Joint Search over the Life Cycle*

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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 disciplined 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

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1 Introduction

The added worker effect (AWE) – labor force entry upon spousal job loss – is considered an important insurance margin for couple households. In this paper, we show that the AWE is predominantly present among young households but limited among the old. We 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 aggregate labor market dynamics 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 to enter the labor force increases by 5.6 percentage points when a primary earner loses their job compared to when they remain employed, corresponding to a 74% increase. We find this effect to be strongly age-dependent. For the youngest age group (26-35), the likelihood of a non-participating spouse to enter the labor force increases by 7.1 percentage points (84%) upon the job loss of the primary earner. Late in working life (age 56-65), the magnitude of the AWE is only 1.4 percentage points (27%). 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 slightly 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 provide suggestive evidence for both the *need for* and *availability of* spousal insurance in determining the strength of the AWE. However, as both assets and labor market prospects are endogenous to households' employment choices over the life cycle, we develop a structural life cycle framework of couples' joint labor supply in a frictional labor market to identify the forces driving the age gradient in the AWE.

[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.

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 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. 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. In line with the data, the model generates an average AWE of 5.2 percentage points, which is strongly declining from 9.4 percentage points at ages 26-35 to 1.2 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, the AWE among young households declines substantially. Allowing arrival rates to adjust amplifies the effect, especially for differences in human capital. Combining the effect of asset holdings, human capital, and arrival rates reduces the AWE among the young to 0.5 percentage points, accounting for the entire difference between young and old.

Assigning old households either the asset holdings or human capital levels of the young has a more limited impact on their AWE. Only when we decrease both their asset and human capital levels simultaneously to those of the young can we generate a substantial increase in the AWE among old households. 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 strongly. In contrast, only if we increase both the need and availability among the old, do we find a large change in their AWE.

Finally, we use the model to study the interaction between public insurance in the form of unemployment benefits 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 5.2% to 3.7%. 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.

In contrast, 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 (2024) and Casella (2022) find sizable extensive margin responses of out of the labor force women to their husband's job loss.[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 a form of insurance.

While the AWE has been studied extensively in the empirical literature, most of the macro-labor literature focuses on the job search problem of single earner households. 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 in accounting for the countercyclicality of women's unemployment rate. Ellieroth (2023) argues that there is precautionary labor supply by spouses whose partners face an increased risk of job loss during recessions. Bardóczy (2022) and Casella (2022) focus on the role of spousal labor supply as an automatic stabilizer for aggregate consumption. We in turn exploit the life cycle dimension to provide insights into the determinants of how households adjust spousal labor supply.

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 dimension of the joint search problem.

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

[2] As in the U.S. data, cross-country evidence supports that spousal labor supply 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.

(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 presents 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. 2023). We first outline the data and sample selection, before we provide empirical evidence of the AWE in our sample and show that its magnitude is declining 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 early 2020 and restrict the sample to couples with both partners between 26 and 65 years old. We include legally married and cohabiting couples, irrespective of their sex. For more details on variables and sample 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 (2024) 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. Throughout the remaining analysis, we label the employed spouse as the "primary earner" and refer to the non-participating spouse as "spouse." That is, our definition of primary earners only reflects their initial labor market status and not (potential) earnings.

A previously employed primary earner 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. The AWE in the third column is computed as the difference between the first and second column. The row "average flow rates of primary earners" reports average transition rates from employment to employment and unemployment of the primary earner.

Overall Effect. Table 1 shows that the likelihood of a spouse entering the labor force increases by 5.55 percentage points (corresponding to a 74% 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 (2024), who find an overall AWE between 6 and 7 percentage points in CPS data from 1976-2019 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 1.72 percentage points, whereas the conditional probability of a spouse transitioning into unemployment increases by 3.83 points. Thus, around two thirds of the overall AWE arise from 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. 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 participation decision: The likelihood of a spouse dropping out of the labor force increases when their partner does the same.

Table 1: Added Worker Effect (Full Sample)

	Primary earner transition EE	EU	AWE
Average flow rates of primary earner:	97.16%	1.00%	
Cond. prob. of spousal NE transition	5.93%	7.65%	1.72%
Cond. prob. of spousal NU transition	1.61%	5.44%	3.83%
Cond. prob. of spousal NN transition	92.46%	86.92%	
AWE (total)			5.55%

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. The first row reports transition probabilities of the primary earner. Data is from the CPS, waves 1994-2020. The data has been adjusted for classification error between U and N as in Elsby, Hobijn, and Şahin (2015). Sample size: 1,280,562.

transitioning into unemployment, highlighting the importance of explicitly distinguishing between unemployed and non-participating individuals.

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 separations.

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 (26 to 35 years), the likelihood that the spouse enters the labor force upon job loss of the primary earner increases by 7.12 percentage points (corresponding to an 84% increase relative to the baseline likelihood of labor force entry), for the young middle aged (36 to 45 years) by 6.83 percentage points (80%), for the older middle aged (46 to 55 years) by 4.57 percentage points (60%), and by only 1.40 percentage points (27%) for the oldest group (56 to 65 years).

For the young, we observe responses from non-participation directly into employment (2.43 percentage points) and unemployment (4.69 percentage points). For the oldest age group, we only find small responses into unemployment (1.89 percentage points) and no response directly into employment (-0.49 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]

[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
I. Age Spouse 26-35:			
Average flow rates of primary earner:	97.67%	1.22%	
Cond. prob. of spousal NE transition	6.53%	8.96%	2.43%
Cond. prob. of spousal NU transition	1.97%	6.66%	4.69%
Cond. prob. of spousal NN transition	91.50%	84.37%	
AWE (total)			7.12%
II. Age Spouse 36-45:			
Average flow rates of primary earner:	97.77%	1.01%	
Cond. prob. of spousal NE transition	6.64%	8.97%	2.33%
Cond. prob. of spousal NU transition	1.86%	6.36%	4.50%
Cond. prob. of spousal NN transition	91.50%	84.67%	
AWE (total)			6.83%
III. Age Spouse 46-55:			
Average flow rates of primary earner:	97.30%	0.92%	
Cond. prob. of spousal NE transition	6.04%	7.41%	1.37%
Cond. prob. of spousal NU transition	1.62%	4.82%	3.20%
Cond. prob. of spousal NN transition	92.34%	87.77%	
AWE (total)			4.57%
IV. Age Spouse 56-65:			
Average flow rates of primary earner:	95.72%	0.81%	
Cond. prob. of spousal NE transition	4.26%	3.77%	-0.49%
Cond. prob. of spousal NU transition	0.89%	2.78%	1.89%
Cond. prob. of spousal NN transition	94.84%	93.45%	
AWE (total)			1.40%

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. The first row of each panel reports transition probabilities of the primary earner. Data is from the CPS, waves 1994-2020. The data has been adjusted for classification error between U and N as in Elsby, Hobijn, and Şahin (2015). Sample size in Panel I: 313,017; in Panel II: 349,892; in Panel III: 314,078; in Panel IV: 303,575.

In addition, old households are less likely than young households to experience an EU transition of the primary earner (0.81%, relative to 1.22% for the youngest age group). Taken together with the strong age-dependency in the AWE, our results therefore imply that young households account for a disproportionate share of the overall AWE transitions in the economy.

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 anticipation or with delay. In addition, certain (household) characteristics such as the presence of children may drive part of the observed age-dependency in labor force entry. 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, state fixed-effects, sex and race of the household head, education of both spouses, number of 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. We report the regression coefficients for these and all following specifications in Appendix D.

Figure 1 shows that the strength of the AWE in the contemporaneous month increases slightly from 5.6 percentage points (Table 1) to 5.8 percentage points when controlling for household observable characteristics.[6] In addition, we find support of both anticipation

[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.

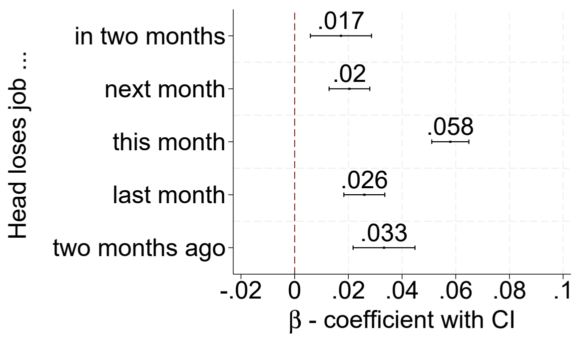


Figure 1: Δ Pr(Spouse enters LF) this month

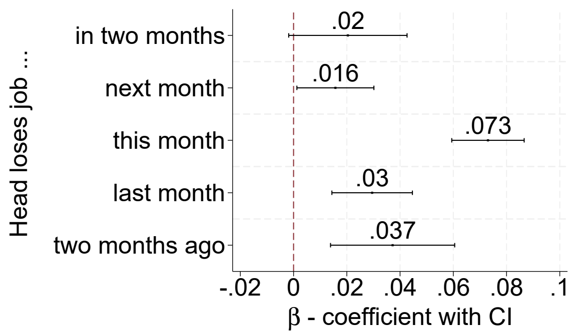
Notes: Figure 1 shows the change in probability that a non-participating spouse enters the labor force (either as unemployed or employed) if the household head loses/lost the job in two months, next month, this month, last month, or two months ago, relative to the baseline in which the household head remains employed. The sample includes couples in which one spouse is employed and one spouse is out of the labor force between age 26 and 65 from the Current Population Survey (CPS), waves 1994 until 2020. The regression producing the coefficients is Equation 1. Appendix Table D.1 lists the corresponding remaining coefficients.

and lagged effects, albeit of smaller 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 results for the two middle age groups (Figure B.1) and by reason for the primary earner's EU transition (Figure B.2) to the appendix.

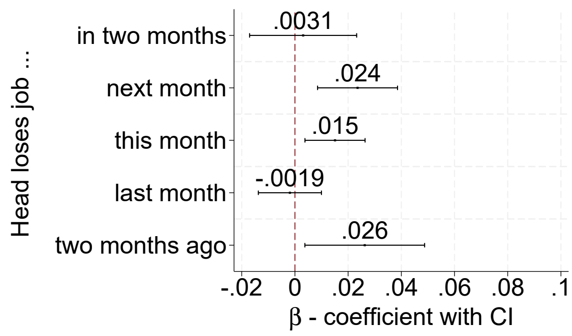
2.4 Need or Availability?

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 through 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 perform the analysis with data from



(a) Age 26 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, relative to the baseline in which the household head remains employed. The sample includes couples in which one spouse is employed and one spouse is out of the labor force between age 26 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. Appendix Tables D.3 and D.6 list the corresponding remaining coefficients.

the Survey of Income and Program Participation (SIPP) when splitting the sample by wealth.[7] Analogous to the CPS, we again only consider couples with one member employed and one member out of the labor force to compute the AWE. As before, we define the initially employed spouse as the "primary earner" and the non-participating spouse as "spouse." Net liquid wealth is defined as net worth minus home and vehicle equity. We use this wealth measure because we are interested in assets that can be liquidated within a relatively short time frame, and hence provide insurance against temporary unemployment shocks.

The data hints 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 (8.87 vs. 5.23 percentage points), suggesting that worse labor market prospects can lower the value of spousal labor supply as an insurance against job loss.[8] When splitting the sample by net liquid wealth, we find a slightly stronger AWE for the bottom half of the sample (6.10 vs. 5.32 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

[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 Appendices A.2 and C for further details on the SIPP data, the sample restrictions we apply, and its comparability to the CPS.

[8]In Appendix Table B.9, we show that the positive relation between the strength of the AWE and education is robust to splitting the sample by age. That is, the pattern in Table 3 does not arise from a positive correlation between age and college attainment, for example because younger cohorts are more likely to have a college degree.

upon spousal transitions into unemployment. However, the difference in the strength of the AWE by net liquid wealth is not statistically significant.[9]

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. The absence of exogenous variation in wealth and labor market prospects makes a direct empirical identification of their relative effects impossible. In addition, the differences by net liquid wealth are not statistically significant and sensitive to the exact definition of wealth. We therefore 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

An evaluation of whether life cycle patterns in the AWE are driven by differences in need for or availability of spousal insurance requires a framework that can account for both margins simultaneously. In this section, we develop a life cycle model of couples with endogenous accumulation of assets and human capital, extensive-margin labor supply and labor market frictions. This framework accommodates both margins and allows to analyze the contribution of other means of insurance (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 can jointly save in a risk-free bond at exogenous interest rate r. Borrowing is not allowed.

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

[9] This result carries over to aggregating the SIPP up to interview frequency, as shown in Appendix C. Also in the aggregated sample, we find a slightly larger AWE for the bottom net liquid wealth half of the sample, but again, the difference between the bottom and top half is not statistically significant.

