transition rate to employment of the 'non-searchers'. In the data the non-searchers have a monthly transition probability to employment equal to 14.5%. We set $p(\underline{s}, \lambda_s)$ equal to 0.16 so as to match this moment. In Section 7 we will report results from alternative calibrations of this parameter. Finally, an exogenous separation rate of 2% is good compromise between matching the EU rate and the EO rate.

4.4.2 Cost of Search

As discussed earlier, s^i may take two values, $\underline{s}$ and $\overline{s}$. Individuals who are out of the labor force choose $\underline{s}$ as the optimal search level. Without loss of generality, we normalize this level to zero. Moreover, we set $\overline{s} > 0$.[24]

The cost of search $\kappa(s^i)$ equals zero when $s^i = \underline{s}$ and it equals $\kappa > 0$ when $s^i = \overline{s}$. We set κ equal to 0.23 to match an unemployment rate of 6.2% in the steady state. This implies that unemployed individuals spend roughly thirty percent less of their time in the market, than employed individuals do. This value may seem high, since we have interpreted search costs as time costs.[25] Note that in the data, individuals who are out of the labor force maybe retired (a fraction 46.6% of the total), disabled (15%), attending high school or college (13.6%) or they maybe out of the labor force for

[23]The model's life cycle structure is simplistic, this explains why individuals live on average too few years in retirement. Had we adopted a less parsimonious life cycle structure and included population growth, we could capture the survival hazard in retirement. Notice however that since retirement is short, the fact that pensions are left outside the model is not crucial. Individuals are not going to save too much to ward off the retirement risk. In the appendix we establish this, and also show that if we include retirement income our results are not influenced.

[24]In the US data, out of the labor force individuals do not exert almost any search effort. For example, the CPS data set records the search methods that individuals utilize to look for jobs. The number of methods can be thought as a proxy for search intensity (see Shimer (2004)). The average number of search methods utilized by O agents is equal to 0.004, very close to zero. The average number of methods for unemployed workers is 1.90. Notice, however, that $\underline{s}$ and $\overline{s}$ are simply normalizations. What matters for allocations are the search cost $\kappa(s)$ and the frictions $p(s, \lambda)$.

[25]It is well known (see for example Mukoyama et al. (2014)), that individuals do not spend a lot of time searching for job opportunities. However, if we assume that looking for a job entails a complete re-organization of a person's life (e.g. giving up on home production and so on) assuming high search costs is reasonable. This argument follows Garibaldi and Wasmer (2005).

'family reasons' (16.8%). Since our model misses some these margins, it requires a large cost of search to generate an unemployment rate that is consistent with the data.

4.4.3 Changes in frictions over the cycle

In the model with aggregate fluctuations, both, the arrival rates of job offers and the separation probabilities change with the aggregate state. To calibrate the parameters our approach is the following: First, as in the steady version of the model, in the economy with aggregate uncertainty the UE rate tracks closely $p_(\overline{s}, \lambda_t)$. To calibrate $p_(\overline{s}, \lambda_t)$ we take the job finding probability from the data, and compute the average between the largest positive, and the (absolute of the) largest negative percentage deviations from the mean: $\xi_p \equiv \frac{(\max(UE_t) - \min(UE_t))}{2 \text{ mean}(UE)}$. We find that $\xi_p = 0.37$ in the data. We then set the highest value of the job finding rate in the model equal to $(1 + \xi_p))\ p_(\overline{s}, \lambda_t)$ and the lowest value equal to $(1 - \xi_p))\ p_(\overline{s}, \lambda_t)$. The remaining values are uniformly distributed in this interval.

Second, we assume that the arrival rates of job offers to O agents behaves in exactly the same way as the one for the unemployed. Therefore, the highest arrival rate for O agents is $(1+\xi_p))p_(\underline{s}, \lambda_s)$ and the lowest is $(1 - \xi_p))p_(\underline{s}, \lambda_s)$.[26]

For separation shocks we apply the same procedure. From the UE rate series in the data we compute ξ_χ, which gives us the maximum deviation. We find $\xi_\chi = 0.28$, therefore $\chi(\lambda_t)$ varies from $(1 - \xi_\chi)\chi(\lambda_s)$ to $(1 + \xi_\chi)\chi(\lambda_s)$ over the cycle.

One final comment is in order: Note that this structure gives an advantage to the model to match the cyclical properties of the flows between employment and unemployment. However, it does not give any advantage to match the transitions between in and out of the labor force. These are determined endogenously through the labor supply of individuals. Thus, these moments are overidentifying restrictions to evaluate the performance of the model.

4.5 Calibration Targets for Bachelors and Complete Markets

The baseline values for the bachelor household and complete markets models have been chosen applying the calibration procedure described in the previous subsections. In Table 7 we summarize these choices. The table is split in two parts. The top panel reports parameter values (technology endowments and frictions) which are common across models. The second part of the table shows parameters (preferences) which differ across models. We have determined these as follows: First, for all of the models we assume the same value of γ. Second, for each model we pick the weight of consumption in utility η, the search cost κ and the discount rate β to hit the employment population, unemployment rate and interest rate targets discussed previously.

Under incomplete financial markets, households work and save more to self-insure against the idiosyncratic risks they face. Therefore, to achieve the employment and interest rate target, the model with bachelor households requires a low β and a low η. The values of η and β increase as we move closer to complete markets.

[26]This choice is consistent with many papers which assume different levels of search effort. For example, in models with on the job search, it is typically assumed employed and unemployed workers receive offers from the same matching function and at proportional rates. The proportionality parameter is their relative search intensities (see for example Barlevy (2002)). Analogously, we could write $p_(\underline{s}, \lambda_t) = \frac{\underline{s}}{\overline{s}} p_(\overline{s}, \lambda_t)$ and re-normalize $\frac{\overline{s}}{\underline{s}} = \frac{0.16}{0.26}$. This ratio will remain constant over the cycle.

5 Steady State Analysis

Before presenting the analysis of aggregate fluctuations we provide information on the model's performance in the steady state. This is useful to understand the working of the model. Its properties will be essential to understand the cyclical behavior we will document subsequently.

5.1 Policy functions

We first illustrate theoretically how the model generates transitions across labor market states. In Figure 1 we show the policy functions h_k^{ij} $(i, j \in \{e, n\}, k = 1, 2)$ for a generic value of ϵ. Without loss of generality we assume that $\epsilon^1 > \epsilon^2$, i.e. individual 1 is more productive than individual 2. The policy rules vary as we vary ϵ. For now we take productivity fixed. Later on we show what happens when productivity changes. The figure consists of three panels which differ by the employment status of the household. The first panel, shows the policy functions in the case where both household members have job offers, the second panel when only the first member has a job offer and the third panel when no one has an offer.[27]

The asset grid in Panel 1 is divided into 3 'regions'. In 'Region 1' the household is relatively poor and therefore finds it optimal to set $h_k^{ee} = \overline{h}$ for $k = 1, 2$ so that both individuals work. Subsequently, the household is somewhat richer in 'Region 2' and therefore sets $h_1^{ee} = \overline{h}$ and $h_2^{ee} = 0$. In this case, agent 1 works and agent 2 flows to out of the labor force. In 'Region 3' the household is even richer and therefore withdraws both household members from the labor market. When both agents have an offer, labor market frictions are essentially irrelevant, the joint employment status is determined through a choice of hours. When the family accumulates assets its members quit employment and at the same time they quits the labor force altogether. This represents a standard wealth effect on labor supply. In response to changes in wealth the model predicts flows from E to O and not from E to U.

5.1.1 Job Hoarding

'Region 4' shows that when agent 1 has a job, agent 2 is unemployed if wealth is low enough. However, in 'Region 5', as wealth increases the couple prefers to send agent 2 to out of the labor force rather than to send her to unemployment.

We also see the following: 'Region 4' does not fully overlap with 'Region 1' in the first panel. Thus, if initially both are employed and household wealth is not too low, and an exogenous separation shock arrives, then agent 2 does not become unemployed but quits the labor force altogether. This is an important property of the model, which was first discussed by Garibaldi and Wasmer (2005). Because of the presence of search costs individuals exert a sort of job hoarding behavior: they want to hold on to their jobs, and wait for the arrival of an exogenous separation shock to drop out of the labor force. The area where this effect is present is bracketed by the blue rectangular.

The last panel shows the case where both household members are non employed. Again, wealth effects explain the search behavior of the couple. At low wealth levels ('Region 6') both individuals

[27] We will later study the labor supply behavior of the couple where agent 2 is employed and agent 1 is not employed. For the sake of brevity we have omitted this case from the figure, the decisions are similar to those portrayed in the second line in figure 1, but the relevant thresholds are shifted to reflect the different productivity levels of agents 1 and 2.

search for jobs. At somewhat higher levels, the couple keeps only its most productive member in unemployment ('Region 7'). At even higher level it withdraws both members from the labor force ('Region 8'). The cut-off wealth levels show that there is another part of the state space where job hoarding occurs. This time it is agent 1 who drops to O when the separation shock arrives. Job hoarding for agent 1 is represented by the red rectangular.

Job hoarding is an important feature of all incomplete market models we will study in this paper. It is also present in the case of bachelor households. A substantial part of the flows from E to O will result from separation shocks hitting relatively wealthy employed individuals.

5.1.2 Productivity Shifts

So far, we have held productivity constant. Suppose now that there is a drop in ϵ^1 but that $\epsilon^1 > \epsilon^2$ still holds. This movement in productivity has an intertemporal substitution effect which decreases the desired labor supply for agent 1. As a consequence, 'Regions' 2, 5 and 7 now become smaller, their upper bounds will shift to the left. At the same time, for agent 2, the movement in productivity has a pure wealth effect, her desired labor supply may increase. This may extend 'Regions' 1, 4 and 6 to the right. On the one hand, the productivity shock may induce agent 1 to drop out of the labor force, if household wealth is sufficiently high, as in 'Region 5'. On the other, the shock may induce agent 2 to join the labor force if wealth is sufficiently low, as in 'Region 5'.

5.2 Wealth and Employment Distributions

5.2.1 The Wealth Distribution

Figure 2 shows the steady state wealth distribution where the horizontal axis shows wealth levels in thousands of US dollars. The graph plots the distribution of wealth for the entire population, as well as separately by the employment status of the household's members and for retired individuals.

The model does not match the level of wealth dispersion we see in the data. In particular, it cannot replicate the thick right tale of the US wealth distribution, it does not give a substantial fraction of the population with a wealth level of several millions of dollars (see for example Cagetti and De Nardi (2006)). This is not surprising. It is well known, that models of heterogeneous infinitely lived agents, which rely only on uncertainty in the labor market to generate unequal wealth distributions, cannot match the US data.[28]

Figure 3 shows the wealth distributions from the couples model and the bachelor model. Two earner households save more than bachelor households do. However, they do not save twice as much. To show this clearly in the dash-dotted line of the graph we scaled up the wealth level of bachelors by a factor of 2. This distribution would obtain in the two earner model if three conditions are met: i) If $\epsilon_t^1 = \epsilon_t^2 \; \forall t$, in other words if productivity shocks are perfectly correlated, ii) if the arrivals of offers

[28] Our life cycle structure is too simplistic for the model to generate wealth dispersion similar to standard life cycle economies (for example Huggett (1996)). Therefore, the performance of the model in matching the wealth distribution is comparable to infinite horizon models. All of the incomplete market models we will consider in this paper yield a GINI coefficient of around 0.5, far below the value of 0.8 observed in the US economy. However, we are not too concerned by this property. Standard ways to generate realistic levels of inequality are to adjust the income process directly to capture top coded earnings (e.g. Castaneda et al. (2003)) or to introduce entrepreneurs and financial frictions (e.g. Cagetti and De Nardi (2006)). Both of these mechanisms are powerful, but it would be surprising if they had much to add to the labor market participation margin, keeping in mind that there are only a few very wealthy households and top coded earners in the US economy.

and exogenous separations are perfectly correlated events (in our calibration they are independent) and iii) if the "choice of hours" available to dual earner households becomes irrelevant for savings.

The fact that conditions i) to iii) are not satisfied means that the incentive of dual earner households to accumulate assets to buffer shocks in labor income is weakened, relative to the model with bachelor households. This holds in spite of the differences in the discount factors across the two models.

5.2.2 Employment Distributions

We now explain how the endogenous wealth distribution produced by the model interacts with the labor supply decisions of households to determine wealth-employment distributions. In Figures 4 and 5 we merge the asset distributions with the employment decision rules studied previously. Each of four panels in the figures corresponds to a different joint labor market status. The top left panel shows the case where both household members have a job offer. The top right, the case where the primary earner (agent 1) has an offer. In the bottom right panel the secondary earner has an offer (and the primary earner is not employed) and finally, the bottom right panel corresponds to the case where both household members are not employed. The shaded areas in the graphs correspond to (some of) the 'Regions' identified previously. To facilitate the exposition the optimal decision rule $S = (i, j)$ (where $i, j \in \{E, U, O\}$) is shown separately for each part of the state space.

Consider first Figure 4. The shaded area in the top left panel shows the range of wealth over which the couple keeps the primary earner employed, the secondary earner drops to out of the labor force. Clearly, the endogenous asset distribution has zero mass at any wealth level within this range (above point A). Where the mass is positive (i.e. the non-shaded area) the couple wants to keep both individuals working. Notice that this decision rule impacts the shape of the distribution in the top right panel: A substantial mass of households is concentrated at point A.

In the bottom left panel where we assume agent 1 is not employed and agent 2 is, given that agent 1 is the primary earner it can only be that she got hit by a χ shock and lost her job. Because χ shocks arrive at a low rate (2%), the mass of agents in the distribution in the bottom left panel is quite small. Roughly 20 times as many households have their primary earners employed (e.g. top right panel), as households that have their their secondary earners employed. Two parts of the state space are highlighted in the figure. The shaded area corresponds to an optimal status $S = (U, E)$ (i.e. agent 1 is unemployed, agent 2 is employed). The non shaded area corresponds to $S = (O, E)$.

Figure 5 shows the decision rules and the wealth distributions assuming different endowments ϵ. We increased the relative productivity of agent 2, but kept agent 1 as the primary earner. We now see that over the entire wealth range the household wishes to keep both of its members employed (e.g. $S = (E, E)$ in the top left panel). Moreover, it is now never optimal for agent 1 to drop to out of the labor force.

L Let us use these figures to illustrate the job hoarding property discussed previously. Consider first the top right panel in Figure 4. Suppose that the household's wealth exceeds point B (roughly 350 thousand dollars). As the optimal rules S illustrate, the primary earner remains employed, but she will withdraw from the labor force if a separation shock arrives (bottom right panel). This situation shows job hoarding by agent 1. Agent 2 may also exert job hoarding behavior. To see this, consider a household in figure 5 which has both members employed and suddenly agent 2 gets hit by a χ shock. As can be seen from the top panels, if household wealth exceeds point C (roughly 65 thousand dollars) then agent 2 will move directly to out of the labor force in response to the exogenous separation shock.

Finally, to understand the effects of a change in productivity, assume that the household initially has both of its members employed and the productivity endowments are the ones which correspond to Figure 5. Suppose that wealth is initially above point C and assume that the household experiences a change in ϵ, the new draw is the one used to construct Figure 4. We will then see agent 2 dropping to out of the labor force.

From Figures 4 and 5 we draw the following conclusions: i) the model will endogenously give us agents who exert job hoarding behavior, these agents will flow from employment to out of the labor force (due to exogenous separation shocks). ii) the model will give a fraction of (secondary earners) which are out of the labor force because they have low productivity.

5.2.3 Out of the Labor Force: Model vs Data

In steady state the total fraction of the population which is out of the labor force is 34%. Out of these 15.78% are retired (this fraction is explicitly targeted) 15.5% are secondary earners (not retired) and 4.2% are primary earners. Moreover, the model gives that 9% of the population, is out of the labor force due to job hoarding.

To compare these numbers to the data, we first need to identify which group of individuals is the empirical counterpart for the agents who exert job hoarding behavior. A (reasonably) good approximation is the non-searchers. As discussed previously, these individuals do not want to pay the search costs, and therefore they are not unemployed. Moreover, we can think of 'non searchers' as (relatively) productive individuals, who move to employment at a relatively high rate. This is consistent with the data observations described in the previous sections. Non-searchers represent 2% of the US population. Therefore, the model overpredicts the number of non-searchers. In Section 6 we will introduce changes to the model's structure to reduce this number.

When we look at the relative out of the labor force populations of primary and secondary earners in the data we find that not retired out of the labor force men are 2.9% of the total and married women represent 11.2%.[29]These numbers are close to the model's predictions. In spite of its simplistic structure the model can match these moments very well.

5.2.4 Within Family Distribution of Labor Market Status

We now evaluate the model's performance in matching the joint distribution of employment status within the family. In Table 8 we show fractions of households in terms of the joint status. 46.5% of households have both of their members employed, 26.5% have one employed member and one out of the labor force and 5.7% one employed and one unemployed member. In the data these numbers are: 51.0% of couples are in state (E, E), 27% in the (E, O) state and 3.5% in state (E, U). In the model there are 0.5% (U, U) couples, the analogous fraction in the data is 0.25 %.

[29]If we consider household heads (see section 2) we find that 3.7% are out of the labor force and not-retired. Note also that the model predicts more non-searchers among secondary earners. In particular, there are twice as many non-searchers in the group of secondary earners. In the data there are three times as many secondary earners who are non-searchers as there are primary earners.

Note that even though we have assumed that household members have identical preferences and therefore, the distinction between primary and secondary earners is solely based on productivity, the fit provided by the model in terms of these moments is remarkably good.[30]

5.3 Labor market flows

5.3.1 Flows in the Couples Model

In Table 9 we summarize the average worker flows. The left panel shows the flow rates of the couple model. The data targets are the transition probabilities for all individuals above age 16 that were shown in Table 3.

[Table 9 About Here]

The model does a good job in matching the empirical worker flows. It matches near perfectly the UE rate (since we chose the parameter $p(\overline{s}, \lambda_s)$ accordingly), and quite accurately the EU rate (1% in the model and 1.34 % in the data). It also performs very well in terms of the OE and the OU rates. It is however, off targets in matching the UO flow rate (7% vs 23% in the data). In light of our previous remarks, this failure of the model is to be anticipated.

As discussed previously, to generate flows out of employment, the model possesses two key mechanisms: the exogenous separation shocks (χ) and the changes in individual productivity ϵ. Because ϵ shocks are persistent, drops in productivity are infrequent, but when they occur they often lead to a transition from E to O. χ shocks may lead either to flows into unemployment or to flows to out of the labor force. This is clearly visible from the table; the steady state (calibrated) value of χ is 2%, but the EU rate is 1%. This suggests that half the times a χ shock hits, individuals flow to O. It is a direct consequence of the job hoarding behavior we previously highlighted.

Bringing these findings together we can note the following important properties: First, transitions between employment and unemployment are explained by the exogenous separation shocks and the frictions. Second, since the OE rate is much lower than 0.16 (the calibrated value of $p(\underline{s}, \lambda_s)$) and there are no frictions between states U and O, the flows in and out of the labor force reflect changes in idiosyncratic productivity and household wealth. Therefore the model, imparts a mechanism which is very similar to that of search and matching models of the labor market (e.g. Pissarides (1984)) to generate transitions between E and U, and a different mechanism, akin to the neoclassical labor supply arguments (e.g. Chang and Kim (2006)) to explain flows in and out of the labor force. Primary earners in the model are typically employed (or unemployed). As we have seen, most of

[30] There is a discrepancy between our calibration target of 62% for the employment population ratio, and the one reported in the last column of Table 8. Our calibration is based on the entire population of ages 16 and above, whereas in the table we report moments for married individuals.

An alternative way to map the data to the dual earner household model is the following: Assume that the economy consists of one household with 3 members: the husband, the wife and the child (whose age is greater than 16). Assume that the husband is employed, the wife and the child are out of the labor force. Denote this by $S = (E, O, O)$. Based on the entire population the participation rate is equal to 33%. However, if we focus only on the married couple, we get a 50% participation rate. One way to deal with this problem is to break down the family into combinations: 3 households two of which have $S = (E, O)$ and one household with $S = (O, O)$. Then, we get a participation rate in the economy of 33% (the right number) and a different division of labor market status within households. When we apply this calculation to the CPS data we get that (E, E) families are roughly 44% of all households, and (E, O) households are 33%. Therefore, our model is in between these two ways of representing the data.

the out of the labor force individuals are secondary earners. Therefore, search frictions are more important for primary earners than they are for secondary earners.

5.3.2 Flow rates under Bachelors and Complete Markets

The difficulty of models of heterogeneous households to match the flow rate from employment to unemployment was first identified by Krusell et al. (2011). This difficulty derives from two model properties: i) shocks are persistent and ii) wealth is run down during unemployment and, as we have seen, poor agents are more likely to remain unemployed.

In the middle and left panels of Table 9 we offer a comparison between our model and the other frameworks we consider: the bachelor model of incomplete markets and the complete market model. This is an important comparison since, under bachelor households we should expect the flow rates to be driven to a larger extent by household wealth, under complete markets it is only the distribution of shocks to labor income which influences the transitions. The couple model is in between.

