

Joint Search over the Life Cycle*

Annika Bacher
BI Oslo

Philipp Grübener
Goethe University Frankfurt

Lukas Nord
Minneapolis Fed

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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 US 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). Either one individually does not generate a sizable response of spousal labor supply to the job loss of a primary earner, but their interaction can account for the observed age differential in the added worker effect.

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 an important insurance margin for couple households (for recent evidence, see e.g., Bredtmann, Otten, and Rulff 2018; Guner, Kulikova, and Valladares-Esteban 2020; Halla, Schmieder, and Weber 2020; Stephens 2002). In this paper, we provide novel empirical evidence that the AWE is predominantly present among young households but limited among the old, and study 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 added worker effect is crucial to inform us about the welfare implications of the empirical patterns, the optimal provision of public insurance over the life cycle, and – in light of demographic change – to predict dynamics of the aggregate labor market in the future.

We begin by providing novel empirical evidence on the added worker effect over the life cycle by using monthly data for the United States from the Current Population Survey (CPS) and the Survey of Income and Program Participation (SIPP). On average across all age groups, the likelihood of a non participating spouse entering the labor force increases by 5.9 percentage points, corresponding to a 57% increase, when the primary earner loses her job compared to when she remains employed. We find this effect to be strongly age-dependent. For the age group 25-34 years, the likelihood of a non-participating spouse entering the labor force increases by 7.5 percentage points (87%) upon the job loss of the primary earner. For the age group just before retirement, the added worker effect is only 1.3 percentage points (25%). In addition, among young households, job loss of the primary earner is associated with a significant increase in the likelihood of a non-participating spouse entering the labor force both directly to employment and unemployment, whereas old spouses transition mainly into unemployment. These findings are robust across education levels, over the business cycle, the presence of children in the household, different reasons for being out of the labor force, and when considering only one cohort.

When further analyzing the weak response among the old, we find a stronger added worker effect for low wealth and better educated households within that age group, suggesting a role for both the *need for* and *availability of* spousal insurance in the data. To isolate the relative importance of each channel and account for the contribution of labor market frictions, we develop a structural life cycle framework of couples’ joint labor supply with

endogenous arrival rates of job offers in a frictional labor market.

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 she has a job offer. While out of the labor force and unemployed individuals can receive job offers, unemployed members increase the chance of finding a job through costly search. Employed individuals can quit their job and additionally face the risk of exogenous 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 differentiate between the different candidate explanations for the age dependency in the added worker effect. Incomplete asset markets give rise to precautionary savings which are a key alternative insurance mechanism against individual unemployment risk. With a realistic life cycle savings profile 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 wedges 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, income, and asset profiles over the life cycle. For the labor market, we focus on matching average transition rates and the joint distribution of couples across labor market states. For income, we match life cycle income profiles and wage losses after non-employment spells. For assets, we target median asset holdings across age groups. The model reproduces well untargted life cycle profiles of labor market transitions and the untargted average and age-dependency of the added worker effect.

By means of counterfactuals, we quantify the relative contribution of age heterogeneity in asset holdings and human capital levels, as well as the effect of age itself (through a horizon effect) in accounting for the declining added worker effect over the life cycle. We simulate the added worker effect for counterfactual distributions of young and old workers over the state space, equating their characteristics to those of the respective other age group for one margin at a time. To tease out the effect these changes have on job arrival rates, we consider two alternative scenarios for each margin: Only adjusting household

decision rules while keeping job arrival rates constant as well as simultaneously adjusting decision rules and arrival rates.

When adjusting separately young households' asset levels or the human capital levels of either spouse to match those of the old, their added worker effect decreases. Differences in arrival rates amplify this effect and in particular reduce spousal transitions directly into employment, disproportionately affecting the insurance value of spousal labor supply. Combining the effect of asset holdings, human capital, and arrival rates can account for almost the entire added worker effect among the young, with age itself playing a limited role. Assigning old households either the asset holdings or human capital levels of the young has almost no impact on their added worker effect. Especially when shutting down the response of arrival rates to changes in households' characteristics, spousal labor supply responds little to a job loss of the primary earner. Only when assigning old households simultaneously the asset and human capital levels of the young are we able to substantially increase their added worker effect.

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

Related Literature. The added worker effect is widely studied in the empirical literature, going back to the seminal contribution of Lundberg (1985). The early literature following this paper does not find much evidence supporting the presence of the added worker effect in the data (Maloney 1987, 1991). More recent literature, however, documents a positive added worker effect as a relevant insurance mechanism against the primary earner's job loss (Bredtmann, Otten, and Rulff 2018; Guner, Kulikova, and Valladares-Esteban 2020; Halla, Schmieder, and Weber 2020; Stephens 2002), using data for a variety of countries. Mankart and Oikonomou (2016b) and Mankart, Oikonomou, and Pascucci (2021) show that the added worker effect has become more important in the U.S. over the last decades. The literature argues that the size of the added worker effect crucially depends on the institutional environment and the state of the business cycle. For example, Cullen and Gruber (2000) show that generous unemployment insurance crowds out a spousal labor supply response. Expanding upon previous work, we argue that there is a sizeable age-dependency in the added worker effect.

While the added worker effect has been studied extensively in the empirical literature, the vast majority of the large macro-labor literature focuses on the job search problem of a single earner household. Guler, Guvenen, and Violante (2012) is among the first

papers to study the joint search problem of a couple by extending the classic single-agent search problems of McCall (1970), Mortensen (1970), and Burdett (1978). A number of recent papers introduces asset accumulation into the joint search framework, expanding 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). The focus of these papers 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. Wang (2019) builds a model showing that joint household search is crucial for accounting for the countercyclicality of womens' unemployment rate. Ellieroth (2019) argues that there is precautionary labor supply by spouses whose partners face an increased job loss risk in recessions. Garcia-Perez and Rendon (2020) focus on the role of household wealth for the added worker effect. Birinci (2019), Choi and Valladares-Esteban (2020), and Fernández-Blanco (2020) investigate the implications of joint search for optimal unemployment insurance. Bardóczy (2020) focuses on the role of spousal labor supply as an automatic stabilizer for aggregate consumption. Relative to these papers, we focus on the life cycle dimension of the joint search problem to analyze whether the age-dependency in the added worker effect is explained by changing opportunities or changing insurance margins.

Life cycle search problems have been studied in the literature, but mostly in single earner frameworks. Chéron, Hairault, and Langot (2011, 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. More closely related to our paper, Haan and Prowse (2017) 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 any age-dependency in the added worker effect. Finally, the current paper is related to a number of studies analyzing life cycle labor supply decisions of couples in incomplete market frameworks (Blundell, Pistaferri, and Saporta-Eksten 2016; Ortigueira and Siassi 2013; Wu and Krueger 2021).

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

2 Empirical Evidence

To establish empirical evidence on the added worker effect over the life cycle, we work with data from the Current Population Survey (CPS) as provided by the Integrated Public Use Microdata Series (IPUMS) (Flood et al. 2020).¹ We first outline the data and our sample selection. Afterwards, we provide robust empirical evidence of the AWE in our sample and show that its magnitude is decreasing in age.

2.1 The Sample

The CPS is a monthly rotating panel which is representative for 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. Our final sample spans from 1994 until 2020 (pre-Covid) and is restricted to couples who are both between 25 and 65 years old. We include legally married and cohabiting couples, irrespectively of their sex, but drop couples who report that one spouse lives permanently outside of the household or is institutionalized. We only keep couples for whom we observe the labor market status of both spouses in every month that they are interviewed. We apply survey weights as provided by the CPS throughout.

2.2 Uncovering the AWE from Joint Labor Market Transitions

We follow the method of Guner, Kulikova, and Valladares-Esteban (2020) to calculate the added worker effect 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. 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 flows 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).

In a next step, we pool all observations for couples with one employed and one non-participating member and compute their joint labor market transition probabilities. A previously employed spouse can either remain employed (EE transition), become unemployed (EU) or drop out of the labor force (EN). Non-participating spouses can either transition from non-participating to employment (NE), from non-participating to un-

¹To analyze the AWE by household wealth, we complement our analysis with data from the Survey of Income and Program Participation (SIPP). See Section 2.4 for details.

Table 1: Added Worker Effect (Full Sample)

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

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

employment (NU) or remain out of the labor force (NN). We define the added worker effect 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 3 display our main results. In each table, the first two columns provide the conditional distribution of transitions for the non-participating spouse if the household’s primary earner makes an employment-to-employment (EE) or employment-to-unemployment (EU) transition respectively. The added worker effect in the third column is computed as the difference between the two.

Overall Effect. Table 1 shows that the likelihood of a spouse entering the labor force increases by 5.9 percentage points if the primary earner becomes unemployed compared to when the primary earner remains employed, confirming the existence of the added worker effect in our sample.² This result is in line with Guner, Kulikova, and Valladares-Esteban (2020), who find an overall AWE of 6.89 percentage points with CPS data spanning from 1976 to 2018 for couples between 25 and 54 years. Zooming in on the precise margin of adjustment, we find that the conditional probability of a spousal transition directly into employment increases by 1.98 percentage points, whereas the conditional probability of a spouse transitioning into unemployment increases by 3.92 points. Thus, around two thirds of the overall AWE arise from individuals transitioning into unemployment, highlighting the importance of explicitly distinguishing between unemployed and non-participating individuals.

²For the added worker effect, we focus on transitions for out of the labor force spouses conditional on EE vs. EU transitions of the primary earner. In the appendix, Tables 13, 14, and 15 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 making joint transitions: The likelihood of a spouse dropping out of the labor force increases when the primary earner does the same.

Table 2: AWE by reasons of Unemployment for Household Head

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

Notes: Table 2 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.

