Beliefs and Responsiveness to Policy Change

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Abstract

The 1983 Amendments to the Social Security Act raised the normal retirement age and the reward for delayed claiming in order to encourage later claims as life expectancy grew. Men born between 1945 and 1949 claimed benefits 0.7 years later, on average, than men born between 1931 and 1935, but this is only half of the 1.4 year increase implied by the change in rules and the gain in longevity between the two cohorts. We ask how much of the change in claiming can be attributed to policy and how beliefs about the program and about longevity have shaped the response. We estimate a life-cycle model of saving, labor supply, and Social Security claiming separately for each cohort, in which individuals hold subjective survival beliefs and uncertain beliefs about the penalty for early claiming. Decomposing the change in claiming, we find that policy accounts for the entire increase, with the response concentrated among married and college educated men. Knowledge of the program improved and uncertainty about it rose, which together raise claiming ages by 0.2 years. This is offset by changes in other inputs, including subjective life expectancies that did not rise with actual longevity. The gap between incentives and behavior reflects unperceived gains in longevity and not a weak response to policy.

Keywords: Social Security, beliefs, life cycle, health, marriage, spousal benefits, survivor benefits, bequest motive, preference heterogeneity, policy change.

JEL Classification Numbers: J14, J26, E21, H55

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1 Introduction

The 1983 Amendments to the Social Security Act were designed to keep workers in the labor force longer and to delay benefit claims as life expectancy grew. A generation later, behavior has moved in the intended direction. On average, men born between 1945 and 1949 claimed Social Security 0.7 years later, increased labor force participation between ages 62 and 69 by 3 percentage points, and increased hours over the same age range by 4 percent relative to men born between 1931 and 1935. This paper asks two questions about that change. However, these changes alone cannot be used as evidence on the efficacy of policy. Rather, understanding the impact of these policy changes on behavior must also consider broader circumstances differ across such groups.

The two cohorts faced different Social Security rules. The early retirement age remained at 62 while the normal retirement age rose from 65 to 66 between these cohorts. Additionally, the delayed retirement credit rose from 5.5 to 8.0 percent per year. These policy adjustments incentivize later benefits claiming by decreasing the size of benefits received for early claims and increasing the growth in benefit sizes for delaying claims beyond the normal retirement age. Specifically, given an age 62 life expectancy of roughly 20 years (the life expectancy of the 1930s cohort), the change in these rules pushes the claiming age that maximized the present discounted value of benefits from 63.6 to 64.2 years. The later cohort, however, also lives longer; life expectancy at age 60 rose from 20.1 to 22.1 years. Under the new rules and the longer lifespan, the present value-maximizing claiming age rises to age 65.0, an increase of 1.4 years.[1]

Observed claiming rose by half the amount predicted by the simple incentives of the policy. Naively, this response implies workers respond to only half of the change implied by policy variation. This interpretation, however, is incomplete for two reasons. First, the cohorts differ in more than the rules they faced. Beyond the details of Social Security and the longer life expectancy detailed previously, these cohorts are different along many margins. Demographically, the 1945–1949 birth cohort is much more likely to have some college experience or higher and slightly less likely to be married. Conditional on being married, men born later are more likely to have a working and higher earning spouse. Second, this calculation assumes that workers are fully informed about Social Security rules, the change induced by the policy, and their own mortality. Previous work shows not only is misperception common but these subjective beliefs also driving claiming behavior and the response to policy reform. (Bairoliya and McKiernan, 2026, 2024).

To better measure how responsive behavior is to policy incentives, we take a more structural approach. We build a life-cycle model of consumption, saving, labor supply, and Social Security claiming. Our model explicitly captures key features of the U.S. Social Security system, including

[1] At the average life expectancy, this shift in the PDV-maximizing claiming age is mainly driven by the change in the normal retirement age. The large jump in the PDV-maximizing claiming age in Figure 4 for life expectancies above 83.6 years is due to the increase in the delayed retirement credit.

the trade-off between claiming age and benefit size, the details of the retirement earnings test, and the presence of spousal and survivors benefits available to married households. Agents are heterogeneous with respect to education and marital status and face exogenous shocks to health, labor productivity, and employment. Additionally, they hold subjective beliefs about life expectancy and penalties for early claiming. Survival beliefs evolve over the life cycle based on age, education, marital status, and health shocks. Agents also recognize that their beliefs about early claiming penalties might be incorrect and thus assign strictly positive probabilities to alternative outcomes. This comprehensive quantitative framework captures the fundamental economic trade-offs shaping labor supply and claiming decisions and detailed policy provisions, such as marital benefits, which may affect individuals differently. The breadth of these features is critical to our estimation strategy.

We estimate the model separately for the two cohorts of interest, those born 1931–1935 and those born 1945–1949, following a two-step process. In the first step, we directly estimate key components from data: health transitions, subjective survival beliefs, family structure, labor productivity, employment status, initial conditions, and policy parameters. In the second step, we appeal to our model and structurally estimate preference parameters and the distribution of subjective beliefs about the Social Security penalty. Preference parameters target the life-cycle evolution of wealth and labor supply, while penalty uncertainty is inferred from observed Social Security claiming behavior.

This data-driven and theoretically grounded approach to estimating subjective program beliefs combines survey responses with structural estimation. We first capture stated beliefs and self-reported confidence directly from the data and then use a revealed preference framework to infer the unobserved probability weights individuals place on alternative penalty outcomes. We incorporate these survey-based belief types and confidence weights into our structural model to quantify the full distribution of subjective beliefs about Social Security penalties. This distribution of beliefs is identified by how the distribution of Social Security claiming ages in a model excluding such subjective beliefs deviates from the distribution observed in the data for each of our cohorts of interest.

This estimation procedure highlights two results related to variation in subjective beliefs across these cohorts. First, despite the increases in life expectancy among the later cohort, subjective survival expectations do not keep up. Rather, we observe small increases (0.1-0.2 years) in subjective life expectancy among college educated individuals but decreases up to 0.5 years among those without college. The stagnation of subjective life expectancy drives individuals to underestimate both the years they will spend in retirement and, thus, the value of the additional annuity income received from delaying Social Security claims. Second, while individuals stated knowledge of Social Security rules improves between these two cohorts, Social Security claiming behavior reveals

that uncertainty increased over time. This higher estimated uncertainty pushes individuals to deviate from the best response of their stated knowledge. In other words, this higher uncertainty offsets the improved efficiency of claiming and labor supply behavior caused by improved knowledge.

Using our estimated model, we then decompose the change in claiming behavior between the cohorts. We start from the estimation of the 1931–1935 cohort and replace one set of objects at a time with that of the 1945–1949 cohort. We consider three sets of objects: Social Security policy rules, the Social Security program beliefs, and all remaining estimated inputs including health transitions, preferences, and longevity expectations. Results highlight the importance of policy. Imposing the later rules on the earlier cohort raises the average claiming age by 0.7 years, the full increase observed in the data. The response is concentrated among those best able to finance a delay. Policy alone raises claiming ages by 1.0 years for college educated men and 1.1 years for married men, compared to 0.5 years for men without a college education and 0.1 years for single men.

Subjective beliefs acts in different direction. Beliefs about longevity held the response back. The later cohort does not perceive the increase in its own life expectancy, and so the additional delay that longer lives should have produced does not occur. Changes in inputs, including survival beliefs along with preferences and family structure, lower the average claiming age by 0.2 years. Beliefs about the program worked in the opposite direction. Despite increased uncertainty, better knowledge of the penalty about its size raise the average claiming age by 0.2 years. Workers delay to insure against an irreversible loss of benefits. These two effects offset each other, which is why policy alone reproduces the observed change.

These results change the interpretation of the gap between incentives and behavior. Workers responded nearly one-for-one to the change in rules: the 0.7 year response to policy is close to the 0.6 year shift in the value-maximizing claiming age that the rules imply. The shortfall relative to the full 1.4 years reflects gains in longevity that workers did not perceive, not a weak response to policy. Reforms to the benefit schedule are therefore effective at changing claiming behavior, but mainly among married and college educated men, and the benefits of longer lives for program finances are not realized unless workers recognize them.

We contribute to a growing literature that uses rich structural life-cycle models of retirement, consumption, and savings to address questions of macroeconomics, labor economics, and public policy (Fan et al., 2022; Jones and Li, 2023; Bairoliya, 2019; Borella et al., 2023; De Nardi et al., 2010; Imrohoroğlu and Kitao, 2012; Jones and Li, 2018; Yu, 2024; French and Jones, 2011; Hubener et al., 2016; French, 2005; Hosseini et al., 2021). Our main contribution is to incorporate subjective beliefs into household decision-making and also to study the evolution of these beliefs over time. Prior structural work incorporating these beliefs has focused primarily on lifespan expectations (Van der Klaauw and Wolpin, 2008; Gan et al., 2015; Heimer et al., 2019; O'Dea and

Sturrock, 2023; de Bresser, 2024). Van der Klaauw and Wolpin (2008) was among the first to integrate subjective expectations into a structural life-cycle model of retirement, studying a sample of relatively poor U.S. households while Gan et al. (2015) and Heimer et al. (2019) examine the role of subjective survival beliefs in wealth accumulation. In contrast to other papers study the interaction between subjective beliefs, retirement, and Social Security claiming (Benitez-Silva et al., 2009; Gustman and Steinmeier, 2015; de Bresser, 2024; Dai et al., 2024), our approach uses data on informed beliefs, varies them across demographic groups, and offers a more empirically disciplined explanation for observed claiming behavior.

In addition to the life-cycle literature, we build on work measuring how retirement and benefit claiming responded to the Social Security rule changes faced by recent cohorts, including the increase in the normal retirement age (Mastrobuoni, 2009; Song and Manchester, 2008; Blau and Goodstein, 2010; Behaghel and Blau, 2012) and the increase in the delayed retirement credit (Pingle, 2006); Kopczuk and Song (2008) document the resulting patterns in administrative data. This literature finds that claiming tracks the normal retirement age closely, while estimated responses of average retirement ages and participation are smaller. A related literature studies how information and its presentation affect these decisions, through the framing of the claiming choice (Brown et al., 2011) and the introduction of the *Social Security Statement* (Mastrobuoni, 2011). We contribute by using a structural model to separate the effect of the rule changes from concurrent changes in cohort characteristics, preferences, and beliefs about the program and longevity.

2 Motivation

Changes in Policy Social Security policy has changed markedly over time, with changes both in the way benefits are calculated and in the way contributions are collected. Figures 1–3 place these rules in the context of the longer history of the program.

The most prominent changes concern the adjustment of benefits for the age at which they are claimed. Figure 1 shows the early and normal retirement ages by birth-year cohort. The early retirement age, the first age at which retirement benefits can be claimed, has remained at 62 throughout. The normal retirement age, at which full benefits are paid, was 65 for all cohorts born in 1937 or earlier. The 1983 Amendments to the Social Security Act raised it in two-month increments to age 66 for those born between 1943 and 1954, and again to age 67 for those born in 1960 or later. Men born between 1931 and 1935 therefore faced a normal retirement age of 65, while those born between 1945 and 1949 faced a normal retirement age of 66. Because the annual penalty for early claims was left unchanged, a later normal retirement age is equivalent to a reduction in benefits at every claiming age: a worker claiming at age 62 receives 80 percent of his full benefit under the earlier rules and roughly 73 percent under the later ones. Over the same

period, the delayed retirement credit was increased in steps of one half of a percentage point for every two birth-year cohorts, from 5.5 percent per year of delay, on average, for the 1931–1935 cohort to 8.0 percent for the 1945–1949 cohort. Together, these two changes lower the benefit available from early claims and raise the reward for claiming after the normal retirement age.