First, notice that the couple model can match better the flows from EU and from EO than the bachelor model, which underpredicts the EU rate and overpredicts the EO rate. In the case of complete markets, however, we obtain $EU = 0.011$ and $EO = 0.031$, closer to the data targets. Second, note that the transition rate between U and O is larger in the dual earner model, than in the single agent household by roughly 1.5 percentage points. Under complete markets the UO rate is 7.1%, the same as in the couples economy.

The relative importance of household wealth and idiosyncratic productivity can explain these patterns. Consider first the differences in terms of the EU and EO rates. Since dual earner households want to keep their productive members in employment, it is more likely that χ shocks lead to flows from employment to unemployment than from employment to out of the labor force. This effect becomes even more powerful in the complete market model. In contrast, in the bachelor household model, wealth becomes a more important state variable, and as we have seen, agents accumulate more wealth than in the couple model. In this case, χ shocks are more likely to lead to a large EO transition probability.

Now consider why the UO rate is larger in the couples economy: As we have seen previously, a significant fraction of households are in state $S = (E, U)$. For these households, wealth is not necessarily run down during unemployment. Moreover, the productivity shocks experienced by the employed household member, influence the labor supply of the unemployed member. If for example, ϵ^1 increases it is very likely that agent 2 will flow to out of the labor force. In the bachelor household model wealth is always decreased during unemployment; and there is only one (persistent) shock which influences labor supply. Both factors tend to make U a more persistent state.

Notice that the results shown in the table suggest that these different mechanisms do not produce vastly different transition probabilities across the three models. Whether we assume one, two or infinitely many agents in the household the flow rates are not dramatically influenced because wealth and productivity are similarly persistent state variables. As we will later see, though the steady state labor market flows are not that far apart, the cyclical properties of the three models are strikingly different.

5.4 Added Worker Effect

5.4.1 Occurrence of the added worker effect in the model

We now explain how the model generates an added worker effect. To do so we briefly revisit the analysis of section 5.2 (Figures 4 and 5). Consider first Figure 4 and assume that the household has its primary earner (agent 1) in employment, the secondary earner is not employed. As the top panels show, in the case where household wealth exceeds point A, agent 2 remains out of the labor force even if she receives an offer. Assume now that agent 1 gets hit by a χ shock and loses his job. Independent of the labor market status of agent 2, agent 1 is unemployed (if wealth is also lower than point B in the graph). If agent 2 receives a job offer (which happens at rate $p(\underline{s}, \lambda_s)$) there are two possibilities: i) wealth is close to point A and ii) wealth is further than A. Note that if i) holds and household wealth is close to the threshold A then agent 2 will accept the offer. In the bottom left panel of the figure the decision rules tell us that the optimal joint status is to set $S = (U, E)$. This holds because the shaded region in the bottom left panel defines a higher wealth threshold (around 120 thousand dollars) than point A. Agent 2 will accept the offer only in the event where agent 1 loses his job; agent 2 will reject the offer otherwise (it is not optimal to set $S = (E, E)$). We therefore have seen an AWE.

Notice that even though the region where the AWE occurs is small, the model places endogenously a large fraction of households in that region. The reason for this is the saving behavior of the couple. Point A represents the long run wealth level of the household, given ϵ and assuming that agent 1 remains employed for many periods. In other words, A is the so called buffer stock of savings. When this wealth level is reached the couple no longer accumulates assets and agent 2 drops to O. The positive mass of households we see at higher wealth levels, represents households that have experienced drops in idiosyncratic productivity and had previously accumulated large stocks of assets. These households will keep agent 1 employed and run down their wealth.

Figure 5 shows a different AWE. Suppose that a couple has an initial wealth endowment slightly larger than point C in the top right panel. Now, suppose that agent 1 loses his job. Since point D in the bottom right graph, represents a higher wealth level than point C in the top right, there is a region where the transition from E to U experienced by agent 1, induces a flow from O to U by agent 2. This AWE involves a transition into unemployment by the secondary earner (rather than an immediate transition into employment as in the previous example).

Finally, the model can give rise to dynamic AWEs. Since the household's wealth is run down when agent 1 loses his job, eventually the wealth stock can be low enough so that agent 2 joins the labor force eventually. This, for instance, is relevant for any wealth level exceeding D in Figure 5.

5.4.2 The added worker effect in the model

We now compute the (dynamic) AWEs from the model and compare them to the previous estimates from the US data. In Table 10 we show the coefficients α_τ for $\tau = -2, -1, 0, 1, 2$. As explained previously, these coefficients represent the increase in the probability that the secondary earner joins the labor force in month τ. The data (model) moments are in Column 1 (2).

[Table 10 About Here]

There are several noteworthy features: First, the model yields $\alpha_{-2} = \alpha_{-1} = 0$ since the job destruction shocks are i.i.d and therefore not predictable. Second, the model generates a contemporaneous value for the AWE equal to 4.7 percentage points, an effect after one month (α_{+1}) equal to 3.1% and an effect after two months equal to 3.4%. These numbers are somewhat smaller than their data counterparts.

Notice that the coefficients α_τ may be smaller in the model than in the data either because the probability that the secondary earner joins the labor force (conditional on the primary earner becoming unemployed) is lower than the data, or because the overall (unconditional) probability that she joins is higher. In Columns 3 and 4 we document the overall entry rates, conditional on spousal unemployment. Consider first the data column; The first row shows the probability that a wife whose husband will become unemployed in two months from now, joins the labor force. The entry rate is equal to 11.4% and is roughly 2 percentage points larger than the unconditional entry rate (9.5%). In the model (4th Column) the entry rate equals 11.4% but the added worker effect α_{-2} is equal to 0%. Therefore, the model overpredicts the unconditional probability. A similar argument applies to the case where $\tau = -1$.

Now consider the 3rd to the 5th rows in the table. We see that the entry rate for wives in the data, is larger than the entry rate for secondary earners in the model when $\tau = 0$. The opposite holds for $\tau = 1$ and $\tau = 2$. In all cases, however, the differences are small; the model matches quite accurately the rates we see in the data.

These points are crucial to show that the model matches very accurately the patterns of insurance we documented in Section 2. Suppose that we increase the coefficients α_τ to match the data counterparts;[31] then the entry rates will be larger than in the data and consequently, a counterfactually large fraction of households will benefit from the AWE.

To make this point more transparent we list (in the last two columns of the table), fractions of families which, across different horizons, benefit from the added worker effect. These numbers are based on simulating a population of families which at the beginning of period -2, have their primary earners employed and the secondary earners out of the labor force. At $\tau = 0$ the primary earners become unemployed. We then calculate, across the different horizons, the fractions of households in which the secondary earner joins the labor force.[32]

The fractions drop with the horizon τ for two reasons: First, because when the secondary earner joins the household is dropped from the sample. Second, many unemployment spells suffered by primary earners are resolved by a transition back to employment. In this case, the couple may move back to $S = (E, O)$. If we add all the rows we obtain the cumulative effect: The total fraction of households who benefit from joint search is 47.4% in the model, and 50.6% in the data. Therefore, the model matches this moment very accurately.

[31] This could be done (for instance) through raising the correlation coefficient of the productivity shocks.

[32] We set the entry rates at $\tau = -1$ and $\tau = -2$ equal to their unconditional means in the model. Even though unemployment shocks are unanticipated, they are mitigated if the both earners are in the labor force. That is to say, if some families are lucky enough and the secondary earner has joined the labor force before the arrival of the χ shock, we should also count them as families who benefit from insurance through labor supply.

6 Fluctuations in the Aggregate Labor Market

In this section we present the results from the business cycle analysis. Aggregate productivity and the job finding and separation probabilities fluctuate over time as described previously. We trace the effects of economic fluctuations on the aggregate labor market.

6.1 Numerical Solutions to the models

To solve the incomplete market models with aggregate fluctuations we used value function iteration applying the bounded rationality method outlined in Krusell and Smith (1998). As them, we found that it is sufficient to approximate the distribution Γ_t using only the first order moment, we do not need to introduce dispersion, skewness and so on to approximate the law of motion of capital. This property of the model is due two features: i) the savings schedules are (close to) linear in wealth ii) non-linearities near the borrowing constraint do not matter much for aggregate behavior, since households in this part of the state space hold very few assets anyway. Notice that these properties also hold in the couple model, in spite of the fact that couples have more options over employment, and do not accumulate as much wealth as singles do. As is well known, idiosyncratic income shocks convexify the program (see for example Gomes, Greenwood and Rebelo (2001)). The value functions both in the bachelor and the couple models are increasing and concave in wealth and the policy rules feature the usual properties. We describe these findings in detail in the numerical appendix.

To solve the complete market allocation, we used the simulations based Parameterized Expectations Algorithm (PEA) of Den Haan and Marcet (1990) [33]. The PEA forms a global approximation of the nonlinear first order conditions from the planning problem. In the context the model which features labor market frictions, the state variables which need to be remembered for the solution are K_t, λ_t and the fraction of employed individuals at every level of productivity ϵ_t. The complete market allocation is therefore a large scale problem. Note that previous work in the literature (for example Veracierto (2008)) has resolved this problem using log-linear approximations. Our non-linear solution algorithm is novel and should be of independent interest. The approach is outlined in the numerical appendix.

6.2 Cyclical Behavior of Employment, Unemployment and LF participation

In Table 11 we show the cyclical behavior of the labor market statistics produced by the models. We also repeat the data moments to facilitate the comparison. As the table shows across all models employment is procyclical, and unemployment is countercyclical, the contemporaneous correlation of these variables with GDP matches the data patterns closely. The striking difference between the models however, is in the behavior of labor force participation. We see that the bachelor household model of incomplete markets generates a very procyclical participation (a correlation coefficient of 0.78). The model of complete markets gives us 0.82. The dual earner model with incomplete markets gives 0.31, very close to the US data moment of 0.34.

[Table 11 About Here]

[33] See also Faraglia, Marcet, Oikonomou and Scott (2014)

Rows 4-6 of the table report the ratio of the standard deviations of employment, unemployment and participation, relative to the standard deviation of aggregate output. The following patterns emerge: First, the cyclical volatility of the labor force is close to the data counterpart only under the couples model. We obtain a value of 0.29 very close to the value of 0.27 we see in the data. In contrast, the models of bachelors households and complete markets tend to overpredict the volatility of the labor force, we obtain 0.54 and 0.56 (99% and 106% higher than the data moment) respectively.

All three models perform similarly in terms of the behavior of aggregate unemployment, in particular, they underpredict the cyclical volatility of the u-rate. However, whereas the couple model also underpredicts the volatility of aggregate employment, the bachelors and complete market models overpredict it. Because the differences in the behavior of unemployment are not substantial across models, the differences in the cyclical volatilities of aggregate employment may only derive through differences in the behavior of labor force participation. Under the bachelor and the complete market models, the higher volatility in employment is driven by a counterfactually procyclical and volatile entry into the labor force.

6.2.1 Why is the labor force procyclical under bachelor households?

To explain these results we need to investigate how the different models generate transitions over the business cycle through demonstrating the impact of the aggregate shocks on the policy rules and the distributions of households across the state space. We begin with the incomplete market models where these distributions are not trivial.

In figure 6 we show the response of the labor force participation (top panel) and employment (bottom panel) to an aggregate shock which reduces TFP from the highest possible level to the second lowest. The solid line represents the case of the couple household model, the dashed line shows the case of bachelor households. The graphs represent simulations from the model. To better highlight the timing of the shock, we label period 0 the period of the change in TFP and denote with negative (positive) integers the periods before (after) the shock occurs. Moreover, from each series we have subtracted its initial value. The responses shown are deviations from that value.

There are several noteworthy features: First, when the shock hits, aggregate employment first rises, subsequently it drops below the initial condition and becomes procyclical. Second, focusing on the bachelor household model the labor force initially rises with aggregate employment, subsequently it drops again following the trail of the employment population ratio. Third, in the couple household model the response of labor force participation is initially the same as it is for employment, but after a few periods the labor force continues to rise, whereas employment drops.[34] Therefore in the couple model the labor force is countercyclical, in the bachelor model it is procyclical.

What explains these patterns? It is easier to start with the model of bachelor households where these decisions concern one individual. In Figure 7 we show labor supply decision rules and distributions borne out of this model. The top panels show the wealth distributions for employed individuals, the bottom panels show the distributions and decision rules for non-employed individuals. To study the properties of the model we have split the population in two parts i) workers of average productivity and ii) highly productive workers.[35]

[34] This pattern is consistent with the detrended US data. We do observe in some periods the labor force moving opposite to aggregate employment.

[35] Workers of low productivity exert roughly the same behavior as i), in the interest of parsimony we drop them

[Figure 7 About Here]

In the top left panel the green shaded area shows the range of wealth over which a worker with medium productivity drops to O when TFP is high. The vertical line and the arrows in the graph denote how this range shifts when TFP drops. Hence, during the boom, the wealth threshold above which the agent prefers to drop out of the labor force is roughly 200 thousand dollars, in the recession it becomes roughly equal to 240 thousand dollars. For highly productive individuals (top right panel) there are no shaded areas; this suggests that these agents never consider dropping out of the labor force.

The distributions shown in the graphs are as follows: With the blue-solid line we denote the wealth distribution right before the aggregate shock occurs. This overlaps strongly with the dashed green line which shows the distribution in the period of the shock. Finally, the red line traces the evolution of the distributions ten periods after the shock.

First, notice that the change in the decision rule in the top left graph imparts a change in the shape of the distribution at high wealth levels. In particular, it adds a mass of agents who previously dropped out of the labor force, now they are willing to remain employed. This explains why aggregate employment rises on impact when TFP drops. Second, note that because the economy is in a recession and the separation shocks are higher, the post shock distributions gradually shift downwards. This is more clearly visible in the (+10 period) red curve. It explains why aggregate employment starts to fall a few periods after the change in TFP.

In the bottom panels of the figure, the green shaded areas correspond to the range of assets in which agents are out of the labor force, the non-shaded areas are ranges over which agents are unemployed. Note that for unproductive workers (bottom left panel), the drop in TFP virtually has no impact on labor force participation, but for highly productive agents participation drops considerably in the recession. Bringing together the top right and bottom right panels we see that a mass of agents moves from in the labor force to out of the labor force in the downturn. This contributes to the procyclicality of participation we see in the bachelor model.

The effects we document in this subsection are standard in macroeconomic models and well known to the literature. The first intertemporal channel (that unproductive workers want to hold on to their jobs) is driven by the tighter frictions during recessions, i.e. the drop in $p(s_t, \lambda_t)$ which makes jobs more valuable to workers (e.g. Garibaldi and Wasmer (2005)). The second channel, that (productive) workers prefer to pay the search costs in economic expansions when the payoffs to labor market search are larger (equivalently when the expected search costs are lower) is a standard intertemporal substitution effect (e.g. Veracierto (2008)). Under incomplete markets, it is only relevant for high earners, because as we have seen, unproductive agents increase their search intensity when they are close to the borrowing limit. The intertemporal substitution effect is thus weakened in this case.

The first channel is present in bachelor household model of Krusell et al. (2012). The second is absent from that model because it is assumed that $p(\overline{s}, \lambda_t) = p(\underline{s}, \lambda_t)$ and that search costs are equal to zero.

from the graphs.

6.2.2 Why is the labor force acyclical in the couple model?

We now study the decision rules and the distributions in the case of the dual earner incomplete market model. Figures 8 and 9 summarize the behavior couples and their responses to the aggregate shock. Note that the figures show the same households we studied in Figures 4 and 5, however, now we augment the graphs to include the effects of the cycle.

[Figures 8 and 9 About Here]

Let us use these graphs to explain the pattern of the labor force participation that we previously documented. First, note that as in the case of bachelor households, couples which have both of their members employed, desire to increase their labor supply in the recession (eg top left panel in figure 8). This contributes to the rise in aggregate employment when the shock hits as we have previously seen. Second, the intertemporal substitution effect which induces rich and productive agents to drop out of the labor force during recessions is clearly visible in the bottom right panel; the vertical line indicates that the wealth threshold at which agent 1 is indifferent between U and O has now moved further to the left. If we put together these two factors we produce a response of participation similar to the bachelor household economy.

Key to understand why participation is acyclical in the couple model is the behavior of secondary earners. Consider a couple which before the recession had agent 1 employed and agent 2 is out of the labor force. Moreover, assume that the wealth of this family is between 90 and 140 thousand dollars. Further assume that in the recession the primary earner loses his job; the couple then moves from the top right graph to the bottom right graph. In this case agent 1 is unemployed and if agent 2 has not (in the meanwhile) received a job offer, she is out of the labor force.

Now suppose that agent 1 remains unemployed for several periods. In spite of the fact that the arrival rate of offers to O individuals is lower (in this example it has dropped from 21.92 to 14.02 percent) there is still a significant probability that agent 2 will receive an offer. Suppose this happens: then as the policy functions in the bottom left panel of Figure 8 indicate, we will see agent 1 remain unemployed and agent 2 become employed. The impact of this channel is clearly manifested in the graphs. Notice that the number of couples who have their primary earner unemployed and their secondary earner employed, dramatically increases in the recession and in particular it increases substantially for households with wealth between 90 and 140 thousand dollars. This rise is explained by the AWE. Moreover, we see a rise in the fraction of couples in state $S = (E, E)$ (in the green area in the top left panel). This is an immediate consequence of the precautionary labor supply behavior described previously. In the longer term however, the fraction of (E, E) may drop due to the higher arrival rates of separation shocks during recessions.

Finally, note that the significance of the added worker effect for the behavior of participation in the couple model can also be illustrated with the aid of Figure 9. In this case, due to the higher separation shocks, individuals experience transitions into unemployment. Families run down their wealth endowment and react through bringing into the labor force their secondary earners. This is clearly illustrated by the significant rise in the mass of households in state $S = (U, U)$, in the bottom right panel. The added worker effect is therefore important also in this case, however, it is mostly dynamic.

6.2.3 Why is the labor force procyclical under complete markets?

We now turn to the case of the complete market economy. The response of the labor force participation and employment in this model is depicted with the crossed line in Figure 6.

To explain the patterns we see in the figure note first that under complete markets unemployment risks are not idiosyncratic, and therefore do not affect the behavior of individuals. The behavior of the economy (given the state variables) is summarized in the behavior of two thresholds: i) the productivity level below which agents flow from employment to out of the labor force and ii) the threshold above which an agent becomes unemployed. Our findings are as follows: First, as in the case of the incomplete market models, the planner reduces the outflow from E to O, keeping less productive individuals employed in recessions. Second, the intertemporal substitution effect is powerful and the unemployment threshold moves up in the recession. This generates a large outflow from the labor force. These findings are similar to the findings of Veracierto (2008).

We have now showed that the response of the labor market in the complete market economy is very similar to the response in the bachelor household model. This is an interesting implication because as we have seen the crucial state variable in the case of incomplete markets is household wealth, under the complete market allocation it is only idiosyncratic productivity that matters. Apparently, the composition effects which derive from these states, lead to similar properties in the aggregate labor market.

6.3 Primary and Secondary Earners over the Business Cycle

We now study the behavior of primary and secondary earners in the model and in the data. In section 2 we saw that in the US data married women (secondary earners) have an employment population ratio which is not volatile nor procyclical. Their labor force participation was found to be negatively correlated with GDP. These are motivating facts for our study.

In the model we have defined the agent with the higher productivity to be the primary earner. Since this is done every period and despite productivity being persistent, the identity of the primary earner changes over time. Since in the data the identity of husbands and wives does not shift we cannot compare the model withe the data based on current productivity only. Therefore, we compute for each household member the average productivity $\bar{\epsilon}^i \equiv \sum_s \epsilon^i_s \frac{1}{s+1}$ over a horizon $s = 0, 1, 2, ..., T_R$, where T_R denotes the date the household retires. [36] We then define as the primary earner the individual with the higher average productivity. To see how this may impact the business cycle moments assume that we see a household with $s = 0$. This household retires tomorrow, hence only current productivity determines the identity of the primary earner. However, if a household never retires then $s \to \infty$ and the average productivity becomes equal across members since both members are ex ante, and therefore also in the long run, identical. In the latter case, the two household members are then simultaneously both, primary and secondary earners. The corresponding business cycle moments are the ones for the aggregate labor market in Table 11. Through averaging across households we obtain a definition of primary and secondary earners which corresponds better to the data. However, we also ensure that we do not exacerbate the differences in the business cycle

[36] T_R varies across households depending on the realizations of the retirement shock. Some households retire after 1 period hence $T_R = 0$, others retire after many periods and so on. We compute $\bar{\epsilon}^i$ based on the realization we observe, we then average across households. See appendix for further details on the computation.

moments.

[Table 12 About Here]

The results are displayed in Table 12. The findings are as follows: First, the correlation of the employment rate of secondary earners with GDP is 0.63 and the volatility ratio is 0.58. In the data these numbers are 0.45 and 0.57 respectively. Second, the correlation of participation for secondary earners is -0.10 in the model and the volatility ratio 0.37 in the model. In the data we have -0.23 and 0.43 respectively. Finally, the model gives us 0.79 and 0.29 for the correlation and volatility of the participation of primary earners. The data objects are 0.12 and 0.21. Therefore, primary earners now have a more procyclical and less volatile participation than secondary earners do, in line with the data observations.[37]

Note that in spite its simplicity the model matches the data patterns closely. In the appendix we show that the success of the model in matching the behavior of primary and secondary earners does not hinge on the persistence of the ϵ process. When we assume higher values of ρ_ϵ we obtain very similar results.

