CENTER FOR HOUSEHOLD FINANCE AND MACROECONOMIC RESEARCH

Working Paper Series
No 5/2024

Joint Search over the Life Cycle

Annika Bacher, Philipp Grübener and Lukas Nord

Joint Search over the Life Cycle*

Annika Bacher
BI Oslo

Philipp Grübener
Goethe University Frankfurt

Lukas Nord
Minneapolis Fed

May 9, 2024

Abstract

This paper provides novel evidence that the added worker effect – labor force entry upon spousal job loss – is substantially stronger for young than old households. Using a life cycle model of two-member households in a frictional labor market, we study whether this age-dependency is driven by heterogeneous *needs for* or *availability of* spousal insurance. Our framework endogenizes asset and human capital accumulation, as well as arrival rates of job offers, and is diciplined against U.S. micro data. By means of counterfactuals, we find a strong complementarity across both margins: A large added worker effect requires both high spousal earnings potential (human capital) relative to the primary earner and limited access to other means of self insurance (assets). Together, both margins can account for the observed age differential in the added worker effect. The model predicts substantial crowding out of spousal labor supply by unemployment benefit extensions among young households, in line with their stronger need for spousal insurance.

Keywords: Unemployment, search, added worker effect, life cycle, family insurance
JEL: E21, E24, J24, J64

*Contact: annika.bacher@bi.no, gruebener@econ.uni-frankfurt.de, lksnord.econ@gmail.com. We are indebted to our advisors, Árpád Ábrahám, Russell Cooper, Thomas Crossley, Axelle Ferriere, and Philipp Kircher, for their continuous guidance and support. Moreover, we thank Mariacristina de Nardi, Nezih Guner, Christian Haefke, Todd Schoellman, our discussant Ben Griffy and participants at various seminars, conferences, and workshops for comments and suggestions that helped to greatly improve this work. All remaining errors are ours. This work was supported by computational resources provided by the BigTex High Performance Computing Group at the Federal Reserve Bank of Dallas and by the FUCHS-CSC cluster at Goethe University Frankfurt. This paper is part of the research activities at the Centre for Household Finance and Macroeconomic Research (HOFIMAR) at the BI Norwegian Business School. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

1 Introduction

The added worker effect (AWE) – labor force entry upon spousal job loss – is an important insurance margin for couple households. In this paper, we first provide evidence that the AWE is predominantly present among young households but limited among the old. We then develop a quantitative life cycle model of couple search to understand whether the observed age-dependency is driven by differences in the *need for* or *availability of* spousal labor supply as an insurance margin.

Different *needs* may arise because older households have other forms of private insurance, such as asset holdings, available to them. In contrast, older spouses may face stronger labor market frictions or have, relative to the household head, lower earnings potential due to extended periods of non-participation. In this case, spousal labor supply is *unavailable* as an insurance margin. Understanding which of these factors drives age differentials in the AWE is crucial to inform us about the welfare implications of the empirical patterns, the optimal provision of public insurance over the life cycle, and – in light of demographic change – to predict dynamics of the aggregate labor market in the future.

We begin by providing novel empirical evidence on the AWE over the life cycle, using monthly data for the United States from the Current Population Survey (CPS). On average across all age groups, the likelihood of a non-participating spouse entering the labor force increases by 5.9 percentage points, corresponding to a 77% increase, when a primary earner loses their job compared to when they remain employed. We find this effect to be strongly age-dependent. For the youngest age group (25-35), the likelihood of a non-participating spouse entering the labor force increases by 7.5 percentage points (87%) upon the job loss of the primary earner. Late in working life (age 56-65), the AWE is only 1.3 percentage points (25%). Among young households, job loss of the primary earner is associated with a significant increase in the likelihood of a non-participating spouse entering the labor force both directly to employment and unemployment, whereas old spouses transition mainly into unemployment. These findings are robust to the presence of children in the household, different reasons for being out of the labor force, when considering only one cohort, and over the business cycle.

Further heterogeneity analysis reveals that the AWE is stronger for low wealth households – who cannot rely on assets for self-insurance – and among spouses with a college degree – who face better labor market prospects.[1] These findings suggest a role for both the *need for* and *availability of* spousal insurance in determining the AWE. However, as both assets and labor market prospects are endogenous to households' employment choices over the life cycle, we rely on a model to identify the forces driving the age gradient in

[1] As the CPS does not contain asset data, we rely on the Survey of Income and Program Participation (SIPP) when computing the AWE by wealth.

the AWE. We develop a structural life cycle framework of couples' joint labor supply in a frictional labor market and employ it to evaluate the relative importance of each channel through counterfactuals.

In the model, a household consists of two members, each of whom can be either employed, unemployed (and actively searching for a job), or out of the labor force. The labor market is frictional; an individual can only take up employment if they have a job offer. While out of the labor force or unemployed, individuals can receive job offers. Choosing unemployment over being out of the labor force increases the chance of finding a job through costly search. Employed individuals can quit their job and additionally face the risk of involuntary separation. Human capital is accumulated while employed but depreciates during non-employment. A couple can jointly save in a risk-free bond. Job arrival rates are determined endogenously as the solution to a vacancy posting problem of single-worker firms in markets segmented by households' state vector.

These model ingredients allow us to isolate the different candidate explanations for the age dependency in the AWE. Incomplete asset markets give rise to precautionary savings which are a key alternative insurance mechanism against individual unemployment risk. By generating the life cycle profile of savings the model can speak to whether differences in asset holdings between young and old are sufficient to explain the difference in the observed AWE. On the other hand, human capital formation and endogenous arrival rates allow for the possibility that older spouses might have fewer opportunities to provide insurance against job loss of the household head. Human capital differences across household members widen endogenously during long spells of household specialization and firms are less willing to hire older individuals as there is less time remaining to recover hiring costs before their entry into retirement.

We calibrate the model to match key features of the U.S. labor market as well as income and asset profiles over the life cycle. For the labor market, we focus on matching average transition rates and life cycle patterns of the joint distribution of couples across labor market states. For income, we target average income across age groups and wage losses after non-employment spells. For assets, we target median asset holdings across age groups. The model reproduces well untargeted labor market transitions by age group. In line with the data, the model generates an average AWE of 5.4 percentage points, which is strongly declining from 9.5 percentage points at ages 25-35 to 1.3 percentage points at ages 56-65.

By means of counterfactuals, we quantify the relative contribution of age differences in asset holdings and human capital levels, and the effect of age itself in accounting for the declining AWE over the life cycle. We simulate the AWE for counterfactual distributions of young and old workers over the state space, equating their characteristics to those of the respective other age group one margin at a time. To isolate the effect these changes have on job arrival rates, we consider two alternative scenarios for each margin: only adjusting household decision rules while keeping job arrival rates constant as well as simultaneously adjusting decision rules and arrival rates.

When adjusting separately young households' asset levels or the human capital levels of either spouse to match those of the old, their AWE declines. Differences in arrival rates amplify the effect of differences in human capital. Combining the effect of asset holdings, human capital, and arrival rates reduces the AWE among the young to 2.8 percentage points, accounting for almost the entire difference to the old. Assigning old households either the asset holdings or human capital levels of the young has a more limited impact on their AWE. Especially when shutting down the response of arrival rates to changes in households' characteristics, the AWE of the old changes little when we adjust each margin separately. Only when we assign old households simultaneously the asset and human capital levels of the young, need and availability interact and substantially increase the AWE of the old.

These patterns suggest a complementarity between the *need for* and *availability of* spousal labor supply as a margin of insurance. If we reduce either the need for or availability of spousal insurance among the young, their AWE declines. In contrast, unless we increase both the need and availability among the old, we do not find a large change in their AWE.

Finally, we use the model to study the interaction between public insurance in the form of benefit duration and private insurance in the form of spousal labor supply. When increasing the duration of unemployment benefits from six to twelve months, the aggregate AWE decreases from 5.4% to 3.8%. This reduction in the AWE is mostly concentrated among young households, suggesting that policy makers should pay close attention to the labor supply response of young individuals *and their spouses* when trading off the provision of public insurance in the form of benefit extensions against the crowding out of labor supply.

Related Literature. The AWE is widely studied in the empirical literature, going back to the seminal contribution of Lundberg (1985). The early literature following her paper based on U.S. data does not find much evidence supporting the presence of the AWE in the data (Maloney 1987; Maloney 1991). Rationalizing this finding, Cullen and Gruber (2000) provide evidence of crowding out of spousal labor supply as an insurance mechanism by generous unemployment insurance and transfers, exploiting cross-state differences in the U.S.

More recent evidence supports the presence of a sizable AWE in the U.S. Mankart and Oikonomou (2016b) and Mankart, Oikonomou, and Pascucci (2022) show that the AWE has become more important in the U.S. over the last decades. Stephens (2002) reports that the labor supply response of wives to their husbands' job losses compensates for more than 25% of the lost income, and Guner, Kulikova, and Valladares-Esteban (2021) and Casella (2022) find sizable extensive margin responses of out of the labor force women to job loss of the husband.[2] Expanding upon this work, we show that a key margin of heterogeneity in the AWE is the age dimension, with young couples relying more strongly on spousal labor supply as an insurance margin.

While the AWE has been studied extensively in the empirical literature, most of the macro-labor literature focuses on the job search problem of a single earner household. Guler, Guvenen, and Violante (2012) is among the first papers to study the joint search problem of a couple by extending the classic single-agent search problems of McCall (1970), Mortensen (1970), and Burdett (1978). The focus of the subsequent literature is mostly on business cycle dynamics. Mankart and Oikonomou (2016a) build a search model with two member households to explain the cyclical properties of employment and labor force participation.[3] Wang (2019) builds a model showing that joint household search is crucial for accounting for the countercyclicality of womens' unemployment rate. Ellieroth (2023) argues that there is precautionary labor supply by spouses whose partners face an increased job loss risk in recessions. Bardóczy (2022) and Casella (2022) focus on the role of spousal labor supply as an automatic stabilizer for aggregate consumption.

Flabbi and Mabli (2018), Pilossoph and Wee (2021), and Morazzoni and Smirnov (2023) study wage determination in joint search frameworks, comparing wage determination under individual search to household search and studying the marital wage premium. Dey and Flinn (2008) and Fang and Shephard (2019) examine the optimal provision of health insurance in joint search environments. Choi and Valladares-Esteban (2020), Birinci (2021), and Fernández-Blanco (2022) investigate the implications of joint search for optimal unemployment insurance. Relative to these papers, we focus on the life cycle

[2]In line with the U.S. data, cross-country evidence also supports that spousal insurance can be an important insurance margin for couples, but only if it is not crowded out by other margins. Bredtmann, Otten, and Rulff (2018) provide cross-country evidence from 28 European countries and the U.S. and conclude that the AWE is less important in countries with more generous unemployment benefits. Other single country studies align well with that finding: there is very little role for spousal labor supply as insurance margin in Sweden (Landais and Spinnewijn 2021), Denmark (Andersen, Jensen, Johannesen, Kreiner, Leth-Petersen, and Sheridan 2023), and Norway (Hardoy and Schøne 2014; Fagereng, Onshuus, and Torstensen 2024), a small AWE in Austria (Halla, Schmieder, and Weber 2020), and more sizable effects in Japan (Kohara 2010), Australia (Gong 2011), and Turkey (Ayhan 2018).

[3]Mankart and Oikonomou (2016a) also introduce asset accumulation into the joint search framework, building on the single agent search problem with asset accumulation as in Lentz (2009), Krusell, Mukoyama, and Şahin (2010), and Krusell, Mukoyama, Rogerson, and Şahin (2017). See also Garcia-Perez and Rendon (2020) who incorporate asset accumulation in a joint search framework, in which they study the AWE, but do not distinguish between unemployment and being out of the labor force.

dimension of the joint search problem to analyze whether the age-dependency in the AWE is explained by changing opportunities or changing insurance margins.

Life cycle search problems have been studied in the literature, but mostly in single earner frameworks. Chéron, Hairault, and Langot (2011) and Chéron, Hairault, and Langot (2013) extend the random search framework of Mortensen and Pissarides (1994) to a life cycle setting. Menzio, Telyukova, and Visschers (2016) build a directed search life cycle model in the tradition of Moen (1997) and Menzio and Shi (2011). Griffy (2021) extends their model by incorporating risk averse workers and borrowing constraints. Michelacci and Ruffo (2015) study optimal age-dependent unemployment insurance. More closely related to our paper, Haan and Prowse (2024) propose a structural life cycle model of labor supply, consumption, and savings of married couples. They focus on the optimal mix of unemployment insurance and social assistance but do not discuss the age-dependency of the AWE. Finally, the current paper is related to a number of studies analyzing life cycle labor supply decisions of couples in incomplete market frameworks without labor market frictions (Ortigueira and Siassi 2013; Blundell, Pistaferri, and Saporta-Eksten 2016; Wu and Krueger 2021).

Roadmap. The paper proceeds as follows. Section 2 contains the empirical evidence. Section 3 introduces the model. Section 4 contains the calibration and Section 5 the results. Section 6 concludes.

2 Empirical Evidence

We establish empirical evidence on the AWE over the life cycle using data from the CPS, provided by the Integrated Public Use Microdata Series (IPUMS) (Flood et al. 2020). We first outline the data and sample selection. Afterwards, we provide empirical evidence of the AWE in our sample and show that its magnitude is decreasing in age.

2.1 The Sample

The CPS is a monthly rotating panel which is representative of the U.S. population. Households enter the survey for four consecutive months, drop out for eight months, and are re-interviewed for another four months. In our setting, the unit of observation is a couple. We use data from 1994 until 2020 (pre-Covid) and restrict the sample to couples who are both between 25 and 65 years old. We include legally married and cohabiting couples, irrespective of their sex. For more details on variables and restrictions, see Appendix A.1.

2.2 Uncovering the AWE from Joint Labor Market Transitions

We follow the method of Guner, Kulikova, and Valladares-Esteban (2021) to calculate the AWE from the data. We apply the CPS classification as either *employed* (E), *unemployed* (U), or *non-participating* (N) at the individual level, yielding nine possible combinations of labor market states for a couple. In a next step, we pool all observations for couples with one employed and one non-participating member and compute their joint labor market transition probabilities. A previously employed spouse can either remain employed (EE transition), become unemployed (EU), or drop out of the labor force (EN). Non-participating spouses can either transition from non-participating to employment (NE), from non-participating to unemployment (NU), or remain out of the labor force (NN). We define the AWE as the change in the conditional probability of a spouse transitioning from non-participating to employment (NE) or from non-participating to unemployment (NU) if the primary earner becomes unemployed (EU) relative to when the primary earner remains employed (EE). Table 1 and Table 2 display our main results. In each table, the first two columns provide the conditional distribution of transitions for the non-participating spouse if the household's primary earner makes an employment-to-employment (EE) or employment-to-unemployment (EU) transition respectively. The AWE in the third column is computed as the difference between the first and second columns.

Overall Effect. Table 1 shows that the likelihood of a spouse entering the labor force increases by 5.9 percentage points (corresponding to a 77% increase relative to the baseline likelihood of labor force entry) if the primary earner becomes unemployed compared to when the primary earner remains employed, confirming the existence of the AWE in our sample.[4] This result is in line with Guner, Kulikova, and Valladares-Esteban (2021), who find an overall AWE between 7-8 percentage points with CPS data on a slightly younger sample (25 to 54 years). Zooming in on the precise margin of adjustment, we find that the conditional probability of a spousal transition directly into employment increases by 1.98 percentage points, whereas the conditional probability of a spouse transitioning into unemployment increases by 3.92 points. Thus, around two thirds of the overall AWE arise from individuals transitioning into unemployment, highlighting the importance of explicitly distinguishing between unemployed and non-participating individuals.