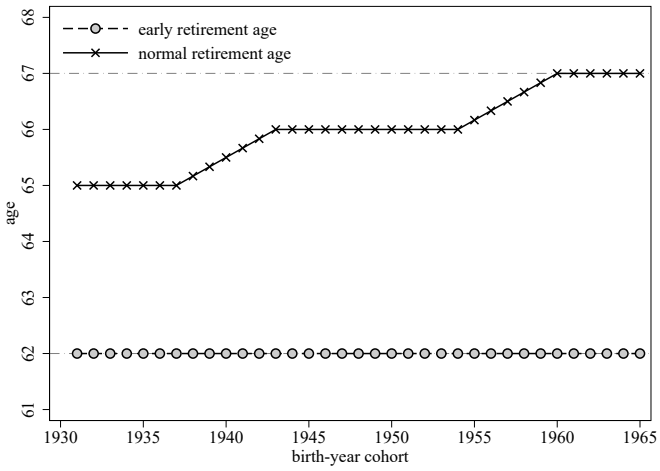
The treatment of beneficiaries who continue to work has also changed. Under the retirement earnings test, benefits are withheld when labor earnings exceed an exempt amount. Figure 3 shows the evolution of this exempt amount in real terms along with the rate at which benefits are withheld. Until 1999, the test applied both before and after the normal retirement age, with a higher exempt amount and, from 1990, a lower withholding rate for older beneficiaries. In 2000, the test was eliminated for beneficiaries who have reached the normal retirement age. The 1931–1935 cohort, who reached age 65 between 1996 and 2000, were for the most part still subject to the test after the normal retirement age, whereas the 1945–1949 cohort faced it only before the normal retirement age. For the later cohort, claiming at the normal retirement age no longer requires giving up benefits while working, which removes one reason to postpone a claim beyond that age.

Finally, the rules that determine contributions have changed. Figure 2 shows the payroll tax rate and the maximum amount of earnings subject to the tax. The tax rate rose from 1.0 percent in the 1940s to 6.2 percent in 1990 and has been constant since. The taxable maximum fell in real terms through 1950, when it was fixed in nominal terms, and has since increased more than fourfold. Because the two cohorts worked in different calendar years, the later cohort faced both a higher tax rate and a higher taxable maximum over its working life: an average rate of 5.84 percent and an average taxable maximum of $64,704 for the 1945–1949 cohort, compared to 5.01 percent and $49,365 for the 1931–1935 cohort. A higher taxable maximum raises contributions for high earners, but it also raises the earnings that are credited toward their future benefits.

Changes in Inputs and Behavior The two cohorts differ both in their characteristics and in their behavior at older ages. Table 1 summarizes these differences. The upper panel shows that the later cohort is more educated and lives longer: the share of men with a college education rises from 48.0 to 66.7 percent, and life expectancy at age 60 increases from 20.1 to 22.1 years. Their households have also changed. The share married falls slightly, from 76.5 to 74.3 percent, and the average age gap between spouses narrows from 3.6 to 2.9 years. The largest change is in the labor supply of wives: spousal participation increases from 43.8 to 61.3 percent, and average spousal earnings rise from $14,500 to $17,430.

The lower panel shows that behavior changed as well. The average Social Security claiming age rises by 0.7 years, from 63.5 to 64.2. Labor supply at ages 62 to 69 rises more modestly: participation increases from 40.9 to 43.9 percent, and men who work supply 82 more hours per year, an increase of roughly 4 percent.

Figure 1: Early, Normal Retirement Ages over Time



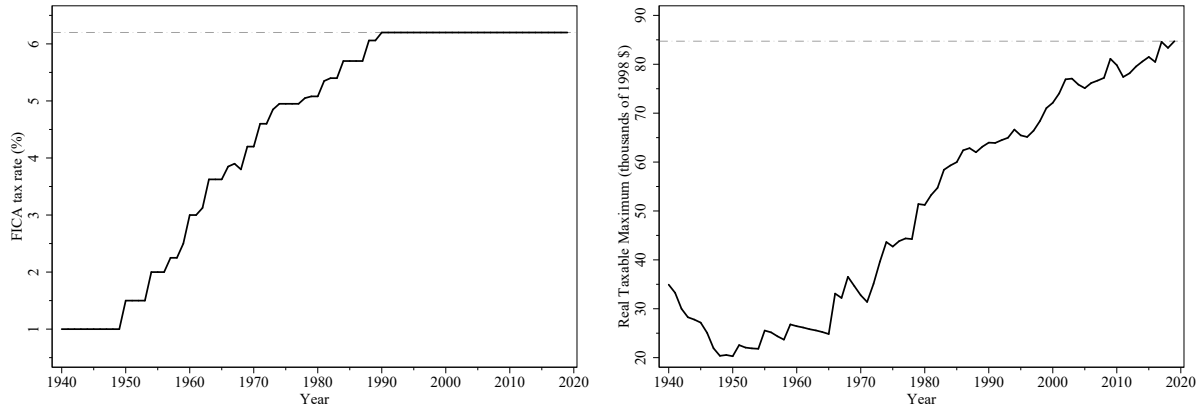
Source: Social Security Administration.

Notes: The figure shows the early retirement age and the normal retirement age by year of birth. The early retirement age is the first age at which Social Security retirement benefits can be claimed; the normal retirement age is the age at which full benefits are paid. Horizontal lines mark ages 62 and 67. The 1931–1935 cohort faced a normal retirement age of 65 and the 1945–1949 cohort a normal retirement age of 66.

Figure 2: Contribution Policy Rules over Time

(a) FICA Rate

(b) Taxable Maximum

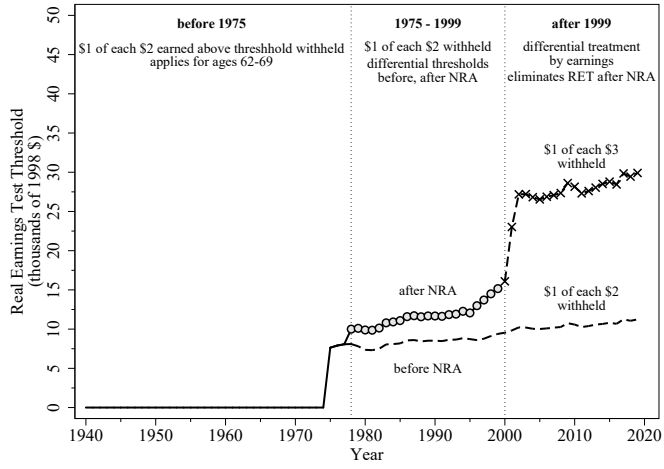


Source: Social Security Administration.

Notes: Panel (a) shows the Social Security (OASDI) payroll tax rate paid by employees in each calendar year. Panel (b) shows the maximum amount of annual earnings subject to the tax, in thousands of 1998 dollars. The horizontal line in each panel marks the most recent value.

The delay in claiming is in the direction the changes in policy would predict, but it does not establish that policy is responsible. More education and longer lives favor later claiming even under unchanged rules, while wives with their own earnings rely less on spousal benefits and a

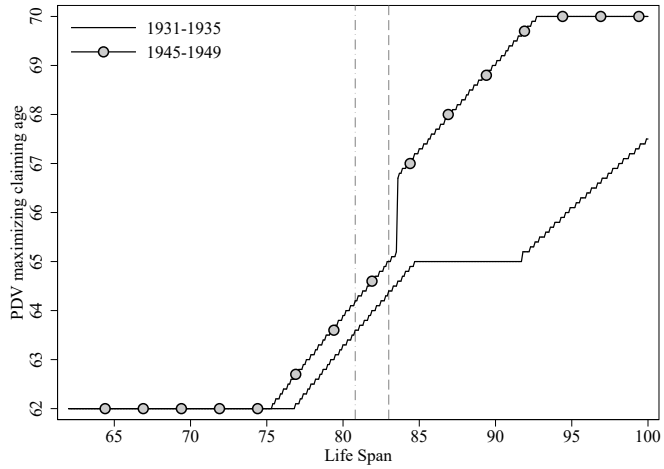
Figure 3: Retirement Earnings Test over Time



Source: Social Security Administration.

Notes: The figure shows the annual exempt amount under the retirement earnings test in thousands of 1998 dollars. Benefits are withheld at the indicated rate for each dollar of earnings above the exempt amount. Where two lines are shown, the lower line is the exempt amount for beneficiaries below the normal retirement age and the upper line is the exempt amount for older beneficiaries (through 1999) or for beneficiaries in the calendar year in which they reach the normal retirement age (from 2000). Vertical lines separate the three policy regimes.

Figure 4: PDV Maximizing Social Security Claiming Age



Source: Social Security Administration.

Notes: The figure shows the annual exempt amount under the retirement earnings test in thousands of 1998 dollars. Benefits are withheld at the indicated rate for each dollar of earnings above the exempt amount. Where two lines are shown, the lower line is the exempt amount for beneficiaries below the normal retirement age and the upper line is the exempt amount for older beneficiaries (through 1999) or for beneficiaries in the calendar year in which they reach the normal retirement age (from 2000). Vertical lines separate the three policy regimes.

Table 1: Changes in Inputs and Behavior by Birth-Year Cohort

	1931–1935	1945–1949	Gap
Panel A: Inputs			
Married (%)	76.5	74.3	−2.2
College (%)	48.0	66.7	18.7
Spousal age gap (years)	3.6	2.9	−0.7
Spousal participation (%)	43.8	61.3	17.5
Spousal earnings (thousands of 1998 $)	14.5	17.4	2.9
Life expectancy at age 60 (years)	20.1	22.1	2.0
Panel B: Behavior			
Participation, ages 62–69 (%)	40.9	43.9	3.0
Annual hours if working, ages 62–69	1,929	2,011	82
Social Security claiming age (years)	63.5	64.2	0.7

Source: Health and Retirement Study (RAND HRS 1992–2020) linked to SSA administrative records, authors' calculations. Men born 1931–1935 and 1945–1949.
Notes: College is defined as some college or above. Participation is defined as having strictly positive labor earnings. Annual hours are for those participating. The gap is the 1945–1949 value minus the 1931–1935 value.

smaller age gap shortens the period over which survivor benefits are collected. Separating the role of policy from these concurrent changes in inputs, and from changes in beliefs about the program, requires a model of the claiming and labor supply decisions, to which we turn in Section 3.

3 Quantitative model

This section presents a structural life-cycle model of retirement and Social Security. We model the consumption (c_t), labor supply (h_t), savings (a_{t+1}), and Social Security benefit application (b_t^{ss}) decisions of a male household head. Individuals make these decisions in every period t and adjust their behavior in response to uncertainty pertaining to employment, wages, health status, subjective survival, and subjective program knowledge.

Individuals live from age $t = 25$ to age $T = 99$ and differ along both fixed characteristics and evolving state variables. Fixed characteristics include birth-year cohort (j), education (e), marital status (q), and subjective SS penalty belief type (k). Marriage is summarized by a pair $q = (m, \iota)$, where m is an indicator variable taking a value of 1 if married and, if married, ι denotes the age gap between spouses. Time-varying states include stochastic labor productivity (η_t); employment status (λ_t); health status (μ_t); liquid assets (a_t); Social Security wealth of the head of household (a_t^{ss}); if applicable, Social Security wealth of a spouse (a_{st}^{ss}); and household benefit application

status (b_{t-1}^{ss}). Given this vector of states $\left(j, e, q, k, \eta_t, \lambda_t, \mu_t, a_t, a_t^{ss}, a_{st}^{ss}, b_{t-1}^{ss}\right)$, individuals choose consumption and labor supply and, if eligible, make Social Security benefit application decisions to maximize the present discounted value of lifetime utility.

Cohorts differ both in the economic environment they face and in the Social Security rules that apply to them. Preferences, the time endowment and participation costs, the wage and unemployment processes, health transitions and survival beliefs, subjective program beliefs, taxes and transfers, and Social Security policy parameters are all permitted to vary by cohort. Throughout, a superscript j denotes a cohort-specific parameter or function. Because an individual from cohort j is age t in calendar year $j+t$, objects indexed by both j and t (for example, the Social Security taxable maximum or the parameters of the retirement earnings test) capture policy rules that change over calendar time. Indexing a parameter by j permits, but does not require, it to differ across cohorts. To simplify notation, we suppress j on state and choice variables, which are understood to be cohort-specific.