Table 2 splits primary earners by the reason for why they became unemployed. We distinguish between laid-off workers (who face a high chance of being recalled), job losses, workers whose temporary contracts ended, and voluntarily quits (job leavers). The AWE is slightly stronger for household members who quit voluntarily relative to those who are exogenously separated (*Job Losers*), suggesting a role for joint optimization decisions of the household. In contrast, the AWE is smaller for households in which the head’s job loss can be seen as expected (*Temp. Job ended*) or possibly temporary (*Layoff*), in line with these events posing an anticipated or smaller shock on the household.

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

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

2.3 Dynamic Response and Controls

So far, we have focused on the probability that a spouse enters the labor force in the *same month* as the head transitions into unemployment and have reported raw transition rates without including controls. Focusing on contemporaneous transitions understates

Table 3: Added Worker Effect by Age

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

Notes: Table 3 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by age group. The added worker effect (AWE) is computed as the EU minus the EE column.

the overall strength of the added worker effect since spousal labor supply responses may 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. To account for these channels, we run the following linear regression specification on the sample of EN-couples:

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

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. The vector of controls X_{it} includes month fixed-effects, year fixed-effects, state fixed-effects, sex,

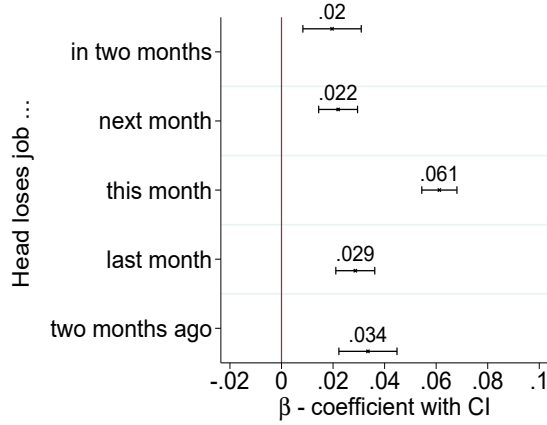


Figure 1: $\Delta \Pr(\text{Spouse enters LF})$ this month

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

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

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). We conduct the analysis for . 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, for Figure 2 we run regressions separately by age group.

Figure 1 shows that the strength of the AWE in the contemporaneous month increases slightly from 5.9 percentage points (Table 1) to 6.1 percentage points when controlling for household observable characteristics.³ In addition, we find support of both anticipation and lagged effects, albeit of lower magnitude. Spousal labor supply responses in the months preceding and in the months after the primary earner's job loss are around half as strong as the direct response. When splitting the sample by age (Figure 2), the contemporaneous effect is statistically significant for all age groups, however it is around five times stronger for the young than for the old. Young households display both lagged responses and anticipation effects, whereas we cannot confirm any clear patterns for households between 56 and 65 years. We relegate the results for the two middle age

³It is possible that household characteristics affect the AWE in a non-linear way. In Appendix A, we therefore show that our baseline results from Section 2 are robust to splitting the sample by number of children, reasons for non-participation, state of the business cycle, gender of the household head, and when repeating the analysis on one cohort of individuals.

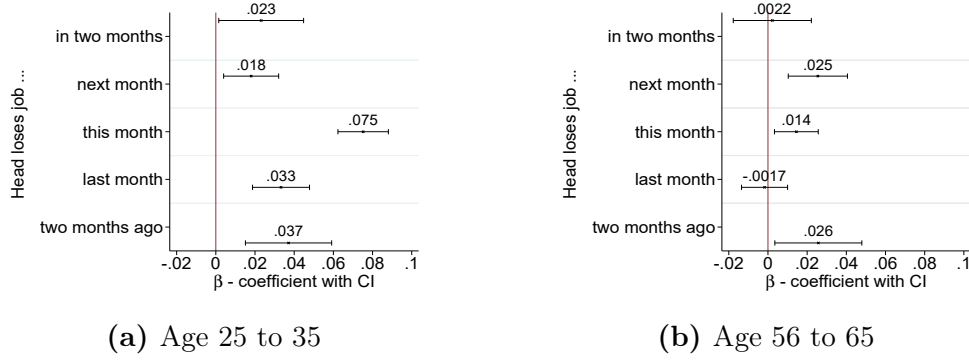


Figure 2: $\Delta \text{Pr}(\text{Spouse enters LF})$ this month

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

groups (Figure 12) and by reason for the primary earner's EU transition (Figure 13) to the appendix, as both are similar to the contemporaneous responses discussed above.

2.4 Exploring the Weak Response Among the Old

Our empirical evidence suggests that spousal labor supply is hardly used as an insurance margin among households above 55 years. Their weak response may indicate that older households are sufficiently well insured by other forms of private insurance, such as asset holdings, reducing the *need* for spousal labor supply. Alternatively, spousal labor supply might not be *available* as an insurance margin to older couples, e.g. because older non-participating spouses have lower human capital after long spells out of the labor force and hence worse labor market prospects.

To explore both of these margins in the data, Table 4 compares the added worker effect among old households by wealth and by education (as a proxy for human capital). Because the CPS does not collect asset information, we complement our analysis with the Survey of Income and Program Participation (SIPP) when analyzing the AWE by wealth.⁴ Our definition of net liquid wealth follows Chetty (2008) and includes total wealth less of home equity, vehicle equity, and unsecured debt. We use this measure because we are interested in wealth holdings that can be liquidated within a relatively short time frame, and hence provide insurance against temporary unemployment shocks.

The data suggest a role for both the *need for* and *availability of* the added worker effect among older couples. Panels I and II in Table 4 document that the added worker effect

⁴See Appendix B for details on this dataset and its comparability to the CPS.

among older spouses is stronger for individuals with than without a college degree (5.2 vs. 1.85 percentage points), suggesting that higher levels of human capital can increase the value of spousal labor supply as an insurance against job loss.⁵ When splitting the sample of older households by net liquid wealth, we find a stronger AWE for the bottom than for the upper half of the population (5.36 vs. 2.28 percentage points, see Panels III and IV in Table 4), in line with the notion that better insurance through asset holdings decreases the need of secondary earners to enter the labor force upon their spouses' transition into unemployment.

Hence, it appears that both the *need for* and *availability of* spousal insurance margin are important for explaining the age-dependency in the added worker effect. To quantify their relative importance and additionally study the role of labor market frictions (which are harder to pin down in the data), we turn to a model of couples' extensive margin labor supply over the life cycle.

3 Model

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

3.1 Environment

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

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

During working life each household member can be in one of four labor market states. A member can be employed (E), in which case the individual receives a wage payment.

⁵To increase the sample size, old households are defined as age 50 or older in Table 4. For this reason, the average AWE across Panels I and II is larger than the baseline AWE of old households in Table 3 which only includes couples above age 55.

Table 4: Added Worker Effect among the Old (Net Liquid Wealth & Education)

	Primary earner transition		
	EE	EU	AWE
<i>I. Spouse College Degree:</i>			
Cond. prob. of spousal NE transition	6.04%	7.72%	1.68%
Cond. prob. of spousal NU transition	1.35%	4.87%	3.52%
Cond. prob. of spousal NN transition	92.61%	87.41%	
AWE (total)			5.20%
<i>II. Spouse No College Degree:</i>			
Cond. prob. of spousal NE transition	4.19%	4.20%	0.01%
Cond. prob. of spousal NU transition	0.99%	2.83%	1.84%
Cond. prob. of spousal NN transition	94.82%	92.97%	
AWE (total)			1.85%
<i>III. Bottom 50% of Net Liquid Wealth (SIPP):</i>			
Cond. prob. of spousal NE transition	1.34%	3.36%	2.02%
Cond. prob. of spousal NU transition	0.69%	4.03%	3.34%
Cond. prob. of spousal NN transition	97.97%	92.61%	
AWE (total)			5.36%
<i>IV. Top 50% of Net Liquid Wealth (SIPP):</i>			
Cond. prob. of spousal NE transition	1.64%	2.29%	0.65%
Cond. prob. of spousal NU transition	0.49%	2.12%	1.63%
Cond. prob. of spousal NN transition	97.87%	95.59%	
AWE (total)			2.28%

Notes: Table 4 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). All columns are restricted to couples with spouses above 50. Panels I and II are based on data from the CPS, Panels III and IV on data from the SIPP. The added worker effect (AWE) is computed as the EU minus the EE column.

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

Each household member is endowed with a level of human capital h , which we interpret as the member's earnings potential capturing both education differences (initial distribution)

and labor market experience (dynamics with job tenure). Over the life cycle, human capital evolves stochastically. If an individual is employed, the human capital will go up by one unit with probability $\phi^{up}(h)$. For non-employed agents, human capital drops by one unit with probability $\phi^{down}(h)$.

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

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

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

3.2 Household Search Problem

Timing in the model is as follows: In the beginning of each period households receive their labor income (wages or unemployment benefits) and their asset income from 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.⁶ Next, potential

⁶We maintain the assumption that separated individuals cannot receive an offer immediately, i.e. have to be without employment for at least one period.