[4] For the AWE, we focus on transitions for out of the labor force spouses conditional on EE vs. EU transitions of the primary earner. In the appendix, Tables B.1, B.2, and B.3 report the conditional transition probabilities for primary earners' EN transitions and for unemployed and employed spouses, respectively. Unemployed spouses are slightly more likely to transition into employment or stay unemployed rather than leaving the labor force if the primary earner loses the job. However, evidence for insurance through spousal labor supply is strongest when considering out of the labor force spouses, which we focus on. We also observe couples re-optimizing their joint particiaption decision: The likelihood of a spouse dropping out of the labor force increases when the primary earner does the same.

Table 1: Added Worker Effect (Full Sample)

	Primary earner transition EE	EU	AWE
Cond. prob. of spousal NE transition	6.03%	8.01%	1.98%
Cond. prob. of spousal NU transition	1.63%	5.55%	3.92%
Cond. prob. of spousal NN transition	92.34%	86.44%	
AWE (total)			5.90%

Notes: Table 1 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions for the entire population of EN-couples. The AWE is computed as the EU minus the EE column.

For Table 1 we consider all EU transitions of the primary earner, including quits, permanent layoffs, temporary layoffs, and temporary jobs ending. We show in Table B.4 that the AWE is of similar magnitude when focusing only on permanent layoffs.

The Added Worker Effect by Age. In Table 2, we split our sample into four brackets by the age of the non-participating spouse and construct joint labor market transitions for each of these groups. The AWE is strongly age-dependent: For the youngest group (25 to 35 years), the likelihood that the spouse enters the labor force upon job loss of the primary earner increases by 7.53 percentage points (corresponding to an 87% increase relative to the baseline likelihood of labor force entry), for the young middle aged (36 to 45 years) by 7.10 percentage points (83%), for the older middle aged (46 to 55 years) by 5.00 percentage points (65%), and by only 1.29 percentage points (25%) for the oldest group (56 to 65 years).

For the young, we observe behavioral responses from non-participation directly into employment (2.64 percentage points) and unemployment (4.89 percentage points). For the oldest age group, we only find small behavioral responses into unemployment (1.85 percentage points) and no response directly into employment (-0.56 points), suggesting that the AWE is a weaker margin of insurance for older workers both through its lower magnitude and the smaller share of spouses transitioning directly into employment.[5]

2.3 Dynamic Response and Controls

So far, we have focused on the raw transition probability that a spouse enters the labor force in the *same month* as the head transitions into unemployment without including controls. Focusing on contemporaneous transitions may understate the overall strength of the AWE since spousal labor supply responses can occur in prior months through

[5]Table B.11 in Appendix B shows that the age pattern in the AWE is robust to restricting the sample to involuntary job losses only.

Table 2: Added Worker Effect by Age

	Primary earner transition EE	EU	AWE
Age Spouse 25-35:			
Cond. prob. of spousal NE transition	6.66%	9.30%	2.64%
Cond. prob. of spousal NU transition	2.00%	6.89%	4.89%
Cond. prob. of spousal NN transition	91.34%	83.81%	
AWE (total)			7.53%
Age Spouse 36-45:			
Cond. prob. of spousal NE transition	6.73%	9.32%	2.59%
Cond. prob. of spousal NU transition	1.86%	6.37%	4.51%
Cond. prob. of spousal NN transition	91.41%	84.31%	
AWE (total)			7.10%
Age Spouse 46-55:			
Cond. prob. of spousal NE transition	6.13%	7.96%	1.83%
Cond. prob. of spousal NU transition	1.62%	4.79%	3.17%
Cond. prob. of spousal NN transition	92.25%	87.25%	
AWE (total)			5.00%
Age Spouse 56-65:			
Cond. prob. of spousal NE transition	4.29%	3.73%	-0.56%
Cond. prob. of spousal NU transition	0.90%	2.75%	1.85%
Cond. prob. of spousal NN transition	94.81%	93.52%	
AWE (total)			1.29%

Notes: Table 2 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by age group. The AWE is computed as the EU minus the EE column.

anticipation or with delay. In addition, certain (household) characteristics such as the presence of children may drive part of the observed age-dependency. To account for these channels, we run the following linear regression specification on the sample of EN-couples:

$$\Delta LFS_{it}^{sp} = \alpha_j + \beta_j \Delta ES_{it+j}^{h} + \gamma_j X_{it} + \epsilon_{jit}, \tag{1}$$

where ΔLFS_{it}^{sp} is a dummy indicating whether the non-participating spouse of couple i transitions either into employment or unemployment between month $t-1$ and t. The term ΔES_{it}^{h} is defined as a dummy taking the value 1 if the primary earner transitions from employment into unemployment, and 0 if the head stays employed. Consistent with our definition of the AWE above, we drop couples in which the head transitions into non-participation. The vector of controls X_{it} includes month fixed-effects, year fixed-effects,

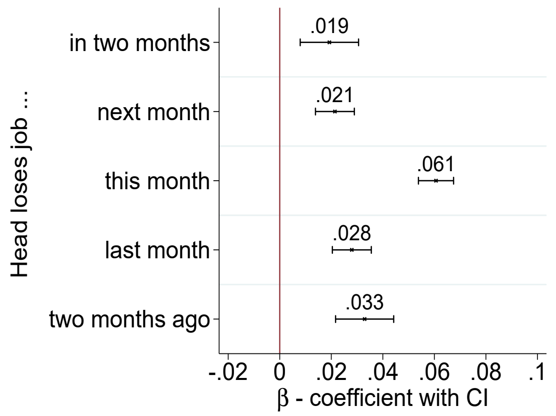


Figure 1: Δ Pr(Spouse enters LF) this month

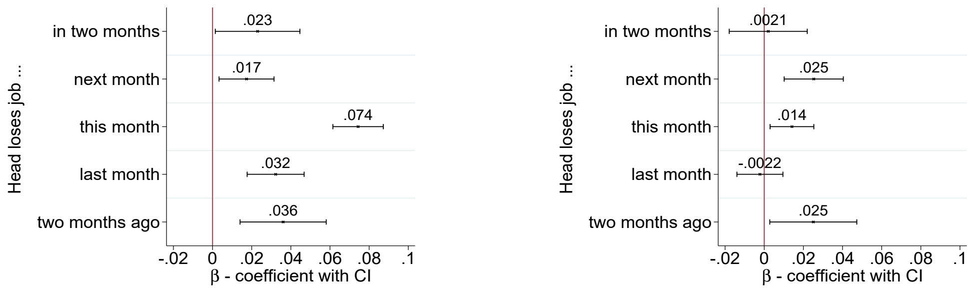
Notes: Figure 1 shows the change in probability that a non-participating spouse enters the labor force (either as unemployed or employed) if the household head loses/lost the job in two months, next month, this month, last month, or two months ago respectively, relative to the baseline in which the household head remains employed. The sample includes couples in which one spouse is working and one spouse is out of the labor force between age 25 and 65 from the Current Population Survey (CPS), waves 1994 until 2020. The regression producing the coefficients is Equation 1.

state fixed-effects, sex, race, education, children, and the quarterly unemployment rate in the couple's state of residence.

We run separate regressions for each lead and lag j. The coefficient β_j denotes the likelihood that the spouse enters the labor force in month t if the household head transitions into unemployment in month $t+j$ relative to when the head remains employed (i.e. the strength of the AWE at lead/lag j). The CPS observes the same couple for a maximum of three consecutive labor market transitions, limiting our analysis to $j = \{-2, -1, 0, 1, 2\}$. Figure 1 reports results for the entire sample of EN-couples, whereas we run regressions separately by age group in Figure 2.

Figure 1 shows that the strength of the AWE in the contemporaneous month increases slightly from 5.9 percentage points (Table 1) to 6.1 percentage points when controlling for household observable characteristics.[6] In addition, we find support of both anticipation and lagged effects, albeit of lower magnitude. Spousal labor supply responses in the months preceding and in the months after the primary earner's job loss are less than half as strong as the direct response. When splitting the sample by age (Figure 2), the contemporaneous effect is statistically significant for both reported age groups, however it is around five times stronger for the young than the old. Young households display both lagged responses and anticipation effects, whereas we cannot confirm any clear patterns for households between 56 and 65 years. We relegate the results for the two middle age

[6] It is possible that household characteristics affect the AWE in a non-linear way. In Appendix B, we therefore show that our baseline results from Section 2.2 are robust to splitting the sample by number of children, reasons for non-participation, spousal education, state of the business cycle, gender of the household head, and when repeating the analysis on one cohort of individuals.



(a) Age 25 to 35 **(b)** Age 56 to 65

Figure 2: Δ Pr(Spouse enters LF) this month

Notes: Figure 2 shows the change in probability that a non-participating spouse enters the labor force (either as unemployed or employed) if the household head loses/lost the job in two months, next month, this month, last month, or two months ago respectively, relative to the baseline in which the household head remains employed. The sample includes couples in which one spouse is working and one spouse is out of the labor force between age 25 and 35 (Figure 2a) and between age 56 and 65 (Figure 2b) from the Current Population Survey (CPS), waves 1994 until 2020. Age refers to the non-participating spouse. The regression producing the coefficients is Equation 1.

groups (Figure B.1) and by reason for the primary earner's EU transition (Figure B.2) to the appendix.

2.4 Need or Availability?

Our empirical evidence shows a strong age dependency in the AWE. The weak AWE among older couples may arise because they are sufficiently well insured by other forms of private insurance, such as asset holdings, reducing the *need* for spousal labor supply. Alternatively, spousal labor supply might not be *available* as an insurance margin to older couples, for example because non-participating spouses above 55 years have worse labor market prospects after long spells of non-participation. In line with the latter channel, Casella (2022) documents that the AWE is stronger for women who have worked in the five years preceding their husband's job loss.

To provide suggestive evidence for both margins in our sample, the upper two panels in Table 3 report the AWE by spousal education (as a proxy for labor market prospects), whereas the bottom two panels of Table 3 split the sample by net liquid wealth. Because the CPS does not collect asset information, we repeat the analysis with data from the Survey of Income and Program Participation (SIPP) when splitting the sample by wealth.[7] Net liquid wealth is defined as net worth minus home and vehicle equity. We use this measure because we are interested in wealth holdings that can be liquidated within a rel-

[7]In contrast to the CPS, respondents in the SIPP are interviewed at most every four months and report their labor market state retrospectively, resulting in well-known under-reporting of transition rates ("seam bias"). See Appendix C for further details on the SIPP data and its comparability to the CPS.

atively short time frame, and hence provide insurance against temporary unemployment shocks.

The data hint towards a role for both the *need for* and *availability of* spousal insurance in explaining heterogeneity in the AWE. Panels I and II in Table 3 document that the AWE is stronger for individuals with a college degree (9.42 vs. 5.58 percentage points), suggesting that worse labor market prospects can lower the value of spousal labor supply as an insurance against job loss. When splitting the sample by net liquid wealth, we find a stronger AWE for the bottom half of the sample (6.48 vs. 5.54 percentage points, see Panels III and IV in Table 3), in line with the notion that better insurance through asset holdings decreases the need of secondary earners to enter the labor force upon spousal transitions into unemployment.[8]

While these findings provide suggestive evidence for the need and availability channels, both labor market prospects and asset holdings are endogenous to households' preferences and decisions. In addition, the differences by net liquid wealth are rather small and sensitive to the exact definition of wealth. The absence of exogenous variation in wealth and labor market prospects makes a direct empirical identification of their relative effects impossible. We turn to a model of couples' extensive margin labor supply over the life cycle, to conduct clean counterfactual exercises and quantify the relative importance of the need for and availability of spousal insurance.

3 Model

Accounting for the emprical evidence outlined in the previous section requires a life cycle model of couples with endogenous accumulation of assets and human capital, extensive-margin labor-supply decisions and labor market frictions. Our framework, introduced in detail below, accomodates all of these features and allows us to analyse the contribution of alternative insurance margins (assets) and labor market opportunities (human capital, labor market frictions) to the decreasing age profile in the AWE.

3.1 Environment

The economy is populated by two-member households. Both members have the same age. Households live for T periods, after which they die deterministically. They retire jointly after a working life of T_W periods, and retirement lasts for $T - T_W$ periods. Households have access to a risk-free bond and can jointly save in this bond at the exogenous interest rate r. Borrowing is not allowed.

[8]This result is robust to aggregating the SIPP up to interview frequency, as shown in Appendix C.

Table 3: Added Worker Effect by Net Liquid Wealth & Education

	Primary earner transition EE	EU	AWE
I. Spouse College Degree:			
Cond. prob. of spousal NE transition	7.03%	11.83%	4.80%
Cond. prob. of spousal NU transition	1.53%	6.15%	4.62%
Cond. prob. of spousal NN transition	91.44%	82.02%	
AWE (total)			9.42%
II. Spouse No College Degree:			
Cond. prob. of spousal NE transition	5.67%	7.45%	1.78%
Cond. prob. of spousal NU transition	1.66%	5.46%	3.80%
Cond. prob. of spousal NN transition	92.67%	87.09%	
AWE (total)			5.58%
III. Bottom 50% *of Net Liquid Wealth (SIPP):*			
Cond. prob. of spousal NE transition	2.23%	5.06%	2.83%
Cond. prob. of spousal NU transition	1.34%	4.99%	3.65%
Cond. prob. of spousal NN transition	96.43%	89.95%	
AWE (total)			6.48%
IV. Top 50% *of Net Liquid Wealth (SIPP):*			
Cond. prob. of spousal NE transition	2.19%	5.54%	3.35%
Cond. prob. of spousal NU transition	0.89%	3.08%	2.19%
Cond. prob. of spousal NN transition	96.92%	91.37%	
AWE (total)			5.54%

Notes: Table 3 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by education (Panel I and II) and net liquid wealth (Panel III and IV). Panels I and II are based on data from the CPS, Panels III and IV on data from the SIPP. The AWE is computed as the EU minus the EE column.

Retired households receive a pension p. Households do not face any risk during retirement and run down their assets optimally to smooth consumption until the deterministic death at age T.

During working life each household member can be in one of four labor market states. A member can be employed (E), in which case the individual receives a wage payment. There are three additional labor market states for non-employed members: First, an individual may be unemployed and receive benefits (U). Second, the individual can be unemployed without receiving benefits (S). In both these states, the individual exerts costly search effort to increase the probability of finding a job. Third, an individual may be out of the labor force (N), avoiding costly search effort at the cost of a lower job-finding probability. Individuals who are not actively searching never receive unemployment benefits. In total, there are 16 joint labor market states for a two-member household: $jk \in \mathcal{J} = \{E, U, S, N\} \times \{E, U, S, N\}$.

Each household member is endowed with a level of human capital h, which we interpret as the member's earnings potential capturing both education differences (initial distribution) and labor market experience (dynamics with job tenure). Over the life cycle, human capital evolves stochastically. If an individual is employed, the human capital will go up by one unit with probability $\phi^{up}(h)$. For non-employed agents, human capital drops by one unit with probability $\phi^{down}(h)$.

Individual labor market transitions are illustrated in Figure 3. An employed agent can receive an exogenous separation shock with probability $\delta(h)$, which depends on the level of human capital. If such a separation shock occurs, the agent transitions to unemployment and receives unemployment benefits. In addition, the agent can choose to immediately leave the labor force. If there is no separation shock, the individual can either stay employed or quit the job. If she chooses to quit, she can either become unemployed without receiving benefits or leave the labor force entirely.

An unemployed agent with benefits receives a job offer with probability $\lambda^U(x_i)$ and transitions to employment if she chooses to accept the offer. The arrival rates with which non-employed agents receive job offers are endogenously determined as the solution to an optimal vacancy posting problem of firms (see below) and for household member i depend on state $x_i = \{t, h_i, h_{-i}, a', jk, sep_{-i}\}$. The term sep_{-i} is an indicator variable relevant only if member i's spouse $-i$ was previously employed, indicating whether the spouse has been separated. An agent can always choose to reject a job offer to avoid the utility cost of working. In addition, an unemployed worker who receives benefits can stochastically lose benefit eligibility with probability ϕ^{US}, capturing that unemployment benefits are limited in time. Finally, she can choose to stop searching and leave the labor force. An unemployed worker without benefits receives job offers with probability $\lambda^S(x_i)$ and can quit the labor force.