3.1 Preferences

In each period t, agents derive utility from consumption c_t and leisure l_t, with non-separable preferences over the two given by:

$$U^{e,m,j}(c_t, l_t) = \frac{1}{1-\rho^{e,m,j}} \left(\left(\frac{c_t}{\zeta_t^{e,m,j}} \right)^{\nu^{e,m,j}} l_t^{1-\nu^{e,m,j}} \right)^{1-\rho^{e,m,j}}$$

where $\rho^{e,m,j}$ is the coefficient of relative risk aversion, $\nu^{e,m,j}$ is the utility weight on consumption, and $\zeta_t^{e,m,j}$ is the consumption equivalence scale. Future utility is discounted at rate $\beta^{e,m,j}$. All of these parameters are permitted to vary by education (e), marital status (m), and birth-year cohort (j). The total amount of leisure in period t is given by:

$$l_t = \bar{l}^{e,m,j} - h_t - \phi_P^{e,m,j}(t)\, \mathbb{I}\{h_t > 0\} - \phi_H^{e,m,j}(\mu_t, t) \tag{1}$$

Here, $\bar{l}^{e,m,j}$ is the total time endowment, h_t is hours worked, $\phi_P^{e,m,j}(t)$ is the participation cost incurred when $h_t > 0$, and $\phi_H^{e,m,j}(\mu_t, t)$ is the time cost of poor health. The participation cost is:

$$\phi_P^{e,m,j}(t) = \frac{\exp(\phi_0^{e,m,j} + \phi_1^{e,m,j} t + \phi_2^{e,m,j} t^2)}{1 + \exp(\phi_0^{e,m,j} + \phi_1^{e,m,j} t + \phi_2^{e,m,j} t^2)} \times \bar{l}^{e,m,j} \tag{2}$$

We adopt the functional form for the health-related time cost from Jones and Li (2023):[2]

$$\phi_H^{e,m,j}(\mu_t, t) = \begin{cases} 0 & \text{if } \mu_t = 0 \\ \{\phi_a^e + \phi_b^e \log(67 - t)\} \times \bar{l}^{e,m,j} & \text{if } \mu_t = 1,\ t \leq 65 \\ \phi_a^e \times \bar{l}^{e,m,j} & \text{if } \mu_t = 1,\ t > 65 \end{cases} \tag{3}$$

Upon dying, individuals value bequests of any leftover bequeathable wealth, A_t^q, according to the utility function developed by De Nardi (2004):

$$\Omega^{e,m,j}(A_t^q) = \frac{\theta_{beq}^{e,m,j}}{1 - \rho^{e,m,j}} \left(A_t^q + \kappa_{beq}^{e,m,j}\right)^{(1-\rho^{e,m,j})\nu^{e,m,j}}$$

Bequeathable wealth, A_t^q, includes remaining assets, a_t, and Social Security survivor benefits, if eligible. Eligibility depends on marital status and the spousal age gap, q (see Section 3.4.3). The strength of the bequest motive is governed by $\theta_{beq}^{e,m,j}$, while $\kappa_{beq}^{e,m,j}$ captures the curvature of the bequest function. Higher values of $\theta_{beq}^{e,m,j}$ increase the marginal utility of bequests, and higher values of $\kappa_{beq}^{e,m,j}$ imply that bequests are more luxury-like. Both parameters vary by education (e), marital status (m), and cohort (j).

3.2 Health and mortality

Individuals face an exogenous health shock every period. Health status μ_t takes a value of 0 in good health and 1 in bad health, and its transition probabilities vary by education, marital status, and cohort. Health affects the time endowment through Equation (3) and shapes survival beliefs: $\pi_t^s(e, m, j, \mu_t)$ denotes the subjective probability that an individual alive at age t survives to age $t + 1$.

3.3 Employment and wages

Individuals face unemployment shocks with cohort-specific probability π^λ. These shocks reduce labor productivity and introduce wage-scarring effects. The hourly wage in each period depends on an education-, marital status-, cohort-, and age-specific component $\omega(e, m, j, t)$; current

[2]The "good health" state in Jones and Li (2023) corresponds to our good health category, while their fair/poor health state maps to our bad health category. We take their estimates of the education-specific parameters ϕ_a^e and ϕ_b^e, which imply that entering bad health at age 25 reduces the effective time endowment by 14.2% for non-college men and 38.7% for college graduates. Because these parameters are taken from external estimates, they are held fixed across cohorts; the cost still scales with the cohort-specific time endowment $\bar{l}^{e,m,j}$.

unemployment status λ_t; and an autoregressive idiosyncratic component η_t:

$$w_t = \xi(\lambda_t) \exp\left(\omega(e, m, j, t) + \eta_t\right); \;\; \eta_t = \rho^{w,j}\eta_{t-1} + \epsilon_t^w; \;\; \epsilon_t^w \sim N\left(0, \sigma^2_{\epsilon^w, j}\right) \tag{4}$$

Individuals receiving an unemployment shock may re-enter the labor market immediately but incur the wage penalty $\xi(\lambda_t)$. This allows the model to capture the wage-scarring effects of unemployment.

3.4 Social Security

Social Security benefits are computed in several steps, and the parameters governing each step depend on the worker's cohort. First, the highest thirty-five years of earnings are averaged to compute the worker's Average Indexed Monthly Earnings (AIME). We use an annualized version of AIME, which we refer to as Social Security wealth, a_t^{ss}. Its evolution is approximated as:

$$a_{t+1}^{ss} = \min\left\{a_t^{ss} + \max\left\{0, \frac{w_t h_t - a_t^{ss}}{35}\right\}, \; \overline{a}_t^j\right\} \tag{5}$$

where $\overline{a}_t^j$ is the cap on Social Security wealth implied by the taxable maximum in calendar year $j + t$, and $w_t h_t$ denotes annual labor earnings in period t. In Equation (5), we assume that a high-earnings year replaces only an average earnings year, as modeling the actual system would require keeping track of the entire earnings history, which is computationally infeasible.

Second, Social Security wealth is converted into the Primary Insurance Amount (PIA) using the following piecewise linear function:

$$\begin{aligned} pia^j(a_t^{ss}) = 0.90 \times \min\{a_t^{ss}, b_0^j\} + 0.32 \times \min\{\max\{a_t^{ss} - b_0^j, 0\}, b_1^j - b_0^j\} \\ + 0.15 \times \max\{a_t^{ss} - b_1^j, 0\} \end{aligned} \tag{6}$$

where the bend points b_0^j and b_1^j are set according to Social Security policy for cohort j.

3.4.1 Adjustments

Social Security benefits, ssb_t, are a function of the primary insurance amount, $pia^j(a_t^{ss})$, and two possible adjustments: a penalty or credit for early or late benefit claims, $\Gamma^j(t^{ss})$, and a temporary reduction in benefits for workers who continue working while claiming benefits, Υ_t^j.

$$ssb_t = pia^j(a_t^{ss}) \cdot \Gamma^j\left(t^{ss}\right) - \Upsilon_t^j\left(pia^j(a_t^{ss}), t^{ss}, w_t h_t\right) \tag{7}$$

Early/late claiming penalty

Social Security benefits can be claimed without penalty at the cohort-specific normal retirement age, t^j_{NRA}, but individuals may claim earlier, from the early retirement age (t_{ERA}) of 62, at a permanent reduction in benefits. For each year claimed before t^j_{NRA}, the benefit amount is reduced by the early claiming penalty, $\gamma_1^{ss,j}$; for each year claimed after t^j_{NRA}, it is increased by the delayed retirement credit, $\gamma_2^{ss,j}$. Both the NRA and the delayed retirement credit vary across cohorts. For a claiming age of t^{ss}, the share of the PIA an individual receives as benefits is:

$$\Gamma^j\left(t^{ss}\right) = \begin{cases} 1 - \left(t^j_{NRA} - t^{ss}\right)\gamma_1^{ss,j} & \text{if } t^{ss} < t^j_{NRA} \\ 1 & \text{if } t^{ss} = t^j_{NRA} \\ 1 + \left(t^{ss} - t^j_{NRA}\right)\gamma_2^{ss,j} & \text{if } t^{ss} > t^j_{NRA} \end{cases} \tag{8}$$

Retirement earnings test

The Social Security retirement earnings test reduces the benefits of beneficiaries who continue to work. For each dollar of labor earnings above an exempt amount $y_t^{et,j}$, benefits are reduced by $\tau_t^{et,j}$ until all benefits are withheld. The exempt amount, the reduction rate, and the ages to which the test applies have changed over time; most notably, the test was eliminated in 2000 for beneficiaries who have reached the NRA. Because age t and cohort j jointly determine the calendar year, we index these parameters by both, applying the test in each period according to the rules in effect in year $j + t$. Benefits withheld through the earnings test are:

$$\Upsilon_t^j\left(pia^j(a_t^{ss}), t^{ss}, w_t h_t\right) = \min\left\{pia^j(a_t^{ss}) \cdot \Gamma^j\left(t^{ss}\right),\ \max\{0, w_t h_t - y_t^{et,j}\}\,\tau_t^{et,j}\right\} \tag{9}$$

The retirement earnings test is not a true tax, as withheld benefits are credited back through permanent increases in future benefits. We implement this in the model through increases in Social Security wealth.[3]

3.4.2 Subjective program beliefs

We model program misinformation by allowing subjective and uncertain beliefs about the annual adjustment factors for early claiming, $\widetilde{\gamma}_1^{ss,j}$, and delayed claiming, $\widetilde{\gamma}_2^{ss,j}$. Individuals have a fixed, observed belief type, k, which represents an agent's best guess of the penalty. However, we allow for uncertainty in subjective penalty beliefs: subjective adjustment factors are distributed according to a belief distribution, $B^{e,m,j}(k)$, that varies by education, marital status, cohort, and

[3] In practice, benefits withheld due to the earnings test are credited back at the normal retirement age. For computational tractability, we assume these are credited immediately.

belief type.

$$\left(\widetilde{\gamma}_1^{ss,j}, \widetilde{\gamma}_2^{ss,j}\right) \sim B^{e,m,j}\left(k\right)$$

The subjective annual adjustments then map into a subjective total adjustment, $\widetilde{\Gamma}^j(t^{ss})$, defined below. Individuals are assumed to know their cohort's normal retirement age.

$$\widetilde{\Gamma}^j\left(t^{ss}\right) = \begin{cases} 1 - \left(t^j_{NRA} - t^{ss}\right)\widetilde{\gamma}_1^{ss,j} & \text{if } t^{ss} < t^j_{NRA} \\ 1 & \text{if } t^{ss} = t^j_{NRA} \\ 1 + \left(t^{ss} - t^j_{NRA}\right)\widetilde{\gamma}_2^{ss,j} & \text{if } t^{ss} > t^j_{NRA} \end{cases} \tag{10}$$

Perceived Social Security benefits, given by Equation (11), are a function of the primary insurance amount, $pia^j(a_t^{ss})$, the uncertain total adjustment, $\widetilde{\Gamma}^j(t^{ss})$, and the retirement earnings test, Υ_t^j.

$$\widetilde{ssb}_t = pia^j\left(a_t^{ss}\right) \cdot \widetilde{\Gamma}^j\left(t^{ss}\right) - \Upsilon_t^j\left(pia^j(a_t^{ss}), t^{ss}, w_t h_t\right) \tag{11}$$

This way of modeling subjective beliefs is akin to agents operating under limited information, with their actions potentially resulting in irreversible claiming mistakes.

3.4.3 Marriage-related benefits

Spousal benefits We assume that married couples claim Social Security benefits jointly. If both spouses are eligible at the time of the household head's claim, both the head's benefits and spousal benefits begin immediately. If the younger spouse is not yet eligible (i.e., under age 62) when the head claims, spousal benefits begin once she reaches age 62.[4] We also assume that subjective beliefs about the early claiming penalty apply to spousal benefits.