6.3.1 Joint Labor Market Status over the Cycle

In Table 13 we look at the business cycle moments of the fraction of dual earner households in state $S = (i, j)$ where $i, j \in \{E, U, O\}$. Each row in the table represents a different joint labor market status. The columns show the correlation of the detrended series with GDP and the relative standard deviations in the model and in the data.

[Table13 About Here]

The results in the table suggest that the model is able to capture quite accurately the joint behavior of couples and in particular the correlations of the joint status of couples with economic activity. For instance, the model predicts that the fraction of families that have both family members employed is strongly procyclical and households in state (E, U) are countercyclical. The fraction of families in state (E, O) is mildly procyclical; its contemporaneous correlation with GDP is 0.40 in the model and 0.49 in the data. The only correlation which is not captured well by the model is that for (O, O) households. The model gives a value of -0.67, the analogous object in the data is -0.02. This can be explained by the fact that these households are typically very wealthy.

These observations are important; they demonstrate that the economic mechanism bestowed by the model on households produces aggregate properties for these fractions which are close to the data. As we have seen the AWE leads to substantial changes in the joint labor market status over the cycle. These changes are in line with the data counterparts.

[37] The too high correlation predicted in the model, 0.79 versus 0.12 in the data, comes from the fact that the model generates too many wealthy households, whose primary earner is close to being indifferent between participating or not. These households are more like single agent households. The participation rate is very procyclical because of the intertemporal substitution effect we previously explained.

6.4 Cyclical Behavior of Flow Rates

In Table 14 we document the behavior of the flow rates in the models and in the data. There are several noteworthy features: First, all the models predict that the flow rates UE are very procyclical and the volatility is close to the data counterpart. This is obviously not surprising, we had previously explained that flows from unemployment to employment are governed by the frictions $p(\overline{s}, \lambda)$. Since these objects are calibrated to the data, the UE rates predicted by the models match the data pattern. Second, all of the models give a procyclical OE rate and a countercyclical OU rate (the correlation coefficients are close to the data counterparts). This feature can also be explained by the movements in the frictions. Since $p(\underline{s}, \lambda)$ increases in economic expansions individuals who are out of the labor force and join the labor force are more likely to experience an immediate transition into employment in booms than in recessions.

Third, notice that the models differ in terms of their performance in the EU rates and in the EO rates. In terms of the EU rates the bachelor model performs worse, it predicts a contemporaneous correlation with GDP of -0.48 (therefore mildly countercyclical). The couples and the complete market models give -0.73 and -0.84 respectively, very close to the data. Multi-member households have their most productive agents in employment. During recessions, when jobs are destroyed at a larger rate, these agents drop to unemployment since they are primary earners. In contrast, the bachelor economy predicts that household heads are relatively wealthy, they flow to out of the labor force when their jobs are destroyed.

Notice that this argument can also explain why the flow rate from E to O is more negatively correlated with economic activity in the bachelor model, than in the complete market model (-0.35 vs. -0.27). However, it cannot explain why the couples model performs better and produces a correlation coefficient of 0.03 and closer to the data moment (0.43). The behavior of secondary earners is pivotal. As we have seen these agents flow into the labor force to provide insurance, and a substantial part of these flows result in employment. When the primary earner finds a job, the secondary earner may return to O if household wealth has not been significantly reduced. During recessions the duration of unemployment is larger, and unemployment shocks deplete household wealth at a faster pace than in expansions. Therefore, secondary earners become more attached to their jobs.

[Table 14 About Here]

This observation is consistent with the our previous finding that the employment population ratio of secondary earners is less procyclical than for primary earners. It is also confirmed by the behavior of the flow rates for primary and for secondary earners in the model and in the data. For instance, in the US data the correlation of the EO flow with GDP is 0.09 for (married) men and 0.44 for women. In the model the analogous correlations are -0.31 for primary earners and 0.18 for secondary earners. The model predicts a more negative correlation than the data but the qualitative patterns are matched.

Note that the mild procyclicality of the EO rate has been interpreted as evidence that workers quit their jobs in expansions (e.g. Hall (2005)). One explanation is that workers flow to out of the labor force when they have another job lined up (e.g. Nagypál (2005)). Here we show that the behavior of primary and secondary earners is also crucial. This new channel is complementary to existing theories.

A final comment is in order: When looking at the behavior of these flows, many researchers have conjectured that the influence of the AWE on the aggregate labor market, can be traced through the relative behavior of the *OU* rate across married men and women (see for example Elsby et al, forthcoming). These flows do not show in the CPS data substantial differences across population groups. For example, the correlation of the *OU* rate in the data is -0.63 for married women and -0.73 for married men. The model produces similar patterns; it yields -0.79 for primary earners and -0.83 for secondary earners. This can be explained as follows: First, as we have seen the *OU* rate is chiefly influenced by the changes in the frictions over the cycle (individuals are more likely to flow to unemployment during recessions than directly to employment). Second, the model predicts that many secondary earners who become unemployed, are individuals with low wealth and high productivity. These agents are closer to primary earners, their labor market participation is not explained by any family insurance effect. The evidence presented in this section shows, in the microfounded model, that family insurance influences primarily the *EO* rates of secondary earners, along with their employment and participation rates.

6.5 The Behavior of Aggregate Wages and Consumption

To complete this intertemporal analysis we document in Table 15 the cyclical behavior of wages, consumption and investment.

6.5.1 Wages

First, note that aggregate wages are measured here to correspond to the average wage value period unit of time (wages divided by hours worked) we observe in the data. As is shown in the table, wages exhibit different patterns in terms of their cyclical volatility and the correlation with GDP across the three models. To understand where these differences derive from, note that in models with heterogeneity, the behavior of average wages is influenced by the entry and exit decisions of individuals into employment and the labor force. If entry is procyclical, it means that in economic expansions unproductive individuals move into employment. The higher entry rate during booms, puts downward pressure on the measured wage. In contrast, if the entry into the labor force is acyclical, heterogeneity matters less.

[Table 15 About Here]

The success of models of heterogeneous agents in producing wages which are not highly correlated with economic activity has been noted by many authors (see for example Chang (2000) and the references therein). When labor supply is strongly procyclical, this mechanism can explain the low correlation between wages and hours worked in the aggregate data. The results presented in the table suggest however a difficulty with respect to this argument: when the participation margin is accounted for, models which give a low correlation between wages and GDP, get the cyclical properties of participation wrong: they rely on a counterfactually procyclical and volatile entry into the labor force. Under complete markets, we obtain a negative correlation (-0.29) since the composition effect is strongest. In the case of the incomplete markets and bachelor households this correlation turns positive (0.35); the composition effect is weakened because now wealth determines the entry into the labor force along with productivity. However, in the dual earner incomplete market model, participation is acyclical, and the correlation between wages and output becomes positive (0.73).

6.5.2 Consumption

Now consider the behavior of aggregate consumption in the models and in the data: We obtain a ratio of standard deviations between consumption and output equal to 0.76 in the US data, 0.74 in the couples economy, 0.52 in the bachelor model and 0.38 in the complete market model. Therefore, the dual earner household model is close to the data observations, the other models underestimate the relative variability of consumption.[38] Moreover, because the standard deviation of aggregate output is similar across models, these differences remain even when we look at the standard deviations of consumption.[39]

To understand these patterns, first note that in the case of incomplete markets (bachelors and couples) idiosyncratic risks add to the variability of household consumption and also increase the aggregate volatility, if these risks are correlated with the business cycle. In our framework this is certainly the case, since unemployment spells last longer in economic recessions and separations shocks become more frequent. When markets are not complete households react to the higher income uncertainty through their self-insurance margins: wealth and joint labor supply. As we have seen the first margin is less important for couples, because the second margin becomes available. However, assets in the model are less risky than labor income, over cycle. Since dual earner households partly substitute the first for the second margin, they experience larger drops in consumption during economic recessions. Another way of saying this is that couples can utilize joint search and labor supply, this helps to protect them from idiosyncratic uncertainty, at the same time it exposes them more to the aggregate component of these risks.

7 Extensions and Robustness

7.1 Increasing the Variance of Earnings Shocks

In the couples model, labor supply decisions are taken jointly in the household. Individual supply is therefore influenced by the productivity and the labor market status of the spouse, it is now the joint process of productivity and employment shocks which determine the overall income of the household. It is interesting to investigate whether the distribution of household earnings is different in the couple economy than in the bachelor household model. When we summarize the distribution into the earnings GINI coefficient we find the following: First, under bachelors, the earnings GINI is 0.52. In the case of couples, the coefficient for individual earnings is 0.52, but for total family income

[38]These estimates pertain to our sample period 1994-2014. When we computed the relative variability of consumption between 1960 and 2006, we obtained of 0.52, the target for this quantity in the early RBC literature. However, when we used data on personal consumption expenditures (a series which is also commonly used), the ratio of standard deviations was found 0.84 between 1994 and 2014 and 0.78 between 1960 and 2006.

[39]For detrended output we obtain 0.0169, 0.0184 and 0.0175 for couples, bachelors and complete markets, respectively. The consumption standard deviations are 0.0125, 0.0096 and 0.0067. Note that these patterns cannot be explained by the fact that utility is non-separable between consumption and leisure. Under complete markets and bachelors households, agents quit the labor force in recessions, this contributes towards mitigating the drop in consumption.

it is 0.46. Clearly, the joint decisions influence earnings inequality between households since shocks to productivity and employment shocks are not perfectly correlated within the household.

We now test the predictions of the couples model when we target the family income GINI of the bachelor economy. To accomplish this we follow De Nardi (2004) and increase the variance of the shocks to productivity. We find that if the standard deviation σ_ϵ becomes 1.5 times as large as under the benchmark calibration, we get a GINI index of 0.52.[40]

The cyclical moments are presented in Table 16 (along with the benchmark calibration for convenience). Note that with the higher uncertainty in income, the participation rate becomes negatively related with aggregate economic activity. Not surprisingly the cyclical volatility of aggregate employment drops slightly. Obviously, the larger are the shocks to the household's labor income, the less cyclical fluctuations matter for labor supply decisions. Put differently, now individuals join the labor force responding more to idiosyncratic productivity and less to the business cycle. Our previous findings on the importance of joint insurance in households, to match the business cycle correlations remain.

7.2 Reducing the Importance of Non-Searchers

Both the couples and the bachelor models predict in equilibrium a large fraction of agents who exert 'job hoarding behavior'. These agents are wealthy, and in response to a χ shock, they drop out of the labor force. Non searchers are also present under complete markets, even in the absence of wealth effects; the planner keeps some agents employed even if their productivity is low. At the arrival of a χ shock these individuals flow to out of the labor force.

Let us recall that the feature of the model which gives rise to the job hoarding behavior, is that search is costly. Search costs under the baseline calibration are high, reducing them will help reduce the number of non-searchers. However, notice that if we lower κ arbitrarily, we have another problem; the unemployment rate increases above the target. To see this consider the following extreme scenario: suppose we set κ to zero and maintain $p(\overline{s}, \lambda_s) > p(\underline{s}, \lambda_s)$. Then, all agents will prefer to become unemployed. [41] We must therefore bring $p(\underline{s}, \lambda_s)$ closer to $p(\overline{s}, \lambda_s)$ when we lower κ.

In Table 17, for each model, we increase the probability
$p(\underline{s}, \lambda) \in \{0.19, 0.22, 0.25\}$ keeping $p(\underline{s}, \lambda) = 0.26$. We set κ to match the unemployment rate target. As the first column of the table shows, the value of κ now drops significantly. When we set $p(\underline{s}, \lambda) = 0.25$ (bottom panel) we obtain for every model $\kappa = 0.02$. This means that unemployed workers spend in market activities roughly 6% of the time employed workers do.

[Table 17 About Here]

[40] Notice that to get a GINI coefficient of 0.63 (Census Data), it does not suffice to increase the variance assuming a symmetric distribution (as we do). A substantially larger GINI can only derive from making the distribution skewed to reflect top coded earnings $\rho_{x,Y}$ (e.g. Castaneda et al. (2003)).

As discussed previously, it seems unlikely that adjusting the process to incorporate individuals with 6 digit annual earnings is important for the participation margin. Moreover, compared to the rest of the literature of infinite horizon incomplete market models, our benchmark GINI is already quite high (see Table 1 in Castaneda et al. (2003) for a summary of different papers).

[41] In the limit $p(\overline{s}, \lambda) = p(\underline{s}, \lambda)$ we need to set $\kappa = 0$ as the only feasible value. However, we then also need to increase the arrival rate of offers to a very large value (above 0.45) to target an unemployment rate of 6.2 percent. In effect unemployment becomes a less important risk to the household.

In the second column of the table we show the fraction of non-searchers over the population: The top panel shows the numbers from the baseline calibration; in the bottom panel we show that non-searchers represent roughly 6% of the population when we set $\kappa = 0.02$. Clearly, the fractions are still higher than the data moment (2%). This illustrates that job hoarding is a very persistent feature of the economic mechanism imparted by the model.

As we know, under incomplete markets, individuals accumulate assets for self-insurance and drop to out of the labor force when they become sufficiently wealthy. Because of these decision rules, the models always give a large mass of agents in the critical region of non-searchers. Moreover, note that when we increase the value of $p(\underline{s}, \lambda_s)$, there is a strong composition effect: the pool of employed individuals now tilts more towards wealthier agents; these are more likely to become non-searchers. A similar composition effect accounts for the patterns we see under complete markets. However, now the key variable is not wealth but individual productivity.[42]

Consider now the performance of the models over the business cycle, under the new calibrations. We see the following: First, in the couples model, the cyclicality of participation is further reduced relative to the benchmark. We obtain a value of 0.09 when we set $p(\overline{s}, \lambda_s) = 0.19$ and a value of -0.33 when $p(\overline{s}, \lambda_s) = 0.25$. Second, there is a reduction in the correlation of labor force participation with GDP also in the case of complete markets. Nevertheless, even when the correlation is 0.42 ($p(\overline{s}, \lambda_s) = 0.22$) the complete market allocation gives a volatile participation margin. Finally, in the case of the bachelor household model, there no significant improvement in these moments relative the benchmark.

To understand these findings note first that higher separation shocks induce employed individuals to drop out of the labor force in recessions. Therefore, when we reduce the number of non searchers, the effects from this channel becomes weaker. This may explain why (in some models) the contemporaneous correlation of participation with GDP drops. Second, the composition effects discussed previously, are also crucial. They yield a larger fraction of unproductive agents in employment under complete markets, and increase the wealth of the employed when markets are incomplete. This differentiates the impact of the business cycle between the models. Under the complete market we now have relatively less individuals close to the unemployment-out of the labor force threshold; this makes the intertemporal substitution effect weaker. The opposite holds in the case of incomplete markets and bachelor households. As we saw previously, (see for example Figure 7) productive and wealthy agents are more responsive to the shift in the expected search costs over the cycle.

In the couple model the higher arrival rates of offers to out of the labor force individuals, means a larger inflow of secondary earners in the labor force during recessions. This effect is pivotal to explain the patterns that we see in the table.

In the final column of the table we provide another statistic which summarizes the performance of the models in matching the participation margin; the correlation between the labor force and aggregate employment. In the de-trended US data this correlation is in the order of 0.69. It echoes the fact that decreases in the employment population ratio in the historical US observations are not accompanied by drops in the labor force participation of similar magnitude, the unemployment population ratio increases to absorb most of the difference (see for example Shimer (2009)). The

[42] In other words, in the case of complete markets the fraction of non-searchers is persistently high because the less productive agents now find jobs at a higher rate. In equilibrium, there is a larger mass of agents who once get hit by a χ shock, flow to out of the labor force.

performance of the models is as follows: The benchmark couples model gives 0.71 for this correlation and therefore fits the data very well. When we increase $p(\underline{s}, \lambda_s)$ in that model we get much lower correlations, because now secondary earners become more important for the aggregate statistics. The bachelor and complete market models give correlations close to 0.9, considerably higher than the data moment.

In the appendix we consider an alternative avenue to minimize the impact of non-searchers in the models. We assume that the separation shocks χ remain constant over the business cycle as they typically do in search and matching models (e.g. Pissarides (1984) and Shimer (2005) among others). This assumption reduces the correlation of participation with GDP. However, the same problems arise with the bachelor and the complete market models, namely the labor force is very volatile and the correlation between employment and the labor force remains counterfactually high. Assuming constant separation is unappealing for an additional reason: in the models it makes the flows from E to U procyclical.

7.3 Models without Frictions

We now briefly describe the effects of removing the frictions from the economy, through setting $p(\underline{s}, \lambda) = p(\overline{s}, \lambda) = 1$. This model under incomplete markets has been studied by Chang and Kim (2006, 2007) and Gomes et al. (2001) and under complete markets by Gourio and Noual (2006) among others.

In the absence of frictions, unemployment is not defined. The labor force is the sum of all employed individuals. Since the properties of these models are not new in the literature, we describe them in detail in the appendix. We show that across all models we obtain a very procyclical participation; the contemporaneous correlation with GDP exceeds 0.9 in all cases.

Note that in the case of the couple household model, the fact that the correlation between participation and output is very large when we remove the frictions, suggests that it is crucial to maintain unemployment as an important risk to the household for our results in this paper. Without frictions, individuals can choose whether or not to work, and it is no longer necessary for secondary earners to join the labor force during recessions to provide insurance.

7.4 Log -Separable Preferences

For the benchmark model we have assumed that consumption and hours are substitutes in utility. We now set $\gamma = 1$ so that utility is of the form: $\eta \log c_t^i + (1-\eta)\log(1-l_t^i)$. We investigate in this paragraph whether the specification of preferences impacts significantly our results.

In Table 18 we show the average labor market flows in the steady state.[43] As can be seen from the table that there is virtually no effect from assuming log separable utility on the estimated transition probabilities.

[Table 18 About Here]

In the online appendix A we show (analytically) that in the case of complete markets if we keep constant the targets of employment and unemployment, then preferences do not matter at all. As

[43]Note that for each of the three models, we recalibrated η, κ and β to find an equilibrium consistent with the targets. The details are contained in the appendix.

discussed previously, the family under complete markets needs to determine two thresholds; the first governs the transitions between E and O, and the second, between U and O. We establish that these thresholds are solely functions of the process of ϵ. Preferences can be identified ex post to satisfy the first order conditions of the planning problem. In the case of incomplete markets, this property need not hold. The difficulty is that now it is not only productivity that matters; wealth becomes an important state variable and the flow rates are determined along with the endogenous wealth distribution. However, the findings presented in the table suggest that preferences do not exert any significant influence also in this case.[44]

Now consider the results from the business cycle version of the model under log preferences. The summary statistics for employment, unemployment and labor force participation are illustrated in Table 18. The moments should be compared with the results of the benchmark calibration (Table 11) to discern whether preferences matter for the business cycle patterns. They do not! In particular, in the incomplete market models considered, we obtain very similar correlations and relative ratios of standard deviations for each variable, to the benchmark calibration. There are only minor differences in the case of the complete market allocation, we now find that labor force participation exhibits even more volatility; this causes a rise in the cyclical volatility of employment. Nevertheless, the results are very close to the benchmark. In the appendix we have a detailed discussion of these results where we also show that the behavior of wages, consumption and investment is very close to the benchmark economy.

A final comment is in order: Many papers have shown that the specification of preferences is important for the behavior of macroeconomic models. For example, Christiano, Eichenbaum and Rebelo (2011) and Galí, López-Salido and Vallés (2007) have demonstrated that preferences are crucial for the propagation of government spending shocks. Hall (2009) reaches a similar conclusion when he tries to reconcile the historical changes in the marginal value time with the movements in the product of labor in the US. Basu and Kimball (2002) show that when consumption and leisure are not-separable, the household Euler equation can be made consistent with the responses of consumption to anticipated changes in labor income.[45] We show here that in a model is which labor supply is formed at the extensive margin and there are frictions in the labor market, after accounting for general equilibrium effects the specification of preferences is not at all important, for labor market flows and for business cycle fluctuations. This result should be of separate interest.

[Table 19 About Here]

7.5 Welfare Costs of Aggregate Fluctuations

We now compute the welfare costs of business cycle fluctuations in our benchmark models. In particular, for each of the models considered we ask 'what is the percentage increment in consumption, needed so that individuals are on average as well off living in an economy with economic fluctuations, as they would be if business cycles were completely eliminated?'. We derive the coefficient of compensating variation through comparing the aggregate uncertainty models (Section 5) with the

[44] In the appendix we show that the wealth distribution is unaffected by the change in preference. The general equilibrium effect (that we recalibrated β to match the interest rate target) is crucial for this finding.