Out of the labor force agents receive job offers with probability $\lambda^N(x_i)$, even though they do not exert active search effort. This assumption is necessary to capture the empirical observation that individuals directly transition from out of the labor force into employment. Non-participating agents can always rejoin the labor force as unemployed without benefits, irrespective of receiving a job offer.

3.2 Household Search Problem

Timing in the model is as follows: In the beginning of each period households receive their labor income (wages or unemployment benefits) and their asset income from in-

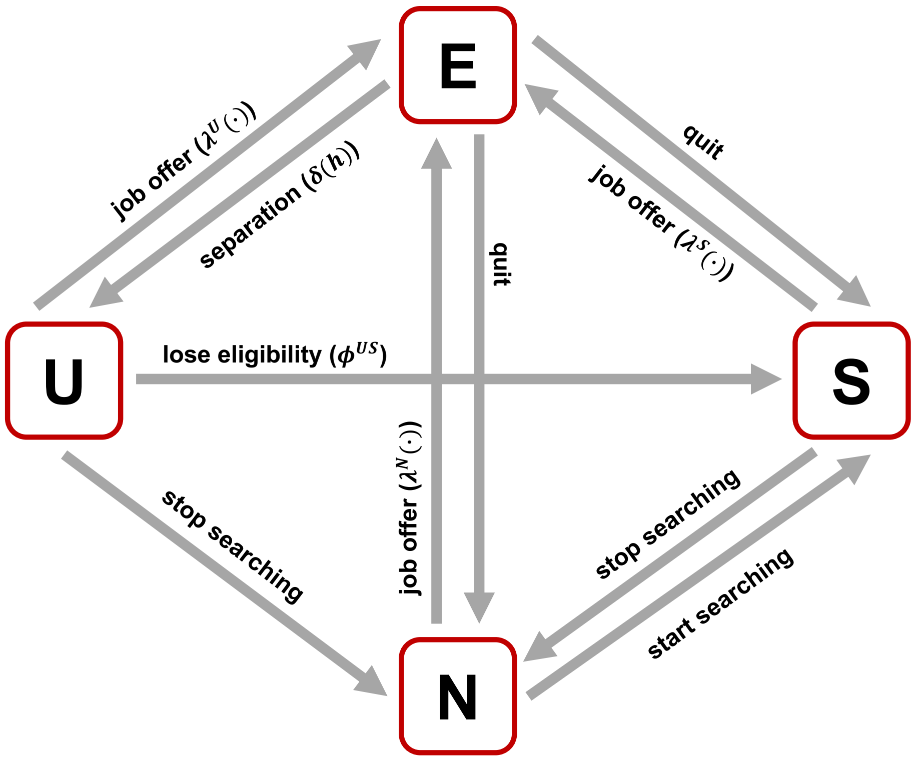


Figure 3: Labor Market Transitions in the Model

vesting in the risk-free bond. Given their budget constraint, households then make a consumption-savings choice. Afterwards, separation shocks are realized. Job offers for previously non-employed spouses arrive after separations are revealed.[9] Next, potential losses of benefit eligibility are realized and human capital transitions are revealed. Finally, households choose their joint future labor market state from the feasible subset of $\mathcal{J}$, which is determined by their previous labor market state, job offers, separations, and benefit eligibility losses.

Table 4 summarizes all possible combinations of job opportunities and unemployment benefit eligibility of the two household members along with the associated choice sets over joint labor market states. The superscripts to $\mathcal{J}$ indicate whether the household members have the opportunity to be employed. An employment opportunity arises either because an agent was employed in the previous period and did not receive a separation shock or because an agent received a job offer while non-employed. If both members have the opportunity to be employed, the superscript is EE. In contrast, X indicates that a member cannot be employed. Hence, EX and XE are the cases in which only one member has a job opportunity, whereas XX indicates that neither household member can be employed in the following period. The subscripts refer to unemployment benefit

[9] We maintain the assumption that separated individuals cannot receive an offer immediately, i.e. have to be without employment for at least one period.

Table 4: Labor Supply Choice Sets

Benefit Eligibility	**Job (Offer)** Both	Member 1	Member 2	None
Both	$\mathcal{J}_{UU}^{EE} = \{E,U,N\} \times\{E,U,N\}$	$\mathcal{J}_{UU}^{EX} = \{E,U,N\} \times\{U,N\}$	$\mathcal{J}_{UU}^{XE} = \{U,N\} \times\{E,U,N\}$	$\mathcal{J}_{UU}^{XX} = \{U,N\} \times\{U,N\}$
Member 1	$\mathcal{J}_{UX}^{EE} = \{E,U,N\} \times\{E,S,N\}$	$\mathcal{J}_{UX}^{EX} = \{E,U,N\} \times\{S,N\}$	$\mathcal{J}_{UX}^{XE} = \{U,N\} \times\{E,S,N\}$	$\mathcal{J}_{UX}^{XX} = \{U,N\} \times\{S,N\}$
Member 2	$\mathcal{J}_{XU}^{EE} = \{E,S,N\} \times\{E,U,N\}$	$\mathcal{J}_{XU}^{EX} = \{E,S,N\} \times\{U,N\}$	$\mathcal{J}_{XU}^{XE} = \{S,N\} \times\{E,U,N\}$	$\mathcal{J}_{XU}^{XX} = \{S,N\} \times\{U,N\}$
None	$\mathcal{J}_{XX}^{EE} = \{E,S,N\} \times\{E,S,N\}$	$\mathcal{J}_{XX}^{EX} = \{E,S,N\} \times\{S,N\}$	$\mathcal{J}_{XX}^{XE} = \{S,N\} \times\{E,S,N\}$	$\mathcal{J}_{XX}^{XX} = \{S,N\} \times\{S,N\}$

eligibility of the individual household member. Again, U indicates eligibility, while X refers to non-eligibility.[10]

We can now formally state the household search problem. The value function of a household of age t in joint labor market state jk is

$$V_t^{jk}(h_1, h_2, a) = \max_{a'} u(c^{jk}(h_1, h_2, a, a')) + \psi_t^{jk} + \beta\Theta_{t+1}^{jk}(h_1, h_2, a'), \tag{2}$$

where the additional state variables are the human capital levels of both household members (h_1, h_2), and joint asset holdings a. Households value pooled consumption c according to the utility function $u(c)$. Additionally, instantaneous utility is affected by ψ which is allowed to depend on the labor market state and age. It captures disutility from work or searching for jobs and the utility of staying at home. Households discount their continuation value Θ, which is described in detail below, with discount factor β.

Households choose assets for the next period subject to their budget constraint

$$\begin{aligned} c^{jk}(h_1, h_2, a, a') = &\underbrace{\mathbb{I}_{j=E}(1-\tau)w(h_1) + \mathbb{I}_{k=E}(1-\tau)w(h_2)}_{\text{labor income}} \\ &+ \underbrace{\mathbb{I}_{j=U}b(h_1) + \mathbb{I}_{k=U}b(h_2)}_{\text{unemployment benefits}} - \underbrace{(a' - (1+r)a)}_{\text{net savings}}. \end{aligned} \tag{3}$$

[10] We assume that household members eligible for benefits cannot choose to forgo these benefits unless they find a job or transition out of the labor force. This assumption is without loss of generality as unemployment with benefits strictly dominates unemployment without benefits given our calibration choices below.

Conditional on their employment status household members receive wage or benefit income, depending on their human capital level. Labor earnings are subject to a flat tax at rate τ. We assume that benefit income has a constant replacement ratio up to a maximum level of benefits, i.e. $b(h) = min\{b^{rep}w(h), b^{max}\}$. In addition, a household can use its assets and interest income to finance consumption and new purchases of the risk-free bond.

To write the continuation utility for one labor market state explicitly, we consider a household with one employed and one non-participating member (EN-couple). We express the continuation value in two steps. First, we take expectations over separation shocks and job offer arrivals, i.e. over the choice sets for future labor market states:

$$\begin{aligned}
&\Theta^{EN}_{t+1}(h_1, h_2, a') = \\
&\quad (1-\delta(h_1))(1-\lambda^N(t, h_2, h_1, a', EN, 0))\ \widetilde{V}^{EN}_{t+1}(h_1, h_2, a', \mathcal{J}^{EX}_{XX}) \\
&\quad +(1-\delta(h_1))\lambda^N(t, h_2, h_1, a', EN, 0)\ \widetilde{V}^{EN}_{t+1}(h_1, h_2, a', \mathcal{J}^{EE}_{XX}) \\
&\quad +\delta(h_1)(1-\lambda^N(t, h_2, h_1, a', EN, 1))\ \widetilde{V}^{EN}_{t+1}(h_1, h_2, a', \mathcal{J}^{XX}_{UX}) \\
&\quad +\delta(h_1)\lambda^N(t, h_2, h_1, a', EN, 1)\ \widetilde{V}^{EN}_{t+1}(h_1, h_2, a', \mathcal{J}^{XE}_{UX}).
\end{aligned} \tag{4}$$

The first two rows consider the cases where the employed member is not separated and the indicator in the arrival rate of the non-participating spouse takes the value $sep_{-i} = 0$. The third and fourth row refer to the cases where the employed member is separated and $sep_{-i} = 1$. As for the choice sets, the previously non-participating spouse can never be eligible for benefits, while the previously employed spouse is eligible only in the case of separation.

In a second step, we consider transitions for human capital h and the household's discrete choice over feasible future labor market states from the available set $\mathcal{J}^{OP}_{QR}$:

$$\begin{aligned}
&\widetilde{V}^{EN}_{t+1}(h_1, h_2, a', \mathcal{J}^{OP}_{QR}) = \\
&\quad \phi^{up}(h_1)\phi^{down}(h_2)\ \mathbb{E}_\epsilon \max_{\widehat{jk}\in\mathcal{J}^{OP}_{QR}} \left\{V^{\widehat{jk}}_{t+1}(h_1+1, h_2-1, a') + \sigma\epsilon^{\widehat{jk}}\right\} \\
&\quad +\phi^{up}(h_1)(1-\phi^{down}(h_2))\ \mathbb{E}_\epsilon \max_{\widehat{jk}\in\mathcal{J}^{OP}_{QR}} \left\{V^{\widehat{jk}}_{t+1}(h_1+1, h_2, a') + \sigma\epsilon^{\widehat{jk}}\right\} \\
&\quad +(1-\phi^{up}(h_1))\phi^{down}(h_2)\ \mathbb{E}_\epsilon \max_{\widehat{jk}\in\mathcal{J}^{OP}_{QR}} \left\{V^{\widehat{jk}}_{t+1}(h_1, h_2-1, a') + \sigma\epsilon^{\widehat{jk}}\right\} \\
&\quad +(1-\phi^{up}(h_1))(1-\phi^{down}(h_2))\ \mathbb{E}_\epsilon \max_{\widehat{jk}\in\mathcal{J}^{OP}_{QR}} \left\{V^{\widehat{jk}}_{t+1}(h_1, h_2, a') + \sigma\epsilon^{\widehat{jk}}\right\}.
\end{aligned} \tag{5}$$

For the previously employed household member human capital can either remain constant or increase, while for the non-participating member it remains constant or decreases. The possible choices of future labor market states can be read off Table 4. The term

$\epsilon \in \mathbb{R}^{|\mathcal{J}_{QR}^{OP}|}$ denotes a vector of iid, Type-I extreme value (Gumbel) shocks with mean zero. We introduce these taste shocks for computational purposes, as they smooth out kinks and discontinuities in the policy functions that arise from the discrete labor market choices. We choose the variance of these taste shocks to be small enough such that they do not affect the solution to the problem in an economically meaningful way.

While we outline here the continuation value for an EN-couple, the problem for all other current joint labor market states evolves in a very similar manner: In equation 4, expectations are formed over the relevant combinations of separations and job offer arrivals. For members previously in the U-state and eligible for benefits, the problem has to be extended by expectations over benefit losses. Equation 5 considers the relevant combinations of human capital transitions.

3.3 Vacancy Posting and Endogenous Arrival Rates

To determine job arrival rates endogenously we consider the optimal vacancy posting problem of single-job firms. Firms post vacancies conditional on the type of a worker $x_i = \{t, h_i, h_{-i}, a', jk, sep_{-i}\}$. We assume free entry of firms and a cost κ of posting a vacancy. Vacancies last for one period and can be renewed by paying κ again. A match between a firm and a worker with human capital h produces per period output $y(h)$, of which the worker receives a constant share χ as a wage $w(h) = \chi y(h)$, yielding firms' per period profit of such match as $\pi(h) = (1-\chi)y(h)$.

The expected future value to a firm of a match with worker i from a household with age t, human capital levels (h_i, h_{-i}), previous labor market state jk, and asset choice a', given that the household can choose the joint future labor market state from set $\mathcal{J}_{QR}^{OP}$, is defined as

$$EJ_{t+1}^{jk}(h_i, h_{-i}, a', \mathcal{J}_{QR}^{OP}) = \mathbb{E}_{h_i'|h_i,j}\mathbb{E}_{h_{-i}'|h_{-i},k}\mathbb{E}_{\hat{j}k\in\mathcal{J}_{QR}^{OP}}\mathbb{I}_{\hat{j}=E}J_{t+1}^{\hat{j}k}(h_i', h_{-i}', a') \tag{6}$$

where $\mathbb{E}_{\hat{j}k\in\mathcal{J}_{QR}^{OP}}\mathbb{I}_{\hat{j}=E}$ is the firms' expectation of the household's joint labor market choice and an indicator of whether for each joint state member i stays with the firm, i.e. firms' expectation over endogenous acceptances and quits. The contemporaneous value to the firm is then given by

$$J_t^{Ek}(h_i, h_{-i}, a) = \pi(h_i) + \frac{1}{1+r}(1-\delta(h_i))\mathbb{E}_{P,R}EJ_{t+1}^{Ek}(h_i, h_{-i}, a', \mathcal{J}_{XR}^{EP}), \tag{7}$$

where $\mathbb{E}_{P,R}$ is a firm's expectation over job loss, job finding, and eligibility transitions of the spouse and $a' = a(t, h_i, h_{-i}, a, Ek)$ is the household's asset choice.

We discuss the determination of endogenous arrival rates using the example of a household with both members unemployed and not eligible for benefits, i.e. a household with initial labor market state SS.[11] Define member i's arrival rate as

$$\lambda^S(t, h_i, h_{-i}, a', SS) = \lambda_S p(\theta_t(h_i, h_{-i}, a', SS)) \tag{8}$$

with arrival rate $p(\theta) = m(1, \theta)$ and corresponding vacancy filling rate $q(\theta) = m(\frac{1}{\theta}, 1)$. $m(U, V) = U^\alpha V^{1-\alpha}$ is the standard Cobb-Douglas matching function, with market tightness θ denoting the ratio of vacancies over searchers in any given submarket. Hence, $p(\theta) = \theta^{1-\alpha}$, $q(\theta) = \theta^{-\alpha}$, and $p(\theta) = \theta q(\theta)$. The term λ_S is an exogenous shifter that only depends on the previous labor market state and reflects the consequences of differences in search effort between unemployed (U or S) and out of the labor force (N) individuals. This distinction is necessary because – conditional on the remaining states of the household – firms will not differentiate across non-employment states when hiring a worker.

Free entry imposes that the expected value of a vacancy (probability of filling times the value if filled) has to equal the cost of posting κ. This condition determines relevant market tightness $\theta_t(h_i, h_{-i}, a', SS)$. The free entry condition needs to satisfy

$$\kappa = q(\theta_t(h_i, h_{-i}, a', SS))\mathbb{E}_P EJ^{jk}_{t+1}(h_i, h_{-i}, a', \mathcal{J}^{EP}_{XX}). \tag{9}$$

Here $\mathbb{E}_P$ captures expectations over the spouse's job finding and depends on the spouse's market tightness $\theta_t(h_{-i}, h_i, a', SS)$ as the spouse is also currently not employed. Hence, in all cases with currently two non-employed household members we have to solve a system of two non-linear equations in two unknowns.