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

	Primary earner transition EE	EU	AWE
I. Spouse College Degree:			
Average flow rates of primary earner:	97.99%	0.49%	
Cond. prob. of spousal NE transition	6.91%	11.16%	4.25%
Cond. prob. of spousal NU transition	1.51%	6.13%	4.62%
Cond. prob. of spousal NN transition	91.58%	82.71%	
AWE (total)			8.87%
II. Spouse No College Degree:			
Average flow rates of primary earner:	96.86%	1.18%	
Cond. prob. of spousal NE transition	5.57%	7.12%	1.55%
Cond. prob. of spousal NU transition	1.65%	5.33%	3.68%
Cond. prob. of spousal NN transition	92.78%	87.54%	
AWE (total)			5.23%
III. Bottom 50% of Net Liquid Wealth (SIPP):			
Average flow rates of primary earner:	98.80%	0.62%	
Cond. prob. of spousal NE transition	2.20%	4.99%	2.79%
Cond. prob. of spousal NU transition	1.14%	4.45%	3.31%
Cond. prob. of spousal NN transition	96.65%	90.56%	
AWE (total)			6.10%
IV. Top 50% of Net Liquid Wealth (SIPP):			
Average flow rates of primary earner:	99.22%	0.24%	
Cond. prob. of spousal NE transition	2.18%	5.47%	3.29%
Cond. prob. of spousal NU transition	0.74%	2.77%	2.03%
Cond. prob. of spousal NN transition	97.08%	91.76%	
AWE (total)			5.32%

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, waves 1994-2020. Panels III and IV on data from the SIPP, waves 1995-2016. The AWE is computed as the EU minus the EE column. The first row of each panel reports transition probabilities of the primary earner. Sample size in Panel I: 339,135; in Panel II: 941,427; in Panel III: 400,815; in Panel IV: 324,275.

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, human capital increases by one unit with probability $\phi^{up}(h)$. For non-employed agents, human capital drops by one unit with probability $\phi^{down}(h)$.

Figure 3 illustrates individual labor market transitions. 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 they choose to quit, they 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 they choose 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 the entire household state vector $x_i = \{t, h_i, h_{-i}, a', jk, sep_{-i}\}$. sep_{-i} is an indicator relevant only if the second household member was previously employed and indicates whether this member has been separated. Accounting for spousal separations is relevant as firms' vacancy posting happens after job separations and hence arrival rates depend on changes in the labor force status of the spouse. 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, they 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 that individuals in the data 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.

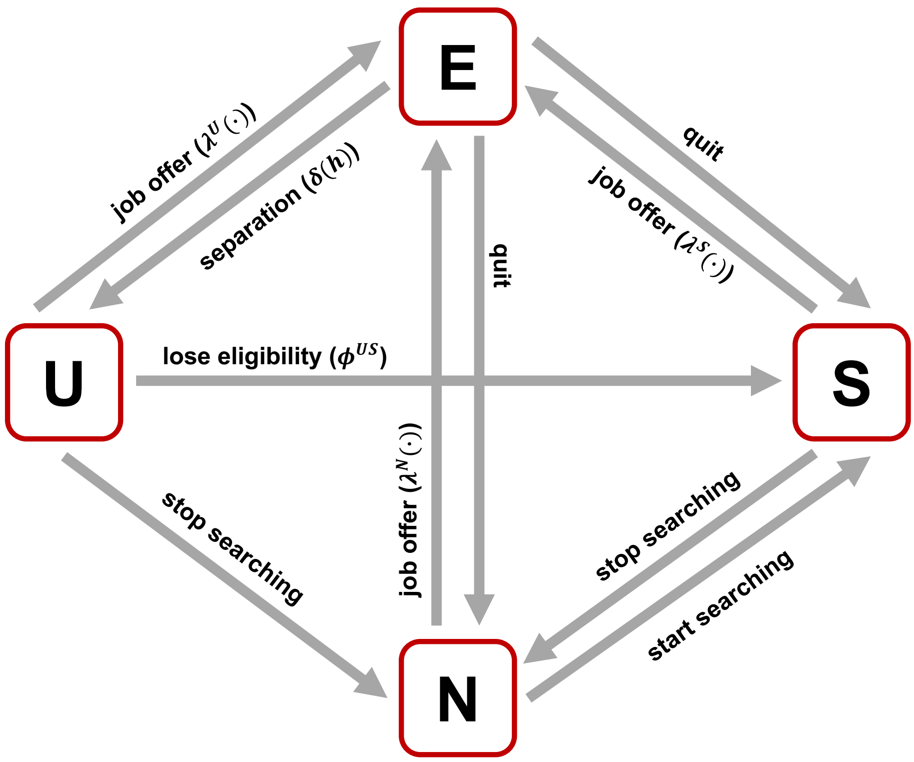


Figure 3: Labor Market Transitions in the Model

Notes: Figure 3 illustrates all possible labor market transitions in the model. **E** refers to employment, **N** to non-participating, **U** to unemployment with benefits, and **S** to unemployment without benefits ('searching').

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 asset income from investing 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.[10] 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

[10] 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	$\mathcal{J}^{EE}_{UU} = \{E,U,N\} \times\{E,U,N\}$	$\mathcal{J}^{EX}_{UU} = \{E,U,N\} \times\{U,N\}$	$\mathcal{J}^{XE}_{UU} = \{U,N\} \times\{E,U,N\}$	$\mathcal{J}^{XX}_{UU} = \{U,N\} \times\{U,N\}$
Member 1	$\mathcal{J}^{EE}_{UX} = \{E,U,N\} \times\{E,S,N\}$	$\mathcal{J}^{EX}_{UX} = \{E,U,N\} \times\{S,N\}$	$\mathcal{J}^{XE}_{UX} = \{U,N\} \times\{E,S,N\}$	$\mathcal{J}^{XX}_{UX} = \{U,N\} \times\{S,N\}$
Member 2	$\mathcal{J}^{EE}_{XU} = \{E,S,N\} \times\{E,U,N\}$	$\mathcal{J}^{EX}_{XU} = \{E,S,N\} \times\{U,N\}$	$\mathcal{J}^{XE}_{XU} = \{S,N\} \times\{E,U,N\}$	$\mathcal{J}^{XX}_{XU} = \{S,N\} \times\{U,N\}$
None	$\mathcal{J}^{EE}_{XX} = \{E,S,N\} \times\{E,S,N\}$	$\mathcal{J}^{EX}_{XX} = \{E,S,N\} \times\{S,N\}$	$\mathcal{J}^{XE}_{XX} = \{S,N\} \times\{E,S,N\}$	$\mathcal{J}^{XX}_{XX} = \{S,N\} \times\{S,N\}$

Notes: Table 4 displays the labor supply choice sets of households, depending on benefit eligibility and job offers of either spouse.

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 eligibility of the individual household member. Again, U indicates eligibility, while X refers to non-eligibility.[11]

We 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

[11]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.

or searching 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

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

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. $b(h) = min\{b^{rep}w(h), b^{max}\}$. 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:

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

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 hence $sep_{-i} = 1$. 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 $\mathcal{J}_{QR}^{OP}$:

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

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.

While we outline 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.[12] 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

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

[12] 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.

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

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

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

This yields

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

and hence

$$\kappa = q(\theta_i)\left[\lambda_S\left[\frac{\kappa}{\lambda^s(\theta_i)EJ_{-i}^{EE} + (1-\lambda^s(\theta_i))EJ_{-i}^{EX}}\right]^{\frac{\alpha-1}{\alpha}} EJ_i^{EE} \right.$$
$$\left. + \left(1 - \lambda_S\left[\frac{\kappa}{\lambda^s(\theta_i)EJ_{-i}^{EE} + (1-\lambda^s(\theta_i))EJ_{-i}^{EX}}\right]^{\frac{\alpha-1}{\alpha}}\right) EJ_i^{EX}\right], \quad (13)$$

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 drastically simplifies computation, 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 equal to human capital

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

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:

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

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

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 impose the exogenous component of job-offer arrival rates to satisfy $\lambda_S = \lambda_U \geq \lambda_N$ 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. We target the initial distribution of assets and human capital to match the wealth and earnings distribution by joint education status of households between 26 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

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	0.9955
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	$1.7 - \frac{0.58}{1+e^{-0.05(t-100)}}$
ψ^{EN}, ψ^{NE}	Disutility of work/search	$1.35 - \frac{0.58}{1+e^{-0.05(t-100)}}$
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	0.3500
Gumbel shock		
σ_ε	Standard deviation of taste shock	0.1000

Notes: Table 5 summarizes all parameter values.

average benefit duration of six months. As in Krueger, Mitman, and Perri (2016), we set the replacement rate to $b^{rep} = 0.5$. In addition, we impose a maximum individual unemployment benefit level of $2,500, and a flat household-level pension of $3,500. The labor income tax is fixed at $\tau = 0.28$ as in Trabandt and Uhlig (2011). Following Petrongolo and Pissarides (2001), we set the elasticity of the matching function α to 0.5 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.[13] 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 than others.

We target average individual transition rates between labor market states. Given a vacancy posting cost κ, flows into employment are closely related to the exogenous components of job arrival rates $\lambda_N, \lambda_S, \lambda_U$. These are also informed by the average level of the AWE, discussed in the next section. 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.[14] The model does well in replicating the empirical patterns, while somewhat understating transitions between non-participation and employment.

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

	Model			Data		
	E	U	N	E	U	N
E	98.0	1.7	0.4	97.4	0.9	1.8
U	25.1	62.7	12.1	25.3	62.4	12.3
N	2.6	1.3	96.1	5.7	1.6	92.7

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, waves 1994-2020. The data has been adjusted for classification error between U and N as in Elsby, Hobijn, and Şahin (2015). See Appendix A.1 for details. Sample size in the data: 9,660,741.

Another important set of targeted moments is the distribution of households over joint labor market states by age group. To compare the model to data, we pool all agents who are unemployed with and without benefits into one group, labeled U. The distribution

[13] 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).

[14] In Figure 4 we only include the sum of EN and EU transitions, which is our target. We report the split between the two in Appendix Figure E.1.

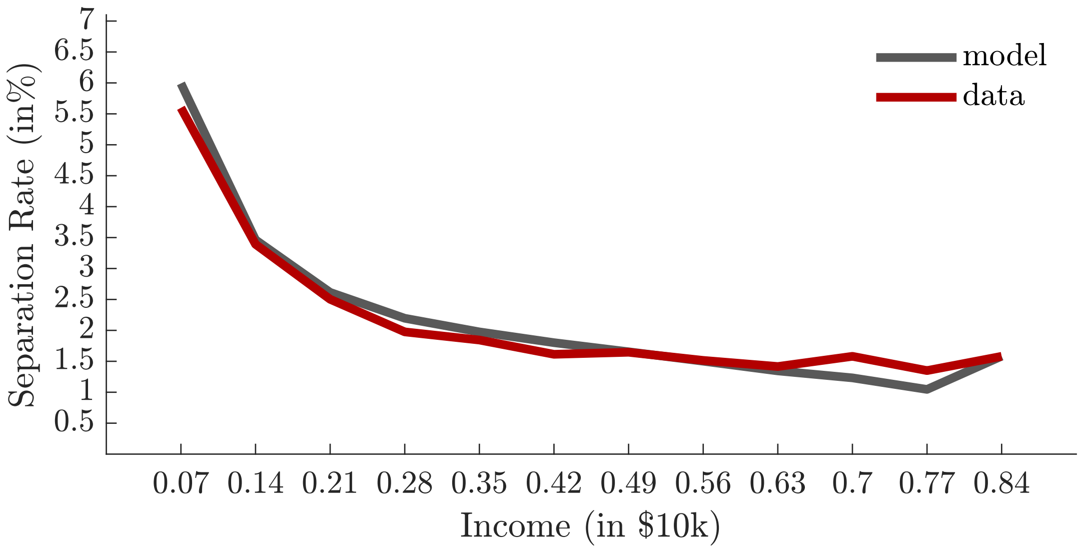


Figure 4: Separation Rates by Income Level (Model vs. Data)

Notes: Figure 4 shows separation rates by pre-tax income level (expressed in $2015). Data moments are the sum of individual *EU* and *EN* transition rates by income bin as computed from the SIPP (waves 1995-2016). SIPP data values are scaled to match aggregate transition rates in the CPS: we multiply SIPP transition rates by the ratio of aggregate transition rates in the CPS over aggregate transition rates in the SIPP.

of households across labor market states informs the preference parameters ψ, i.e. the disutility of work and search. Figure 5 shows that 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.[15]

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

[15] 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.