[45] More generally the specification of preferences is intimately related with the consumption puzzles in the early literature (see for example Cochrane (1991) and the literature on the consumption retirement puzzle).

steady state versions discussed in Section 4. In particular we compute the value $\widetilde{\xi}$ which satisfies:[46]

$$\sum_{(ij):i,j\in\{e,n\}} \int E_b \sum \beta^t \sum_{i=1}^{2} u(c_t^i(1+\widetilde{\xi}), l_t^i) d\Gamma_s^{ij} + \int E_b \sum \beta^t \sum_{i=1}^{2} u(c_t^i(1+\widetilde{\xi}), l_t^i) d\Gamma_s^R$$
$$= \sum_{(ij):i,j\in\{e,n\}} \int E_{nb} \sum \beta^t \sum_{i=1}^{2} u(c_t^i, l_t^i) d\Gamma_s^{ij} + \int E_{nb} \sum \beta^t \sum_{i=1}^{2} u(c_t^i, l_t^i) d\Gamma_s^R$$

where E_b denotes the expectation operator in the presence of aggregate fluctuations and E_{nb} the analogous object when we eliminate business cycles. Moreover, Γ_s is the long run steady state distribution of households across the state space. For brevity we omit the analogous expressions for bachelors and complete markets.

[Table 20 About Here]

The results are displayed in Table 20. The estimated values are the following: In the bachelor model we obtain a compensating variation equal to 0.96%; in the dual earner household model we obtain 0.84%, and in the case of the complete market economy, we get 0.54%. Notice that these values are at least an order of magnitude larger than the analogous calculations in Lucas (1987). However, our welfare measure is not based on the variability of consumption. It is worth noting that if we had performed the calculation based on aggregate consumption data, then the welfare costs would be larger in the couple model; as we saw previously, the couple model gives us the most volatile consumption series.

We can explain this pattern as follows: It is well known, that in models where consumption risks are not purely aggregate, but also they are idiosyncratic, the welfare costs of fluctuations are convex in the overall background economic risk that households face. The larger the overall risk, the larger the welfare gain from eliminating the small fraction of uncertainty attributed to business cycles. This argument is discussed (for example) in De Santis (2007).

We previously explained that households in the couple model are able to ward off idiosyncratic risks through joint labor supply. This presents them with the tradeoff: Since jobs are risky assets (over the cycle) relying on family insurance (as opposed to insurance through the financial market) increases the exposure of consumption to business cycle shocks. This, however, does not translate into a larger welfare gain from eliminating business cycles because the overall background economic risk (aggregate + idiosyncratic) does not increase.

To demonstrate this point, we have calculated the idiosyncratic consumption uncertainty in the two incomplete market models (bachelors and couples). In particular, we computed the between household variance of the log of consumption. We obtained the following: First, the cross sectional

[46] Other papers which compute the welfare costs of fluctuations in heterogeneous agent economies follow different approaches: Imrohoroğlu (1989) reconstructs the steady state version of her model so that average duration of unemployment is the same as in aggregate uncertainty version of her model. Krusell, Mukoyama, Şahin and Smith (2009) propose a similar correction, mapping their two state (employment, unemployment) aggregate uncertainty model, into a three state model without fluctuations (employed, short and long term unemployed). Our approach which follows Gomes et al. (2001), simply removes the business cycle through setting λ_t to the average value, and the arrival rates of offers and separation probabilities equal to their steady state values. We adopt this approach for two main reasons: First, because since in the model the choice of labor market status is important, the approach of Krusell et al. (2009) cannot be easily applied in our context. Second, we are mainly interested here in comparing the welfare costs across the three economies, any other approach considered in the literature should be equivalent in terms of this comparison.

variance in the bachelor model is roughly 40 percent larger than in the couple model (0.352 vs. 0.252). Second, as we saw previously, the volatility of aggregate consumption is several times smaller than the idiosyncratic risk households face (the variances were 0.0125^2 for the couple model and 0.0096^2 under bachelors). These patterns are consistent with the above argument.

Finally, to understand why the welfare costs are substantial in all the economies considered, note that with search of the labor market, economic fluctuations lead to a drop in the average employment rate. This is because aggregate employment is a non-linear function of the job finding probability ($p(\overline{s}, \lambda)$ and $p(\underline{s}, \lambda)$). The more volatile the cycle, the lower is aggregate employment, this level effect increases considerably the welfare costs from fluctuations. This point has been made (for example) by Hairault, Langot and Osotimehin (2010). This property holds also in our models; The employment population ratio in simulations is lowered by roughly 0.2 percentage points in the models, thus making the welfare costs of business cycles sizable.

In the appendix we discuss these findings further. We also study the cross sectional patterns of the welfare costs in the incomplete market models. We find that between couples and the bachelor models there is a difference in these patterns: Under bachelor the welfare costs of fluctuations are smallest for families between the 25th and the 75th percentiles of the wealth distributions, they are largest for very poor and very rich households. In the case of couples, however, very rich households suffer the least from economic fluctuations. This difference is explained once again by the relative importance of wealth and labor supply in the two models.

8 Conclusion

The findings of this paper are easy to summarize. We have shown that families provide insurance against labor income risks, and in particular against unemployment shocks. When the primary earner of a household becomes unemployed, the secondary earner joins the labor force. In the US data this pattern emerges clearly when we look at married couples.

We then construct a general equilibrium model in the spirit of the heterogeneous agents literature. We add a second member to the household. We demonstrate that this new framework can be used to explain a persistent puzzle; that the participation in the labor market in the historical US data is not strongly procyclical, as macroeconomic models typically predict. The dual earner household model that we propose in this paper can resolve this puzzle. It is able to do so because the family insurance effect that we identify, counterbalances the standard intertemporal substitution channel of the business cycle.

Our model brings together the two key mechanisms which in macroeconomic theory have been widely used to explain fluctuations in the aggregate labor market. On the one hand, the search frictions are shown to be important for primary earners. On the other hand, the neoclassical reservation wage arguments are important for secondary earners. A considerable literature has claimed that secondary earners are likely to be important for fluctuations in aggregate employment since these individuals typically show in empirical studies a larger elasticity of labor supply. The data on the employment and participation patterns of married women show quite the opposite. The employment of married women is not strongly procyclical and is not volatile. Participation in the labor market is countercyclical. The model we present in this paper is consistent with these patterns.

Our analysis focuses on the macroeconomic implications of joint household search. A number of extensions of the framework and of the analysis presented can be fruitful. First, through bringing to the model a more elaborate life cycle structure we can quantify the welfare benefit from insurance against unemployment risks. Second, it is important to understand better the effects of the presence of other family members beyond married women in the household. Most of the 'single agents' we find in the data are young individuals living with their parents. Further research is needed to investigate whether these individuals can be viewed as secondary earners. A preliminary reading of the data indicates that this is not obvious. The complex patterns deserve to be studied further.

A number of policy implications also emerge from this paper. Because families can insure against unemployment risks they need to rely less on precautionary savings. A large literature has shown that the incentive of households to accumulate wealth to buffer shocks to the labor income is firstly, more urgent when shocks are temporary (e.g. unemployment shocks) and second, it exerts an important influence on policy. These effects can be studied further through the lenses of the theory and the evidence presented in this paper.

9 References

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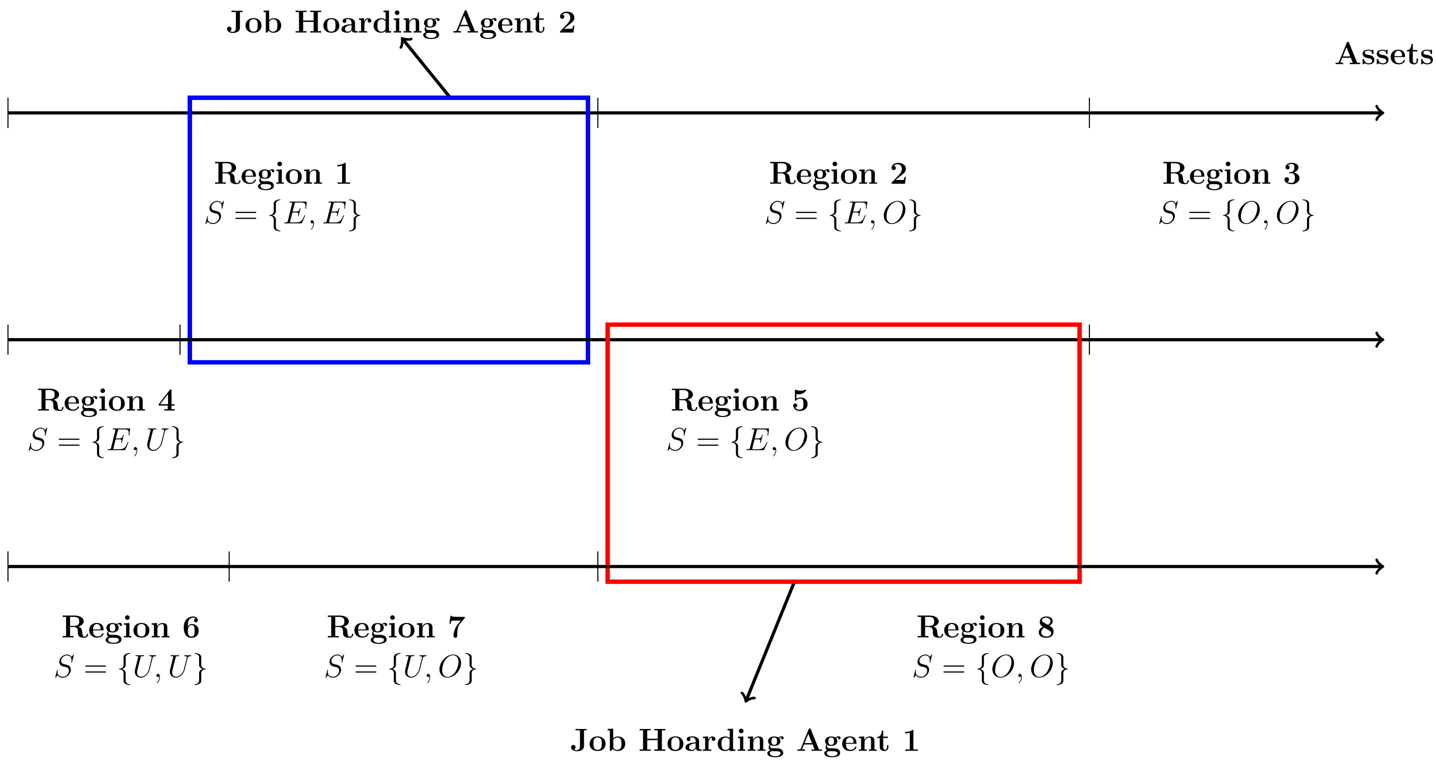
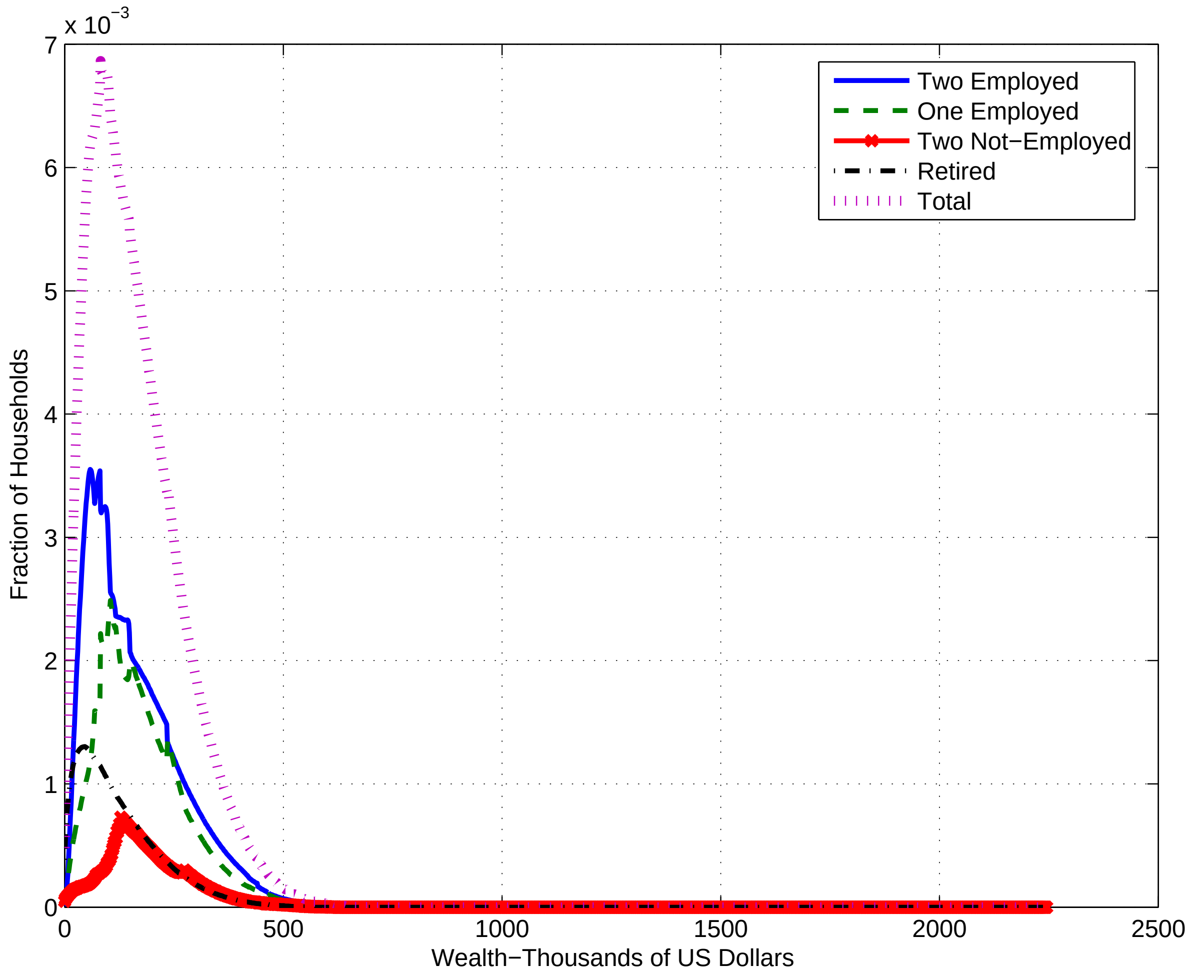
10 Figures

Figure 1: Policy Functions- Labor Supply Over the Wealth Grid



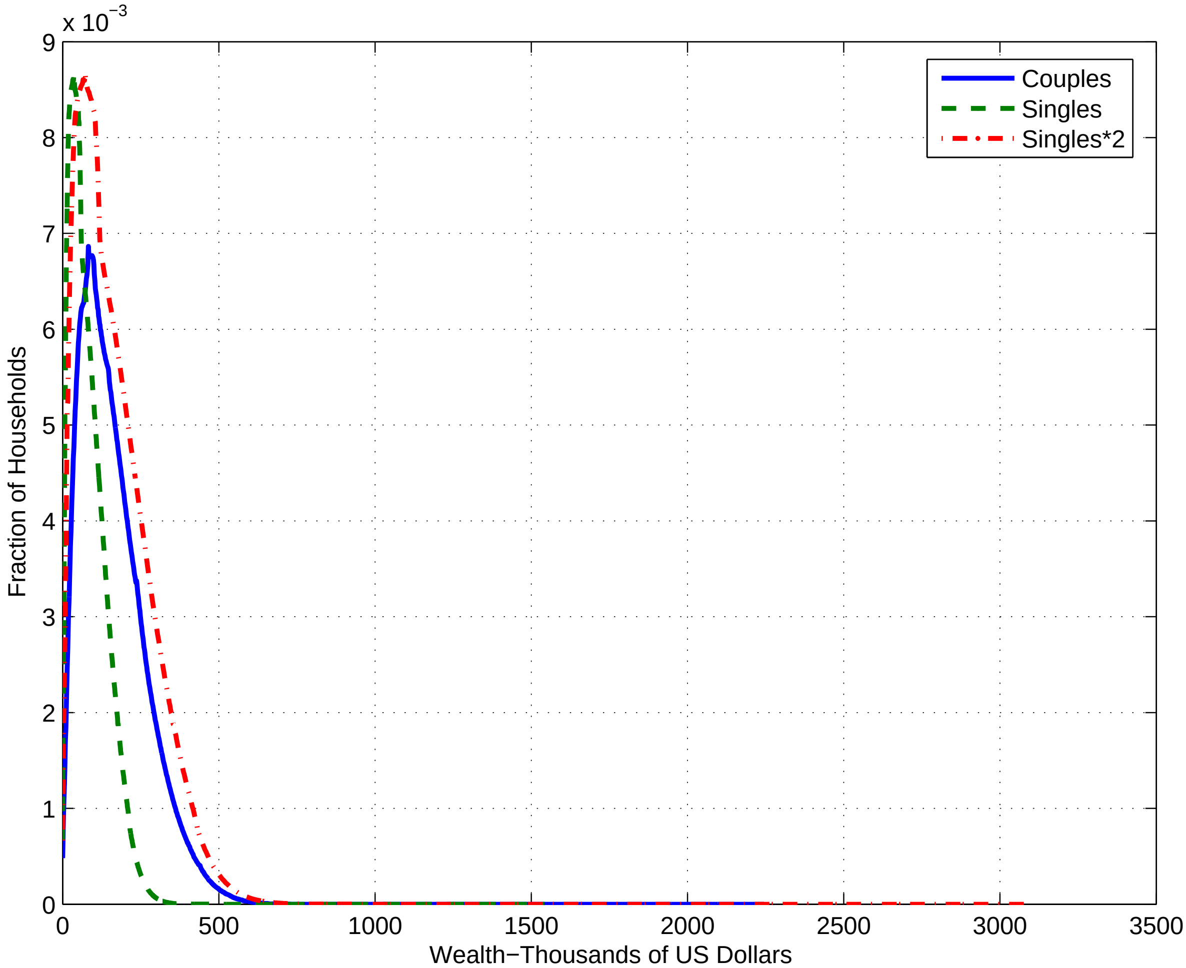
Note: The Figure plots the labor supply rule for couples, given productivity ϵ and over the wealth grid. S denotes the joint labor market status of family members. The first panel shows the case where both family members have job offers. The second shows the case where agent 1 has an offer, wheras in the third panel none of them has an offer.

Figure 2: Wealth Distribution - Couples Model



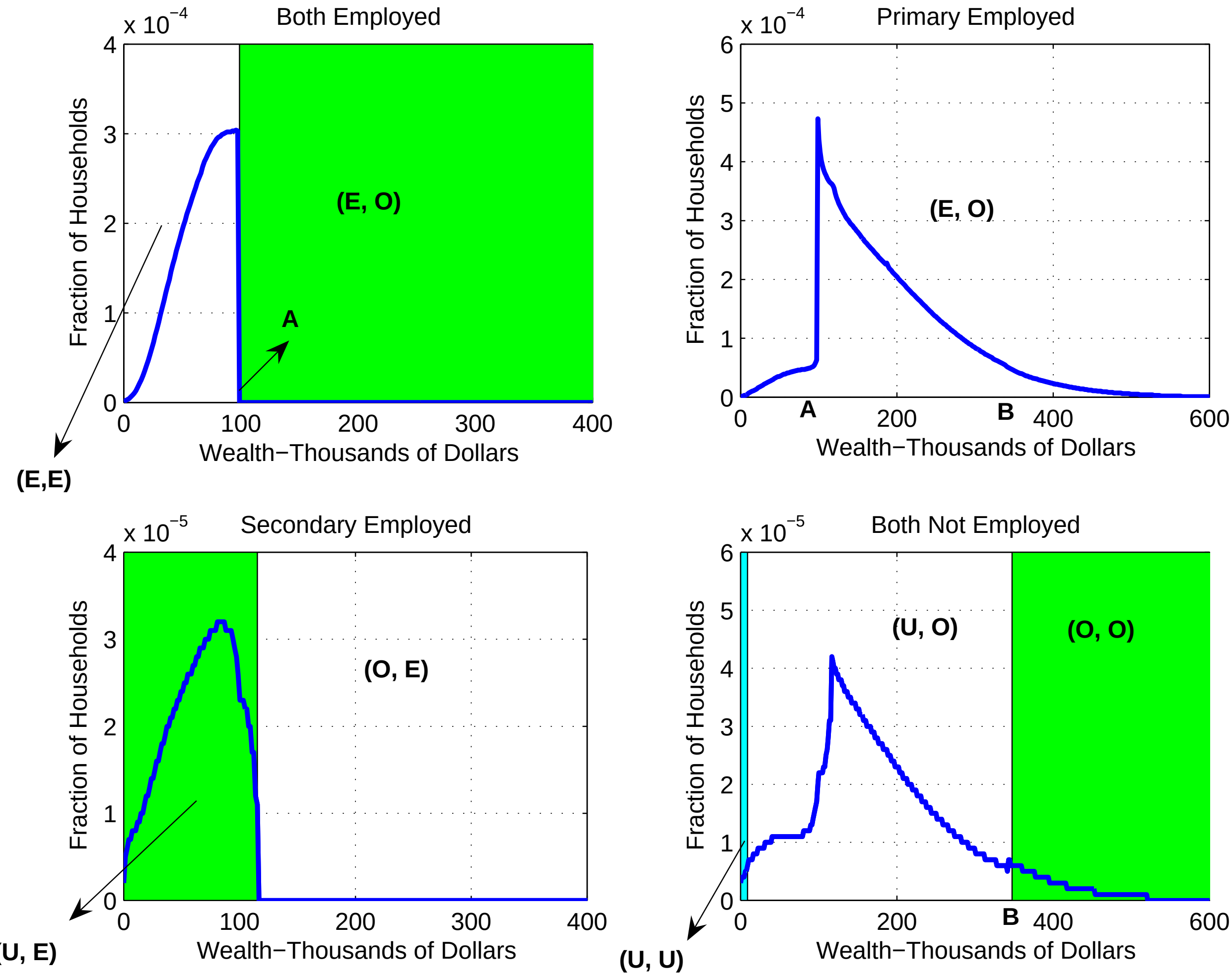
Note: The graph shows the long run steady state distribution of assets in the benchmark model with dual earner households. The dotted line corresponds to all households in the economy. he solid line shows the case of households with two employed members, the dashed line one employed member, the cross line households with both members not employed and the dashed dotted line retired households. The horizontal axis shows wealth (in thousands of US dollars of 2014) the vertical axis shows the fractions of the households holding a particular wealth level.