With slight abuse of notation the two equations solving for two θs can be written as

$$\kappa = q(\theta_i)[\lambda^s(\theta_{-i})\underbrace{EJ^{SS}_{t+1}(h_i, h_{-i}, a', \mathcal{J}^{EE}_{XX})}_{EJ^{EE}_i} + (1 - \lambda^s(\theta_{-i}))\underbrace{EJ^{SS}_{t+1}(h_i, h_{-i}, a', \mathcal{J}^{EX}_{XX})}_{EJ^{EX}_i}], \tag{10}$$

$$\kappa = q(\theta_{-i})[\lambda^s(\theta_i)\underbrace{EJ^{SS}_{t+1}(h_{-i}, h_i, a', \mathcal{J}^{EE}_{XX})}_{EJ^{EE}_{-i}} + (1 - \lambda^s(\theta_i))\underbrace{EJ^{SS}_{t+1}(h_{-i}, h_i, a', \mathcal{J}^{EX}_{XX})}_{EJ^{EX}_{-i}}]. \tag{11}$$

This yields

$$\theta_{-i} = \left[\frac{\kappa}{\lambda(\theta_i)EJ^{EE}_{-i} + (1 - \lambda(\theta_i))EJ^{EX}_{-i}}\right]^{-\frac{1}{\alpha}} \tag{12}$$

[11] For ease of notation we omit the spousal separation indicator sep_{-i} from the state space as it is irrelevant in the case of two non-employed household members.

and hence

$$\kappa = q(\theta_i)\left[\lambda_S\left[\frac{\kappa}{\lambda(\theta_i)EJ^{EE}_{-i} + (1-\lambda(\theta_i))EJ^{EX}_{-i}}\right]^{\frac{\alpha-1}{\alpha}} EJ^{EE}_i \right. \\ \left. + \left(1-\lambda_S\left[\frac{\kappa}{\lambda(\theta_i)EJ^{EE}_{-i} + (1-\lambda(\theta_i))EJ^{EX}_{-i}}\right]^{\frac{\alpha-1}{\alpha}}\right) EJ^{EX}_i\right], \tag{13}$$

which is a non-linear equation in one unknown and can be solved numerically.

The endogenous arrival rates can be derived in a similar fashion for all other original labor market states. In each case, the exogenous component of λ needs to be adjusted to reflect whether an agent is unemployed or out of the labor force. If one spouse has been previously employed there is only a single θ, i.e. we only solve one equation with one unknown conditional on whether the previously employed member has been separated or not as per the timing assumptions discussed above.

Given this setup, job finding probabilities of an individual depend on all state variables, i.e. assets, age, own and spousal human capital, and spousal employment status. While it is intuitive that arrival rates may depend on age and own human capital, it is potentially less appealing to condition on spouse's state variables. Doing so is necessary because spousal characteristics affect the probabilities of accepting a job offer and quitting later on. However, spouses' human capital and employment status affect arrival rates *only* through their influence on acceptance probabilities and future quits, i.e. the setup can be understood as firms being able to forecast acceptance and quitting probabilities perfectly at the individual level. Having different submarkets conditional on a worker's state and free entry in each active submarket simplifies computation drastically, as we do not need to know the distribution of individuals across states to solve for arrival rates.

3.4 Numerical Implementation

We solve the retirement problem using the endogenous grid method (EGM) of Carroll (2006) to obtain a terminal condition for the household problem during working life. The baseline EGM is not applicable for problems with discrete-continuous choices, such as a continuous asset choice combined with discrete labor supply decisions. We therefore solve the household problem for all ages before retirement following Iskhakov, Jørgensen, Rust, and Schjerning (2017), who extend the EGM of Carroll (2006) to problems with discrete and continuous choices.

The algorithm proceeds as follows: Within each period, given future value functions of both the household and firm, we begin by determining households' choices over future labor market states for each potential choice set. Given these choices, we are able to solve firms' vacancy posting problem and determine endogenous arrival rates. Given endogenous arrival rates, we can solve households' consumption-savings problem as described above. In a final step, we update households' and firms' value functions making use of households' policy functions and again the endogenous arrival rates.

4 Calibration

We solve the model at monthly frequency, corresponding to the frequency at which we observe labor market transitions in the data. The period of working life lasts for 480 months (40 years). The retirement period lasts for 120 months (10 years).

4.1 Functional Form Assumptions and Parameter Restrictions

Households value consumption with CRRA utility function

$$u\left(c\right)=\frac{c^{1-\gamma}-1}{1-\gamma}, \tag{14}$$

where γ is the coefficient of relative risk aversion. The second part of instantaneous utility are the parameters ψ_t^{jk} across joint labor market states, reflecting disutility of work and search. We allow the disutility of work and search to vary by age, but restrict ψ_t^{jk} to be symmetric across household members and assume equal disutility of search with and without benefit eligibility, i.e. we impose

$$\psi^{EU}=\psi^{UE}=\psi^{ES}=\psi^{SE} \tag{15}$$

$$\psi^{UU}=\psi^{SS}=\psi^{SU}=\psi^{US} \tag{16}$$

$$\psi^{UN}=\psi^{NU}=\psi^{SN}=\psi^{NS} \tag{17}$$

$$\psi^{EN}=\psi^{NE}. \tag{18}$$

Output is assumed to be equal to human capital

$$y\left(h\right)=h. \tag{19}$$

Human capital is defined on an equidistant grid with 12 points. The probabilities of moving to a higher (lower) human capital level when employed (non-employed) are given by the following processes:

$$\phi^{up}\left(i\right)=\bar{\phi}^{up}i^{\underline{\phi}^{up}} \tag{20}$$

$$\phi^{down}\left(i\right)=\bar{\phi}^{down}i^{\underline{\phi}^{down}}, \tag{21}$$

where i indicates the grid point rather than the level of human capital. This process is able to capture both increasing or decreasing probabilities of moving along the human capital ladder.

Finally, we have to make an assumption on the exogenous component of job-offer arrival rates λ and separation rates δ. We impose $\lambda_S = \lambda_U \geq \lambda_N$ and allow the separation rate to vary with human capital according to:

$$\delta(i) = \bar{\delta} i^{\underline{\delta}}. \tag{22}$$

4.2 Parameters and Moments

To bring the model to the data and identify the parameters of interest, we simulate the full life cycle of 160,000 households and compute model-implied moments of this simulation. We initialize the distribution of households across labor market states consistent with CPS data and target the initial distribution of assets and human capital to match the wealth and earnings distribution by joint education status of households between 25 and 30 years in the SIPP. Table 5 summarizes all calibrated parameter values, and we discuss their identification below.

We start by setting a number of parameters without solving the model. We set the monthly net interest rate to 0.17%, corresponding to an annual interest rate of 2%. We assume a probability of losing unemployment benefits of $\phi^{US} = 1/6$, consistent with an average benefit duration of six months. We set the replacement rate to $b^{rep} = 0.5$, consistent with Krueger, Mitman, and Perri (2016), impose a maximum individual unemployment benefit level of $2,500, and a flat household-level pension of $4,000. The labor income tax is fixed at $\tau = 0.28$ as in Trabandt and Uhlig (2011). We set the elasticity of the matching function α to 0.5, as in Petrongolo and Pissarides (2001) and the labor share of match output allocated to workers to $\chi = 0.7$. We set the vacancy posting cost to $\kappa = 8$, which in our model includes all non-wage expenses from a match.[12] Finally, we fix the variance of the taste shock to $\sigma_\varepsilon = 0.1$. All remaining parameter values are determined by matching simulated moments with evidence on life cycle profiles of income, assets, and labor market outcomes. While all parameters are determined jointly, each targeted moment is more informative regarding certain parameters. We discuss the mapping between moments and parameters below.

[12] In the model, κ determines the endogenous component of arrival rates, i.e. how arrival rates change with household characteristics. We validate our parameter choice for κ by showing that our model generates a realistic drop in the U to E transition rate between the youngest and the oldest age groups (see Table 9).

Table 5: Parameter Values

Parameter	Interpretation	Value
Demographics		
T	Length of life in months	600
T_W	Length of working life in months	480
Preferences		
β	Discount factor	0.9950
γ	Risk aversion	1.7500
ψ^{EE}	Disutility of work/search	0.0000
$\psi^{EU}, \psi^{UE}, \psi^{ES}, \psi^{SE}$	Disutility of work/search	0.2000
$\psi^{UU}, \psi^{SS}, \psi^{SU}, \psi^{US}$	Disutility of work/search	0.5000
$\psi^{UN}, \psi^{NU}, \psi^{SN}, \psi^{NS}$	Disutility of work/search	$1.6 - \frac{0.55}{1+e^{-0.05(t-100)}}$
ψ^{EN}, ψ^{NE}	Disutility of work/search	$1.25 - \frac{0.55}{1+e^{-0.05(t-100)}}$
ψ^{NN}	Disutility of work/search	2.2000
Financial Assets		
r	Interest rate	0.0017
Labor Market		
$\bar{\delta}$	Level parameter separation rate	0.0500
$\underline{\delta}$	Curvature parameter separation rate	-0.6500
λ_U, λ_S	Probability of job offer for unemployed	0.3000
λ_N	Probability of job offer out of labor force	0.2000
Human Capital		
$\underline{h}$	Lower bound h	0.1429
$\bar{h}$	Upper bound h	1.7143
$\bar{\phi}^{up}$	Level parameter prob. h rise	0.1000
$\underline{\phi}^{up}$	Curvature parameter prob. h rise	-1.8000
$\bar{\phi}^{down}$	Level parameter prob. h fall	0.0500
$\underline{\phi}^{down}$	Curvature parameter prob. h fall	0.0000
Firms		
χ	Labor share of output	0.7000
κ	Cost of vacancy posting	8.0000
α	Matching elasticity	0.5000
Government		
τ	Labor income tax	0.2800
b^{rep}	Unemployment benefit replacement rate	0.5000
b^{max}	Unemployment benefit maximum	0.2500
ϕ^{US}	Probability of losing benefits	0.1667
p	Pension	0.4000
Gumbel shock		
σ_ε	Standard deviation of taste shock	0.1000

Figure 4: Separation Rates by Income Level (Model vs. Data)

Notes: Figure 4 shows separation rates by pre-tax income level. Data moments are the sum of individual *EU* and *EN* transition rates by income bin as computed from the SIPP, scaled to match aggregate transition rates in the CPS.

We target average individual transition rates between labor market states. Given a vancancy posting cost κ, flows into employment are closely related to the exogenous components of job arrival rates $\lambda_N, \lambda_S, \lambda_U$. The average EU and EN rates pin down the level of separation rates $\bar{\delta}$ while we target the curvature parameter $\underline{\delta}$ to match evidence on transitions out of employment by income level from the SIPP. Table 6 reports the fit for overall transition rates while Figure 4 shows the fit for separation rates by income level. The model does well in replicating the empirical patterns, while somewhat understating transitions out of non-participation.

Table 6: Individual Labor Market Transition Rates (Model vs. Data)

	Model			Data		
	E	U	N	E	U	N
E	98.0	1.6	0.5	97.3	0.9	1.8
U	26.2	60.8	13.0	25.4	62.2	12.4
N	2.6	1.4	96.0	5.9	1.6	92.5

Notes: Table 6 shows individual labor market transition rates at monthly frequency in percent. For the model, U combines unemployment with and without benefits. Data is from the CPS.

Another important set of targeted moments is the distribution of households over joint labor market states by age group. To compare the model to the data, we pool all agents who are unemployed with and without benefits into one group, labeled U. The distribution of households across labor market states informs the preference parameters ψ, i.e. the disutility of work and search. Joint labor market states in the data and in the model are shown in Figure 5. The model captures the distribution of joint labor market states well. In particular, it replicates the relative share of households with one employed vs. two employed members over the life cycle, and the increase in non-participation during old age. To achieve the reported fit, we keep all preference parameters constant by age, except for $\psi^{EN} = \psi^{NE}$ and $\psi^{UN} = \psi^{NU} = \psi^{SN} = \psi^{NS}$, which we assume to be logistically decreasing with age at the same rate. While the model reproduces the share of households in other labor market states without age dependency in preferences, allowing for a declining utility of one non-participating member is necessary to reproduce the relatively high share of households with one non-participating member at young ages. We interpret this age-dependency as capturing child-care needs of young households in a parsimonious way.[13]

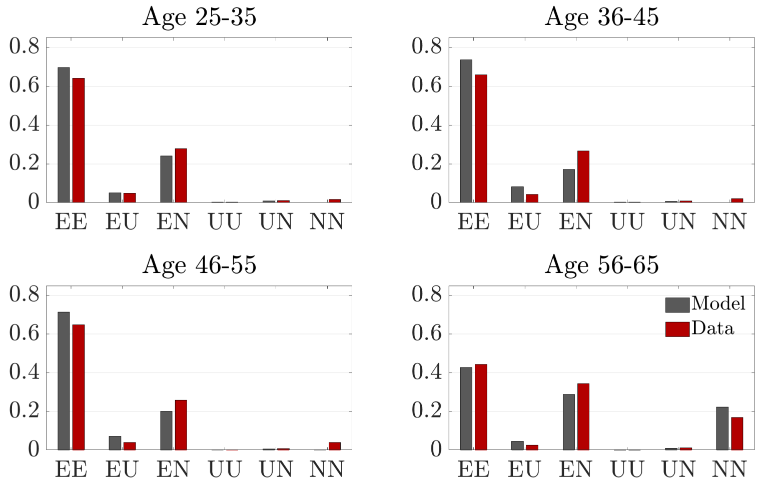


Figure 5: Joint Labor Market States of Couples (Model vs. Data)

Notes: Figure 5 shows the joint labor market states of couples in the model and data. For the model, U combines unemployment with and without benefits. Data is from the CPS.

The discount factor β and the coefficient of relative risk aversion γ jointly determine the life cycle asset profile. As in Section 2, we define assets as net worth minus home and vehicle equity (net liquid wealth). We target median net liquid wealth holdings by age group. The first two columns of Table 7 report the fit of the life cycle asset profile. The model replicates the steep increase of liquid asset holdings over the life cycle but somewhat underpredicts overall asset levels, especially for the middle age groups. Most important for our detailed analysis of the AWE over the life cycle below is the difference in asset holdings between the youngest and oldest age groups, which the model reproduces reasonably well.[14]

[13] To match the data on joint labor market states, it is primarily important to let $\psi^{EN} = \psi^{NE}$ be age dependent. We extend this age dependency to $\psi^{UN} = \psi^{NU} = \psi^{SN} = \psi^{NS}$ to keep the difference between ψ^{EN} and ψ^{UN} constant in age and avoid distorting relative preferences over labor market states upon job loss of the primary earner.

[14] The fact that the model slightly underpredicts this moment implies that the model implied contribution of asset levels to explaining the age difference in the AWE is a conservative estimate.

Table 7: Assets and Income by Age Group

	Assets		Income	
	Model	Data	Model	Data
Aggregate	2.79	3.22	0.52	0.48
Age 25-35	1.85	0.27	0.48	0.41
Age 35-45	1.85	2.59	0.51	0.50
Age 45-55	3.84	5.94	0.54	0.52
Age 55-65	10.33	10.77	0.57	0.50
Δ 55-65 to 25-35	8.48	10.50	0.09	0.09

Notes: The first two columns compare median asset holdings by age group in the model and data. In the data, assets are defined as net worth less of home and vehicle equity. The last two columns compare monthly earned income conditional on employment by age group in the model and in the data. Data is from the SIPP. In the data, income is reported conditional on employed individuals who report to have monthly earnings $\geq$ \$100. 1 unit corresponds to \$10,000.

