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Abstract

This paper develops and estimates a dynamic life-cycle model to quantify why households save and work. The model incorporates multiple sources of risk—health, marital status, wages, medical expenses, and mortality—as well as endogenous labor supply and human capital accumulation, retirement, and bequest motives at the death of the first and last household member. We estimate it using PSID and HRS data for the 1941–1945 cohort via the Method of Simulated Moments. Eliminating bequest motives reduces aggregate wealth by 23.8% and labor earnings by 1.2%; removing medical expenses lowers them by 13.1% and 0.7%. Wage risk is crucial for early-life saving: its removal reduces wealth by 10.4% but raises earnings by 2.3%. Eliminating marriage and divorce dynamics leads couples—numerous and wealthier—to save and work slightly less, and singles—fewer and poorer—to save and work considerably more. These effects largely offset in the aggregate. Removing all saving motives beyond retirement needs and lifespan uncertainty lowers wealth by 56.9% and earnings by 2.7%. These findings show that capturing multiple risks and behavioral margins jointly is essential to understanding household saving and labor supply.

JEL Classification: E20, I1, J0

Keywords: savings, labor supply, couples and singles, precautionary savings, bequest motives, medical expenses

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1 Introduction

How do wage, marital, health, and longevity risks shape households' savings and labor supply decisions over the life cycle? How important are bequest motives and medical expenses in determining these behaviors? These questions are central to understanding the evolution of household wealth and labor market activity and to evaluating the effects of social insurance policies. Yet most existing studies abstract from key risks and motives, focus either on the working life or on retirement, and either abstract from marital status or study singles and couples separately, limiting the model's ability to capture the full implications of these decisions.

This paper develops and estimates a rich dynamic life-cycle model that jointly captures the savings and labor supply decisions of single and married individuals from entry into the labor market until death. The model incorporates endogenous human capital accumulation and endogenous retirement, wage and health shocks, marital transitions, medical expenses, and bequest motives at the death of both the first and the last household member. By distinguishing between couples and singles, it allows for different risks, incentives–including those generated by the government–, and constraints across groups.

Our model also accounts for selection into marriage and divorce and for the fact that, consistent with the data, higher-income individuals are healthier and live longer. As a result, both health and survival are, to some extent, endogenous and shaped by human capital and earlier choices. These selection mechanisms are important to explain the differences in saving and labor supply across groups. These group-specific patterns and their selection over the life cycle have not been jointly captured in prior work, making this a novel contribution of our paper.

We estimate our model using Panel Study of Income Dynamics (PSID) and Health and Retirement Study (HRS) data for the 1945 birth cohort, fitting labor supply and wealth profiles by marital status over the life cycle. Our estimated model delivers new insights into the formation of key economic aggregates and their heterogeneity by groups and over the life cycle.

We find substantial heterogeneity in behavior and responses. Married men exhibit high and persistent labor force participation, saving substantially throughout life in response to family risks and bequest motives. Married women's labor supply peaks in middle age and is more elastic, responding strongly to expected marital transitions and wage shocks. Without divorce risk, couples save less and work less, reflecting the reduced need for precautionary behavior. Single men show steeper declines in labor force participation and savings after age 40 than married men, and adjust their behavior earlier in life in response to changes. Single women work less than single men, including at younger ages, and accumulate less wealth, partly reflecting differences in earnings, child-rearing costs, and marriage prospects. Both single men and women respond strongly to the absence of marriage prospects, substantially increasing their labor supply and savings starting early in life.

In this regard, our model's predictions by group match the patterns in the data and make substantial progress compared to previous studies. Relative to Borella, De Nardi, and Yang (2023b), who modeled working life but abstracted from detailed retirement risks and bequest motives, we find that old-age risks and bequests have sizable feedback effects on working-age savings and labor supply. Compared to De Nardi, French, Jones, and McGee (2025), who focused on retirement behavior conditional on observed wealth at age 70, we show that marriage and labor supply choices earlier in life are critical to understanding savings at older ages and we endogenize the effects of human capital on health and mortality dynamics.

Turning to the aggregate implications of our findings, eliminating all voluntary bequest motives reduces aggregate wealth by 23.8% and aggregate earnings by 1.2%. While previous literature is silent about the effects of bequest motives on earnings, it does provide several estimates about their effects on wealth. Notable previous literature on this includes Kotlikoff and Summers (1981), Modigliani (1988), Gale and Scholz (1994), Lockwood (2012, 2018), Ameriks et al. (2020) and De Nardi, French, Jones, and McGee (2025). Their estimates suggest that bequests account for between 20% to 80% of aggregate wealth. Our rich model of saving and labor supply thus indicates that, while bequest motives explain a large part of accumulated wealth, many of those previous works over-estimate the effects of bequest motives on wealth.

We also find that removing medical expenses reduces aggregate wealth by 13.1% and aggregate earnings by 0.7%. De Nardi, French, Jones, and McGee (2025) studies the effects of medical expenses on people aged 72 and older and conclude that they boost retirement savings by 3.1%. Unsurprisingly, we find a bigger effect. This is because households can adjust both their savings and labor supply earlier in life and choose to work less in the absence of medical expenses. Kopecky and Koreshkova (2014) develop and calibrate a simpler life-cycle model with exogenous labor supply and find that medical expenses account for 13.5% of aggregate savings—an amount very close to ours. This similarity may arise because, while their model does not allow households to adjust labor supply, it also omits the sharp rise in medical expenses prior to death, potentially leading to an underestimate of medical spending.

Next, we turn to contributing to the literature on precautionary savings by eliminating wage risk and finding that aggregate wealth would be 10.4% lower and aggregate earnings 2.3% higher in the absence of wage risk. Aiyagari (1994) finds relatively small effects–5-14%–but his model features an infinitely-lived agent facing only unemployment risk. In contrast, more realistic life-cycle models that incorporate richer earnings processes and mortality risk find much larger effects. Hubbard, Skinner, and Zeldes (1994a,b, 1995), Carroll and Samwick (1997), Gourinchas and Parker (2002), and Cagetti (2003) estimate that precautionary savings account for up to 70% of wealth, with 50% being a common estimate. Our model includes more risks and additional margins of adjustment (including the more elastic labor supply of married women). As a result, it implies precautionary savings towards the lower end of the range found in the previous life-cycle literature with exogenous earnings. This result is consistent with the branch of the literature that studies labor supply as an insurance mechanism. In life-cycle models with endogenous hours, households smooth consumption not only through savings but also by adjusting labor supply in response to wage shocks. Low (2005) shows that approximately one quarter of earnings risk is absorbed through adjustments in hours worked. Pijoan-Mas (2006) highlights that households increase labor effort in response to uninsurable wage shocks, reducing reliance on precautionary saving. At the household level, Blundell, Pistaferri, and Saporta-Eksten (2016b) find that family labor supply, especially through the secondary earner, insures about 64% of wage shocks, with savings smoothing the remainder. These findings help explain why models that allow for labor market responses–like ours–produce lower estimates of precautionary wealth accumulation.

Finally, we quantify the effects of marriage and divorce dynamics: eliminating new marriages raises savings among singles, while removing divorce risk lowers labor supply and earnings among married individuals, especially married women. On net, the effects of eliminating marriage and divorce risks on aggregate wealth are small (0.7%), but mask substantial heterogeneity across groups. We find that marriage and divorce have the strongest effect on labor earnings, which would be 2.0% higher in the absence of changes in marital status after age 26. The most related previous contribution is by Cubeddu and Ríos-Rull (2003), that studies the effects of changes in marital patterns on savings in a model where marriage formation and dissolution are the only source of risk. Because their experiments differ significantly from ours—for instance, by altering the timing of marital dynamics over the life cycle—they are not directly comparable to our results.

Removing all saving motives other than retirement needs and uncertain and heterogeneous lifespans reduces lifetime wealth accumulation by 56.9% and aggregate earnings by 2.7%. As there are no other models with all of these rich features, ours is the first estimate in this regard.

Our research design and findings differ in important ways from previous studies. While prior work emphasized medical expense risk mainly after age 70, we show that expectations about late-life health costs affect savings and labor supply starting much earlier. Our decomposition exercises reveal that marriage and divorce risks have substantial labor market effects, especially for women, a dimension that models of elderly retirees or singles alone cannot capture. Finally, we quantify the combined importance of multiple saving motives, showing that excluding any one risk leads to large and heterogeneous changes in wealth and labor supply across groups and ages.

As a result, our paper makes several contributions. First, we develop a unified model that captures key features of both the working and retirement stages of life, modeling the decisions of singles and couples and accounting for transitions between them. Second, we estimate the model over the full adult life cycle, matching detailed profiles of participation, hours, wealth, and marital status across groups and ages, and accounting for survival and health selection effects. Third, we use the estimated model to quantify the separate and joint contributions of wage, marital, health, and longevity risks, as well as bequest motives and medical expenses, to lifetime savings and labor supply patterns. Our findings reveal the critical role of these risks and motives in shaping behavior, the importance of modeling singles and couples jointly, and the limits of models that abstract from these features. By integrating life-cycle labor supply, saving, marriage, and retirement risks into a unified framework, our paper provides a richer and more complete understanding of the forces shaping household behavior and the role of policy interventions in mitigating risks over the life cycle.

2 Savings and labor supply over the life cycle

We use data from the PSID, supplemented with the HRS to improve coverage at older ages, focusing on the 1941–1945 birth cohort (henceforth, the 1945 cohort). Although this cohort is older, it offers a key advantage: we observe both their working years and most of their retirement period. This allows us to estimate retirement risks and bequest motives, which are central to understanding saving at older ages.

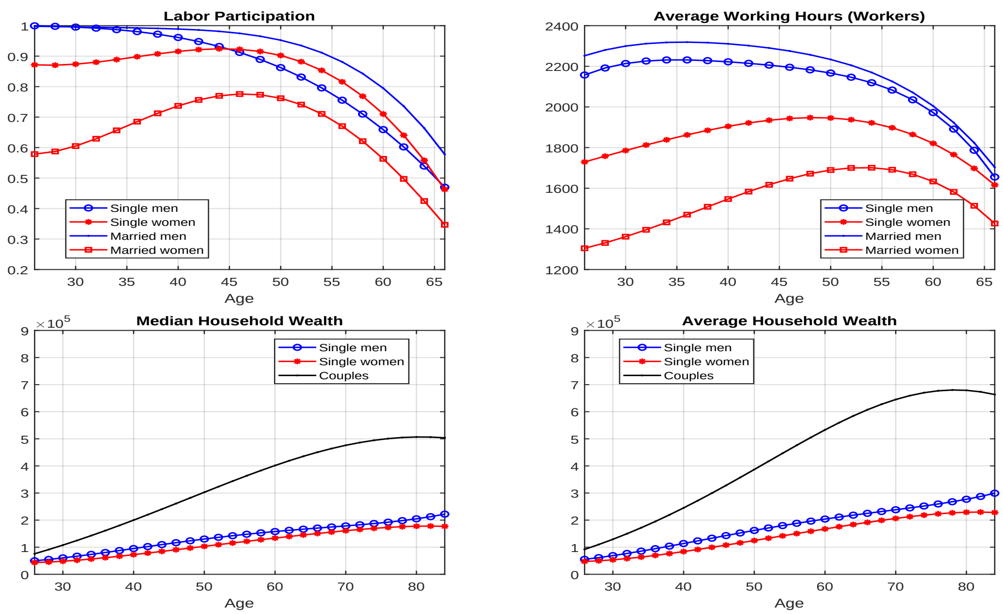


Figure 1: Life-cycle profiles by gender and marital status, PSID.

The top panels of Figure 1 show average labor force participation and hours worked for single and married men and women.[1] The data for couples include only households in which both spouses are alive and remain married. The data for singles include individuals who are single at age 26 as well as those who are single at a given age due to divorce or widowhood. The left-hand-side panel shows that married men have the highest participation rate, with only a gradual decline after age 45, while single men experience a much steeper drop. Single women begin about 10 percentage points lower than single men and increase participation until peaking around age 50.

[1] We include cohabiting couples among married couples. In the PSID, it is not possible to distinguish between legal marriage and cohabitation prior to 1983. In that year, only 2% of couples in our cohort were not legally married. The profiles are estimated by fitting a fourth-order polynomial in age, fully interacted with marital status and cohort dummies, separately for each gender. We express all monetary values in 2018 dollars.

Married women have the lowest participation rates: around 57% at age 26, rising to 78% between ages 40 and 50, then declining similarly to the other groups. The top-right panel shows that married men work more hours, on average, and that women work fewer hours than men, even conditional on participation.

These labor supply differences reflect both behavioral and compositional factors: individuals with higher wages are more likely to marry and remain married. Our analysis accounts for these compositional differences both at model entry (age 26) and through subsequent marital transitions, which shape the evolving composition of married and single individuals.

The bottom panels of Figure 1 show median and average net worth by age and marital status. Two features stand out. First, despite economies of scale, couples hold more than twice the wealth of singles at all ages. Second, wealth declines only modestly after retirement, contrary to the predictions of a basic life-cycle model.

This limited drawdown reflects both saving motives and mortality bias. Saving for medical expenses and bequest motives can lead households to hold more wealth at older ages. Mortality bias also matters: wealthier individuals live longer, even conditional on gender and marital status. This has two important implications. Because wealthier individuals survive longer, average wealth among the surviving population flattens or even rises after age 66. In addition, since couples are wealthier than singles, those who become single through widowhood tend to be wealthier than those who were always single, further stabilizing singles' wealth profiles after retirement.

Much of the existing literature focuses on the elderly and treats wealth at retirement as given. Our analysis extends this by examining how medical expenses, bequest motives, and selection effects shape wealth and labor supply decisions across the full life cycle. It also accounts for mortality bias and for marital transitions earlier in life, both of which are salient in the data.

3 The model

Life is divided into three stages.[2] The first is a working stage (ages 26 to 61), followed by an early retirement stage (ages 62 to 65), and finally a retirement stage (age 66 to the maximum age of 99). Our model period is two years long, consistent with the frequency of our data.

During the **working stage**, single and married individuals decide how much to work and save. Wages are subject to shocks and depend on one's human capital endogenously accumulated through work. Married people face divorce shocks, and single people may meet partners and get married.

We model (and estimate) how available time is split between working and leisure, allowing it to depend on gender and marital status. We interpret available time as net of home production, child care, and elderly care—tasks that are difficult to outsource.

All workers incur fixed costs of working, which vary by age, gender, and marital status. These costs represent commuting, preparing for work, and making arrangements to be able to work.

Single and married women have children, with the number of children depending on maternal age and marital status. Raising children imposes both time and monetary costs. Time costs reduce the available hours for work and leisure. Monetary costs arise from increased consumption needs, modeled through equivalence scales, and child care expenses. For working mothers, child care costs vary based on the number and age of their children as well as their earnings. Consequently, child care costs are a normal good–women with higher earnings pay for more expensive child care.

During the **early retirement stage**, people still experience wage shocks, but single people no longer marry, and couples no longer divorce. These assumptions are data-driven[3] and help keep our model tractable. For tractability, if they claim Social Security, they can no longer work, and couples claim Social Security jointly.

During the first year of the **retirement stage**, those who have not already claimed

[2]This model builds on Borella, De Nardi, and Yang (2023b), particularly in its structure and exposition of the working-life stage. We retain many modeling features from that earlier framework and follow its exposition where content overlaps. However, this paper introduces several key innovations, including a richer treatment of the retirement period, endogenous life expectancy, and new estimation moments. These improvements significantly extend the earlier model and are essential to addressing the questions posed in this paper.

[3]Only 1% of couples divorce and 4% of singles marry between ages 62 and 72 in the HRS data for our 1945 cohort.

Social Security do so and stop working. People face health shocks, medical expenses, and mortality shocks. Thus, each married person faces the risk of his or her spouse dying, in addition to their own. Mortality and health risks, as well as medical expenses depend on age, gender, health status, human capital, and marital status. Because human capital is, at least to some extent, endogenous, so are lifespan, healthspan, and medical expenses.

Because we explicitly model labor force participation and hours for both spouses, savings, bequest motives at the death of the first and last spouse, and medical expenses in old age, the model is computationally intensive (see Appendix E for details). For tractability, we also assume the following. First, marriage and divorce are exogenous processes that we estimate from the data. Second, the amount of time spent in home production is fixed. Third, fertility is exogenous; women have an age-varying number of children that depends on their age and marital status (which we estimate from the data). Fourth, people who are married to each other are of the same age. Lastly, divorced and never-married people face the same problem (we thus abstract from Social Security benefits entitlement for divorcees).

3.1 Preferences

Let t be age, with people entering at age 26 and dying by the end of age 99. Households discount the future at a rate β. The superscript i denotes gender, with $i = 1, 2$ being a man or a woman, respectively. The superscript j denotes marital status, with $j = 1, 2$ being single or in a couple, respectively.

Utility from consumption and leisure. Each **single person** has preferences over consumption and leisure, and the period flow of utility is given by the standard CRRA utility function

$$v^i(c_t, l_t, \eta_t^{i,1}) = \frac{((c_t/\eta_t^{i,1})^\omega l_t^{1-\omega})^{1-\gamma} - 1}{1-\gamma} + b,$$

c_t is consumption, $\eta_t^{i,1}$ is the equivalence scale for singles and $\eta_t^{i,2}$ is the one for couples, $l_t^{i,j}$ is leisure, and $b \geq 0$ is the value of life.[4] Leisure is given by

$$l_t^{i,j} = L^{i,j} - n_t^i - P_t^{i,j} I_{n_t^i}, \tag{1}$$

where $L^{i,j}$ is available time, net of home production, which can be different for single and married men and women. The functional form we use for it is

$$L^{i,j} = \frac{L}{1 + \exp(FL^{i,j})}, \tag{2}$$

where we normalize L to 112 hours a week and estimate $FL^{i,j}$ using our structural model. The term n_t^i, is hours worked, $I_{n_t^i}$ is an indicator function that equals 1 when hours worked are positive.

The term $P_t^{i,j}$ is the fixed time cost of work, which depends on gender, marital status, and age. It assumes the following functional form, whose parameters we estimate using our structural model

$$P_t^{i,j} = \frac{\exp(p_0^{i,j} + p_1^{i,j} t + p_2^{i,j} t^2)}{1 + \exp(p_0^{i,j} + p_1^{i,j} t + p_2^{i,j} t^2)}. \tag{3}$$

We assume that **couples** maximize their joint utility function

$$w(c_t, l_t^1, l_t^2, \eta_t^{i,j}) = \frac{((c_t/\eta_t^{i,j})^{\omega}(l_t^1)^{1-\omega})^{1-\gamma} - 1}{1-\gamma} + b + \frac{((c_t/\eta_t^{i,j})^{\omega}(l_t^2)^{1-\omega})^{1-\gamma} - 1}{1-\gamma} + b.$$

Note that for couples, $\eta_t^{i,j}$ does not depend on gender and $j = 2$.

Utility from bequests. We model utility from two types of bequests: those distributed to heirs other than the spouse at the death of the first household member and those at the death of the last. While the latter has been extensively studied, the former was recently introduced and estimated by De Nardi, French, Jones, and McGee (2025) in a model of couples and singles over age 70. Their analysis shows that, upon a spousal death, over 30% of cases involve substantial "side" bequests to heirs other than the surviving spouse, which significantly influence household saving

[4] Given that, to some extent, our life expectancy is endogenous, we follow the approach in Hall and Jones (2007) in adding a parameter that ensures that people are happy to be alive.

and bequest behavior. Households may allocate side bequests at this time because a spousal death resolves uncertainty about the deceased spouse's remaining lifespan and potential medical expenses.

The household derives utility $\theta_j(e)$ from leaving a bequest $e \geq 0$ to heirs other than the spouse. Specifically, $\theta_1(e)$ represents the utility of bequests when there is one person in the household (and thus no surviving spouse), and $\theta_2(e)$ captures the utility from bequests to non-spousal heirs when there are two spouses and one survives. The bequest function is defined as

$$\theta_j(e) = \phi_j \frac{(e + k_j)^{1-\gamma}}{1-\gamma}$$

where k_j determines the curvature of the bequest function, and ϕ_j governs its intensity.

De Nardi (2004) employed this functional form to explain life-cycle savings behavior. It accommodates several interpretations of the "bequest motive," including dynastic or "warm glow" altruism (Becker and Tomes, 1986; Abel and Warshawsky, 1988; Andreoni, 1989), strategic motives (Bernheim, Shleifer, and Summers, 1985; Brown, 2003), and utility derived directly from wealth (Carroll, 1998; Hurd, 1989).

3.2 Human capital and wages

We define human capital, $\bar{y}_t^i$, as the average past earnings of an individual at each age (see Equation (12) for a formal definition). This measure depends on initial wages, which reflect schooling, as well as on subsequent labor market experience and earnings, rather than solely on cumulative time worked.

This definition offers two key advantages. First, it aligns with empirical findings that individuals with higher education levels enjoy greater returns on their labor market experience (Blundell, Costa Dias, Meghir, and Shaw, 2016a; Costa Dias, Joyce, and Parodi, 2020). Second, it enables the use of a single state variable to track both human capital and Social Security contributions, ensuring computational tractability within our framework.

In the model, human capital, combined with stochastic wage shocks, determines effective wages. Wages are composed of two components: a deterministic function of age, gender, and human capital, $z_t^i(\bar{y}_t^i)$, and a persistent stochastic shock, ϵ_t^i, which evolves as

$$\ln \epsilon^i_{t+1} = \rho^i_\epsilon \ln \epsilon^i_t + \upsilon^i_t, \qquad \upsilon^i_t \sim N(0, (\sigma^i_\upsilon)^2).$$

The effective hourly wage is given by the product of $z^i_t(\bar{y}^i_t)$ and ϵ^i_t. This formulation captures both systematic wage variation, influenced by demographic and human capital factors, and idiosyncratic wage shocks.

3.3 Marriage and divorce

During the working period, the probability of a single individual marrying at the beginning of the next period depends on their age, gender, and wage shock at age t: $\nu_{t+1}(\cdot) = \nu_{t+1}(i, \epsilon^i_t)$. To allow for assortative mating, conditional on meeting a partner, the probability of meeting with a partner p with wage shock ϵ^p_{t+1} is

$$\xi_{t+1}(\cdot) = \xi_{t+1}(\epsilon^p_{t+1} | \epsilon^i_{t+1}, i). \tag{4}$$

We assume random matching over wealth a_{t+1} and partner's human capital $\bar{y}^p_{t+1}$, conditional on the partner's wage shock. Thus, we have

$$\iota_{t+1}(\cdot) = \iota_{t+1}(a^p_{t+1}, \bar{y}^p_{t+1} | \epsilon^p_{t+1}). \tag{5}$$

For working-age couples, divorce can occur as a result of a shock that depends on the age and wage shocks of both partners. This probability is denoted by $\zeta_{t+1}(\cdot) = \zeta_{t+1}(\epsilon^1_t, \epsilon^2_t)$. If a couple divorces, their wealth is split equally. For simplicity, we abstract from alimony payments.

3.4 Costs of raising children and running a household

We keep track of the total number of children and their ages as a function of the mothers' age and marital status. The number of children aged 0-5 is denoted by $f^{0,5}_t(i, j)$, and the corresponding childcare cost for each child is $\tau^{0,5}_c$. Similarly, the number of children age 6-11 is $f^{6,11}_t(i, j)$ and the corresponding child care cost per child is $\tau^{6,11}_c$.

3.5 Health, medical expenses, and death

At age 66, individuals are endowed with a health state h_{66}, which can be good, bad, or in a nursing home (disabled). The distribution of this initial health state depends on gender, marital status, and one's human capital, allowing the model to capture observed patterns where women, married individuals, and those with higher incomes typically enjoy better health outcomes.

After age 66, health evolves according to a Markov process. For singles, the transition probability is a function of age, gender, marital status, current health, and human capital and can be written as $\pi_t^{i,1}\left(h_t^i, \bar{y}_r^i\right)$. For individuals in couples, we also allow the transition probability to depend on the human capital of both partners and can thus be expressed as $\pi_t^{i,2}\left(h_t^i, \bar{y}_r^i, \bar{y}_r^p\right)$.

We allow the medical expenses of singles to be a function of age, gender, marital status, current health, and human capital: $m_t^{i,1}\left(h_t^i, \bar{y}_r^i\right)$, while the medical expenses of couples can depend on both partners' human capital $m_t^{i,2}\left(h_t^i, \bar{y}_r^i, \bar{y}_r^p\right)$.

To capture the sharp rise in medical expenses during the period preceding death and the additional costs associated with funerals and burials, the model includes an additional expense shock at death. For singles it is given by $d_t^{i,1}\left(h_t^i, \bar{y}_r^i\right)$ and for couples, by $d_t^{i,2}\left(h_t^i, \bar{y}_r^i, \bar{y}_r^p\right)$.

Survival probabilities $s_t^{i,j}(h_t^i, \bar{y}_r^i)$ depend on age, gender, marital status, current health, and human capital.

3.6 Initial conditions

We take the fraction of single and married people at age 26 and their distribution over the relevant state variables (wealth, human capital, and wage shocks, with the latter two being for each of the spouses in the case of couples) from the PSID.

3.7 Government

Our cohort faces the effective time-varying tax rates that it experienced in the data and that we estimate from the PSID. As Benabou (2002), we adopt a functional form that allows for negative tax rates and thus incorporates the EITC. We allow our effective tax rates to depend on marital status, gender, and age (thus time). Taxes paid are a function of total income Y

$$T(Y, i, j, t) = (1 - \lambda_t^{i,j} Y^{-\tau_t^{i,j}})Y. \tag{6}$$

The government imposes a proportional payroll tax τ_t^{SS}, applied to earnings up to a Social Security cap $\widetilde{y}_t$. These revenues help finance old-age Social Security benefits, which depend on average past earnings (human capital, as discussed in Section 3.2). We also allow the payroll tax and the Social Security cap to change over time, as in the data. Households are assumed to have anticipated these changes.

The insurance provided by the government, such as Medicaid and SSI, is captured by a means-tested consumption floor, $\underline{c}(j)$, as in Hubbard, Skinner, and Zeldes (1995).[5]

3.8 Recursive formulation

We compute nine value functions for different groups and stages of life. For brevity, we report in the main text only those that are most informative about our modeling choices and economic mechanisms. The remaining ones pertain to early retirement for couples and singles, and those of individuals in couples, and in Appendix B.

3.8.1 The value function of working-age singles

The value function of a working-age single person ($j = 1$) depends on age t, gender i, wealth a_t^i, persistent earnings shock ϵ_t^i, and human capital $\bar{y}_t^i$. Net worth a_t earns a rate of return r.

$$W^s(t, i, a_t^i, \epsilon_t^i, \bar{y}_t^i) = \max_{c_t, a_{t+1}, n_t^i} \Bigg(v^i(c_t, l_t, \eta_t^{i,j}) + \beta(1 - \nu_{t+1}(i)) E_t W^s(t+1, i, a_{t+1}^i, \epsilon_{t+1}^i, \bar{y}_{t+1}^i) + \beta \nu_{t+1}(i) E_t \Big[\hat{W}^c(t+1, i, a_{t+1}^i + a_{t+1}^p, \epsilon_{t+1}^i, \epsilon_{t+1}^p, \bar{y}_{t+1}^i, \bar{y}_{t+1}^p) \Big] \Bigg), \tag{7}$$

subject to Equation (1) and

$$Y_t^i = z_t^{i,j}(\bar{y}_t^i)\epsilon_t^i n_t^i, \tag{8}$$

$$\tau_c(i, j, t) = \tau_c^{0,5} f_t^{0,5}(i, j) + \tau_c^{6,11} f_t^{6,11}(i, j), \tag{9}$$

[5] Borella, De Nardi, and French (2018) discuss Medicaid rules and observed outcomes after retirement.

$$T(\cdot) = T(ra_t + Y_t, i, j, t), \tag{10}$$

$$c_t + a^i_{t+1} = (1+r)a^i_t + Y^i_t(1 - \tau_c(i,j,t)) - \tau^{SS}_t \min(Y^i_t, \widetilde{y}_t) - T(\cdot), \tag{11}$$

$$\bar{y}^i_{t+1} = (\bar{y}^i_t(t - t_0) + (\min(Y^i_t, \widetilde{y}_t)))/(t + 1 - t_0), \tag{12}$$

$$a_{t+1} \geq 0, \tag{13}$$

$$n^i_t \geq 0. \tag{14}$$

The expectation of the value function for the next period if one remains single integrates over one's wage shock next period. If one gets married, it also integrates over the distribution of the partner's state variables. The value function $\hat{W}^c$ is the person's discounted present value of utility once he or she is in a married relationship with someone with given state variables. Equation (12) describes the evolution of human capital, measured as average accumulated earnings (up to the Social Security earnings cap $\widetilde{y}_t$) and in which $t_0 = 26$.