Figure 3: Wealth Distributions - Couples vs Bachelors Economies



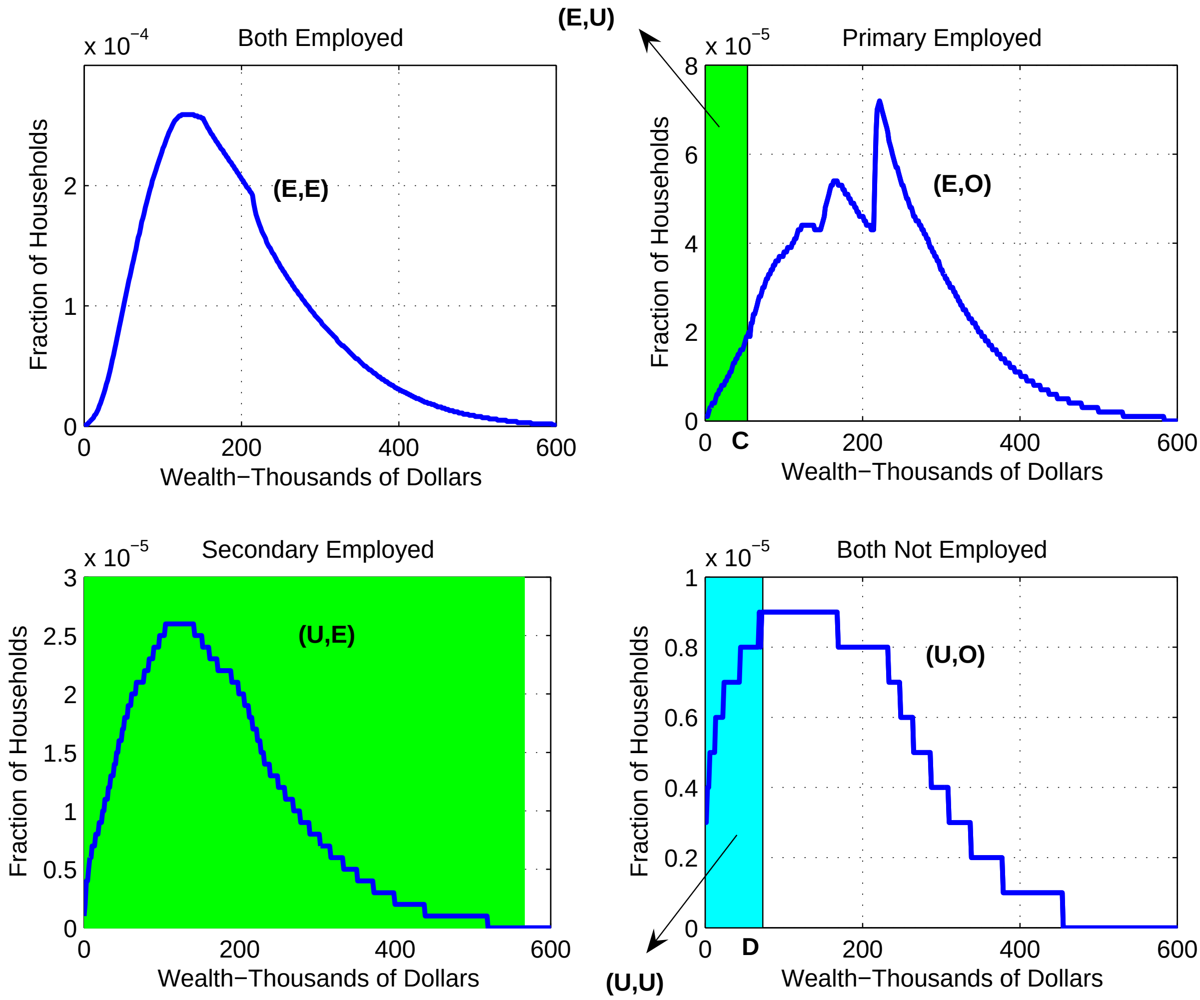
Note: The graph shows the long run steady state distribution of assets in the benchmark model with dual earner households, and the bachelor household incomplete market model. The horizontal axis shows wealth (in thousands of US dollars of 2014) the vertical axis shows the fractions of the households holding a particular wealth level. The red (dash-dotted) line shows the hypothetical distribution when wealth of each individual in the bachelor economy was doubled.

Figure 4: The Wealth Distribution and Employment Decision Rules (1)



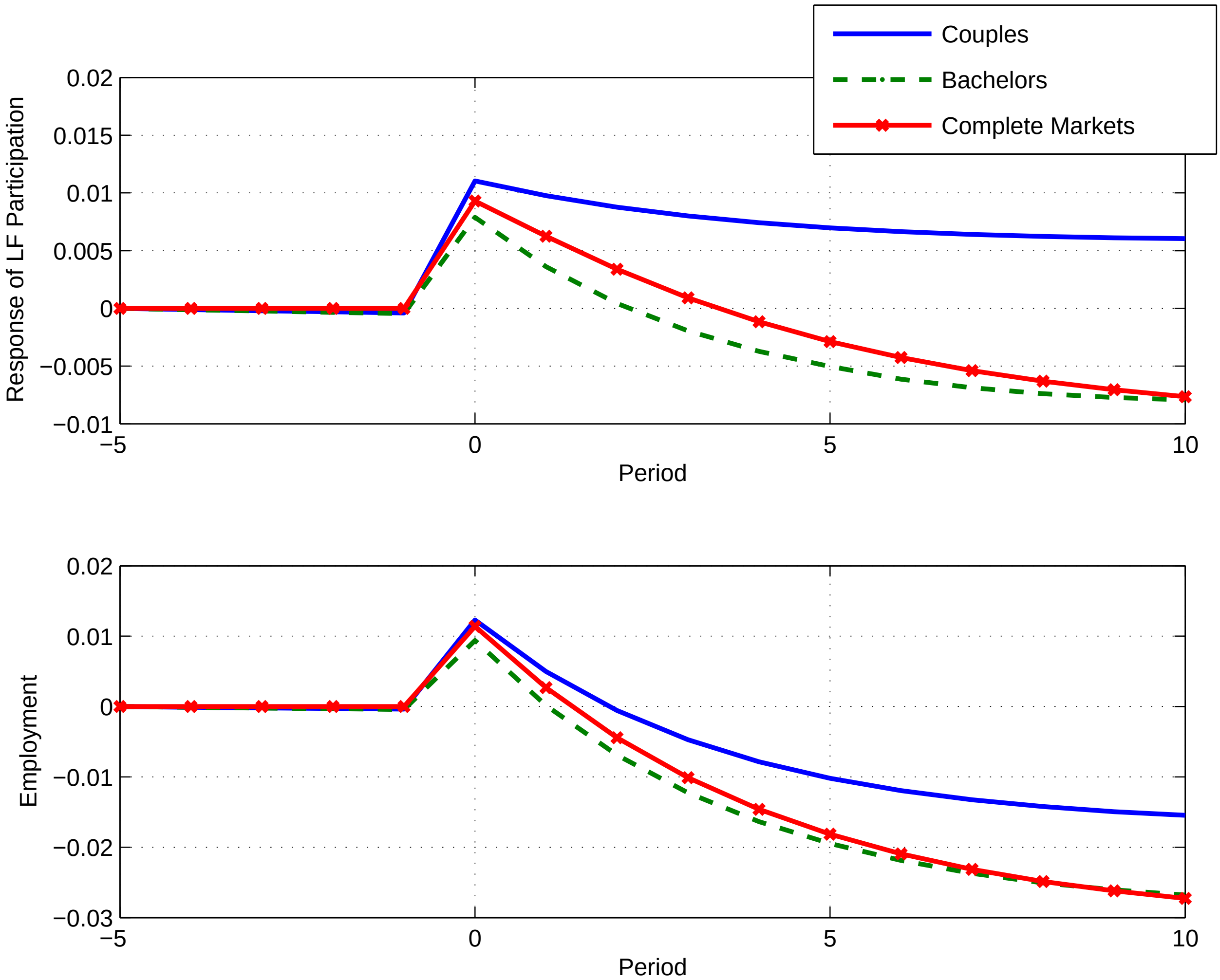
Note: The graph shows the distributions of assets conditional on idiosyncratic productivity and labor market status. The top left panel illustrates the distributions in the case where both household members have a job offer. The top right (bottom left) panel assumes that the primary (secondary) earner is employed, the secondary (primary) earner is not employed. The bottom right panel corresponds to the case where both household members are not employed. The shaded areas in the graphs show the decision rules over labor market status (see main text for details).

Figure 5: The Wealth Distribution and Employment Decision Rules (2)



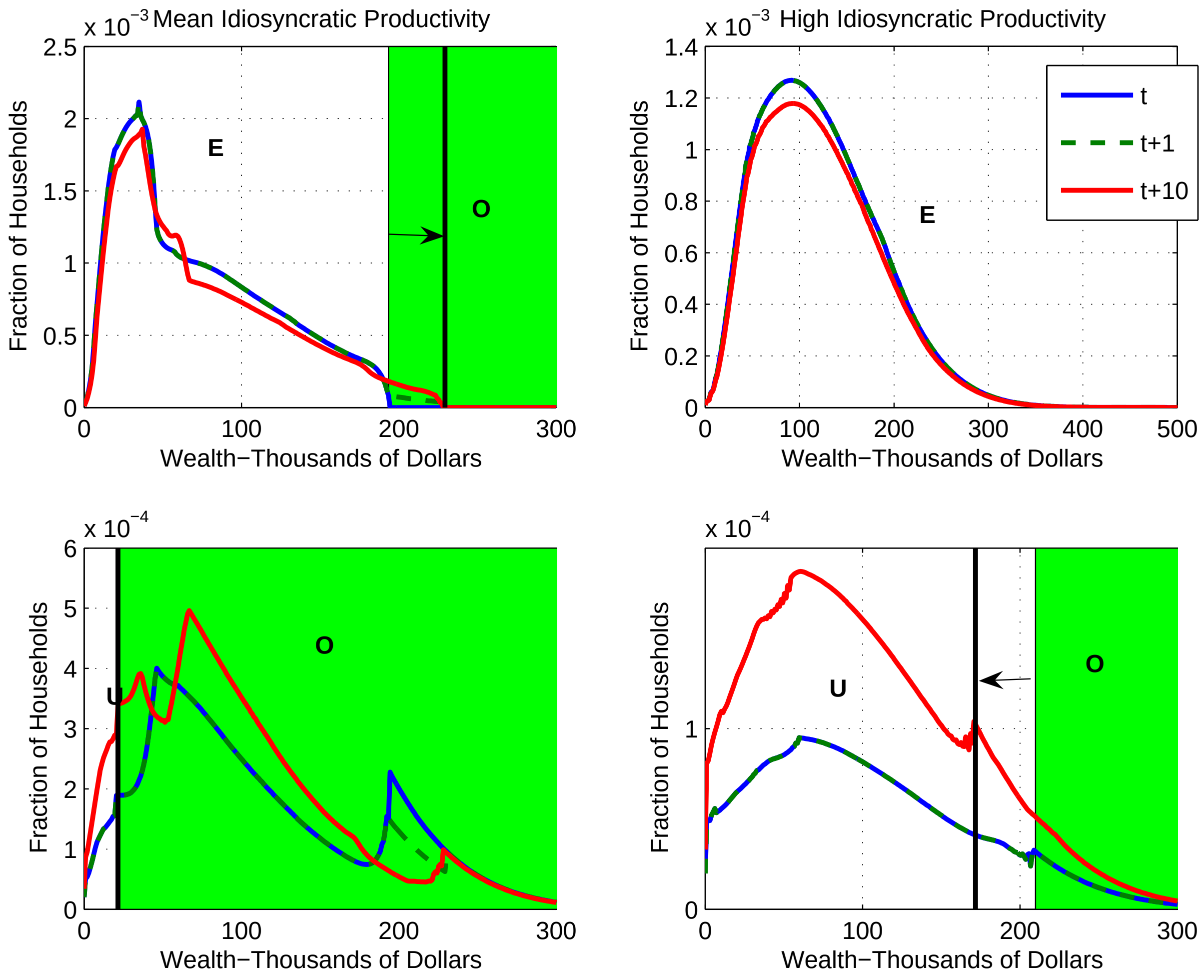
Note: The graph shows the distributions of assets conditional on idiosyncratic productivity and labor market status. Compared to 4, agent 1 here is less produtive but productivity of agent is unchanged. The top left panel illustrates the distributions in the case where both household members have a job offer. The top right (bottom left) panel assumes that the primary (secondary) earner is employed, the secondary (primary) earner is not employed. The bottom right panel corresponds to the case where both household members are not employed. The shaded areas in the graphs show the decision rules over labor market status (see main text for details).

Figure 6: Responses of Employment and Participation to a TFP Shock



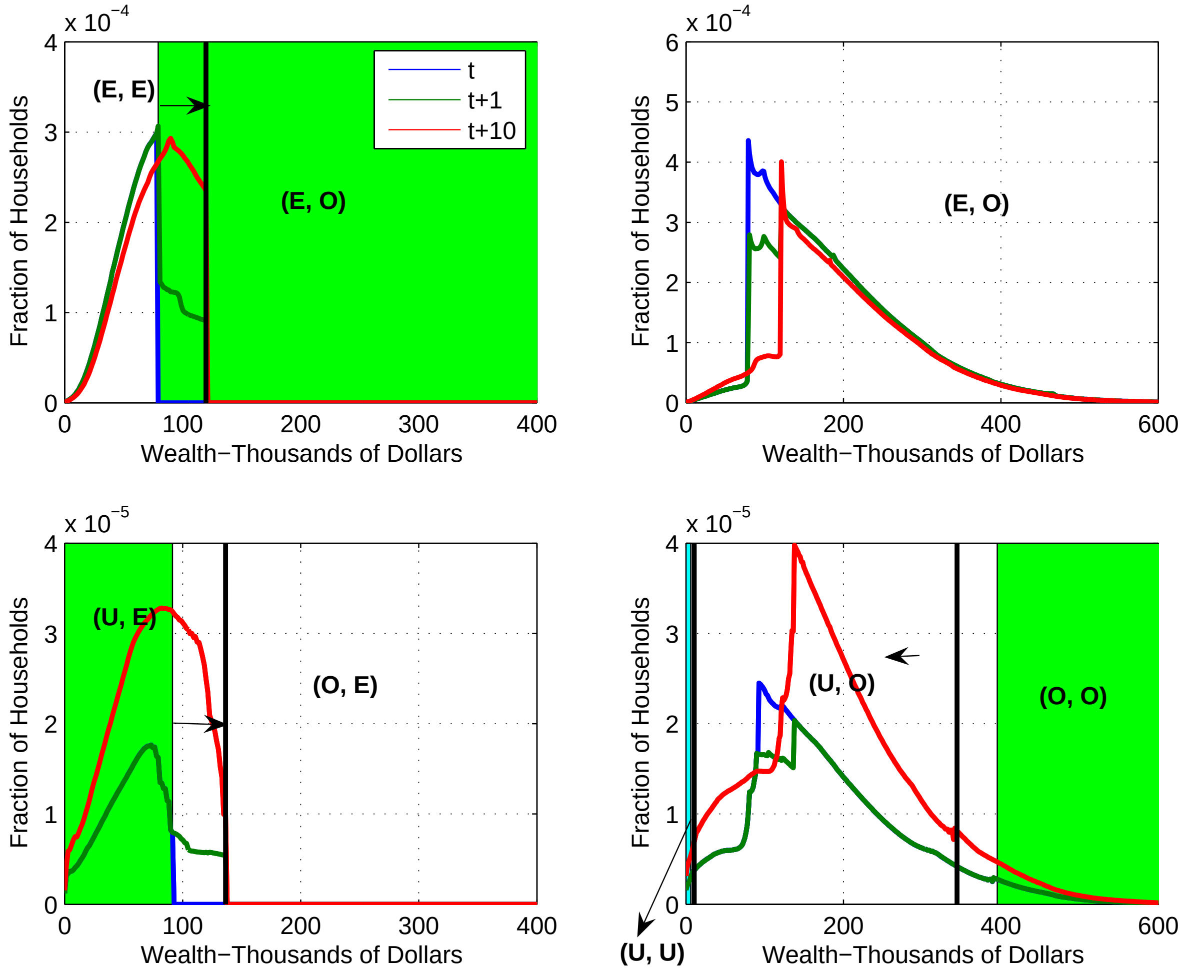
Note: The graph shows the adjustment of aggregate employment and LF participation assuming that TFP is equal to the highest possible level in periods -5 to -1 and in period 0 it drops to the second lowest value. The top panel shows the adjustment of participation, the bottom of the employment rate. The graphs corresponds to simulations from the model. In all cases we have subtracted the first period value for the series as a normalization. Therefore the responses represent deviations from the initial value of each statistic. The solid line corresponds to the couples model, the dashed line to the bachelor household model and finally the crossed line to the complete market model.

Figure 7: The Effects of a TFP Shock on the Wealth Distribution and Employment Decision Rules in the Bachelor economy



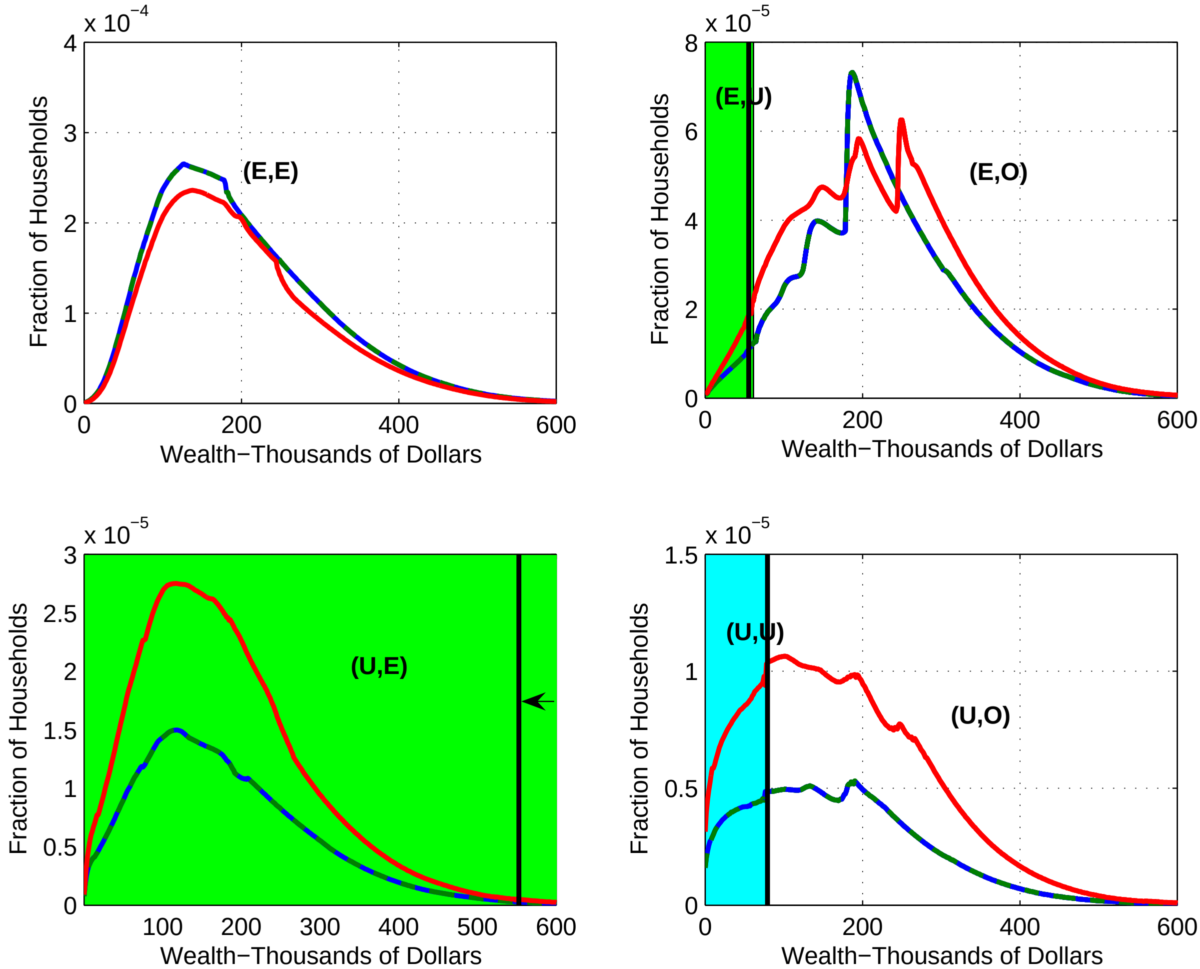
Note: The graph shows the distributions of assets conditional on idiosyncratic productivity and labor market status on the bachelor economy. In the top row, the agents have a job, whereas in the bottom row the agents hare non-emplyed. The left panels show agents with mean productivity, whereas the right panels show agents with high productivity. The steady state distribution is shown in blue, the distribution directly after the shock in greeen and tem periods after the shock in red. The shaded areas in the graphs show when the agent drops out of the labor force. The bold vertical line and the arrow show the how the reservation productivity level changes in response to a TFP shock.