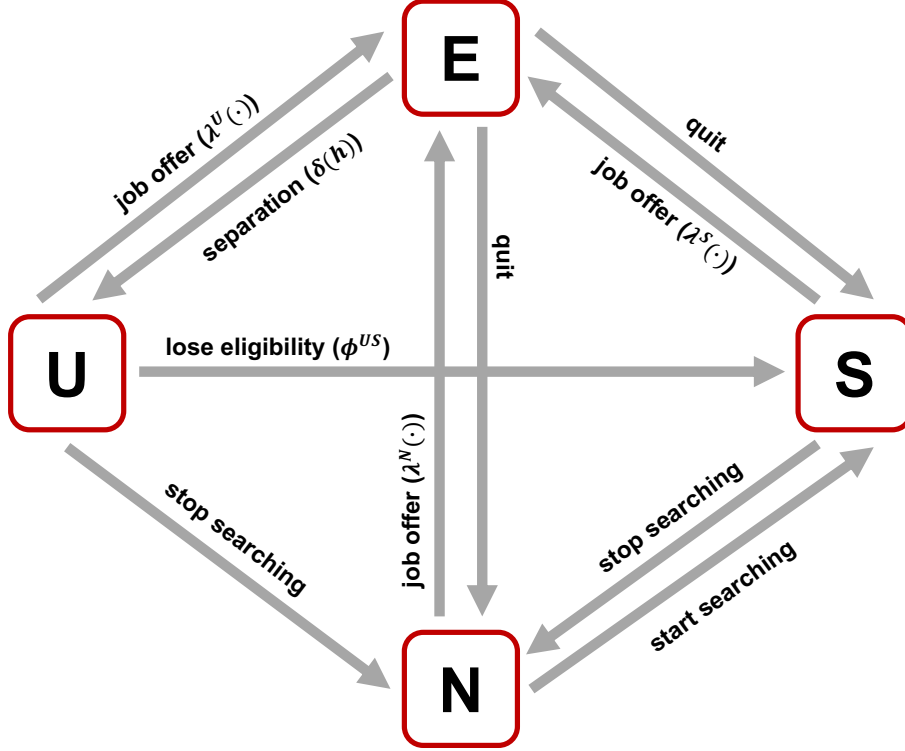


Figure 3: Labor Market Transitions in the Model

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

We can now formally state the household search problem. The value function of a house-

Table 5: Labor Supply Choice Sets

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

hold of age t in joint labor market state jk is

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

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

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

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

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. $b(h) = \min\{b^{rep}w(h), b^{max}\}$. In addition, a household can use its assets and interest income to finance consumption and new purchases of the risk-free bond.

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

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

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 forth row refer to the cases where the employed member is separated and $sep_{-i} = 1$. As for the choice sets, the previously non-participating spouse can never be eligible for benefits, while the previously employed spouse is eligible only in the case of separation.

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

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

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

While we outline here the continuation value for an EN-couple, the problem for all other

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

3.3 Vacancy Posting and Endogenous Arrival Rates

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

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

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

where $\mathbb{E}_{\hat{jk} \in \mathcal{J}_{QR}^{OP}} \mathbb{I}_{\hat{j}=E}$ 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

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

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 .⁷ Define member i 's arrival rate as

$$\lambda^S(t, h_i, h_{-i}, a, SS) = \lambda_{sp}(\theta_t(h_i, h_{-i}, a, SS)) \quad (8)$$

⁷For 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.

with arrival rate $p(\theta) = m(1, \theta)$ and corresponding vacancy filling rate $q(\theta) = m(\frac{1}{\theta}, 1)$. $m(U, V)$ 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

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

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

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

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

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

This yields

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

and hence

$$\begin{aligned} \kappa = q(\theta_i) & \left[\lambda_S \left[\frac{\kappa}{\lambda(\theta_i) E J_{-i}^{EE} + (1 - \lambda(\theta_i)) E J_{-i}^{EX}} \right]^{\frac{\alpha-1}{\alpha}} E J_i^{EE} \right. \\ & \left. + \left(1 - \lambda_S \left[\frac{\kappa}{\lambda(\theta_i) E J_{-i}^{EE} + (1 - \lambda(\theta_i)) E J_{-i}^{EX}} \right]^{\frac{\alpha-1}{\alpha}} \right) E J_i^{EX} \right], \end{aligned} \quad (13)$$

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 simplifies computation drastically, as we do not need to know the distribution of individuals across states to solve for arrival rates.

3.4 Numerical Implementation

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

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

4 Calibration

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

4.1 Functional Form Assumptions and Parameter Restrictions

Households value consumption with CRRA utility function

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

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 by age. 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

$$\psi^{EU} = \psi^{UE} = \psi^{ES} = \psi^{SE} \quad (15)$$

$$\psi^{UU} = \psi^{SS} = \psi^{SU} = \psi^{US} \quad (16)$$

$$\psi^{UN} = \psi^{NU} = \psi^{SN} = \psi^{NS} \quad (17)$$

$$\psi^{EN} = \psi^{NE}. \quad (18)$$

Output is assumed to be equal to human capital

$$y(h) = h. \quad (19)$$

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:

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

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

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

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

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

4.2 Parameters and Moments

To bring the model to the data and identify the parameters of interest, we simulate the full life cycle of 160,000 households and compute model-implied moments of this simulation. We initialize the distribution of households across labor market states consistent with CPS data and target the initial distribution of assets and human capital to match the wealth and earnings distribution by college/non-college of 25-year-old households in the SIPP. Table 6 summarizes all calibrated parameter values, and we discuss their identification below.

We start by setting a number of parameters without solving the model. We exogenously fix the coefficient of relative risk aversion to $\gamma = 1.75$, a in line with values used in the literature. We set the monthly net interest rate to 0.17%, corresponding to an annual interest rate of 2%. We assume a probability of losing unemployment benefits of $\phi^{US} = 1/6$, consistent with an average duration of benefit receipt of six months, and set the replacement rate to $b^{rep} = 0.5$ up to a maximum benefit level of \$1,750. The labor income tax is fixed at $\tau = 0.28$ as in Trabandt and Uhlig 2011. We set the elasticity of the matching function α to 0.5, as in Petrongolo and Pissarides (2001), and the share of match output allocated to workers to $\chi = 0.7$. Finally, we fix the variance of the taste shock as $\sigma_\epsilon = 0.1$.⁸ All remaining parameter values are identified by matching simulated moments with evidence on life cycle profiles of income, assets, and labor market outcomes. While all parameters are determined jointly, each targeted moment is more informative regarding certain parameters. We discuss the identification of parameters below.

We target average individual transition rates between labor market states. Flows into employment are closely related to the parameters $\lambda_N, \lambda_S, \lambda_U$, and the vacancy posting cost κ which pins down the endogenous component of arrival rates from the firms' problem. 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 7 reports the fit for overall transition rates while Figure 4 shows the fit for separation rates by income level. The model does well in replicating the empirical patterns, while somewhat overstating transitions from unemployment to non-participation and understating transitions from non-participation into employment.

Another important set of targeted moments is the distribution of households over joint labor market states by age group. To compare the model to the data, we pool all agents who are unemployed with and without benefits into one group, labeled U . The distribution of households across labor market states informs the preference parameters ψ , i.e. the disutility of work and search. Joint labor market states in the data and in the model

⁸Using a lower variance of 0.05 instead does not meaningfully impact our results.

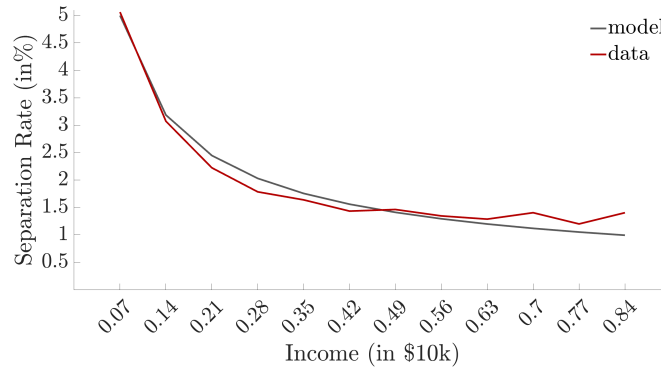
Table 6: Parameter Values

Parameter	Interpretation	Value
Demographics		
T	Length of life in months	600
T_W	Length of working life in months	480
Preferences		
β	Discount factor	0.9945
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	1.2000
ψ^{NN}	Disutility of work/search	2.2000
ψ^{EN}, ψ^{NE}	Disutility of work/search	$1.25 + \frac{0.7-1.25}{1+e^{-0.05(t-100)}}$
Financial Assets		
r	Interest rate	0.0017
Labor Market		
$\bar{\delta}$	Level parameter separation rate	0.0500
δ	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	0.1000
\bar{h}	Upper bound h	1.2000
$\bar{\phi}^{up}$	Level parameter prob. h rise	0.1900
ϕ^{up}	Curvature parameter prob. h rise	-1.8000
$\bar{\phi}^{down}$	Level parameter prob. h fall	0.0500
ϕ^{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	0.1750
ϕ^{US}	Probability of losing benefits	0.1667
p	Pension	0.4000
Gumbel shock		
σ_ε	Standard deviation of taste shock	0.1000

Table 7: Individual Labor Market Transition Rates (Model vs. Data)

	Model			Data		
	E	U	N	E	U	N
E	0.98	0.01	0.01	0.97	0.01	0.02
U	0.27	0.57	0.15	0.25	0.63	0.11
N	0.02	0.01	0.97	0.07	0.02	0.91

Notes: Table 7 shows individual labor market transition rates at monthly frequency. For the model, U combines unemployment with and without benefits. Data is from the CPS.

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

Notes: Figure 7 shows separation rates by income level. Data moments are the sum of individual EU and EN transition rates by income bin as computed from the SIPP, scaled to match aggregate transition rates in the CPS.

are shown in Figure 5. The model captures the distribution of joint labor market states well. In particular, it replicates that the share of households with one employed and one non-participating member (EN) is roughly constant over the life cycle, while the share of two earner households is lower particularly in the oldest age group. To achieve the reported fit, we keep all preference parameters constant by age except for $\psi^{EN} = \psi^{NE}$, which we assume to be logistically decreasing with age. While the model reproduces the share of households in other labor market states without age dependency in preferences, allowing for a declining ψ^{EN} is necessary to reproduce the relatively high share of EN -couples at young ages. We interpret the age-dependency in ψ^{EN} as capturing child-care needs of young households in a parsimonious way.