Parameters for the human capital process are chosen to match income dynamics over the life cycle. In the data, these moments are constructed from the SIPP. We set the bounds of the grid for human capital to match the 5th and 95th percentile of individual monthly earnings in the SIPP, conditional on being employed and reporting monthly earnings $\geq$ \$100. The probability of moving up the human capital ladder is decreasing in the human capital level (i.e. $\underline{\phi}^{up} < 0$), generating earnings growth that is decreasing in individual labor market experience. Table 7 reports the related model fit for income levels by age groups. The model is able to replicate that earnings are increasing for the age groups 25-35, 35-45, and 45-55 but fails to reproduce the fall in income for the oldest group. The mismatch for the oldest age group arises from a strong selection effect for non-participation in the model. Many agents with relatively low human capital drop out of the labor force, driving up the average income among the employed. Nevertheless, the model generates a realistic difference in labor earnings of employed individuals between the youngest and oldest age group, which is the moment most closely connected to our analysis of the AWE below.

Human capital decay of the non-employed allows us to capture that newly employed individuals have lower wages than long-time employed and that job losses lead to persistent wage drops in the data (Davis and von Wachter 2011; Jarosch 2015; Kospentaris 2021). The probability of losing human capital when non-employed is disciplined by SIPP data on earnings losses upon reemployment after non-employment spells of 1-3, 4-12, and 13-24 months respectively. Table 8 compares the empirical moments to their model implied counterparts. To match the data, the model calls for a probability of depreciation that is constant across human capital levels ($\underline{\phi}^{down} = 0$).

Table 8: Earnings Losses after Non-Employment

	Data	Model
Δwage_{1-3m}	-0%	-2%
$\Delta\text{wage}_{4-12m}$	-7%	-7%
$\Delta\text{wage}_{13-24m}$	-19%	-21%

Notes: Table 8 reports earnings losses upon reemployment, computed as earnings in the first month of reemployment relative to to earnings in the final month of the previous employment spell by length of non-employment spells. Data is from the SIPP.

4.3 Validation: Life Cycle Profiles of Labor Market Transitions

We have not included labor market transition rates by age groups in the set of targeted moments. We make this choice to leave the age-dependency of the AWE, closely linked to labor market transitions by age group, untargeted. As a validation to our model, Table 9 compares model implied labor market transitions to CPS data. Again, in the model U comprises the group of unemployed who receive benefits and those who exert costly search effort without receiving benefits.

First, consider transitions from employment across age groups (first row in each age panel). The model captures that the likelihood of remaining employed slightly falls towards the end of working life, though the monthly transition probability out of employment never falls below 95%. The counterpart to this transition in model and data is a corresponding increase in the likelihood of moving from employment to out of the labor force. Especially agents with relatively low human capital decide to leave the labor force close to retirement, while their younger counterparts choose to remain employed. Several model mechanisms account for this difference. First, young agents have a longer time horizon until retirement, so that they need labor income to cover consumption needs during working life. In contrast, old agents hold higher levels of assets which they can use to finance consumption. Second, human capital is only accumulated while employed. Remaining employed to accumulate human capital is more valuable for the young as they can benefit from it for a longer time period.

Next, consider the transitions out of unemployment (second row in each age panel). The model replicates that across the entire life cycle the most likely transition is to remain unemployed. It also matches well that the probability of transitioning to employment declines with age, whereas the probability of leaving the labor force increases with age for similar reasons as discussed above. Finally, the model generates a fall in transitions from out of the labor force into employment (third row in each age panel) and matches the high and increasing persistence of non-participation.

Overall, the model generates too few transitions between out of the labor force and employment/unemployment. This mis-match most likely arises because we leave many important life events related to temporary transitions to non-participation such as child birth, marital transitions, and health shocks unmodeled. We will show in the next section that the model captures well the impact of one key life event, job loss of the primary earner, on the labor force participation of out of the labor force spouses.

Table 9: Individual Labor Market Transition Rates (Model vs. Data)

Age 25-35	Model			Data		
	E	U	N	E	U	N
E	97.9	1.4	0.6	97.1	1.1	1.9
U	28.2	58.5	13.4	28.1	58.7	13.2
N	6.8	1.4	91.9	7.3	2.3	90.5
Age 36-45	Model			Data		
	E	U	N	E	U	N
E	98.1	1.8	0.1	97.6	0.9	1.5
U	27.6	62.2	10.2	26.5	61.6	11.9
N	3.4	3.2	93.4	7.2	2.1	90.7
Age 46-55	Model			Data		
	E	U	N	E	U	N
E	98.2	1.7	0.1	97.7	0.8	1.5
U	27.7	60.1	12.3	23.7	64.8	11.5
N	3.1	2.6	94.4	6.2	1.6	92.2
Age 56-65	Model			Data		
	E	U	N	E	U	N
E	97.4	1.5	1.1	96.4	0.8	2.8
U	19.9	62.3	17.8	21.4	65.1	13.5
N	0.9	0.6	98.5	3.8	0.7	95.5

Notes: Table 9 shows individual labor market transition rates at monthly frequency across age groups. For the model, U combines unemployment with and without benefits. Data is from the CPS.

5 The Added Worker Effect over the Life Cycle

In this section, we first show that our model reproduces the AWE and its decline in age. Second, we use the model to construct counterfactuals and analyze which channels are responsible for the age-dependency, distinguishing between the *need* for and *availability* of spousal insurance among the young and old. Third, we turn to the interaction of the AWE with the public provision of unemployment insurance.

5.1 The Added Worker Effect in the Model

To evaluate whether the model can replicate our main empirical finding – the age dependency in the AWE – we recreate Tables 1 and 2 from Section 2 with simulated model data in Table 10. For the entire population, the model generates an AWE close to the data (5.37% vs. 5.90%), split similarly between transitions into employment and unemployment. As outlined in Section 4, the model generally underestimates the probability of spousal transitions from non-participation directly into employment independently of the primary earner's transition. However, it captures very well the difference in transition probabilities conditional on the primary earner's transition, which is the AWE.

In addition to capturing the overall AWE in the population, the model also does well at generating the empirical difference in the AWE between the young and old. For the young, the model reproduces the strong increase in labor force participation upon job loss of the primary earner observed in the data (9.53% vs. 7.53%), but generates somewhat fewer direct transitions into employment. For the old, both the model and data produce a much smaller AWE than for the young (1.31% vs. 1.29%).

To analyze anticipation effects and lagged responses, Figure 6 replicates Equation (1) on model simulated output, separately by age. In line with the data, the model produces larger contemporaneous and lagged effects for the young than for the old, but muted lead effects for all age groups as separation shocks in the model cannot be anticipated. Three mechanisms generate lagged responses for the young in the model: First, after becoming unemployed the primary earner may lose human capital which decreases potential human capital differences across spouses and reduces relative arrival rates for the head. Consequently, it may be optimal that both spouses search or to re-optimize on the actively searching household member. Second, unemployment benefits can expire. Third, households without any employed member may run down their assets to finance consumption. A loss in benefits or a decline in asset holdings increase the need for additional labor income, inducing a lagged response of spousal labor supply.

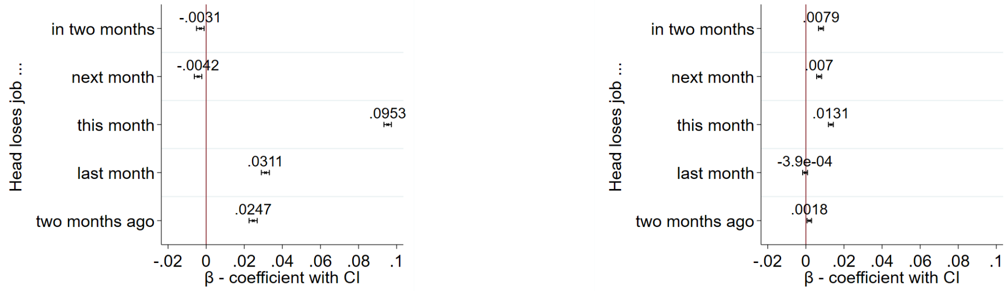
5.2 Determinants of the Added Worker Effect

In the model, differences in the AWE by age can be explained by two potential forces. First, the endogenous distribution of old and young households across the state space – assets and human capital – differs across age groups. Heterogeneity in state variables affects the AWE directly through households' decisions in the labor market and indirectly through the arrival rates posted by firms. Second, conditional on all other states of the household, age itself has an effect on both households' decisions and their arrival rates. The effect of age arises from the distance to retirement and age dependent preferences for the EN-, UN-, and SN-state.

Table 10: Joint Labor Market Transitions by Age (Model vs. Data)

	Primary earner transition		
	EE	EU/ES	AWE
All Households:			
Cond. prob. of spousal NE transition	3.50%	4.55%	1.05%
	6.03%	8.01%	1.98%
Cond. prob. of spousal NS transition	1.82%	6.13%	4.31%
	1.63%	5.55%	3.92%
Cond. prob. of spousal NN transition	94.68%	89.31%	
	92.34%	86.44%	
AWE (total)			5.37%
			5.90%
Young (25-35):			
Cond. prob. of spousal NE transition	6.67%	7.27%	0.60%
	6.66%	9.30%	2.64%
Cond. prob. of spousal NS transition	0.96%	9.89%	8.93%
	2.00%	6.89%	4.89%
Cond. prob. of spousal NN transition	92.37%	82.84%	
	91.34%	83.81%	
AWE (total)			9.53%
			7.53%
Old (56-65):			
Cond. prob. of spousal NE transition	1.45%	2.16%	0.71%
	4.29%	3.73%	-0.56%
Cond. prob. of spousal NS transition	1.34%	1.94%	0.60%
	0.90%	2.75%	1.85%
Cond. prob. of spousal NN transition	97.21%	95.89%	
	94.81%	93.52%	
AWE (total)			1.31%
			1.29%

Notes: Table 10 shows the model implied AWE, constructed from simulated labor market transitions. Data results are equivalent to those reported in Tables 1 and 2 in Section 2.



(a) Young: 25-35 years

(b) Old: 56-65 years

Figure 6: Dynamic Response: AWE by Age in the Model

Notes: Figure 6 shows the change in the probability that a non-participating spouse enters the labor force (either as unemployed or employed) this month if household head loses/lost the job in two months, next month, this month, last month, or two months ago respectively, relative to the baseline in which the household head remains employed. Figure 6a shows the model results for young households; Figure 6b shows the model results for old households. The regression producing the coefficients is Equation (1).

Differences in endogenous states. Old households are on average substantially richer than young households (Table 7), which also applies to EN-couples only. As Figure 7 shows, old couples with one employed and one non-participating spouse are on average more than twice as rich as their young counterparts. Figures 8 and 9 report the distribution of human capital for non-participating and employed spouses of young and old EN-couples respectively. Young non-participating spouses have on average higher human capital than old non-participating spouses. The reverse is true for the employed spouse, implying a larger gap in human capital levels within old households. Age-dependent differences in human capital arise from initial conditions and the process for human capital accumulation, with longer periods of human capital appreciation for the old during persistent employment spells and depreciation during persistent non-employment spells.

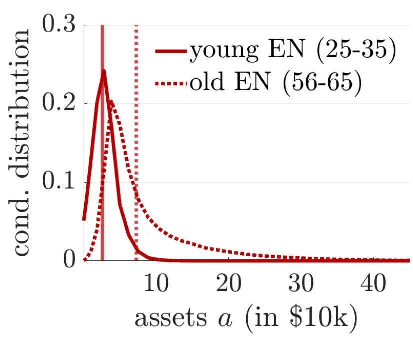


Figure 7: Asset Distribution: EN-Couples

Notes: Figure 7 shows the marginal distribution of assets conditional on EN-state by age group in the model. Vertical lines indicate average asset levels by age group.

Differences in labor market frictions. Arrival rates differ across age groups because firms respond endogenously with their vacancy posting to the likelihood of job acceptances and future quits. Figure 10 plots the average arrival rates for non-employed spouses in

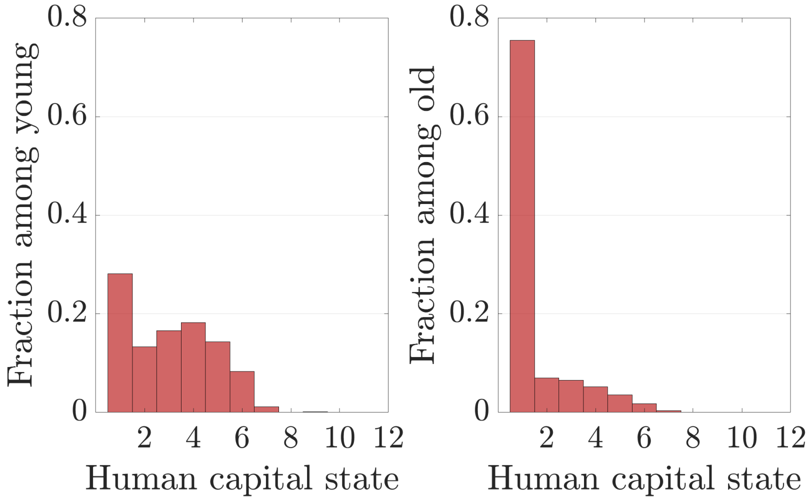


Figure 8: Distribution of Human Capital: Non-Employed Spouse

Notes: Figure 8 shows the distribution of human capital of the non-participating (N) spouse in EN-couples by age group in the model. The left graph refers to young households, whereas the right graph refers to old households.

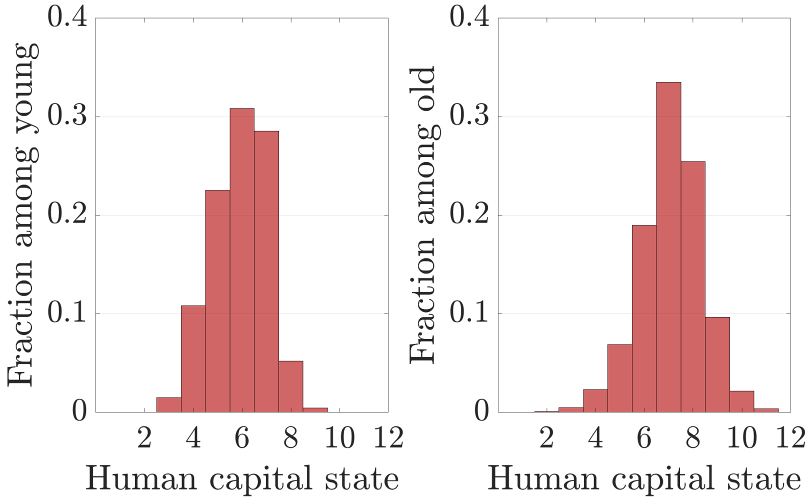


Figure 9: Distribution of Human Capital: Employed Spouse

Notes: Figure 9 shows the distribution of human capital for the employed (E) spouse in EN-couples by age group in the model. The left graph refers to young households, whereas the right graph refers to old households.

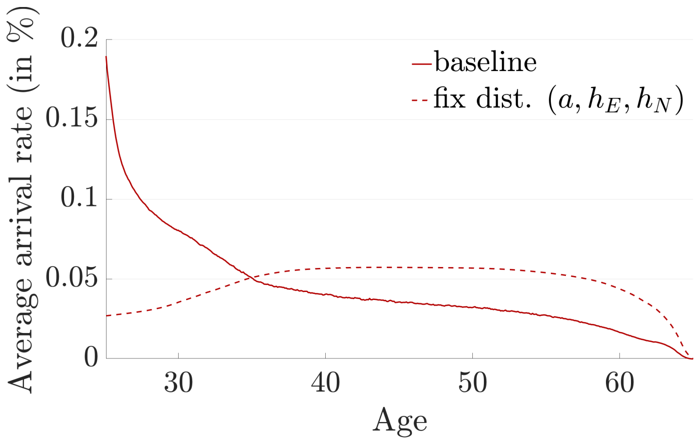


Figure 10: Life Cycle Arrival Rates: Non-Employed Spouse in EN-couple

Notes: Figure 10 shows the arrival rates for non-employed spouses in EN couples by age. The solid line displays the unconditional arrival rates, whereas the dashed line fixes the distribution of households over (a, h_E, h_N) within each age group.