Figure 8: The Effects of a TFP Shock on the Wealth Distribution and Employment Decision Rules in the Couple Economy (1)



Note: The graph shows the distributions of assets conditional on idiosyncratic productivity and labor market status. This figure correspons to Figure 4. The top left panel illustrates the distributions in the case where both household members have a job offer. The top right (bottom left) panel assumes that the primary (secondary) earner is employed, the secondary (primary) earner is not employed. The bottom right panel corresponds to the case where both household members are not employed. The shaded areas in the graphs show the decision rules over labor market status. The steady state distribution is shown in blue, the distribution directly after the shock in greeen and tem periods after the shock in red. The bold vertical line and the arrow show the how the reservation productivity level changes in response to a TFP shock.

Figure 9: The Effects of a TFP Shock on the Wealth Distribution and Employment Decision Rules in the Couple Economy (2)



Note: The graph shows the distributions of assets conditional on idiosyncratic productivity and labor market status. Compared to 8, agent 1 here is less produtive but productivity of agent 2 is unchanged. The top left panel illustrates the distributions in the case where both household members have a job offer. The top right (bottom left) panel assumes that the primary (secondary) earner is employed, the secondary (primary) earner is not employed. The bottom right panel corresponds to the case where both household members are not employed. The shaded areas in the graphs show the decision rules over labor market status The steady state distribution is shown in blue, the distribution directly after the shock in greeen and tem periods after the shock in red. The bold vertical line and the arrow show the how the reservation productivity level changes in response to a TFP shock.

11 Tables

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Table 1: Aggregate Labor Market Business Cycle Statistics

	E-pop	U-rate	LF	LF+NS
$\frac{\sigma_x}{\sigma_Y}$	0.86	10.15	0.27	0.22
$\rho_{x,Y}$	0.81	-0.90	0.34	0.09

Note: The table shows averages of labor market aggregates. The data are extracted from the CPS and correspond to the years 1994 (January)-2014 (October). E-pop is the employment population rate, U-rate is the unemployment rate (total number of unemployed over number of employed + unemployed) and LF ($LF + NS$) refers to the labor force participation rate (including non-searchers, see description in text). All data are quarterly, seasonally adjusted, logged and HP-filtered with a parameter of 1600. See online data appendix for further details on the variables.

Table 2: Labor Market Business Cycle Statistic For Selected Population Groups

		E-pop	U-rate	LF	LF+NS
A: Married men	$\frac{\sigma_x}{\sigma_Y}$	0.71	14.71	0.21	0.19
	$\rho_{x,Y}$	0.79	-0.90	0.12	-0.11
B: Married Women	$\frac{\sigma_x}{\sigma_Y}$	0.57	10.38	0.43	0.42
	$\rho_{x,Y}$	0.45	-0.85	-0.23	-0.36
C: Household Heads	$\frac{\sigma_x}{\sigma_Y}$	0.79	13.27	0.22	0.48
	$\rho_{x,Y}$	0.81	-0.87	0.27	-0.01
D: Women + Children	$\frac{\sigma_x}{\sigma_Y}$	0.95	8.67	0.37	0.60
	$\rho_{x,Y}$	0.77	-0.88	0.30	-0.10

Note: The table shows averages of labor market aggregates for selected subgroups from the CPS 1994-2014. Rows 1-4 show the business cycle labor market moments for married men and women. Rows 5-6 study the behavior of 'household heads'. Rows 7-8 consider the moments for women and children. Deatils on the data can be found in the online appendix.

Table 3: Monthly Flow Rates: Aggregate

	To		
From	E	U	O
E	0.959	0.013	0.028
U	0.249	0.516	0.235
O	0.045	0.026	0.930

Note: The table shows average monthly transition probabilities across the three labor market states: employment E, unemployment U and O. The flows are computed from the CPS data and correspond to the years 1994-2014. Deatils on the data can be found in the online appendix.

Table 4: Monthly Flow Rates: Selected Groups

	A: Married Men To			B: Married Women To			C: Household Heads To		
From	E	U	O	E	U	O	E	U	O
E	0.976	0.010	0.015	0.961	0.008	0.031	0.973	0.011	0.016
U	0.288	0.564	0.148	0.241	0.488	0.271	0.252	0.572	0.176
O	0.037	0.015	0.948	0.040	0.016	0.944	0.029	0.017	0.955

Note: The table shows average monthly transition probabilities across the three labor market states : employment E, unemployment U and O for selected subgroups. Panels A and B show the flow rates for husbands and wives, respectively, while panel C shows the rates for household heads. See Table 3 and the online data appendix for further details.

Table 5: Static Added Worker Effect

	1	2
EU_m	0.0773***	
	(0.0047)	
$Loss_m$		0.1036***
		(0.0069)
$Layoff_m$		0.039***
		(0.0073)
$Quit_m$		0.0905***
		(0.0175)
No of Kids	-0.0004	-0.0003
	(0.0004)	(0.0004)
No of Kids ≤ 5	-0.0238***	-0.0238***
	(0.0007)	(0.0007)
$White_f$	0.0118***	0.0117***
	(0.0016)	(0.0016)
$Black_f$	0.0505***	0.0504***
	(0.0028)	(0.0028)
$Educ._f$	0.0045*	0.0044*
	(0.0025)	(0.0025)
$Educ._m$	0.0209***	0.0208***
	(0.0023)	(0.0023)
$Educ._f{}^2$	0.0012***	0.0013***
	(0.0004)	(0.0004)
$Educ._m{}^2$	-0.0048***	-0.0048***
	(0.0004)	(0.0004)
Age_f	-0.0027	-0.0024
	(0.0049)	(0.0049)
$Age_f{}^2$	0.0001	0.0001
	(0.0001)	(0.0001)
$Age_f{}^3$	-1.4E-06	-1.32E-06
	(1.05E-06)	(1.05E-06)
Age_m	-0.0218***	-0.0213***
	(0.0053)	(0.0053)
$Age_m{}^2$	0.0005***	0.0005***
	(0.0001)	(0.0001)
$Age_m{}^3$	-3.7E-06***	-3.64E-06***
	(1.08E-06)	(1.08E-06)
R^2	0.0101	0.0101
Observations	401793	401543

Note: The table shows estimates from the linear probability model. The data are monthly and stem from the CPS and span the years 1994-204. The sample is composed of married individuals (age 25-55). All regressions include month (time) dummies. Regression 1 is the AWE for all unemployment categories. Regression 2 differentiates the three unemployment categories as discussed in the main text. *** is Significant at 1 percent. ** is Significant at 5 percent and * is Significant at 10 percent level.

Table 6: Dynamic Added Worker Effect

	1: All spells	2: Quits	3:Layoffs	4: Losses
Month_{t-2}	0.0187**	0.0244***	0.0255***	0.0202**
	(0.0078)	(0.008)	(0.0079)	(0.0079)
Month_{t-1}	0.0315***	0.0332***	0.0317***	0.0325***
	(0.0054)	(0.0055)	(0.0055)	(0.0055)
Month_{t}	0.0779***	0.1076***	0.0422***	0.0991***
	(0.0044)	(0.0167)	(0.0067)	(0.0066)
Month_{t+1}	0.0510***	0.1221***	0.0359***	0.0537***
	(0.0054)	(0.0215)	(0.0084)	(0.0082)
Month_{t+2}	0.0396***	0.0297***	0.0265***	0.0453***
	(0.0074)	(0.0104)	(0.0094)	(0.0085)
No of Kids	-0.0003	-0.0004	-0.0004	-0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
No of Kids ≤ 5	-0.0224***	-0.0224***	-0.0224***	-0.0224***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
White_f	0.0077***	0.0078***	0.0077***	0.0078***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Black_f	0.0474***	0.0464***	0.0467***	0.047***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Educ._f	0.0039*	0.0038*	0.0039*	0.0034
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Educ._m	0.0172***	0.0174***	0.0175***	0.0177***
	(0.002)	(0.002)	(0.002)	(0.002)
$\text{Educ.}_f{}^2$	0.0013***	0.0013***	0.0013***	0.0014***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$\text{Educ.}_m{}^2$	-0.0042***	-0.0042***	-0.0041***	-0.0042***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Age_f	-0.0005	-0.0003	-0.0005	-0.0006
	(0.0043)	(0.0043)	(0.0043)	(0.0043)
$\text{Age}_f{}^2$	-2.79E-05	2.45E-05	2.76E-05	3.15E-05
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age_fc e	-6.31E-07	-6.09E-07	-6.31E-07	-6.69E-07
	(9.23E-07)	(9.27E-07)	(9.25E-07)	(9.26E-07)
Age_m	-0.0238***	-0.0233***	-0.0234***	-0.0232***
	(0.0047)	(0.0047)	(0.0047)	(0.0047)
$\text{Age}_m{}^2$	0.0006***	0.0005***	0.0005***	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\text{Age}_m{}^3$	-4.17E-06***	-4.05E-06***	-4.09E-06***	-4.02E-06***
	(9.49E-07)	(9.53E-07)	(9.50E-07)	(9.51E-07)
R^2	0.0097	0.0091	0.0091	0.0095
Observations	540942	533678	5363285	536669

Note: The table shows estimates of the dynamic responses to spousal unemployment. Model 1 shows the result for all spells. Models 2-4 show the results by 'unemployment category' as described in the main text. See Table 5 and the online appendix for details. *** is Significant at or below 1 percent. ** is Significant at or below 5 percent and * is Significant at or below 10 percent level.

Table 7: The Model Parameters (Monthly Values)

Parameter	Symbol	Value	Target
		A: Technology and endowments	
Standard Dev. TFP	σ_λ	.0041	US DATA
AR(1) of TFP shock	ρ_λ	0.983	
Share of Capital	α	0.33	
Depreciation Rate	δ	.0083	
Time Working	$\overline{h}$	$\frac{1}{3}$	Normalization
AR(1) of idiosyncratic productivity	ρ_ϵ	0.98	CK (2006)
Standard Dev. of idiosyncratic productivity	σ_ϵ	0.11	CK (2006)
Correlation (ϵ^1, ϵ^2)	$\tilde{\rho}_{(\epsilon^1,\epsilon^2)}$	0.3	AWE
		B: Retirement	
Retirement Rate	ϕ_R	.00945	CPS data
Reentry Rate	ϕ_A	0.0507	US Retired Population
		C: Search frictions	
Offer Rate: O	$p(\underline{s}, \lambda_s)$	0.16	Worker Flows
Offer Rate: U	$p(\overline{s}, \lambda_s)$	0.26	
Exogenous Separation Rate	$\chi(\overline{\lambda})$	.02	
Fluctuations in $p(s,\lambda)$	ξ_p	0.37	CPS DATA
Fluctuations in $\chi(\lambda)$	ξ_χ	0.28	

D: Model specific parameters

Parameter	Symbol	Couples	Bachelors	Com. Markets	Target
	γ	2	2	2	Blundel et al (2014)
Consumption Weight	η	0.44	0.41	0.50	E-pop = 0.62
Cost of Search	κ	0.233	0.2500	0.256	Urate =0.062
Discount Factor	β	0.9916	0.9905	0.9959	Equilibrium r

Note: The table summarizes the values of the model parameters under the baseline calibration. Panels A-C of the table show the specification of the technology and the endowments which is common across models (couples, bachelors and complete markets). Panel D of the table shows preferences parameters which differ across models. These parameters are calibrated so that the model replicates the observed employment population ratio, the unemployment rate and the interest rate, respectively.

Table 8: Joint Labor Market Status

S	E,E	E,O	E,U	U,U	U,O	U,U	E-pop
Model	0.465	0.253	0.057	0.005	0.017	0.205	0.620
Data	0.510	0.273	0.035	0.003	0.010	0.170	0.664

The table shows the distribution of the joint labor market status of household members in the model and the data. The data statistic refers to married couples in the US, it is constructed from the CPS survey and corresponds to the years 1994-2014. $S = (i,j)$ denotes the joint status where $i, j \in \{E, U, O\}$. The last column shows the employment population ratio in the model and the one of married couples in the data.

Table 9: Steady State Flows in the Models

	A: Couples To			B: Bachelors To			C: Complete Markets To		
From	E	U	O	E	U	O	E	U	O
E	0.956	0.010	0.034	0.947	0.007	0.046	0.958	0.011	0.031
U	0.257	0.672	0.071	0.257	0.687	0.056	0.257	0.672	0.071
O	0.061	0.031	0.908	0.049	0.031	0.920	0.046	0.018	0.936

Note: The table shows average transition probabilities across labor market states from the 3 models: Panel A shows the baseline with dual earner households, panel B shows the model of bachelor households, and panel C shows the complete market model. E represents employment, U unemployment and O out of the labor force.

Table 10: Dynamic Added Worker Effect: Data and Model

	α_τ		Entry Rates		% of Households	
τ	Data	Model	Data	Model	Data	Model
-2	1.9%	0	11.4%	11.4%	11.4%	11.4%
-1	3.2%	0	12.1%	11.4%	10.7%	10.0%
0	7.8%	4.7%	16. %	16.1%	13.0%	13.1%
+1	5.1%	3.1%	13.9%	14.2%	9.1%	9.8%
+2	3.9%	3.6%	12.8%	14.3%	3.2%	6.3%

Note: The Table shows the estimates of the added worker effect in the data (Column 1) and the model (Column 2). Columns 3 and 4 show the entry rates into the labor force for secondary earners (married women in the data) when primary earners (husbands) become unemployed at $\tau = 0$. Columns 5 and 6 show fractions of households who benefit from the added worker effect (see text for further details).

Table 11: Business Cycle Properties: Data and Models

		Data	Couples	Bachelors	Complete
$\rho_{x,Y}$	E-pop	0.82	0.87	0.91	0.93
	U-rate	-0.90	-0.93	-0.92	-0.95
	LF	0.34	0.32	0.77	0.82
$\sigma_{x,Y}$	E-pop	0.86	0.72	0.93	1.04
	u-rate	10.15	7.48	7.19	7.63
	LF	0.27	0.29	0.54	0.56

Note: The table shows the business cycle properties of the aggregate labor market. Column 3 shows the same data as Table 1 where also details about the data can be found. Column 4 shows the corresponding result of the dual earner household, column 5 of the single earner household and column 6 of the complete markets economy. All series are logged and HP filtered with smoothing parameter equal to 1600.

Table 12: Business Cycle Properties: Primary and Secondary Earners

	Primary Earners			Secondary Earners		
	E-pop	U-rate	LF	E-pop	U-rate	LF
$\rho_{x,Y}$	0.95	-0.95	0.73	0.63	-0.92	-0.10
$\sigma_{x,Y}$	0.89	7.75	0.27	0.58	7.12	0.38

Note: The table shows the cyclical properties of employment, unemployment and participation of primary and secondary earners in the baseline model. $\rho_{x,Y}$ is the contemporaneous correlation of variable x with GDP. $\sigma_{x,Y}$ is the ratio of standard deviations between x and Y. All series are logged and HP filtered with smoothing parameter equal to 1600.

Table 13: Joint Labor Market Status- Cyclical Properties

	Data		Model	
S	$\rho_{x,Y}$	$\frac{\sigma_x}{\sigma_Y}$	$\rho_{x,Y}$	$\frac{\sigma_x}{\sigma_Y}$
EE	0.72	1.06	0.83	1.36
EO	0.49	1.12	0.40	1.03
EU	-0.90	11.75	-0.90	7.02
UU	-0.81	21.47	-0.97	10.46
UO	-0.88	12.66	-0.96	6.93
OO	-0.03	0.80	-0.67	0.37

The table shows the contemporaneous correlation $\rho_{x,Y}$ and the relative standard deviation $\frac{\sigma_x}{\sigma_Y}$ between the fraction of households in state $S = ij$ where $i, j \in \{E, U, O\}$ and aggregate output. The data corresponds to married couples in the US in the period 1994-2014. Details can be found Table 4 and the online data appendix. The model is the baseline couples model. All series are logged and HP filtered with smoothing parameter equal to 1600.

Table 14: Flow Rates- Cyclical Properties

	Data		Couples		Bachelors		Complete	
	$\rho_{x,Y}$	$\frac{\sigma_x}{\sigma_Y}$	$\rho_{x,Y}$	$\frac{\sigma_x}{\sigma_Y}$	$\rho_{x,Y}$	$\frac{\sigma_x}{\sigma_Y}$	$\rho_{x,Y}$	$\frac{\sigma_x}{\sigma_Y}$
EU	-0.83	6.41	-0.73	3.87	-0.48	3.22	-0.84	4.81
EO	0.49	2.62	0.03	2.60	-0.35	2.78	-0.27	1.89
UE	0.87	7.11	0.92	7.06	0.92	6.47	0.92	6.75
UO	0.74	4.18	-0.53	3.04	-0.29	3.41	-0.49	3.13
OE	0.62	3.30	0.75	2.70	0.71	2.87	0.76	4.46
OU	-0.81	6.73	-0.84	3.91	-0.79	6.16	-0.74	3.86

Note: The table shows the contemporaneous correlation $\rho_{x,Y}$ and the relative standard deviations $\frac{\sigma_x}{\sigma_Y}$ between labor market flows and de-trended GDP. Columns 2 and 3 are report U.S. data. Details on the data can be found Table 4 and the online data appendix. Columns 4 and 5 show the results of the baseline couples model. Columns 6 and 7 show the results of the bachelors model while columns 8 and 9 show the results of the complete markets model. All series are logged and HP filtered with smoothing parameter equal to 1600.

Table 15: Wages, Consumption and Investment - Cyclical Properties

	Data		Couples		Bachelors		Complete	
	$\rho_{x,Y}$	$\frac{\sigma_x}{\sigma_Y}$	$\rho_{x,Y}$	$\frac{\sigma_x}{\sigma_Y}$	$\rho_{x,Y}$	$\frac{\sigma_x}{\sigma_Y}$	$\rho_{x,Y}$	$\frac{\sigma_x}{\sigma_Y}$
Wages	0.13	0.81	0.73	0.52	0.35	0.40	-0.29	0.40
Consumption	0.83	0.76	0.99	0.74	0.95	0.52	0.95	0.38
Investment	4.50	0.91	0.98	3.11	0.97	2.87	0.98	3.33

Note: The table shows the contemporaneous correlation $\rho_{x,Y}$ and the relative standard deviation $\frac{\sigma_x}{\sigma_Y}$ between variable x (consumption, wages, investment) and GDP. The data are extracted from the FRED database for the years 1994-2014. Consumption refers to non-durable goods and services, wages correspond to hourly compensation in the non-farm business sector, investment is private investment (fixed capital). All series are logged and HP filtered with smoothing parameter equal to 1600.

Table 16: Higher Uncertainty Model

	A: Benchmark (Gini=0.46)			B: Higher uncertainty (Gini=0.52)		
	E-pop	U-rtae	LF	E-pop	U-rate	LF
$\frac{\sigma_x}{\sigma_y}$	0.72	7.48	0.29	0.58	7.14	0.29
$\rho_{x,y}$	0.87	-0.93	0.32	0.76	-0.94	-0.07

Note: The table shows the results of the couples benchmark model in panel A. The Gini coefficient of total household earnings in this model is 0.46. Panel B shows the results of the model when we recalibrate the income process to generate a Gini coefficient of 0.52 that is to the value we obtain in the bachelor economy. The results are the aggregate labor market statistic (employment, unemployment and participation). The behavior of wages consumption and investment for this model are discussed in the appendix.