3.8.2 The value function of retired singles

The value function of a retired single ($j = 1$) with health h^i_t, human capital $\bar{y}^i_r$, and Social Security claiming age tr is

$$R^s(t, i, a_t, h^i_t, \bar{y}^i_r, tr) = \max_{c_t, a_{t+1}} \Bigg(v^i(c_t, L^{i,j}, \eta^{i,j}_t) + \beta s^{i,j}_t(\cdot) E_t R^s(t+j, i, a^i_{t+1}, h^i_{t+1}, \bar{y}^i_r, tr) + \beta(1 - s^{i,j}_t(\cdot))\theta_0[\max(0, (a^i_{t+1} - d^{i,j}_t\left(h^i_t, \bar{y}^i_r\right))] \Bigg), \tag{15}$$

subject to equations (10) and (13) in the main text and (29) in Appendix B, and there is a consumption floor determined by

$$B(\cdot) = \max\Big\{0, \underline{c}(j) - \big[(1+r)a^i_t + Y_t - m^{i,1}_t\left(h^i_t, \bar{y}^i_r\right) - T(\cdot)\big]\Big\}, \tag{16}$$

where $m^{i,1}_t\left(h^i_t, \bar{y}^i_r\right)$ are medical expenses (out-of-pocket plus Medicaid payments) and $d^{i,j}_t\left(h^i_t, \bar{y}^i_r\right)$ are additional expenses at death. Also,

$$a^i_{t+1} = 0 \quad \text{if} \quad B(\cdot) > 0, \tag{17}$$

and the budget constraint is given by

$$c_t + a_{t+1}^i = (1+r)a_t^i + Y_t + B(\cdot) - m_t^{i,1}\left(h_t^i, \bar{y}_r^i\right) - T(\cdot). \tag{18}$$

3.8.3 The value function of working-age couples

The value function of a married couple at this stage depends on both partners' state variables, where 1 and 2 refer to gender, and $j = 2$.

$$\begin{aligned} W^c(t, a_t, \epsilon_t^1, \epsilon_t^2, \bar{y}_t^1, \bar{y}_t^2) = \max_{c_t, a_{t+1}, n_t^1, n_t^2} \Bigg(& w(c_t, l_t^{1,j}, l_t^{2,j}, \eta_t^{i,j}) \\ & + (1 - \zeta_{t+1}(\cdot))\beta E_t W^c(t+1, a_{t+1}, \epsilon_{t+1}^1, \epsilon_{t+1}^2, \bar{y}_{t+1}^1, \bar{y}_{t+1}^2) \\ & + \zeta_{t+1}(\cdot)\beta \sum_{i=1}^{2} \Big(E_t W^s(t+1, i, a_{t+1}/2, \epsilon_{t+1}^i, \bar{y}_{t+1}^i) \Big) \Bigg), \end{aligned} \tag{19}$$

subject to equations (1), (8), (9), (12), and

$$T(\cdot) = T(ra_t + Y_t^1 + Y_t^2, i, j, t), \tag{20}$$

$$c_t + a_{t+1} = (1+r)a_t + Y_t^1 + Y_t^2(1 - \tau_c(2,2,t)) - \tau_t^{SS}(\min(Y_t^1, \widetilde{y}_t) + \min(Y_t^2, \widetilde{y}_t)) - T(\cdot), \tag{21}$$

$$a_t \geq 0, \qquad n_t^1, n_t^2 \geq 0. \tag{22}$$

The expected value of the couple's value function is taken with respect to the conditional probabilities of the wage shocks for each of the spouses (we assume independent draws). The expected values for the newly divorced people are taken using the appropriate conditional distribution for their own wage shocks. The term $\zeta_{t+1}(\cdot)$ represents the probability of divorce.

3.8.4 The value function of retired couples

During this stage, the married couple's recursive problem ($j = 2$) depends on each of the spouses health shocks h_t^i and there are survival shocks $s_t^{i,j}(\cdot)$ and medical expenses $m_t^{i,j}(\cdot)$ of each spouse. We assume that the health shocks of each spouse are independent of each other and that the death shocks of each spouse are also independent of each other. The couple also decides, in the case that each spouse dies, the distribution of bequests towards other heirs and the survivor.

$$R^c(t,a_t,h_t^1,h_t^2,\bar{y}_r^1,\bar{y}_r^2,tr) = \max_{c_t,a_{t+1},e_t^1,e_t^2}\Bigg(w(c_t,L^{1,j},L^{2,j},\eta_t^{i,j})+ \tag{23}$$
$$\beta s_t^{1,j}(\cdot)s_t^{2,j}(\cdot)E_tR^c(t+1,a_{t+1},h_{t+1}^1,h_{t+1}^2,\bar{y}_r^1,\bar{y}_r^2,tr)+$$
$$\beta s_t^{1,j}(\cdot)(1-s_t^{2,j}(\cdot))\Big(\theta_1(e_t^2)+E_tR^s(t+1,1,a_{t+1}-e_t^2-d_t^{2,j}\left(h_t^i,\bar{y}_r^i,\bar{y}_r^p\right),h_{t+1}^1,\bar{\bar{y}}_r^1,tr)\Big)+$$
$$\beta s_t^{2,j}(\cdot)(1-s_t^{1,j}(\cdot))\Big(\theta_1(e_t^1)+E_tR^s(t+1,2,a_{t+1}-e_t^1-d_t^{1,j}\left(h_t^i,\bar{y}_r^i,\bar{y}_r^p\right),h_{t+1}^2,\bar{\bar{y}}_r^2,tr)\Big)+$$
$$2\beta(1-s_t^{1,j}(\cdot))(1-s_t^{2,j}(\cdot))\theta_0(\max(0,(a_{t+1}-d_t^{1,j}\left(h_t^i,\bar{y}_r^i,\bar{y}_r^p\right)-d_t^{2,j}\left(h_t^i,\bar{y}_r^i,\bar{y}_r^p\right))/2))\Bigg),$$

subject to equations (10), (13), (17) in the main text, and (35) in Appendix B, and

$$\bar{\bar{y}}_r^i = \max(\bar{y}_r^1,\bar{y}_r^2), \tag{24}$$

$$B(\cdot) = \max\Big\{0,\underline{c}(j)-\big[(1+r)a_t+Y_t-m_t^{1,j}\left(h_t^i,\bar{y}_r^i,\bar{y}_r^p\right)-m_t^{2,j}\left(h_t^i,\bar{y}_r^i,\bar{y}_r^p\right)-T(\cdot)\big]\Big\} \tag{25}$$

$$c_t+a_{t+1} = (1+r)a_t+Y_t+B(\cdot)-m_t^{1,j}\left(h_t^i,\bar{y}_r^i,\bar{y}_r^p\right)-m_t^{2,j}\left(h_t^i,\bar{y}_r^i,\bar{y}_r^p\right)-T(\cdot). \tag{26}$$

$$e_t^i \in [0,a_{t+1}] \tag{27}$$

A survivor collects benefits based on the higher amount between their own contributions and those of their deceased spouse (Equation (24)).

4 Estimation

We estimate our model by adopting a two-step estimation strategy (as Gourinchas and Parker (2002)). In the first step, we calibrate some parameters (see Appendix D) and estimate others (see next subsection and Appendices C and G). In the second step, we use the MSM (See Subsection 4.2 and Appendix G). We normalize the time endowment for single men and estimate 21 model parameters, including the discount factor (β), the leisure weight in utility (ω), the parameters governing labor participation costs ($p_0^{i,j}, p_1^{i,j}, p_2^{i,j}$), the time endowment by gender and marital status ($L^{i,j}$), and the parameters related to the curvature and intensity of the bequest functions (ϕ_1, k_1, ϕ_0, k_0).

We estimate the model using 334 moments that capture key features of the data.

These include labor market participation and hours worked (conditional on working) for married and single men and women ages 26 to 64, as well as average and median wealth profiles for couples and single men and women from ages 28 to 84. We stop matching wealth moments after age 84 due to the limited sample size at older ages.

4.1 First-step calibration and estimation

For brevity in this subsection, we only discuss the first-step inputs that we change in our counterfactuals. Table 12 in Appendix D reports the parameters that we calibrate. Appendix C discussed all of our first-step estimation in detail.

Wage Risks. The persistence of wage shocks is 0.9360 for men and 0.9484 for women, while the variance of shocks is larger for men (0.0312) than for women (0.0206).

Marriage and Divorce Risks. Figure 16 shows marriage and divorce probabilities by gender, age, and wage shocks up to age 62, when individuals can still experience marital transitions in the model. At age 26, marriage probabilities are about 35% for men and 30% for women, declining to 5% and 3%, respectively, by age 60. Divorce probabilities start at around 8% for both genders early in life and fall to about 1% later on. There is notable dispersion in these probabilities by wage shocks, particularly for men: higher-wage individuals are generally more likely to marry and less likely to divorce.

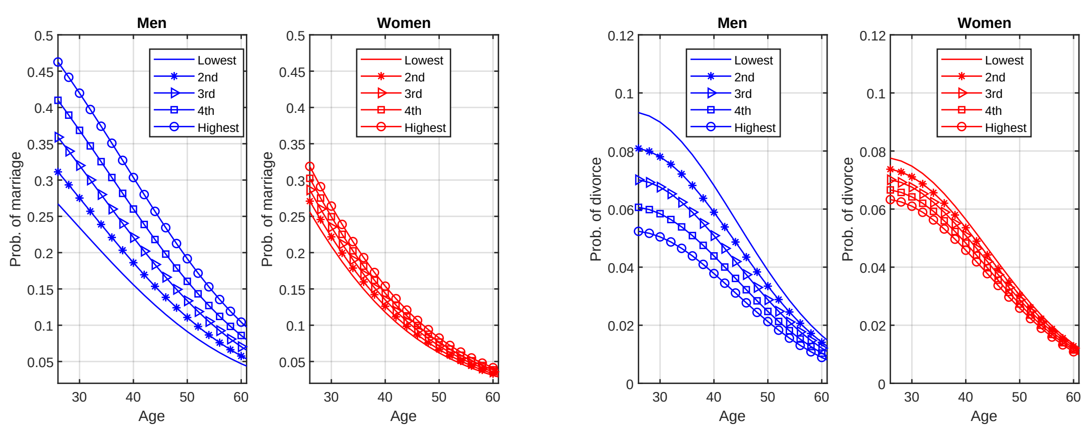


Figure 2: Marriage (on the left) and divorce (on the right) probabilities by gender, age, and one's wage shock. PSID data.

Medical expenses. Figure 3 shows medical expenses (out-of-pocket plus Medi-

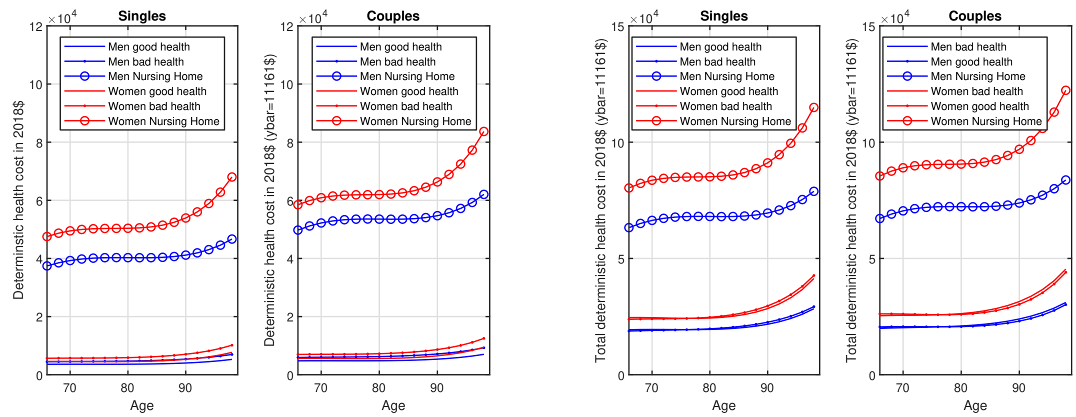


Figure 3: Medical expenses (out-of-pocket plus Medicaid payments) by age, gender, ybar, and marital and health status. Left panel: conditional on survival during the period. Right panel: conditional on dying during the period. HRS data.

caid) by age, gender, and marital and health status. The left panel reports average expenses for individuals who survive the period. The right panel shows medical expenses incurred by individuals who die during the period, which reflect the sharp rise in healthcare use typically associated with the end of life—such as hospitalizations and nursing home care. Among survivors, average medical expenses remain relatively low even at older ages, except for those in nursing homes. In contrast, medical expenses in the period of death are substantially higher across all health states.

4.2 Second-step estimation

Table 1 presents our estimated preference parameters (Appendix G reports all of our parameter estimates and their standard errors). Our estimated discount factor is very similar to that estimated by De Nardi, French, and Jones (2016) for elderly retirees, and our estimated weight on consumption is 0.4497. We normalize the time endowment of single men to 112 hours a week (and 5,840 hours a year). Single women have a time endowment of 104 hours a week. We interpret this as their having to spend eight more hours a week managing their household, rearing children, and taking care of elderly parents. The time endowments for married men and women are 108 and 74 hours. This implies that people in the latter two groups spend 4 and 38 hours a week on home production activities, respectively. These estimates are remarkably similar to those from time diary data in Aguiar and Hurst (2007) and Dotsey, Li, and

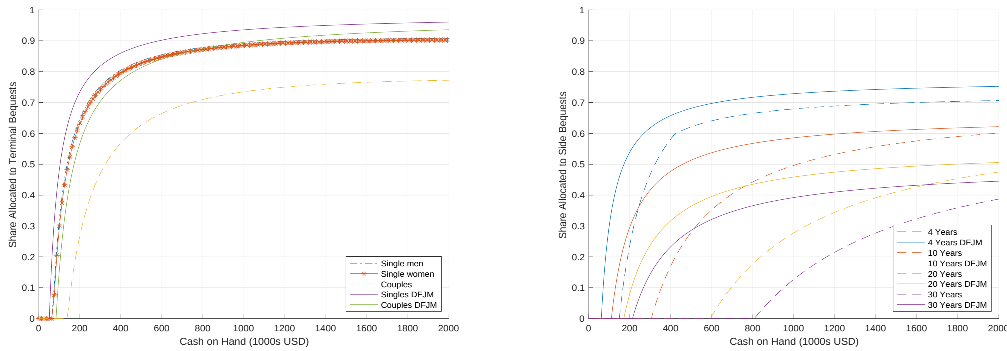
Estimated parameters	
β: Discount factor	0.9958
ω: Consumption weight	0.4478
$L^{2,1}$: Time endowment (weekly hours), single women	104
$L^{1,2}$: Time endowment (weekly hours), married men	108
$L^{2,2}$: Time endowment (weekly hours), married women	74
$P_t^{i,j}$: Partic. cost	Fig. 10 App. G
ϕ_0: Terminal bequest, strength	1,902,590
k_0: Terminal bequest, shifter	975,581
ϕ_1: Side bequest, strength	38,703,874
k_1: Side bequest, shifter	2,826,257

Table 1: Second-step estimated model parameters

Yang (2014).

Figure 21 in Appendix G reports the age-varying time costs of working by age, expressed as a fraction of the time endowment of single men. Our estimated participation costs are relatively high when people are younger and increase again after 45. The time costs of going to work might include factors other than commuting time. For instance, they might be higher when children are youngest, because during that period, parents might need additional time to transport their children back and forth from day care. They also show that, conditional on all aspects of our environment, the participation costs of married women are the lowest ones because married women face lower wages, have a smaller time endowment (because of time spent engaging in home production and child care), and tend to have higher-wage husbands who work.

The bequest parameters are difficult to interpret. To clarify their implications, we follow De Nardi, French, Jones, and McGee (2025) and plot the share of resources allocated to bequests that they imply. Figure 4, Panel (a), shows the share of terminal bequests as a function of total resources for singles and couples facing certain death in the next period. Bequests behave as a luxury good for singles, and even more so for couples. Panel (b) displays side bequests for couples when one spouse dies, as a function of total resources and the expected remaining lifespan of the surviving spouse. Consistent with De Nardi, French, Jones, and McGee (2025), we find that the longer the survivor's planning horizon, the smaller the share allocated to side bequests, however, our model implies that both terminal and side bequests exhibit stronger luxury behavior than in their framework.



(a) Estimates terminal bequests

(b) Estimates side bequests

Figure 4: Implications of our estimated bequest parameters. Panel (a): Share of total resources allocated to terminal bequests for couples and single men and women, who face certain death next period. **Panel (b):** Share allocated to side bequests by couples, upon death of ones spouse, under varying survivor lifespans.

4.3 Model fit

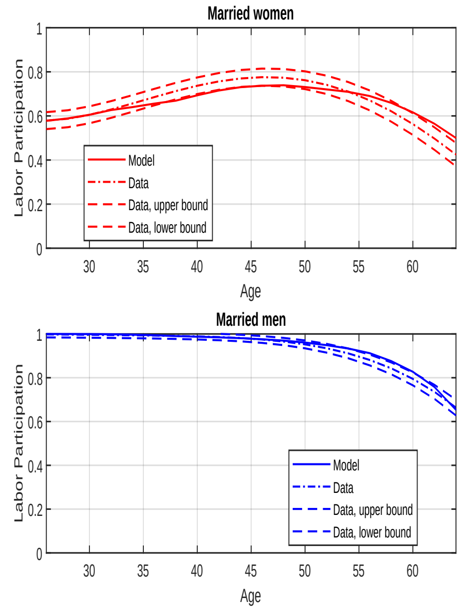
Figures 5 and 6 report the moments from the data and their 95% confidence intervals, and the moments implied by our model. Our model fits the targeted data well, which is remarkable given that it is tightly parameterized: we have 334 targets, and we estimate 21 parameters.

4.4 Model-implied labor supply elasticities

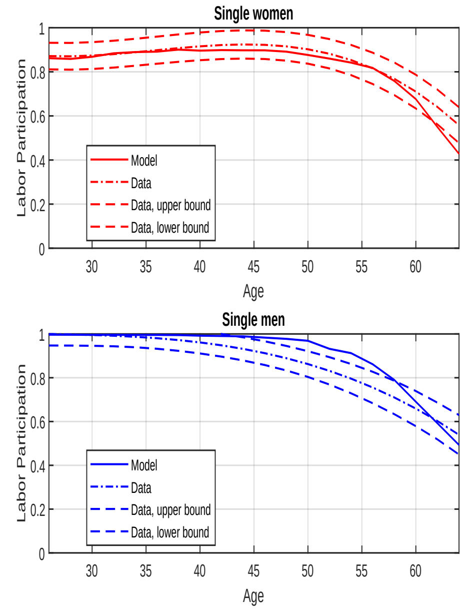
Table 2 reports the model-implied elasticities of labor force participation and hours worked (conditional on working) in response to a temporary, anticipated increase in own wages.[6] We find that women's participation elasticities are larger than men's, and that married men are the least responsive group. For all groups, participation elasticities increase sharply near retirement age—a pattern consistent with earlier findings by French (2000) for men.

Our elasticity estimates align well with those in Liebman, Luttmer, and Seif (2009), Blundell and Macurdy (1999), and Attanasio, Levell, Low, and Sánchez-

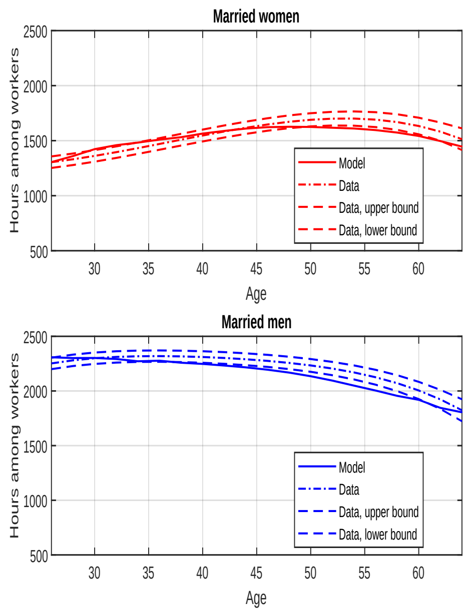
[6]Each elasticity is computed by raising the wage of a given group (married men, married women, single men, or single women) by 5% at a single age, holding all else constant. The change is not compensated elsewhere, but its lifetime impact is negligible. For example, at age 40, the present value of this temporary wage change amounts to just 0.04% of average discounted family income. The analogous figures at ages 50 and 60 are 0.03% and 0.02%, respectively.



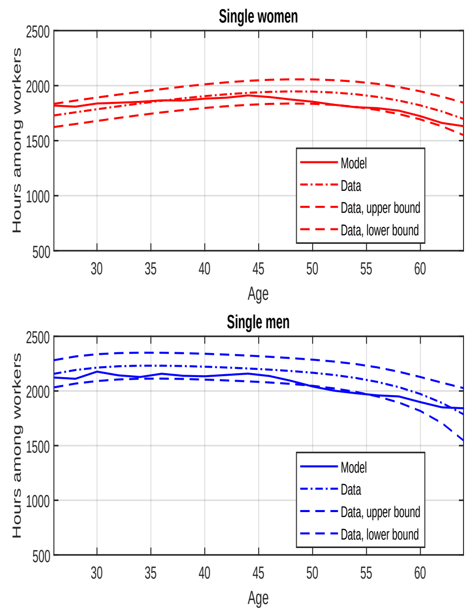
(a) Participation, couples



(b) Participation, singles

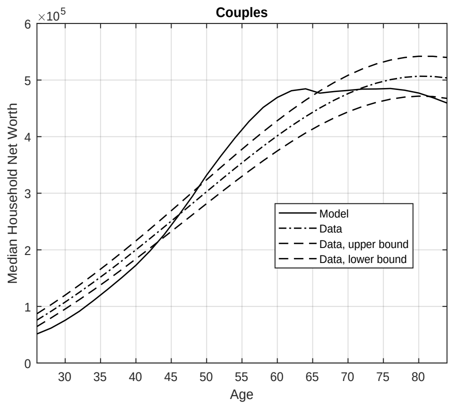


(c) Hours for workers, couples

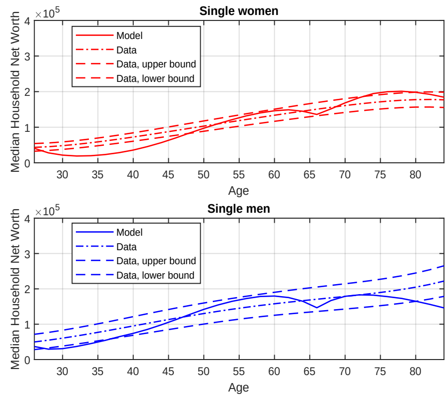


(d) Hours for workers, singles

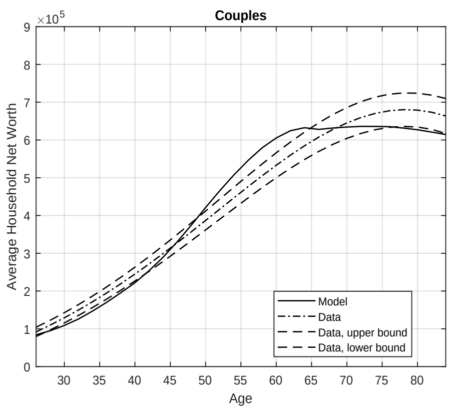
Figure 5: Model-implied participation and hours, and average and 95% confidence intervals from the PSID.



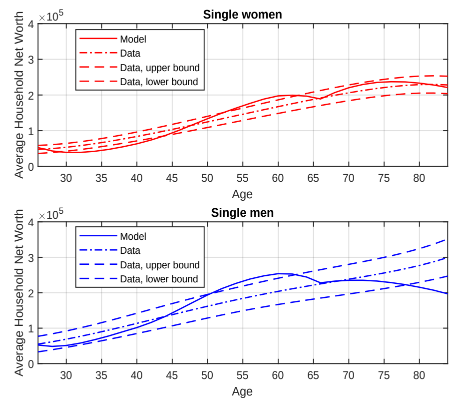
(a) Median wealth, couples



(b) Median wealth, singles



(c) Average wealth, couples



(d) Average wealth, singles

Figure 6: Model-implied median and average wealth and 95% confidence intervals from the PSID.

Marcos (2018) and reflect the role of endogenous family structure, participation costs, and time constraints. Married women's high elasticities stem from joint decision-making, marital risk, and child-rearing responsibilities—channels absent in models with fixed households or exogenous labor supply. These mechanisms amplify labor supply responses and highlight its role as a key margin of insurance against income and family shocks.

4.5 The economic forces driving identification

In this subsection, we provide a broad overview of the economic forces driving our model parameters' identification. We provide a detailed exploration of how each

	Participation				Hours among workers			
	Married		Single		Married		Single	
	W	M	W	M	W	M	W	M
40	0.6	0.1	0.4	0.1	0.2	0.1	0.4	0.3
50	0.5	0.2	0.5	0.3	0.2	0.1	0.5	0.3
60	1.0	0.5	1.6	1.7	0.2	0.0	0.3	0.1

Table 2: Model-implied elasticities of labor supply.

parameter affects our target moments individually in Appendix H.

Although every parameter affects more than one set of our target moments, there are broad economic forces driving the identification of our model's parameters. The discount factor and bequest motives both tend to increase savings across all groups of households, but in distinct ways. The discount factor affects wealth profiles starting at younger ages, whereas bequest motives tend to raise wealth later in life, typically after age 40.

Terminal and side bequests differ in their effects across groups. Reducing the importance of terminal bequests lowers the wealth of both couples and singles during retirement. In contrast, reducing the desire to leave side bequests increases the wealth of newly singles, who inherit more from their deceased spouse, and thus raises the retirement wealth of all singles.

The strength and luxuriousness of bequest motives further separate their effects. Stronger bequest motives influence a broader set of households and wealth earlier during retirement. Luxury-good bequest motives, instead, mainly affect richer households, who are more likely to survive to older ages. As a result, making bequests more of a luxury good increases savings more at older ages than at younger ones during the retirement period.

The weight on consumption in the utility function has a large effect on the desire to work for all household groups. In contrast, available time and participation costs mainly affect the labor market behavior of the group they are calibrated for. For couples, there is some spillover from the parameters for husbands to wives and vice versa, but this separation broadly holds.

While available time tends to have the largest effect on hours worked, the level parameter in participation costs has a larger effect on participation. These effects are intuitive for the following reasons. First, an upward shift in the time cost of participating makes participation less attractive. Among those who still participate, there is less time available for work and leisure, so hours worked also decline. Second, a reduction in available time applies to everyone—regardless of participation status and at all ages. As a result, it implies a larger reduction in leisure over the life cycle (until consumption adjusts) than an equivalent increase in the cost of participating. Reducing available time thus leads to a larger decline in hours worked than raising participation costs, especially later in life. Finally, because available time affects both participants and non-participants, it has a smaller effect on the participation margin.

The linear and quadratic terms in participation costs shape the slopes of both participation and hours worked over the life cycle: the linear term matters more early in life, while the quadratic term becomes more important later in the working period.

In sum, the identification of our model's key parameters relies on intuitive economic forces: the life-cycle evolution of wealth and labor supply, heterogeneity across marital groups, and the dynamic responses to risks and incentives. The combination of dynamic optimization, selection into marriage and health, and rich heterogeneity in observed profiles provides substantial leverage for estimating the parameters governing saving, labor supply, and bequest motives. Our approach ensures that key margins are pinned down by meaningful and interpretable patterns in the data.

5 What drives savings and earnings?

What drives household savings and earnings, and how do these forces vary over the life cycle? We address this question using a sequence of decomposition exercises. Specifically, we hold all model inputs and parameters at their benchmark values and alter one feature of the environment at a time.

In this section, we report how each change affects the life-cycle profiles of labor supply and savings for the household groups we study. The next section turns to the implications for aggregate savings and earnings over the full life cycle of our cohort.

5.1 Bequest motives

No side bequest motives. To understand the role of bequest motives, we begin by removing the utility from leaving side bequests, that is, bequests to heirs other than the spouse when the first member of a couple dies. Since side bequests are never accidental, this change also eliminates all bequests upon the first spouse's death.

The top row of Figure 7 displays the life cycle profiles for median wealth and the percentage change in average labor income for our model economy with and without side bequests. Starting from couples, the left-hand-side graph shows that eliminating the desire to leave side bequests substantially reduces couples' wealth, with larger effects at older ages. By age 80, median wealth declines by more than 35%. The right-hand-side graph illustrates labor income changes: removing side bequests lowers earnings for both married men and women, with a larger reduction for women–about 2% over much of their working lives, compared to about 1% for men past age 55. The additional wealth accumulation from side bequests is financed through both increased labor supply and reduced consumption. Hence, these findings indicate that side bequests have large effects on couples' savings and non-negligible impacts on their labor supply and that both effects are already present by age 50, well before retirement.

The effects on singles are also noteworthy. Without side bequest motives, singles save slightly less until age 66, anticipating that after marriage, they would inherit more wealth in case their spouse dies. After age 66, the saving patterns of singles reflect both the earlier decrease in retirement savings and a composition effect. In this counterfactual, couples save less and leave no side bequests, resulting in new widows and widowers inheriting more wealth than existing singles. As more individuals lose their spouse, this wealth gap raises median wealth among singles, generating the bump in percentage differences in wealth accumulation seen in the top right panel. Side bequests have small effects on the labor market behavior of singles. Young singles save less in the absence of side bequests and expect larger inheritances if they marry, leading them to work slightly less until age 50. As they age and the probability of marriage declines, they eventually work more to compensate for lower savings accumulated earlier. Thus, while side bequest motives affect singles, the largest impact arises from differences in the wealth of the newly single individuals who lose a spouse.

No terminal bequest motives. The graphs in the middle row in Figure 7 examine the effects of removing the utility from terminal bequests, for both couples and singles. In our model, households do not fully annuitize their wealth, and uncertain lifespans generate accidental bequests. Eliminating terminal bequest motives removes only voluntary bequests at the death of the last household member, but not side bequests and accidental bequests.

The middle-left graph shows that removing terminal bequests reduces couples' wealth throughout the life cycle, though the effect of terminal bequests is smaller than that of side bequests. At age 80, median wealth is about 15% lower without terminal bequests but over 35% lower without side bequests. The additional wealth accumulation due to terminal bequests is financed by increased labor supply from married women during all of the working period, a small reduction of earnings of married men in middle age, and a slight reduction in consumption over much of married life.