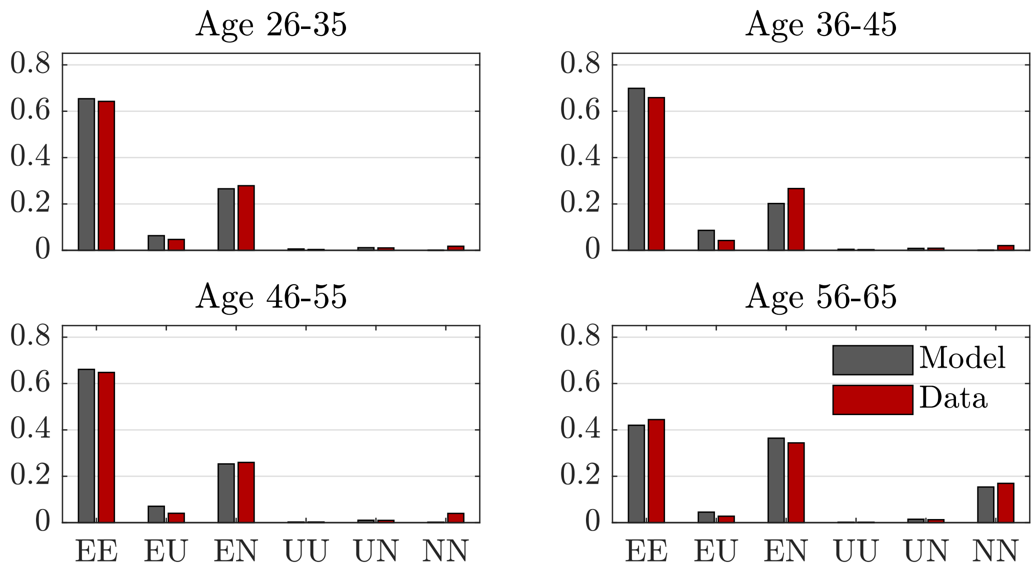


Figure 5: Joint Labor Market States of Couples (Model vs. Data)

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, waves 1994-2020. The data has been adjusted for classification error between U and N as in Elsby, Hobijn, and Şahin (2015). See Appendix A.1 for details. Sample size in the data: Panel I: 1,462,855, Panel II: 2,060,094, Panel III: 1,966,992, Panel IV: 1,397,890.

somewhat underpredicts overall asset levels, especially for the middle age groups. Most important for our comparison of the AWE over the life cycle is the difference in asset holdings between the youngest and oldest age group. The model slightly underpredicts this moment and overpredicts the asset holdings of the young. It therefore follows that the model implied contribution of asset levels to explaining the age difference in the AWE (as done in Section 5.2) is a conservative estimate.

Parameters for the human capital process are chosen to match income dynamics over the life cycle. 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 of at least \$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 26-35, 36-45, and 46-55 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

Table 7: Assets and Income by Age Group

	Assets		Income	
	Model	Data	Model	Data
Aggregate	2.79	3.30	0.47	0.49
Age 26-35	1.85	0.27	0.41	0.41
Age 36-45	1.85	2.56	0.46	0.50
Age 46-55	3.84	5.93	0.51	0.52
Age 56-65	10.33	10.76	0.55	0.50

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, waves 1995-2016. In the data, income is computed for the sample of employed individuals who report to have monthly earnings $\geq$ \$100. Assets and income are expressed in \$2015. 1 unit corresponds to \$10,000. Total number of observations in the data: 310,417 for assets, 4,198,416 for income.

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 (Davis and von Wachter 2011; Jarosch 2023; 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

	Model	Data
Δwage_{1-3m}	-2%	-1%
$\Delta\text{wage}_{4-12m}$	-8%	-7%
$\Delta\text{wage}_{13-24m}$	-25%	-20%

Notes: Table 8 reports earnings losses upon reemployment, computed as earnings in the first month of reemployment relative to earnings in the final month of the previous employment spell by length of non-employment spells. Data is from the SIPP, waves 1995-2016. Sample sizes by group: 7,339; 6,634; 955.

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. As a validation of our model, Table 9 compares model implied labor market transitions by age groups 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). As in the data, the model generates a mildly hump-shaped pattern in the likelihood of remaining employed over the working life, though the monthly transition probability out of employment never falls below 95%. The counterpart to this transition is a mild U-shape in the likelihood of moving from employment to out of the labor force, with both the youngest and oldest age groups leaving the labor force more frequently than the middle age group.

Next, consider the transitions out of unemployment (second row in each age panel). The model matches well that the probability of transitioning to employment is substantially lower for old than young households, whereas the probability of leaving the labor force is U-shaped in age. Finally, the model generates a fall in transitions from out of the labor force into employment (third row in each age panel) and generates high a persistence of non-participation that is increasing in age.

Overall, the model generates too few transitions between out of the labor force and employment/unemployment. This mismatch most likely arises because we leave many important life events related to temporary transitions to non-participation such as child birth, marital transitions, or 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 responses of out of the labor force spouses.

5 The Added Worker Effect over the Life Cycle

In this section, we first show that our model not only matches the average level of the AWE, but also endogenously reproduces its untargeted decline over the life cycle. Second, we use the model to construct counterfactuals and analyze which channels are responsible for the observed age-dependency, distinguishing between the *need for* and *availability of* spousal insurance across the young and old. Third, we turn to interactions of the AWE with the public provision of unemployment insurance.

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

Age 26-35	Model			Data		
	E	U	N	E	U	N
E	97.7	1.7	0.6	97.2	1.0	1.8
U	25.0	62.8	12.2	27.8	59.1	13.1
N	6.0	1.7	92.4	7.1	2.3	90.7
Age 36-45	Model			Data		
	E	U	N	E	U	N
E	98.0	1.9	0.1	97.6	0.9	1.5
U	26.4	63.8	9.8	26.5	61.7	11.9
N	3.1	2.6	94.3	7.1	2.1	90.8
Age 46-55	Model			Data		
	E	U	N	E	U	N
E	98.1	1.7	0.1	97.7	0.8	1.5
U	27.2	61.2	11.6	23.6	64.9	11.5
N	2.6	1.8	95.6	6.1	1.6	92.3
Age 56-65	Model			Data		
	E	U	N	E	U	N
E	97.6	1.6	0.9	96.5	0.8	2.8
U	20.4	63.1	16.5	21.4	65.1	13.5
N	1.1	0.5	98.4	3.7	0.7	95.6

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 values are from the CPS, waves 1994-2020. The data has been adjusted for classification error between U and N as in Elsby, Hobijn, and Şahin (2015). See Appendix A.1 for details. Sample size in the data: Panel I: 2,103,464, Panel II: 2,916,720, Panel III: 2,771,900, Panel IV: 1,868,657.

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 (5.16% vs. 5.55%). 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

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

	Primary earner transition		
	EE	EU/ES	AWE
I. All Households:			
Cond. prob. of spousal NE transition	2.99%	4.14%	1.15%
	5.93%	7.65%	1.72%
Cond. prob. of spousal NS transition	1.41%	5.42%	4.01%
	1.61%	5.44%	3.83%
Cond. prob. of spousal NN transition	95.60%	90.44%	
	92.46%	86.92%	
AWE (total)			5.16%
			5.55%
II. Young (26-35):			
Cond. prob. of spousal NE transition	5.88%	6.74%	0.86%
	6.53%	8.96%	2.43%
Cond. prob. of spousal NS transition	1.23%	9.71%	8.48%
	1.97%	6.66%	4.69%
Cond. prob. of spousal NN transition	92.90%	83.55%	
	91.50%	84.37%	
AWE (total)			9.35%
			7.12%
III. Old (56-65):			
Cond. prob. of spousal NE transition	1.28%	1.87%	0.59%
	4.26%	3.77%	-0.49%
Cond. prob. of spousal NS transition	0.77%	1.40%	0.63%
	0.89%	2.78%	1.89%
Cond. prob. of spousal NN transition	97.95%	96.73%	
	94.84%	93.45%	
AWE (total)			1.22%
			1.40%

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. Data values are from the CPS, waves 1994-2020. CPS sample size in Panel I: 1,280,562; in Panel II: 313,017; in Panel III: 303,575.

loss of the primary earner observed in the data (9.35% vs. 7.12%). For the old, both the model and data produce a much smaller AWE (1.22% vs. 1.40%). Appendix Table E.1 shows that the decline is monotonous in age.[16]

[16]There may be a concern that the age-dependency in the AWE is purely driven by changing preferences for the EN-, UN-, and SN-states over age. As we argue in the calibration, we need the age-dependency to match joint household labor market states by age. However, to alleviate the concern that the age-dependency drives the age pattern of the AWE, we have investigated cases in which we fix the preferences for these states at the levels of either the youngest or oldest households. In these scenarios, the mag-

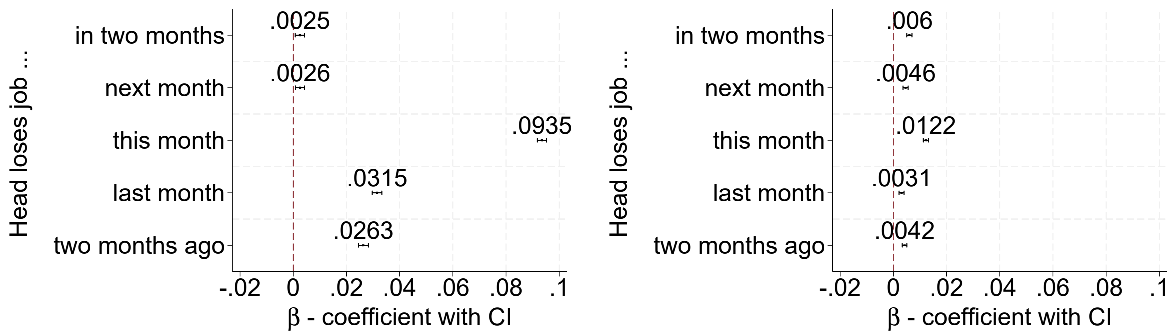
Compared to the data, the model implied AWE operates more strongly through entry into unemployment, especially for the youngest age group. One possible explanation for the inability of the model to generate the empirical split between transitions to employment and unemployment is a mismatch in the timing of separations between model and data. In the model, all separations occur at the end of a period and non-participating spouses have to spend the following period in unemployment to benefit from higher arrival rates. In the data, separations can occur at any time between two interview dates, giving spouses an opportunity for *within-period* adjustments of search effort and the benefit of higher arrival rates already before the next interview. It is likely that some of the spouses which we observe as direct entries into employment in the data would have satisfied the criteria for being considered unemployed at some point between two interviews. In the following, we focus on the overall added worker effect which captures the general intention to take up work, is less prone to the timing issue, and therefore more comparable between the model and data.

To analyze anticipation effects and lagged responses, Figure 6 estimates Equation (1) on model simulated data, 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 arise from two potential forces. First, the endogenous distribution 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 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.

nitude of the overall AWE changes along with the distribution of joint labor market states, but the age-dependency persists.



(a) Age 26 to 35

(b) Age 56 to 65

Figure 6: Δ Pr(Spouse enters LF) this month: 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. Figure 7 shows that 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. On average, the employed spouse in young EN couples has 3.1 times higher human capital than the non-participating spouse, whereas this ratio increases to 5.7 for 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. Young employed spouses are on average employed for 33 months more than their non-participating partners. This difference increases to about 200 months for old households, driving the larger difference in human capital levels.

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 average arrival rates for non-employed spouses in 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. Hence, the dashed line can be interpreted as the direct effect of age on arrival rates,

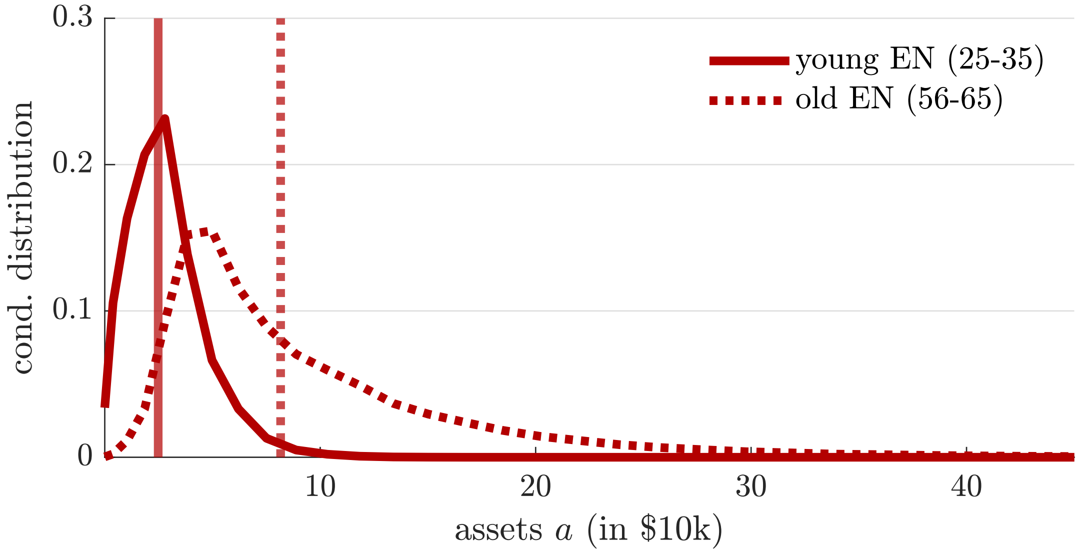


Figure 7: Asset Distribution: EN-Couples

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.

while the difference between the dashed and solid line captures the effect of age-specific distributions across the state variables (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). The graph shows that 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.