The pension level p and the discount factor β are determined by the life cycle asset profile. As in Section 2, we follow Chetty (2008) in our asset definition and target median net liquid wealth holdings by age group. Table 8 reports the fit of the life cycle asset profile. The model replicates the steep increase of liquid asset holdings over the life cycle but somewhat overpredicts asset levels especially at young ages.

Parameters for the human capital process are chosen to match income dynamics over the

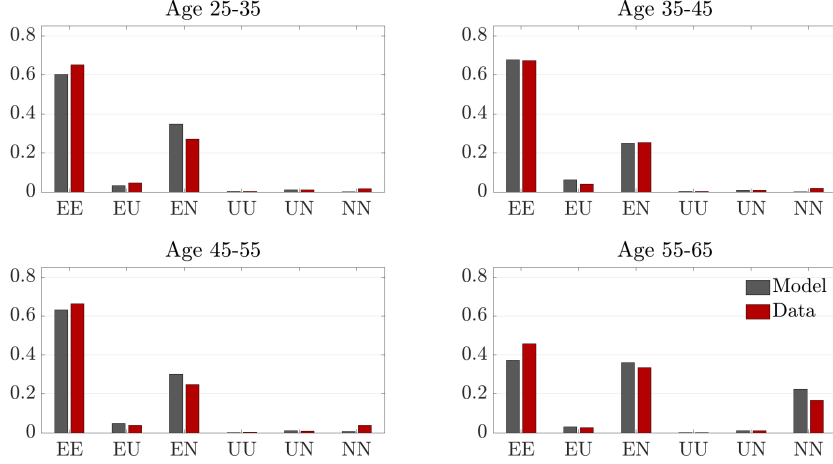


Figure 5: Joint Labor Market States of Couples (Model vs. Data)

Notes: Figure 5 shows the joint labor market states of couples in the model and in the data. For the model, U includes both unemployed receiving benefits and searchers who do not receive benefits. Data from the CPS.

Table 8: Asset Levels

	Model	Data
Aggregate	6.11	4.33
Age 25-35	2.03	0.52
Age 35-45	2.03	3.70
Age 45-55	5.33	7.58
Age 55-65	15.03	12.28

Notes: Table 8 compares median asset holdings by age group in the model and in the data. In the data, assets are defined as total wealth less of home equity, vehicle equity, and unsecured debt. Data from the SIPP. 1 unit corresponds to \$10,000.

life cycle. In the data, these moments are constructed from the SIPP. We set the bounds of the grid for human capital such that we capture the range of individual monthly earned income observed in the SIPP, conditional on being employed and reporting monthly earnings $\geq \$100$. The probability of moving up the human capital ladder is decreasing in the human capital level (i.e. $\phi^{up} < 0$), generating a concave income profile. Table 9 reports the related model fit for income levels by age groups. The model is able to replicate the increase in income for the age groups 25-35, 35-45, and 45-55 but fails to reproduce the fall in income for the oldest group. The mismatch for the oldest age group arises from a strong selection effect for non-participation in the model. Many agents with relatively low human capital drop out of the labor force, driving up the average income among the employed.

Human capital decay of non-employed allows us to capture that newly employed indi-

Table 9: Income Levels

	Model	Data
Aggregate	0.43	0.48
Age 25-35	0.36	0.41
Age 35-45	0.41	0.50
Age 45-55	0.46	0.52
Age 55-65	0.50	0.50

Notes: Table 9 compares monthly earned income conditional on employment by age group in the model and in the data. Data is from the SIPP and conditions on employed individuals who report to have monthly earnings $\geq \$100$. 1 unit corresponds to \$10,000.

viduals have lower wages than long-time employed and that job losses lead to persistent wage drops in the data (Davis and von Wachter 2011; Jarosch 2015; Kospentaris 2021). The probability of losing human capital when non-employed is disciplined by SIPP data on wage losses upon reemployment after non-employment of 1-3, 4-12, and 13-24 months respectively. Table 10 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 ($\phi^{down} = 0$).

Table 10: Earnings Losses after Non-Employment

	Data	Model
$\Delta \text{wage}_{1-3m}$	-1%	-1.5%
$\Delta \text{wage}_{4-12m}$	-7%	-5.9%
$\Delta \text{wage}_{13-24m}$	-19%	-16.4%

Notes: Table 10 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.

4.3 Validation: Life Cycle Profiles of Labor Market Transitions

We have not included the life cycle profiles of labor market transition rates in the set of targeted moments. We make this choice to leave the life cycle profile of the added worker effect, closely linked to labor market transitions by age group, untargeted. As a validation to our model, Figure 6 compares model implied life cycle profiles of labor market transitions to CPS data. Again, in the model U comprises the group of unemployed who receive benefits and those who exert costly search effort without receiving benefits.

First, consider transitions from employment over the life cycle (Figure 6a to 6c). The model captures that the likelihood of remaining in employment falls towards the end of working life, though the monthly transition probability out of employment never falls

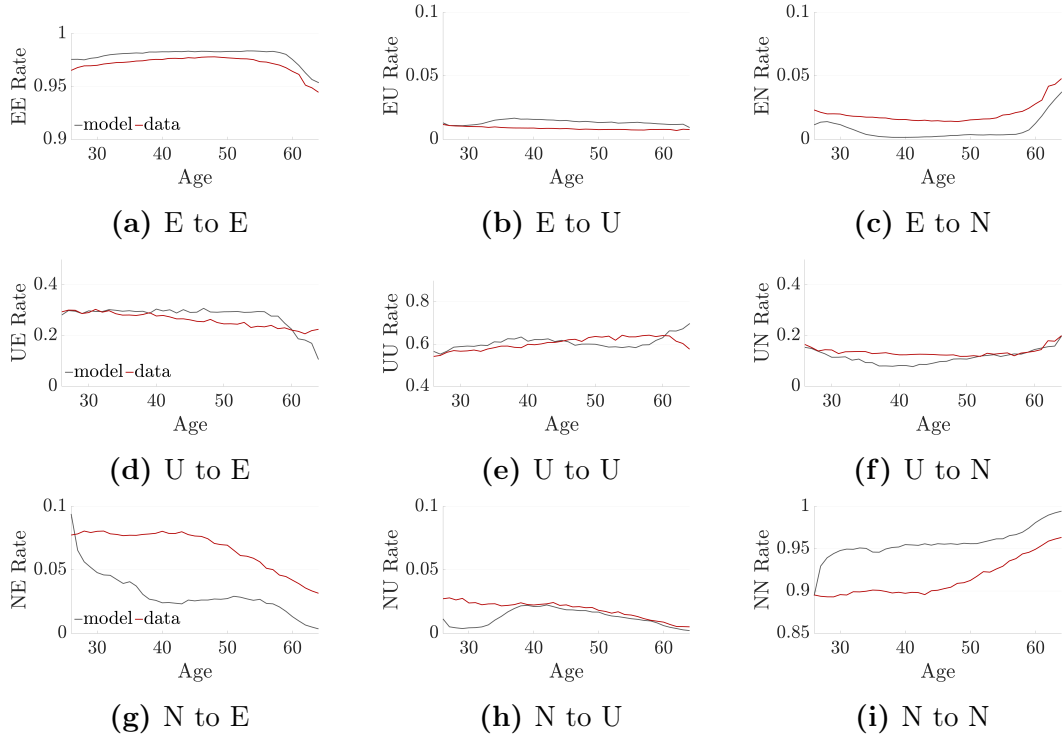


Figure 6: Labor Market Transitions over the Life Cycle

Notes: Figure 6 compares individual labor market transitions in the data and model. For the model, U includes both unemployed receiving benefits and searchers who do not receive benefits. Data is from the CPS.

below 95%. The counterpart to this in model and data is a corresponding increase in the likelihood of moving from employment to out of the labor force. Especially agents with relatively low human capital decide to leave the labor force close to retirement, while their younger counterparts choose to remain in employment. Several model mechanisms account for this difference. First, young agents have a longer time horizon until retirement, so that they need labor income to cover consumption needs during working life. In contrast, old agents hold much higher levels of assets which they can use to finance consumption. Second, human capital is only accumulated while employed. Remaining employed to accumulate human capital is more valuable for the young as they can benefit from it for a longer time period.

Next, consider the transitions out of unemployment (Figure 6d to 6f). The model replicates that across the entire life cycle the most likely transition is to remain unemployed. It also matches well that the probability of transitioning to employment declines with age, whereas the probability of leaving the labor force increases with age for similar reasons as discussed above. Finally, the model generates a fall in transitions from out of the labor force into employment (Figure 6g) but understates the likelihood to transition into unemployment (Figure 6h) at the beginning of the life cycle, while it matches well the high and increasing persistence of non-participation (Figure 6i).

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

5 The Added Worker Effect over the Life Cycle

In this section, we first show that our model reproduces the untargeted added worker effect and its decline in age. Second, we use the model to construct counterfactuals and analyze which channels are responsible for the age-dependency, distinguishing differences in *need* and *availability* between the young and old.

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 added worker effect – we recreate Tables 1 and 3 from Section 2 with simulated model data in Table 11. For the entire population, the model generates an added worker effect very close to the data (5.45% vs. 5.90%), split similarly between transitions into employment and unemployment. As outlined in Section 4, the model generally underestimates the probability of spousal transitions from non-participation directly into employment independently of the primary earner’s transition. However, it captures very well the difference in transition probabilities conditional on the primary earner’s transition, which is the added worker effect.