When the head is age t, his spouse is age $t - \iota$ and therefore belongs to birth cohort $j + \iota$; the Social Security rules applied to her own record are those of her cohort. Spousal Social Security wealth, a_{st}^{ss}, and the spousal PIA, $pia^{j+\iota}(a_{st}^{ss})$, evolve based on exogenous spousal income, y_{st}, following the rules defined in Equations (5) and (6). The resulting spousal PIA is then used to determine Social Security benefits, as specified in Equation (12). If the benefits a spouse qualifies for based on her own earnings record exceed 50 percent of her husband's PIA, she receives those primary benefits. Otherwise, if her own earnings entitle her to no or relatively small benefits, she receives auxiliary spousal benefits equal to up to 50 percent of the household head's PIA. Perceived spousal benefits are computed as:

$$\widetilde{ssb}_t^s = \max\left\{pia^{j+\iota}\left(a_{st}^{ss}\right) \cdot \widetilde{\Gamma}_{st},\ 0.5 \cdot pia^j(a_t^{ss}) \cdot \min\{\widetilde{\Gamma}_{st}, 1\}\right\} \tag{12}$$

[4]This assumption is supported by data for the 1931–1935 cohort: over 65% of eligible couples claimed within a year of each other, and over 70% of ineligible younger spouses claimed at age 62.

where $\widetilde{\Gamma}_{st} \equiv \widetilde{\Gamma}^{j+\iota}\left(\max\left\{t^{ss}-\iota, 62\right\}\right)$ is the subjective adjustment for the spouse's claiming age, computed as in Equation (10) using the NRA of the spouse's cohort. We assume that spouses have retired by the time they claim; thus, spousal benefits are not adjusted for the retirement earnings test. Policy rules also stipulate that auxiliary spousal benefits do not accumulate delayed retirement credits, so the claiming age adjustment applied to them cannot exceed 1.

Survivor benefits Married individuals may also leave their Social Security benefits, net of any spousal benefits already being received, to their surviving spouses upon death.[5] We model these survivor benefits as part of bequeathable wealth, A_t^q, which is defined as follows:

$$A_t^q = \begin{cases} a_t + \sum_{s=t-\iota}^{T} \frac{\pi_s^{sp,j+\iota}}{(1+\bar{r})^{s-(t-\iota)}} \max\left\{\widetilde{ssb}_t - \widetilde{ssb}_t^s, 0\right\} & \text{if } m=1 \text{ and } t-\iota \geq 62 \\ a_t & \text{otherwise} \end{cases} \tag{13}$$

where $\pi_s^{sp,j+\iota}$ is the probability that the spouse, a member of cohort $j+\iota$, survives from her current age $t-\iota$ to age s. In addition to any leftover assets, a_t, bequeathable wealth includes the value of Social Security survivor benefits if the individual is married and the spouse is at least 62.[6] These survivor benefits are calculated as the present value of the expected stream of additional benefits a spouse would receive from the death of the household head until the end of her own life. This present value is a function of the household head's age t, his cohort j, the spousal age gap ι, and the difference in perceived benefits between the head of household and spouse.[7] Once Social Security benefits are claimed, survivor benefits are a function of actual retirement benefits, ssb_t and ssb_t^s.

3.5 Budget constraint

Before claiming Social Security, individuals face the following budget constraint:

$$c_t + a_{t+1} = a_t + W\left(y_t, y_{st}^j, \bar{r}a_t, \tau_t^j\right) + \mathbb{I}\left\{b_t^{ss}=1\right\} \times \left(\widetilde{ssb}_t + \mathbb{I}\left\{t-\iota \geq 62\right\} \times \widetilde{ssb}_t^s\right) + tr_t^j + pb_t^j \tag{14}$$

An individual's disposable household income, $W(\cdot)$, includes several components: labor income from hours worked, $y_t = w_t h_t$; exogenous spousal income, y_{st} (if married); and asset returns, $\bar{r}a_t$.

[5] In practice, after a beneficiary's death, the surviving spouse receives the larger of her own or the deceased spouse's benefits. Accordingly, we assume the value of survivor benefits generating warm-glow utility equals the difference between the two.

[6] Under Social Security's survivor benefit provisions, surviving spouses may receive reduced benefits starting at age 60 and full benefits at their own full retirement age. In our model, we choose an intermediate eligibility age of 62. We exclude child benefit provisions under OASDI, as early-life beneficiary death is sufficiently rare.

[7] Further details of spousal and survivor benefit calculations are provided in Appendix A.

In addition, individuals may receive government transfers, tr_t^j (defined in Equation (16)), and private pension benefits, pb_t^j, and they pay taxes according to the tax schedule τ_t^j in effect in calendar year $j+t$. Importantly, before claiming, individuals base their decisions on perceived Social Security benefits, $\widetilde{ssb}_t$, and perceived future spousal benefits (conditional on spousal eligibility), $\widetilde{ssb}_t^s$. Once Social Security benefits are claimed (i.e., when $b_t^{ss} = 1$), actual retirement benefits, ssb_t and ssb_t^s, are revealed.

There is a standard borrowing constraint on assets and a consumption floor that guarantees a minimum level of consumption (Hubbard et al., 1995):

$$a_{t+1} \geq 0;\ c_t \geq \underline{c}^j\ \forall t \tag{15}$$

Government transfers, tr_t, bridge the gap between this minimum level of consumption and the individual's liquid resources. This is a simple approximation to federal safety net programs in the U.S. such as the Supplemental Nutrition Assistance Program (SNAP), Supplemental Security Income (SSI), and Temporary Assistance for Needy Families (TANF), among others. The consumption floor is permitted to vary by cohort to reflect changes in the generosity of these programs over time.

$$tr_t^j = \max\left\{0, \underline{c}^j - \left(a_t + W_t + \mathbb{I}\left\{b_t^{ss} = 1\right\} \times \left(ssb_t + \mathbb{I}\left\{t - \iota \geq 62\right\} \times ssb_t^s\right) + pb_t^j\right)\right\} \tag{16}$$

where W_t is total disposable household income as defined in Equation (14).

3.6 Recursive formulation

Individuals solve a dynamic life-cycle optimization problem, choosing consumption, hours worked, and Social Security benefit application to maximize expected discounted lifetime utility. They do so subject to exogenous processes for wages, health, employment, subjective survival, and program beliefs; budget, borrowing, and time constraints; transfer rules; taxes; and the Social Security policy of their cohort. The life cycle is separated into three phases: (1) the employment phase (ages 25–61), during which individuals choose consumption, savings, and labor supply;[8] (2) the retirement choice phase (ages 62–69), during which individuals continue to make consumption, labor supply, and savings decisions but also decide whether to claim Social Security benefits; and (3) the retirement phase (ages 70–99), during which individuals make only consumption and savings decisions.

We present below a general value function for a household head from cohort j with education level e, marital status q, and Social Security belief type k. Time-varying states are as defined

[8] We abstract from disability insurance (DI) and focus on those who claim benefits through the non-DI pathway.

above. Expectations are taken over productivity (η_{t+1}), employment (λ_{t+1}), health (μ_{t+1}), and Social Security program beliefs. Phase-specific decision problems, which incorporate life-stage-dependent constraints and transitions, are provided in Appendix B.

$$
\begin{aligned}
V^{j}_{e,q,k,t}(a_t, a^{ss}_t, a^{ss}_{st}, \eta_t, \lambda_t, \mu_t, b^{ss}_{t-1}) = \max_{\{c_t, h_t, b^{ss}_t\}} \Bigg\{ & U^{e,m,j}(c_t, l_t) \\
& + \beta^{e,m,j} \pi^{s}_{t}(e, m, j, \mu_t)\, E\Big[V^{j}_{e,q,k,t+1}(a_{t+1}, a^{ss}_{t+1}, a^{ss}_{st+1}, \eta_{t+1}, \lambda_{t+1}, \mu_{t+1}, b^{ss}_{t}) \Big] \\
& + \beta^{e,m,j} \left(1 - \pi^{s}_{t}(e, m, j, \mu_t)\right) \Omega^{e,m,j}(A^{q}_{t+1}) \Bigg\}
\end{aligned}
$$

s.t. (1), (5)–(12), (13), (14), (15), and (16).

4 Estimation

We estimate the model for male household heads in two cohorts. (i) those born between 1931 and 1935 and (ii) those born between 1945 and 1949. For each cohort we use a two-step strategy following Gourinchas and Parker (2002). In the first step, we estimate processes that can be identified independently of the structural model using data from the Panel Study of Income Dynamics (PSID), Health and Retirement Study (HRS), the Household Component of the Medical Expenditure Panel Survey (MEPS), and the Understanding America Study (UAS).[9] In the second step, we combine initial conditions for the cohort at hand with the structural model and first-step estimates to identify preference parameters and uncertainty about subjective program beliefs.

4.1 First step

4.1.1 Health and subjective survival beliefs

Health takes two values, $\mu_t \in \{\text{good}, \text{bad}\}$, and is identified using self-reported health status from MEPS and HRS.[10] Health transitions are estimated from the MEPS Household Component using data on men ages 20–90. We estimate an ordered probit regression of self-reported health status on lagged health, education, marital status, and a cubic function of age. Estimation details are provided in Appendix D.1.

[9] Details on data source, samples are in Appendix C; details on the first stage estimation are in Appendix D.

[10] Both surveys ask respondents to rate their health on a 1–5 scale, from "Excellent" (1) to "Poor" (5). For computational simplicity, we collapse this into a binary measure: responses of "Excellent," "Very Good," or "Good" are classified as good health; "Fair" or "Poor" as poor health. Alternatively we could model an objective measure, such as frailty index in Hosseini et al. (2022). However, as Miller and Bairoliya (2021) discusses, self-rated health remains predictive of mortality even after controlling for objective measures.

We estimate subjective survival beliefs for each cohort using a three-step procedure. First, we construct objective survival probabilities by combining MEPS and HRS data: MEPS for individuals under age 50, and HRS for those 50 and older. We rely on HRS beyond age 50 as MEPS excludes the institutionalized population, potentially biasing survival estimates at older ages. We estimate objective survival probabilities using an ordered probit model of the death indicator regressed on lagged health status interacted with a third-order polynomial in age. We also include interactions of education (college), marital status, and gender with the same age polynomial as well as birth-year cohort controls. Because these objective probabilities are central to identifying subjective survival beliefs, we scale the estimated annual survival probabilities so that life expectancies at ages 50, 60, and 70 align with Social Security Administration life tables for men in our cohorts of interest.[11] The resulting objective survival probabilities by age, education, marital status, and self-reported health are depicted as dashed lines in Figure D.5.

Second, we assume that prior to age 50 objective and subjective survival probabilities are identical and estimate cumulative subjective survival curves for those age 50 and above using a method similar to O'Dea and Sturrock (2023). This method fits a Weibull distribution—a two-parameter distribution commonly used to model aging—to subjective reports of the probability of survival to given ages. While O'Dea and Sturrock (2023) estimates individual-level survival curves in the context of the United Kingdom, this level of granularity is infeasible in our structural model. Rather, we extend their methodology to estimate education, marital status, and self-reported health specific curves using median subjective survival probability reports for each group from the HRS.

In the final step, we use the estimated subjective cumulative survival curves and objective survival probabilities to compute an age-dependent scaling factor for each education–marital status–health group. This factor is such that when it is multiplied by the objective annual survival probabilities the resulting cumulative objective survival curve exactly matches the estimated subjective survival curve. The scaled subjective survival probabilities used in our quantitative model are presented as colored, marked lines in Appendix Figure D.5. Additional methodological details are provided in Appendix D.2.

Table 2 shows how subjective and objective life expectancy has changed between these two cohorts. Consistent with improvements in health and longevity among later cohort, we find that objective life expectancies have increased for each of the groups consider with the largest increases coming from college educated and married individuals (+1.3 years) and those in good health (+1.5 years, on average). Subjective life expectancies, however, do not show this same increase. Rather, subjective life expectancies remain stagnant or even decrease. These cases are split along education lines: subjective life expectancies decrease by around 0.5 years among the non-college and increase

[11] This scaling is modest:survival probabilities are multiplied by 1.002 between ages 50–59, 1.0035 between 60–69, and 1.006 for ages 70 and older. These comparisons are reported in Table D.2.

by only 0.1-0.2 years for the college educated. These results highlight that although advances in health may have increased longevity, individual perceptions of longevity have not kept up with these increases.