For singles, eliminating terminal bequest motives leads to significantly lower median wealth at all ages, with a larger percentage change effect than for couples. This occurs because couples still retain side bequest motives, while singles never have them. Singles save less before age 66 because they no longer wish to leave a terminal bequest, whether they remain single or marry. After 66, a composition effect further lowers their wealth. Since couples are poorer without terminal bequests but still leave side bequests, widows and widowers inherit less, narrowing the wealth gap between new and existing singles. Consequently, median wealth among singles during retirement is much lower than in the benchmark: at age 80, it is more than 50% lower for men and about 30% lower for women. In the absence of terminal bequest motives, single men work slightly less, and both single men and women consume slightly more.

No bequest motives. The bottom two panels of Figure 7 show that eliminating all voluntary bequests compounds the effects of the previous two experiments. Wealth declines significantly across all household groups: at age 50, it 10% lower for all three groups, and at age 80, it falls by 50% for couples, over 25% for single men, and 20% for single women. The impact on married women's labor income is also larger than in the benchmark, being almost 2% lower throughout their working lives. Also, notably, when all bequest motives are removed, the model has a hard time explaining why people retain so much wealth at very advanced ages, even in the presence of rich heterogeneity in lifespans, health spans, and medical expenses. In fact, in that case, the model generates the more typical hump-shaped wealth that one expects from a standard life cycle model, and which is not very similar to the observed saving behavior during retirement.

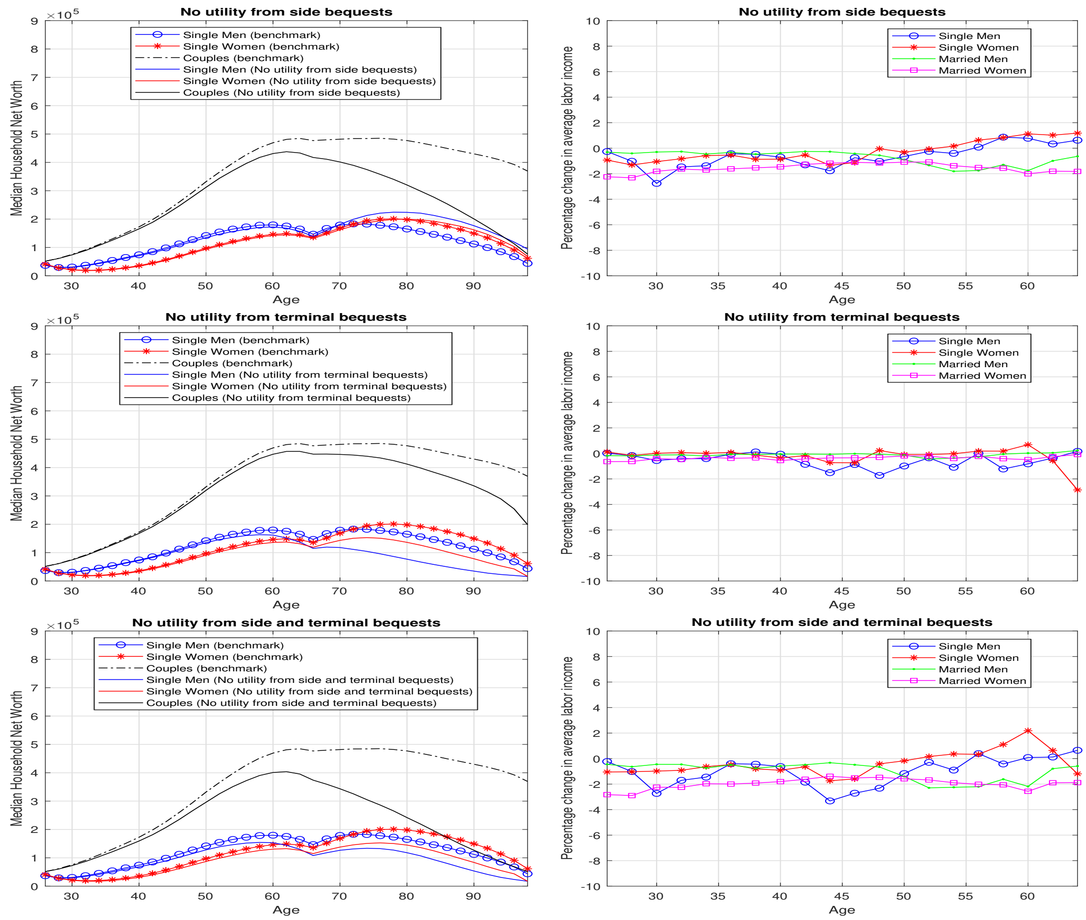


Figure 7: The effects of bequests

5.2 Medical expenses

What are the effects of medical expenses during retirement? Eliminating these expenses reduces both household risk and expenses–lowering both precautionary savings and the need to save for retirement.

Medical expenses also increase the likelihood that individuals will rely on the consumption floor. This is because, in this case, households face a "disaster risk" of living long and incurring high medical costs, which can deplete their resources. This low-probability but high-cost risk is difficult to insure through precautionary savings and disproportionately affects singles, and particularly women, who tend to live longer and require extended nursing home care.

In the absence of medical expenses, households can more easily self-insure through savings and rely less on the consumption floor. As a result, the disincentive effects of the consumption floor on saving, highlighted by Hubbard et al. (1994b,a,b), are weaker. This suggests that some households might actually save more—rather than less—when medical expenses are lower and a consumption floor is present.

No additional medical expenses at death. The top two panels in Figure 8 show changes in median wealth and average labor income when we eliminate the spike in medical expenses at death while maintaining regular medical expenditure risk in all periods. The top left panel shows that wealth holdings remain nearly unchanged until age 60 for all three groups of households. After that age, saving behavior becomes more heterogeneous: couples hold slightly less wealth, while singles' wealth stagnates but then rises fast after age 90. To understand these patterns is important to keep in mind that the wealth of singles after age 66 is also affected by a composition effect: widows and widowers, who inherit wealth from their spouses and tend to be richer than previously singles individuals, enter the singles population after that age. Thus, their wealth is affected by both this composition effect and by the fact that the consumption floor provides less of an implicit tax on savings in the absence of medical expenses. The right panel indicates that this change has little effect on labor income.

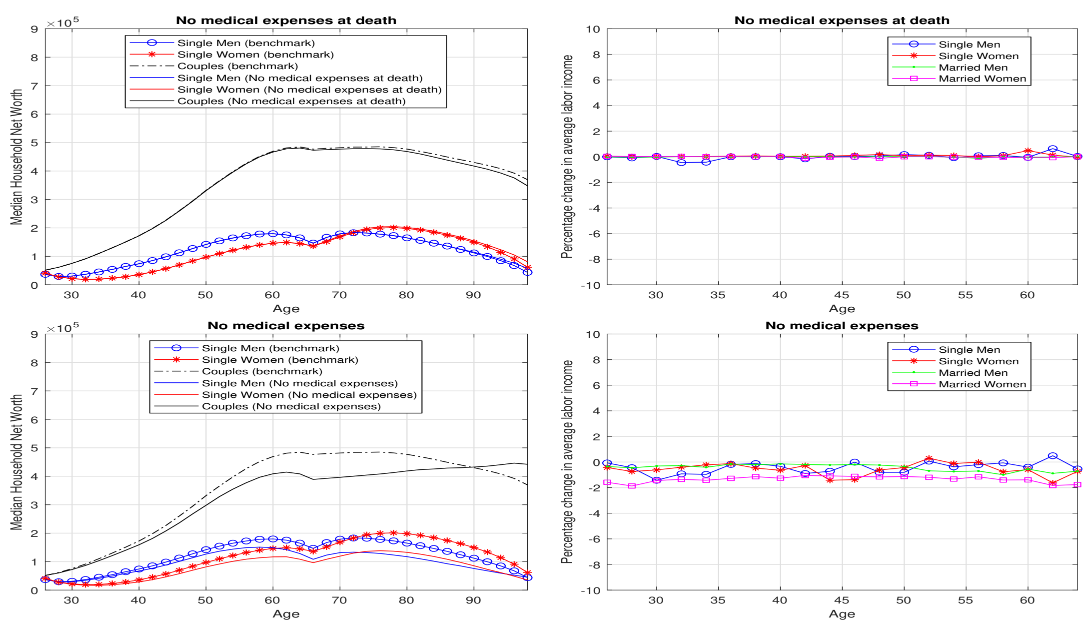


Figure 8: The effects of medical expenses during retirement

No medical expenses. The bottom left panel of Figure 8 shows that in the absence of medical expenses after age 66, single men and women hold less wealth during their entire lives. Couples hold less wealth until very advanced ages. The bottom right panel displays average labor income. Married women's earnings decline, with the largest gap at age 65, when they earn 2% less than in the benchmark case. Married men earn slightly less over all of their working period. The earnings of single men and single women remain largely unchanged throughout their working lives.

5.3 Bequest motives and medical expenses

No bequest motives and no medical expenses. The right panel of Figure 9 compares median wealth in our benchmark economy with a counterfactual scenario where all bequest motives and medical expenses are eliminated. Under this counterfactual, median household wealth at age 55 is about 25% lower for all household types. By age 70, it is 45% lower for single women and about 55% lower for couples and single men. These savings motives are thus key drivers of wealth accumulation throughout the life cycle.

Nonetheless, even in the absence of these saving motives, households still hold substantial wealth at older ages. This contrasts with the standard life-cycle model without lifespan uncertainty and underscores the role of both lifespan uncertainty and health risks in our framework. Households can be in good or poor health or in a nursing home. While medical expenses are eliminated in this scenario, life expectancy remains health-dependent.

The left panel shows that these savings motives also shape labor market behavior. Labor income declines for married men and women throughout their working years and for single men over most of their careers, with smaller effects on single women. Consequently, consumption is higher in this counterfactual, particularly for couples and single men, while single women allocate more resources to leisure.

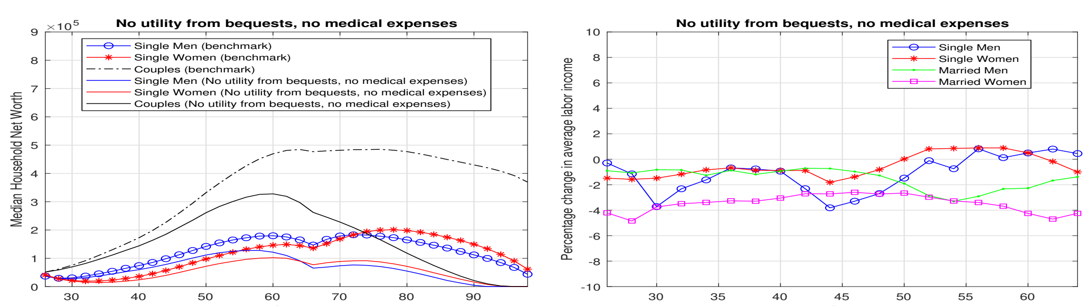


Figure 9: The effects of bequest motives and medical expenses during retirement

5.4 Wage risks and their effects

No wage risk. We eliminate wage risk by assuming that individuals retain their initial wage shock from age 26 until retirement and adjusting the deterministic portion of wages by age and gender to keep the exogenous portion of wages unchanged.[7] This preserves initial heterogeneity and the exogenous portion of wages but removes wage risk after entering the economy.

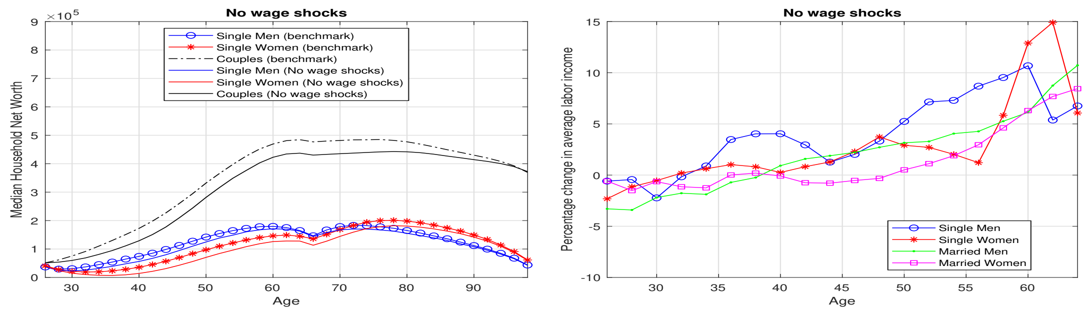


Figure 10: The effects of wage shocks

The left panel of Figure 10 shows that eliminating wage risk reduces the median savings of our three groups for most of their adult lives. The largest drop in median savings occurs around age 38 for single women (-68%), at age 35 for single men (-30%), and at age 36 for couples (-27%). These effects on savings are in line with the finding that precautionary savings against earnings risk are especially important during the first part of the life cycle, as found for instance by Gourinchas and Parker (2002). Compared to them, we find a longer-lasting savings reduction over the life cycle.

There are also some non-trivial effects on labor market behavior. The right panel of Figure 10 shows that labor earnings before age 30-35 are lower for both married and single women, as reduced precautionary savings needs lead to people working less. After that, they work more to catch up with their lower income and savings.

[7]For couples, this means that both spouses keep their initial wage shock for all of the working period, including if they divorce. For singles, their own wage shock is fixed. If they marry, they face the same uncertainty about their spouse's wage shock upon marriage, but after that, their spouse's shock will also be fixed during all of the working period.

5.5 Marriage and divorce risks

No new marriages. When marriage is no longer an option, two main forces shape outcomes. First, individuals adjust their expectations about the future and modify their behavior accordingly. Second, a composition effect emerges, changing who remains single and who marries after entering our model. In our benchmark economy, as in the data, higher-wage men and women are more likely to marry. As a result, during the working years, the group of single individuals in the benchmark economy tends to include more lower-wage individuals than in the no-new-marriages counterfactual.

The top left panel of Figure 11 compares the fraction of married men and women in our benchmark and counterfactual economies. At age 26, about 87% of both men and women in our cohort are married, and this fraction declines only gradually until age 66, reaching 80% for women and 85% for men. After that age, mortality drives further declines in marriage. The counterfactual with no new marriages reveals that, given historically realized divorce rates, new marriages play a crucial role in sustaining the married population. Without them, the fraction of married men and women falls below 40% by age 66 and continues to decline rapidly thereafter. This highlights the potentially large impact of the composition effect on household dynamics.

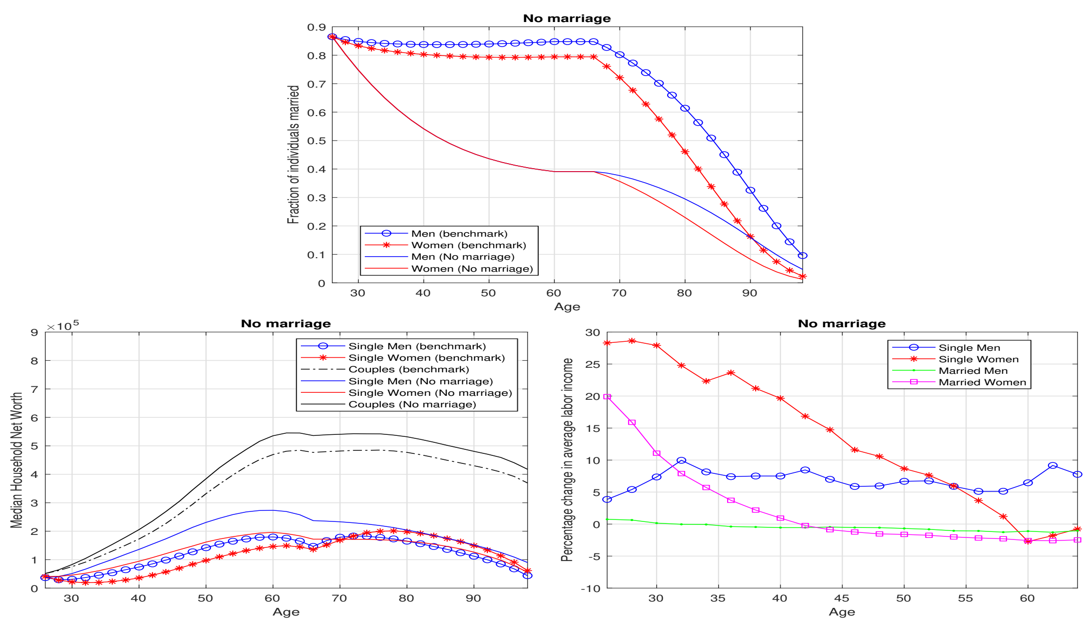


Figure 11: The effects of not having any new marriages

The bottom left panel of Figure 11 shows that until retirement, both single men and single women hold more wealth in the counterfactual economy with no new marriages. For instance, at age 38, single women and men hold over 200% more and 80% more wealth, respectively. This increase partly occurs because, without new marriages, individuals can no longer rely on finding a spouse and benefiting from the economies of scale in marriage. And partly, because single individuals now tend to have higher wages due to a composition effect of higher-wages singles not marrying. Later on in life, the savings patterns of single women and single men differ. Single women's wealth decreases fast after age 66. As their wealth at retirement is lower, they find it more advantageous to save less and rely on the consumption floor to insure against longevity risk and medical expenses. In contrast, single men, who have higher wages during their working ages, hold more wealth at retirement and depend less on social insurance, hence, they self-insure through savings and stay wealthier even after that age. Couples also hold more wealth–up to 20% more at age 40—since they know that if they divorce, they will not remarry and must rely solely on their own resources. This effect is partly counteracted by the fact that low-wage couples, who are poorer, are now staying married. What we measure is the net effect of these two forces.

The bottom right panel shows that these changes in wealth holdings are accompanied by a large increase in labor income for all groups, except married men. Single women's labor income is about 28% higher around age 30 and remains elevated for much of their working life. Married women's labor income also rises–about 20% at age 26–as they anticipate needing financial independence if they divorce and can no longer remarry. As their probability of divorce decreases, their labor income gradually converges to that in the benchmark, around age 45, and falls slightly below it thereafter. This rise in married women's labor income helps finance couples' increased savings. Single men's labor income also increases. In contrast, married men experience a small decline in labor income, which becomes more pronounced after age 35. The large increases in wealth that we observe in the absence of new marriages turn out to be financed not only by higher earnings, but also by reduced consumption until age 40 for both single men and women, and couples. After making the sacrifice of working more (and thus accumulating more human capital) and consuming less when young, they enjoy more consumption through much of their remaining lives.

No divorce. When couples no longer divorce, almost all men and women in our cohort end up married by age 66 (see top left panel of figure 12). The bottom

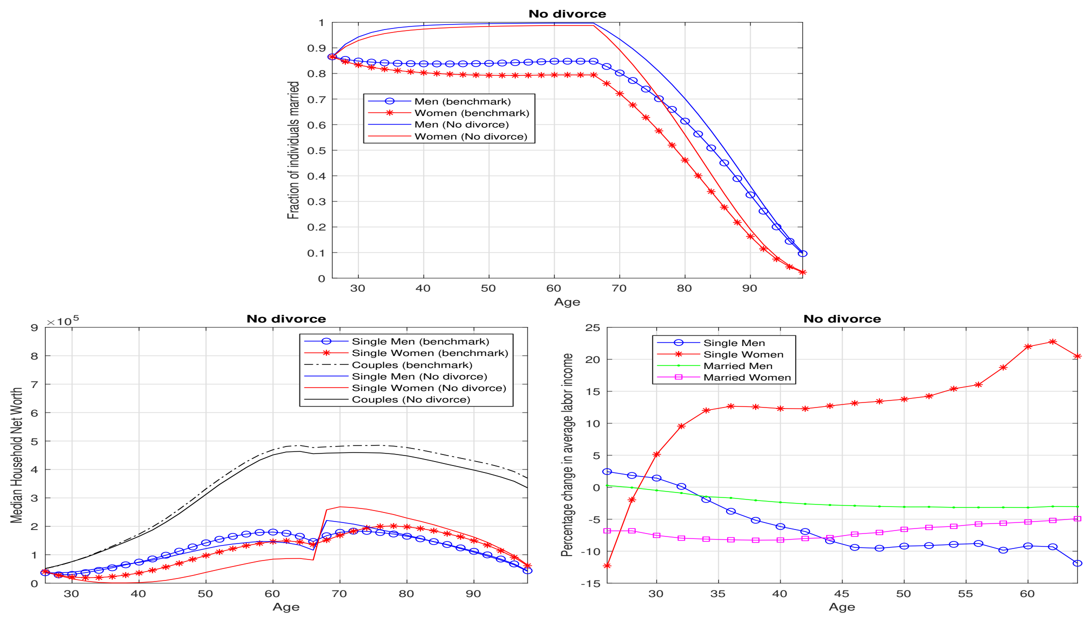


Figure 12: The effects of not divorcing

right panel displays median wealth for couples and singles. In the absence of divorce, couples hold less wealth, partly because the pool of couples now includes individuals who would have divorced in the benchmark economy—-who tend to have lower wealth and human capital, and partly because they no longer need to save for when they divorce. Because single women expect to marry men with higher wages than theirs, the absence of divorce makes marriage an even better deal. Thus, they save much less when they are young and still have a high probability of marrying. Single men also expect to marry, but typically with women with lower wages than theirs, hence the effect on their wealth is smaller and actually positive early on, when their probability of marriage is highest. A notable pattern is the wealth jump at age 66 for singles. Without divorce, no newly divorced individuals–who tend to be wealthier–join the singles group. However, at age 66, some individuals lose their spouses and enter the singles pool with significantly higher wealth. This effect is particularly strong for single women, because new widows tend to be much wealthier than lifelong single women.

The bottom right panel of Figure 12 shows that the effects of eliminating divorce on labor income are highly heterogeneous. Young single men maintain stable earnings until age 30 but then work less, as they are less likely to marry and support a lower-wage spouse. Consequently, their earnings decline by about 10% by retirement time. Young single women, who have a high probability of marrying and staying married–typically to higher-wage men–work less before age 30. However, as their likelihood of marriage declines after that age, they increase their labor supply to save for retirement. For married women, labor income drops by over 5% during all of the working period. For married men, we observe a steady decline, reaching over 3% by age 66. This decline in labor income during working years is also reflected in decreased consumption.

No marriage and no divorce. The top left panel of Figure 13 shows that eliminating marriage and divorce after age 26 leaves the fraction of married men largely unchanged, while the fraction of married women before retirement rises from 80% to 87%, matching the share of married women at age 26. In this counterfactual, those who start married remain so–at least until retirement, when their partner may pass–while those who begin single experience no change in marital status throughout their lives. This counterfactual incorporates all the forces discussed in the previous

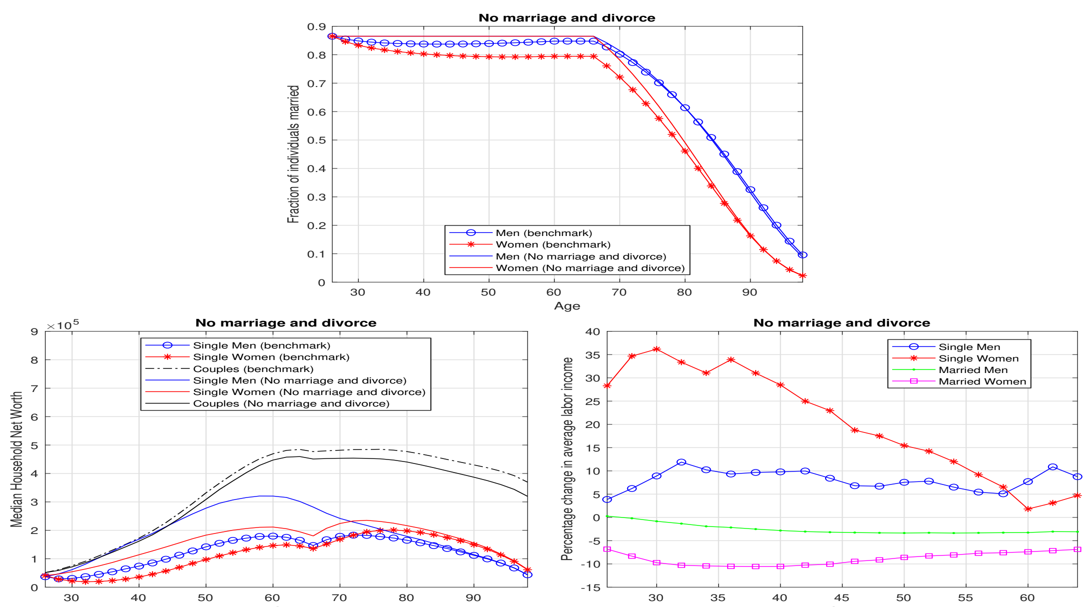


Figure 13: The effects of no new marriages and divorces

two scenarios. The bottom left panel of Figure 13 shows a decline in the wealth holdings of married households during all of their life cycle. In contrast, single men and women hold more wealth at all ages, as they must rely solely on their own resources. After retirement, this pattern also reflects that at older ages, wealthier new widows and widowers join the group of singles.

The bottom right panel of Figure 13 shows that single men and women finance their increased savings through a substantial rise in labor supply, while married men and women reduce their labor supply. Since couples hold only slightly lower wealth levels but work less, they consume less throughout most of their lives. Singles, by contrast, work significantly more at younger ages, which boosts their human capital. However, their focus on rapid wealth accumulation leads them to consume less until age 35, after which they offset the disutility of greater labor effort with higher consumption.

5.6 All previous saving motives combined

In this experiment, we remove all of the saving motives previously discussed. Specifically, we eliminate utility from leaving side and terminal bequests, medical expenses, wage risk, and marriage and divorce dynamics.

Why do households still save in this version of the model? The remaining motives are to finance retirement consumption and to self-insure against longevity risk. Even these saving motives are highly heterogeneous across households, also reflecting differences in health and longevity, which are uncertain and vary systematically with gender, marital status, age, and human capital. In addition, retirement income depends on Social Security rules, which themselves vary with marital status and part contributions. Figure 14 displays the results for this counterfactual. If couples were to

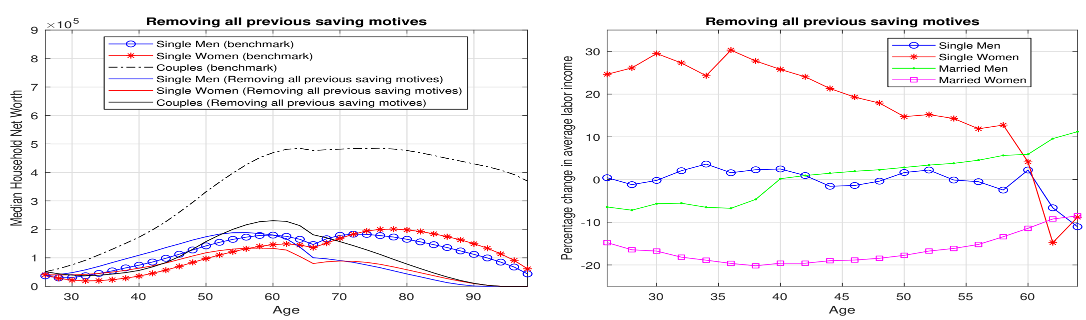


Figure 14: The effects of removing all of the previously considered saving motives: utility from leaving both side bequests and terminal bequests, medical expenses, wage risks, and marriage and divorce dynamics.

save only to finance their consumption during retirement in the presence of uncertain and heterogeneous lifetimes, they would hold 50% less wealth between the ages of 50 and 60, and almost 100% less wealth by age 90. For singles, their lack of marriage prospects would dominate until age 58. Single men would hold 50% more wealth at age 30, and single women would hold 90% more wealth at that age. However, after retirement, removing the other saving motives would drastically reduce wealth holdings. Thus, for instance, at age 70, single men and women would hold almost 50% less wealth.

Looking at earnings, reveals that the earnings of married women would be 15-20% lower over their working period, that the earnings of married men would initially be 6% lower, only to peak at 10% higher by retirement time. While the earnings of single men display no big changes over the working period, those of single women would be over 25% higher until age 40.

6 What drives aggregate savings and earnings?

Counterfactual	Couples	SM	SW	All
No utility from side bequests	-16.5	15.9	14.4	-9.6
No utility from terminal bequests	-6.6	-32.5	-28.5	-11.7
No utility from bequests	-25.0	-21.0	-18.6	-23.8
No medical expenses at death	-0.8	-0.6	0.4	-0.6
No medical expenses	-11.3	-16.0	-21.9	-13.1
No utility from bequests + no med. exp.	-39.8	-42.6	-46.1	-40.9
No wage shocks	-10.3	-9.4	-11.8	-10.4
No marriage	-5.7	48.9	14.7	6.6
No divorce	-4.3	-4.2	21.7	-0.1
No marriage and divorce	-7.2	41.4	24.1	0.7
Removing all previous saving motives	-60.6	-35.0	-48.3	-56.9

Table 3: Changes in average wealth per person (in % from our benchmark economy). SM: single men, SW: single women

In this section, we aggregate the previous results over the life cycle (first for each group and then overall) and compare averages for the benchmark and the counterfactual economy. If demographics were stationary, the overall changes in wealth and earnings for all groups over the life cycle would amount to changes in aggregate average wealth and earnings as features of our model economy are changed.