For the young, the model produces a strong increase in labor force participation upon job loss of the primary earner. While generating direct transitions into employment of similar magnitude as in the data, the model overpredicts transitions into unemployment, leading to an overshoot in the overall added worker effect among the young. For the old, both the model and data produce a much smaller added worker effect than for the young. As in the data, the model replicates no substantial increase in the likelihood of a spouse entering the labor force when the primary earner loses a job in an old household.

To analyze anticipation effects and lagged responses, Figure 7 replicates Equation (1) on model simulated output, separately by age. In line with the data, the model produces larger contemporaneous and lagged effects for the young than for the old, but muted lead effects for all age groups as separation shocks in the model cannot be anticipated. Three mechanisms generate lagged responses in the model: First, after becoming unemployed the primary earner may lose human capital which decreases potential human capital dif-

Table 11: Joint Labor Market Transitions by Age (Model vs. Data)

	Primary earner transition		
	EE	EU/ES	AWE
All Households:			
Cond. prob. of spousal NE transition	2.87%	4.06%	1.20%
	6.03%	8.01%	1.98%
Cond. prob. of spousal NS transition	1.10%	5.35%	4.25%
	1.63%	5.55%	3.92%
Cond. prob. of spousal NN transition	96.03%	90.58%	
	92.34%	86.44%	
AWE (total)			5.45%
			5.90%
Young (25-35):			
Cond. prob. of spousal NE transition	5.36%	6.97%	1.60%
	6.66%	9.30%	2.64%
Cond. prob. of spousal NS transition	0.36%	11.66%	11.30%
	2.00%	6.89%	4.89%
Cond. prob. of spousal NN transition	94.28%	81.37%	
	91.34%	83.81%	
AWE (total)			12.90%
			7.53%
Old (55-65):			
Cond. prob. of spousal NE transition	1.12%	1.42%	0.31%
	4.29%	3.73%	-0.56%
Cond. prob. of spousal NS transition	0.92%	0.41%	-0.51%
	0.90%	2.75%	1.85%
Cond. prob. of spousal NN transition	97.97%	98.17%	
	94.81%	93.52%	
AWE (total)			-0.20%
			1.29%

Notes: Table 11 shows the model implied added worker effect, constructed from simulated labor market transitions. Negative AWEs among the old are due to simulation variance of transition rates close to zero. Data results are equivalent to those reported in Tables 1 and 3 in Section 2.

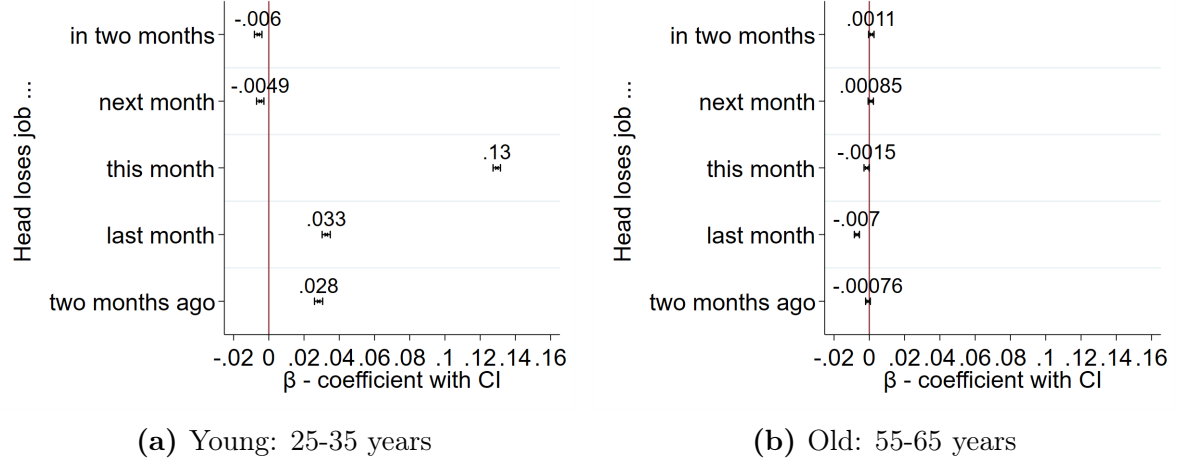


Figure 7: Dynamic Response: AWE by Age in the Model

Notes: Figure 7 shows the change in the probability that a non-participating spouse enters the labor force (either as unemployed or as 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 7a shows the model results for young households; Figure 7b shows the model results for old households. The regression producing the coefficients is Equation (1).

ferences 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 added worker effect by age can be explained by two potential forces. First, the endogenous distribution of old and young households across the state space – assets and human capital – differs across age groups. Heterogeneity in state variables affects the added worker effect directly through households' decisions in the labor market and indirectly through the arrival rates posted by firms. Second, conditional on all other states of the household, age itself has an effect on both households' decisions and their arrival rates. The effect of age arises from the distance to retirement and age dependent preferences for the EN-state. We discuss differences in household characteristics across age groups in the model and construct counterfactuals to quantify the contribution of each of these factors to the age differential in the added worker effect, allowing us to distinguish the relative role of *need* vs. *availability*.

Differences in endogenous states. Old households are on average substantially richer than young households (Table 8), which also applies to EN-couples only. As Figure 8 shows, old couples with one employed and one non-participating spouse are on average

about twice as rich as their young counterparts. Figures 9 and 10 report the distribution of human capital for non-participating and employed spouses of young and old EN-couples respectively. Young non-participating spouses have on average higher human capital than old non-participating spouses. The reverse is true for the employed spouse, implying a larger gap in human capital levels within old households. Age-dependent differences in human capital arise from initial conditions and the process for human capital accumulation, with longer periods of human capital appreciation for the old during persistent employment spells and depreciation during persistent non-employment spells.

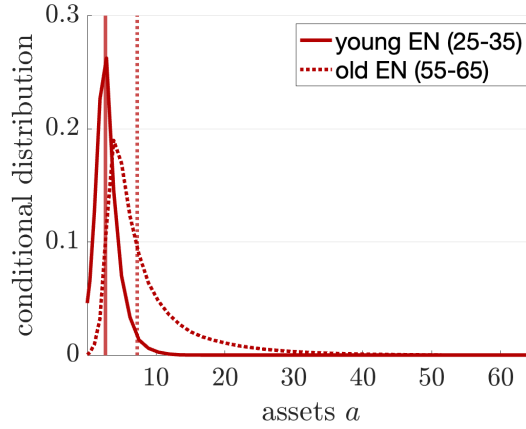


Figure 8: Asset Distribution: EN-Couples

Notes: Figure 8 shows the marginal distribution of assets conditional on EN-state by age group in the model. Vertical lines indicate average asset levels by age group.

Differences in labor market frictions. Arrival rates differ across age groups because firms respond endogenously with their vacancy posting to the likelihood of job acceptances and future quits. Figure 11 plots the 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 11 reports a counterfactual arrival rate by age, assuming that the distribution over (a, h_E, h_N) at each age is equal to the unconditional distribution over all EN-couples. This counterfactual can be interpreted as the direct effect of age on arrival rates, while the difference between the dashed and solid line captures the effect of age-specific distributions across (a, h_E, h_N) . Age itself affects arrival rates in the beginning (through ψ_{EN}) and end of the life cycle (through a horizon effect until retirement), however 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 relative contribution of each channel outlined above to the age-dependency in the added worker effect. 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*

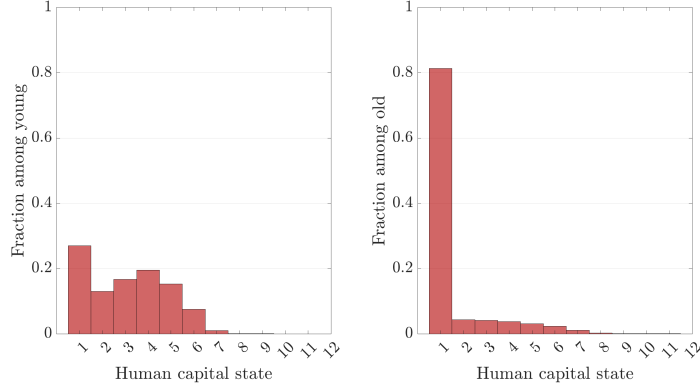


Figure 9: Distribution of Human Capital: Non-Employed Spouse

Notes: Figure 9 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.

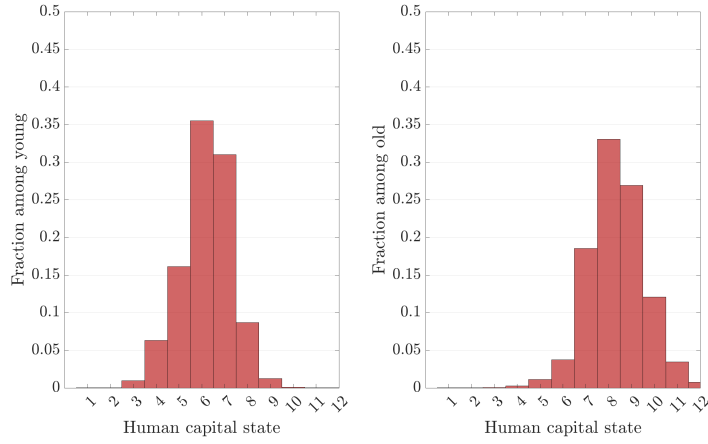


Figure 10: Distribution of Human Capital: Employed Spouse

Notes: Figure 10 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.