EN-couples by age of the household, conditional on the job loss of the primary earner (solid line). The average arrival rate is decreasing over the life cycle. The dashed line in Figure 10 reports a counterfactual arrival rate by age, assuming that the distribution over (a, h_E, h_N) at each age is equal to the unconditional distribution over all EN-couples. This counterfactual can be interpreted as the direct effect of age on arrival rates, while the difference between the dashed and solid line captures the effect of age-specific distributions across (a, h_E, h_N). Age itself affects arrival rates in the beginning (through preferences ψ_{EN}, ψ_{UN}, and ψ_{SN}) and end of the life cycle (through a horizon effect until retirement). Still, a substantial share of the decline in arrival rates over the life cycle can be linked to differences in the distribution across (a, h_E, h_N).

Designing counterfactuals. We construct counterfactuals to evaluate the determinants of the age-dependency in the AWE. The general spirit of these counterfactuals follows the logic *How would young (old) households behave if they were to be similar to old (young) households along margin X?*, where we consider assets, human capital of employed spouses, human capital of non-participating spouses, and age as possible margins.

We provide two complementary sets of counterfactuals, one starting from the young and equating margin by margin to the old and one starting from the old and equating them margin by margin to the young. To make young and old households comparable along the asset margin, we scale each households' asset holdings with the ratio of old-to-young average assets. By doing so, we preserve the relative distribution of assets within each age group while shifting the average to be equalized to the respective other age group. To make age groups comparable along the human capital margin, we add to each households' state the average difference in human capital gridpoints between young and old employed or non-participating spouses respectively, again allowing us to preserve the distribution while shifting the mean. To account for the effect of age we keep households' states constant but shift their age by 30 years.

For each of the four margins we take the simulated distribution of EN-couples by age group in the baseline economy, adjust their state and simulate one period of labor market transitions to construct counterfactual transition matrices. We consider two alternative counterfactuals: First, we adjust only households' decision rules – i.e. assign them the optimal savings choice and decision over future joint labor market states conditional on the adjusted asset and human capital level – but keep the contemporaneous arrival rates for the non-participating spouse constant. Second, we also adjust for the effect on contemporaneous arrival rates. The difference between the two steps isolates the contribution of labor market frictions.

Determinants of the age-dependent AWE. We report the overall AWE into both employment and unemployment for each counterfactual in Table 11, relegating the split into the two margins to Table D.1 in the appendix. The top panel of Table 11 answers the question *"Why is the AWE of young households so large?"*, i.e. it reports counterfactuals when starting from the distribution of young households. The bottom panel reports the corresponding counterfactuals when starting from the distribution of old households, thereby providing an answer to the question *"Why is the AWE of old households so small?"*.

Columns (1)-(3) in the top panel of Table 11 show that increasing asset holdings, increasing the human capital level of the originally employed spouse, or decreasing the human capital level of the non-participating spouse all reduce the AWE among the young age group. With higher asset holdings, the young are better insured against the job loss of a primary earner. A higher human capital of the employed spouse implies higher unemployment benefits (which are proportional to earnings), makes it more likely that this spouse will find a new job quickly (due to higher future arrival rates), and also makes household reoptimization more costly due to the larger difference in potential earnings. The direct effect of asset holdings and human capital of the employed spouse can be seen as evidence for a stronger *need* of the AWE as an insurance margin among the young. Lowering the human capital of the non-participating household member reduces their earnings conditional on finding a job, decreasing their incentive to enter the labor force and the *availability* of spousal labor supply as an insurance margin.

Adjusting contemporaneous arrival rates (that is, when comparing rows "constant λ" to "adjusted λ" for each counterfactual in Table 11) further reduces the *availability* of spousal insurance. Higher asset holdings, higher human capital of the E-spouse, and lower human capital of the N-spouse all make it more likely that the N-spouse will quit a job quickly, thereby lowering the arrival rates that firms are willing to post. In addition, lower human capital of the N-spouse reduces arrival rates by directly lowering firms' per-period profits of a match. This effect, together with the decline in incentives to permanently re-optimize labor supply within the household, makes arrival rates particularly responsive to differences in human capital levels.

Taking into account their respective effect on arrival rates, assets, the human capital of the E- and N-spouse individually account for 52%, 41% and 26% of the difference in the baseline added worker effect respectively. Adjusting all endogenous states and arrival rates jointly reduces the AWE of the young from 9.53% to 2.81% (column (4), row "adjusted λ"). It is important to note that adjusting all states jointly has a smaller impact on the added worker effect than summing up the individual contributions of the three margins considered, pointing to significant interactions.

The finding of significant interaction effects between all margins is confirmed when considering counterfactuals starting for old households in the second panel of Table 11: Equating their asset and human capital levels to those of the young leads to an increase in the AWE of the old (columns (1)-(3)). When changing each margin indivdually, the differences to the baseline are of smaller magnitude compared to the respective counterfactuals starting from the young. The qualitative response is explained by the same mechanisms as for the counterfactuals starting from the young, now operating in reverse. The quantitatively smaller effect can be attributed to the interactions between asset and human capital levels in shaping the AWE: Increasing the need through a reduction in old households' assets while preserving large differences in human capital levels across spouses increases the need for the AWE but does not make spousal labor supply sufficiently valuable as insurance. In reverse, keeping asset levels high but closing the intra-household gap in human capital makes spousal insurance more valuable but does not create a substantial need. Therefore, when changing all margins at the same time and generating both the *need for* and *availability of* spousal insurance, the AWE of the old increases beyond the sum of individual contributions of each margin (column (4)), accounting for more than 100% of the difference in the AWE between young and old.

Assets and human capital accounting for more than the difference in the baseline AWE is due to the effect of age itself, as reported in column (5). The effect of age arises from a strong savings motive close to retirement: A household that has the low asset levels of the young but is close to retirement cannot afford to forgo all labor income, and will hence exhibit a stronger AWE compared to a similar household at the beginning of working life.

Overall, our results suggest that a strong AWE relies on the complementarity between the *need for* and *availability of* spousal insurance. Young households, for whom spousal

Table 11: Added Worker Effect: Counterfactuals

		counterfactuals				
		(1)	(2)	(3)	(4)	(5)
	baseline	a	h_E	h_N	(a, h_E, h_N)	age
Young (25-35):						
constant λ	9.53%	5.25%	7.25%	8.06%	3.66%	15.93%
		(52%)	(28%)	(18%)	(71%)	(-78%)
adjusted λ		5.22%	6.17%	7.42%	2.81%	14.86%
		(52%)	(41%)	(26%)	(82%)	(-65%)
Old (55-65):						
constant λ	1.31%	3.93%	2.18%	2.06%	10.45%	0.35%
		(32%)	(11%)	(9%)	(111%)	(-12%)
adjusted λ		4.67%	2.88%	2.60%	11.43%	0.23%
		(41%)	(19%)	(16%)	(123%)	(-13%)

Notes: Table 11 shows the counterfactual added worker effect. Shares in parentheses indicate the contribution of each margin to the difference in the baseline AWE of the young vs. old.

insurance is both available and needed, respond strongly to the job loss of the household head. Reducing either margin lowers their AWE. In contrast, old households lack both the need for and availability of spousal insurance. For them, increasing both margins jointly makes spousal labor supply attractive and generates a strong AWE.

5.3 Public Insurance and the Added Worker Effect

Having established the importance of the *need for* and *availability of* spousal insurance in determining the AWE over the life cycle, we now turn to its interaction with public insurance. We employ our model to study how the AWE of the young and old changes in response to variation in the duration of unemployment benefits.

We focus on unemployment benefit extensions because they are a common policy tool in the U.S. to provide additional insurance in times of recession. Their effect on the unemployment rate has received considerable attention in the literature (Chodorow-Reich, Coglianese, and Karabarbounis 2019; Hagedorn et al. 2019; Mitman and Rabinovich 2021). While previous work is mostly concerned with the effect of benefit extensions on the job search behavior of the receipients themselves, we focus on the implications for the labor supply response of their spouses.[15]

[15] Cullen and Gruber (2000), Choi and Valladares-Esteban (2020), Birinci (2021), and Fernández-Blanco (2022) highlight the importance of benefit levels for determining the strength of spousal labor supply responses, whereas our focus is on benefit duration.

Table 12: Added Worker Effect: Benefit Duration

	All			Young (25-35)			Old (56-65)		
ϕ^{US}	$\frac{1}{6}$	$\frac{1}{12}$	1	$\frac{1}{6}$	$\frac{1}{12}$	1	$\frac{1}{6}$	$\frac{1}{12}$	1
AWE	5.37%	3.80%	8.92%	9.53%	6.93%	16.27%	1.31%	0.98%	2.26%
to E	1.05%	0.92%	1.51%	0.60%	0.59%	0.55%	0.71%	0.68%	1.15%
to U	4.31%	2.88%	7.41%	8.93%	6.34%	15.72%	0.60%	0.30%	1.11%

Notes: Table 12 compares the AWE in the model across different values for unemployment benefit duration ϕ^{US}. The model is calibrated under the baseline of $\phi^{US} = 1/6$. When changing ϕ^{US} across counterfactuals we leave other parameters unchanged. *All* refers to the full sample of simulated households across all ages.

We quantify the implications of unemployment benefit duration for spousal labor supply by solving and simulating the model economy under different calibrations for the parameter ϕ^{US}, which determines the expected duration of unemployment benefits. In addition to our baseline calibration of $\phi^{US} = 1/6$, we consider a calibration of $\phi^{US} = 1/12$, corresponding to an average duration of twelve months in line with benefit extensions applied across U.S. states during the Great Recession. We also consider a calibration of $\phi^{US} = 1$, which implies that benefits run out after one month. Table 12 reports the results, both for the entire sample and by age group.

Table 12 shows a strong response of the model implied AWE to changes in benefit duration. When benefits are extended from six to twelve months, the AWE decreases from 5.37% to 3.80% for the full sample. For young households, the AWE decreases from 9.53% to 6.93%. For old households, the AWE decreases from 1.31% to 0.98%. In contrast, when we reduce the benefit duration to one month the AWE increases to 8.92% for the full sample, to 16.27% for young, and to 2.26% for old households.[16]

These results highlight the substitutability of public insurance in the form of unemployment benefits and private insurance through spousal labor supply. The presence of public insurance to sustain households' income in case of a job loss reduces the *need* for private insurance through the AWE. Consistent with the previous section, the interaction between public and private insurance of households' income is strongest for young households who are less insured through savings.

Based on Table 12, we can quantify the contribution of different age groups to changes in the aggregate AWE. Assuming that young households account for approximately 25% of the population of EN-couples (see Figure 5) and focusing on the counterfactual with

[16]The decrease of the AWE directly into employment for young households under $\phi^{US} = 1$ can be accounted for by a base effect: If unemployment benefits run out immediately, young non-participating spouses take job offers almost surely even when the head remains employed, leaving little margin to adjust when the head transitions into unemployment

$\phi^{US} = 1/12$, the 2.60 percentage point decrease in the AWE among young households contributes $0.25 * 2.60 = 0.65$ percentage points to the decrease in the aggregate AWE. The youngest age group accounts for 41% of the overall decline in the AWE in response to unemployment benefit extensions, despite representing only one fourth of the population.

Our findings suggest that when trading off the provision of public insurance in form of benefit extensions against crowding out of labor supply, policy makers should pay close attention to the response of spousal labor force participation. Previous work on the provision of unemployment benefits over the life cycle has found smaller crowding out effects on the labor supply of young *benefit recepients* due to their strong incentive to accumulate human capital (Michelacci and Ruffo 2015). The results presented in this section suggest that the crowding out is stronger for the *spouses* in young households, making the effect on overall labor supply ambigous.

6 Conclusion

We provide novel empirical evidence that the AWE decreases over the life cycle. When the primary earner transitions from employment to unemployment, an out of the labor force spouse is on average 5.9 percentage points more likely to enter the labor force compared to when the primary earner remains employed. This spousal labor supply response declines from 7.5pp for households aged 25-35 to 1.3pp for households at ages 56-65. To analyze the mechanisms that drive the documented age-dependency, we build a life cycle model of two-member households in a frictional labor market. We calibrate the model economy to match salient features of the U.S. labor market. The model endogenously generates the average AWE and its decrease in age.

By means of counterfactual, we show that the declining AWE over the life cycle is driven by the complementarity of a *need for* and *availability of* spousal insurance. Higher asset holdings and higher human capital levels of primary earners decrease the need for spousal labor supply among the old relative to the young. Labor market frictions (lower job arrival rates) and a lower human capital of non-participating spouses reduce the availability of spousal labor supply as an insurance margin for the old age group. Adjusting either need or availability individually does not lead to a substantial increase in the AWE among the old. Only when high need for and the availability of spousal insurance act together (as they do among young households), can we generate a strong AWE among the old.

Finally, we show that variation in the duration of unemployment benefits strongly impacts the AWE, in particular among young households. This result highlights that policy makers should take into account the search behavior of both the unemployed and their spouses when determining the optimal length of benefit duration.

References

Andersen, Asger Lau, Amalie Sofie Jensen, Niels Johannesen, Claus Thustrup Kreiner, Søren Leth-Petersen, and Adam Sheridan (2023). "How do households respond to job loss? lessons from multiple high-frequency datasets." *American Economic Journal: Applied Economics* 15.4, pp. 1–29.

Ayhan, Sinem H. (2018). "Married womens added worker effect during the 2008 economic crisisThe case of Turkey." *Review of Economics of the Household* 16.3, pp. 767–790.

Bardóczy, Bence (2022). "Spousal Insurance and the Amplification of Business Cycles." *Working Paper*.

Birinci, Serdar (2021). "Spousal Labor Supply Response to Job Displacement and Implications for Optimal Transfers." *Working Paper*.

Blundell, Richard, Luigi Pistaferri, and Itay Saporta-Eksten (2016). "Consumption inequality and family labor supply." *The American Economic Review* 106.2, pp. 387–435.

Bredtmann, Julia, Sebastian Otten, and Christian Rulff (2018). "Husbands unemployment and wifes labor supply: the added worker effect across Europe." *ILR Review* 71.5, pp. 1201–1231.

Burdett, Kenneth (1978). "A theory of employee job search and quit rates." *The American Economic Review* 68.1, pp. 212–220.

Carroll, Christopher D. (2006). "The method of endogenous gridpoints for solving dynamic stochastic optimization problems." *Economics Letters* 91.3, pp. 312–320.

Casella, Sara (2022). "Womens Labor Force Participation and the Business Cycle." *Working Paper*.

Chéron, Arnaud, Jean-Olivier Hairault, and François Langot (2011). "Age-dependent employment protection." *The Economic Journal* 121.557, pp. 1477–1504.

– (2013). "Life-cycle equilibrium unemployment." *Journal of Labor Economics* 31.4, pp. 843–882.

Chodorow-Reich, Gabriel, John Coglianese, and Loukas Karabarbounis (2019). "The macro effects of unemployment benefit extensions: a measurement error approach." *The Quarterly Journal of Economics* 134.1, pp. 227–279.

Choi, Sekyu and Arnau Valladares-Esteban (2020). "On households and unemployment insurance." *Quantitative Economics* 11.1, pp. 437–469.

Cullen, Julie Berry and Jonathan Gruber (2000). "Does unemployment insurance crowd out spousal labor supply?" *Journal of Labor Economics* 18.3, pp. 546–572.

Czajka, J. (1983). "Subannual income estimation." *Technical, Conceptual and Administrative Lessons of the Income Survey Development Program (ISDP)*, pp. 87–97.

Davis, Steven J. and Till von Wachter (2011). "Recessions and the costs of job loss." *Brookings Papers on Economic Activity*, pp. 1–73.

Dey, Matthew and Christopher Flinn (2008). "Household search and health insurance coverage." *Journal of Econometrics* 145.1-2, pp. 43–63.