Table 17: Changing the frictions

	κ	% NS	E-pop		U-rate		LF		$\rho_{E,LF}$
			$\sigma_{E,Y}$	$\rho_{E,Y}$	$\sigma_{U,Y}$	$\rho_{U,Y}$	$\sigma_{LF,Y}$	$\rho_{LF,Y}$	
A: $p\left(\underline{s}, \bar{\lambda}\right) = 0.16$									
Couples	0.24	0.090	0.71	0.87	7.49	-0.94	0.29	0.32	0.71
Bachelors	0.25	0.092	0.94	0.91	7.27	-0.93	0.54	0.76	0.94
Complete Markets	0.26	0.087	1.18	0.95	8.62	-0.95	0.63	0.85	0.97
B: $p\left(\underline{s}, \bar{\lambda}\right) = 0.19$									
Couples	0.17	0.080	0.67	0.87	8.03	-0.94	0.25	0.09	0.54
Bachelors	0.17	0.081	0.84	0.93	7.94	-0.93	0.40	0.78	0.93
Complete Markets	0.19	0.071	0.94	0.90	9.28	-0.95	0.41	0.50	0.81
C: $p\left(\underline{s}, \bar{\lambda}\right) = 0.22$									
Couples	0.09	0.071	0.66	0.87	8.58	-0.95	0.24	-0.13	0.36
Bachelors	0.06	0.072	0.79	0.92	8.57	-0.94	0.30	0.78	0.94
Complete Markets	0.07	0.066	0.95	0.89	9.62	-0.96	0.48	0.42	0.89
D: $p\left(\underline{s}, \bar{\lambda}\right) = 0.25$									
Couples	0.02	0.063	0.66	0.86	9.08	-0.95	0.25	-0.33	0.16
Bachelors	0.02	0.064	0.80	0.90	9.16	-0.95	0.31	0.64	0.90
Complete Markets	0.02	0.057	1.06	0.90	9.85	-0.95	0.59	0.66	0.90

Note: The table shows the results of the three models when the probability of receiving a job offer for out of the labor force workers is increased relative to the benchmark calibration which is repeated for convenience in panel A. Panel B shows the case where $p\left(\underline{s}, \bar{\lambda}\right) = 0.19$, panel C where $p\left(\underline{s}, \bar{\lambda}\right) = 0.22$ and panel D where $p\left(\underline{s}, \bar{\lambda}\right) = 0.25$. κ the cost of search parameter. %NS is the fraction of non-searchers over the population. $\sigma_{x,Y}$ is the ratio of the standard deviation of x relative to GDP. $\rho_{x,Y}$ is the correlation coefficient between x and Y. The last column of the table shows the correlation coefficient between labor force participation and employment ($\rho_{E,LF}$) which in the data is 0.69.

Table 18: Steady State Flows: Log Utility

	A: Couples To			B: Bachelors To			C: Complete Markets To		
From	E	U	O	E	U	O	E	U	O
E	0.956	0.010	0.034	0.947	0.007	0.046	0.958	0.011	0.031
U	0.257	0.672	0.071	0.257	0.685	0.058	0.257	0.672	0.071
O	0.062	0.032	0.906	0.049	0.033	0.918	0.046	0.018	0.936

Note: The table shows average transition probabilities across labor market states from the 3 models: Panel A shows the baseline with dual earner households, panel B shows the model of bachelor households, and panel C shows the complete market model. E represents employment, U unemployment and O out of the labor force.

Table 19: Business Cycle Properties Log Utility

		Data	Couples	Bachelors	Complete
$\rho_{x,Y}$	E-pop	0.82	0.87	0.91	0.93
	U-rate	-0.90	-0.94	-0.94	-0.95
	LF	0.34	0.30	0.72	0.82
$\sigma_{x,Y}$	E-pop	0.81	0.71	0.91	1.17
	U-rate	10.14	7.51	7.45	8.59
	LF	0.27	0.27	0.47	0.64

Note: The table shows the business cycle properties of the aggregate labor market for the log utility model. Column 3 shows the same data as Table 1 where also details about the data can be found. Column 4 shows the corresponding result of the dual earner household, column 5 of the single earner household and column 6 of the complete markets economy. All series are logged and HP filtered with smoothing parameter equal to 1600.

Table 20: Welfare Costs of Business Cycles

	Couples	Bachelors	Complete
$\widetilde{\xi}$	0.83%	0.96%	0.54%

Note: The table shows the compensating variation, the percentage increment in consumption required by individuals in the economy with business cycle fluctuations to be as well off as they would be in an economy without fluctuations. See the online appendix for details on calculations.

12 Supplementary Appendix: Not for Publication

12.1 Additional Moments and Calibrated Parameters

We now discuss the calibrated parameters for the extensions of the model presented in Section 6. We also show additional moments from the simulations with aggregate shocks. The models discussed are the log separable utility model (section 7.4) the model without frictions (section 7.3) and finally the model of section 7.2 where we assume lower search costs.

In Table 21 we show the output for the model without frictions. As noted in text when we assume incomplete markets the models become similar to the models studied Chang and Kim (2006, 2008). The first two columns report the preference parameters, the 3rd and 4th columns report the properties of aggregate employment. The remaining columns show wages investment and consumption.

[Table 21 About Here]

Let us briefly comment on the patterns documented in the table: Note that the volatility of aggregate employment is considerably lower under incomplete markets than it is under the complete market allocation. This is not surprising. In the complete market economy and without frictions the planner keeps the most productive agents in employment and adjusts over the cycle the threshold productivity. Changes in TFP have a substantial effect on this margin. In the case of incomplete markets however, the composition effects derive (also) from household wealth. This mitigates the effects of TFP shocks because households become poorer during recessions. Because of the lower volatility in the incomplete market models, aggregate wages now become strongly procyclical since they are influenced mostly by TFP.

It is well known (see for example Gurio and Noella (2006)) that neoclassical models with heterogeneity can generate large fluctuations in the labor market, if the distributions are such that a large number of individuals are indifferent between employment and non-employment (the wage is close to their reservation wage). This happens in the case of the complete market allocation, but not under incomplete markets. Note, however, that the results in the table, confirm that across all models the employment population ratio is very procyclical. As discussed in text this means that labor force participation is also strongly procyclical.

Table 22 shows the calibrated parameters and business cycles properties of aggregate consumption, wages and investment in the case of the log utility model. The moments are very similar to those reported in Table 11 in the main text. Therefore the specification of utility is not important for the business cycle behavior of the models more broadly.

In Figure 10 we show the wealth distributions under the benchmark model (solid lines) and the log utility model dashed lines. The top panels refer to the bachelor economy; on the left we show the distributions conditional on the individuals being employed, on the right we show the analogous objects when the individual is not employed. In the bottom panels we show the wealth distributions and denote with the symbol S on each graph the joint status of the household members for each sub-figure. Note that when we assume log utility the wealth distributions do not change significantly relative to the benchmark model. This proves the claim we made in text.

[Tables 22 and 23 About Here]

[Figure 10 About Here]

Finally, Table 23 shows additional output from the model of Section 7.2.

12.2 Modelling Retirement Income

We now extend the baseline version of the model to include positive income in retirement We only consider the impact of this feature in the case of incomplete markets; under complete markets all income in the economy is pooled hence retirement benefits do not matter at all for the optimal allocation.

We add retirement income to the model assuming a constant replacement ratio over average labor income. All workers in the economy receive the same level of benefits.[47] To finance the benefits we assume that a constant (payroll) tax is levied on the employed population. Following Conesa and Krueger (2006), we assume that the tax rate is equal to 12.5% in the steady state. The government runs a balanced budget. We find that in steady state the level of benefits in this economy is equal to 80% of the average income in the economy. Note that though this is a large number, we wish to show here that the inclusion of retirement income to the model does not alter our conclusions. Since we will prove that with zero benefits and with very large benefits the behavior of the models is very similar, the same principle will hold if we target a level of income from social security between the two extremes.

When we move to the economy with aggregate fluctuations we assume that the government holds the payroll tax and the level of benefits constant. The excess of tax revenues over benefit payments in economic expansions becomes government savings. In recessions, the opposite holds, the government runs a deficit and this deficit leads to debt accumulation. In the long run the government's intertemporal budget is balanced.[48]

In Table 24 we show the business cycle properties of the model with social security. The parameters $p(\overline{s}, \lambda_s)$,$p(\underline{s}, \lambda_s)$ and $\chi(\lambda_s)$ are as in the baseline version of the model. The preference parameters are again recalibrated to hit the targets. For the sake of brevity we only present the results from the dual earner household model. The results are very similar to the benchmark calibration. We now get that the relative standard deviation of participation is 0.29 and the correlation coefficient with GDP is 0.29.

Note that assuming positive retirement income does not impact the behavior of the economy significantly, because the duration of retirement in the model is not as large as in the data (this also explains why the replacement ratio is high, given that the payroll tax is realistically calibrated). We have chosen the probability ϕ^A to match the retired population, but since our model's demographic structure is too simplistic we obtained $\phi^A = 0.0507$. This means that on average individuals spend less than 20 months in the retirement state. Hence, even in the absence of any social social security income, individuals do not over-save in the model to buffer the retirement shock.

[47] This is a simplification made for computational purposes. Since ours is essentially an infinite horizon model it is difficult to keep track of the lifetime earnings of individuals (some individuals become retired after a few periods and others after many periods).

[48] Payroll taxes in the US have been roughly constant over time and the business cycle. Tax changes happened in response to changes in the demographic structure of the US population. These factors are left outside the model. Moreover, social security since the 1980s has invested its surpluses in long term government debt (the so called social security Trust fund). The objective is clearly to smooth taxes over time.

[Table 24 About Here]

12.3 Increasing the Persistence of Shocks.

In the baseline model we had calibrated the idiosyncratic income process using the empirical estimates of Chang and Kim (2006). This gave us $\rho_\epsilon = 0.78$ and $\sigma_\epsilon = 0.331$. We now report the robustness of our findings to higher values of ρ_ϵ. We consider the following three cases $\rho_\epsilon \in \{0.82, 0.85, 0.88\}$. In each case (following Aiyagari (1994)) we adjust the variance of the innovation (σ_ϵ^2) to keep constant the unconditional variance of the ϵ process.

Let us first explain the impact from having a more persistent process: Suppose that in the family it holds that $\epsilon_1 > \epsilon_2$. Suppose further that $\rho_\epsilon \approx 0$. In this case, the family becomes indifferent between having agent 1 in the labor market or agent 2. When shocks are i.i.d there is no advantage from having agent 1 unemployed and agent 2 our of the labor force even if today $\epsilon_1 > \epsilon_2$. In the next period when new shocks are drawn, agent 1 and agent 2 will have on average the same productivity. Now suppose that $\rho_\epsilon \approx 1$. In this case any difference in productivity between the household members is magnified in terms of the permanent income. The family strictly prefers to have agent 1 in the labor market.

This intuition applies when we increase ρ_ϵ. Because the gap in terms of permanent income now becomes larger, for any realization of (ϵ_1, ϵ_2), the added worker effect decreases in the model. This leads to a smaller number of households that benefit from the joint labor supply insurance channel than in the US data (see section 4 for details), if we hold all other model parameters constant. We therefore have to adjust some parameters to make the models consistent with the patterns we saw in section 4.

There are two ways to resolve this: i) we can increase the correlation of the shocks within the household, and ii) we can increase the probability $p(\underline{s}, \lambda_s)$ to hit the targets. We choose to do the latter.[49] In the case where ρ_ϵ equals 0.82 we found that a value $p(\underline{s}, \lambda_s) = 0.18$ is needed to generate entry rates into the labor force similar to the rates documented in the baseline model.[50] When $\rho_\epsilon = 0.85$ we have to set $p(\underline{s}, \lambda_s) = 0.20$, and when $\rho_\epsilon = 0.88$ we need $p(\underline{s}, \lambda_s) = 0.24$.

[Table 25 About Here]

The business cycle behavior of aggregate employment, unemployment and participation are displayed in Table 25. The top panel in the table shows the correlation between the labor market aggregates and GDP. The bottom panel shows the relative standard deviations. Note that across all versions of the couple model, the correlation of the labor force with GDP is in line with the data. We get 0.25 when $\rho_\epsilon = 0.82$, 0.27 when $\rho_\epsilon = 0.85$ and 0.17 when $\rho_\epsilon = 0.88$. The standard deviation of participation is low, again consistent with the data moments. These results suggest that higher values of ρ_ϵ produce similar moments as under the benchmark model.

[49] As discussed previously, the correlation of wages within US households is around 0.3 (e.g. Hyslop (2001)). The probability $p(\underline{s}, \lambda_s)$ was calibrated to 0.16 to produce a transition rate for the most productive out of the labor force individuals (non-searchers) in line with the data. Therefore, both changes violate some target. However, when we increase the correlation of shocks within the household, we obtain a counterfactually low fraction of *EO* households. For example, when the correlation becomes 0.4, 21% of families are in state *EO*. The data number is 27%. When we increase the $p(\underline{s}, \lambda_s)$ probability we obtain numbers closer to the data. For instance, in the case where $\rho_\epsilon = 0.88$ and $p(\underline{s}, \lambda_s) = 0.24$ we get 26.8% of families in the *EO* state. The other two calibrations are between the baseline output and the data moment.

[50] The preference parameters have been recalibrated for every model; for the sake of brevity we omit the values.

12.4 Primary and Secondary Earners

We now further explain how we computed the business cycle moments for primary and secondary earners reported in text and also show the effect of increasing the correlation coefficient ρ_ϵ. on these moments

As discussed in text, to create the moments, we used the average productivity $\bar{\epsilon}^i \equiv \sum_s \epsilon_s^i \frac{1}{s+1}$ of each individual letting $s = 0, 1, 2, ...T_R$. s has an impact on the moments. For instance, if we maintain $s = 0$ (using current productivity only to determine primary and secondary earners) then the baseline model yields the following; i) a value $\rho_{LF,Y}$ equal to -0.44 for secondary earners (and $\rho_{LF,Y} = 0.94$ for primary earners) ii) a ratio $\sigma_{LF,Y}$ equal to 0.61 for secondary earners and iii) and employment rate of secondary earners not correlated with GDP (and a volatility ratio of 0.61). The model thus exacerbates the differences between primary and secondary earners. The other extreme is to set $s \to \infty$. In this case, the cyclical behavior of primary and secondary earners is identical to the aggregate behavior.

As we explained in text, the right approach to construct the moments, is to account for the fact that households differ in s. Some households retire after one period hence $s = 0$ for them, others retire after many years and therefore s is a large number. In our calculation we took this into account and averaged across households, to construct a representative population.

To be precise we defined a lottery $\tilde{\omega}(\epsilon, s)$, the probability that the member with the highest productivity today (given the levels ϵ) is the primary earner in terms of average productivity between today (period 0) and period s. To obtain $\tilde{\omega}(\epsilon, s)$ we used Monte Carlo simulations. We then averaged across s using as weights the retirement probabilities. For $s = 0$ the weight is $\frac{1}{\sum_s^\infty (1-\phi_R)^{s-1}}$, for $s = 1$ it is $\frac{1-\phi_R}{\sum_s^\infty (1-\phi_R)^{s-1}}$ and so on. We then construct the probability $\tilde{\tilde{\omega}}(\epsilon) = \sum_s \frac{(1-\phi_R)^{s-1}}{\sum_j^\infty (1-\phi_R)^{j-1}} \tilde{\omega}(\epsilon, s)$.

In the numerical solution of the model we defined the E-pop ratios for primary earners as follows: 1) We take the E-pop ratio for all households with the same ϵ (i.e. integrating over the wealth grid). 2) If we only consider the current productivity we have: if $\epsilon^1 > \epsilon^2$, then the quantity $E{-}pop^{primary,*}(\epsilon)$ is the employment population of agents 1 in the model and $E-pop^{secondary,*}(\epsilon)$ is the ratio for agents 2. To construct the E-pop ratios based on average productivity we define $E - pop^{primary}(\epsilon, s) = \tilde{\tilde{\omega}}(\epsilon) E{-}pop^{primary,*}(\epsilon) + (1 - \tilde{\tilde{\omega}}(\epsilon)) E{-}pop^{secondary,*}(\epsilon)$. In other words, we take the weighted average of the E-pop ratios based on current productivity only. Mathematically this is equivalent to simulating populations and looking ex post at the realized productivities of the individuals. However, since we solve the model using the approach of Young (2010) to avoid sampling errors, we work with histograms rather than simulate panel data of households. This is why we need use the approach just above.

In Table 26 we show the behavior of primary and secondary earners when we assume $\rho_\epsilon = 0.88$. As the table shows we now obtain i) $\rho_{LF,Y} = -0.37$ for secondary earners (vs. -0.23 in the data) ii) a ratio $\sigma_{LF,Y}$ equal to 0.38 for secondary earners (vs. 0.41 in the data). iii) the correlation coefficient between employment and GDP is 0.58 (0.57 in the data) and iv) a ratio $\sigma_{E-pop,Y} = 0.53$ (0.45) in the data.[51] The basic patterns which we saw under the benchmark calibration remain.

[Table 26 About Here]

[51] Note that with a higher value of ρ_ϵ the horizon s matters less for these moments. This is because with the higher persistence the identity of the main earner of the value changes less frequently. When $\rho_\epsilon = 0.88$ we obtain very similar implications if we use only the $s = 0$ values.

12.5 Reducing the variance of separation shocks.

In this subsection we document the behavior of the models when we reduce the importance of χ shocks in aggregate fluctuations. As discussed in text, in the baseline version we assumed that χ takes four values uniformly distributed in the interval $[0.72\chi_s, 1.28\chi_s]$. We now experiment with the following two calibrations of separation shocks: i) we set $\chi_t = \chi_s = 0.02\ \forall t$ and ii) we let χ_t fluctuate within the interval $[0.86\chi_s, 1.14\chi_s]$ (again assuming a uniform distribution of the nodes).

Note that assumption i) is typical in the literature of search and matching models (e.g. Pissarides (1984, 2000)).[52] Therefore, it is worth investigating the behavior of the model when we make this assumption.

[Table 27 About Here]

In Table 27 we show the model output, summarized (for brevity) in the moments of 4 variables: employment, unemployment, participation and the EU flow rate. There are several noteworthy features: Consider first the top panel of the table which shows the case of constant separations. We see that across all models the volatility of aggregate employment has dropped, and labor force participation has become less procyclical. In the case of complete markets, the contemporaneous correlation between the labor force and output is 0.68, in the bachelor economy it is 0.52, and in the case of the dual earner household model it becomes very negative (-0.48). Moreover, note that the volatility of the participation margin remains large in the case of bachelors and complete markets (0.48 and 0.52 respectively); it is closer to the data moment in the case of couples (0.34).

To explain these findings note that under the benchmark model, the increase in separations during recessions increased the outflow of individuals from the labor force. This was due to the fact that many agents are non-searchers (they drop out of the labor force when a χ shock arrives); it was also due to the fact that many non-employed individuals quit unemployment during recessions to flow to O because the expected search costs are larger. Keeping separations constant, therefore, reduces the importance of these margins. In the case of couples, constant separations also mean that secondary earners can hold on to their jobs for longer periods. This contributes towards making the participation for these individuals even more countercyclical; we now observe a very negative correlation between the labor force and GDP.

In the 4th row of the table we show the cyclical behavior of the EU rate. We see, that in the case of the bachelor and the complete market models the transitions from employment to unemployment become procyclical. In the case of couples the opposite holds; the flow remains countercyclical because secondary earners join the labor force during recessions.

These results do not contradict our conclusions in text. We cannot (for instance) claim that the bachelor model now matches (quite well) the data patterns for several reasons: First, because the flow from E to U is counterfactual. Second, because even though the correlation between GDP and participation has dropped, the correlation between employment and the labor force remains very high. In particular, we obtain a correlation coefficient exceeding 0.9 in the case of the bachelor and

[52] In these models, when separations are endogenous, the correlation between unemployment and vacancies becomes positive. In the data this correlation is (at business cycle frequency) very negative. This is the main reason why constant separations provide a useful benchmark. However, note that assuming constant separations in our model is counterfactual; as we illustrate in this section the EU rate becomes procyclical when $\chi_t = \chi_s$.

the complete market models. The analogous statistic in the couples economy is 0.53 and, therefore, lower than the data moment (0.69).

12.6 Welfare costs of fluctuations in the cross section

We now discuss further the welfare costs of business cycles in the models. In Figure 11 we show the cross sectional standard deviation of the log of household consumption in the couple model and the bachelor model. The figure shows the behavior of this statistic over 100 periods. Between periods 1-51 the economy is in the high TFP state (expansion); then TFP drops and the economy is in recession. The figure shows that the standard deviation is larger in the case of the bachelor economy. Moreover, in both models the dispersion of consumption increases during recessions. This can be explained by the fact that employment risks are larger during recessions.

To give better sense of the magnitudes of consumption differences across households, in Figure 12 we show the cross sectional distributions of consumption (summarized in terms of percentage deviations from the mean) in the two models. Note that a few households have a consumption level 100 percent above the mean; however, many (poor) households consume much less than the mean value.

[Figures 11 and 12 About Here]

In Table 28 we document the cross sectional patterns of the welfare costs of fluctuations. Notice that individuals near the borrowing constraint (first two columns in the table) suffer more from fluctuations. In the model these are households that want to find jobs (they are unemployed) but during economic downturns cannot. This means that recessions are particularly painful to these households. The first column shows that for households at the bottom 1% of the wealth distribution, the compensating variation is substantial (1.55% for couples and 2.47% for singles). The difference in the numbers across the models can be explained by the fact that wealth poor couples, can insure against the risk of fluctuations better through joint search. The same pattern is documented in the second column which shows the costs for families at the bottom 5% of the wealth distribution. The third column considers the case of households which are between the 25th and the 75th percentiles. For these families fluctuations matter even less.

Notice that as we move up the wealth distribution (top 5% - 4th column and top 1%- 5th column) the bachelor model predicts that welfare costs increase, the couple model predicts the opposite.[53]. To understand this pattern note that in the economy with bachelor households, the top percentiles of the wealth distribution consist mostly of very productive agents, who wish to remain employed and accumulate large amounts of wealth. These assets are then used to buffer shocks to productivity, retirement and employment. For these individuals losing their jobs is particularly painful; it robs them from the opportunity to build a buffer stock of savings. This explains the pattern for bachelor households. In the case of couples, however, joint search can help mitigate these risks. First, because the precautionary savings motive is less urgent (as we previously established), and second because, joint search makes employment risks more moderate (in particular in families where both members are productive).