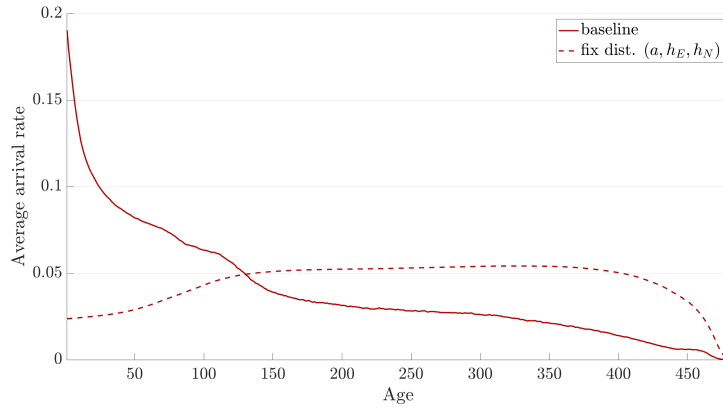


Figure 11: Life Cycle Arrival Rates: Non-Employed Spouse in EN-couple

Notes: Figure 11 shows the arrival rates for non-employed spouses in EN couples by age. The solid line displays the unconditional arrival rates, whereas the dashed line fixes the distribution of households over (a, h_E, h_N) within each age group.

$X?$, where we consider assets, the human capital of employed spouses, the 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 difference in average human capital between young and old employed or non-participating spouses respectively, again allowing us to preserve the distribution while shifting the mean. To account for the effect of age we keep households' states constant but shift their age by 30 years.

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

Determinants of the age-dependent AWE. We report the added worker effect for each counterfactual in Table 12 and relegate further details of the full transition matrices to Appendix C. The top panel of Table 12 answers the question “*Why is the added worker effect of young households so large?*”, i.e. it reports counterfactuals when starting from the distribution of young households. The bottom panel reports the corresponding counterfactuals when starting from the distribution of old households, thereby providing an answer to the question “*Why is the added worker effect of old households so small?*”.

Equating asset holdings and human capital levels of the young to those of the old can account for the strong added worker effect early in life. Columns (1)-(3) in the top panel of Table 12 show that increasing asset holdings, increasing the human capital level of the originally employed spouse, or decreasing the human capital level of the non-participating spouse all reduce the added worker effect among the young age group.

With higher asset holdings, the young are better insured against the job loss of a primary earner. A higher human capital of the employed spouse implies higher unemployment benefits (which are proportionate to earnings), makes it more likely that this spouse will

find a new job quickly (due to higher future arrival rates) and also makes household reoptimization more costly due to the larger difference in potential earnings. The direct effect of asset holdings and human capital of the employed spouse can be seen as evidence for a stronger *need* of the added worker effect 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 12) 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. This effect is particularly strong when changing human capital levels, due to the decline in incentives to re-optimize labor supply within the household. Arrival rates change the added worker effect almost entirely through a reduction in transitions directly into employment, lowering the insurance value of spousal labor supply disproportionately.

Adjusting all endogenous states and arrival rates jointly reduces the added worker effect of the young from 12.90% to 0.99% (column (4), row “adjusted λ ”), accounting for almost the entire age heterogeneity observed in the baseline framework. The effect of age itself is reported in column (5) and reduces the added worker effect to 7.3%. This reduction is in large part due to a base effect: As Table 26 in Appendix C shows, if households with the state of the young were to be 30 years older, the likelihood of a spousal transition into the labor force increases substantially independent of the primary earner’s transition, arising from a strong savings motive close to retirement. The baseline increase in spousal labor supply closes the gap between couples whose primary earner does / does not get separated and hence reduces the added worker effect.

The second panel of Table 12 documents the corresponding counterfactuals when starting from old households. In contrast to before, individually equating their asset and human capital levels to those of the young does not lead to a significant increase in the added worker effect within that age group, especially when keeping arrival rates constant (columns (1)-(3)). The reason for this weak response is an interaction between the *need for* and *availability of* spousal insurance margin. Increasing the need through a reduction in old households’ assets while preserving large differences in human capital levels across spouses increases the need but does not make spousal labor supply sufficiently valuable as insurance. In reverse, keeping asset levels high but closing the intra-household gap in human capital makes spousal insurance more valuable but does not create a sufficient need. Only when changing all margins at the same time (column (4)), and thereby gener-

ating both the *need for* and *availability of* spousal insurance, are we able to significantly increase the added worker effect among the old.

Table 12: Added Worker Effect: Counterfactuals

			counterfactuals				
			(1)	(2)	(3)	(4)	(5)
			baseline	a	h_E	h_N	(a, h_E, h_N)
Young (25-35):							
constant λ	AWE	12.90%	8.59%	8.73%	10.71%	3.65%	9.36%
	<i>to E</i>	1.60%	0.93%	4.79%	4.40%	3.03%	3.79%
	<i>to U</i>	11.30%	7.66%	3.95%	6.31%	0.62%	5.58%
adjusted λ	AWE		8.06%	5.36%	8.56%	0.99%	7.30%
	<i>to E</i>		0.42%	1.47%	1.88%	0.36%	1.19%
	<i>to U</i>		7.64%	3.90%	6.68%	0.63%	6.11%
Old (55-65):							
constant λ	AWE	-0.20%	0.13%	-0.33%	-0.18%	6.67%	0.54%
	<i>to E</i>	0.31%	0.11%	0.17%	0.26%	0.01%	0.22%
	<i>to U</i>	-0.51%	0.02%	-0.50%	-0.44%	6.66%	0.32%
adjusted λ	AWE		1.28%	0.77%	1.17%	7.77%	0.28%
	<i>to E</i>		1.29%	1.09%	1.60%	1.14%	-0.03%
	<i>to U</i>		-0.01%	-0.32%	-0.43%	6.63%	0.31%

Notes: Table 12 shows the counterfactual joint labor market transition probabilities.

Overall, our results suggest that a strong added worker effect 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. However, reducing either margin leads to a noticeable reduction in their added worker effect. In contrast, old households lack both the need for and availability of spousal insurance. For them, it is not sufficient to increase either margin individually, but only their interaction makes spousal labor supply sufficiently attractive to generate a strong added worker effect.

6 Conclusion

We provide novel empirical evidence that the strength of the added worker effect decreases over the life cycle. When the primary earner transitions from employment to unemployment, an out of the labor force spouse is on average 5.9 percentage points more likely to enter the labor force compared to when the primary earner remains employed. This spousal labor supply response declines from 7.5pp for households aged 25-35 to 1.3pp for

households at ages 55-65.

To analyze the mechanisms that drive this 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 US labor market. The model endogenously generates the untargeted average added worker effect and its decreasing pattern over the life cycle. We employ the model to construct counterfactuals, allowing us to isolate the drivers of the age-differential in the added worker effect.

Our results suggest that the declining added worker effect over the life cycle is driven by the complementarity of a *need for* and *availability of* spousal insurance. Higher asset holdings and higher human capital levels of primary earners decrease the need for spousal labor supply among the old relative to the young. Labor market frictions (lower job arrival rates) and a lower human capital of non-participating spouses reduce the availability of spousal labor supply as an insurance margin for the old age group. Our results suggest that adjusting either need or availability individually is not sufficient to increase the added worker effect towards the end of the life cycle. Only when high need for and the availability of spousal insurance act together (as they do among young households), can we generate a strong added worker effect among the old.

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A Empirical Robustness Exercises

A.1 Additional Transition Rates (Full Sample)

Table 13: Joint Labor Market Transitions (Full Sample): Spouse Non-Participating

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

Notes: Table 13 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions for the entire population.

Table 14: Joint Labor Market Transitions (Full Sample): Spouse Unemployed

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

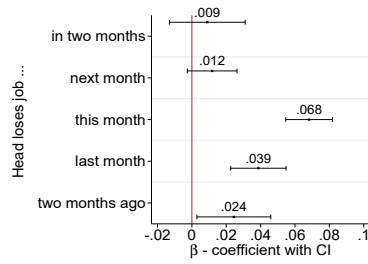
Notes: Table 14 shows the probability of a spousal transition from unemployment conditional on primary earner transitions for the entire population.

Table 15: Joint Labor Market Transitions (Full Sample): Spouse Employed

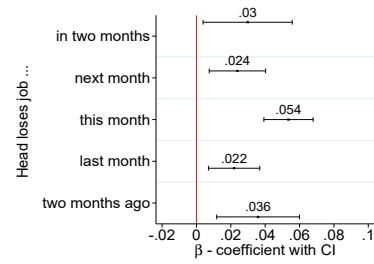
	Primary earner transition		
	EE	EU	EN
Cond. prob. of spousal EE transition	97.61%	91.49%	88.84%
Cond. prob. of spousal EU transition	0.77%	5.78%	1.25%
Cond. prob. of spousal EN transition	1.62%	2.72%	9.92%

Notes: Table 15 shows the probability of a spousal transition from employment conditional on primary earner transitions for the entire population.

A.2 Dynamic Response for Additional Age Groups



(a) Age 36 to 45



(b) Age 46 to 55

Figure 12: $\Delta \Pr(\text{Spouse enters LF})$ this month

Notes: Figure 12 shows the change in probability that a non-participating spouse enters the labor force (either as unemployed or as 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 12a) and between age 46 and 55 (Figure 12b) 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.