Table 2: Age 60 Life Expectancy: Objective and Subjective by Cohort

	All		Bad Health		Good health	
	Objective	Subjective	Objective	Subjective	Objective	Subjective
Panel A: 1931-1935 Cohort						
Non-college singles	15.6	17.8	11.4	17.0	23.4	19.4
College singles	19.2	19.8	12.1	16.9	24.4	21.0
Non-college married	19.4	17.8	14.3	16.2	26.6	19.5
College married	23.5	19.8	14.7	16.0	27.4	21.1
Panel B: 1945-1949 Cohort						
Non-college singles	16.2	17.4	11.8	16.5	24.7	19.1
College singles	20.1	19.8	12.5	17.0	25.8	21.1
Non-college married	20.3	17.3	14.9	16.1	28.2	18.7
College married	24.8	20.0	15.3	16.1	29.0	21.2
Panel C: Difference (Panel B - Panel A)						
Non-college singles	0.6	-0.4	0.4	-0.6	1.3	-0.3
College singles	0.9	0.1	0.4	0.1	1.4	0.1
Non-college married	0.9	-0.5	0.6	-0.2	1.6	-0.8
College married	1.3	0.2	0.6	0.1	1.7	0.2

Notes: objective and subjective life expectancy at age 60 from the HRS, reported by birth cohort (1931-1935 in Panel A and 1945-1949 in Panel B) and health status. refers to the top three categories of self-reported health; corresponds to the bottom two. Panel C reports the difference between the 1945-1949 and 1931-1935 cohorts.

4.1.2 Family structure

Family structure determines three inputs for married men: the consumption equivalence scale, $\zeta_t^{e,m,j}$, the spousal age gap, ι, and spousal income, y_{st}^j. We allow these to vary by cohort

The equivalence scale which adjusts household consumption is based on family size and varies by education and marital status. For single households, this parameter is fixed at 1. For married households, the scale reflects the presence of a spouse and the average number of children living in the household. We estimate the number of children age 0-17 by age and education using data from the PSID. We then map these family sizes to values of $\zeta_t^{e,m,j}$ using the OECD equivalence scale.[12]

[12]The OECD scale assigns a weight of 1 to the household head, 0.5 to the spouse, and 0.3 to each child.

The spousal age gap for married men is modeled using the empirical distribution of age differences between husbands and wives observed in the PSID for the relevant cohort. We discretize this distribution using four representative values: 0, 1, 4, and 8 years. The mass at each point is assigned based on observed frequencies. For the 1931-1935 cohort, 8.7% of couples have no age gap, 26.2% have a one-year gap, 46.1% have a four-year gap, and 19% have an eight-year gap. The average age gap decreases from 3.6 years for the 1931-1935 cohort to 2.9 years for the 1945-1949 cohort. Much of this drop is driven by an increase in the share of couples with no age gap (8.7% $\rightarrow$ 14.0%) and a drop in the share with an age gap of 8 years (19.0% $\rightarrow$ 10.7%). Additional estimation details related to children and spousal age gaps are provided in Appendix D.3

Spousal income, y_{st}^{j}, is estimated using the restricted Social Security Administration Summary Earnings file linked to the HRS. It is modeled as a function of the household head's state variables: age, education level, spousal age gap, and labor income. To allow for zero spousal earnings, we adopt a two-step approach. First, we estimate spousal labor force participation as a function of the household head's characteristics. Then, conditional on participation, spousal earnings are predicted using the same set of state variables. For both of these steps an indicator of participation or real spousal labor earnings in thousands of 1998 dollars are regressed on a fourth-order age polynomial, the labor income of the head interacted with this fourth-order age polynomial, and education and spousal age gap interacted with age. This estimation is done separately for each cohort, and estimation details are provided in Appendix D.4.

4.1.3 Labor productivity, employment shocks, and wage scarring

Wages are modeled as the sum of two components: (1) a deterministic component varying by age, education, and marital status, and (2) a persistent stochastic shock. These components are estimated from the PSID in two steps. First, we estimate the deterministic wage profiles for each cohort by age, education, and marital status using a Heckman two-step procedure to account for selection into employment. Second, we estimate the persistence and standard deviation of the wage shocks by fitting an AR(1) process to the residuals from the first step using a minimum distance estimator.

Individuals face an exogenous employment shock characterized by involuntary labor market separation and a wage penalty. This shock, λ, is assumed constant across education and marital groups and calibrated to match an annual separation rate of $\lambda = 0.056$. The wage penalty, ξ, represents the proportional wage loss one year after displacement and is estimated from the PSID by regressing log hourly wages on indicators for years since displacement, along with standard controls, including quadratic terms in age and experience. We estimate a 14% wage loss one

year after displacement ($\xi = 0.86$).[13] The exogenous employment shock and the wage penalty is assumed constant across cohorts.

While we address the selection issue from unobserved wages among the non-employed using a Heckman selection model, the resulting profiles remain biased due to wage scarring from unemployment spells. Observed wages reflect the cumulative impact of past unemployment on current and future earnings. Since our structural model explicitly incorporates unemployment shocks and their wage-scarring effects, we correct the exogenously estimated wage profiles to avoid double-counting. We calibrate adjusted profiles so that wages simulated from the process in Equation (4)—which includes the unemployment term $\xi(\lambda)$—match those from the original unadjusted profiles using a modified process that excludes unemployment effects (i.e., setting $\xi(\lambda) = 1$). Appendix Figure D.9 shows the estimated age-wage profiles $\omega(e, m, j, t)$, both unadjusted and adjusted, for each education-marital group.

4.1.4 Social Security and private pensions

For the cohort of men born between 1931 and 1935, we set the early claiming age to 62 and the normal retirement age to 65. Benefits are reduced by 6.7 percent per year for early claiming and increased by 5.5 percent per year for delays beyond the NRA, up to age 70. We calibrate Social Security parameters using the 1998 rules (see Section 3.4). The bend points in the benefit formula, b_0 and b_1 in Equation (6), are \$5,724 and \$34,500, respectively, and do not vary with claiming age. Earnings above \$9,120 before the NRA are subject to a 50 percent tax rate, while post-NRA earnings above \$14,500 are taxed at 33 percent.

Policy changes lead to different Social Security parameters for the 1945 – 1949 cohort. We set the early claiming age to 62 and the normal retirement age to 66. Benefits are reduced by 6.7 percent per year for early claiming and increased by 8.0 percent per year for delays beyond the NRA, up to age 70. We calibrate Social Security parameters using the 1998 rules (see Section 3.4). The bend points in the benefit formula, b_0 and b_1 in Equation (6), are \$6,534 and \$39,393, respectively, and do not vary with claiming age. For this cohort, the retirement earnings test applies only before the NRA. Earnings above \$10,393 are subject to a 50 percent tax rate, while earnings above \$27,602 are taxed at 33 percent. These rules for each cohort are summarized in Table 3.

We model private pensions to reflect the core features of defined benefit (DB) plans (benefits are illiquid before a fixed eligibility age assumed to be 62 in the model), and non-linear pension accrual profiles generate sharp work disincentives at certain ages. To capture these features, pb_t is imputed as a function of an individual's primary insurance amount and modeled analogously to French (2005):

[13] This estimate aligns with the wage-scarring literature (Jacobson et al., 1993; Huff Stevens, 1997; Huckfeldt, 2016). Further wage estimation details and separation rate and wage penalty estimation are in Appendix D.5.

Table 3: Benefits Policy Rules by Birth-Year Cohort

	Birth-Year Cohort	
	1931-1935	1945-1949
Retirement Ages		
early retirement age (ERA)	62	62
normal retirement age (NRA)	65	66
Adjustments for Claiming Age		
early claim penalty	6.7%	6.7%
delayed claim credit	5.5%	8.0%
Primary Insurance Amount (PIA) Formula		
first bend point	\$5,724	\$6,534
second bend point	\$34,500	\$39,393
Retirement Earnings Test (RET)	applies to ages 62-70	applies before the NRA
50% withheld threshold	\$9,120 (before NRA)	\$10,393
33% withheld threshold	\$14,500 (after NRA)	\$27,602

Notes: Delayed claiming credit differed within the 1931-1935 cohort. Those born 1931-1932 experienced a credit of 5.0%, 1933-1934 had a credit of 5.5%, and those born 1935 faced a credit of 6.0%.

All dollars values are in 1998 dollars. For the bend points of the PIA formula and the thresholds of the RET, rules from 1998 are used for the 1931-1935 cohort while rules from 2012 are used for the 1945-1949 cohort.

$$pb_t = pb(pia_t) + \epsilon_t^p$$

where $pb(pia_t)$ is a regressive function of lifetime earnings, and ϵ_t^p reflects age-specific pension accrual. To reflect the significant heterogeneity in pension wealth across education and marital groups, we adjust the scale parameter in the $pb(pia_t)$ function from French (2005) separately for each group. These adjustments ensure that predicted average pension benefits at older ages match observed values in the HRS data (see Appendix D.6 for details).

4.1.5 Taxes

Individuals in the model pay a proportional payroll tax, $\tau_{t,j}^{ss}$, and labor income taxes, $\tau_t^{e,m,j}$.

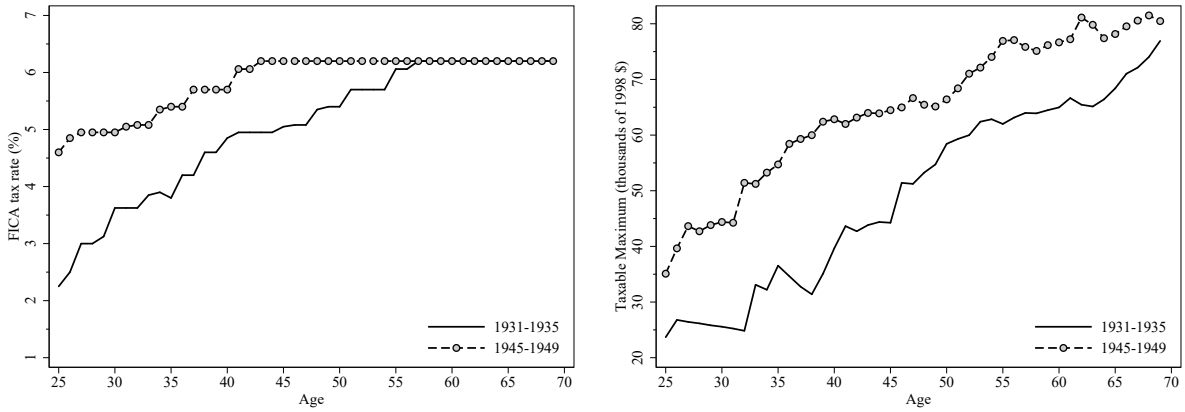
The proportional payroll tax includes both the Social Security payroll tax on income up to the taxable maximum, $\overline{a}^j$ and the Medicare tax of 1.45 percent on total labor income.[14] Both the FICA

[14]The Medicare (SECA) tax has alsoe been changing over time. The tax was introduced in 1966 at 0.35% and increased gradually to 1.45% by 1986. The 1931-1935 cohort experienced an average SECA tax of 1.12% while the 1945-1949 cohort faced a SECA tax of 1.33%.

tax rate and the taxable maximum vary by calendar year, creating differences in the tax rate by age across our two cohorts. (see Figure 5). As the FICA tax has been steadily increasing over time, our earlier cohort faced lower rates early in the life-cycle. This cohort also has a lower taxable maximum limit. On average, the 1931–1935 cohort had a FICA rate of 5.01% and a taxable maximum of $49,365 while the 1945–1949 cohort had a FICA rate of 5.84% and a taxable maximum of $64,704.

Figure 5: Contribution Policy Rules by Cohort

(a) FICA Rate (b) Taxable Maximum



Notes: Figure shows the FICA tax rate (Panel (a)) and the taxable maximum (Panel (b)) by age for each of the two cohorts. The 1931–1935 cohort was age 25 in 1956–1960 and age 70 in 2001 – 2005; the 1945–1949 cohort was age 25 in 1970-1974 and age 70 in 2015-2019.