[53] Obtaining non-monotomic patterns of business cycles costs across the wealth distribution is very common in models of heterogeneous agents and wealth accumulation.

Table 21: No frictions: Parameters and Business Cycle Moments

	Preferences		*Business Cycle Moments*							
	β	η	E-pop		w		I		C	
			$\sigma_{E,Y}$	$\rho_{E,Y}$	$\sigma_{E,Y}$	$\rho_{E,Y}$	$\sigma_{U,Y}$	$\rho_{U,Y}$	$\sigma_{LF,Y}$	$\rho_{LF,Y}$
Couples	0.992	0.435	0.30	0.95	0.89	0.99	3.20	0.98	0.72	0.95
Bachelors	0.991	0.414	0.32	0.93	0.88	0.99	3.13	0.98	0.45	0.92
Complete Markets	0.996	0.475	1.63	0.89	0.88	-0.51	3.11	0.99	0.41	0.97

Notes: The table shows the specification of preferences and the business cycle moments (aggregate employment E, wages w, consumption c and investment I) in the three models where we assume no frictions. As discussed in text, the unemployment rate is not defined in this model, the civilian labor force coincides with aggregate employment. The preference parameters β and η are such that the models produce an $E - pop$ ratio of 62% in steady state.

Table 22: Log-Separable Utility: Parameters and Business Cycle Patterns

	Preferences			*Business Cycle Moments*					
	β	η	κ	w		I		C	
				$\sigma_{E,Y}$	$\rho_{E,Y}$	$\sigma_{U,Y}$	$\rho_{U,Y}$	$\sigma_{LF,Y}$	$\rho_{LF,Y}$
Couples	0.991	0.444	0.229	0.52	0.74	3.33	0.98	0.72	0.99
Bachelors	0.992	0.424	0.247	0.41	0.42	3.16	0.98	0.45	0.93
Complete Markets	0.996	0.509	0.252	0.43	-0.23	3.57	0.98	0.34	0.88

Notes: The table shows the specification of preferences and the business cycle moments for wages w, consumption c and investment I in the three models when we assume log-separable utility. The preference parameters β, κ and η are such that the models produce an $E - pop$ ratio of 62% and an unemployment rate of 6.2% in steady state.

Table 23: Changing the frictions: additional results

	κ	NS	E-pop		U-rate		LF		$\rho_{E-pop,LF}$	w		C		I	
			$\sigma_{E-pop,Y}$	$\rho_{E-pop,Y}$	$\sigma_{U-rate,Y}$	$\rho_{U-rate,Y}$	$\sigma_{LF,Y}$	$\rho_{LF,Y}$		$\sigma_{w,Y}$	$\rho_{w,Y}$	$\sigma_{C,Y}$	$\rho_{C,Y}$	$\sigma_{I,Y}$	$\rho_{I,Y}$
$p\left(\underline{s},\bar{\lambda}\right)=0.19$															
Couples	0.17	0.080	0.67	0.87	8.03	-0.94	0.25	0.09	0.54	0.53	0.77	0.75	0.99	3.11	0.99
Bachelors	0.17	0.081	0.84	0.93	7.94	-0.93	0.40	0.78	0.93	0.39	0.58	0.52	0.96	2.88	0.98
Complete Markets	0.19	0.071	0.94	0.90	9.28	-0.95	0.41	0.50	0.81	0.43	0.34	0.37	0.93	3.38	0.99
$p\left(\underline{s},\bar{\lambda}\right)=0.22$															
Couples	0.05	0.071	0.66	0.87	8.58	-0.95	0.24	-0.13	0.36	0.54	0.79	0.75	0.99	3.10	0.99
Bachelors	0.06	0.072	0.79	0.92	8.57	-0.94	0.30	0.78	0.94	0.40	0.66	0.51	0.96	2.89	0.98
Complete Markets	0.07	0.066	0.95	0.89	9.62	-0.96	0.48	0.42	0.89	0.47	0.33	0.37	0.94	3.38	0.99
$p\left(\underline{s},\bar{\lambda}\right)=0.25$															
Couples	0.02	0.063	0.66	0.86	9.08	-0.95	0.25	-0.33	0.16	0.54	0.79	0.75	0.99	3.11	0.99
Bachelors	0.02	0.064	0.80	0.90	9.16	-0.95	0.31	0.64	0.90	0.44	0.62	0.51	0.96	2.90	0.98
Complete Markets	0.02	0.057	1.06	0.90	9.85	-0.95	0.59	0.66	0.90	0.45	0.10	0.37	0.94	3.36	0.99

Notes: The table shows the results of the three models when the probability of receiving a job offer for out of the labor force individuals is increased. The benchmark value is 0.16 which is chosen to match the flow rate of non searchers, which is 0.153 in the data.

Table 24: **Business Cycle Properties-Retirement Income Model**

	E-pop		U-rate		LF		w	
	$\sigma_{E-pop,Y}$	$\rho_{E-pop,Y}$	$\sigma_{U-rate,Y}$	$\rho_{U-rate,Y}$	$\sigma_{LF,Y}$	$\rho_{LF,Y}$	$\sigma_{w,Y}$	$\rho_{w,Y}$
Couples baseline	0.72	0.87	7.48	-0.96	0.29	0.32	0.52	0.73
Couples with benefits	0.74	0.88	7.53	-0.95	0.29	0.29	0.49	0.86

Notes: The table shows the behavior of labor market aggregates (employment, unemployment rate and LF participation) when we assume a positive income for retired individuals. The moments refer to the baseline couple model.

Table 25: **Business Cycle Properties -More Persistent Shocks**

		$\rho_\epsilon = 0.82$	$\rho_\epsilon = 0.85$	$\rho_\epsilon = 0.88$
$\rho_{x,Y}$	E-pop	0.89	0.91	0.92
	U-rate	-0.95	-0.95	-0.95
	LF	0.25	0.27	0.17
$\sigma_{x,Y}$	E-pop	0.73	0.75	0.77
	U-rate	8.07	8.52	9.21
	LF	0.25	0.22	0.19

Notes: The table shows the business cycle behavior of employment, unemployment and participation when we increase the persistence of idiosyncratic productivity shocks.

Table 26: **Business Cycle Properties -Primary and Secondary Earners**

		A: Primary Earners			*B: Secondary Earners*		
		E-pop	U-rate	LF	E-pop	U-rate	LF
$\rho_\epsilon = 0.88$	$\rho_{x,Y}$	0.98	-0.96	0.88	0.58	-0.94	-0.37
	$\sigma_{x,Y}$	1.03	9.41	0.19	0.53	8.87	0.37
Baseline	$\rho_{x,Y}$	0.95	-0.95	0.73	0.63	-0.92	-0.10
	$\sigma_{x,Y}$	0.89	7.75	0.27	0.58	7.12	0.38

Notes: The table shows the cyclical properties of employment, unemployment and participation of primary and secondary earners. $\rho_{x,Y}$ is the contemporaneous correlation of variable x with GDP. $\sigma_{x,Y}$ is the ratio of standard deviations between x and Y.

Table 27: **Business Cycle Properties - Lower Variance of χ shocks**

		Couples	Bachelors	Complete
		A: Constant Separations		
$\rho_{x,Y}$	E-pop	0.59	0.82	0.87
	U-rate	-0.93	-0.92	-0.94
	LF	-0.48	0.52	0.68
	EU flow	-0.83	0.85	0.32
$\sigma_{x,Y}$	E-pop	0.50	0.79	0.89
	u-rate	6.60	6.56	6.43
	LF	0.34	0.48	0.52
	EU flow	5.78	3.77	1.44
		Low Variance Separations		
$\rho_{x,Y}$	E-pop	0.79	0.88	0.91
	U-rate	-0.94	-0.92	-0.95
	LF	-0.03	0.68	0.78
	EU flow	-0.89	0.24	-0.79
$\sigma_{x,Y}$	E-pop	0.61	0.88	0.97
	U-rate	7.09	6.90	7.07
	LF	0.29	0.51	0.54
	EU flow	4.95	2.03	2.34

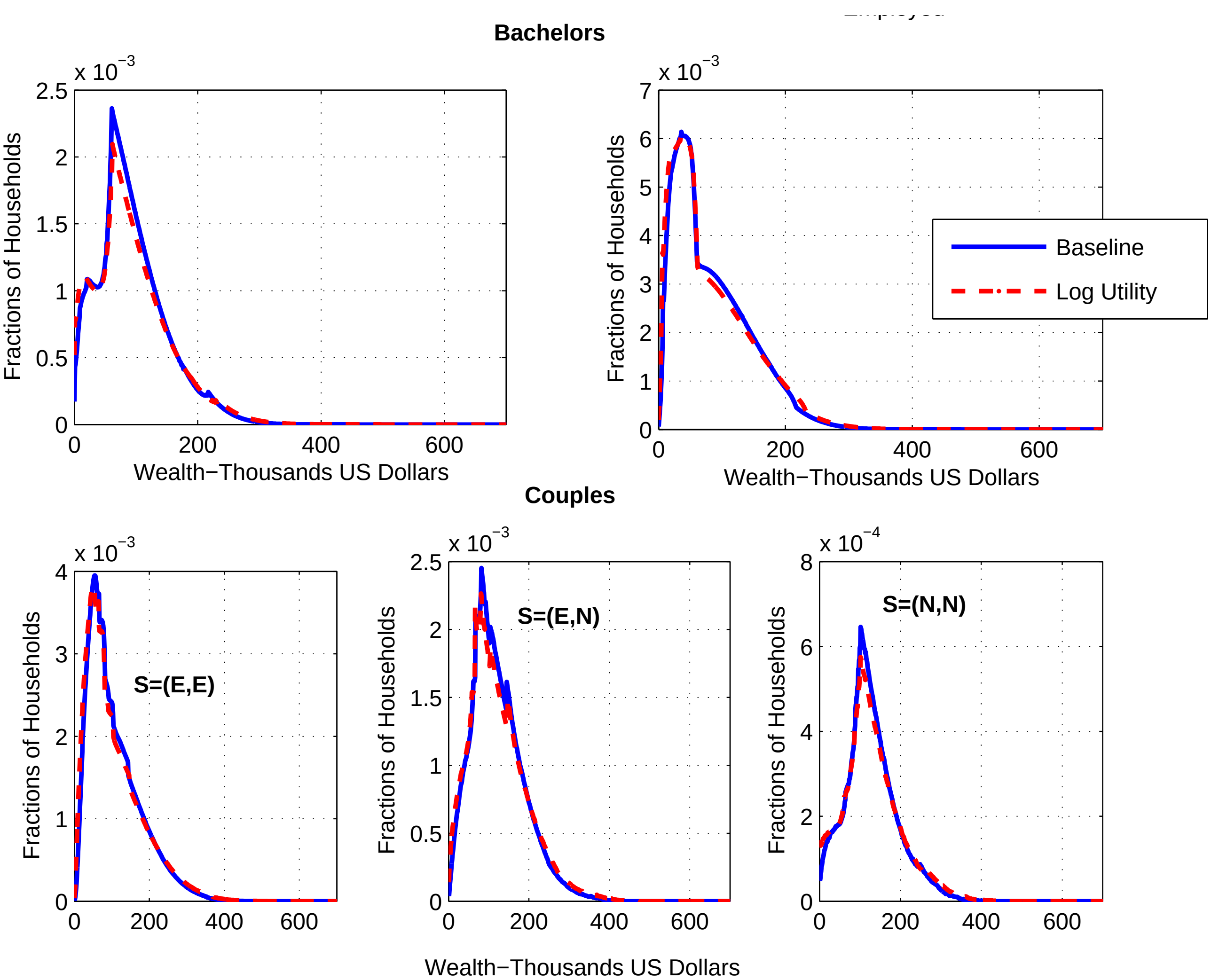
Notes: The table shows the cyclical behavior of labor market aggregates in model simulations when we assume that separation shocks i) are constant over the cycle (top panel) and ii) have 50% of the variance in the benchmark calibration (bottom panel). All data are log and HP filtered. $\rho_{x,Y}$ is the correlation of x with GDP. $\sigma_{x,Y}$ is the relative standard deviation. *EU* flow is the transition probability from employment to unemployment.

Table 28: Welfare Costs of Business Cycles

	99%	95%	75%	75%-25%	$\geq 5\%$	$\geq 1\%$
Couples	1.55%	1.19%	0.97%	0.79%	0.71%	0.68%
Bachelors	2.47%	1.58%	1.01%	0.85%	1.31%	1.45%

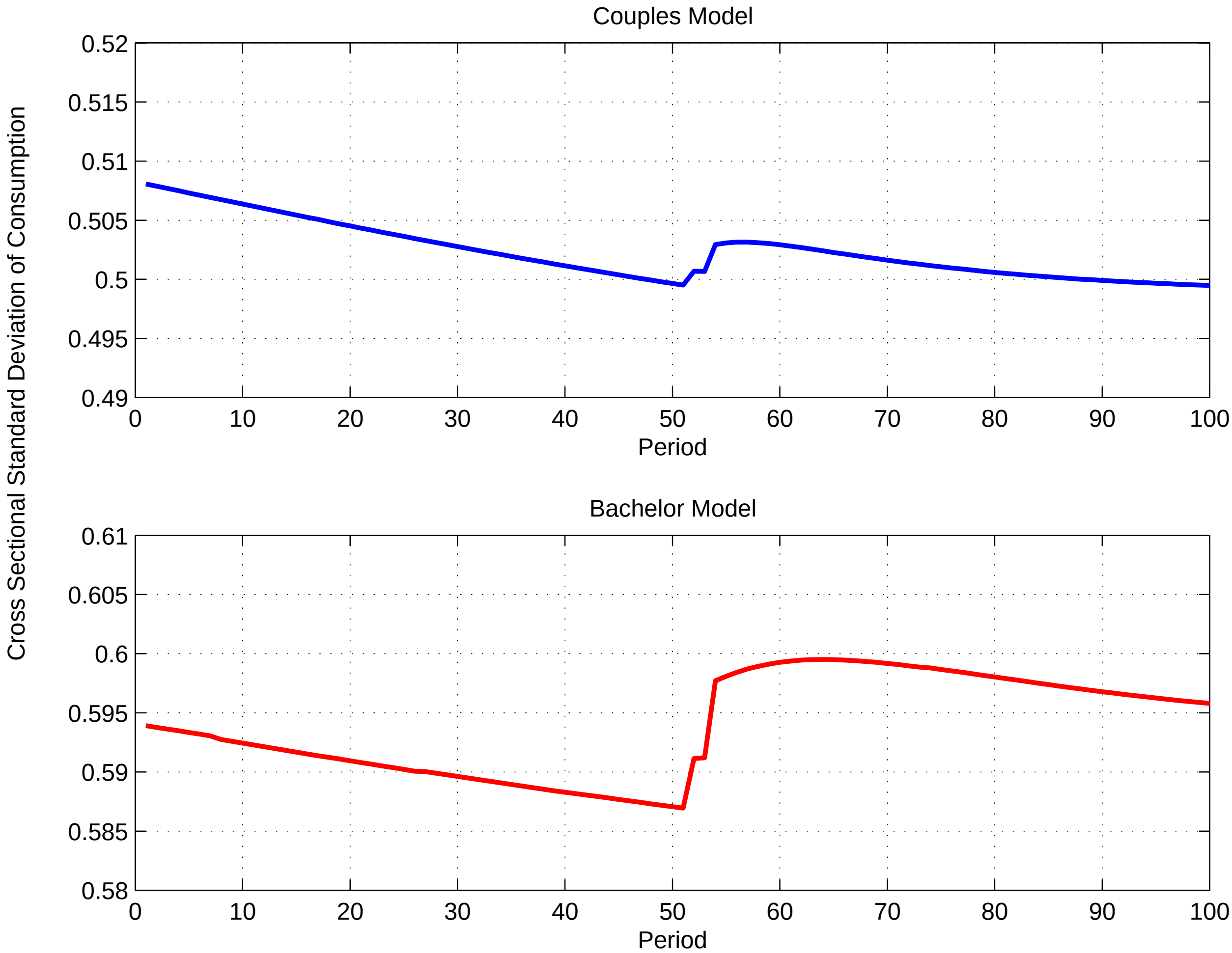
Notes: The table shows the welfare cost of business cycles for individuals at different parts of the wealth distribution. 99% (95%, 75%) represents households who are at the bottom 1 percent (5 percent, 25 percent) of the wealth distribution. 75%-25% is households between the 25th and 75th percentiles. $\geq 5\%$ ($\geq 1\%$) is households at the top 5 (1) percent of the wealth distribution. The welfare costs are calculated using the formula discussed in section 7.5 in text. For each subgroup we have computed the compensating variation the increment in consumption that individuals require to be as well off in an economy with business cycles, as without fluctuations.

Figure 10: Wealth Distributions: Benchmark Model vs. Log Utility



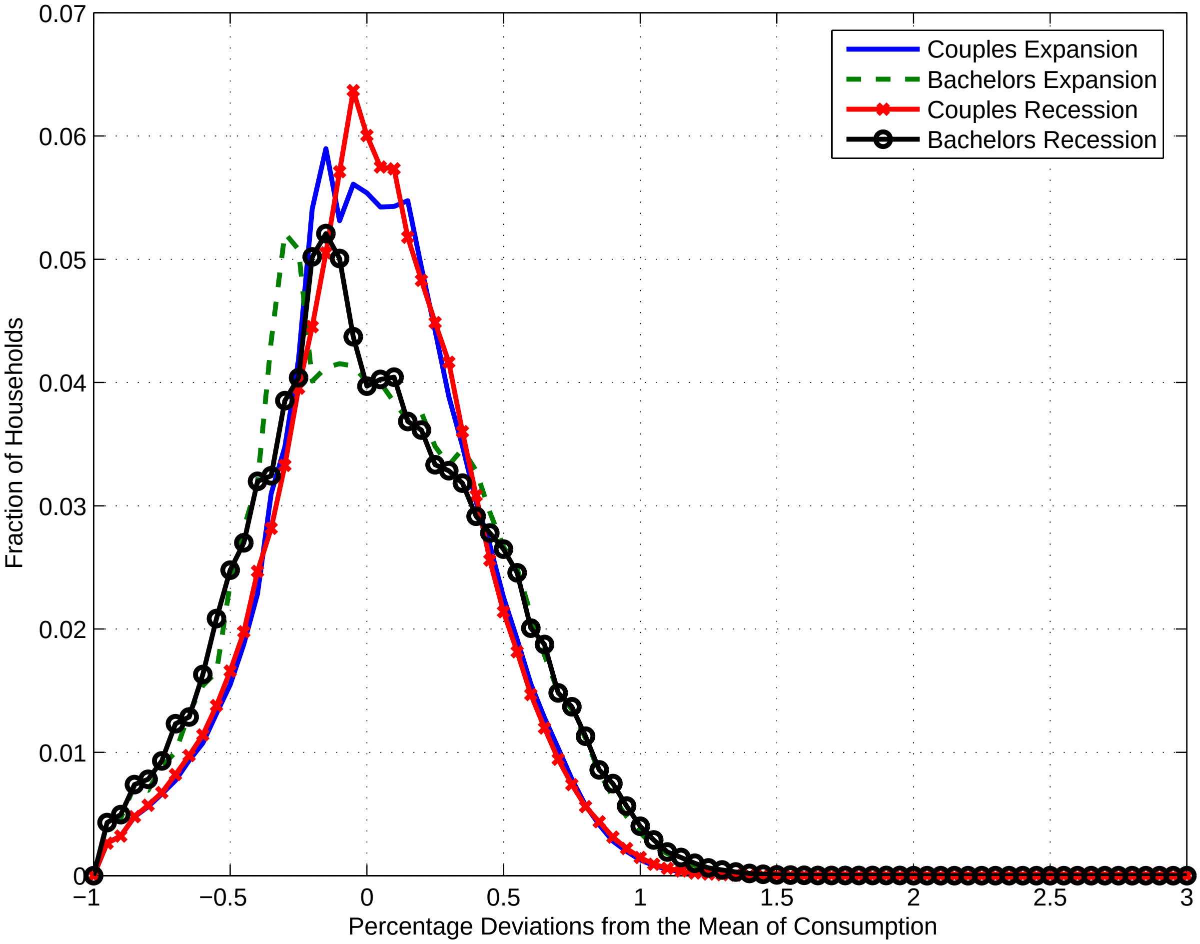
Notes: The figure plots the steady state distributions of wealth in the benchmark model (solid line) and the log utility model (dashed line) for the bachelor and the couple households models. The top graphs (left and right) show the case of bachelors. The top left panel shows the wealth distribution for employed households and the top right the distribution for non-employed households. The bottom graphs represent the couple model. The joint status of household members in this case is denoted on each graph.

Figure 11: Standard Deviation of Consumption: Bachelors vs. Couples



Notes: The figure plots over 100 model periods the cross sectional standard deviation of consumption in the couple model (top panel) and the bachelor model (bottom). The sample is chosen as follows: Between periods 1 and 51 the TFP takes the highest possible value (the economy is in the expansion). From period 52 the value of TFP drops and the economy is in recession.

Figure 12: Cross-Sectional Distribution of Consumption Bachelors vs. Couples



Notes: The figure plots the cross-sectional distributions of household consumption (the graphs show deviations from the mean consumption) in the bachelor and the couple models, in recessions and expansions.