A.3 Dynamic Response by Reason for Unemployment

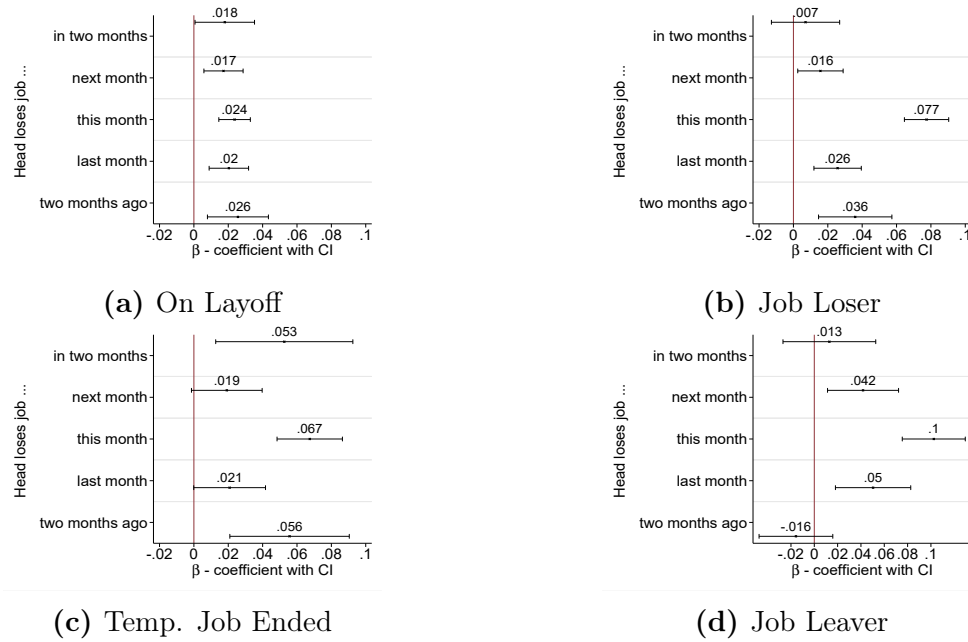


Figure 13: $\Delta \Pr(\text{Spouse enters LF})$ this month

Notes: Figure 13 shows the change in probability that a non-participating spouse enters the labor force (either as unemployed or as 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 13a shows the results if the household head is on layoff, Figure 13b if the household head lost his job, Figure 13c if a temporary job ended and Figure 13d if the head voluntarily quit his or her job. The sample includes couples in which one spouse is working and one spouse is out of the labor force between age 25 and 65 from the Current Population Survey (CPS), waves 1994 until 2020. The regression producing the coefficients is Equation 1.

A.4 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 added worker effect may be driven by these underlying preference shifts. We address this concern in two ways. First, we split our sample by gender and age. Table 16 (Panels I and II) shows that although the overall probability of the spouse joining the labor force is higher when the non-participating member is a man, we do not find significant changes in the strength of the AWE. Even when focusing on male non-participating spouses, young households still show a stronger AWE than older ones, reducing concerns about changing gender norms driving the age-dependency. Second, we repeat the empirical exercise on one cohort of households in which the non-participating spouse was born between 1960 and 1970. We choose this timespan to ensure sufficiently many observations both for the young and for the old age brackets. Table 16 (Panel III and IV) confirms the magnitude of the decline in the AWE over the life cycle for this particular cohort, i.e. for the same cohort when young and old.

Table 16: Added Worker Effect by Age (Gender and Cohort Effects)

	Primary earner transition		
	EE	EU	AWE
<i>I. Spouse is a Man (Young) :</i>			
Cond. prob. of spousal NE transition	13.54%	14.07%	0.62%
Cond. prob. of spousal NU transition	6.19%	11.69%	5.50%
Cond. prob. of spousal NN transition	80.27%	74.24%	
AWE (total)			6.12%
<i>II. Spouse is a Man (Old):</i>			
Cond. prob. of spousal NE transition	4.50%	4.59%	0.09%
Cond. prob. of spousal NU transition	1.13%	3.23%	2.10%
Cond. prob. of spousal NN transition	94.37%	92.18 %	
AWE (total)			2.19%
<i>III. Spouse born between 1960-70 (Young):</i>			
Cond. prob. of spousal NE transition	6.98%	8.62%	1.64%
Cond. prob. of spousal NU transition	1.89%	6.70%	4.81%
Cond. prob. of spousal NN transition	91.13%	84.68%	
AWE (total)			6.45%
<i>IV. Spouse born between 1960-70 (Old)</i>			
Cond. prob. of spousal NE transition	4.28%	2.94%	-1.34%
Cond. prob. of spousal NU transition	1.11%	3.68%	2.57%
Cond. prob. of spousal NN transition	94.61%	93.38%	
AWE (total)			1.23%

Notes: Table 16 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by gender and cohort. The added worker effect (AWE) is computed as the EU minus the EE column.

A.5 Children

Young couples are more likely to have children living in their household, which arguably affects labor supply behavior. To address this issue, Table 17 reports the AWE for couples below age 40 (to avoid picking up age-effects) with and without children as well as for couples below age 40 with and without children under age five (who require the most childcare). While out of the labor force spouses in couples without children have a higher baseline probability of entering the labor force, we do not find economically significant differences in the overall strength of the AWE between young couples with and without children.

Table 17: Added Worker Effect for Age < 40 (Presence of Children)

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

Notes: Table 17 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 added worker effect (AWE) is computed as the EU minus the EE column.

A.6 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 potential pension payments. Similarly, if the non-participating spouse dropped out because of bad health, she or he might simply be unable to start working again. Arguably, both retirement and health related non-participation are more prevalent among the old. Therefore, Table 18 repeats the empirical analysis excluding retired spouses (Panels I and II), disabled or ill spouses (Panels III and IV), as well as excluding both retired and disabled/ill spouses (Panels V and VI). We do not find any significant impact on the strength of the AWE among the old, increasing our confidence that the observed age-heterogeneity is not driven by age-dependent reasons for non-participation.

Table 18: Added Worker Effect by Age (Reason for Non-Participation)

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

Notes: Table 18 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by reasons for non-participation. The added worker effect (AWE) is computed as the EU minus the EE column.

A.7 Business Cycle

If the primary earner loses her job in a recession, it might be harder to find a job again, making spousal labor supply could more important during downturns. On the other hand, it could also be harder for an out of the labor force spouse to find a job and provide this insurance. In Table 19, we split the sample by NBER recessions and expansions. We do not find large differences in the age-dependency of the AWE across aggregate states.

Table 19: Added Worker Effect by Age (Business Cycle)

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

Notes: Table 19 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 added worker effect (AWE) is computed as the EU minus the EE column.

B Additional Results with SIPP Data

In contrast to the CPS, the Survey of Income and Program Participation (SIPP) collects asset information and the labor market state of both spouses. We work with waves 1994-2016 and apply the same sample restrictions as in the CPS. In the SIPP, households are interviewed every four months and report their monthly labor market states retrospectively, instead of being interviewed at a monthly frequency.⁹ As a result, labor market transitions within each four-months interview waves 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 20 reports the baseline AWE in the CPS and SIPP. Even though the baseline transitions tend to be underreported in the SIPP, the strength of the AWE is similar across datasets (5.90% in the CPS vs. 6.56% in the SIPP).

As an additional robustness check, we aggregate the SIPP data up to interview frequency. Within each aggregated time interval, we assign individuals the labor market state that they report to be in most often. Table 21 compares the AWE among old households by net liquid wealth within this aggregated data. The patterns are similar to those on monthly frequency (Table 4), in that old low wealth households have a stronger AWE than old high wealth households, suggesting a role for asset holdings as an insurance margin against job loss.

Table 20: Added Worker Effect – CPS vs. SIPP

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

Notes: Table 20 shows compares the probability of a spousal transition from out of the labor force conditional on primary earner transitions between the CPS and SIPP datasets. The added worker effect (AWE) is computed as the EU minus the EE column.

⁹In panel 2016, interviews took place once a year.

Table 21: Added Worker Effect among the Old (SIPP, aggregated, Net Liquid Wealth)

	Primary earner transition		
	EE	EU	AWE
<i>Bottom 50% of Net Liquid Wealth:</i>			
Cond. prob. of spousal NE transition	4.66%	5.63%	0.97%
Cond. prob. of spousal NU transition	2.15%	7.81%	5.66%
Cond. prob. of spousal NN transition	93.19%	86.56%	
AWE (total)			6.63%
<i>Top 50% of Net Liquid Wealth:</i>			
Cond. prob. of spousal NE transition	6.38%	6.09%	-0.29%
Cond. prob. of spousal NU transition	1.68%	3.52%	1.84%
Cond. prob. of spousal NN transition	91.95%	90.45%	
AWE (total)			1.55%

Notes: Table 21 shows the probability of a spousal transition from out of the labor force conditional on primary earner transitions by asset holdings for households with spouses older than age 50. Data are aggregated to interview panel length (4-month intervals). The added worker effect (AWE) is computed as the EU minus the EE column.

C Added Worker Effect: Counterfactuals

Table 22: Counterfactual Added Worker Effect: a (Young)

	Primary earner transition		
	EE	EU/ES	AWE
constant λ			
Cond. prob. of spousal NE transition	4.18%	5.10%	0.93%
	5.36%	6.97%	1.60%
Cond. prob. of spousal NU transition	0.27%	7.93%	7.66%
	0.36%	11.66%	11.30%
Cond. prob. of spousal NN transition	95.55%	86.96%	
	94.28%	81.37%	
AWE (total)			8.59%
			12.90%
adjusted λ			
Cond. prob. of spousal NE transition	3.58%	4.01%	0.42%
	5.36%	6.97%	1.60%
Cond. prob. of spousal NU transition	0.27%	7.92%	7.64%
	0.36%	11.66%	11.30%
Cond. prob. of spousal NN transition	96.14%	88.08%	
	94.28%	81.37%	
AWE (total)			6.12%
			12.90%

Notes: Table 22 shows spousal transitions in the model under counterfactual simulation, assigning young households the asset level of the old. Numbers reported in gray are corresponding baseline results from the model.