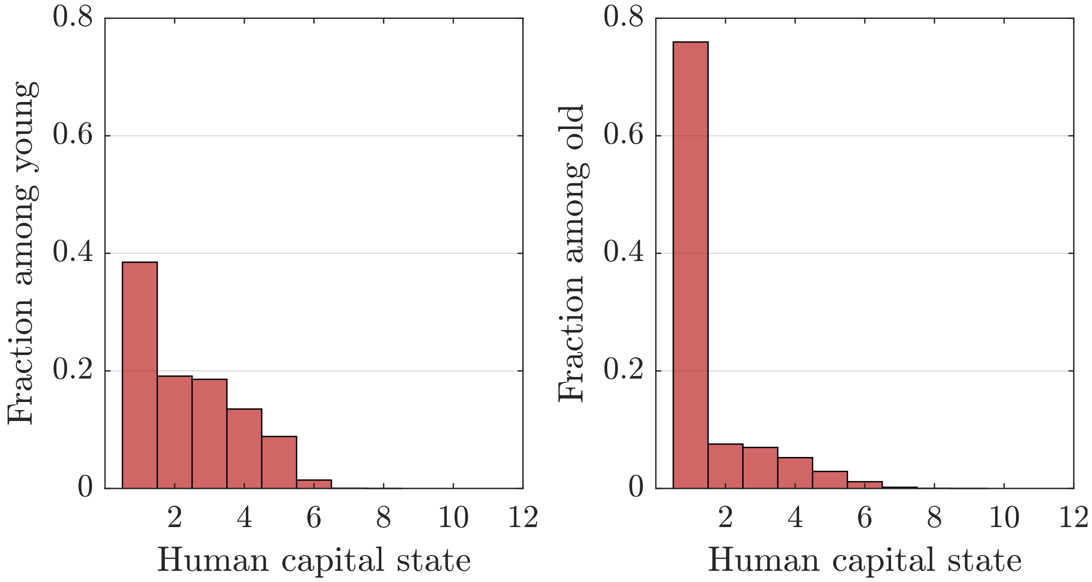


Figure 8: Distribution of Human Capital: Non-Employed Spouse

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.

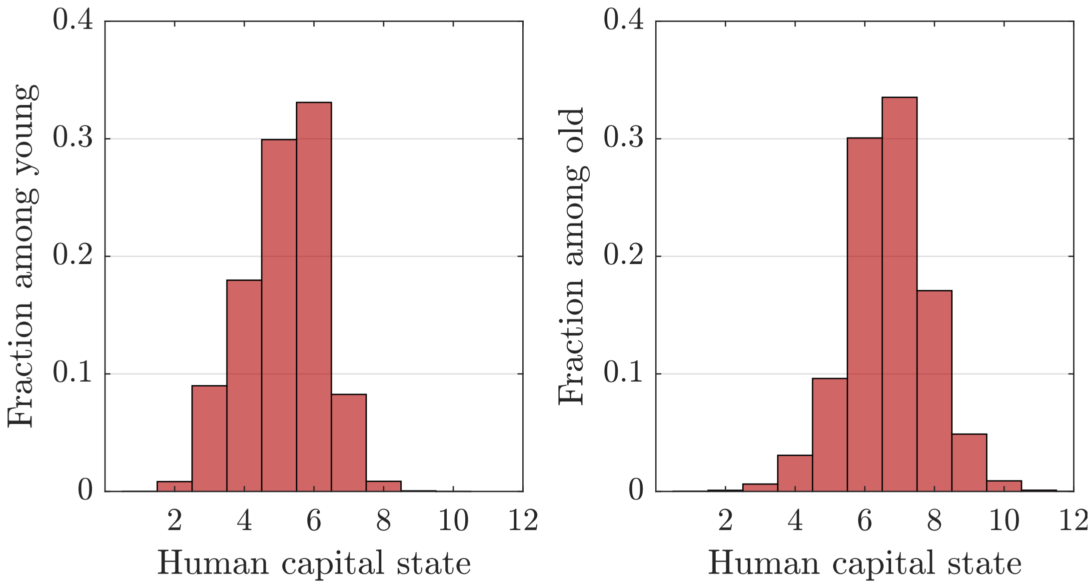


Figure 9: Distribution of Human Capital: Employed Spouse

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.

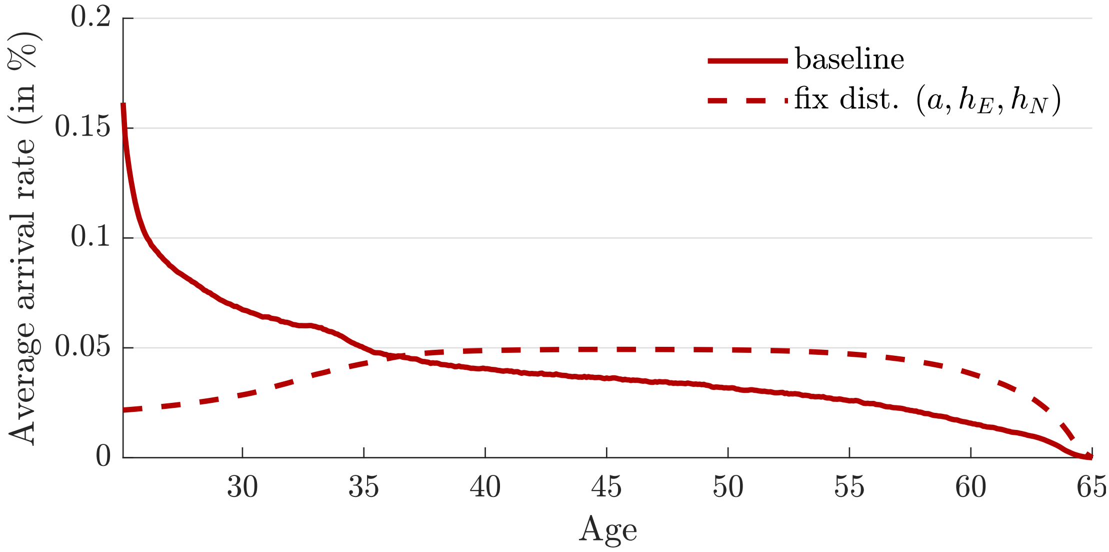


Figure 10: Life Cycle Arrival Rates: Non-Employed Spouse in EN-couple

Notes: Figure 10 shows the arrival rates for non-employed spouses in EN couples by age. The solid line displays arrival rates by age, averaged across households by the model implied distribution of (a, h_E, h_N) conditional on age. The dashed line averages over households at each age with the unconditional distribution (a, h_E, h_N) for all EN couples.

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 of changing state variables on contemporaneous arrival rates. The difference between the two approaches isolates the contribution of labor market frictions.

Determinants of the age-dependent AWE. We report the overall AWE into either employment or unemployment for each counterfactual in Table 11, relegating the split between the two margins to Appendix Table E.2. 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, 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 to the respective level among the old all reduce the AWE of 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 less beneficial 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.

The counterfactuals that start from old households in the second panel of Table 11 yield similar conclusions on the qualitative effect of each margin: 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)). The respective increase in the AWE is explained by the same mechanisms as for the counterfactuals starting from the young, now operating in reverse.

However, adjusting each margin individually leads to substantially smaller effects on the overall AWE when starting from the old than from the young, pointing to significant interactions between the need for and availability of margin of spousal insurance. Young households have both a strong need for insurance (due to low asset levels and low primary earner human capital) and the opportunity of adjusting spousal labor supply (due to higher human capital of the non-participating spouse and higher arrival rates). Reducing either margin individually leads to a substantial reduction in their AWE. In contrast, old households have neither the need nor opportunity to adjust spousal labor supply. For them, increasing either margin individually does not change their AWE significantly.

The interaction between need and opportunity becomes also evident when jointly adjusting all margins. When starting from the young and taking into account their respective effect on arrival rates, assets, human capital of the employed spouse, and human capital of the non-participating spouse individually account for 67%, 93%, and 29% of the difference in the baseline AWE between young and old households respectively. Adjusting all three endogenous states and arrival rates jointly reduces the AWE of the young from 9.35% to 0.48% (column (4), row "adjusted λ"), accounting for 109% of the age gap – which is less than the sum of its parts. In reverse, adjusting all margins simultaneously for old households increases the AWE considerably more than the sum of the individual contributions (240% vs. 40%, 45%, and 12%). These findings underline the complementarity between the need for and availability of spousal labor supply in generating a strong added worker effect among the young, where each margin reinforces the effect of the other.

In addition, age itself contributes to the pattern that the joint difference in assets, human capital, and arrival rates accounts for more than the observed gap in the AWE between young and old households in the model. Age has a direct effect on the AWE due to the age-dependency in preferences (older households forgo less utility when both members are in the labor force) and a stronger savings motive close to retirement. With equal asset holdings and human capital of both spouses, an old household will therefore exhibit a stronger AWE compared its young counterpart. The model confirms this mechanism: When we adjust the age of the young (old) to be 30 years older (younger) while keeping all other state variables fixed, the difference in the AWE between the two age groups increases compared to the baseline, as reported in column (5) of Table 11.

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 (26-35):						
constant λ	9.35%	3.98%	4.08%	7.37%	1.74%	17.03%
		(66%)	(65%)	(24%)	(94%)	(-94%)
adjusted λ		3.94%	1.82%	6.98%	0.48%	16.23%
		(67%)	(93%)	(29%)	(109%)	(-85%)
Old (56-65):						
constant λ	1.22%	3.88%	3.39%	1.83%	19.59%	0.21%
		(33%)	(26%)	(8%)	(226%)	(-12%)
adjusted λ		4.48%	4.88%	2.20%	20.73%	0.11%
		(40%)	(45%)	(12%)	(240%)	(-14%)

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

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 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, only increasing both margins jointly makes spousal labor supply attractive as a form of insurance 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. Previous work has mostly considered interactions between the level of unemployment benefits and spousal labor supply (Cullen and Gruber 2000; Choi and Valladares-Esteban 2020; Birinci 2021; Fernández-Blanco 2022). We employ our model to study how the AWE over the life cycle changes with the duration of benefits, which is a common margin of adjustment for unemployment insurance policy in the US.[17]

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 $\phi^{US} = 1/12$, doubling the average duration of benefits to twelve months. We also consider a calibration of $\phi^{US} = 1$, which implies that benefits run out after one month. For each counterfactual we keep all other parameter values constant relative to the baseline calibration and solve and simulate the entire household problem with alternative ϕ^{US}. Table 12 reports the results, both for the entire sample and by age group.

Table 12: Added Worker Effect: Benefit Duration

	All			Young (26-35)			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	5.16%	3.68%	8.34%	9.35%	6.93%	15.91%	1.22%	0.81%	2.12%
to E	1.15%	0.98%	1.39%	0.86%	0.94%	0.50%	0.59%	0.38%	0.92%
to U	4.01%	2.70%	6.95%	8.48%	5.99%	15.41%	0.63%	0.43%	1.20%

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

[17] Expansions of benefit duration during recessions and their effect on the unemployment rate have 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 temporary benefit extensions on the job search behavior of the recipients themselves, we simulate a permanent extension of benefits and focus on the implications for spousal labor supply responses.

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 for the full sample decreases from 5.16% to 3.68%. For young households, the AWE decreases from 9.35% to 6.93%. For old households, the AWE decreases from 1.22% to 0.81%. In contrast, when we reduce the benefit duration to one month the AWE increases to 8.34% for the full sample, to 15.91% for the young, and to 2.12% for the old.[18]

The observed changes in the AWE can arise from two forces. First, shifts in the distribution of endogenous state variables (human capital and assets) alter the strength of the AWE, due to their impact on the relative need for and availability of spousal insurance. Appendix Figure E.2 shows that the distribution of human capital hardly changes across model versions with different benefit duration, while asset holdings increase when losing benefit eligibility becomes more likely (due to increased self insurance). Higher asset levels in the model version with larger ϕ^{US} should, everything else equal, lead to a reduction in the AWE. However, Table 12 shows that the AWE becomes *stronger* if we increase ϕ^{US}. Hence, the reported pattern in Table 12 must be driven by a second effect: Conditional on the same human capital and asset level, households are more likely to make use of the AWE if the availability of public insurance is limited.

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 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.[19]

Overall, 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 recipients* 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 more ambiguous.

[18]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.

[19]Another important determinant of the effect of unemployment benefits is the correlation between spouses labor market risk, e.g. due to assortative mating on industries or occupations. While the model does not incorporate correlated shocks across spouses, it does imply an endogenous correlation between separation and arrival rates across household members through spouses' human capital. To the extent that human capital is correlated in the initial distribution of households and accumulated in parallel over the life cycle, it leads to correlation in separation rates and arrival rates across members.

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 5.6 percentage points more likely to enter the labor force compared to when the primary earner remains employed. This spousal labor supply response declines from 7.1 percentage points for households aged 26-35 to 1.4 percentage points 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.

By means of counterfactuals, we show that the declining AWE in age is driven by a 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.