Ellieroth, Kathrin (2023). "Spousal Insurance, Precautionary Labor Supply, and the Business Cycle." *Working Paper*.

Elsby, Michael W. L., Bart Hobijn, and Ayşegül Şahin (2015). "On the importance of the participation margin for labor market fluctuations." *Journal of Monetary Economics* 72, pp. 64–82.

Fagereng, Andreas, Helene Onshuus, and Kjersti N. Torstensen (2024). "The consumption expenditure response to unemployment: Evidence from Norwegian households." *Journal of Monetary Economics*, p. 103578.

Fang, Hanming and Andrew J. Shephard (2019). "Household labor search, spousal insurance, and health care reform." *Working Paper*.

Fernández-Blanco, Javier (2022). "Unemployment risks and intra-household insurance." *Journal of Economic Theory* 203, p. 105477.

Flabbi, Luca and James Mabli (2018). "Household search or individual search: Does it matter?" *Journal of Labor Economics* 36.1, pp. 1–46.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren (2020). "Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS." *Dataset*.

Garcia-Perez, J. and Sílvio Rendon (2020). "Family job search and wealth: the added worker effect revisited." *Quantitative Economics* 11.4.

Gong, Xiaodong (2011). "The added worker effect for married women in Australia." *Economic Record* 87.278, pp. 414–426.

Griffy, Benjamin S. (2021). "Search and the sources of life-cycle inequality." *International Economic Review*.

Guler, Bulent, Fatih Guvenen, and Giovanni L. Violante (2012). "Joint-search theory: New opportunities and new frictions." *Journal of Monetary Economics* 59.4, pp. 352–369.

Guner, Nezih, Yuliy Kulikova, and Arnau Valladares-Esteban (2021). "Does the Added Worker Effect Matter?" *Working Paper*.

Haan, Peter and Victoria Prowse (2024). “The Heterogeneous Effects of Social Assistance and Unemployment Insurance: Evidence from a Life Cycle Model of Family Labor Supply and Savings.” *American Economic Journal: Macroeconomics* 16.2, pp. 127–81.

Hagedorn, Marcus, Fatih Karahan, Iourii Manovskii, and Kurt Mitman (2019). “Unemployment benefits and unemployment in the Great Recession: the role of equilibrium effects.” *Working Paper*.

Halla, Martin, Julia Schmieder, and Andrea Weber (2020). “Job displacement, family dynamics, and spousal labor supply.” *American Economic Journal: Applied Economics* 12.4, pp. 253–87.

Hardoy, Inés and Pål Schøne (2014). “Displacement and household adaptation: insured by the spouse or the state?” *Journal of Population Economics* 27, pp. 683–703.

Iskhakov, Fedor, Thomas H. Jørgensen, John Rust, and Bertel Schjerning (2017). “The endogenous grid method for discrete-continuous dynamic choice models with (or without) taste shocks.” *Quantitative Economics* 8.2, pp. 317–365.

Jarosch, Gregor (2015). “Searching for job security and the consequences of job loss.” *Working Paper*.

Kohara, Miki (2010). “The response of Japanese wives labor supply to husbands job loss.” *Journal of Population Economics* 23, pp. 1133–1149.

Kospentaris, Ioannis (2021). “Unobserved heterogeneity and skill loss in a structural model of duration dependence.” *Review of Economic Dynamics* 39, pp. 280–303.

Krueger, Dirk, Kurt Mitman, and Fabrizio Perri (2016). “Macroeconomics and Household Heterogeneity.” *Handbook of Macroeconomics* 2, pp. 843–921.

Krusell, Per, Toshihiko Mukoyama, Richard Rogerson, and Ayşegül Şahin (2017). “Gross worker flows over the business cycle.” *The American Economic Review* 107.11, pp. 3447–76.

Krusell, Per, Toshihiko Mukoyama, and Ayşegül Şahin (2010). “Labour-market matching with precautionary savings and aggregate fluctuations.” *The Review of Economic Studies* 77.4, pp. 1477–1507.

Landais, Camille and Johannes Spinnewijn (2021). “The value of unemployment insurance.” *The Review of Economic Studies* 88.6, pp. 3041–3085.

Lentz, Rasmus (2009). “Optimal unemployment insurance in an estimated job search model with savings.” *Review of Economic Dynamics* 12.1, pp. 37–57.

Lundberg, Shelly (1985). “The added worker effect.” *Journal of Labor Economics* 3.1, Part 1, pp. 11–37.

Maloney, Tim (1987). “Employment constraints and the labor supply of married women: A reexamination of the added worker effect.” *Journal of Human Resources*, pp. 51–61.

– (1991). “Unobserved variables and the elusive added worker effect.” *Economica*, pp. 173–187.

Mankart, Jochen and Rigas Oikonomou (2016a). “Household search and the aggregate labour market.” *The Review of Economic Studies* 84.4, pp. 1735–1788.

– (2016b). “The rise of the added worker effect.” *Economics Letters* 143, pp. 48–51.

Mankart, Jochen, Rigas Oikonomou, and Francesco Pascucci (2022). “The rise of household insurance.” *Working Paper*.

McCall, John Joseph (1970). “Economics of information and job search.” *The Quarterly Journal of Economics*, pp. 113–126.

Menzio, Guido and Shouyong Shi (2011). “Efficient search on the job and the business cycle.” *Journal of Political Economy* 119.3, pp. 468–510.

Menzio, Guido, Irina A. Telyukova, and Ludo Visschers (2016). “Directed search over the life cycle.” *Review of Economic Dynamics* 19, pp. 38–62.

Michelacci, Claudio and Hernán Ruffo (2015). “Optimal life cycle unemployment insurance.” *The American Economic Review* 105.2, pp. 816–59.

Mitman, Kurt and Stanislav Rabinovich (2021). “Whether, when and how to extend unemployment benefits: Theory and application to COVID-19.” *Journal of Public Economics* 200, p. 104447.

Moen, Espen R. (1997). “Competitive search equilibrium.” *Journal of Political Economy* 105.2, pp. 385–411.

Moore, Jeffrey C (2008). “Seam bias in the 2004 SIPP panel: Much improved, but much bias still remains.” *US Census Bureau Statistical Research Division Survey Methodology Research Report Series* 3, p. 2008.

Morazzoni, Marta and Danila Smirnov (2023). “Labor and Family Dynamics in a Joint-Search Framework.” *Working Paper*.

Mortensen, Dale T. (1970). “A theory of wage and employment dynamics.” *Microeconomic foundations of employment and inflation theory*, pp. 167–211.

Mortensen, Dale T. and Christopher A. Pissarides (1994). “Job creation and job destruction in the theory of unemployment.” *The Review of Economic Studies* 61.3, pp. 397–415.

Ortigueira, Salvador and Nawid Siassi (2013). “How important is intra-household risk sharing for savings and labor supply?” *Journal of Monetary Economics* 60.6, pp. 650–666.

Petrongolo, Barbara and Christopher A. Pissarides (2001). “Looking into the black box: A survey of the matching function.” *Journal of Economic Literature* 39.2, pp. 390–431.

Pilossoph, Laura and Shu Lin Wee (2021). “Household search and the marital wage premium.” *American Economic Journal: Macroeconomics* 13.4, pp. 55–109.

Stephens, Melvin (2002). “Worker displacement and the added worker effect.” *Journal of Labor Economics* 20.3, pp. 504–537.

Trabandt, Mathias and Harald Uhlig (2011). “The Laffer Curve Revisited.” *Journal of Monetary Economics* 58.4, pp. 305–327.

Wang, Haomin (2019). “Intra-household risk sharing and job search over the business cycle.” *Review of Economic Dynamics* 34, pp. 165–182.

Wu, Chunzan and Dirk Krueger (2021). “Consumption insurance against wage risk: Family labor supply and optimal progressive income taxation.” *American Economic Journal: Macroeconomics* 13.1, pp. 79–113.

A Data

A.1 CPS

The main data source we use is the CPS as provided by IPUMS. Our sample consists of couples, where we consider the household head and married or unmarried partners of same or opposite sex. The data contains 1,912,284 observations of couples with one spouse employed and the other out of the labor force. By age group, there are 430,807, 524,835, 487,067, and 469,575 EN couples. In total, there are 7,022,155 couple observations.

Labor market variables. We follow the standard definition in the CPS and consider as employed an individual who reports to be employed (at work), employed (not at work last week), or in the armed forces. Individuals are classified as unemployed if they do not work for pay and are actively looking for work, including individuals who are temporarily laid off. The non-employed may be doing housework, be unable to work, at school, doing unpaid work for less than 15 hours, or be retired.

A common issue when considering multiple non-employment states is misclassification between unemployment and non-participation, resulting in implausibly high transition rates across the two. We therefore adjust the individual labor market states as in Elsby, Hobijn, and Şahin (2015) and re-classify individuals who report to be unemployed (non-participating) in one month but to be out of the labor force (unemployed) in the following and previous month as non-participating (unemployed).

Other control variables. Most control variables are taken straight from the CPS (year, month, state, sex, race, number of children, number of children under 5). As college educated we define individuals who hold a bachelor's degree, master's degree, professional school degree, or doctorate.

We merge to the CPS as one additional control variable from an outside source state unemployment rates from the Federal Reserve Economic Data (FRED).

A.2 SIPP

The CPS does not collect asset information. Therefore, to compute the AWE by wealth, we complement the analysis with data from the Survey of Income and Program Participation (SIPP). We work with waves 1994-2016 and apply the same sample restrictions as in the CPS. One exception is the definition of couples across datasets: because the SIPP does not label cohabiting couples as a distinct marital status category, we restrict the sample to married individuals.

Sample Size. The SIPP sample contains 3,038,591 couple observations, among which 779,803 report to have one member employed and one member out of the labor force. For the age group 25-35, the sample contains 673,328 couples, among which 173,373 report to have one member employed and one member out of the labor force. For the age group 56-65, the sample contains 718,147 couples, among which 186,875 report to have one member employed and one member out of the labor force.

Income and Wealth Definition. To measure income, we work with the SIPP variable on total person's earned income for the reference month, and condition on reporting to be employed and having earned at least \$100. We define wealth as net liquid wealth, computed as net worth minus home and vehicle equity. We take net worth, home equity, and vehicle equity directly from the SIPP's topical asset modules. Households report their asset holdings only once per interview wave. To construct monthly asset holdings, we linearly interpolate and extrapolate households' wealth across non-interview months. All financial variables are converted to 2015 dollars using the CPI.

B Empirical Robustness Exercises

B.1 Additional Transition Rates (Full Sample)

Table B.1: Joint Labor Market Transitions (Full Sample): Spouse Non-Participating

	Primary earner transition		
	EE	EU	EN
Cond. prob. of spousal NE transition	6.03%	8.01%	16.79%
Cond. prob. of spousal NU transition	1.63%	5.55%	1.33%
Cond. prob. of spousal NN transition	92.34%	86.44%	81.88%

Notes: Table B.1 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions for the entire population.

Table B.2: Joint Labor Market Transitions (Full Sample): Spouse Unemployed

	Primary earner transition		
	EE	EU	EN
Cond. prob. of spousal UE transition	25.29%	26.27%	34.11%
Cond. prob. of spousal UU transition	61.97%	63.33%	46.01%
Cond. prob. of spousal UN transition	12.74%	10.41%	19.87%

Notes: Table B.2 shows the probability of a spousal transition from unemployment conditional on primary earner transitions for the entire population.

Table B.3: Joint Labor Market Transitions (Full Sample): Spouse Employed

	Primary earner transition		
	EE	EU	EN
Cond. prob. of spousal EE transition	97.61%	91.49%	88.84%
Cond. prob. of spousal EU transition	0.77%	5.78%	1.25%
Cond. prob. of spousal EN transition	1.62%	2.72%	9.92%

Notes: Table B.3 shows the probability of a spousal transition from employment conditional on primary earner transitions for the entire population.

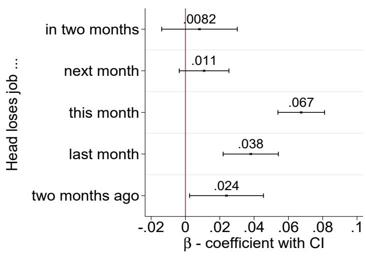
B.2 AWE by Reason for Unemployment

Table B.4: AWE by reasons of Unemployment for Household Head

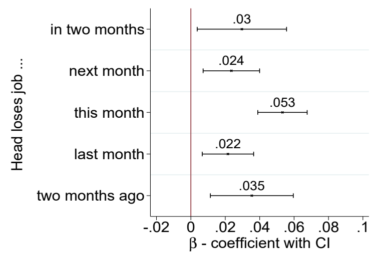
	EE	EU (by reasons for U)			
		Layoff	Job Loser	Temp. Job ended	Job Leaver
NE	6.03%	6.13%	8.81%	7.56%	10.47%
NU	1.63%	3.51%	6.66%	6.59%	7.68%
NN	92.34%	90.35%	84.53%	85.85%	81.86 %

Notes: Table B.4 shows the probabilities of spousal labor market transitions (rows) conditional on the transition of the primary earner (columns), splitting EU transitions of the primary earner by reason for unemployment.

B.3 Dynamic Response for Additional Age Groups



(a) Age 36 to 45

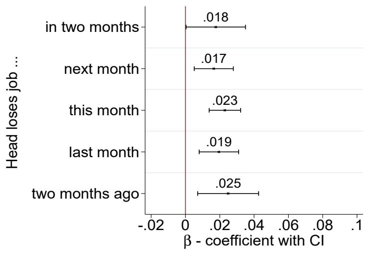


(b) Age 46 to 55

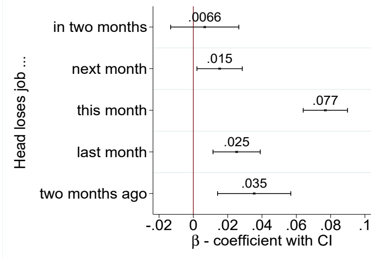
Figure B.1: Δ Pr(Spouse enters LF) this month

Notes: Figure B.1 shows the change in probability that a non-participating spouse enters the labor force (either as unemployed or employed) if the household head loses/lost the job in two months, next month, this month, last month, or two months ago respectively, relative to the baseline in which the household head remains employed. The sample includes couples in which one spouse is working and one spouse is out of the labor force between age 36 and 45 (Figure B.1a) and between age 46 and 55 (Figure B.1b) from the Current Population Survey (CPS), waves 1994 until 2020. Age refers to the non-participating spouse. The regression producing the coefficients is Equation 1.

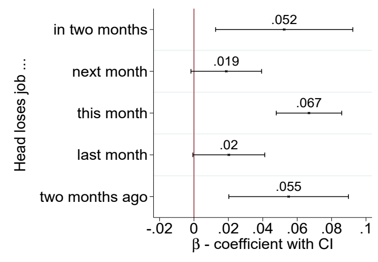
B.4 Dynamic Response by Reason for Unemployment



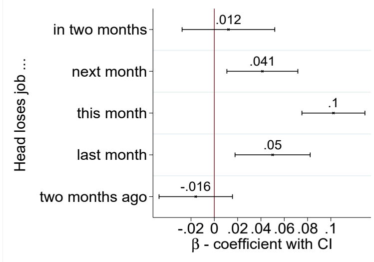
(a) On Layoff



(b) Job Loser



(c) Temp. Job Ended



(d) Job Leaver

Figure B.2: Δ Pr(Spouse enters LF) this month

Notes: Figure B.2 shows the change in probability that a non-participating spouse enters the labor force (either as unemployed or employed) if the household head loses/lost the job in two months, next month, this month, last month, or two months ago respectively, relative to the baseline in which the household head remains employed; split by reasons for unemployment of the household head. Specifically, Figure B.2a shows the results if the household head is on layoff, Figure B.2b if the household head lost his job, Figure B.2c if a temporary job ended and Figure B.2d if the head voluntarily quit his or her job. The sample includes couples in which one spouse is working and one spouse is out of the labor force between age 25 and 65 from the Current Population Survey (CPS), waves 1994 until 2020. The regression producing the coefficients is Equation 1.