Following the literature, we adopt a smooth functional form for the labor income tax that allows for negative tax rates in order to incorporate Earned Income Tax Credit (EITC). Total taxes paid, $T(y_t)$, on income y_t is given by:

$$T(y_t) = y_t - \lambda_t y_t^{1-\xi_t}.$$

We allow parameters of this tax function to vary by age, education, marital status, and cohort and estimate the function using PSID data. Age-dependent parameters capture changes in tax policy over our cohort's life cycle while education-specific parameters reflect differences in the number of children (refer to Appendix D.7 for estimation details).

4.2 Second step estimation

In the second step, we use initial conditions for the 1931–1935 and 1945–1949 cohorts alongside our structural model and the parameters from the first step to estimate the preference parameter

vector and belief-specific uncertainty over SS penalty $\{\beta, \rho, \nu, \theta_{beq}, \kappa_{beq}, \phi_P(t), \bar{l}, B(k)\}$ by education, marital status, and birth-year cohort. We employ the Method of Simulated Moments (MSM) to find the parameter values that allow model simulated moments to best match the data profiles for this cohort of male household heads according to a GMM criterion function.[15] Additional details on the second-step estimation are discussed in Appendix E.

Preferences

We allow preference parameters to differ by education, marital status, and cohort in order to match variation in wealth and labor supply across these groups. Heterogeneity in discount factors allows for differences in wealth growth early in the life cycle, while heterogeneous bequest motives capture differential rates of dis-saving late in life. Time endowments and the time cost of working vary across groups to match differences in the extensive and intensive margins of labor supply.

The estimation of the preference parameters is informed by 31 data moments for each education, marital status, and cohort group: labor market participation and hours worked conditional on participation of male household heads in 5-year age bins between ages 25 and 69, and median household assets in 5-year age bins between ages 25 and 99.[16] We fix the interest rate, r, to 0.03 for all groups. Table 4 reports the estimates of $(\beta^{e,m,j}, \rho^{e,m,j}, \nu^{e,m,j}, \theta_{beq}^{e,m,j}, \kappa_{beq}^{e,m,j}, \bar{l}^{e,m,j})$ for both cohorts. Two results stand out. Differences across education and marital groups are large and take the same form in both cohorts, while differences across cohorts within a group are small.

Discounting, risk aversion, and consumption. In both cohorts the estimated discount factor, $\beta^{e,m,j}$, rises with education and is higher for married than for single men.[17] It ranges from 0.961 for single, non-college educated men to 1.071 for married college graduates in the 1931–1935 cohort, and from 0.954 to 1.069 for the same groups in the 1945–1949 cohort. Effective discounting also incorporates subjective survival probabilities, which fall below objective probabilities on average for the married groups, so the model estimates somewhat higher discount factors than literature that does not account for subjective survival expectations. Across cohorts, discount factors are lower for the later cohort in every group, by between 0.002 for married college graduates and 0.010 for single college graduates. The coefficient of relative risk aversion, $\rho^{e,m,j}$, is highest for single, non-college educated men and lowest for married, non-college educated men in both cohorts. It falls for the later cohort among non-college singles (from 3.68 to 3.49), non-college married men (1.84 to 1.70), and married college graduates (2.50 to 2.36), and is unchanged at 2.45 for single college graduates. The consumption weight, $\nu^{e,m,j}$, ranges from roughly 0.52 for married, non-college

[15] We use the identity matrix for weighting (see Altonji and Segal, 1996).

[16] Discussion on the construction of profiles used in the estimation is included in Appendix E.1.

[17] Previous literature, including Becker and Mulligan (1997) and Doepke and Zilibotti (2008), has also demonstrated that increasing education increases the patience of individuals.

educated men to 0.66 for married college graduates and moves by 0.014 or less in any group.

Bequests. The parameters $\theta_{beq}^{e,m,j}$ and $\kappa_{beq}^{e,m,j}$ govern the strength and curvature of the bequest motive. In both cohorts, $\theta_{beq}^{e,m,j}$ is higher for married than for single men and, within marital status, higher for college graduates, while $\kappa_{beq}^{e,m,j}$ is largest for single, non-college educated men and smallest for married, non-college educated men. Across cohorts, bequest intensity is lower for the later cohort among singles of both education levels and among married college graduates, where it falls from 1.63 to 1.53, and is essentially unchanged for married, non-college educated men. The curvature parameter differs by about $5,000 or less for any group. For all groups, estimated bequest motives are less of a luxury good than inLockwood (2012); De Nardi et al. (2010, 2021), but closer to French (2005) and Ameriks et al. (2020).

Time endowment and the cost of working. The time endowment, $\bar{l}^{e,m,j}$, is estimated to be between 4,989 hours annually (96 hours a week) for married college graduates and 5,784 hours (111 hours a week) for non-college singles in the 1931–1935 cohort, and between 5,077 hours (98 hours a week) for married, non-college educated men and 5,661 hours (109 hours a week) for non-college singles in the 1945–1949 cohort. In both cohorts, married men without a college education have a lower time endowment than their single counterparts, consistent with child-care responsibilities and home production. Unlike the other parameters, the time endowment changes across cohorts in a way that differs by education. It falls for non-college educated men, by 123 hours for singles and 144 hours for married men, and rises for college graduates, by 232 hours for singles and 356 hours for married men. In the 1931–1935 cohort the time endowment is higher for non-college educated men within each marital status, which helps to match their hours worked despite their lower wages.[18] In the 1945–1949 cohort this gap narrows from 550 to 195 hours among singles and reverses among married men, for whom college graduates have the higher time endowment (5,345 compared to 5,077 hours). Finally, we estimate the coefficients of the participation cost in Equation 2 for each education, marital status, and cohort group.

Differences across cohorts. Taken together, the estimates indicate that preferences changed little between the two cohorts. The ranking of groups is preserved for every parameter except the time endowment of married men. The differences that do exist are systematic: relative to the 1931–1935 cohort, men in the 1945–1949 cohort are estimated to be slightly less patient and, in three of the four groups, slightly less risk averse and to have a weaker bequest motive. Each of these lowers the incentive to accumulate wealth and reduces the value of the larger annuity obtained by delaying Social Security claims. We return to the consequences of these differences for claiming in Section 5.

[18] Aguiar and Hurst (2008) show that less-educated individuals consume more leisure than their higher-educated counterparts, even when working.

Table 4: Estimated Preference Parameters Across Cohorts

Parameter	Description	Singles		Married	
		Non-college	College	Non-college	College
1931-1935 Cohort					
β	discount factor	0.961	0.971	1.030	1.071
ρ	relative risk aversion	3.684	2.452	1.837	2.501
ν	consumption weight	0.583	0.579	0.528	0.662
θ_{beq}	bequest intensity	0.794	0.991	1.245	1.631
κ_{beq} (in 000s)	bequest curvature	214.0	109.2	37.6	65.1
$\bar{l}$	time endowment	5784	5234	5221	4989
1945-1949 Cohort					
β		0.954	0.961	1.025	1.069
ρ		3.492	2.450	1.702	2.356
ν		0.569	0.569	0.516	0.663
θ_{beq}		0.761	0.912	1.249	1.530
κ_{beq} (in 000s)		212.7	108.9	42.9	67.1
$\bar{l}$		5661	5466	5077	5345

Social Security program beliefs

Our quantitative model includes uncertain beliefs about the size of the early-claiming penalty for Social Security benefits. This section discusses the how we estimate the subjective belief distribution over the annual early-claiming penalty, $B^{e,m,j}(k)$, that individuals use when evaluating the claiming decision.

Data inputs: belief types and confidence. The Understanding America Study (UAS) asks respondents about how Social Security benefits change with claiming age. The question presents respondents with four discrete options for the perceived annual early-claiming penalty,

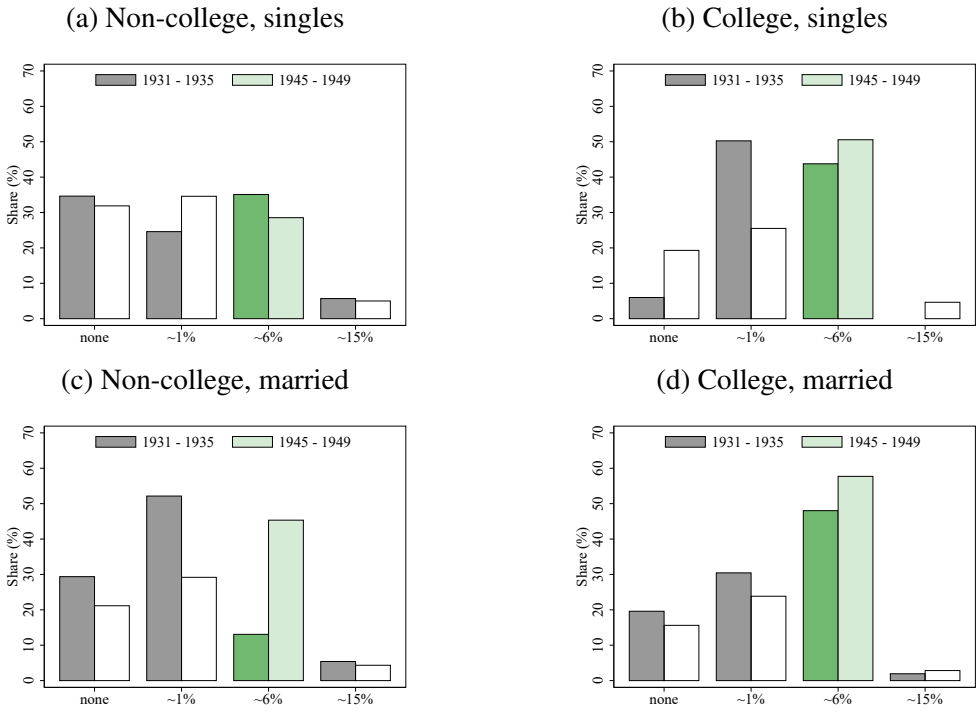
$$\tilde{\gamma}_1^k \in \{0.0,\ 0.01,\ 0.067,\ 0.15\}.$$

We define an individual's *belief type* $k \in \{1, 2, 3, 4\}$ as the option they select. Figure 6 shows the distribution of responses across these options for each education, marital status, and cohort. There is not only variation across socioeconomic statuses, but also across these cohorts. On average, the share of individuals who respond correctly increases from 34% to 48% between the 1931–1935 and 1945–1949 cohorts, which the largest share among the non-college, married group. The

average penalty belief (the average response, weighted by the share of individual reporting the response) has increased by 0.7-1.8 percentage for the married and the college educated singles while dropping 0.4 percentage points for the non-college educated, married group. This difference indicate that the change in fixed beliefs is pushing for later claiming among most but somewhat earlier claiming so the non-college, singles.

Table 5 reports a second UAS measure that asks how knowledgeable respondents feel about the relationship between claiming age and benefits. We map this self-assessed knowledge into a numerical confidence scale and use the group-by-type average, denoted by ACS, as a directly observed measure of the weight that type k places on its penalty belief.[19] This confidence level is held constant across cohorts.[20]

Figure 6: Program Knowledge by Cohort



Source: Understanding America Study (UAS), authors' calculations.

Notes: For each education-marital status group, the figure reports the distribution of responses across the four belief survey options for each cohort. Correct response shown in green.

Modeling belief uncertainty. We allow individuals to be uncertain about the true penalty and to assign positive probability to each of the three alternative penalty values from the UAS question.

[19]The confidence scale is: very knowledgeable (1.0), somewhat knowledgeable (0.75), not too knowledgeable (0.25), and not at all knowledgeable (0.0).

[20]While average levels of confidence is lower among later cohort, this seems to be driven by difference in age at interview. Given the short panel of the UAS data, it is difficult to separate age effects from cohort effects.

Table 5: Program misinformation confidence

	Belief Type, k			
	$\tilde{\gamma}_1^k = 0.0$	$\tilde{\gamma}_1^k = 0.01$	$\tilde{\gamma}_1^k = 0.067$	$\tilde{\gamma}_1^k = 0.15$
Non-college, single	0.464	0.495	0.556	0.507
College, single	0.651	0.535	0.710	0.847
Non-college, married	0.604	0.592	0.658	0.546
College, married	0.658	0.671	0.756	0.719

Source: Understanding America Study (UAS), authors' calculations.