Table 3 shows that, as we have seen in the previous section, **removing the desire to save to leave side bequests** reduces the wealth holding of couples (by

Counterfactual	MM	MW	SM	SW	All
No utility from side bequests	-0.8	-1.5	-0.6	-0.2	-0.9
No utility from terminal bequests	-0.1	-0.4	-0.6	-0.2	-0.2
No utility from bequests	-1.0	-1.9	-1.1	-0.3	-1.2
No medical expenses at death	-0.0	-0.0	0.0	0.1	-0.0
No medical expenses	-0.4	-1.3	-0.4	-0.6	-0.7
No utility from bequests + no med. exp.	-1.6	-3.4	-1.3	-0.4	-1.9
No wage shocks	2.3	1.5	4.2	3.0	2.3
No marriage	-2.2	-3.8	6.9	11.5	0.8
No divorce	-2.3	-7.1	-8.4	-0.1	-2.2
No marriage and divorce	-2.9	-10.1	7.4	19.3	-2.0
Removing all previous saving motives	0.2	-17.6	-0.6	16.9	-2.7

Table 4: Changes in average labor income. MM: married men, MW: married women, SM: single men, SW: single women

16.5% on average over the life cycle), but increases those of single men and women (by 15.9% and 14.4%, respectively). In the aggregate, couples are much richer than singles. Hence, overall, the average aggregate wealth of our cohort drops by 9.6%. This saving motive also has non-trivial, but heterogeneous effects on average labor earnings which drop for all groups (table 4). The largest drop happens for married women (1.5%), whose labor supply is more elastic, followed by married men (0.8%), single men (0.6%), and single women (0.2%). Overall, earnings drop by 0.9%

Removing the desire to leave terminal bequests, instead, reduces the savings of all three of our groups, and by more for singles (32.5% for men and 28.5% for women) than for couples (6.6%). Overall, this change in saving motives reduces average aggregate wealth by 11.7%. It also reduces labor earnings for all groups (and here slightly more so for single men than for married women), resulting in a decrease in average labor earnings by 0.2%.

The third counterfactual (in table 3) shows that **eliminating the desire to leave any bequests** has large negative effects on the average wealth holdings by all three of our three groups (25.0% for couples, 21.0% for single men, and 18.6% for single women. Average wealth is 23.8% lower as a result. The corresponding lines in table 4 illustrate that 1.2% of average labor income are due to the fact that households want to leave a bequest. Thus, bequest motives account for almost one-quarter of average savings over the life cycle and for 1.2% of average earnings.

The next two lines of tables 3 and 4 turn to studying the role of medical expenses during retirement. As the jump in medical expenses in the period preceding death is large, **eliminating medical expenses at death** has non-trivial negative effects on wealth: declines of 0.8% for couples, 0.6% for single men, and an increase in 0.4% for single women. The aggregate effect on average wealth is a decline of 0.9%. Table 4 shows that they, instead, have little effect on labor earnings.

Eliminating all medical expenses has even larger effects, which are negative for all of our three groups of households: 11.3% for couples, 16.0% for single men, and 21.9% for single women. Average wealth for our cohort is 13.1% lower in the absence of medical expenses. The effects of this change on the labor market are also non-trivial. Table 4 shows that medical expenses drive 0.7% of average labor earnings.

Eliminating all bequest motives and medical expenses drastically reduces the wealth holdings of all groups, from 39.8% for couples, to 42.6% for single women, and 46.1% for single men, resulting in a drop in average wealth over the life cycle of 40.9%. It also reduces earnings, with the largest effect on married women (3.4%) and the smallest for single women (0.4%). Across all groups, average earnings over the life cycle drop by 1.9%.

Removing wage risk, also decreases aggregate savings: by 10.3% for couples, 9.4% for single men, and 11.8% for single women. Overall, wage risk does drive 10.4% of average savings in our economy. Interestingly, the effects on earnings are positive because, while all groups work a little less earlier in life, they then have to work more later on to make up for lower savings and income from savings. The response in average earnings over the life cycle is 2.3% for married men, 1.5% for married women, 4.2% for single men, and 3.0% for single women, and is thus smaller for married than for single individuals, which makes sense because there are two people who can potentially adjust their labor supply in a couple. Overall, average earnings over the life cycle increase by 2.3% in the absence of wage risk.

As we have discussed in the previous section, **removing the possibility of marriage** has large and heterogeneous effects on wealth. Its aggregate implications are that, without new marriages, wealth would be 6.6% lower and earnings 0.8% lower. **Without divorce**, average wealth would be 0.1% lower and average earnings 2.2% lower. **Without marriage and divorce risk**, average wealth would be 0.7% lower and earnings 2.0% lower.

These findings indicate that bequest motives are the largest among the forces for wealth accumulation that we study (23.8%), followed by medical expenses (13.1%), wage risk (10.4%) and marriage and divorce risks (0.7%). While the latter are small in the aggregate, they large and have countervailing effects on couples and singles, and thus crucially depend on demographic structure.

In terms of labor income, wage risk has the largest effects: without it, average earnings over the life cycle would be 2.3% lower, followed by marriage and divorce dynamics, without which average earnings would be 2.0% lower. In particular, divorce risk alone, accounts for 2.2% of average earnings over the life cycle. Bequest motives and medical expenses account, respectively for 1.2% and 0.7% of labor earnings.

Finally, removing all of these saving motives results in drops of wealth holdings of 60.6%, 35.0%, and 48.3% for couples, single men, and single women, respectively, and by 56.9% overall. This indicates that the remaining saving motive, that of saving for a retirement period of uncertain length, is also a sizable saving determinant, even when all of the additional saving motives that we consider are taken into account.

7 Conclusions and directions for future research

This paper develops and estimates a dynamic life-cycle model that captures how wage risk, marital dynamics, health and longevity risks, bequest motives, and medical expenses shape savings and labor supply. The model jointly tracks the behavior of single and married individuals from labor market entry until death, accounts for selection into marriage and divorce, and allows health and survival to depend on income and prior choices, consistent with the data.

We show that these risks and motives play distinct roles across groups and stages of the life cycle. Bequest motives, medical expenses, and wage risk each account for substantial shares of aggregate wealth, with bequest motives alone responsible for 23.8%. While the effects of marital dynamics on aggregate wealth are modest in the aggregate, they generate large heterogeneity by group. Wage risk, in particular, plays a dominant role in early-life behavior, substantially increasing savings at younger ages. On the labor margin, marital dynamics and wage risk significantly alter earnings profiles, with aggregate earnings falling when marriage and divorce transitions are removed, and rising when wage risk is eliminated due to increased late-career labor supply. Removing all saving motives other than retirement needs reduces lifetime wealth accumulation by 60.6% and aggregate labor earnings by 2.7%.

These findings underscore the importance of jointly modeling wage, marital, and health risks, bequest motives, and medical expenses to understand the distribution and dynamics of savings and labor supply. Even when aggregate effects appear modest, group-specific responses can be large and policy-relevant. By integrating these dimensions into a unified life-cycle framework, our paper provides a more complete understanding of household behavior and the channels through which risk and policy interact.

Our model makes several simplifying assumptions. First, we hold rates of return constant. This abstraction allows us to focus on the effects of wage, marital, health, and longevity risks without introducing additional intertemporal price variation. That said, incorporating trend variation or return risk is a natural extension and appears computationally feasible within our framework—at least as a robustness exercise. Second, we treat marriage and divorce as exogenous. Although empirical work suggests limited responsiveness to economic incentives (Dickert-Conlin and Meghea, 2004; Goda, Shoven, and Slavov, 2007; Dillender, 2016; Alm and Whittington, 1995, 1997, 1999), larger shifts in policy or norms could alter marriage patterns in ways that warrant endogenous modeling. Third, we fix home production and do not allow time use to adjust in response to counterfactuals. Given the large labor supply responses we estimate—especially for women—allowing home production to adjust would be a valuable extension. Finally, we treat fertility as exogenous and simplify the distribution of children by maternal age and marital status. While relaxing this additional set of assumptions would enhance realism, it would also introduce substantial computational complexity.

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Appendix A. Data: The PSID and the HRS

The PSID is a longitudinal study of a representative sample of the U.S. population that started in 1968. We select all individuals in the main sample who were interviewed at least twice during the years 1968-2019 (34,856 individuals); only heads and their wives (including cohabiting partners), if present (20,759); people born between 1941 and 1965 (7,581); and those between the ages of 23 and 70 (6,721). The resulting sample includes 121,603 observations.

The HRS is a biennial survey that started collecting information on people born between 1931 and 1941 in 1992. Other cohorts were introduced over the years. Our data set is based on the RAND HRS files for the period 1995-2018 (waves 3 to 14), to which we add the Exit files to include information on the wave right after death. Our sample selection is as follows. Of the 38,915 people initially present, we drop people for whom marital status is not observed (11 people). We then select people born between 1911 to 1965 and drop people older than 100, obtaining a sample of 37,287 people and 225,073 observations.

All monetary values reported throughout the paper are in 2018 U.S. dollars.

Appendix B. Additional value functions

Singles during the early retirement stage

The recursive problem for singles ($j = 1$) who has claimed Social Security at age tr but is younger than age 66 is

$$S^s(t, i, a_t^i, \bar{y}_r^i, tr) = \max_{c_t, a_{t+1}} \left(v^i(c_t, L^{i,j}, \eta_t^{i,j}) + \beta E_t S^s(t+1, i, a_{t+1}^i, \bar{y}_r^i, tr) \right), \tag{28}$$

subject to Equations (10), (13), and

$$Y_t = SS(\bar{y}_r^i, tr), \tag{29}$$

$$c_t + a_{t+1}^i = (1+r)a_t^i + Y_t - T(\cdot). \tag{30}$$

The term $SS(\bar{y_r}^i, tr)$ is a function of the income that the single person earned during his or her working life, $\bar{y}_r^i$, and claiming age tr.

Let $N^s(t,i,a_t^i,\epsilon_t^i,\bar{y}_t^i)$ denote the value function of a person during the early retirement period who has not yet claimed benefits and decide not to claim benefits this period.

$$N^s(t,i,a_t^i,\epsilon_t^i,\bar{y}_t^i) = \max_{c_t,a_{t+1},n_t^i}\left(v^i(c_t,l_t^{i,j},\eta_t^{i,1}) + \beta E_t V^s(t+1,i,a_{t+1}^i,\epsilon_{t+1}^i,\bar{y}_{t+1}^i)\right), \quad (31)$$

subject to equations (1), (8), (10), (12), (13), (14), and

$$c_t + a_{t+1}^i = (1+r)a_t^i + Y_t^i - \tau_t^{SS}\min(Y_t,\widetilde{y}_t) - T(\cdot). \quad (32)$$

Let $V^s(t,i,a_t^i,\epsilon_t^i,\bar{y}_t^i)$ denote the value function for a person during the early retirement stage who has not yet claimed and who, at the beginning of each period, chooses whether to claim or not, where D_t^i is an indicator function for claiming

$$V^s(t,i,a_t^i,\epsilon_t^i,\bar{y}_t^i) = \max_{D_t^i}\left((1-D_t^i)N^s(t,i,a_t^i,\epsilon_t^i,\bar{y}_t^i) + D_t^i S^s(t,i,a_t^i,\bar{y}_t^i,t)\right). \quad (33)$$

Couples during the early retirement period

The recursive problem for couples ($j=2$) that have claimed Social Security at age tr but are younger than 66 is

$$S^c(t,a_t,\bar{y}_r^1,\bar{y}_r^2,tr) = \max_{c_t,a_{t+1}}\left(w(c_t,L^{1,j},L^{2,j},\eta_t^{i,j}) + \beta E_t S^c(t+1,a_{t+1},\bar{y}_r^1,\bar{y}_r^2,tr)\right), \quad (34)$$

subject to equations (10), (30), (13), and

$$Y_t = \max\Big\{(SS(\bar{y}_r^1,tr) + SS(\bar{y}_r^2,tr), \frac{3}{2}\max(SS(\bar{y}_r^1,tr),SS(\bar{y}_r^2,tr))\Big\}. \quad (35)$$

The variable Y_t represents the Social Security spousal benefit: a married person receives the highest amount between one's own benefit and half of their spouse's benefit.

The value function of a couple that has not yet claimed benefits and decides not to claim benefits this period is

$$N^c(t, a_t, \epsilon_t^1, \epsilon_t^2, \bar{y}_t^1, \bar{y}_t^2) = \max_{c_t, a_{t+1}, n_t^1, n_t^2} \Bigg(w(c_t, l_t^{1,j}, l_t^{2,j}, \eta_t^{i,j}) \\ + \beta E_t V^c(t+1, a_{t+1}, \epsilon_{t+1}^1, \epsilon_{t+1}^2, \bar{y}_{t+1}^1, \bar{y}_{t+1}^2) \Bigg), \tag{36}$$

subject to equations (1), (8), (12), (20), (22), and

$$c_t + a_{t+1} = (1+r)a_t + Y_t^1 + Y_t^2 - \tau_t^{SS}(\min(Y_t^1, \widetilde{y}_t) + \min(Y_t^2, \widetilde{y}_t)) - T(\cdot). \tag{37}$$

The value function of a married couple during the early retirement stage that has not yet claimed Social Security benefits is

$$V^c(t, a_t, \epsilon_t^1, \epsilon_t^2, \bar{y}_t^1, \bar{y}_t^2) = \max_{D_t} \Big((1 - D_t) N^c(t, a_t, \epsilon_t^1, \epsilon_t^2, \bar{y}_t^1, \bar{y}_t^2) + D_t S^c(t, a_t, \bar{y}_t^1, \bar{y}_t^2, t) \Big). \tag{38}$$

Individuals in couples

We have to compute the joint value function of the couple to appropriately compute joint labor supply and savings under the married couple's available resources. However, when computing the value of marrying for a single person, the relevant object for that person is his or her discounted present value of utility in the marriage. We compute this object for a person of gender i who is married to a specific partner by using the policy functions of the corresponding couple and the present and future utility of the person for whom we are computing the value function.

Let $\hat{c}_t(\cdot)$, $\hat{l}_t^{i,j}(\cdot)$, $\hat{a}_{t+1}(\cdot)$, $\hat{e}_t^p(\cdot)$ and $\hat{D}_t(\cdot)$ denote, respectively, the optimal consumption, leisure, saving, side bequest, and claiming decision for an individual of gender i in a couple with a given set of state variables. During the working period, we have

$$\hat{W}^c(t, i, a_t, \epsilon_t^1, \epsilon_t^2, \bar{y}_t^1, \bar{y}_t^2) = v^i(\hat{c}_t(\cdot), \hat{l}_t^{i,j}, \eta_t^{i,j}) + \\ \beta(1 - \zeta(\cdot)) E_t \hat{W}^c(t+1, i, \hat{a}_{t+1}(\cdot), \epsilon_{t+1}^1, \epsilon_{t+1}^2, \bar{y}_{t+1}^1, \bar{y}_{t+1}^2) + \\ \beta\zeta(\cdot) E_t W^s(t+1, i, \hat{a}_{t+1}(\cdot)/2, \epsilon_{t+1}^i, \bar{y}_{t+1}^i). \tag{39}$$

During the early retirement period, we have

$$\hat{N}^c(t,i,a_t,\epsilon_t^1,\epsilon_t^2,\bar{y}_t^1,\bar{y}_t^2) = v^i(\hat{c}_t(\cdot),\hat{l}_t^{i,j},\eta_t^{i,j}) + \beta E_t \hat{V}^c(t+1,i,\hat{a}_{t+1}(\cdot),\epsilon_{t+1}^1,\epsilon_{t+1}^2,\bar{y}_{t+1}^1,\bar{y}_{t+1}^2) \tag{40}$$

$$\hat{S}^c(t,i,a_t,\bar{y}_r^1,\bar{y}_r^2,tr) = v^i(\hat{c}_t(\cdot),L^{i,j},\eta_t^{i,j}) + \beta E_t S^c(t+1,i,\hat{a}_{t+1}(\cdot),\bar{y}_r^1,\bar{y}_r^2,tr) \tag{41}$$

$$\hat{V}^c(t,i,a_t,\epsilon_t^1,\epsilon_t^2,\bar{y}_t^1,\bar{y}_t^2) = (1-\hat{D}_t(\cdot))\hat{N}^c(t,i,a_t,\epsilon_t^1,\epsilon_t^2,\bar{y}_t^1,\bar{y}_t^2) + \hat{D}_t(\cdot)\hat{S}^c(t,i,a_t,\bar{y}_r^1,\bar{y}_r^2,t). \tag{42}$$

During the retirement period, we have

$$\begin{aligned}
&\hat{R}^c(t,i,a_t,h_t^1,h_t^2,\bar{y}_r^2,\bar{y}_r^1,\bar{y}_r^2,tr) = v^i(\hat{c}_t(\cdot),L^{i,j},\eta_t^{i,j})+\\
&\beta s_t^{i,j}(\cdot)s_t^{p,j}(\cdot)E_t\hat{R}^c(t+1,i,\hat{a}_{t+1}(\cdot),h_{t+1}^1,h_{t+1}^2,\bar{y}_r^1,\bar{y}_r^2,tr)+\\
&\beta s_t^{i,j}(\cdot)(1-s_t^{p,j}(\cdot))E_tR^s(t+1,i,\hat{a}_{t+1}(\cdot)-\hat{e}_t^p(\cdot)-d_t^{p,j}\left(h_t^i,\bar{y}_r^i,\bar{y}_r^p\right),h_{t+1}^i,\bar{\bar{y}}_r^i,tr)+\\
&\beta(1-s_t^{i,j}(\cdot))s_t^{p,j}(\cdot)\theta_1(\hat{e}_t^i(\cdot))+\\
&\beta(1-s_t^{i,j}(\cdot))(1-s_t^{p,j}(\cdot))\theta_0(\max(0,(\hat{a}_{t+1}-d_t^{i,j}\left(h_t^i,\bar{y}_r^i,\bar{y}_r^p\right)-d_t^{p,j}\left(h_t^i,\bar{y}_r^i,\bar{y}_r^p\right))/2)),
\end{aligned} \tag{43}$$

where $s_t^{p,j}(\cdot)$ is the survival probability of the partner of the person of gender i.

Appendix C. First step estimation

Wages

Our initial conditions, assortative matching in marriage, and marriage and divorce probabilities depend on the realized values of wage shocks. We estimate these values as follows. First, we impute potential wages for non-workers using fixed effects regressions. (As shown in Borella, De Nardi, and Yang (2023b), our results are robust to using a Heckman selection correction instead.) Second, we use both observed and imputed wages to estimate wage functions by age, gender, and human capital. Third, we estimate the persistence and variance of the unobserved wage component. Finally, we recover the realized wage shocks using Kalman smoothing.

Missing wages imputation. The observed wage rate is defined as annual earnings divided by annual hours worked. Gross annual earnings refer to labor income during the previous year; annual hours reflect total hours spent working for pay over

Estimated processes		Source
Working period		
$z_t^{i,j}(\cdot)$	Endogenous age-efficiency profiles	PSID
ϵ_t^i	Wage shocks	PSID
$\zeta_t(\cdot)$	Divorce probability	PSID
$\nu_t(\cdot)$	Probability of marrying	PSID
$\xi_t(\cdot)$	Matching probability	PSID
$\iota_t(\cdot)$	Partner's wealth and earnings	PSID
$f_t^{0,5}(i,j)$	Number of children ages 0-5	PSID
$f_t^{6,11}(i,j)$	Number of children ages 6-11	PSID
Retirement period		
$\pi_t^{i,j}(\cdot)$	Transition matrix for health status	HRS
$m_t^{i,j}(\cdot)$	Medical expenses	HRS
$d_t^{i,j}(\cdot)$	End of life medical expenses	HRS
$s_t^{i,j}(h_t^i, \bar{y}^i)$	Survival probability	HRS
b	Value of life	See Appendix
Government policy		
λ_t^j, τ_t^j	Income tax	See Appendix

Table 5: First-step estimated inputs

the same period. We set to missing any observations with hourly wage rates below half the minimum wage ($7.5) , or above $350, both expressed in 2018 dollars.

We impute missing wages using fixed effects regressions estimated separately by gender:

$$\ln wage_{kt} = f_k + Z'_{kt}\beta_z + \varsigma_{kt}.$$

The dependent variable is the log hourly wage; f_k denotes individual fixed effects, and ς_{kt} is an idiosyncratic error term. The vector Z_{kt} includes a rich set of explanatory variables: a fifth-order polynomial in age; a third-order polynomial in labor market experience (measured as years of participation); marital status (indicator for being single); family size (categorical dummies); number of children; age of youngest child; and an indicator for whether the partner works (if married). To capture health, we use an indicator for whether bad health limits work capacity–the only health variable consistently available in the PSID. Since this variable is not collected for wives, we omit it from the regression for married women. Both regressions also include interaction terms among regressors. Time-invariant variables are absorbed by the individual fixed effect f_k. To avoid endpoint issues in the age polynomials, we include individuals ages 24 to 70 in the sample.

We define potential wages $\ln \widetilde{wage}_{kt}$ as observed wages when available and imputed wages otherwise.

Wage function estimation. The wage function in our structural model depends on age, gender, and human capital, measured as average realized earnings accrued up to the beginning of age t, $\bar{y}_t$.

We estimate it in two stages. In the first stage, we run a fixed effects regression for the logarithm of potential wages:

$$\ln \widetilde{wage}_{kt} = d_k + f^i(t) + \sum_{g=1}^{G} \beta_g D_g \ln(\bar{y}_{kt} + \delta_y) + u_{kt}, \tag{44}$$

where d_k is an individual fixed effect, $f^i(t)$ is a fifth-order polynomial in age specific to each marital status–gender group, and D_g is a set of dummies for these groups. The earnings shifter $\delta_y = \$5{,}000$ avoids taking logs of small values.[8] We also experimented with including marital status dummies to capture short-term effects of marital transitions, but they were not statistically significant once average earnings were controlled for.

Second, to fix the constant of the wage profile, we regress the sum of the residuals and fixed effects,

$$w_{kt+1} = d_k + u_{kt+1}, \tag{45}$$

on cohort dummies to compute the average effects for the cohorts born in 1941-1945.[9]

Table 6 reports the coefficients from the first-stage regression, and Table 7 reports the second-stage cohort adjustments.

Figure 15 shows the average wage profiles implied by our estimated processes. Consistent with the evidence on the marriage premium, married men earn more than single men. In contrast, single women earn more than married women throughout the working life of this cohort.

The shock in log wages is modeled separately by gender as the sum of a persistent component and a white noise term, which we interpret as measurement

[8] While we compute average earnings using income subject to the Social Security cap, using uncapped earnings in the regression yields very similar results.

[9] Our sample includes individuals born in more cohorts than those directly analyzed in our study in order to ensure an adequate sample size, which tends to be quite small–especially for single men.

	Coefficient	Standard Error
$\ln(\bar{y}_t + \delta_y)$	0.501***	(0.0101)
$\ln(\bar{y}_t + \delta_y)$*female	-0.188***	(0.0115)
$\ln(\bar{y}_t + \delta_y)$*single	-0.0532***	(0.0148)
$\ln(\bar{y}_t + \delta_y)$*single*female	0.0598***	(0.0169)
Age	0.170***	(0.0260)
$Age^2/(10^2)$	-0.533***	(0.0932)
$Age^3/(10^4)$	0.813***	(0.143)
$Age^4/(10^6)$	-0.492***	(0.0799)
Age*female	-0.174***	(0.0349)
$Age^2/(10^2)$*female	0.556***	(0.126)
$Age^3/(10^4)$*female	-0.781***	(0.194)
$Age^4/(10^6)$*female	0.413***	(0.109)
$Single$	-1.877***	(0.470)
Age*single	0.230***	(0.0480)
$Age^2/(10^2)$*single	-0.785***	(0.175)
$Age^3/(10^4)$*single	1.143***	(0.276)
$Age^4/(10^6)$*single	-0.601***	(0.158)
Age*single*female	-0.0706***	(0.0189)
$Age^2/(10^2)$*single*female	0.283***	(0.0804)
$Age^3/(10^4)$*single*female	-0.464***	(0.149)
$Age^4/(10^6)$*single*female	0.265***	(0.0979)
Constant	-2.343***	(0.201)
N	113163	
R-sq	0.130	

Table 6: Dependent variable: $\ln \widetilde{wage}_{kt}$. Coefficients from fixed effects regressions. PSID data. Robust standard errors in parentheses, clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

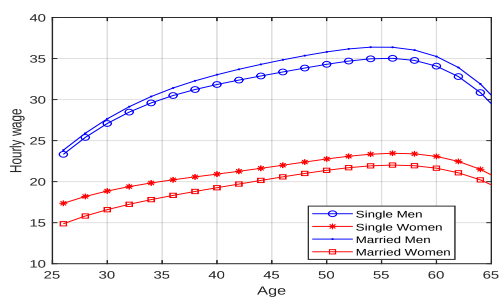

Figure 15: Average wage over the life cycle for the 1945 birth cohort, PSID data

error:

$$\tilde{w}_{kt+1} = \ln \epsilon_{kt+1} + \xi_{kt+1} \tag{46}$$

$$\ln \epsilon_{kt+1} = \rho_\epsilon \ln \epsilon_{kt} + v_{kt+1}, \tag{47}$$

where $\tilde{w}_{kt+1}$ denotes the residual from the second-stage wage regression, and ξ_{kt+1} and v_{kt+1} are independent white-noise processes with zero mean and variances σ_ξ^2 and σ_v^2, respectively. We estimate this system using equations (46) and (47) to recover

	Men	Women
Born in 1946-50	0.0269***	0.0681***
	(0.00720)	(0.00679)
Born in 1951-55	-0.00703	0.0554***
	(0.00726)	(0.00666)
Born in 1956-60	-0.00708	0.0359***
	(0.00751)	(0.00696)
Born in 1961-65	-0.0451***	0.0414***
	(0.00818)	(0.00733)
Constant	-2.000***	1.851***
	(0.00566)	(0.00536)
N	55016	58147
R-sq	0.002	0.002

Table 7: Dependent variable: w_{kt+1}. Coefficients from fixed effects regressions. PSID data. Robust standard errors in parentheses, clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

the persistence and variances of the underlying shocks, as well as the realized wage shocks for each individual via Kalman smoothing.

Specifically, we first estimate the persistence and variances by maximum likelihood, assuming that the initial state and the shocks are Gaussian, and using standard Kalman filter recursions.[10] Given these estimates, we then obtain smoothed values of the latent state—that is, $\ln \epsilon_{kt}$ for $t = 1, \dots, T$.

Average realized earnings

Our model tracks each individual's average past accumulated earnings ($\bar{y}_{kt}$) over time, subject to a time-varying Social Security cap on yearly earnings. To initialize this variable, we require data on average accumulated earnings at age 26, when individuals enter the model. Using the PSID data, we assume individuals begin working at age 22. Those who enter our data before age 26 are assigned zero average accumulated earnings until they are first observed. For those entering our data after age 26, we impute their initial average earnings using a regression-based approach. Specifically, we estimate a regression of capped earnings on a fourth-order polynomial in age, fully interacted with gender. The regression also includes education dummies, their interactions with gender, marital status, and race dummies interacted with gender, as well as cohort dummies. The predicted values from this regression determine the ini-

[10] We limit the age range to 26–66 and drop the largest 0.5% of residuals for both men and women. This trimming avoids undue influence from outliers on the estimated variances and has negligible effects on our results.

tial average earnings for entrants above age 26. After entry, the model updates each individual's average accumulated earnings based on their observed earnings history.

In our model, average past accumulated earnings at the time of retirement ($\bar{y}_{kr}$) influence post-retirement health, medical expenses, and survival probabilities. These relationships are estimated using HRS data, in which average past accumulated earnings are not directly observable. We therefore impute this variable using the following procedure. We start by estimating the relationship between average past accumulated earnings at retirement ($\bar{y}_{kr}$) and retirement income using PSID data. Specifically, we regress $\bar{y}_{kr}$ on a flexible specification that includes retirement income, education, gender, and marital status. Then, we use the estimated coefficients from this regression to impute $\bar{y}_{kr}$ for each individual in the HRS.

Wealth

We define wealth, or net worth, as all assets less all liabilities. Wealth in the PSID is recorded only in 1984, 1989, and 1994, and then in each (biennial) wave from 1999 onward. We rely on an imputation procedure to compute wealth in the missing years, starting in 1968. This imputation is based on the following fixed-effect regression:

$$\ln(a_{kt} + \delta_a) = Z'_{kt}\beta_z + da_k + wa_{kt}, \tag{48}$$

where k denotes the individual and t is age. The parameter δ_a is a shifter for wealth to have only positive values and to be able to take logs. The variables Z include polynomials in age, also interacted with health status and with average earnings (uncapped), family size, and a dummy for health status. The term da_k is the individual fixed effect, and wa_{kt} is a white-noise error term. Equation (48) is estimated separately for single men, single women, and couples, as wealth is measured at the household level.

To estimate the wealth profile up to older ages, we merge individuals from the PSID—where we observe the active part of the life cycle well—and from the HRS sample, which provides information on the retirement years. When combining the samples, we account for two key issues. First, the sample designs in the PSID and HRS differ: in particular, the HRS oversamples non-white individuals. Second, the definitions of wealth in the two surveys are not exactly the same.

We address the first issue by using sample weights when estimating the profiles. Specifically, we assign a weight of 1 to individuals in the PSID and white individuals in the HRS sample, and a weight of 0.5 to non-white individuals in the HRS sample.[11]

To address the second issue—the differences in wealth definitions between the two surveys—we include a dummy variable indicating whether the individual comes from the HRS or PSID sample, using the PSID level as the benchmark in our profiles.

We then use the estimated wealth profiles as target moments and to parameterize the joint distribution of initial wealth, average realized earnings, and wage shocks for single men, single women, and couples.