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A Data

A.1 CPS

The main data source we use is the CPS as provided by IPUMS.[20] We work with the CPS because it is the dataset upon which official labor market statistics in the U.S. are based. The CPS collects monthly data at the household level, but contains detailed individual information on demographic characteristics and labor market outcomes for all household members. Households are interviewed for four consecutive months, then drop out of the survey for eight months, and reenter for another four consecutive months. To link observations longitudinally, we rely on the variable `cpsidv`. This variable is created by IPUMS, validating that Census assigned identifiers have consistent sex and race values over time and that age changes in expected ways.[21] Using this eliminates the need to post-validate the identifiers longitudinally ourselves.

We restrict our sample to the period from January 1994 to April 2020 and couple households who are both between 26 and 65 years old. We consider the household head and married or unmarried partners of same or opposite sex. Our sample contains 6,887,831 couple observations, among which 1,875,061 have one spouse employed and the other out of the labor force. By age group (as defined in Table 2), there are 395,886, 522,993, 486,717, and 469,465 EN couples.

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-participating 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

[20] We last downloaded the IPUMS CPS, Version 11.0, on August 22, 2024.

[21] See Rodgers and Flood (2023) for a detailed description of how the identifier is generated and validated.

college educated we define individuals who hold a bachelor's degree, master's degree, professional school degree, or doctorate. We top-code the number of children at three (i.e., the last category we consider is to have "three or more children"), and recode the race variable to a dummy that takes the value one if the individual reports to be white.

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. To compute the AWE by wealth, we therefore complement the analysis with data from the Survey of Income and Program Participation (SIPP). The SIPP contains monthly data on individual demographics and labor market outcomes, as well as household-level asset holdings. In the SIPP, interviews take place every four months (except in panel 2014 where interviews took place once a year) and respondents report monthly variables retrospectively. Households remain in the survey for the entire panel (subject to attrition). We work with data from 1995 to 2016 (i.e., SIPP panels 1996, 2001, 2004, 2008, and 2014) and apply the same sample restrictions as in the CPS, except for the definition of couples: because the SIPP does not label cohabiting couples as a distinct marital status category, we restrict the sample to married individuals. Asset data is not part of the SIPP core questionnaire, but only available in topical modules. We restrict ourselves to households for which we have some asset information from the topical modules.

Sample Size. The SIPP sample contains 3,018,217 couple observations, among which 769,119 report to have one member employed and one member out of the labor force. For the age group 26-35, the sample contains 646,973 couples, among which 161,148 report to have one member employed and one member out of the labor force. For the age group 56-65, the sample contains 720,917 couples, among which 187,660 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)

The main joint labor market transition of interest in this paper is the transition out of the labor force when an employed spouse transitions to unemployment relative to when the employed spouse remains employed. In this appendix we report a number of additional joint transitions based on the full sample of households. First, in Table B.1, we additionally report for EN couples also the conditional probability of a spouse moving to employment or unemployment or staying in non-employment when the primary earner leaves the labor force from employment. A primary earner transition from employment to out of the labor force is associated with a significantly increased probability of the out of the labor force spouse taking up employment. This may reflect a form of spousal insurance, but also switches in household specialization.

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

	Primary earner transition		
	EE	EU	EN
Average flow rates of primary earner:	97.16%	1.00%	1.84%
Cond. prob. of spousal NE transition	5.93%	7.65%	16.00%
Cond. prob. of spousal NU transition	1.61%	5.44%	1.31%
Cond. prob. of spousal NN transition	92.46%	86.92%	82.68%

Notes: Table B.1 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions. The first row of each panel reports transition probabilities of the primary earner. Data is from the CPS, waves 1994-2020. The data has been adjusted for classification error between U and N as in Elsby, Hobijn, and Şahin (2015). Sample size: 1,304,664.

Tables B.2 and B.3 report the probabilities of a spousal transition from unemployment and employment, respectively, conditional on primary earner transitions. For EU couples, if the primary earner transitions to unemployment or non-employment, this is associated with an increased probability of the unemployed spouse to take up employment relative to the case where the primary earner remains employed. For EE couples, there is strong suggestive evidence of joint optimization, with the conditional probability of one partner leaving the labor force being much higher when the other does so as well.

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

	Primary earner transition		
	EE	EU	EN
Average flow rates of primary earner:	96.33%	2.00%	1.67%
Cond. prob. of spousal UE transition	25.14%	25.75%	33.63%
Cond. prob. of spousal UU transition	62.19%	63.79%	46.52%
Cond. prob. of spousal UN transition	12.67%	10.46%	19.85%

Notes: Table B.2 shows the probability of a spousal transition from unemployment conditional on primary earner transitions. The first row of each panel reports transition probabilities of the primary earner. Data is from the CPS, waves 1994-2020. The data has been adjusted for classification error between U and N as in Elsby, Hobijn, and Şahin (2015). Sample size: 184,183.

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

	Primary earner transition		
	EE	EU	EN
Average flow rates of primary earner:	97.45%	0.82%	1.73%
Cond. prob. of spousal EE transition	97.64%	91.62%	88.94%
Cond. prob. of spousal EU transition	0.76%	5.71%	1.22%
Cond. prob. of spousal EN transition	1.60%	2.67%	9.83%

Notes: Table B.3 shows the probability of a spousal transition from employment conditional on primary earner transitions. The first row of each panel reports transition probabilities of the primary earner. Data is from the CPS, waves 1994-2020. The data has been adjusted for classification error between U and N as in Elsby, Hobijn, and Şahin (2015). Sample size: 6,033,891.

B.2 AWE by Reason for Unemployment

In Table B.4 we show the AWE separately for different reasons for the unemployment transition of the primary earner. As expected, the AWE is larger for permanent job loss and quits than for potentially temporary layoffs.

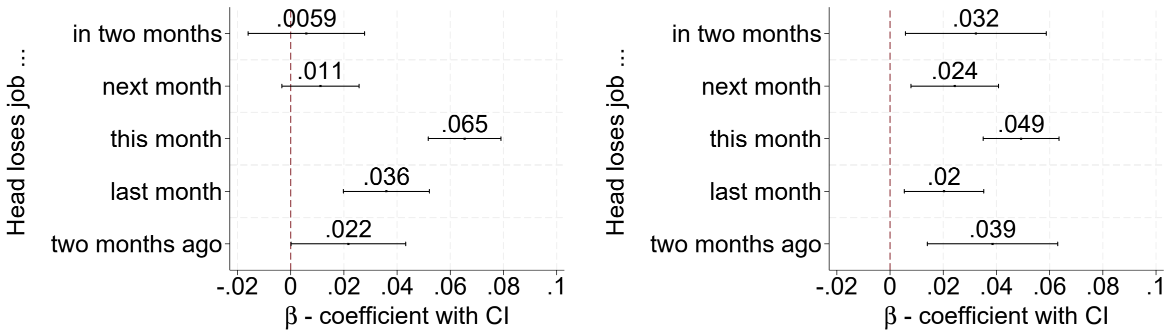
Table B.4: AWE by reasons of Unemployment for Household Head

	EE	EU (by reasons for U)			
		Layoff	Job Loser	Temp. Job ended	Job Leaver
NE	5.93%	5.68%	8.31%	7.64%	10.51%
NU	1.61%	3.42%	6.46%	6.53%	7.70%
NN	92.46%	90.90%	85.23%	85.83%	81.79%

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. Data is from the CPS, waves 1994-2020. The data has been adjusted for classification error between U and N as in Elsby, Hobijn, and Şahin (2015). Sample size for EE column: 1,268,085; for EU column "Layoff": 5,333; for EU column "Job Loser": 3,666; for EU column "Temp. Job ended": 1,593; for EU column "Job Leaver": 938.

B.3 Dynamic Response for Additional Age Groups

Figure B.1 shows the dynamic AWE for the two middle age groups, to be compared to the youngest and oldest age groups shown in Figure 2.



(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. Appendix Tables D.4 and D.5 list the corresponding remaining coefficients.

B.4 AWE with EN Transition as Adverse Event

Instead of interpreting the EU transition as the adverse event to compute the AWE, one could also use the EN transition of the primary earner. An EN transition is arguably a more permanent change in earnings prospects. However, these transitions very likely also include a large amount of household specialization reoptimization. Still, in this subsection, we reproduce Table 2 using an EN transition of the employed spouse as the adverse event instead of an EU transition. Also in this specification we find a large age gradient in spousal transitions.

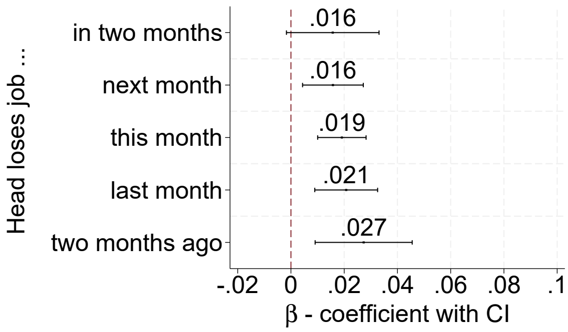
Table B.5: Added Worker Effect by Age - EN Transition as Adverse Event

	Primary earner transition EE	EN	AWE
I. Age Spouse 26-35:			
Average flow rates of primary earner:	97.67%	1.11%	
Cond. prob. of spousal NE transition	6.53%	26.11%	19.58%
Cond. prob. of spousal NU transition	1.97%	1.92%	-0.05%
Cond. prob. of spousal NN transition	91.50%	71.97%	
AWE (total)			19.53%
II. Age Spouse 36-45:			
Average flow rates of primary earner:	97.77%	1.21%	
Cond. prob. of spousal NE transition	6.64%	25.83%	19.19%
Cond. prob. of spousal NU transition	1.86%	2.12%	0.26%
Cond. prob. of spousal NN transition	91.50%	72.04%	
AWE (total)			19.45%
III. Age Spouse 46-55:			
Average flow rates of primary earner:	97.30%	1.78%	
Cond. prob. of spousal NE transition	6.04%	15.94%	9.90%
Cond. prob. of spousal NU transition	1.62%	1.71%	0.09%
Cond. prob. of spousal NN transition	92.34%	82.35%	
AWE (total)			9.99%
IV. Age Spouse 56-65:			
Average flow rates of primary earner:	95.72%	3.47%	
Cond. prob. of spousal NE transition	4.26%	8.38%	4.12%
Cond. prob. of spousal NU transition	0.89%	0.55%	-0.34%
Cond. prob. of spousal NN transition	94.84%	91.07%	
AWE (total)			3.78%

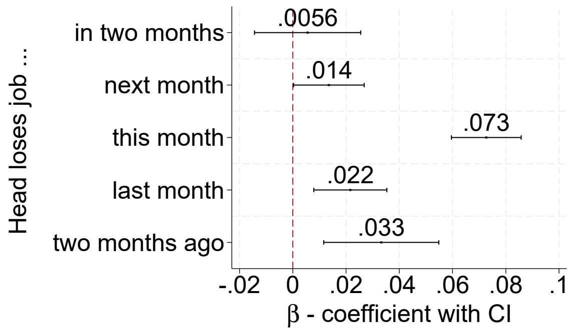
Notes: Table B.5 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by age group. The AWE is computed as the EN minus the EE column. The first row of each panel reports transition probabilities of the primary earner. Data is from the CPS, waves 1994-2020. The data has been adjusted for classification error between U and N as in Elsby, Hobijn, and Şahin (2015). Sample size in Panel I: 312,693; in Panel II: 350,584; in Panel III: 316,866; in Panel IV: 312,044.

B.5 Dynamic Response by Reason for Unemployment

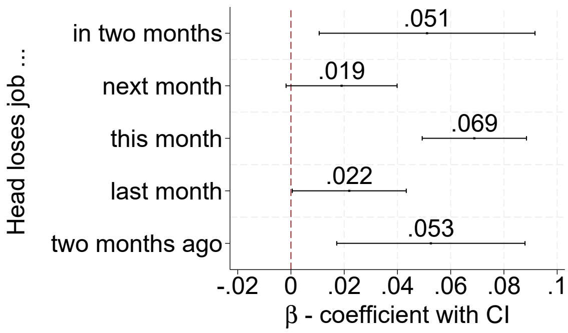
Figure B.2 shows leads and lags for the AWE by reason for the unemployment transition of the primary earner.



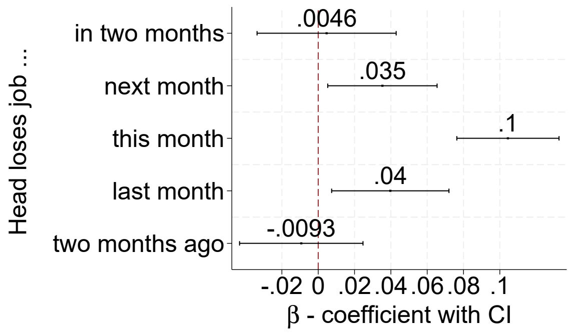
(a) On Layoff



(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 26 and 65 from the Current Population Survey (CPS), waves 1994 until 2020. The regression producing the coefficients is Equation 1. Appendix Tables D.7 to D.10 list the corresponding remaining coefficients.