B.5 Gender and Cohort Effects

If preferences for labor supply or within household insurance differ by cohorts (e.g. due to changing gender norms), any age-dependency in the AWE may be driven by these underlying preference shifts. We address this concern in two ways. First, we split our sample by gender and age. Table B.5 (Panels I and II) shows that young households still show a stronger AWE when the non-participating spouse is a man, reducing concerns about changing gender norms driving the age-dependency. Second, we repeat the empirical exercise on one cohort of households in which the non-participating spouse was born between 1960 and 1970. We choose this timespan to ensure sufficiently many observations both for the young and old age brackets. Table B.5 (Panel III and IV) confirms the declining AWE over the life cycle for this particular cohort, i.e. for the same cohort when young and old.

Table B.5: Added Worker Effect by Age (Gender and Cohort Effects)

	Primary earner transition		
	EE	EU	AWE
I. Spouse is a Man (Young) :			
Cond. prob. of spousal NE transition	13.54%	14.07%	0.53%
Cond. prob. of spousal NU transition	6.19%	11.69%	5.50%
Cond. prob. of spousal NN transition	80.27%	74.24%	
AWE (total)			6.03%
II. Spouse is a Man (Old):			
Cond. prob. of spousal NE transition	4.50%	4.59%	0.09%
Cond. prob. of spousal NU transition	1.13%	3.23%	2.10%
Cond. prob. of spousal NN transition	94.37%	92.18 %	
AWE (total)			2.19%
III. Spouse born between 1960-70 (Young):			
Cond. prob. of spousal NE transition	6.98%	8.62%	1.64%
Cond. prob. of spousal NU transition	1.89%	6.70%	4.81%
Cond. prob. of spousal NN transition	91.13%	84.68%	
AWE (total)			6.45%
IV. Spouse born between 1960-70 (Old)			
Cond. prob. of spousal NE transition	4.28%	2.94%	-1.34%
Cond. prob. of spousal NU transition	1.11%	3.68%	2.57%
Cond. prob. of spousal NN transition	94.61%	93.38%	
AWE (total)			1.23%

Notes: Table B.5 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by gender and cohort. The AWE is computed as the EU minus the EE column.

B.6 Children

Young couples are more likely to have children living in their household, which affects labor supply behavior. To address this issue, Table B.6 reports the AWE for couples below age 40 (to avoid picking up age-effects) with and without children, and for couples below age 40 with and without children under age five (who require the most childcare). We do not find strong differences in the overall strength of the AWE between young couples with and without children.

Table B.6: Added Worker Effect for Age < 40 (Presence of Children)

	Primary earner transition EE	EU	AWE
I. Have Children:			
Cond. prob. of spousal NE transition	6.26%	8.71%	2.45%
Cond. prob. of spousal NU transition	1.75%	6.65%	4.90%
Cond. prob. of spousal NN transition	91.98%	84.64%	
AWE (total)			7.35%
II. No Children:			
Cond. prob. of spousal NE transition	9.68%	12.68%	3.00%
Cond. prob. of spousal NU transition	3.40%	8.54%	5.14%
Cond. prob. of spousal NN transition	86.91%	78.78%	
AWE (total)			8.14%
III. Have Children below 5:			
Cond. prob. of spousal NE transition	5.63%	8.55%	2.92%
Cond. prob. of spousal NU transition	1.47%	6.14%	4.67%
Cond. prob. of spousal NN transition	92.90%	85.31%	
AWE (total)			7.59%
IV. No Children below 5:			
Cond. prob. of spousal NE transition	8.08%	9.95%	1.87%
Cond. prob. of spousal NU transition	2.60%	7.80%	5.20%
Cond. prob. of spousal NN transition	89.32%	82.24%	
AWE (total)			7.07%

Notes: Table B.6 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by presence of children in the household. The AWE is computed as the EU minus the EE column.

B.7 Reasons for Non-Participation

If the non-participating spouse is retired, transitioning back into the labor force can have a smaller insurance value because of the loss in pension payments. Similarly, if the non-participating spouse dropped out because of bad health, they might not be able to start working again. Both retirement and health related non-participation are more prevalent among the old. Therefore, Table B.7 repeats the empirical analysis excluding retired spouses (Panels I and II), disabled or ill spouses (Panels III and IV), and both retired and disabled/ill spouses (Panels V and VI). We do not find any significant impact on the strength of the AWE, increasing our confidence that the observed age-heterogeneity is not driven by age-dependent reasons for non-participation.

Table B.7: Added Worker Effect by Age (Reason for Non-Participation)

	Primary earner transition		
	EE	EU	AWE
I. Excluding Retirement (Young):			
Cond. prob. of spousal NE transition	6.66%	9.32%	2.66%
Cond. prob. of spousal NU transition	2.00%	6.91%	4.91%
Cond. prob. of spousal NN transition	91.33%	83.77%	
AWE (total)			7.57%
II. Excluding Retirement (Old):			
Cond. prob. of spousal NE transition	4.95%	4.15%	-0.80%
Cond. prob. of spousal NU transition	1.18%	3.33%	2.15%
Cond. prob. of spousal NN transition	93.87%	92.52%	
AWE (total)			1.35%
III. Excluding Disabled/Ill (Young):			
Cond. prob. of spousal NE transition	6.55%	9.34%	2.79%
Cond. prob. of spousal NU transition	1.96%	6.94%	4.98%
Cond. prob. of spousal NN transition	91.49%	83.72%	
AWE (total)			7.77%
IV. Excluding Disabled/Ill (Old):			
Cond. prob. of spousal NE transition	4.17%	3.42%	-0.75%
Cond. prob. of spousal NU transition	0.88%	2.77%	1.89%
Cond. prob. of spousal NN transition	94.95%	93.81%	
AWE (total)			1.14%
V. Excluding Retired and Disabled/Ill (Young):			
Cond. prob. of spousal NE transition	6.55%	9.36%	2.81%
Cond. prob. of spousal NU transition	1.97%	6.96%	4.99%
Cond. prob. of spousal NN transition	91.48%	83.68%	
AWE (total)			7.80%
VI. Excluding Retired and Disabled/Ill (Old):			
Cond. prob. of spousal NE transition	4.74%	3.62%	-1.12%
Cond. prob. of spousal NU transition	1.16%	3.40%	2.24%
Cond. prob. of spousal NN transition	94.11%	92.99%	
AWE (total)			1.12%

Notes: Table B.7 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by reasons for non-participation. The AWE is computed as the EU minus the EE column.

B.8 Education

In Table B.8, we split the sample by spouses with and without a college degree.

Table B.8: Added Worker Effect by Age (Education)

	Primary earner transition		
	EE	EU	AWE
Spouse College, Young			
Cond. prob. of spousal NE transition	7.60%	16.03%	8.43%
Cond. prob. of spousal NU transition	1.63%	7.15%	5.52%
Cond. prob. of spousal NN transition	90.77%	76.82%	
AWE (total)			13.95%
Spouse College, Old			
Cond. prob. of spousal NE transition	5.83%	6.35%	0.52%
Cond. prob. of spousal NU transition	1.14%	2.64%	1.50%
Cond. prob. of spousal NN transition	93.03%	91.01%	
AWE (total)			2.02%
Spouse No College, Young			
Cond. prob. of spousal NE transition	6.31%	8.51%	2.20%
Cond. prob. of spousal NU transition	2.14%	6.86%	4.72%
Cond. prob. of spousal NN transition	91.55%	84.62%	
AWE (total)			6.92%
Spouse No College, Old			
Cond. prob. of spousal NE transition	3.81%	3.16%	-0.65%
Cond. prob. of spousal NU transition	0.82%	2.77%	1.95%
Cond. prob. of spousal NN transition	95.37%	94.06%	
AWE (total)			1.30%

Notes: Table B.8 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions for spouses with and without a college degree. The AWE is computed as the EU minus the EE column.

B.9 Business Cycle

In Table B.9, we split the sample by NBER recessions and expansions. We confirm the age-dependency of the AWE across aggregate states.

Table B.9: Added Worker Effect by Age (Business Cycle)

	Primary earner transition		
	EE	EU	AWE
NBER Recession, Young			
Cond. prob. of spousal NE transition	6.48%	7.74%	1.26%
Cond. prob. of spousal NU transition	1.98%	8.73%	6.75%
Cond. prob. of spousal NN transition	91.55%	83.53%	
AWE (total)			8.01%
NBER Recession, Old			
Cond. prob. of spousal NE transition	4.14%	5.43%	1.29%
Cond. prob. of spousal NU transition	0.83%	2.76%	1.93%
Cond. prob. of spousal NN transition	95.03%	91.81%	
AWE (total)			3.22%
No NBER Recession, Young			
Cond. prob. of spousal NE transition	6.68%	9.53%	2.85%
Cond. prob. of spousal NU transition	2.00%	6.63%	4.63%
Cond. prob. of spousal NN transition	91.31%	83.85%	
AWE (total)			7.48%
No NBER Recession, Old			
Cond. prob. of spousal NE transition	4.30%	3.46%	-0.84%
Cond. prob. of spousal NU transition	0.91%	2.75%	1.84%
Cond. prob. of spousal NN transition	94.79%	93.79%	
AWE (total)			1.00%

Notes: Table B.9 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by state of the business cycle. The AWE is computed as the EU minus the EE column.

In Table B.10, instead of considering NBER recessions, we separate the Great Recession and the ensuing slow recovery from 2007 to 2016.

Table B.10: Added Worker Effect by Age (Excluding Great Recession / Slow Recovery)

	Primary earner transition EE	EU	AWE
2007-2016, Young			
Cond. prob. of spousal NE transition	5.91%	8.20%	2.29%
Cond. prob. of spousal NU transition	2.15%	7.73%	5.58%
Cond. prob. of spousal NN transition	91.94%	84.07%	
AWE (total)			7.87%
2007-2016, Old			
Cond. prob. of spousal NE transition	4.08%	3.96%	-0.39%
Cond. prob. of spousal NU transition	1.10%	2.91%	1.81%
Cond. prob. of spousal NN transition	94.82%	93.41%	
AWE (total)			1.42%
Without 2007-2016, Young			
Cond. prob. of spousal NE transition	7.13%	10.20%	3.07%
Cond. prob. of spousal NU transition	1.91%	6.21%	4.30%
Cond. prob. of spousal NN transition	90.96%	83.59%	
AWE (total)			7.37%
Without 2007-2016, Old			
Cond. prob. of spousal NE transition	4.45%	3.77%	-0.68%
Cond. prob. of spousal NU transition	0.74%	2.61%	1.87%
Cond. prob. of spousal NN transition	94.81%	93.62%	
AWE (total)			1.19%

Notes: Table B.10 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by state of the business cycle. The AWE is computed as the EU minus the EE column.

B.10 Job Loss

In Table B.11, we report the AWE by age for cases when the primary reports their $E \to U$ transition as an involuntary job loss rather than quit.

Table B.11: Added Worker Effect by Age (Job Losers)

	Primary earner transition		
	EE	EU	AWE
Age Spouse 25-35:			
Cond. prob. of spousal NE transition	6.66%	9.98%	3.32%
Cond. prob. of spousal NU transition	2.00%	8.41%	6.41%
Cond. prob. of spousal NN transition	91.34%	81.61%	
AWE (total)			9.73%
Age Spouse 56-65:			
Cond. prob. of spousal NE transition	4.29%	3.79%	-0.50%
Cond. prob. of spousal NU transition	0.90%	3.53%	2.63%
Cond. prob. of spousal NN transition	94.81%	92.67%	
AWE (total)			2.13%

Notes: Table B.11 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions if the $E \to U$ transition is an involuntary job loss. The AWE is computed as the EU minus the EE column.

C Additional Results with SIPP Data

In the SIPP, households are interviewed every four months (except for panel 2014, during which interviews took place once a year) and report their monthly labor market states retrospectively. As a result, labor market transitions within each interview wave tend to be underreported, whereas those across interview waves are overreported, commonly referred to as "seam bias" (Czajka 1983; Moore 2008). To assess the comparability of both data sources, Table C.1 reports the baseline AWE in the CPS and SIPP. Even though the baseline transitions tend to be underreported in the SIPP, the strength of the AWE is similar across datasets (5.90% in the CPS vs. 6.56% in the SIPP).

As an additional robustness check, we aggregate the SIPP data up to interview frequency. Within each aggregated time interval, we assign individuals the labor market state that they report to be in most often. Table C.2 compares the AWE by net liquid wealth within this aggregated sample. The patterns are similar to those on monthly frequency (Table 3), in that low wealth households have a stronger AWE than high wealth households, suggesting a role for asset holdings as an insurance margin against job loss.

Table C.1: Added Worker Effect – CPS vs. SIPP

	Primary earner transition		
	EE	EU	AWE
CPS:			
Cond. prob. of spousal NE transition	6.03%	8.01%	1.98%
Cond. prob. of spousal NU transition	1.63%	5.55%	3.92%
Cond. prob. of spousal NN transition	92.34%	86.44%	
AWE (total)			5.90%
SIPP:			
Cond. prob. of spousal NE transition	2.23%	5.36%	3.13%
Cond. prob. of spousal NU transition	1.14%	4.57%	3.43%
Cond. prob. of spousal NN transition	96.63%	90.07%	
AWE (total)			6.56%

Notes: Table C.1 shows compares the probability of a spousal transition from out of the labor force conditional on primary earner transitions between the CPS and SIPP datasets. The AWE is computed as the EU minus the EE column.

Table C.2: Added Worker Effect by Net Liquid Wealth (SIPP, aggregated)

	Primary earner transition		
	EE	EU	AWE
Bottom 50% of Net Liquid Wealth:			
Cond. prob. of spousal NE transition	8.44%	10.65%	2.21%
Cond. prob. of spousal NU transition	3.75%	9.28%	5.53%
Cond. prob. of spousal NN transition	87.82%	80.07%	
AWE (total)			7.74%
Top 50% of Net Liquid Wealth:			
Cond. prob. of spousal NE transition	8.35%	10.02%	1.67%
Cond. prob. of spousal NU transition	2.33%	6.20%	3.87%
Cond. prob. of spousal NN transition	89.32%	83.78%	
AWE (total)			5.54%

Notes: Table C.2 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by net liquid wealth (net worth minus home and vehicle equity). Data are aggregated to interview panel length. The AWE is computed as the EU minus the EE column.

D Added Worker Effect: Counterfactuals

Table D.1: Added Worker Effect: Counterfactuals (E vs. U)

			counterfactuals				
		baseline	(1) a	(2) h_E	(3) h_N	(4) (a, h_E, h_N)	(5) age
Young (25-35):							
constant λ	**AWE**	9.53%	5.25%	7.25%	8.06%	3.66%	15.93%
	to E	0.60%	-0.60%	1.83%	1.96%	1.40%	2.75%
	to U	8.93%	5.84%	5.43%	6.11%	2.26%	13.18%
adjusted λ	**AWE**		5.22%	6.17%	7.42%	2.81%	14.86%
	to E		-0.63%	0.84%	1.07%	0.54%	0.94%
	to U		5.85%	5.33%	6.35%	2.28%	13.92%
Old (55-65):							
constant λ	**AWE**	1.31%	3.93%	2.18%	2.06%	10.45%	0.35%
	to E	0.71%	0.37%	0.56%	0.71%	0.35%	-0.03%
	to U	0.60%	3.57%	1.62%	1.35%	10.10%	0.38%
adjusted λ	**AWE**		4.67%	2.88%	2.60%	11.43%	0.23%
	to E		1.12%	0.98%	1.29%	1.11%	-0.12%
	to U		3.54%	1.90%	1.31%	10.32%	0.35%

Notes: Table D.1 shows the counterfactual added worker effect, separately into employment and unemplyoment.