Initial distributions

For single men and women, we separately parameterize the joint distribution of initial wealth, average realized earnings, and wage shocks at each age as a joint lognormal distribution

$$\begin{pmatrix} \ln(a_t^i + \delta_a^i) \\ \ln(\bar{y}_t^i) \\ \ln \epsilon_t^i \end{pmatrix} \sim N \begin{pmatrix} \mu_{at}^i + \delta_a^i & \\ \mu_{\bar{y}t}^i & , \Sigma_{st}^i \\ \mu_{\epsilon t}^i & \end{pmatrix}, \tag{49}$$

where $\Sigma^i st$ is a 3×3 covariance matrix. We estimate its mean and variance as functions of age t. For the mean, we regress the logarithm of wealth (plus a shift parameter), average earnings, and the wage shock $\ln \hat{\epsilon}_t^i$ on a third-order polynomial in age and cohort dummies. The predicted age profiles for the 1945 cohort provide age-specific estimates of the mean of the lognormal distribution. Using the residuals from these regressions, we estimate the elements of the variance-covariance matrix by computing the relevant squares and cross-products. We then regress each squared residual or cross-product on a third-order polynomial in age to obtain smooth, age-specific estimates of each element of the variance-covariance matrix.

For couples, we compute the age-26 initial joint distribution of the following vari-

[11] We implement this simple strategy because the sample weights provided by the two surveys follow different methodologies and are not comparable.

ables

$$\begin{pmatrix} \ln(a+\delta_a) \\ \ln(\bar{y}^1) \\ \ln(\bar{y}^2) \\ \ln(\epsilon^1) \\ \ln(\epsilon^2) \end{pmatrix} \sim N \begin{pmatrix} \begin{pmatrix} \mu_a+\delta_a \\ \mu_{\bar{y}1} \\ \mu_{\bar{y}2} \\ \mu_{\epsilon1} \\ \mu_{\epsilon2} \end{pmatrix}, \Sigma_c \end{pmatrix}, \tag{50}$$

where Σ_c is a 5×5 covariance matrix estimated using data for married or cohabiting couples.

Marriage and divorce probabilities

We model the probability of marrying, ν_{t+1}, as a function of gender, age, and the wage shock. Using PSID data, we perform the estimation separately for men and women. Our estimated equation is

$$\nu^i_{t+1} = Prob(Married_{t+1} = 1 | Married_t = 0, Z_t) = F(Z'_t \beta_m),$$

where F denotes the standard logistic function and Z_t includes a polynomial in age, cohort dummies, and the logarithm of the wage shock.[12] Using the estimated coefficients on the cohort dummies, we then adjust the marriage probability for the 1945 cohort.

We estimate the probability of divorcing as

$$\zeta_t = Prob(Divorced_{t+1} = 1 | Married_t = 1, Z_t) = F(Z'_t \beta_d),$$

where Z_t includes a polynomial in age, the husband's wage shock, the wife's wage shock, and cohort dummies.

Table 8 reports our estimated coefficients from the marriage and divorce regressions.

Conditional on meeting a partner, the probability of meeting a partner p with wage shock ϵ^p_{t+1} is $\xi_{t+1}(\cdot) = \xi_{t+1}(\epsilon^p_{t+1} | \epsilon^i_{t+1}, i)$. Using our estimated wage shocks and partitioning households into three age groups (26–35, 36–45, and 46–65), we compute the variance-covariance matrix of newly matched partners' wage shocks within each

[12] The PSID shifted from a yearly to a biennial frequency in 1997. To estimate the biennial probabilities required by our model, we use only the waves collected in odd years.

	Single Men Marriage	Single Women Marriage	Couples Divorce
Age	-0.0181	-0.0585	0.0722**
	(0.0415)	(0.0409)	(0.0338)
$Age^2/10^2$	-0.0479	-0.0134	-0.146***
	(0.0493)	(0.0485)	(0.0388)
$\ln \epsilon_{kt}$	0.602***	0.247*	-0.449***
	(0.147)	(0.132)	(0.0982)
Spouse's $\ln \epsilon_{kt}$			-0.185*
			(0.105)
Born in 1946-50	-0.115	-0.297	-0.0201
	(0.211)	(0.189)	(0.129)
Born in 1951-55	-0.303	-0.262	-0.00545
	(0.203)	(0.179)	(0.127)
Born in 1956-60	-0.307	-0.134	-0.0928
	(0.203)	(0.177)	(0.129)
Born in 1961-65	-0.460**	-0.205	-0.0547
	(0.204)	(0.177)	(0.140)
Constant	0.196	0.695	-3.477***
	(0.857)	(0.830)	(0.717)
N	4001	6196	22234
Pseudo R-sq	0.059	0.066	0.034

Table 8: Column 1: Marriage of single men; column 2: marriage of single women; column 3: divorce of couples. Estimated coefficients from logistic regressions. PSID data. Robust standard errors in parentheses, clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

age group. We then derive the conditional distribution of partner characteristics under the assumption of lognormality.

Spousal wealth and Social Security benefits

We assume random matching over a partner's wealth and lifetime income, conditional on the partner's wage shock. Accordingly, we compute $\iota_{t+1}(\cdot) = \iota_{t+1}(a^p_{t+1}, \bar{y}^p_{t+1} | \epsilon^p_{t+1})$ using sample values of wealth, average capped earnings, and wage shocks. Specifically, we assume that ι_{t+1} follows a lognormal distribution at each age, with its mean and variance estimated from the data. Wealth includes a shift term, as described in the construction of the joint distribution at age 26 (see the "Initial Distributions" subsection of this Appendix).

Figure 16 presents average spousal wealth (left panel) and Social Security–covered earnings (right panel) by the spouse's wage shock. The dispersion of these resources increases rapidly with age, indicating that individuals who marry later face a more dispersed distribution of spousal resources.

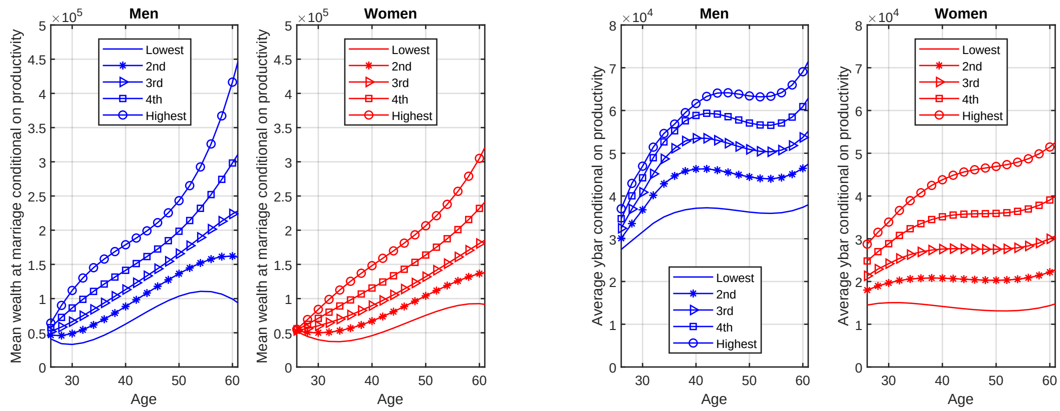

Figure 16: Average spousal wealth (on the left) and Social Security Earnings (on the right) by spousal wage shocks in case of marriage. PSID data.

Number of children

To compute the average number of children by age group, we use individual-level information from the PSID and classify as children of the family those in the following categories: sons or daughters of the head, stepsons or stepdaughters of the head, sons or daughters of the cohabiting partner but not of the head, foster sons or daughters (not legally adopted), and children of the cohabitant but not of the head. We then sum the number of children in each age category (0–5, 6–11, and 0–17 for the total number) and regress the resulting count on a fifth-order polynomial in the mother's age, interacted with marital status and cohort dummies. This yields the average age profile of children in each group for single and married women. Figure 17 displays these profiles.

Health Status at Retirement

We define health status as a categorical variable with three possible states: "good," "bad," or "nursing home." We assign individuals to the nursing "home state" if they meet one of the following criteria: (1) they spend at least 120 days in a nursing home between interviews (on average, 60 days per year), or (2) they spend at least 60 days in a nursing home before the next scheduled interview and die before that interview. For those not in a nursing home, we classify their health as "good" if they report excellent, very good, or good health, and as "bad" if they report fair or poor health.

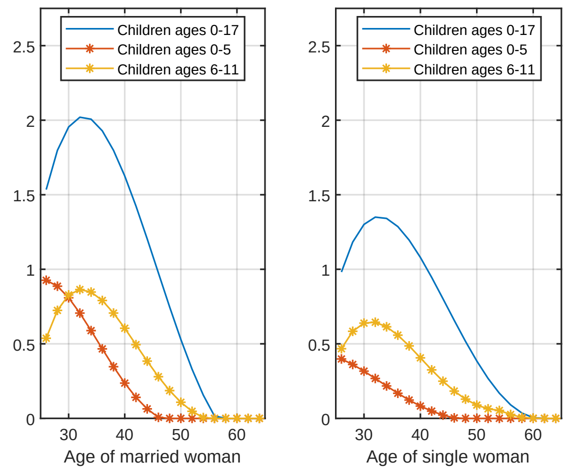

Figure 17: Number of children for married (on the left) and single women (on the right) for the 1945 cohort, PSID data.

We estimate the probability of each health state at age 66 as a function of average past earnings, using a multinomial logit model. We run separate estimations for single men and single women, using individuals aged 65–67 and controlling for cohort dummies and average earnings. For couples, we estimate a multinomial logit model for the six possible joint health states (e.g., both partners in good health; one partner in good health and the other in bad health, etc.), using the same explanatory variables and restricting the husband's age to 65–67.

Health dynamics after retirement

We model transitions across the three health states–good, bad, and nursing home–using a multinomial logit model. The probability of being in health state i at time t equals

$$\pi^i_{ht} = \text{Prob}\left(h_t = i \mid X^h_t\right) = \frac{\exp\left(X^{h\prime}_t \beta^h_i\right)}{\sum_{j=0}^2 \exp\left(X^{h\prime}_t \beta^h_j\right)},$$

where i indexes the health state and X^h_t includes age, gender, average earnings $\bar{y}_t$, marital status, previous-period health status, and interactions between these variables.

Table 9 presents the estimated coefficients, and Figure 18 shows the transition probabilities by gender, age, marital status, and prior health status.

	Coefficient	SE
Health state: Bad Health		
Age	-0.0246**	(0.0125)
Age^2	0.0301***	(0.0087)
$health_{t-1}$ = Bad	-1.1151*	(0.6128)
$health_{t-1}$ = Nursing Home	-2.8882	(5.0913)
$health_{t-1}$ = Bad × Age	0.1257***	(0.0175)
$health_{t-1}$ = Nursing Home × Age	0.1849	(0.1331)
$health_{t-1}$ = Bad × Age^2	-0.1022***	(0.0122)
$health_{t-1}$ = Nursing Home × Age^2	-0.1548*	(0.0860)
$\bar{y}_r$	-0.1725***	(0.0038)
Male	0.2928***	(0.0244)
Male × Married	0.0008	(0.0306)
Spouse $\bar{y}_r$ × Married	-0.0816***	(0.0041)
Married	0.1131***	(0.0249)
Born 1911-1915	0.2066***	(0.0529)
Born 1916-1920	0.2287***	(0.0411)
Born 1921-1925	0.1845***	(0.0352)
Born 1926-1930	0.1019***	(0.0317)
Born 1931-1935	0.0814***	(0.0269)
Born 1936-1940	0.0614**	(0.0245)
Born 1946-1950	0.0322	(0.0275)
Born 1951-1955	0.0480	(0.0297)
Born 1956-1960	0.0110	(0.0350)
Born 1961-1965	0.0467	(0.0544)
Constant	-1.0906**	(0.4434)
Health state: Nursing Home		
Age	0.1070*	(0.0560)
Age^2	0.0164	(0.0347)
$health_{t-1}$ = Bad	1.5597	(2.6158)
$health_{t-1}$ = Nursing Home	10.0765**	(4.8246)
$health_{t-1}$ = Bad × Age	0.0704	(0.0670)
$health_{t-1}$ = Nursing Home × Age	0.0412	(0.1240)
$health_{t-1}$ = Bad × Age^2	-0.0790*	(0.0426)
$health_{t-1}$ = Nursing Home × Age^2	-0.1156	(0.0789)
$\bar{y}_r$	-0.1294***	(0.0136)
Male	0.3516***	(0.0632)
Male × Married	-0.3454***	(0.1058)
Spouse $\bar{y}_r$ × Married	-0.0087	(0.0199)
Married	-0.6671***	(0.1078)
Born 1911-1915	0.4521***	(0.1383)
Born 1916-1920	0.4343***	(0.1296)
Born 1921-1925	0.3116**	(0.1253)
Born 1926-1930	0.1816	(0.1238)
Born 1931-1935	0.2052*	(0.1163)
Born 1936-1940	-0.0587	(0.1175)
Born 1946-1950	-0.1752	(0.1582)
Born 1951-1955	-0.2920	(0.2006)
Born 1956-1960	-0.0385	(0.2445)
Born 1961-1965	0.3877	(0.3811)
Constant	-13.1377***	(2.2299)
N	175103	
Pseudo-R^2	0.291	

Table 9: Health dynamics over two-year periods. Multinomial logit coefficients for health state transitions. HRS data. Robust standard errors in parentheses clustered at the individual level. * p<0.1, ** p<0.05, *** p<0.01.

Figure 18 shows health transition probabilities, conditional on survival, for singles and couples by age, gender, and initial health status and $\bar{y}$ (which we set to $17,439$). These transitions vary substantially, particularly in the likelihood of being in good or bad health in the next period, conditional on current health.

The top panel illustrates that, at age 70, individuals in good health face an approximately 80% chance of remaining in good health. Those in bad health recover with a probability of around 20–25%, while individuals in nursing homes have less than a 10% chance of returning to good health. Across all ages and initial health states, women remain in good health more often than men.

The middle panel shows the probability of being in bad health in the next period. At age 70, individuals already in bad health face a roughly 75% chance of remaining in that state. The probability of transitioning into bad health is about 15–20% for those currently in good health or in a nursing home. As individuals age, the likelihood of entering a nursing home in the next period rises for those in good health but declines for those already in a nursing home.

The bottom panel shows the probability of being in a nursing home in the next period. This probability remains highest—around 70–80%–for individuals already in a nursing home and stays relatively flat across ages. In contrast, those in good or bad health at age 70 face less than a 5% chance of entering a nursing home.

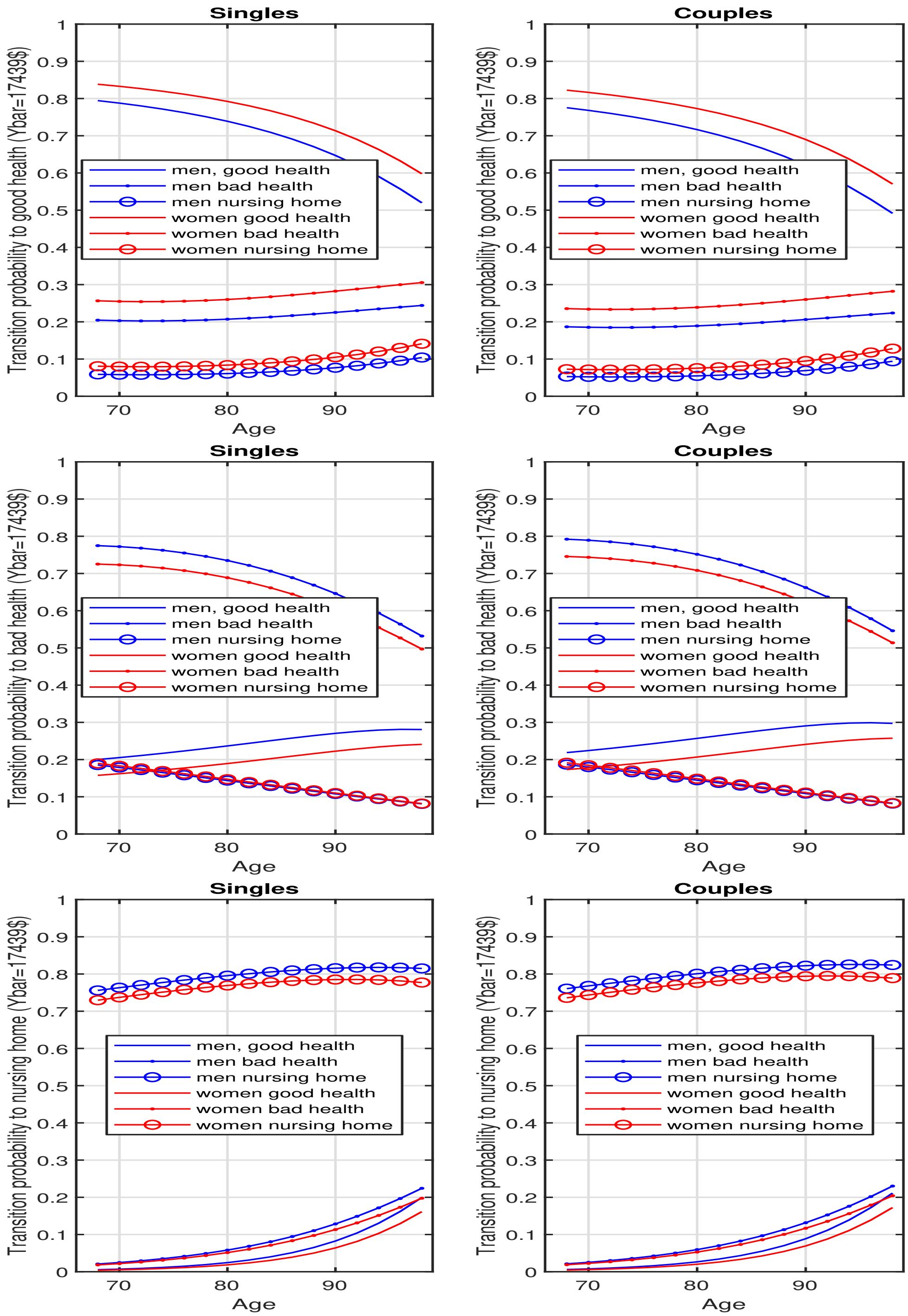

Figure 18: Health transition probabilities, conditional on surviving, for singles and couples by age, HRS data.

Survival probabilities

We model the probability of being alive at time t as a logistic function:

$$s_t = \text{Prob}\left(\text{Alive}_t = 1 \mid X_t^s\right) = F\left(X_t^{s\prime}\beta^s\right),$$

where X_t^s is the vector of explanatory variables at time t, and β^s denotes the estimated coefficients. The covariates include a third-order polynomial in age, gender, marital status, human capital $\bar{y}_r$, and previous-period health status, along with interaction terms included when statistically significant.

Table 10 reports the estimated coefficients from the logistic regression.

	Coefficient	SE
Age	-0.3078**	(0.1345)
Age^2	0.3667**	(0.1773)
Age^3	-0.1971**	(0.0771)
$\bar{y}_r$	0.0723***	(0.0064)
$health_{t-1}$ = Bad	-3.4617***	(0.1667)
$health_{t-1}$ = Nursing Home	-7.6339***	(0.3571)
$health_{t-1}$ = Bad × Age	0.0295***	(0.0021)
$health_{t-1}$ = Nursing Home × Age	0.0637***	(0.0043)
Male	-0.6434***	(0.0255)
Married	0.0892***	(0.0225)
Born 1911-1915	-0.1151*	(0.0646)
Born 1916-1920	-0.1500**	(0.0587)
Born 1921-1925	-0.1637***	(0.0553)
Born 1926-1930	-0.1559***	(0.0531)
Born 1931-1935	-0.0876*	(0.0490)
Born 1936-1940	-0.0308	(0.0474)
Born 1946-1950	0.1886***	(0.0617)
Born 1951-1955	0.2147***	(0.0705)
Born 1956-1960	0.3441***	(0.0946)
Born 1961-1965	0.3448**	(0.1614)
Constant	14.1139***	(3.3715)
N	187853	
Pseudo-R^2	0.198	

Table 10: Survival over a two-year period. Logistic regression coefficients. HRS data. Robust standard errors in parentheses clustered at the individual level. * p<0.1, ** p<0.05, *** p<0.01.

Figure 19 reports survival probabilities. Survival is more likely for women, individuals in better health, younger individuals, and those who are married.

Medical expenses

We model and estimate medical expenses using a comprehensive approach that captures spending patterns throughout life, including end-of-life expenditures.

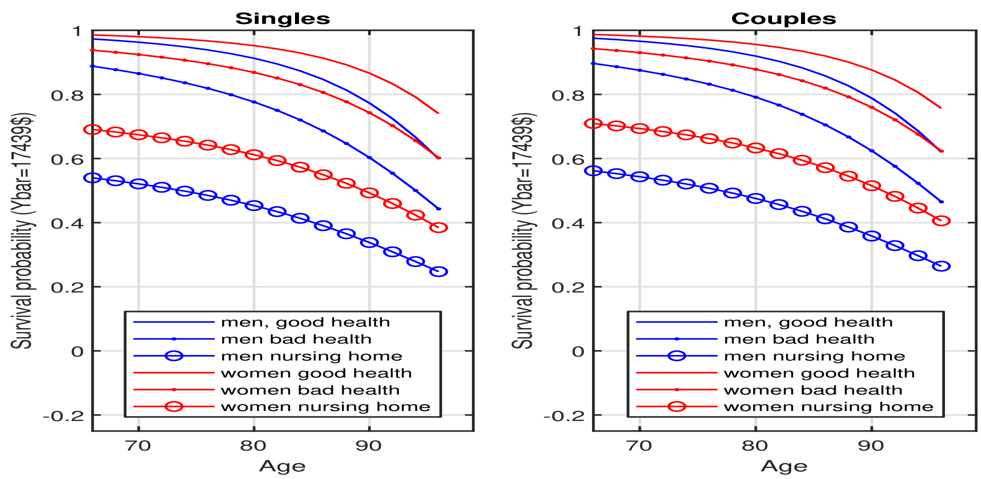

Figure 19: Survival probability by age, gender, and marital and health status, HRS data.

Because our model explicitly accounts for out-of-pocket medical expenses and treats Medicaid payments as part of the consumption floor, the relevant measure of medical expenses must include both components. While the HRS provides data on out-of-pocket medical expenditures, it lacks direct information on Medicaid spending. To fill this gap, we impute Medicaid payments by combining HRS data with administrative records from the Medicare Current Beneficiary Survey (MCBS), following the method described in De Nardi, French, Jones, and McGee (2025).

We define out-of-pocket medical expenses as total individual spending on hospital and nursing home stays, doctor visits, dental care, outpatient surgery, monthly prescription drugs, home health care, special facilities charges, and insurance premia for private plans and Medicare. These payments are made directly by individuals and exclude amounts covered by insurance. For deceased individuals, we also include death-related expenses–such as funeral costs, unpaid insurance premia, and legal fees–using information from HRS exit interviews.

Because our model assumes that medical expenses are deterministic conditional on observable states–age, gender, marital status, and health–we do not include stochastic shocks to medical spending. Instead, we estimate a flexible specification of log medical expenses as a function of these state variables, along with interactions that capture end-of-life spending. To recover the average level of medical spending–not just its logarithm–we assume that residuals are normally distributed (i.e., medical expenses are log-normally distributed). We therefore adjust the conditional means of $\ln m_{kt}$

by adding half the estimated residual variance before exponentiating. This yields smooth, state-dependent profiles of expected medical spending, consistent with the model's structure and inputs.

The estimation equation for out-of-pocket medical expenses plus Medicaid payments is:

$$\ln(m_{kt}) = \alpha_k^m + X_{kt}^{m\prime}\beta^m + \delta_{\text{death}} \cdot D_{\text{death},t} + (X_{kt}^m \times D_{\text{death},t})' \gamma^m + u_{kt}^m,$$

where m_{kt} denotes out-of-pocket medical expenses plus Medicaid payments for individual k at time t, including both during life and in the period of death. The vector X_{kt}^m includes age (up to a third-order polynomial), gender, health status, marital status, and relevant interactions (e.g., age–gender). The indicator $D_{\text{death},t}$ equals one if the individual dies during the period, and its interaction with covariates, $(X_{kt}^m \times D_{\text{death},t})' \gamma^m$, allows health and demographic characteristics to affect medical expenses differently in the period of death. This captures heterogeneity in death-period costs by, for example, chronic conditions, nursing home status, and gender. The term α_k^m denotes individual fixed effects. We estimate the specification using a fixed effects model to control for persistent unobserved heterogeneity—such as differential mortality—that could otherwise bias the estimated age profiles, as discussed in De Nardi, French, and Jones (2010).

Then, we regress the sum of residuals and fixed effects from this equation on cohort, gender, average past earnings at retirement, and marital status dummies to estimate average medical expenses for each group of interest. Table 11 reports the estimated coefficients, and Figure 3 displays medical expenses by age, gender, and marital and health status.

Finally, we model the variance of medical expense shocks by regressing the squared residuals (in logs) on a second-order polynomial in age, fully interacted with current health status, as well as on a death-period indicator and cohort, gender, and marital status dummies. We use these estimates to construct average medical expenses as a function of age by adding half the estimated variance to the predicted mean in logs prior to exponentiation.

First Stage: Fixed Effects Regression	Coefficient	SE
Age	0.541***	(0.0451)
Age^2	-0.743***	(0.0644)
Age^3	0.337***	(0.0302)
$Health = Bad$	2.811*	(1.529)
$Health = NursingHome$	-4.432	(9.973)
$Health = Bad \times Age$	-0.106	(0.0659)
$Health = NursingHome \times Age$	0.162	(0.390)
$Health = Bad \times Age^2$	0.137	(0.0934)
$Health = NursingHome \times Age^2$	-0.114	(0.502)
$Health = Bad \times Age^3$	-0.0569	(0.0436)
$Health = NursingHome \times Age^3$	0.0150	(0.213)
Male $\times Age$	-0.106	(0.0671)
Male $\times Age^2$	0.157	(0.0957)
Male $\times Age^3$	-0.0767*	(0.0449)
Married	0.0693***	(0.0114)
Dead	1.651***	(0.0260)
$Health = Bad \times$ Dead	-0.196***	(0.0285)
$Health = NursingHome \times$ Dead	-0.998***	(0.0511)
Dead $\times$ Married	-0.145***	(0.0268)
Constant	-3.978***	(0.864)
Second Stage: Residual Regression	Coefficient	SE
$\bar{y}_r$	0.0517***	(0.000986)
Spouse $\bar{y}_r$ $\times$ Married	0.0176***	(0.00116)
Male	2.083***	(0.00898)
Married	0.0478***	(0.00830)
Male $\times$ Married	0.0774***	(0.0111)
Dead	0.0894***	(0.0142)
Male $\times$ Married $\times$ Dead	-0.0795***	(0.0248)
Born 1911-1915	0.0821***	(0.0152)
Born 1916-1920	0.0560***	(0.0122)
Born 1921-1925	0.0345***	(0.0108)
Born 1926-1930	-0.00959	(0.0102)
Born 1931-1935	-0.0317***	(0.00915)
Born 1936-1940	-0.0467***	(0.00874)
Born 1946-1950	0.0705***	(0.00977)
Born 1951-1955	0.0773***	(0.0101)
Born 1956-1960	0.0886***	(0.0110)
Born 1961-1965	0.0757***	(0.0148)
Constant	-1.178***	(0.00831)
Observations	219670	
R^2 First Stage	0.0249	
R^2 Second Stage	0.5132	

Table 11: Estimates for the logarithm of medical expenses. First stage (fixed effects) and second stage (residual regression). Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

The parameter b and the value of life

The parameter b implies a value of statistical life (VSL) for each person. The VSL is defined as the compensation that people require to bear an increase in their probability of death, expressed as "dollars per death." For example, suppose that people are willing to tolerate an additional fatality risk of 1/10,000 during a given period for a compensation of \$500 per person. Among 10,000 people, there will be one death, and it will cost the society 10,000 times \$500 = \$5 million, which is the implied VSL. We set b so that the implied VSL is to \$2.4 million, which is in the range of those estimated by the literature. Our results are not very sensitive to the value of this parameter.

Taxes

We model taxes T on total income Y as

$$T(Y) = Y - \lambda Y^{1-\tau},$$

where τ governs the degree of progressivity and λ determines the average level of taxation. This implies

$$Y - T(Y) = \lambda Y^{1-\tau} \quad \text{and} \quad \ln(Y - T(Y)) = \ln(\lambda) + (1-\tau)\ln(Y).$$

We estimate τ and λ by regressing the logarithm of after-tax household income on a constant and the logarithm of pre-tax household income, separately by cohort, year, and household type (single men, single women, and couples).

We use PSID data from 1968 to 2017 to estimate cohort– and time-specific tax functions. Up to 1991, the PSID provides reported information on federal taxes paid. For years after 1991, we compute taxes using TAXSIM, the NBER simulation program. Specifically, we use the version developed by Borella, De Nardi, Pak, Russo, and Yang (2023a), which extends the earlier work of Kimberlin, Kim, and Shaefer (2015) to prepare PSID input files for TAXSIM.[13]

[13] Kimberlin, Kim, and Shaefer (2015) developed code to prepare TAXSIM input files for PSID data from 1999 to 2011, based on the specifications in Butrica and Burkhauser (1997). Their approach differs from simplified PSID-TAXSIM interfaces in that it identifies multiple tax units within a PSID family. Cohabiting couples are treated as two separate tax units, and children are assigned to the appropriate unit (head or cohabitant) based on relationship codes. We extended their program to

We define before-tax household income as the sum of all income received by the spouses (or by the individual if single) in a given tax year. It includes the labor income of the head and wife (if present), asset income from farms, businesses, roomers, rent, interest, and dividends, and the wife's income from wealth. It also includes transfer income such as Social Security, pensions, annuities, other retirement income, welfare, aid to dependent children, unemployment or workers' compensation, help from relatives, alimony, and child support. We define after-tax household income as before-tax income minus the federal income tax liability. The latter includes capital gains taxes, surtaxes, the alternative minimum tax, and refundable and non-refundable credits, as computed using TAXSIM.