B.6 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 shifts. Moreover, if the share of female primary earners increased over time, changes in the AWE may arise from differences in male and female labor market transitions. We address these concerns in two ways. First, we split our sample by gender and age. Table B.6 (Panels I and II) shows that young households still show a stronger AWE when the non-participating spouse is a man. Moreover, throughout our sample period, the share of female primary earners only increased slightly from 17% in 1994 to 22% in 2020. Second, we repeat the empirical exercise on one cohort of households in which the non-participating spouse was born between 1960 and 1970. Table B.6 (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.6: Added Worker Effect by Age (Gender and Cohort Effects)

	Primary earner transition		
	EE	EU	AWE
I. Spouse is a Man (Young) :			
Average flow rates of primary earner:	95.04%	1.21%	
Cond. prob. of spousal NE transition	13.04%	12.47%	-0.57%
Cond. prob. of spousal NU transition	6.20%	11.68%	5.48%
Cond. prob. of spousal NN transition	80.75%	75.85%	
AWE (total)			4.91%
II. Spouse is a Man (Old):			
Average flow rates of primary earner:	95.49%	0.76%	
Cond. prob. of spousal NE transition	4.48%	4.63%	0.15%
Cond. prob. of spousal NU transition	1.13%	3.26%	2.13%
Cond. prob. of spousal NN transition	94.39%	92.11 %	
AWE (total)			2.28%
III. Spouse born between 1960-70 (Young):			
Average flow rates of primary earner:	97.97%	1.11%	
Cond. prob. of spousal NE transition	6.84%	8.59%	1.75%
Cond. prob. of spousal NU transition	1.88%	6.14%	4.26%
Cond. prob. of spousal NN transition	91.28%	85.26%	
AWE (total)			6.01%
IV. Spouse born between 1960-70 (Old)			
Average flow rates of primary earner:	96.36%	1.10%	
Cond. prob. of spousal NE transition	4.25%	2.96%	-1.29%
Cond. prob. of spousal NU transition	1.09%	3.71%	2.62%
Cond. prob. of spousal NN transition	94.66%	93.34%	
AWE (total)			1.33%

Notes: Table B.6 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. The first row of each panel reports transition probabilities of the primary earner. Sample size in Panel I: 22,661; in Panel II: 133,550; in Panel III: 113,844; in Panel IV: 35,984.

B.7 Children

Young couples are more likely to have children living in their household, which affects labor supply behavior. To address this issue, Table B.7 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.7: Added Worker Effect for Age < 40 (Presence of Children)

	Primary earner transition EE	EU	AWE
I. Have Children:			
Average flow rates of primary earner:	97.83%	1.15%	
Cond. prob. of spousal NE transition	6.19%	8.42%	2.23%
Cond. prob. of spousal NU transition	1.74%	6.43%	4.69%
Cond. prob. of spousal NN transition	92.07%	85.15%	
AWE (total)			6.92%
II. No Children:			
Average flow rates of primary earner:	96.92%	1.15%	
Cond. prob. of spousal NE transition	9.46%	11.55%	2.09%
Cond. prob. of spousal NU transition	3.37%	8.81%	5.44%
Cond. prob. of spousal NN transition	87.17%	79.64%	
AWE (total)			7.53%
III. Have Children below 5:			
Average flow rates of primary earner:	97.97%	1.10%	
Cond. prob. of spousal NE transition	5.55%	8.12%	2.57%
Cond. prob. of spousal NU transition	1.44%	5.73%	4.29%
Cond. prob. of spousal NN transition	93.01%	86.15%	
AWE (total)			6.86%
IV. No Children below 5:			
Average flow rates of primary earner:	97.40%	1.23%	
Cond. prob. of spousal NE transition	7.90%	9.56%	1.66%
Cond. prob. of spousal NU transition	2.57%	7.85%	5.28%
Cond. prob. of spousal NN transition	89.53%	82.59%	
AWE (total)			6.94%

Notes: Table B.7 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. The first row of each panel reports transition probabilities of the primary earner. Sample size in Panel I: 410,718; in Panel II: 50,462; in Panel III: 265,317; in Panel IV: 195,863.

B.8 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.8 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 mainly driven by these age-dependent reasons for non-participation.

Table B.8: Added Worker Effect by Age (Reason for Non-Participation)

	Primary earner transition EE	EU	AWE
I. Excluding Retirement (Young):			
Average flow rates of primary earner:	97.69%	1.22%	
Cond. prob. of spousal NE transition	6.54%	8.99%	2.45%
Cond. prob. of spousal NU transition	1.97%	6.68%	4.71%
Cond. prob. of spousal NN transition	91.49%	84.33%	
AWE (total)			7.16%
II. Excluding Retirement (Old):			
Average flow rates of primary earner:	96.34%	0.94%	
Cond. prob. of spousal NE transition	4.91%	4.20%	-0.71%
Cond. prob. of spousal NU transition	1.17%	3.37%	2.20%
Cond. prob. of spousal NN transition	93.92%	92.43%	
AWE (total)			1.49%
III. Excluding Disabled/Ill (Young):			
Average flow rates of primary earner:	97.69%	1.21%	
Cond. prob. of spousal NE transition	6.42%	9.00%	2.58%
Cond. prob. of spousal NU transition	1.93%	6.72%	4.79%
Cond. prob. of spousal NN transition	91.64%	84.27%	
AWE (total)			7.37%
IV. Excluding Disabled/Ill (Old):			
Average flow rates of primary earner:	95.73%	0.80%	
Cond. prob. of spousal NE transition	4.14%	3.46%	-0.68%
Cond. prob. of spousal NU transition	0.88%	2.80%	1.92%
Cond. prob. of spousal NN transition	94.98%	93.74%	
AWE (total)			1.24%
V. Excluding Retired and Disabled/Ill (Young):			
Average flow rates of primary earner:	97.71%	1.22%	
Cond. prob. of spousal NE transition	6.43%	9.03%	2.60%
Cond. prob. of spousal NU transition	1.94%	6.74%	4.80%
Cond. prob. of spousal NN transition	91.64%	84.23%	
AWE (total)			7.40%
VI. Excluding Retired and Disabled/Ill (Old):			
Average flow rates of primary earner:	96.39%	0.93%	
Cond. prob. of spousal NE transition	4.69%	3.66%	-1.03%
Cond. prob. of spousal NU transition	1.15%	3.44%	2.29%
Cond. prob. of spousal NN transition	94.16%	92.90%	
AWE (total)			1.26%

Notes: Table B.8 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. The first row of each panel reports transition probabilities of the primary earner. Sample size in Panel I: 311,927; in Panel II: 149,465; in Panel III: 309,182; in Panel IV: 297,468; in Panel V: 308,092; in Panel VI: 143,358.

B.9 Education

In Table B.9, we split the sample by spouses with and without a college degree.

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

	Primary earner transition		
	EE	EU	AWE
I. Spouse College, Young			
Average flow rates of primary earner:	98.60%	0.47%	
Cond. prob. of spousal NE transition	7.40%	15.13%	7.73%
Cond. prob. of spousal NU transition	1.59%	6.69%	5.10%
Cond. prob. of spousal NN transition	91.01%	78.19%	
AWE (total)			12.83%
II. Spouse College, Old			
Average flow rates of primary earner:	95.91%	0.61%	
Cond. prob. of spousal NE transition	5.78%	6.40%	0.62%
Cond. prob. of spousal NU transition	1.14%	2.66%	1.52%
Cond. prob. of spousal NN transition	93.07%	90.94%	
AWE (total)			2.14%
III. Spouse No College, Young			
Average flow rates of primary earner:	97.31%	1.51%	
Cond. prob. of spousal NE transition	6.20%	8.24%	2.04%
Cond. prob. of spousal NU transition	2.12%	6.66%	4.54%
Cond. prob. of spousal NN transition	91.69%	85.11%	
AWE (total)			6.58%
IV. Spouse No College, Old			
Average flow rates of primary earner:	95.66%	0.87%	
Cond. prob. of spousal NE transition	3.78%	3.20%	-0.58%
Cond. prob. of spousal NU transition	0.82%	2.81%	1.99%
Cond. prob. of spousal NN transition	95.40%	93.99%	
AWE (total)			1.41%

Notes: Table B.9 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. The first row of each panel reports transition probabilities of the primary earner. Sample size in Panel I: 87,140; in Panel II: 72,210; in Panel III: 225,877; in Panel IV: 231,365.

B.10 Business Cycle

In Table B.10, we split the sample by NBER recessions and expansions. We confirm the age-dependency of the AWE across aggregate states. The pattern looks similar when we separate the Great Recession and the ensuing slow recovery from 2007 to 2016. Moreover, Table D.2 reports the results for regression (1) when interacting the AWE coefficient with the local unemployment rate. In line with Table B.10, we find this interaction term to be not statistically different from zero. Nevertheless, given that EU transitions of the primary earner are more likely during recessions, *on aggregate* the AWE plays a bigger role in recessions.

Table B.10: Added Worker Effect by Age (Business Cycle)

	Primary earner transition EE	EU	AWE
I. NBER Recession, Young			
Average flow rates of primary earner:	97.17%	1.62%	
Cond. prob. of spousal NE transition	6.43%	7.13%	0.70%
Cond. prob. of spousal NU transition	1.95%	8.32%	6.37%
Cond. prob. of spousal NN transition	91.62%	84.55%	
AWE (total)			7.07%
II. NBER Recession, Old			
Average flow rates of primary earner:	95.35%	1.15%	
Cond. prob. of spousal NE transition	4.13%	5.43%	1.30%
Cond. prob. of spousal NU transition	0.82%	2.76%	1.94%
Cond. prob. of spousal NN transition	95.05%	91.81%	
AWE (total)			3.24%
III. No NBER Recession, Young			
Average flow rates of primary earner:	97.72%	1.18%	
Cond. prob. of spousal NE transition	6.54%	9.23%	2.69%
Cond. prob. of spousal NU transition	1.97%	6.42%	4.45%
Cond. prob. of spousal NN transition	91.48%	84.35%	
AWE (total)			7.14%
IV. No NBER Recession, Old			
Average flow rates of primary earner:	95.76%	0.77%	
Cond. prob. of spousal NE transition	4.28%	3.50%	-0.78%
Cond. prob. of spousal NU transition	0.90%	2.78%	1.88%
Cond. prob. of spousal NN transition	94.82%	93.71%	
AWE (total)			1.10%

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. The first row of each panel reports transition probabilities of the primary earner. Sample size in Panel I: 29,820; in Panel II: 30,438; in Panel III: 283,197; in Panel IV: 273,137.

B.11 Job Loss

In Table B.11, we report the AWE by age for cases when the primary earner 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
I. Age Spouse 26-35:			
Average flow rates of primary earner:	97.67%	0.37%	
Cond. prob. of spousal NE transition	6.53%	9.24%	2.71%
Cond. prob. of spousal NU transition	1.97%	8.15%	6.18%
Cond. prob. of spousal NN transition	91.50%	81.61%	
AWE (total)			8.89%
II. Age Spouse 56-65:			
Average flow rates of primary earner:	95.72%	0.20%	
Cond. prob. of spousal NE transition	4.26%	3.84%	-0.42%
Cond. prob. of spousal NU transition	0.89%	3.58%	2.69%
Cond. prob. of spousal NN transition	94.84%	92.58%	
AWE (total)			2.27%

Notes: Table B.11 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions if the EU transition is an involuntary job loss. The AWE is computed as the EU minus the EE column. The first row of each panel reports transition probabilities of the primary earner. When computing average flow rates of the primary earner, individuals who report a EU transition other than an involuntary quit are labeled as EN. Sample size in Panel I: 310,497; in Panel II: 301,663.

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 strength of the AWE is similar across datasets (5.75%pts in the CPS vs. 6.23%pts in the SIPP), the relative increase (i.e., by how many percent does the likelihood of the spouse entering the labor force increase if the primary earner makes an EU transition?) differs quite significantly (75% in the CPS vs. 197% increase in the SIPP) due to the lower baseline transitions in the SIPP.[22]

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 slightly stronger AWE than high wealth households. However, as in Table 3 the difference in the AWE between the top and bottom net liquid wealth sample is not statistically significant.

[22] To make the AWE across both datasets in Table C.1 comparable, we restrict the CPS to align with the SIPP sample period (1995-2016).

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

	Primary earner transition		
	EE	EU	AWE
Pnael I: CPS			
Average flow rates of primary earner:	97.19%	1.01%	
Cond. prob. of spousal NE transition	5.95%	7.77%	1.82%
Cond. prob. of spousal NU transition	1.67%	5.60%	3.93%
Cond. prob. of spousal NN transition	92.38%	86.63%	
AWE (total)			5.75%
Panel II: SIPP			
Average flow rates of primary earner:	98.99%	0.45%	
Cond. prob. of spousal NE transition	2.20%	5.31%	3.11%
Cond. prob. of spousal NU transition	0.97%	4.09%	3.12%
Cond. prob. of spousal NN transition	96.83%	90.59%	
AWE (total)			6.23%

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. Both datasets cover the years 1995-2016. The AWE is computed as the EU minus the EE column. The first row of each panel reports transition probabilities of the primary earner. Sample size in Panel I: 1,086,589; in Panel II: 745,334.