Notes: For each education-marital status group, the columns report the average confidence scale (ACS), $\varepsilon_{k,k}^{ss}$, among respondents of belief type k, where belief types are defined by the stated annual early claiming penalty, $\tilde{\gamma}_1^k$. The confidence scale is based on self-assessed knowledge: very knowledgeable (1.0), somewhat knowledgeable (0.75), not too knowledgeable (0.25), or not at all knowledgeable (0.0). The ACS is the average of these scores within the group and belief type.

Formally, we represent program-belief uncertainty by a probability vector

$$\boldsymbol{\varepsilon}_k^{ss} \equiv \left(\varepsilon_{k,1}^{ss}, \varepsilon_{k,2}^{ss}, \varepsilon_{k,3}^{ss}, \varepsilon_{k,4}^{ss}\right), \qquad \varepsilon_{k,j}^{ss} \geq 0, \ \sum_{j=1}^{4} \varepsilon_{k,j}^{ss} = 1.$$

We set the diagonal elements using the survey-based confidence measure, $\varepsilon_{k,k}^{ss} = \text{ACS}_k$, and interpret the remaining mass as the probability that respondents attach to other penalty values.

Because choices depend on continuation values (not only the mean penalty), individuals form expectations over penalty schedules when evaluating the claiming decision. For exposition, we summarize the implied distribution by the type-specific uncertainty weighted penalty:

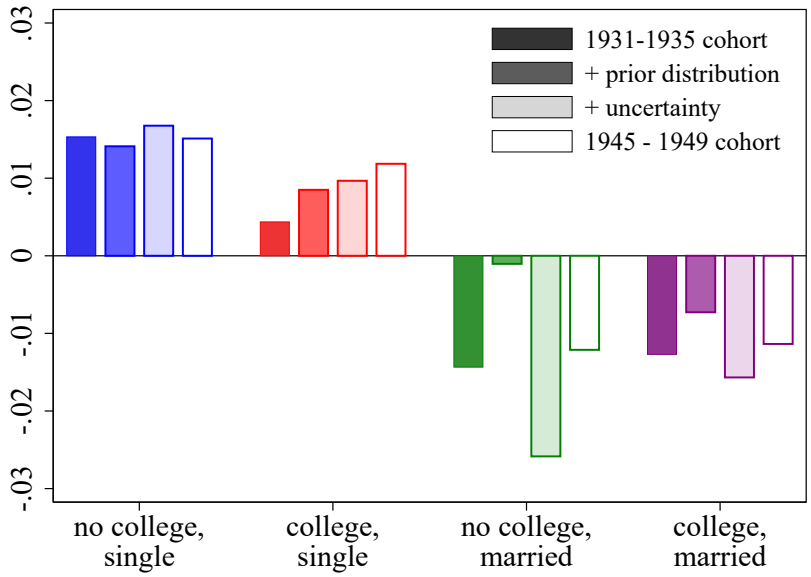
$$\mathbb{E}[\tilde{\gamma}_1^{ss} \mid k] = \sum_{j=1}^{4} \varepsilon_{k,j}^{ss} \, \tilde{\gamma}_1^j = \varepsilon_{k,k}^{ss} \tilde{\gamma}_1^k + \sum_{j \neq k} \varepsilon_{k,j}^{ss} \tilde{\gamma}_1^j. \tag{17}$$

Estimation and identification. The UAS identifies $\tilde{\gamma}_1^k$, the distribution of these belief types across education and marital groups, and $\varepsilon_{k,k}^{ss}$, the weight placed on the individual's own belief, but it does not reveal how the remaining probability mass is allocated across $j \neq k$. We estimate the off-diagonal elements $\{\varepsilon_{k,j}^{ss}\}_{j \neq k}$ within the structural model using claiming behavior. Specifically, for each education and marital group, we match observed cumulative claiming rates between ages 62 and 69. Because each row k of $\boldsymbol{\varepsilon}_k^{ss}$ has three off-diagonal elements that sum to $1 - \text{ACS}_k$, each row contributes two free parameters; with four belief types this yields $4 \times 2 = 8$ free parameters per group. We match eight claiming moments per group, so the claiming distribution tightly disciplines these uncertainty weights.

This approach assumes that the model captures all major drivers of claiming behavior and any residual mismatch between the model and observed claiming distributions reflects uncertainty in beliefs about the penalty. This assumption is reasonable within our rich quantitative framework, as uncertainty about program rules can also serve as a proxy for broader social influences, such as peer effects which are known to shape both retirement savings and timing decisions (Duflo and Saez, 2002; Brown and Laschever, 2012); uncertainty about the solvency of the Social Security system, which has been shown to encourage individuals to move claims earlier (Gustman and Steinmeier, 2015; Benitez-Silva et al., 2009); or other behavioral mechanisms including reference dependent behavior (Behaghel and Blau, 2012).

These off-diagonal weights are identified by how the claiming age distributions by education, marital status, and cohort in a model without subjective beliefs differ from those distributions observed in the data. Increasing the probability weight on larger penalty values incentivizes later claiming while higher weight on low options pushes earlier claiming. Therefore, the deviations between the uncertainty-weighted penalty in Equation 17 and the statutory penalty of 6.7% is informative of how changes in the knowledge structure and uncertainty influence claiming. Figure 7 show how this deviation differs across theses cohorts.

Figure 7: Estimated Beliefs Across Cohorts



Notes: Figure shows the deviation of the model estimated uncertainty-weighted penalty from the statutory penalty, $\mathbb{E}[\tilde{\gamma}_1^{ss} \mid k] - 0.067$. The four bars for each education-marital status group are (from left to right): (1) the prior distribution and uncertainty weights from the 1931–1935 cohort, (2) prior distribution from the 1945–1949 cohort and uncertainty weights from the 1931–1935 cohort, (3) prior distribution from the 1931–1935 cohort and uncertainty weights from the 1945–1949 cohort, and (4) the prior distribution and uncertainty weights from the 1945–1949 cohort.

The first bar within each socioeconomic status cluster shows how the uncertainty weighted

penalty for the 1931–1935 cohort deviated from the statutory penalty. We observe that knowledge and uncertainty impact singles and married individuals differently. Among singles of both education levels, the uncertainty weighted penalty is larger than the statutory penalty (indicated by the positive deviation) while the uncertainty-weighted penalty falls below the statutory penalty among the married. The final bar within each group shows the same calculation for the 1945–1949 cohort. For married individuals and non-college singles, this deviation falls slightly between the two cohort. This indicates that the combined role of knowledge (the fixed belief type) and uncertainty is less important for the later cohort – claiming behavior in a model without subjective knowledge is more similar to the data-observed claiming behavior for this later cohort.

The remaining bars isolate the independent roles of the fixed knowledge and the uncertainty. First, we update the knowledge distribution (as shown in Figure 6) to that of the later cohort while keeping the estimated uncertainty weights (ε_k^{ss}) fixed at those from the previous cohort. This show how the improvement of knowledge across these cohorts impacts the calculation. Outside of the college, single group, the deviation between the uncertainty-weighted penalty and statutory penalty moves towards zero when this knowledge distribution is updated. This highlights that the larger share of correct responses pushes the uncertainty-weighted and statutory penalties together. The last remaining bar changes the uncertainty weights to those of the 1945–1949 cohort while holding the fixed knowledge distribution at the level of the 1931–1935 cohort. For all groups, this change pushes the uncertainty-weighted and statutory penalty further apart. This indicates that for the later cohort, the improvement in the knowledge distribution along with policy and input changes, lead to larger differences between the model implied claiming distributions and the claiming distribution in the data. This means the estimation placed larger importance on the uncertainty weights. This highlights that uncertainty plays a more important role among later cohorts that earlier ones.

5 Decomposing Claiming Changes

The average claiming age rose by 0.7 years between the 1931–1935 and 1945–1949 cohorts. Because the model is estimated separately for each cohort, the two estimated models differ along three dimensions that together account for this change. The first, which we refer to as *inputs*, collects the first-step processes and the estimated preference parameters: health transitions and subjective survival beliefs, family structure, wages, initial conditions, and the preference parameters in Table 4. The second, *beliefs*, is the subjective distribution over the early-claiming penalty, which consists of the distribution of belief types k and the uncertainty weights ε_k^{ss}. The third, *policy*, is the set of statutory Social Security rules summarized in Table 3 and Figure 5: the normal retirement age, the delayed retirement credit, the bend points of the PIA formula, and the retirement earnings test.

To isolate the role of each mechanism, we start from the model estimated for the 1931–1935 cohort and replace one set of objects at a time with its 1945–1949 counterpart, holding the other two fixed at their 1931–1935 values. Table 6 reports the average claiming age in each experiment, along with the change relative to the 1931–1935 cohort in parentheses. The final row reports the model estimated for the 1945–1949 cohort, in which all three sets of objects are updated together. Because each experiment changes a single mechanism, the individual effects need not sum to the total change; any difference reflects interactions between the mechanisms.

Table 6: Decomposition of the Change in Average Claiming Age

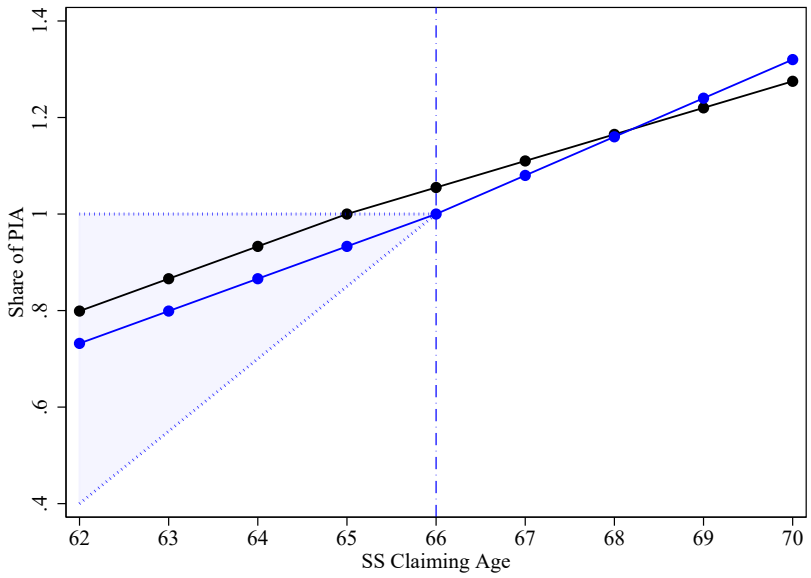
Experiment	All	Education status		Marital status	
		Non-college	College	Singles	Married
1931-1935 Cohort	63.5	63.0	63.8	63.3	63.5
+ inputs	63.3	63.0	63.6	63.2	63.4
	(-0.2)	(+0.0)	(-0.2)	(-0.1)	(-0.1)
+ beliefs	63.7	63.3	64.1	63.5	63.9
	(+0.2)	(+0.3)	(+0.3)	(+0.2)	(+0.4)
+ policy	64.2	63.5	64.8	63.4	64.6
	(+0.7)	(+0.5)	(+1.0)	(+0.1)	(+1.1)
1945-1949 Cohort	64.2	63.5	64.6	63.5	64.5
	(+0.7)	(+0.5)	(+0.8)	(+0.2)	(+1.0)

Notes: Each cell reports the model-simulated average Social Security claiming age. Rows labeled "+ inputs", "+ beliefs", and "+ policy" start from the model estimated for the 1931–1935 cohort and replace only the indicated set of objects with those of the 1945–1949 cohort. Changes relative to the 1931–1935 cohort are in parentheses.

Policy rules. The change in statutory rules is the dominant mechanism. Imposing the 1945–1949 rules on the 1931–1935 cohort raises the average claiming age by 0.7 years, from 63.5 to 64.2, which is the entire increase between the two cohorts. Figure 8 shows the source of this response. The increase in the normal retirement age from 65 to 66 lowers the share of the PIA received at every claiming age before 66, so that a worker must claim one year later to receive the same benefit. The increase in the delayed retirement credit from 5.5 to 8.0 percent raises the return to each year of delay beyond the normal retirement age.