All inputs required by TAXSIM come from the PSID for the years 1992–2017. However, medical expenses and charitable contributions are not available prior to 1999 and must be imputed. We do so by pooling data from 1999–2015, regressing the sum of these two items on a set of observables, and predicting their values for earlier years using the estimated coefficients. The explanatory variables include demographic and income characteristics: family size, employment status of the head and spouse, state of residence, wages, pensions, other income, education, number of children, age, and marital status.

To preserve the variance of the imputed values, we follow the procedure in David, Little, Samuhel, and Triest (1986) and French and Jones (2011). Specifically, we:

1. Regress the sum of medical expenses and charitable contributions on observables for the sample of heads who itemize:

$$deduc_i = x_i\beta + \epsilon_i.$$

2. For each household i with non-missing *deduc*, compute the predicted value $\widehat{deduc}_i = x_i\hat{\beta}$ and residual $\hat{e}_i = deduc_i - \widehat{deduc}_i$.

3. Sort $\widehat{deduc}_i$ into deciles and retain all corresponding $\hat{e}_i$ values within each decile.

4. For households j with missing *deduc*, compute $\widehat{deduc}_j = x_j\hat{\beta}$, assign it to a decile, and draw a random residual $\hat{e}_i$ from the same decile in the non-missing sample.

cover the full range from 1992 to 2017.

5. Impute $deduc_j$ as $\widehat{deduc}_j + \hat{e}_i$.

This procedure ensures that the imputed distribution preserves both the conditional mean and variance structure of the observed data.

Appendix D. Calibrated model parameters

Table 12 summarizes our first-step calibrated model inputs. We set the interest rate r to 4%, the curvature of the utility function, γ, to 2.5, and the equivalence scales to $\eta_t^{i,j} = (j + 0.7 * f_t^{i,j})^{0.7}$ (as estimated by Citro and Michael (1995)). The term $f_t^{i,j}$ refers to the average total number of children for single and married men and women by age. Our equivalence scale implies that \$1 spent by a household in a couple with two children gives each household member a consumption of 0.42 cents.

While we do not have data on childcare costs by age of children as a fraction of maternal earnings, the PSID data report both childcare costs for all children aged 0-11 in a household and maternal earnings. We thus calibrate our per-child child care costs to match the observed data on total childcare costs as a fraction of earnings for working women with children age 0-11. The range of per-woman total childcare costs as a fraction of her earnings implied by our model ranges from about 5% to 10% of mothers' salaries before age 38, depending on age and mother's marital status and matches the range that we estimate from the PSID data.

De Nardi, French, Jones, and McGee (2025) estimate a model of Medicaid recipiency in old age for single and married people and obtain a utility floor that corresponds to consuming \$4,101 (in 2017 dollars, which is \$4,347 in 2018 dollars) a year for singles. Consistent with the statutory rules, we assume that the one for couples is 1.5 that for singles.

The Social Security benefit at age 66 is calculated to mimic the Old Age and Survivors' Insurance component of the Social Security system:

$$SS(\bar{y}_r) = \left\{ \begin{array}{ll} 0.9\bar{y}_r, & \bar{y}_r < 11,112 \\ 10,001 + 0.32(\bar{y}_r - 11,112), & 11,112 \leq \bar{y}_r < 66,996 \\ 27,885 + 0.15(\bar{y}_r - 0.6725), & 66,996 \leq \bar{y}_r < y_t^{cap} \end{array} \right\},$$

where the marginal rates and bend points come from the Social Security Administration.[14] The Social Security tax and Social Security cap, shown in Figure 20, have

[14] Social Security Administration "Benefit Formula Bend Points": https://www.ssa.gov/oact/cola/bendpoints.html. We use values for 2019.

Calibrated parameters		Source
Preferences and returns		
r	Interest rate	4% De Nardi, French, and Jones (2016)
γ	Utility curvature parameter	2.5 see text
η_t	Equivalence scales	Citro and Michael (1995)
Proportional child care cost		
$\tau_c^{0,5}$	For each child age 0-5	9.00%
$\tau_c^{6,11}$	For each child age 6-11	7.50%
Government policy		
$SS(\bar{y}_r^i)$	Social Security benefit	See text
τ_t^{SS}	Social Security tax rate	See text
$\widetilde{y}_t$	Social Security cap	See text
$\underline{c}(1)$	Minimum consumption, singles	\$4,347, See text
$\underline{c}(2)$	Minimum consumption, couples	\$4,347*1.5, See text

Table 12: First-step calibrated inputs summary.

been changing over time.

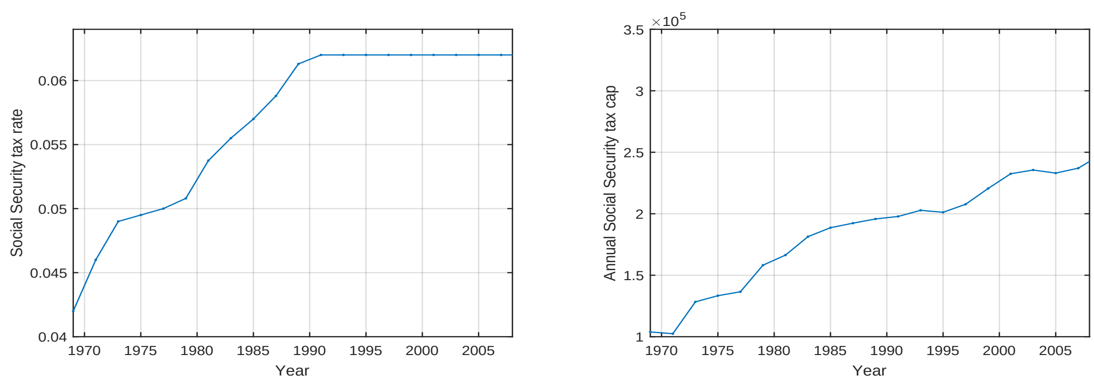

Figure 20: Social Security tax (left) and cap (right) over time, for the 1945 cohort in 2018 dollars.

Appendix E. Solution algorithm We solve for the value functions and policy functions, and then we simulate our model economy. In the latter step, we use our estimated marriage and divorce probabilities both to compute the dynamic programming problem and to generate the distribution of people by state variables that is generated by our policy functions. Finally, we estimate our model parameters following the procedures that we describe in Appendix F.

We optimize over six value functions over multiple time periods, compute three more value functions, and have six continuous state variables. In addition, there can be kinks in the value functions because both husbands and wives choose their participation. Thus, to have reliable solutions, we compute them brute force on a grid. To get a sense of dimensionality, the value function for working couples has the following dimensions in terms of state variables: age, wealth, wage shocks for each spouse, and human capital for each spouse. Over these grids, we evaluate choices for consumption, savings, and labor supply of both household members, and we compute all of the relevant expected values at each and marital status for each of the value functions.

Even if we parallelize our model in C on high-end workstations, the model requires almost 2 minutes for each set of parameter values to be solved. Estimating the model implies solving it thousands of times, which thus requires at least three or four weeks each time. We re-estimate our model for many times to check for local minima, robustness, and so on. The computation time required is substantial.

During the retirement stage, single people do not get married anymore; hence, their value function can be computed independently of the other value functions. The value function of couples depends on their own future continuation value and that of singles, in case of death of a spouse. Then there is the value function of each person in a couple, which depends on the optimal policy function of the couple, taking the appropriate expected values. We compute the value functions as follows:

1. Compute the value function of a retired single person for all time periods after retirement by backward iteration starting from the last period.

2. Compute the value function of a retired couple for all time periods after retirement by backward induction starting from the last period. This also uses the value function for the retired single person in case of death of one of the spouses.

3. Compute the value function of the single person in a marriage for all time periods after retirement.

During the early retirement stage, single people do not get married, and married people do not divorce or die; hence, the value function of the single person and that of the couple can be computed independently. We compute them as follows:

1. Compute the value function of the single person for all time periods by backward iteration starting from the last period in the early retirement stage.

2. Compute the value function of the couple for all time periods by backward iteration starting from the last period in the early retirement stage.

3. Compute the value function of each individual in a marriage for all time periods in the early retirement stage.

During the working age, the value functions are interconnected; hence, we solve each of them at time t, working backward over the life cycle, at each period:

1. Take as given the value of being a single person in a married couple for next period and the value function of being single next period, which have been previously computed, and compute the value function of being single this period.

2. Given the value function of being single, compute the value function of the couple for the same age.

3. Given the optimal policy function of the couple, use the implied policy functions to compute the value function for a person in a couple.

4. Keep going back in time until the first period.

Appendix F. Estimation strategy

In this appendix, we review the two-step estimation strategy, the moment conditions, and the asymptotic distribution of our estimator.

In the first step, we estimate the vector χ, which consists of the set of parameters that can be estimated without explicitly using our model. In the second step, we use the method of simulated moments (MSM) to estimate the remaining parameters, which are contained in the $M \times 1$ vector Δ. For the 1945 cohort, the elements of Δ are the 21 model parameters (β, ω, $(\phi_0^{i,j}, \phi_1^{i,j}, \phi_2^{i,j})$, $L^{i,j}$).[15] Our estimate, $\hat{\Delta}$, of the "true" parameter vector Δ_0 is the value of Δ that minimizes the (weighted) distance between the lifecycle profiles found in the data and the simulated profiles generated by the model.

More specifically, we match median and average wealth for single men, single women, and couples from ages 28 to 84, and working hours and participation for

[15] We normalize the time endowment of single men.

single men, single women, married men, and married women from ages 26 to 64. For the generic variable z equal to hours (H), participation (In), and wealth (a), $x_{k,t}^{i,j}$ denotes the sample observation relative to person k, of gender i, marital status j, and age t. Using $x_t^{i,j}(\Delta,\chi)$ to denote the model-predicted expected value of x for age i, gender i, and marital status j, where χ is the vector of parameters estimated in the first step, we write the moment conditions as

$$E[a_{k,t}^{i,j} - a_t^{i,j}(\Delta_0,\chi_0)] = 0, \quad \forall t = 2, ..., 41 \tag{51}$$

$$E[H_{k,t}^{i,j} - H_t^{i,j}(\Delta_0,\chi_0)] = 0, \quad \forall t = 1, ..., 41 \tag{52}$$

$$E[In_{k,t}^{i,j} - In_t^{i,j}(\Delta_0,\chi_0)] = 0, \quad \forall t = 1, ..., 41. \tag{53}$$

Note that wealth for couples, $a_{k,t}^{i,j}$, does not depend on gender when marital status is $j = 2$. Also, as wealth at age 26 ($t = 1$) is an initial condition, it is matched by construction. In practice, we compute the sample expectations in equations (51), (52), and (53) conditional on a flexible polynomial in age. More specifically, we regress each variable x on a fourth-order polynomial in age and on a set cohort of dummies, fully interacted with marital status and separately for each gender. We then compute the conditional expectations using the estimated marital- and gender-specific polynomial in age and coefficients relative to that cohort. These average age profiles, conditional on gender, marital status, and cohort, are those shown in the figures in the main text.

Suppose we have a data set of K persons who are each observed at up to T separate calendar years. Let $\varphi(\Delta;\chi_0)$ denote the J-element vector of our moment conditions, and let $\hat{\varphi}_K(.)$ denote its sample analog.

If we let $\widehat{\mathbf{W}}_K$ denote a $J \times J$ positive definite weighting matrix, the MSM estimator $\hat{\Delta}$ is given by

$$\underset{\Delta}{\operatorname{argmin}}\ \hat{\varphi}_K(\Delta;\chi_0)'\widehat{\mathbf{W}}_K\hat{\varphi}_K(\Delta;\chi_0). \tag{54}$$

Note that we also estimate χ_0. For tractability reasons, and following much of the literature, we treat it as known.

Under the regularity conditions stated in Pakes and Pollard (1989) and Duffie and Singleton (1993), the MSM estimator $\hat{\Delta}$ is both consistent and asymptotically normally distributed:

$$\sqrt{K}\left(\hat{\Delta} - \Delta_0\right) \rightsquigarrow N(0,\mathbf{V}), \tag{55}$$

with the variance-covariance matrix $\mathbf{V}$ given by

$$\mathbf{V} = (\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\mathbf{S}\mathbf{W}\mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}, \tag{56}$$

where $\mathbf{S}$ is the variance-covariance matrix of the data;

$$\mathbf{D} = \frac{\partial\varphi(\Delta;\chi_0)}{\partial\Delta'}\Big|_{\Delta=\Delta_0} \tag{57}$$

is the $J\times M$ gradient matrix of the population moment vector; and $\mathbf{W} = \text{plim}_{K\to\infty}\{\widehat{\mathbf{W}}_K\}$. When $\mathbf{W} = \mathbf{S}^{-1}$, $\mathbf{V}$ simplifies to $(\mathbf{D}'\mathbf{S}^{-1}\mathbf{D})^{-1}$.

The asymptotically efficient weighting matrix arises when $\widehat{\mathbf{W}}_K$ converges to $\mathbf{S}^{-1}$. However, as Altonji and Segal (1996) point out, the optimal weighting matrix is likely to suffer from small sample bias. We thus use a diagonal weighting matrix that is the same as $\mathbf{S}$ along the diagonal and has zeros off the diagonal of the matrix. We estimate $\mathbf{D}$ and $\mathbf{W}$ with their sample analogs.

Appendix G. Parameter estimates

	Coeff.	Std. Err.
β: Discount factor	0.9958	(0.00036)
ω: Consumption weight	0.4478	(0.00184)
ϕ_0: Terminal bequest, strength	1379.3442	(96.64710)
k_0: Terminal bequest, shifter	987.7149	(42.31610)
ϕ_1: Side bequest, strength	6221.2437	(230.86900)
k_1: Side bequest, shifter	1681.1474	(29.12160)
Time endowment parameters:		
$FL^{2,1}$: single women	-1.6060	(0.05834)
$FL^{1,2}$: married men	-2.5873	(0.10860)
$FL^{2,2}$: married women	-3.3447	(0.26815)
Participation cost parameters:		
$p_2^{1,1}$: Single men: quadratic term	0.0005	(0.00003)
$p_1^{1,1}$: Single men: linear term	-0.0093	(0.00141)
$p_0^{1,1}$: Single men: constant term	-0.6683	(0.02469)
$p_2^{2,1}$: Single women: quadratic term	0.0004	(0.00001)
$p_1^{2,1}$: Single women: linear term	-0.0044	(0.00084)
$p_0^{2,1}$: Single women: constant term	-0.8599	(0.03491)
$p_2^{1,2}$: Married men: quadratic term	0.0004	(0.00002)
$p_1^{1,2}$: Married men: linear term	-0.0048	(0.00087)
$p_0^{1,2}$: Married men: constant term	-0.7686	(0.01991)
$p_2^{2,2}$: Married women: quadratic term	0.0015	(0.00011)
$p_1^{2,2}$: Married women: linear term	-0.0725	(0.00441)
$p_0^{2,2}$: Married women: constant term	-1.6060	(0.05834)

Table 13: Estimated parameters from the structural model. Standard errors in parentheses.

Table 13 reports all of our structural model estimates and their standard errors.

Appendix H. What drives our estimates and identification

This appendix studies how the model's target moments change when we vary one of our 21 estimated parameters at a time (Table 1). These changes help us understand how our model's parameters are identified by the target moments we use.

The **discount factor** β is the only parameter with a large effect on the savings of both couples and singles across much of the life cycle (Figure 22). Decreasing patience lowers the participation of married women at all ages and slightly tilts the

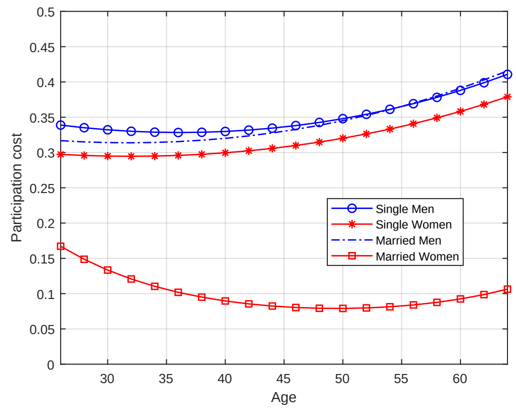

Figure 21: Participation cost

participation profile of single women, reducing it before age 40 and raising it after age 50. Hours change little.

The **weight on consumption** ω (Figure 23) is the only parameter that shifts both participation and hours worked (conditional on participation) for all four subgroups (single and married men and women). As expected, reducing ω weakens incentives to work. It also lowers savings for couples and singles after age 60.

Turning to the effects of **bequest motives**, all of the parameters affecting terminal and side bequests have much larger effects on savings than on labor market outcomes. For the changes in parameter values that we examine here, large changes in bequest motives have large effects on savings, but little to no effect on participation and hours worked. It is worth noting that in the paper we show that eliminating bequests entirely can have substantial effects on labor supply. This is because this is a much larger change in parameters. Turning to the effects on wealth, terminal and side bequest motives have very different implications for couples and singles. Reducing the desire to leave terminal bequests lowers the wealth held by both couples and singles after age 60. In contrast, reducing the desire to leave side bequests reduces the wealth held by couples but tends to increase that of singles because the new singles turn out to be wealthier. Comparing the effects of the intensity and the shifter of the bequest parameters, we find that the shifter tilts the wealth-age profile more sharply at older ages, when those who survive tend to be those with higher lifetime income.

We next examine how **available time and participation costs** affect labor market outcomes. Reducing married women's available time by three hours per week (Figure 28) lowers their participation by more than ten percentage points at age

26. It also reduces hours worked across the life cycle, although by less than the mechanical weekly three-hours reduction, implying a decrease in their leisure. This change induces higher participation among husbands at older ages without affecting their hours worked, and reduces couples' wealth after age 55.

Participation costs vary across groups and are governed by a quadratic function of age (Equation 3). For each group, we estimate three parameters and plot the implied fixed costs for each parameter change.

Raising the constant term in married women's participation cost by three hours (Figure 29) lowers participation among younger married women even further and steepens their participation profile, with a much smaller effect on hours worked. The effects on married men's participation and couples' wealth are in the same direction but smaller. Increasing the linear term in the participation cost (Figure 30) raises costs with age, driving married women's participation to zero at older ages and reducing their hours worked, especially later in life. It also raises married men's participation after age 40 and reduces the participation of single women by expanding the pool of divorced women with lower human capital. The resulting decline in couples' retirement wealth is large. Adjusting the quadratic term in the participation cost (Figure 31) steepens them later on, shifting the timing of participation.

We then study changes in available time and participation costs for married men. Reducing their available time by three hours per week (Figure 32) has little effect at younger ages but leads to faster declines in participation and hours worked later in life. Married women respond by increasing participation, although their hours remain stable. Couples' wealth holdings decline. Raising married men's participation cost reduces participation at older ages and decreases hours worked more sharply than reducing available time. Changes in the linear and quadratic terms of the participation cost function similarly alter the slopes of participation and hours over the life cycle.

We next turn to single women. Figures 36 to 39 show that reducing available time lowers both participation and hours worked, with a larger effect on participation. Lowering the constant in their participation cost reduces participation even more and has a smaller effect on hours. Changes in the linear and quadratic terms affect the age profiles of participation and hours differently, shifting both timing and magnitude.

Finally, we examine single men. Figures 40 to 42 show the effects of adjusting the constant, linear, and quadratic terms of their participation costs (with a normalized time endowment). Changes in these terms affect participation at different points in the life cycle—earlier for the constant term, and later for the linear and quadratic terms—and similarly influence hours worked conditional on participation.

Our model's identification thus rests on the distinct ways structural parameters map into savings, participation, hours worked, and wealth profiles across groups and over the life cycle. Preference parameters such as β and ω influence savings and labor supply differently across subgroups, allowing their identification. Bequest motives affect savings but leave labor supply largely unchanged for the range of parameter changes considered, and their differential effects on couples versus singles allow us to separately identify side and terminal bequests. Participation costs and time endowments are identified through their differential impacts on participation rates versus hours worked, exploiting variation over age, gender, and marital status. The rich structure of life-cycle behavior across demographic groups provides the variation necessary to pin down each parameter.

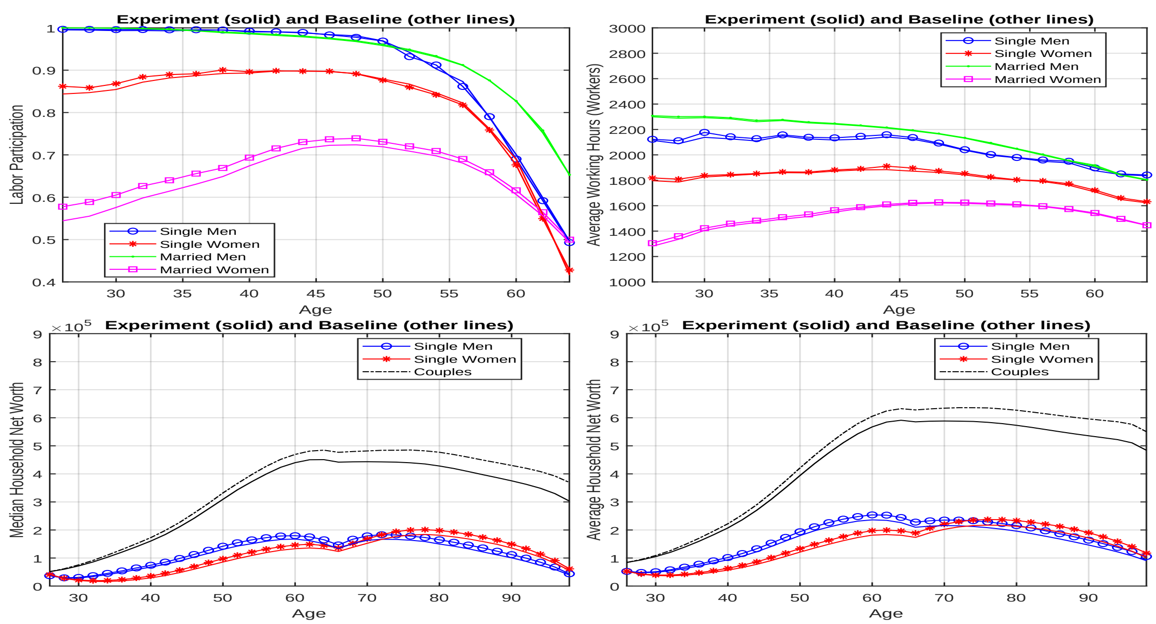

Figure 22: Discount factor decreased by 0.2% (solid), benchmark (other lines)

Table 14 in Appendix H reports the GMM criterion disaggregated by group and outcome for the benchmark model and for experiments varying one parameter at a time. In all cases, the GMM criterion rises, confirming that the model's parameters are well identified given the target moments we have chosen.

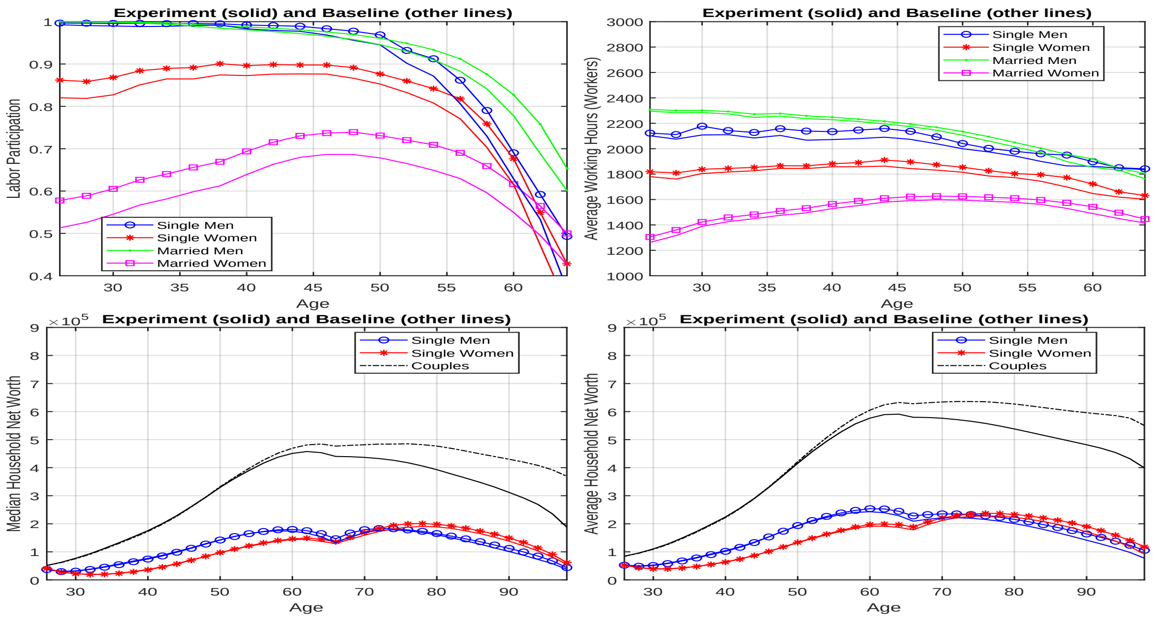

Figure 23: Weight on consumption decreased by 2.0% (solid), benchmark (other lines)

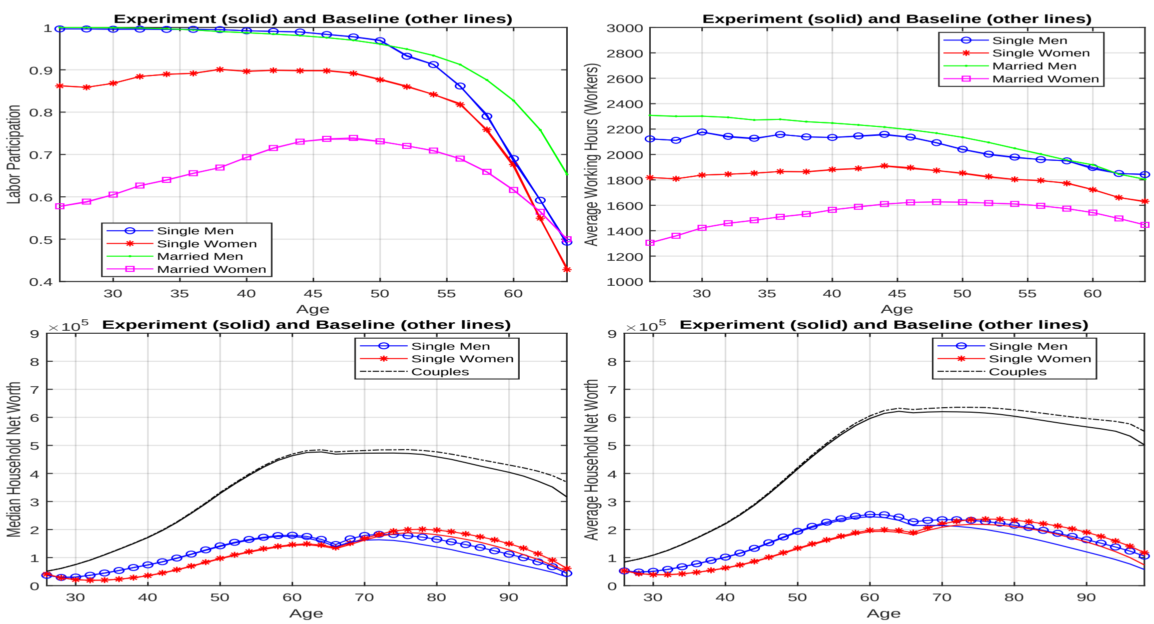

Figure 24: Terminal bequest strength decreased by 20% (solid), benchmark (other lines)

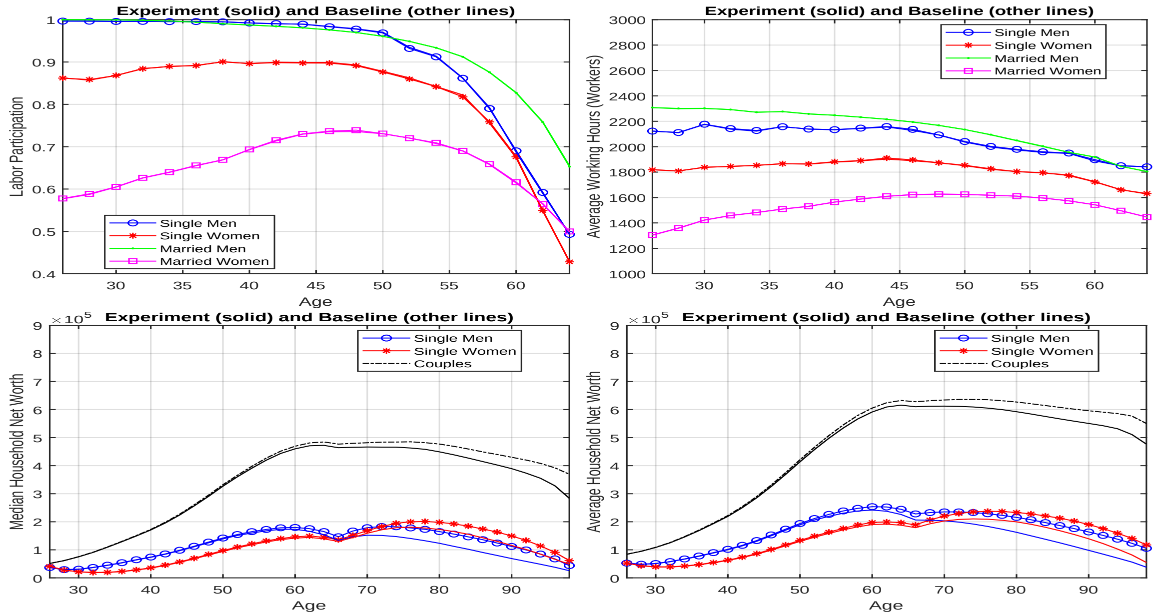

Figure 25: Terminal bequest shifter increased by 20% (solid), benchmark (other lines)