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

	Primary earner transition EE	EU	AWE
Panel I: Bottom 50% of Net Liquid Wealth:			
Average flow rates of primary earner:	96.23%	1.68%	
Cond. prob. of spousal NE transition	8.35%	10.70%	2.35%
Cond. prob. of spousal NU transition	3.64%	9.09%	5.45%
Cond. prob. of spousal NN transition	88.01%	80.21%	
AWE (total)			7.80%
Panel II: Top 50% of Net Liquid Wealth:			
Average flow rates of primary earner:	97.24%	0.69%	
Cond. prob. of spousal NE transition	8.31%	9.99%	1.68%
Cond. prob. of spousal NU transition	2.27%	6.15%	3.88%
Cond. prob. of spousal NN transition	89.41%	83.86%	
AWE (total)			5.56%

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 from the SIPP (years 1995-2016) and aggregated to interview panel length. The AWE is computed as the EU minus the EE column. The first row of each panel reports transition probabilities of the primary earner. Sample size in Panel I: 77,768; in Panel II: 63,585.

D Regression Results

Table D.1: Regression Coefficients - Full Sample

	(1) 2m lead	(2) 1m lead	(3) Contemp.	(4) 1m lag	(5) 2m lag
AWE	0.017***	0.020***	0.058***	0.026***	0.033***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.006)
Female	0.033***	0.031***	0.026***	0.023***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
White	-0.010***	-0.008***	-0.009***	-0.009***	-0.011***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
# children = 1	0.007***	0.008***	0.011***	0.014***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children = 2	0.009***	0.011***	0.015***	0.019***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children >= 3	0.005***	0.005***	0.009***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College	-0.010***	-0.010***	-0.011***	-0.011***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College spouse	0.023***	0.021***	0.019***	0.019***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
UR	0.001	0.000	0.001***	0.001***	0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	0.058***	0.060***	0.056***	0.052***	0.044***
	(0.006)	(0.004)	(0.003)	(0.004)	(0.006)
Observations	368,363	790,149	1,255,343	802,850	382,015
R^2	0.006	0.005	0.005	0.005	0.006
Month dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
State dummies	✓	✓	✓	✓	✓

Notes: Table D.1 shows the results for regression (1) based on the full sample of couples in which one spouse is working and one spouse is out of the labor force between age 26 and 65 from the Current Population Survey (CPS), waves 1994 until 2020. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.2: Regression Coefficients - Full Sample

	(1) Baseline	(2) Interactions
AWE	0.058***	0.069**
	(0.004)	(0.029)
Female	0.026***	0.026***
	(0.001)	(0.001)
White	-0.009***	-0.009***
	(0.001)	(0.001)
# children = 1	0.011***	0.011***
	(0.001)	(0.001)
# children = 2	0.015***	0.015***
	(0.001)	(0.001)
# children >= 3	0.009***	0.009***
	(0.001)	(0.001)
College	-0.011***	-0.011***
	(0.001)	(0.001)
College spouse	0.019***	0.019***
	(0.001)	(0.001)
UR	0.001***	0.001***
	(0.000)	(0.000)
Female × AWE		0.006
		(0.009)
White × AWE		-0.032***
		(0.011)
College × AWE		0.012
		(0.011)
College spouse × AWE		0.028**
		(0.013)
UR × AWE		0.000
		(0.003)
Constant	0.056***	0.055***
	(0.003)	(0.003)
Observations	1,255,343	1,255,343
R^2	0.005	0.005
Month dummies	✓	✓
Year dummies	✓	✓
State dummies	✓	✓

Notes: Table D.2 shows the based on the full sample of couples in which one spouse is working and one spouse is out of the labor force between results for regression (1) age 26 and 65 from the Current Population Survey (CPS), waves 1994 until 2020, comparing the baseline to a version with additional interaction terms. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.3: Regression Coefficients - Age 26 to 35

VARIABLES	(1) 2m lead	(2) 1m lead	(3) Contemp.	(4) 1m lag	(5) 2m lag
AWE	0.020*	0.016**	0.073***	0.030***	0.037***
	(0.011)	(0.007)	(0.007)	(0.008)	(0.012)
Female	0.132***	0.118***	0.107***	0.094***	0.105***
	(0.006)	(0.004)	(0.003)	(0.004)	(0.006)
White	-0.003	-0.002	-0.005***	-0.005**	-0.009***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
# children = 1	-0.043***	-0.037***	-0.032***	-0.024***	-0.027***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
# children = 2	-0.054***	-0.047***	-0.042***	-0.034***	-0.037***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)
# children >= 3	-0.062***	-0.055***	-0.051***	-0.043***	-0.048***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)
College	-0.024***	-0.023***	-0.024***	-0.023***	-0.029***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
College spouse	0.021***	0.020***	0.018***	0.018***	0.021***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
UR	0.001	0.000	0.001*	0.002*	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.119***	0.125***	0.119***	0.113***	0.108***
	(0.014)	(0.009)	(0.008)	(0.010)	(0.015)
Observations	84,236	184,653	299,574	187,583	86,979
R^2	0.025	0.021	0.018	0.014	0.017
Month dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
State dummies	✓	✓	✓	✓	✓

Notes: Table D.3 shows the results for regression (1) based on the sample of couples in which one spouse is working and one spouse is out of the labor force between age 26 and 35 from the Current Population Survey (CPS), waves 1994 until 2020. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.4: Regression Coefficients - Age 36 to 45

	(1) 2m lead	(2) 1m lead	(3) Contemp.	(4) 1m lag	(5) 2m lag
AWE	0.006	0.011	0.065***	0.036***	0.022**
	(0.011)	(0.007)	(0.007)	(0.008)	(0.011)
Female	0.079***	0.076***	0.067***	0.062***	0.070***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)
White	-0.013***	-0.010***	-0.012***	-0.013***	-0.017***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
# children = 1	-0.012***	-0.012***	-0.008***	-0.004	0.000
	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)
# children = 2	-0.016***	-0.015***	-0.010***	-0.005**	-0.004
	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)
# children >= 3	-0.021***	-0.022***	-0.018***	-0.013***	-0.014***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)
College	-0.020***	-0.020***	-0.020***	-0.020***	-0.021***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
College spouse	0.019***	0.017***	0.014***	0.014***	0.014***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
UR	0.001	0.001	0.001*	0.002**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.094***	0.089***	0.087***	0.081***	0.071***
	(0.013)	(0.009)	(0.007)	(0.009)	(0.013)
Observations	98,714	213,595	341,941	216,629	101,619
R^2	0.014	0.013	0.012	0.011	0.012
Month dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
State dummies	✓	✓	✓	✓	✓

Notes: Table D.4 shows the results for regression (1) based on the sample of couples in which one spouse is working and one spouse is out of the labor force between age 36 and 45 from the Current Population Survey (CPS), waves 1994 until 2020. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.5: Regression Coefficients - Age 46 to 55

	(1) 2m lead	(2) 1m lead	(3) Contemp.	(4) 1m lag	(5) 2m lag
AWE	0.032**	0.024***	0.049***	0.020***	0.039***
	(0.014)	(0.008)	(0.007)	(0.008)	(0.013)
Female	0.034***	0.030***	0.027***	0.025***	0.032***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
White	-0.008**	-0.005**	-0.005***	-0.005**	-0.007**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
# children = 1	-0.002	0.002	0.004***	0.007***	0.007***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
# children = 2	0.002	0.005***	0.009***	0.013***	0.014***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
# children >= 3	-0.000	0.002	0.004**	0.007***	0.005
	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
College	-0.005*	-0.007***	-0.007***	-0.008***	-0.012***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
College spouse	0.029***	0.027***	0.025***	0.026***	0.033***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
UR	0.001	0.000	0.001*	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.043***	0.052***	0.042***	0.040***	0.030**
	(0.012)	(0.008)	(0.006)	(0.008)	(0.012)
Observations	90,966	195,620	311,537	198,749	94,499
R^2	0.009	0.007	0.006	0.005	0.008
Month dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
State dummies	✓	✓	✓	✓	✓

Notes: Table D.5 shows the results for regression (1) based on the sample of couples in which one spouse is working and one spouse is out of the labor force between age 46 and 55 from the Current Population Survey (CPS), waves 1994 until 2020. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.6: Regression Coefficients - Age 56 to 65

	(1) 2m lead	(2) 1m lead	(3) Contemp.	(4) 1m lag	(5) 2m lag
AWE	0.003	0.024***	0.015***	-0.002	0.026**
	(0.010)	(0.008)	(0.006)	(0.006)	(0.011)
Female	0.010***	0.010***	0.008***	0.008***	0.009***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
White	-0.004	-0.004*	-0.004**	-0.003*	-0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
# children = 1	0.001	0.003*	0.003***	0.003*	0.003
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
# children = 2	0.007*	0.009***	0.015***	0.017***	0.024***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)
# children >= 3	0.018**	0.018***	0.019***	0.019***	0.009
	(0.008)	(0.005)	(0.004)	(0.005)	(0.007)
College	-0.002	-0.000	-0.001	0.001	0.003
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
College spouse	0.027***	0.027***	0.023***	0.023***	0.021***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
UR	-0.001	-0.000	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.048***	0.040***	0.038***	0.031***	0.030***
	(0.011)	(0.007)	(0.006)	(0.007)	(0.011)
Observations	89,238	190,657	302,291	194,492	93,607
R^2	0.005	0.005	0.004	0.005	0.006
Month dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
State dummies	✓	✓	✓	✓	✓

Notes: Table D.6 shows the results for regression (1) based on the sample of couples in which one spouse is working and one spouse is out of the labor force between age 56 and 65 from the Current Population Survey (CPS), waves 1994 until 2020. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.7: Regression Coefficients - Layoff

	(1) 2m lead	(2) 1m lead	(3) Contemp.	(4) 1m lag	(5) 2m lag
AWE	0.016*	0.016***	0.019***	0.021***	0.027***
	(0.009)	(0.006)	(0.005)	(0.006)	(0.009)
Female	0.033***	0.031***	0.026***	0.023***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
White	-0.010***	-0.008***	-0.009***	-0.009***	-0.011***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
# children = 1	0.007***	0.008***	0.011***	0.013***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children = 2	0.009***	0.011***	0.015***	0.019***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children >= 3	0.005***	0.005***	0.008***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College	-0.010***	-0.011***	-0.011***	-0.011***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College spouse	0.023***	0.021***	0.019***	0.019***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
UR	0.001	0.000	0.001***	0.001***	0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	0.056***	0.059***	0.056***	0.052***	0.045***
	(0.006)	(0.004)	(0.003)	(0.004)	(0.006)
Observations	364,763	786,015	1,248,246	794,819	377,410
R^2	0.006	0.005	0.005	0.005	0.005
Month dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
State dummies	✓	✓	✓	✓	✓

Notes: Table D.7 shows the results for regression (1) based on the sample of couples in which one spouse is working and one spouse is out of the labor force between age 26 and 65 from the Current Population Survey (CPS), waves 1994 until 2020, restricting the EU transitions to layoffs. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.8: Regression Coefficients - Job Loss

	(1) 2m lead	(2) 1m lead	(3) Contemp.	(4) 1m lag	(5) 2m lag
AWE	0.006	0.014**	0.073***	0.022***	0.033***
	(0.010)	(0.007)	(0.007)	(0.007)	(0.011)
Female	0.033***	0.031***	0.025***	0.023***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
White	-0.010***	-0.008***	-0.009***	-0.009***	-0.011***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
# children = 1	0.006***	0.008***	0.011***	0.013***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children = 2	0.009***	0.011***	0.015***	0.019***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children = 3	0.005***	0.005***	0.008***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College	-0.010***	-0.011***	-0.011***	-0.011***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College spouse	0.023***	0.021***	0.019***	0.019***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
UR	0.001	0.000	0.001***	0.001***	0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	0.058***	0.059***	0.056***	0.052***	0.044***
	(0.006)	(0.004)	(0.003)	(0.004)	(0.006)
Observations	363,844	784,949	1,246,780	793,069	376,757
R^2	0.006	0.005	0.005	0.005	0.005
Month dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
State dummies	✓	✓	✓	✓	✓

Notes: Table D.8 shows the results for regression (1) based on the sample of couples in which one spouse is working and one spouse is out of the labor force between age 26 and 65 from the Current Population Survey (CPS), waves 1994 until 2020, restricting the EU transitions to permanent job losses. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.9: Regression Coefficients - Temporary Job Ended