Table 23: Counterfactual Added Worker Effect: h_E (Young)

	Primary earner transition		
	EE	EU/ES	AWE
constant λ			
Cond. prob. of spousal NE transition	3.50%	8.29%	4.79%
	5.36%	6.97%	1.60%
Cond. prob. of spousal NU transition	0.03%	3.98%	3.95%
	0.36%	11.66%	11.30%
Cond. prob. of spousal NN transition	96.46%	87.73%	
	94.28%	81.37%	
AWE (total)			8.73%
			12.90%
adjusted λ			
Cond. prob. of spousal NE transition	1.35%	2.82%	1.47%
	5.36%	6.97%	1.60%
Cond. prob. of spousal NU transition	0.03%	3.93%	3.90%
	0.36%	11.66%	11.30%
Cond. prob. of spousal NN transition	98.62%	93.26%	
	94.28%	81.37%	
AWE (total)			5.36%
			12.90%

Notes: Table 23 shows spousal transitions in the model under counterfactual simulation, assigning young employed spouses the human capital level of the old. Numbers reported in gray are corresponding baseline results from the model.

Table 24: Counterfactual Added Worker Effect: h_N (Young)

	Primary earner transition		
	EE	EU/ES	AWE
constant λ			
Cond. prob. of spousal NE transition	3.86%	8.26%	4.40%
	5.36%	6.97%	1.60%
Cond. prob. of spousal NU transition	0.12%	6.43%	6.31%
	0.36%	11.66%	11.30%
Cond. prob. of spousal NN transition	96.02%	85.31%	
	94.28%	81.37%	
AWE (total)			10.71%
			12.90%
adjusted λ			
Cond. prob. of spousal NE transition	2.30%	4.18%	1.88%
	5.36%	6.97%	1.60%
Cond. prob. of spousal NU transition	0.12%	6.80%	6.68%
	0.36%	11.66%	11.30%
Cond. prob. of spousal NN transition	97.57%	89.01%	
	94.28%	81.37%	
AWE (total)			8.56%
			12.90%

Notes: Table 24 shows spousal transitions in the model under counterfactual simulation, assigning young non-participating spouses the human capital of the old. Numbers reported in gray are corresponding baseline results from the model.

Table 25: Counterfactual Added Worker Effect: (a, h_E, h_N) (Young)

	Primary earner transition		
	EE	EU/ES	AWE
constant λ			
Cond. prob. of spousal NE transition	0.77%	3.80%	3.03%
	5.36%	6.97%	1.60%
Cond. prob. of spousal NU transition	0.02%	0.65%	0.62%
	0.36%	11.66%	11.30%
Cond. prob. of spousal NN transition	99.20%	95.55%	
	94.28%	81.37%	
AWE (total)			3.65%
			12.90%
adjusted λ			
Cond. prob. of spousal NE transition	0.16%	0.51%	0.35%
	5.36%	6.97%	1.60%
Cond. prob. of spousal NU transition	0.02%	0.66%	0.63%
	0.36%	11.66%	11.30%
Cond. prob. of spousal NN transition	99.82%	98.83%	
	94.28%	81.37%	
AWE (total)			0.99%
			12.90%

Notes: Table 25 shows spousal transitions in the model under counterfactual simulation, assigning young households the asset and human capital levels of the old. Numbers reported in gray are corresponding baseline results from the model.

Table 26: Counterfactual Added Worker Effect: Age (Young)

	Primary earner transition		
	EE	EU/ES	AWE
constant λ			
Cond. prob. of spousal NE transition	5.48%	9.27%	3.79%
	5.36%	6.97%	1.60%
Cond. prob. of spousal NU transition	10.42%	16.00%	5.58%
	0.36%	11.66%	11.30%
Cond. prob. of spousal NN transition	84.10%	74.74%	
	94.28%	81.37%	
AWE (total)			9.36%
			12.90%
adjusted λ			
Cond. prob. of spousal NE transition	9.78%	10.97%	1.19%
	5.36%	6.97%	1.60%
Cond. prob. of spousal NU transition	10.45%	16.56%	6.11%
	0.36%	11.66%	11.30%
Cond. prob. of spousal NN transition	79.77%	72.47%	
	94.28%	81.37%	
AWE (total)			7.30%
			12.90%

Notes: Table 26 shows spousal transitions in the model under counterfactual simulation, assuming young households keep their states but are 30 years older. Numbers reported in gray are corresponding baseline results from the model.

Table 27: Counterfactual Added Worker Effect: a (Old)

	Primary earner transition		
	EE	EU/ES	AWE
constant λ			
Cond. prob. of spousal NE transition	1.12%	1.24%	0.11%
	1.12%	1.42%	0.31%
Cond. prob. of spousal NU transition	1.28%	1.29%	0.02%
	0.92%	0.41%	-0.51%
Cond. prob. of spousal NN transition	97.60%	97.47%	
	97.97%	98.17%	
AWE (total)			9.36%
			-0.20%
adjusted λ			
Cond. prob. of spousal NE transition	1.76%	3.05%	1.29%
	1.12%	1.42%	0.31%
Cond. prob. of spousal NU transition	1.26%	1.25%	-0.01%
	0.92%	0.41%	-0.51%
Cond. prob. of spousal NN transition	96.98%	95.70%	
	97.97%	98.17%	
AWE (total)			1.28%
			-0.20%

Notes: Table 27 shows spousal transitions in the model under counterfactual simulation. Numbers reported in gray are corresponding baseline results from the model.

Table 28: Counterfactual Added Worker Effect: h_E (Old)

	Primary earner transition		
	EE	EU/ES	AWE
constant λ			
Cond. prob. of spousal NE transition	1.18%	1.36%	0.17%
	1.12%	1.42%	0.31%
Cond. prob. of spousal NU transition	1.78%	1.28%	-0.50%
	0.92%	0.41%	-0.51%
Cond. prob. of spousal NN transition	97.04%	97.37%	
	97.97%	98.17%	
AWE (total)			-0.33%
			-0.20%
adjusted λ			
Cond. prob. of spousal NE transition	2.83%	3.92%	1.09%
	1.12%	1.42%	0.31%
Cond. prob. of spousal NU transition	1.74%	1.43%	-0.32%
	0.92%	0.41%	-0.51%
Cond. prob. of spousal NN transition	95.43%	94.66%	
	97.97%	98.17%	
AWE (total)			0.77%
			-0.20%

Notes: Table 28 shows spousal transitions in the model under counterfactual simulation. Numbers reported in gray are corresponding baseline results from the model.

Table 29: Counterfactual Added Worker Effect: h_N (Old)

	Primary earner transition		
	EE	EU/ES	AWE
constant λ			
Cond. prob. of spousal NE transition	1.15%	1.41%	0.26%
	1.12%	1.42%	0.31%
Cond. prob. of spousal NU transition	1.34%	0.90%	-0.44%
	0.92%	0.41%	-0.51%
Cond. prob. of spousal NN transition	97.51%	97.70%	
	97.97%	98.17%	
AWE (total)			-0.18%
			-0.20%
adjusted λ			
Cond. prob. of spousal NE transition	3.81%	5.41%	1.60%
	1.12%	1.42%	0.31%
Cond. prob. of spousal NU transition	1.28%	0.85%	-0.43%
	0.92%	0.41%	-0.51%
Cond. prob. of spousal NN transition	94.91%	93.74%	
	97.97%	98.17%	
AWE (total)			1.17%
			-0.20%

Notes: Table 29 shows spousal transitions in the model under counterfactual simulation. Numbers reported in gray are corresponding baseline results from the model.

Table 30: Counterfactual Added Worker Effect: (a, h_E, h_N) (Old)

	Primary earner transition		
	EE	EU/ES	AWE
constant λ			
Cond. prob. of spousal NE transition	1.11%	1.12%	0.01%
	1.12%	1.42%	0.31%
Cond. prob. of spousal NU transition	8.37%	15.03%	6.66%
	0.92%	0.41%	-0.51%
Cond. prob. of spousal NN transition	90.52%	83.85%	
	97.97%	98.17%	
AWE (total)			6.67%
			-0.20%
adjusted λ			
Cond. prob. of spousal NE transition	9.47%	10.60%	1.14%
	1.12%	1.42%	0.31%
Cond. prob. of spousal NU transition	7.52%	14.15%	6.63%
	0.92%	0.41%	-0.51%
Cond. prob. of spousal NN transition	83.01%	75.24%	
	97.97%	98.17%	
AWE (total)			7.77%
			-0.20%

Notes: Table 30 shows spousal transitions in the model under counterfactual simulation. Numbers reported in gray are corresponding baseline results from the model.

Table 31: Counterfactual Added Worker Effect: Age (Old)

	Primary earner transition		
	EE	EU/ES	AWE
constant λ			
Cond. prob. of spousal NE transition	0.24%	0.45%	0.23%
	1.12%	1.42%	0.31%
Cond. prob. of spousal NU transition	0.05%	0.37%	0.32%
	0.92%	0.41%	-0.51%
Cond. prob. of spousal NN transition	99.71%	99.17%	
	97.97%	98.17%	
AWE (total)			0.54%
			-0.20%
adjusted λ			
Cond. prob. of spousal NE transition	0.27%	0.24%	-0.03%
	1.12%	1.42%	0.31%
Cond. prob. of spousal NU transition	0.05%	0.36%	0.31%
	0.92%	0.41%	-0.51%
Cond. prob. of spousal NN transition	99.68%	99.40%	
	97.97%	98.17%	
AWE (total)			0.28%
			-0.20%

Notes: Table 31 shows spousal transitions in the model under counterfactual simulation. Numbers reported in gray are corresponding baseline results from the model.