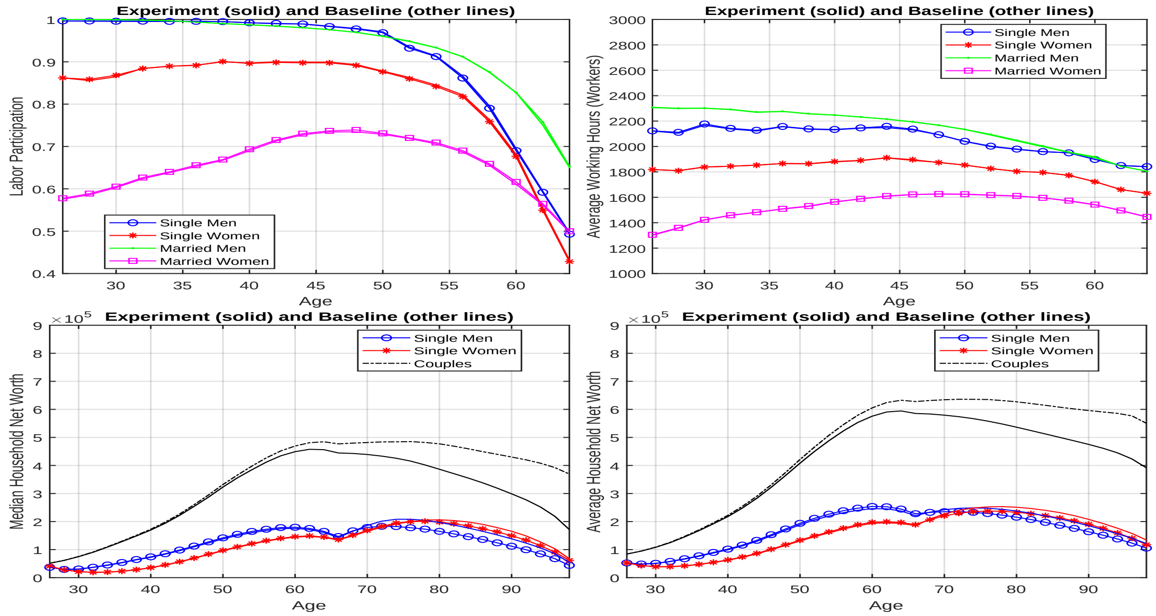

Figure 26: Side bequest strength decreased by 20% (solid), benchmark (other lines)

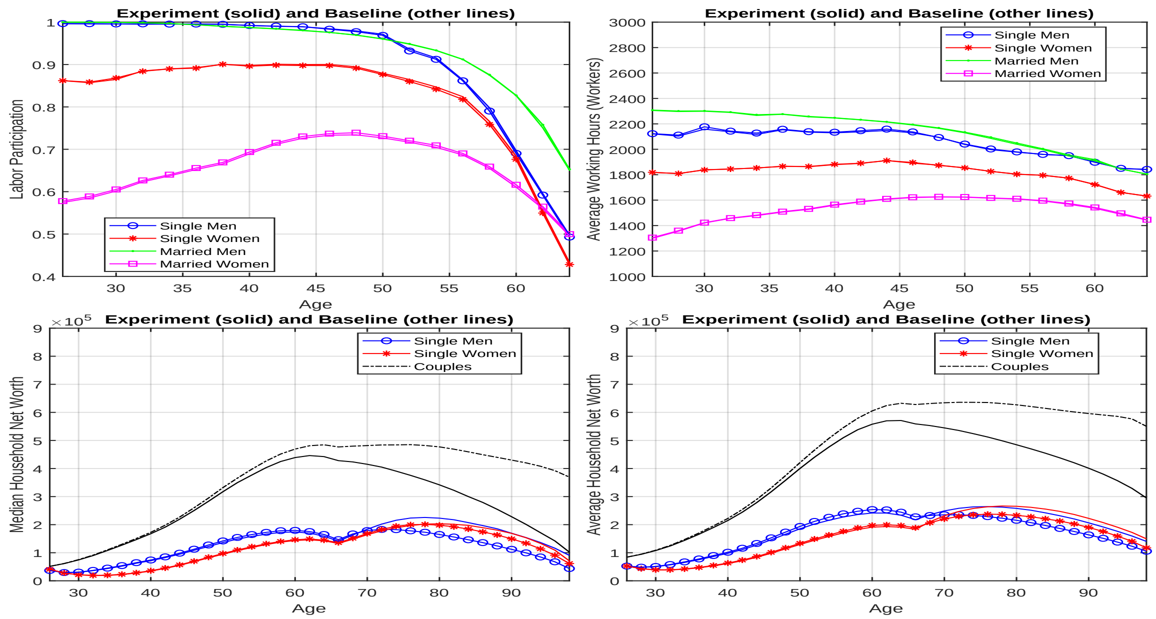

Figure 27: Side bequest shifter increased by 20% (solid), benchmark (other lines)

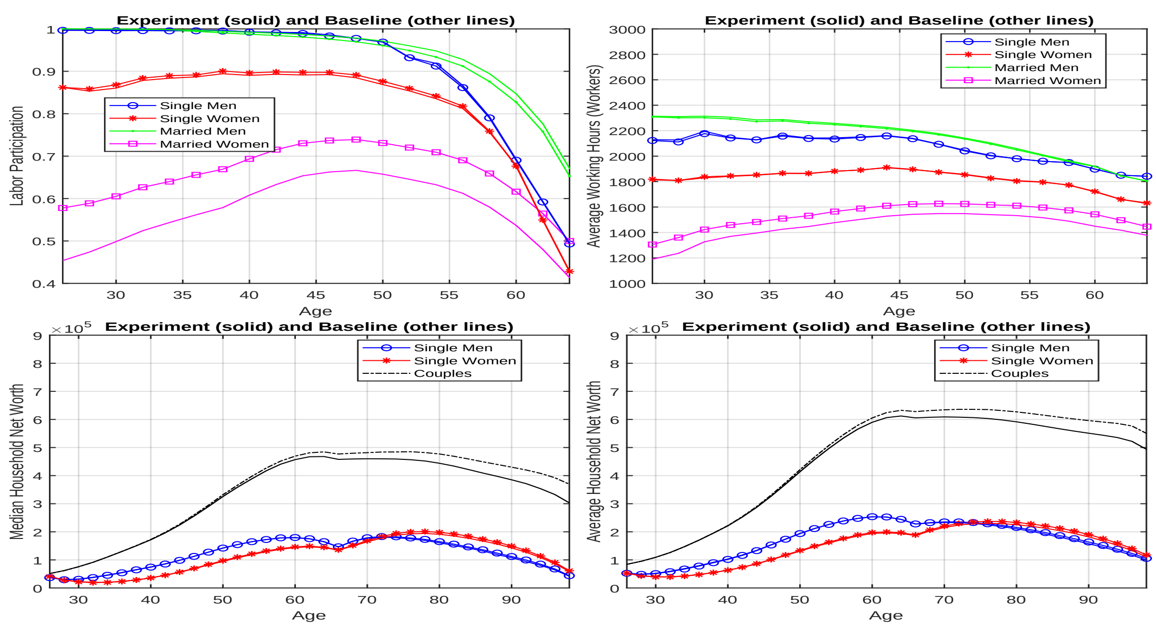

Figure 28: Married women's available time decreased by 3 hours a week (solid), benchmark (other lines)

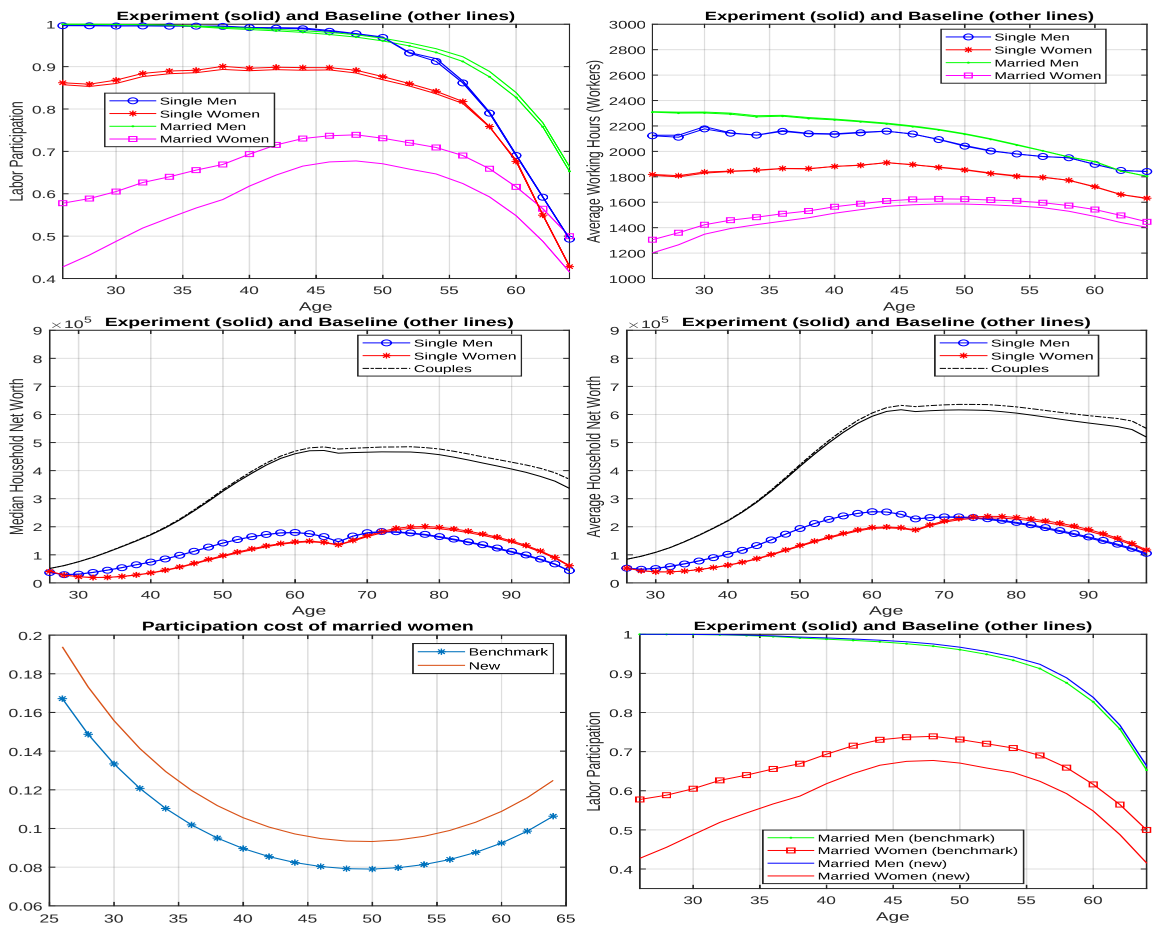

Figure 29: Married women: constant in the participation cost increased by 3 hours per week (solid), benchmark (other lines)

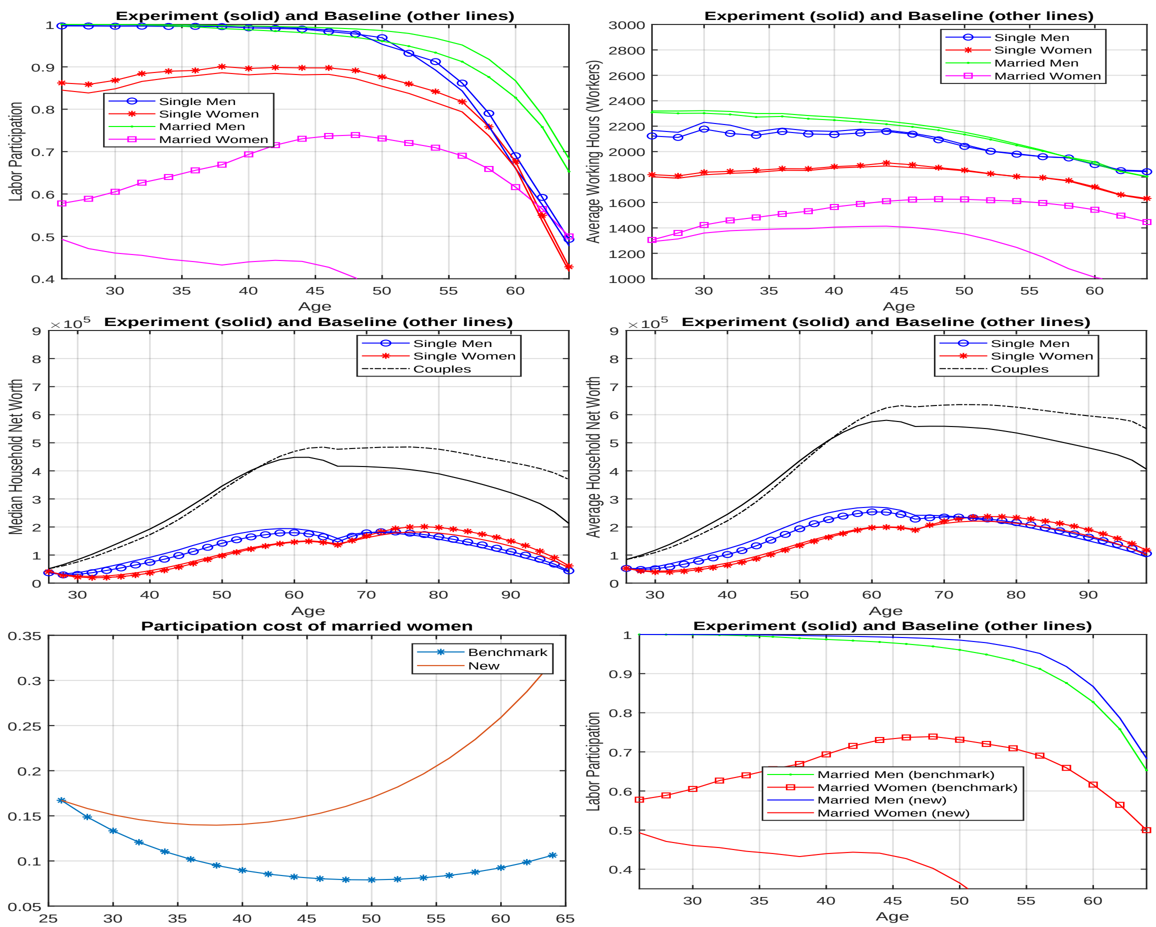

Figure 30: Married women: linear term in age in the participation cost ($p_1^{2,2}$) increased by 50% (solid), benchmark (other lines)

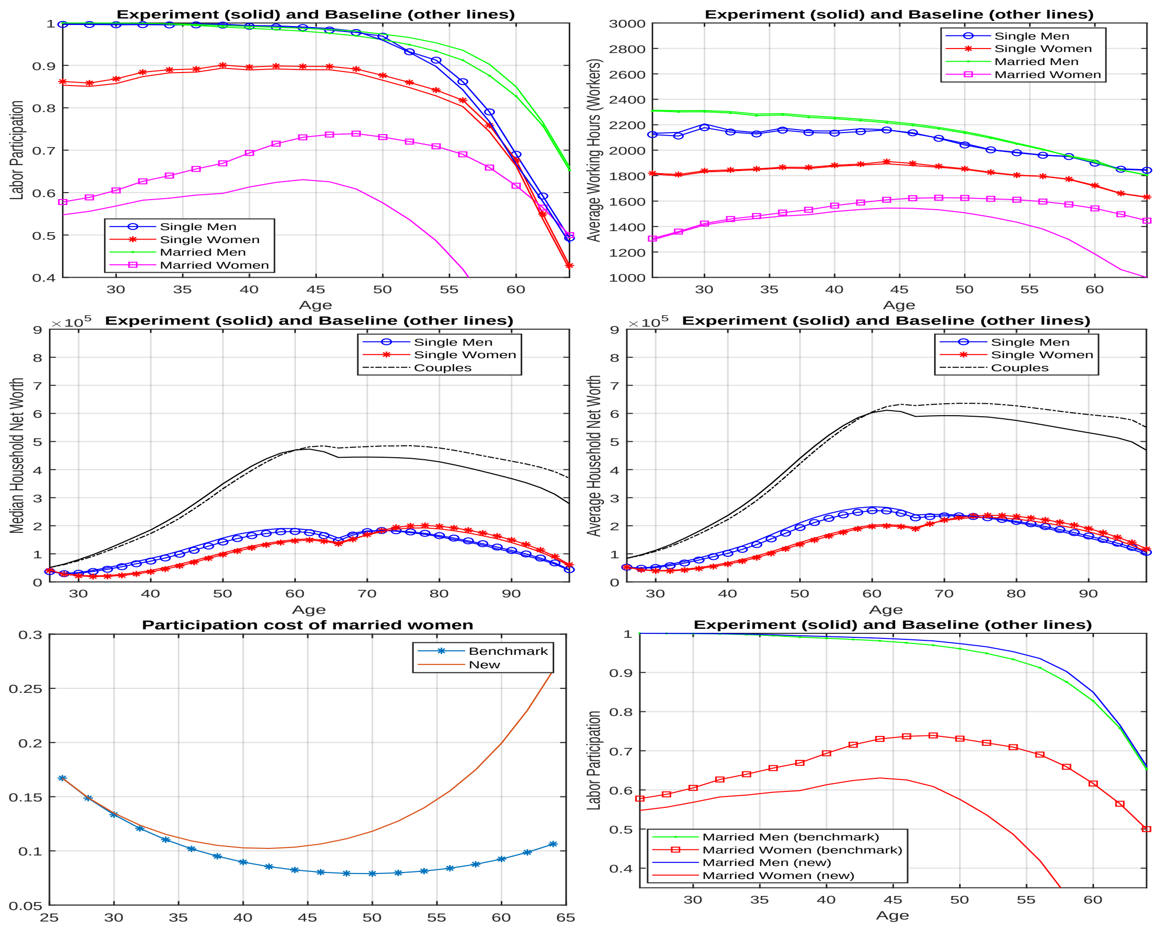

Figure 31: Married women: quadratic term in age in the participation cost ($p_2^{2,2}$) increased by 50% (solid), benchmark (other lines)

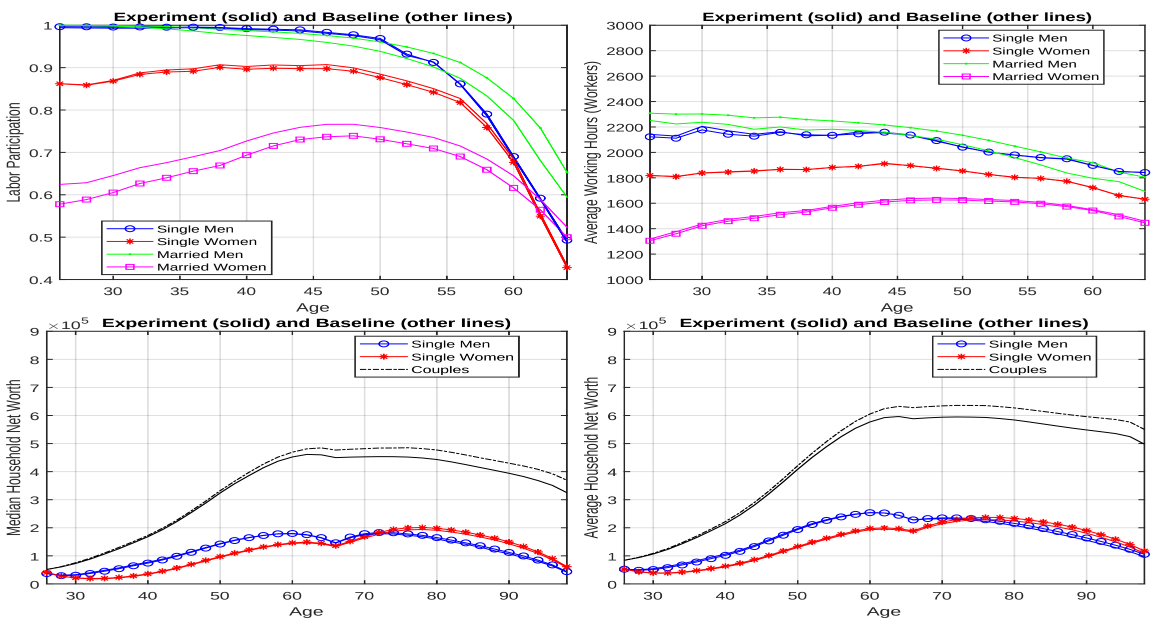

Figure 32: Married men's available time decreased by 5 hours per week (solid), benchmark (other lines)

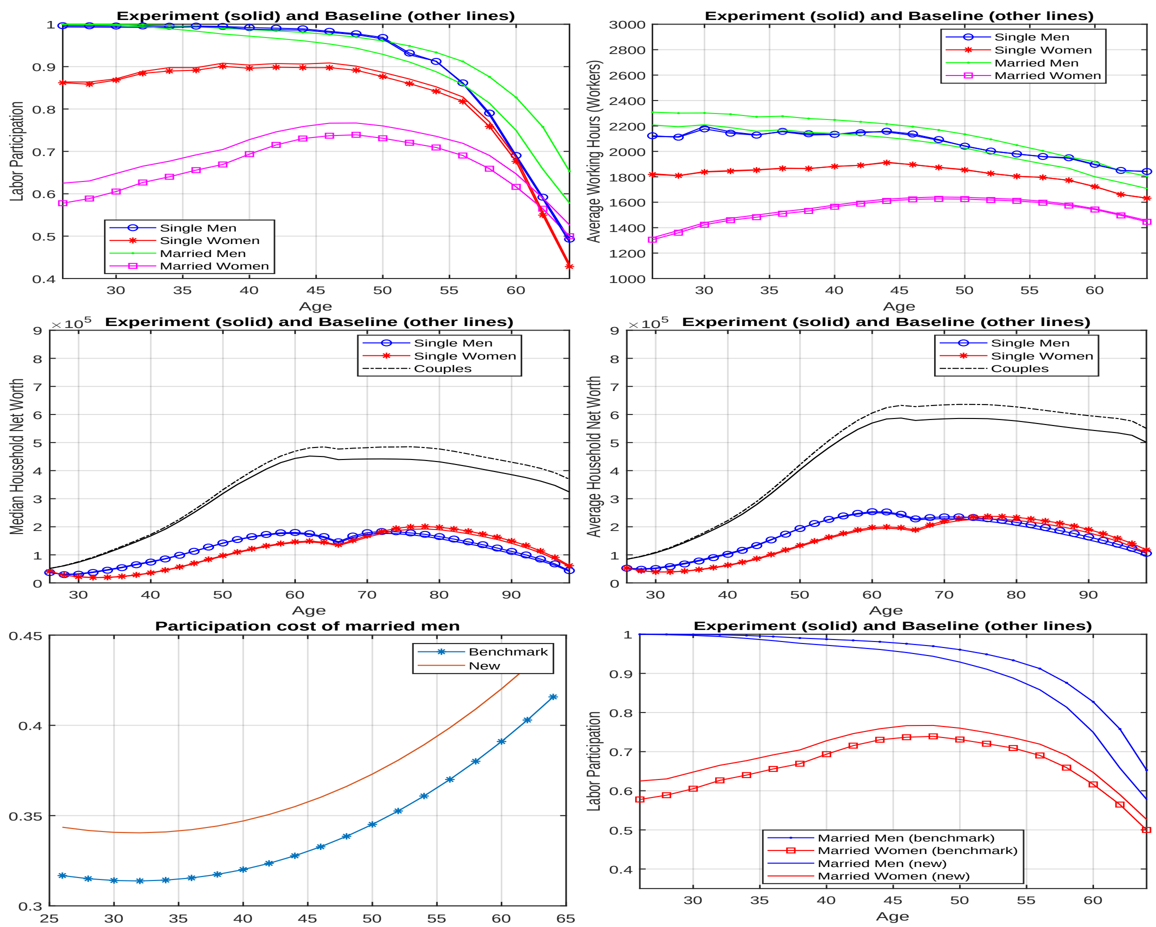

Figure 33: Married men: constant in the participation cost increased by 3 hours per week (solid), benchmark (other lines)

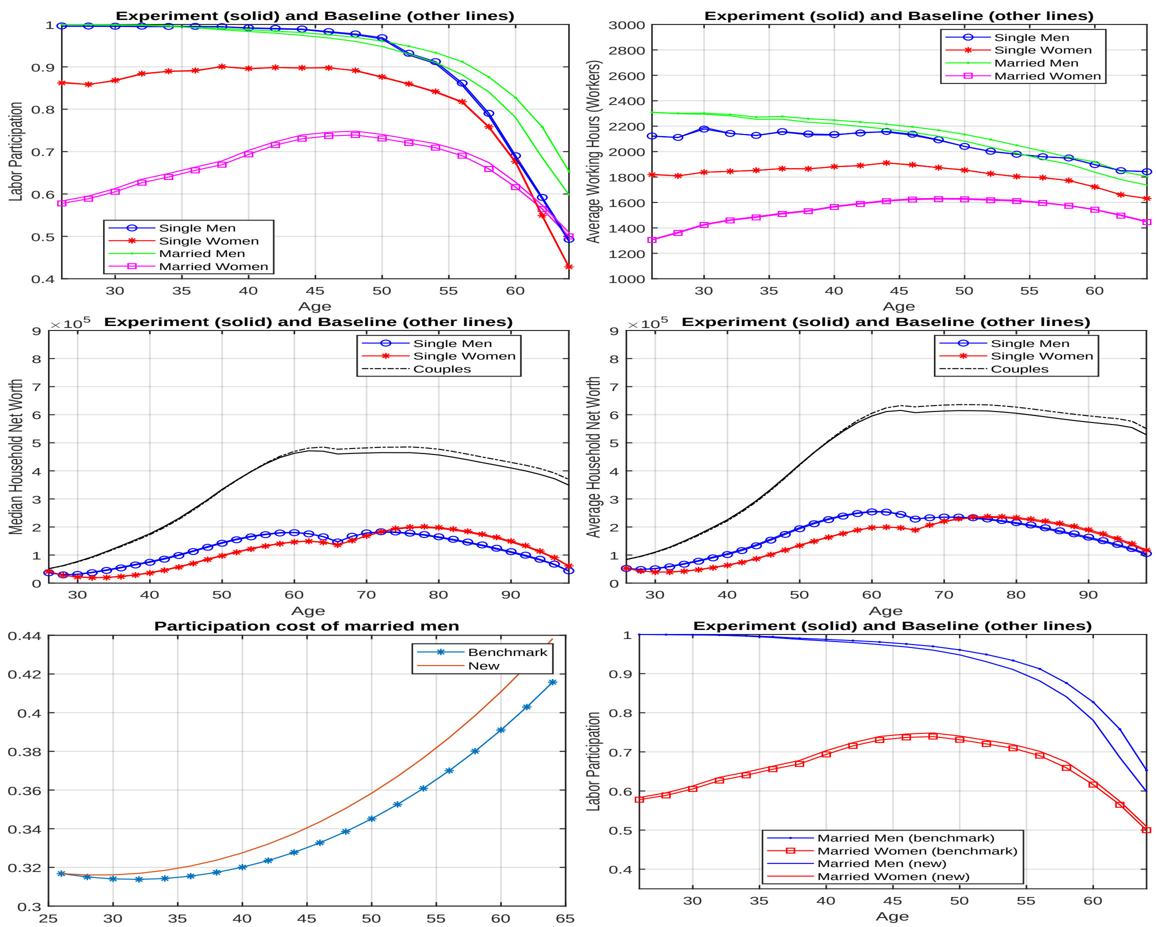

Figure 34: Married men: linear term in age in the participation cost ($p_1^{1,2}$) increased by 50% (solid), benchmark (other lines)

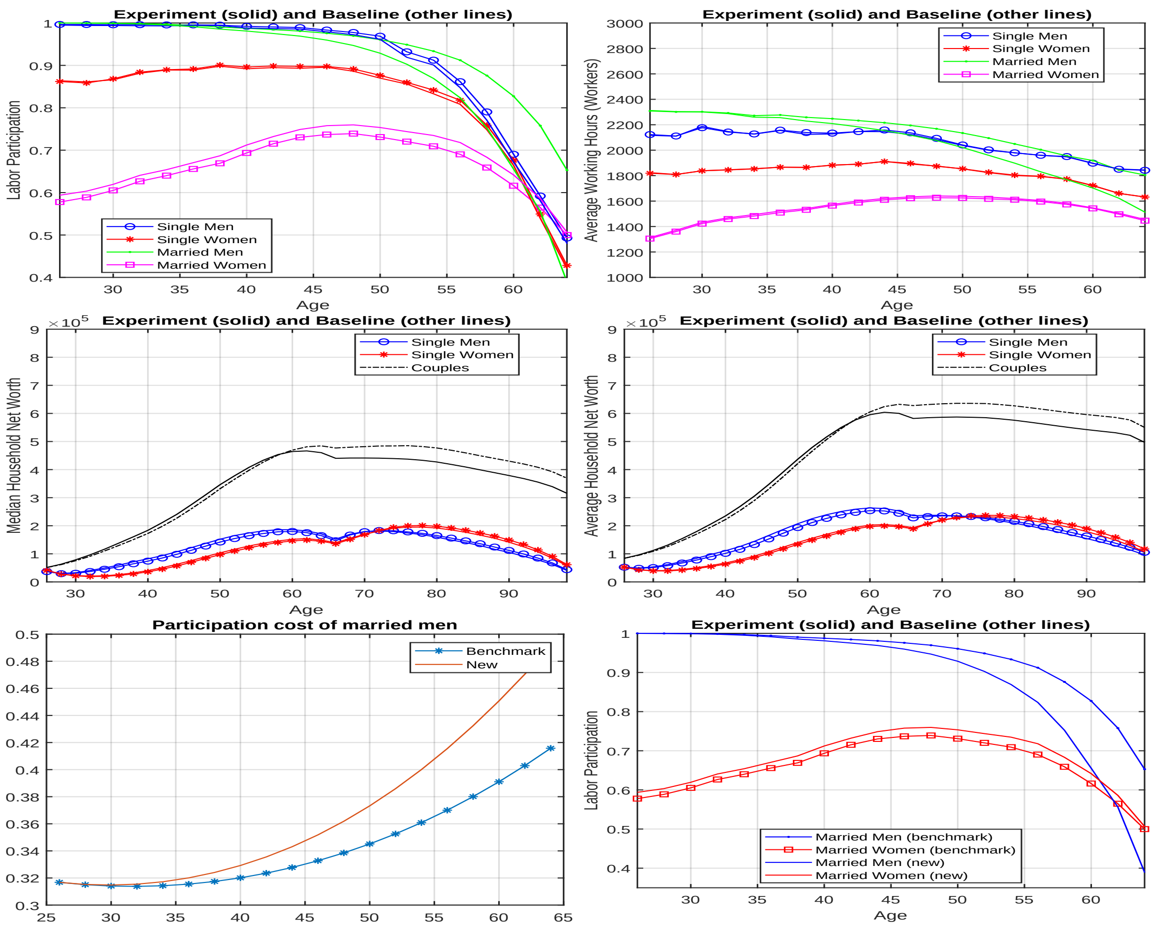

Figure 35: Married men: quadratic term in age in the participation cost ($p_2^{1,2}$) increased by 50% (solid), benchmark (other lines)