	(1) 2m lead	(2) 1m lead	(3) Contemp.	(4) 1m lag	(5) 2m lag
AWE	0.051**	0.019*	0.069***	0.022**	0.053***
	(0.021)	(0.011)	(0.010)	(0.011)	(0.018)
Female	0.033***	0.031***	0.025***	0.023***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
White	-0.010***	-0.008***	-0.009***	-0.009***	-0.011***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
# children = 1	0.006***	0.008***	0.011***	0.013***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children = 2	0.009***	0.011***	0.015***	0.019***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children >= 3	0.005***	0.005***	0.008***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College	-0.010***	-0.011***	-0.011***	-0.011***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College spouse	0.023***	0.021***	0.019***	0.019***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
UR	0.001	0.000	0.001***	0.001***	0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	0.058***	0.059***	0.056***	0.052***	0.045***
	(0.006)	(0.004)	(0.003)	(0.004)	(0.006)
Observations	362,887	783,741	1,244,718	790,643	375,176
R^2	0.006	0.005	0.005	0.005	0.005
Month dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
State dummies	✓	✓	✓	✓	✓

Notes: Table D.9 shows the results for regression (1) based on the sample of couples in which one spouse is working and one spouse is out of the labor force between age 26 and 65 from the Current Population Survey (CPS), waves 1994 until 2020, restricting the EU transitions to temporary jobs ending. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.10: Regression Coefficients - Quits

	(1) 2m lead	(2) 1m lead	(3) Contemp.	(4) 1m lag	(5) 2m lag
AWE	0.005	0.035**	0.104***	0.040**	-0.009
	(0.020)	(0.015)	(0.014)	(0.016)	(0.017)
Female	0.033***	0.031***	0.025***	0.023***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
White	-0.010***	-0.008***	-0.009***	-0.009***	-0.011***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
# children = 1	0.006***	0.008***	0.011***	0.013***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children = 2	0.009***	0.011***	0.015***	0.019***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children >= 3	0.005***	0.005***	0.008***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College	-0.010***	-0.011***	-0.011***	-0.011***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College spouse	0.023***	0.021***	0.019***	0.019***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
UR	0.001	0.000	0.001***	0.001***	0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	0.057***	0.059***	0.056***	0.052***	0.044***
	(0.006)	(0.004)	(0.003)	(0.004)	(0.006)
Observations	362,688	783,304	1,244,051	789,978	374,892
R^2	0.006	0.005	0.005	0.005	0.005
Month dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
State dummies	✓	✓	✓	✓	✓

Notes: Table D.10 shows the results for regression (1) based on the sample of couples in which one spouse is working and one spouse is out of the labor force between age 26 and 65 from the Current Population Survey (CPS), waves 1994 until 2020, restricting the EU transitions to quits. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.11: Regression Coefficients - CPS (1995 to 2016)

	(1) 2m	(2) 1m lead	(3) Contemp.	(4) 1m lag	(5) 2m lag
AWE	0.018***	0.019***	0.058***	0.028***	0.036***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.006)
Female	0.033***	0.031***	0.026***	0.023***	0.027***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
White	-0.011***	-0.008***	-0.010***	-0.010***	-0.013***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
# children = 1	0.006***	0.008***	0.011***	0.014***	0.017***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
# children = 2	0.009***	0.011***	0.016***	0.019***	0.023***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
# children >= 3	0.005***	0.005***	0.009***	0.012***	0.013***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
College	-0.011***	-0.011***	-0.012***	-0.012***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College spouse	0.022***	0.021***	0.019***	0.019***	0.020***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
UR	0.001	0.000	0.001***	0.001***	0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	0.054***	0.052***	0.048***	0.040***	0.037***
	(0.007)	(0.004)	(0.003)	(0.004)	(0.007)
Observations	313,357	672,065	1,068,224	683,209	325,169
R^2	0.006	0.005	0.005	0.005	0.006
Month dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
State dummies	✓	✓	✓	✓	✓

Notes: Table D.11 shows the results for regression (1) based on the sample of couples in which one spouse is working and one spouse is out of the labor force between age 26 and 65 from the Current Population Survey (CPS), waves 1995 until 2016, such that it covers the same years as the SIPP results in Table D.12. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.12: Regression Coefficients - SIPP (1995 to 2016)

	(1) 2m	(2) 1m lead	(3) Contemp.	(4) 1m lag	(5) 2m lag
AWE	0.008**	0.014***	0.061***	0.016***	0.021***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Female	0.017***	0.017***	0.015***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
White	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children = 1	0.012***	0.012***	0.011***	0.011***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children = 2	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# children >= 3	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College spouse	0.011***	0.011***	0.010***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.049***	0.048***	0.047***	0.050***	0.053***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	683,999	714,151	743,890	714,671	686,526
R^2	0.006	0.006	0.007	0.006	0.007
Month dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
State dummies	✓	✓	✓	✓	✓

Notes: Table D.12 shows the results for regression (1) based on the sample of couples in which one spouse is working and one spouse is out of the labor force between age 26 and 65 from the Survey of Income and Program Participation (SIPP), waves 1995 until 2016, such that it covers the same years as the CPS results in Table D.11. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

E Additional Model Results

Figure E.1 splits the separation rate from employment into EU and EN transitions. The model captures that both these rates are falling in income, with a particularly strong decline in the EN rate at low income levels. Overall, the model accounts for the overall separation rate from employment with too many transitions to unemployment rather than non-employment, as is already apparent from Table 6.

Table E.1 compares the AWE in model and data for the two middle age groups–aged 36-45 and 46-55. In combination with Table 2 in the main text, we can conclude that the AWE is monotonically declining in age in both data and model.

Table E.2 is a more detailed version of Table 11 in the main text. It decomposes the AWE of the counterfactuals into the AWE directly into employment and the AWE into unemployment.

Figure E.2 shows the distributions of human capital and assets across model versions with different benefit duration. As discussed in the main text, the distribution of human capital is very similar across these versions, whereas asset holdings increase when UI benefits expire more quickly.

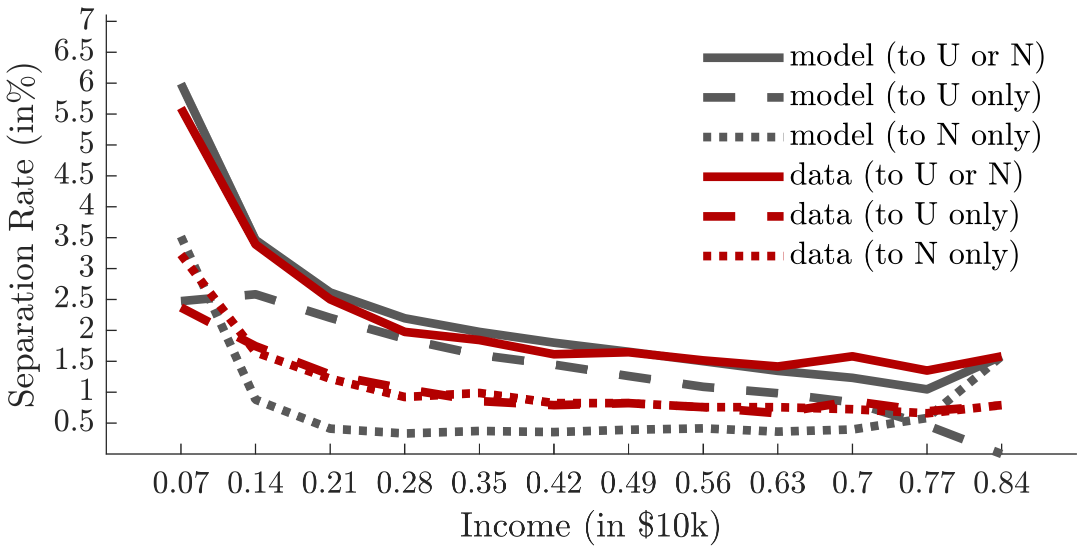


Figure E.1: Separation Rates by Income Level (Model vs. Data) - Decomposition

Notes: Figure E.1 shows separation rates by pre-tax income level (expressed in $2015). Data moments are the individual *EU* and *EN* transition rates by income bin as computed from the SIPP (waves 1995-2016), as well as their sum. SIPP data values are scaled to match aggregate transition rates in the CPS: we multiply SIPP transition rates by the ratio of aggregate transition rates in the CPS over aggregate transition rates in the SIPP.

Table E.1: Joint Labor Market Transitions for Additional Age Groups (Model vs. Data)

	Primary earner transition		
	EE	EU/ES	AWE
I. Young Middle (36-45):			
Cond. prob. of spousal NE transition	3.02%	4.32%	1.29%
	6.64%	8.97%	2.33%
Cond. prob. of spousal NS transition	2.44%	7.16%	4.72%
	1.86%	6.36%	4.50%
Cond. prob. of spousal NN transition	94.53%	88.52%	
	91.50%	84.67%	
AWE (total)			6.01%
			6.83%
III. Old Middle (46-55):			
Cond. prob. of spousal NE transition	2.39%	3.54%	1.16%
	6.04%	7.41%	1.37%
Cond. prob. of spousal NS transition	1.68%	3.54%	1.86%
	1.62%	4.82%	3.20%
Cond. prob. of spousal NN transition	95.93%	92.91%	
	92.34%	87.77%	
AWE (total)			3.01%
			4.57%

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

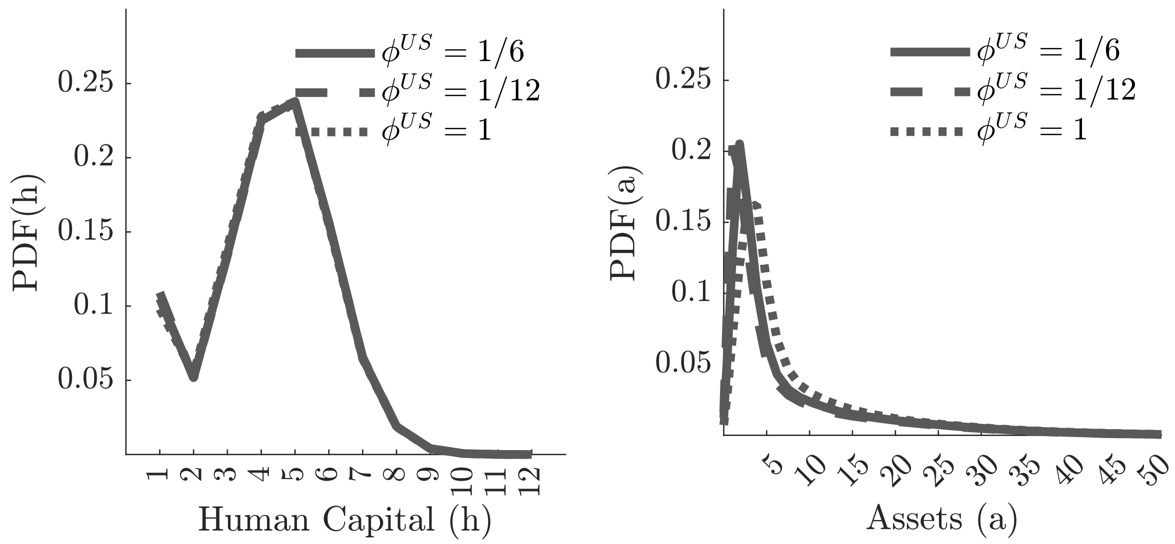


Figure E.2: Policy Counterfactuals: Distribution of Endogenous State Variables

Notes: Figure E.2 shows the distribution of human capital and assets in the model economy under different parameter values for unemployment benefit duration ϕ^{US}. $\phi^{US} = \frac{1}{6}$ is the value under the baseline calibration of the model. Households of all age groups and labor market states are included in the distribution.

Table E.2: Added Worker Effect: Counterfactuals (E vs. U)

		baseline	(1) a	(2) h_E	(3) h_N	(4) (a, h_E, h_N)	(5) age
Young (26-35):							
constant λ	**AWE**	9.35%	3.98%	4.08%	7.37%	1.74%	17.03%
	to E	0.86%	-0.22%	3.32%	1.61%	1.60%	1.82%
	to U	8.48%	4.21%	0.76%	5.75%	0.13%	15.20%
adjusted λ	**AWE**		3.94%	1.82%	6.98%	0.48%	16.23%
	to E		-0.26%	1.12%	1.05%	0.34%	0.44%
	to U		4.21%	0.70%	5.93%	0.13%	15.78%
Old (56-65):							
constant λ	**AWE**	1.22%	3.88%	3.39%	1.83%	19.59%	0.21%
	to E	0.59%	0.29%	0.32%	0.52%	0.20%	-0.04%
	to U	0.63%	3.59%	3.06%	1.30%	19.40%	0.25%
adjusted λ	**AWE**		4.48%	4.88%	2.20%	20.73%	0.11%
	to E		0.94%	0.75%	0.98%	0.44%	-0.11%
	to U		3.54%	4.13%	1.23%	20.28%	0.22%

Columns (1)–(5) are grouped under "counterfactuals".

Notes: Table E.2 shows the counterfactual AWE, separately into employment and unemployment.