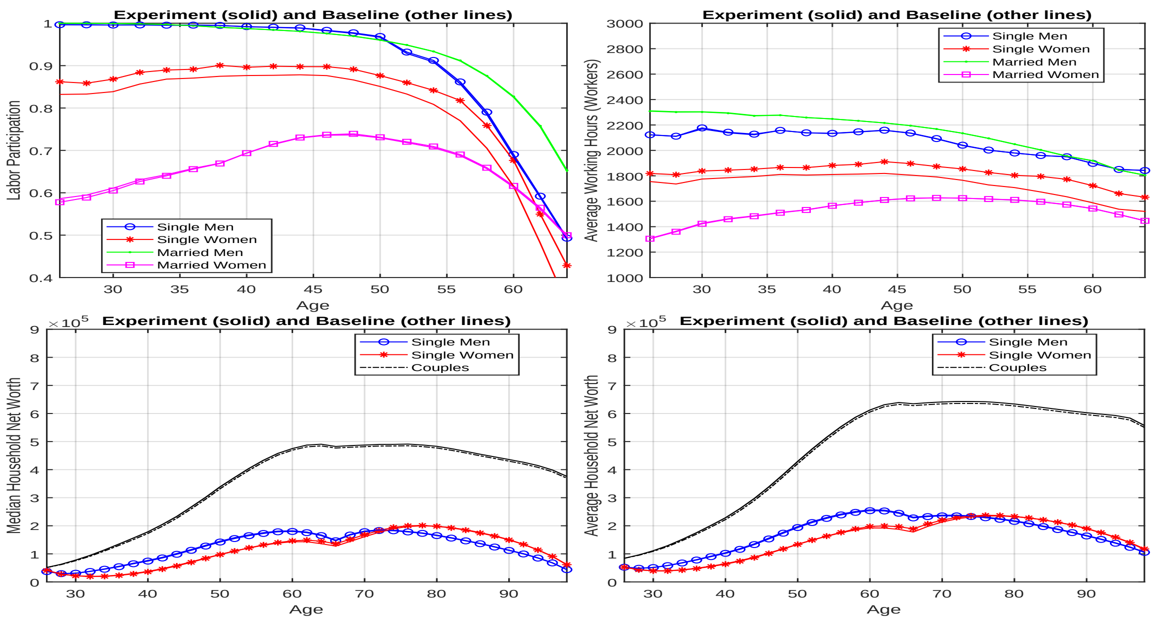

Figure 36: Single women: available time decreased by 3 hours per week (solid), benchmark (other lines)

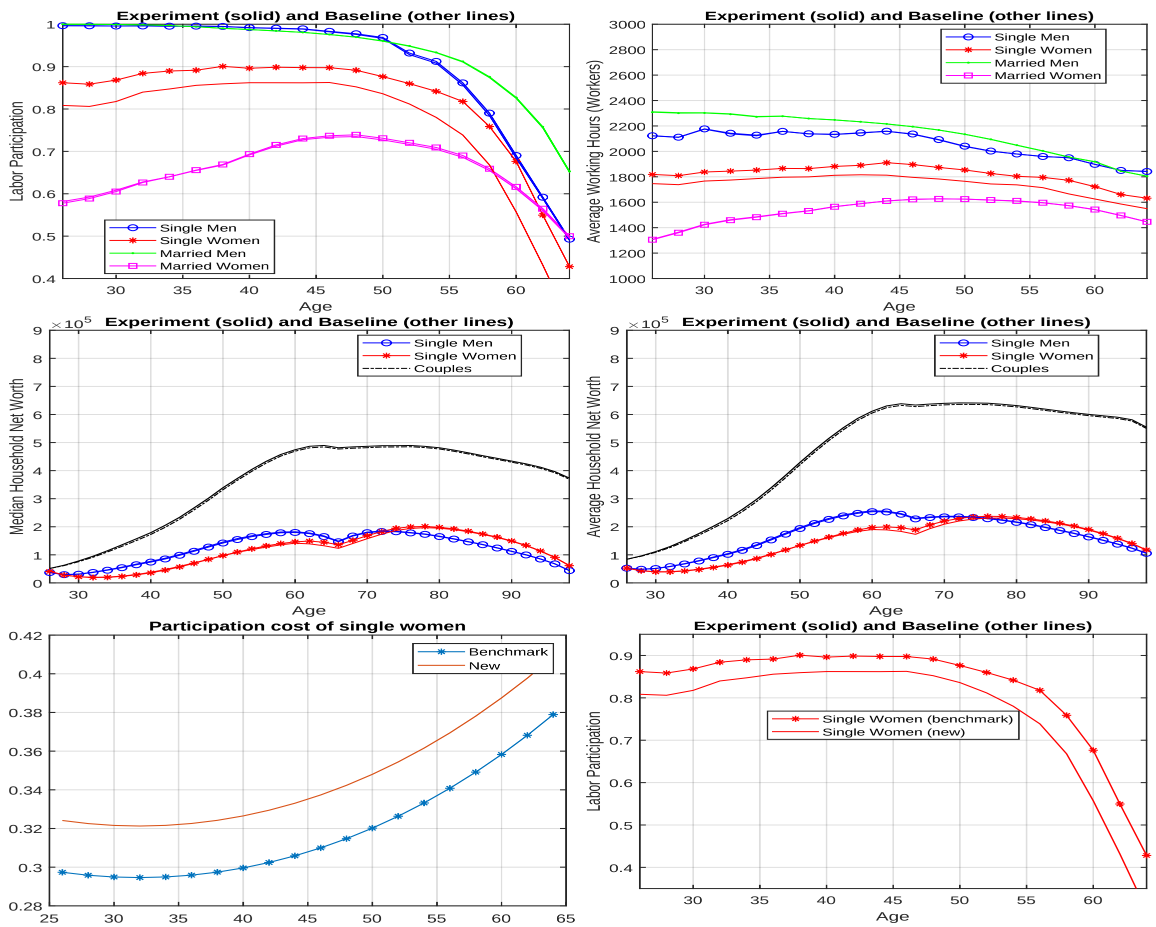

Figure 37: Single women: constant in the participation cost increased by 3 hours per week (solid), benchmark (other lines)

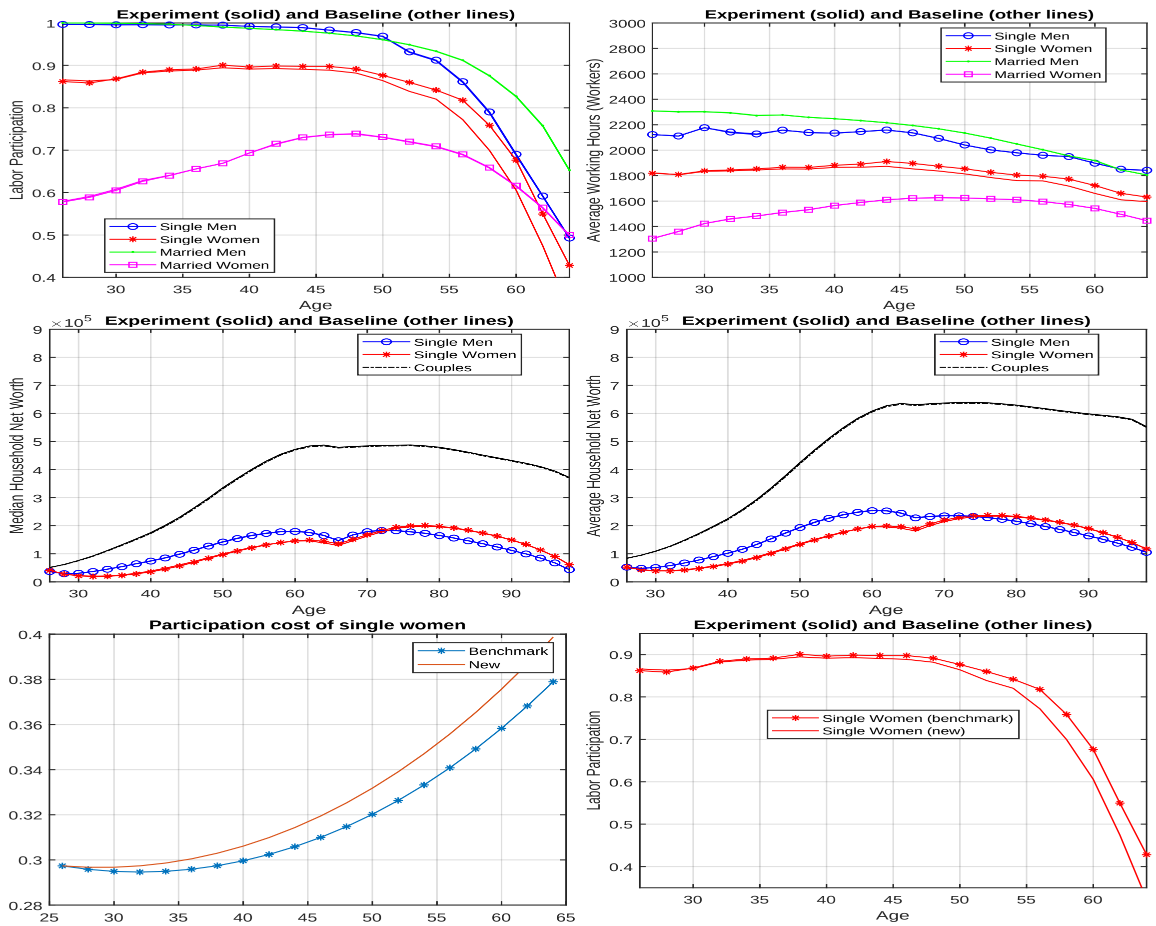

Figure 38: Single women: linear term in age in participation cost ($p_1^{2,1}$) increased by 50% (solid), benchmark (other lines)

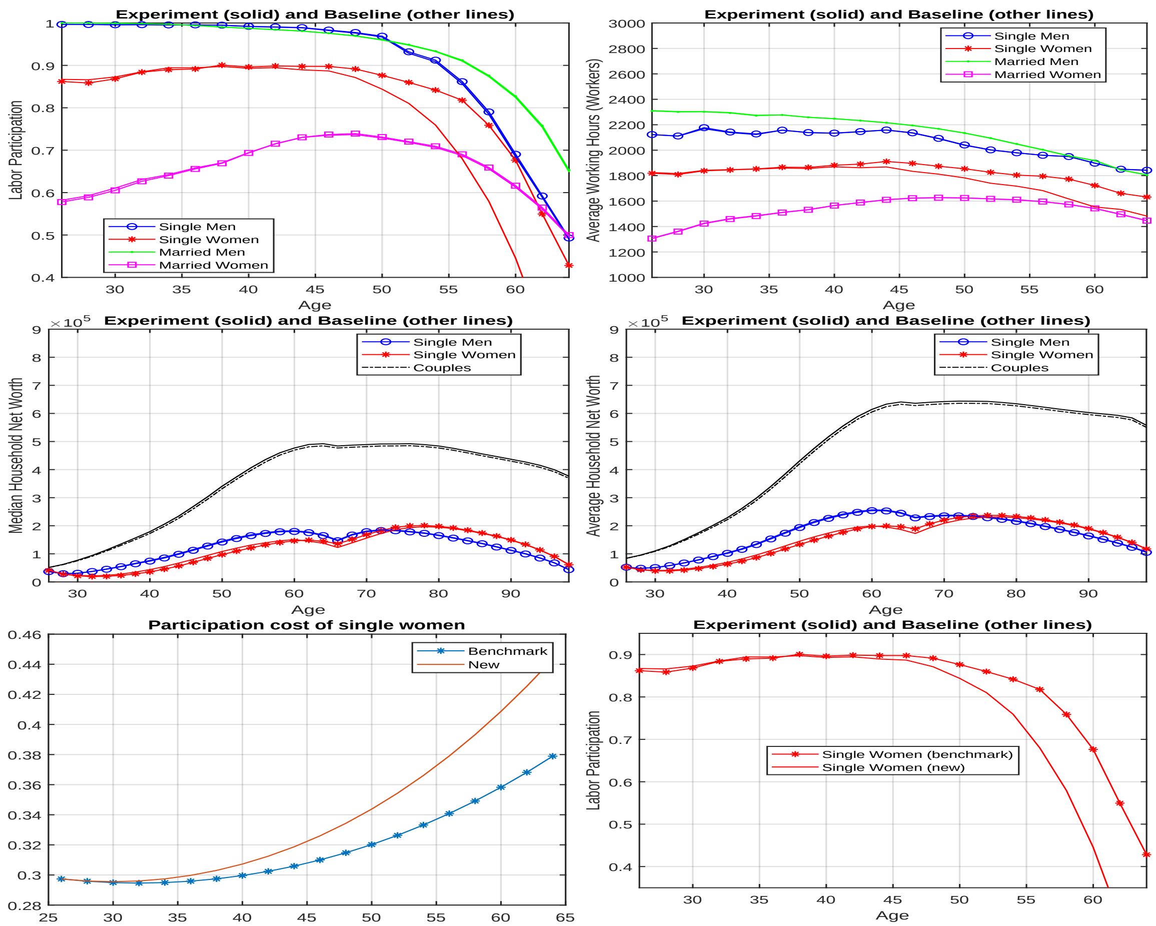

Figure 39: Single women: quadratic term in age in the participation cost ($p_2^{2,1}$) increased by 50% (solid), benchmark (other lines)

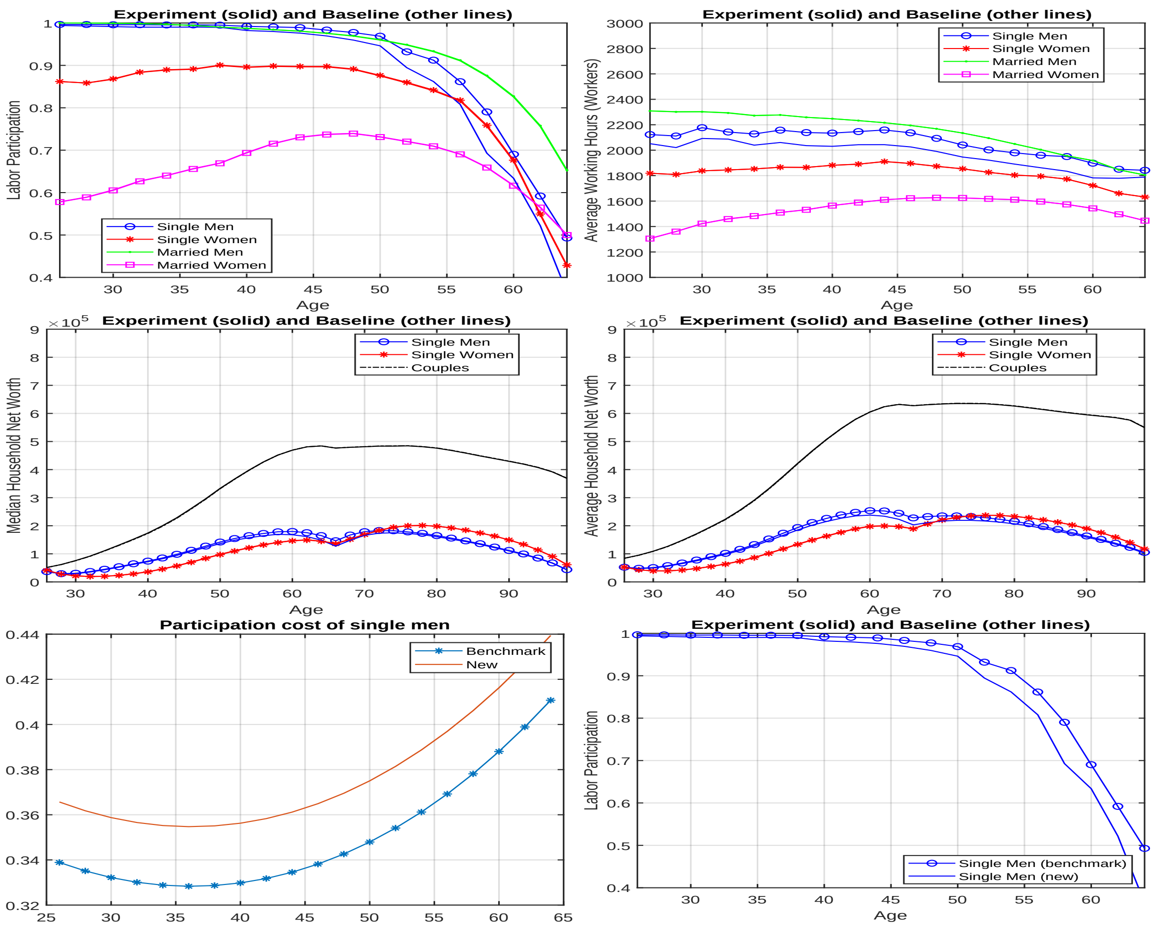

Figure 40: Single men: constant term in the participation cost ($p_0^{1,1}$) increased by 50% (solid), benchmark (other lines)

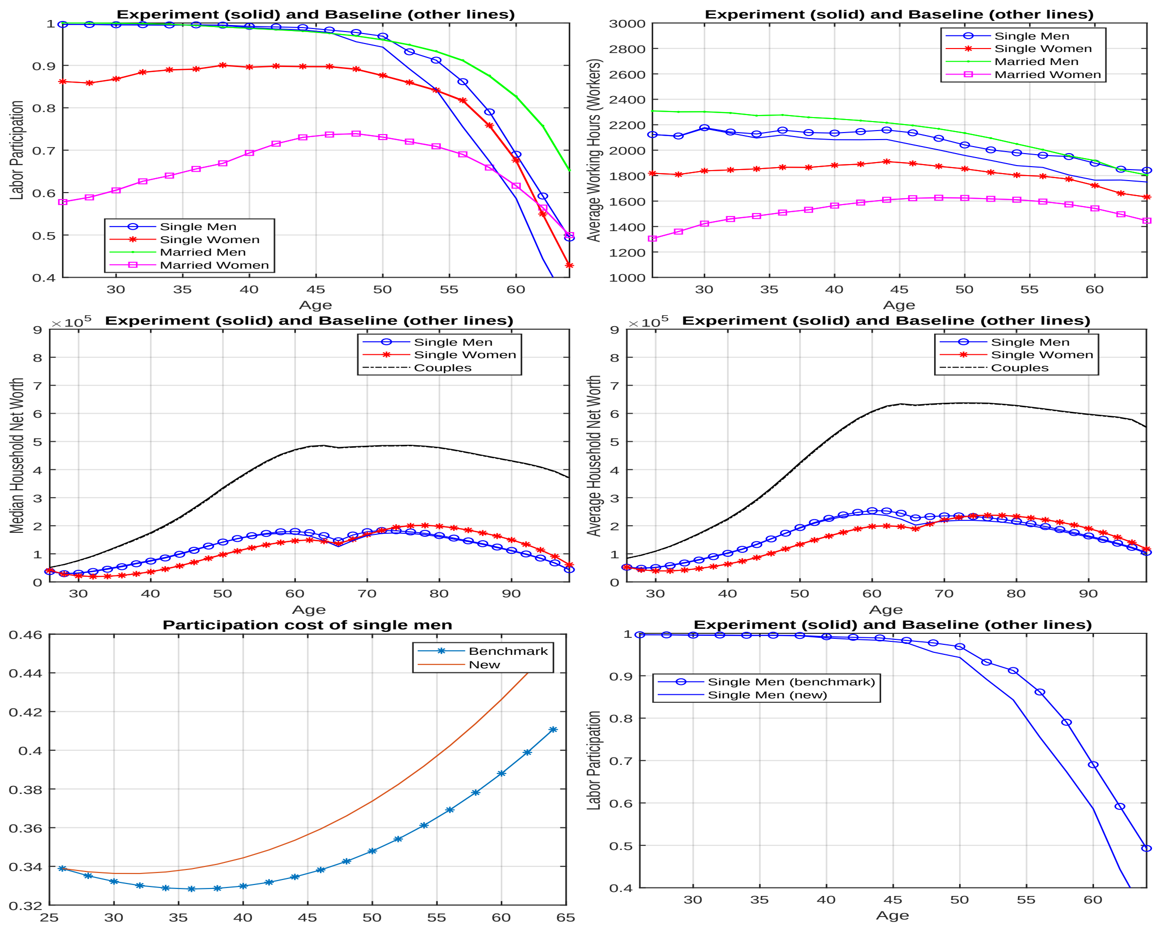

Figure 41: Single men: linear term in age in the participation cost ($p_1^{1,1}$) increased by 50% (solid), benchmark (other lines)

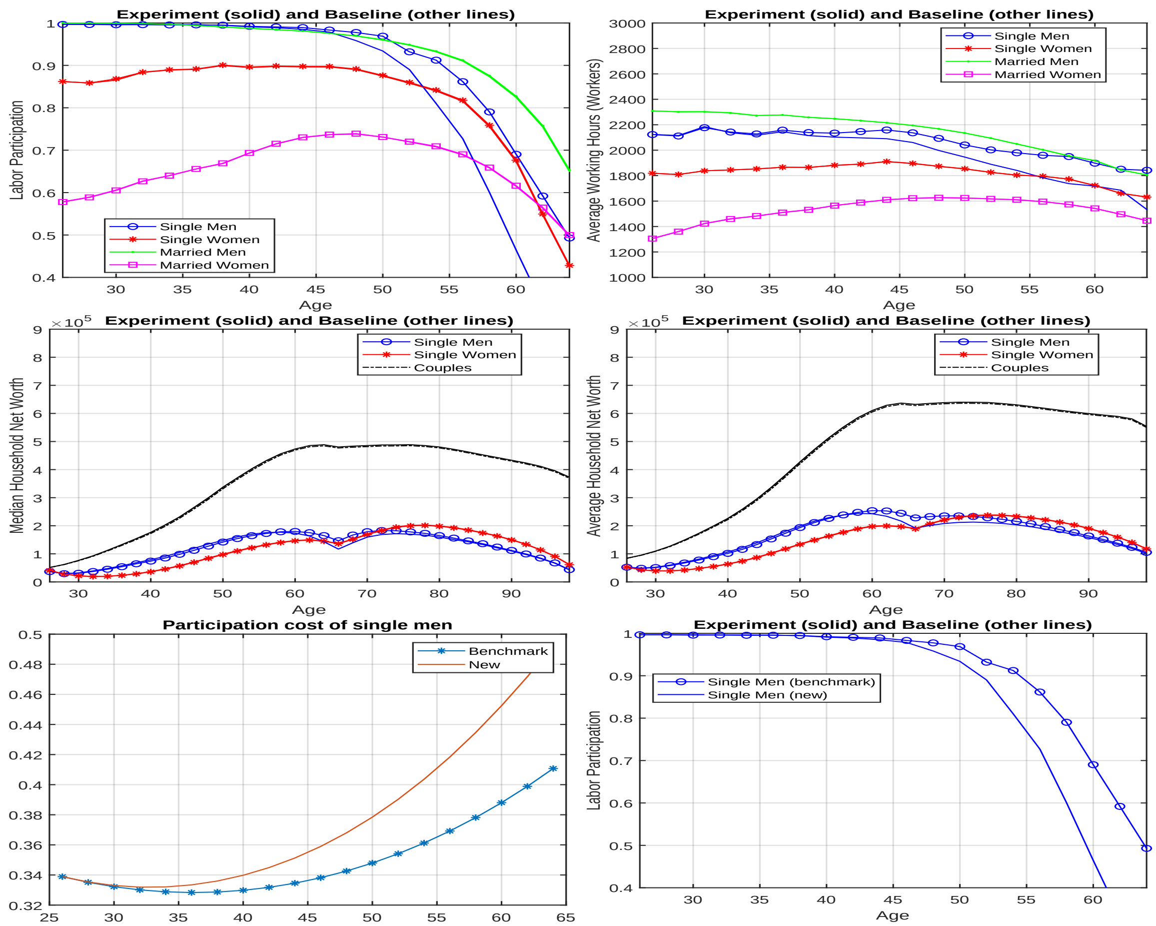

Figure 42: Single men: quadratic term in age in the participation cost ($p_2^{1,1}$) increased by 50% (solid), benchmark (other lines).

	Mean wealth			Median wealth			Hours among workers				Participation				
Specification	SM	SW	C	SM	SW	C	SM	SW	MM	MW	SM	SW	MM	MW	Total
Benchmark	96	210	138	74	322	340	75	20	27	54	38	29	119	67	1608
$\beta \downarrow 0.2\%$	11%	39%	14%	38%	25%	28%	4%	9%	-13%	83%	30%	14%	12%	-4%	24.1%
$\omega \downarrow 2.0\%$	8%	65%	-16%	6%	43%	-10%	-30%	332%	13%	372%	138%	102%	77%	68%	43.5%
$\phi_0 \downarrow 20\%$	44%	4%	-1%	52%	0%	-3%	2%	-2%	1%	2%	5%	4%	1%	-1%	5.3%
$k_0 \uparrow 20\%$	83%	10%	12%	98%	3%	-1%	2%	-1%	1%	2%	8%	3%	1%	-1%	12.7%
$\phi_1 \downarrow 20\%$	-33%	72%	14%	-22%	55%	6%	4%	-7%	-8%	5%	7%	1%	6%	1%	20.8%
$k_1 \uparrow 20\%$	-49%	174%	40%	-21%	129%	6%	5%	-12%	-8%	8%	10%	0%	11%	3%	50.7%
$p_2^{1,1} \uparrow 50\%$	19%	4%	2%	21%	2%	-2%	86%	7%	-15%	-1%	277%	1%	1%	3%	13.2%
$p_1^{1,1} \uparrow 50\%$	-0%	1%	1%	7%	-1%	-2%	-6%	5%	-10%	-0%	205%	1%	1%	2%	4.5%
$p_0^{1,1} \uparrow 18\%$	91	207	138	85	315	331	52	21	24	54	155	29	120	68	1689
$p_2^{2,1} \uparrow 50\%$	4%	9%	-2%	-2%	5%	-24%	-5%	1288%	-14%	-3%	3%	299%	2%	5%	18.3%
$p_1^{2,1} \uparrow 50\%$	2%	2%	-12%	-1%	0%	-12%	-2%	251%	-6%	-0%	2%	101%	1%	2%	1.7%
$p_0^{2,1} \uparrow 15\%$	100	216	109	72	318	313	70	142	24	56	39	103	121	70	1755
$p_2^{1,2} \uparrow 50\%$	35%	43%	3%	8%	23%	-16%	-18%	24%	1924%	-2%	8%	4%	415%	-2%	71.6%
$p_1^{1,2} \uparrow 50\%$	9%	0%	-4%	-0%	-5%	-7%	-7%	4%	4%	-6%	3%	1%	134%	-2%	7.3%
$p_0^{1,2} \uparrow 16\%$	102	258	130	77	354	335	70	16	117	73	39	29	633	70	2303
$p_2^{2,2} \uparrow 50\%$	45%	53%	-1%	14%	28%	-22%	-10%	45%	238%	2715%	-17%	7%	-15%	1077%	149.9%
$p_1^{2,2} \uparrow 50\%$	74%	86%	-17%	25%	47%	-37%	-11%	85%	548%	9435%	-30%	6%	-26%	2718%	454.4%
$p_0^{2,2} \uparrow 11\%$	98	211	126	76	316	339	79	23	53	488	36	27	109	145	2124
$L^{2,1} \downarrow 3\%$	4%	4%	-16%	-3%	0%	-7%	-5%	287%	-7%	-2%	4%	322%	1%	5%	7.2%
$L^{1,2} \downarrow 3\%$	9%	19%	0%	-1%	8%	4%	-5%	-20%	101%	26%	-7%	-0%	284%	2%	28.6%
$L^{2,2} \downarrow 4\%$	4%	6%	-13%	2%	1%	-6%	6%	14%	177%	843%	-8%	-4%	-17%	300%	41.6%

Table 14: Effects of parameter changes on GMM criteria. SM: single men; SW: single women; C: couples; MM: married men; MW: married women.