The response to policy is far from uniform. The policy change alone raises the average claiming age by 1.0 years among college educated men and by 1.1 years among married men, compared to 0.5 years among non-college educated men and only 0.1 years among singles. Measured against the total change for each group, policy accounts for between 50 percent (singles) and 125 percent

Figure 8: Change in Policy Across Cohorts



Notes: The figure plots the share of PIA paid as a function of the claiming age for the 1931–1935 cohort (black) and the 1945–1949 cohort (blue). The solid line corresponds to the schedule implied by the accurate annual adjustment (6.7%), while the shaded region spans the schedules implied by the extreme belief types (0% and 15%). The change in the NRA for the later cohort shows up as a shift in the age at which this share is 1. The increase in the delayed credit appears as the steeper slope of the blue line after the normal retirement age.

(college educated) of the increase in claiming ages. The groups that respond most strongly are those with the greatest capacity to finance a delay. College educated and married men hold more wealth and have longer life expectancies (Table 2), which both lowers the cost of postponing benefits and raises the value of the larger annuity that delay provides. For married men, the return to delay is amplified because the head's claiming age also determines the survivor benefits left to his spouse. Singles, in contrast, have fewer resources to draw on before claiming and little scope to respond to changes in the benefit schedule.

Beliefs. Updating subjective program beliefs to those of the 1945–1949 cohort raises the average claiming age by 0.2 years. The effect is positive for every group, ranging from 0.2 years for singles to 0.4 years for married men. Two changes are at work. The share of individuals who correctly identify the early-claiming penalty rises from 34 to 48 percent across cohorts (Figure 6), which moves perceived penalties toward the statutory value. At the same time, the estimated uncertainty weights shift. As shown in Figure 7, the uncertainty-weighted penalty of the later cohort is at or above that of the earlier cohort in each education and marital group. A larger perceived penalty for early claims, and in particular more weight on the possibility of a large penalty, leads individuals to delay claiming as insurance against an irreversible reduction in benefits.

Inputs. Changes in inputs work in the opposite direction. Replacing the first-step processes and preference parameters of the 1931–1935 cohort with those of the 1945–1949 cohort lowers the average claiming age by 0.2 years, with effects between 0.0 and -0.2 years across groups. This is notable given that objective life expectancy at age 60 increased by 0.6 to 1.3 years across these cohorts, a change that on its own would raise the return to delayed claiming. However, claiming decisions in the model depend on subjective rather than objective survival, and subjective life expectancies are essentially unchanged for college educated men and fall by roughly half a year for non-college educated men (Table 2). In addition, the later cohort is estimated to have slightly lower discount factors and lower risk aversion (Table 4). Less patient and less risk averse individuals accumulate less wealth and place a lower value on the insurance provided by a larger annuity, both of which lead to earlier claims.

Non-linearities and interactions The three mechanisms do not act independently. Each experiment in Table 6 changes one set of objects while holding the other two at their 1931–1935 values, so the individual effects sum to the total change only if the model is additive in the three mechanisms. It is not. Among married men, the individual effects sum to 1.4 years while the total change is 1.0 years. Among the college educated they sum to 1.1 years against a total change of 0.8 years, and among the non-college educated to 0.8 years against 0.5 years. In each case the

mechanisms are sub-additive: the response to all three changes together is smaller than the sum of the responses to each change alone. For college educated and married men, policy alone generates a larger increase in claiming ages than the entire change observed across cohorts.

Three features of the claiming problem generate these non-linearities. First, claiming is a discrete choice made against a kinked benefit schedule. The return to an additional year of delay changes discretely at the normal retirement age, and the benefit-maximizing claiming age is a step function of life expectancy rather than a smooth one. Whether a change in rules moves an individual therefore depends on how close he is to a threshold, and that distance is determined by his preferences, wealth, survival beliefs, and perceived penalty. The response to policy is a function of the inputs and beliefs at which it is evaluated.

Second, the mechanisms that encourage delay act on the same margin. A worker who postpones his claim from 65 to 66 because he places more weight on a large early-claiming penalty cannot be moved across that threshold a second time by the increase in the normal retirement age. Because the belief and policy changes both push the same marginal claimants over the same thresholds, their effects overlap when they are imposed jointly and the sum of the individual effects overstates the combined response. This overlap is largest for the groups with the most mass near the normal retirement age, namely college educated and married men, which are also the groups for which the gap between the summed and total effects is largest.

Third, the inputs of the later cohort dampen the response to policy. Delaying a claim requires financing consumption out of wealth or earnings in the interim. The 1945–1949 cohort is estimated to be slightly less patient and less risk averse, and does not perceive the gains in longevity that occurred between the two cohorts. Each of these lowers the value of trading current benefits for a larger annuity, so that the new rules induce less delay when evaluated at the inputs of the later cohort than at those of the earlier one.

An implication is that the contribution assigned to any one mechanism depends on the point at which it is evaluated. The effects in Table 6 measure the response of the 1931–1935 cohort to each change in isolation. They are upper bounds on the contribution of policy for college educated and married men, for whom the total change is smaller than the policy effect alone.

Share attributable to policy. We summarize the role of policy by the share of the total change in the average claiming age that the change in rules accounts for on its own. For the population as a whole, this share is 100 percent: imposing the 1945–1949 rules on the 1931–1935 cohort raises the average claiming age by 0.7 years, the same as the total change between the two cohorts. Changes in inputs and beliefs each move the average claiming age by 0.2 years, but in opposite directions, so they cancel. The increase in claiming ages across these cohorts is therefore the result of the reforms to the normal retirement age and delayed retirement credit, and not of concurrent

changes in longevity, preferences, or program beliefs. The share differs across groups. Policy accounts for all of the change among non-college educated men, and for more than all of it among college educated (125 percent) and married men (110 percent). For these two groups, the new rules alone would have raised claiming ages by more than was observed, and the other changes across cohorts partially offset the response. Singles are the exception: their average claiming age rises by only 0.2 years, and policy accounts for half of that. Most of the response to the reforms thus comes from married and college educated men, while the claiming behavior of single men is largely unchanged.

6 Conclusion

Men born between 1945 and 1949 claimed Social Security 0.7 years later than men born between 1931 and 1935. Using a life-cycle model estimated separately for each cohort, we find that the 1983 reforms account for the entire increase. The response is uneven: the new rules raise claiming ages by about one year for college educated and married men, half as much for men without a college education, and hardly at all for single men.

Beliefs shape the response in two directions. Better knowledge of the early-claiming penalty and greater uncertainty about its size raise claiming ages by 0.2 years. This is offset by changes in other inputs, including subjective life expectancies that did not rise with actual longevity. The gap between the change in incentives and the change in behavior therefore reflects gains in longevity that workers did not perceive, and not a weak response to the rules.

These findings bear on reforms still under way, including the increase in the normal retirement age to 67. Such changes will delay claims, but mainly among married and college educated workers, and their effect will depend on what workers believe about the program and about their own longevity. Isolating the role of survival beliefs, and extending the decomposition to labor supply, are left for future work.

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Online appendix

A Spousal and survivors benefits

Spousal benefits The early application penalty applies to both the old-age benefits of the head of household and the spousal benefits while delayed retirement credits are only awards to the head's benefits. Therefore, in practice, the benefits received at a household level (old age benefits + spousal benefits) are a function of the claiming age of both the head and the spouse. In order to reduce the computational burden of our model, we abstract from a separate claiming decision of the spouse and assume that all couples claim together. In the event that the spouse is not benefit eligible at the time of the head's claiming, we assume that spousal benefits are received as soon as the spouse is age 62. Therefore, spousal claiming age in the model—and thus any early claiming penalty incurred on spousal benefits received—is completely determined by head's claiming age and the age gap between the spouse and the head of household.

Survivors benefits There are two important rules pertaining to survivors benefits that we try to replicate in the model. First, individuals can leave behind their Social Security benefits for their surviving spouses (even if they have not claimed their benefits at the time of the death). We allow this feature in the model as well. In the scenario where the head dies without claiming their benefits, survivors benefits in the model are calculated using the Primary Insurance Amount at the time of death. However, if the head has already claimed their benefits at the time of death, then survivors benefits are calculated using any adjustments that were applied to the head's benefits. Second, in practice, surviving spouses can receive reduced benefits as early as age 60 (age 50 in the case of disability and even earlier if they have not remarried and are caring for the deceased husband's child who is under the age of 16). For computational simplicity we abstract from some of these details and allow full survivors benefits to be bequeathed as long as the spouse is age 62.

B Recursive formulation

The life cycle is separated into three phases. The first is the employment phase (ages 25–61), during which individuals choose consumption, savings, and labor supply. The second is the retirement choice phase (ages 62–69), during which individuals continue to make consumption, labor supply, and savings decisions and also decide whether to claim Social Security benefits. The third is the retirement phase (ages 70–99), during which individuals no longer work or claim benefits and make only consumption and savings decisions. The decision problem for each phase of a household head from cohort j with education level e, marital status q, and Social Security belief type k is given below. As in the main text, a superscript j denotes a cohort-specific parameter or function, and j is suppressed on state and choice variables.

Employment phase

$$V^j_{e,q,k,t}(a_t, a^{ss}_t, a^{ss}_{st}, \eta_t, \lambda_t, \mu_t) = \max_{\{c_t, h_t\}} \Bigg\{ U^{e,m,j}(c_t, l_t) + \beta^{e,m,j} \pi^s_t(e, m, j, \mu_t)\, E\left[V^j_{e,q,k,t+1}(a_{t+1}, a^{ss}_{t+1}, a^{ss}_{st+1}, \eta_{t+1}, \lambda_{t+1}, \mu_{t+1}) \right] + \beta^{e,m,j} \left(1 - \pi^s_t(e, m, j, \mu_t)\right) \Omega^{e,m,j}(A^q_{t+1}) \Bigg\} \quad \text{s.t.}$$

$$a_{t+1} = a_t + W\left(y_t, y_{st}, \bar{r} a_t, \tau^j_t\right) + tr_t - c_t,$$
(1), (5)–(12), (13), (15), and (16).

where $y_t + y_{st} + \bar{r} a_t$ is total pre-tax income and $W(\cdot, \tau^j_t)$ gives post-tax income under the tax schedule τ^j_t in effect in calendar year $j + t$. The expectation is taken with respect to wage, employment, Social Security program belief, and health uncertainty.

Retirement choice phase Starting at age 62, individuals also make benefit-claiming decisions, which are one-time choices. Benefits are determined by the age at which individuals first claim. When making these decisions, individuals consider the perceived benefits implied by their belief type:

$$V^j_{e,q,k,t}(a_t, a^{ss}_t, a^{ss}_{st}, \eta_t, \lambda_t, \mu_t, b^{ss}_{t-1}) = \max_{\{c_t, h_t, b^{ss}_t\}} \Bigg\{ U^{e,m,j}(c_t, l_t) + \beta^{e,m,j} \pi^s_t(e, m, j, \mu_t)\, E\left[V^j_{e,q,k,t+1}(a_{t+1}, a^{ss}_{t+1}, a^{ss}_{st+1}, \eta_{t+1}, \lambda_{t+1}, \mu_{t+1}, b^{ss}_t) \right] + \beta^{e,m,j} \left(1 - \pi^s_t(e, m, j, \mu_t)\right) \Omega^{e,m,j}(A^q_{t+1}) \Bigg\} \quad \text{s.t.}$$

$$a_{t+1} = a_t + W\left(y_t, y_{st}, \bar{r} a_t, \tau^j_t\right) + \mathbb{I}\left\{b^{ss}_t = 1\right\} \times \left(\widetilde{ssb}_t + \mathbb{I}\left\{t - \iota \geq 62\right\} \times \widetilde{ssb}^{\,s}_t \right) + tr_t + pb_t - c_t,$$
(1), (5)–(12), (13), (15), and (16).

Once benefits are claimed, perceived benefits $\widetilde{ssb}_t$ and $\widetilde{ssb}^{\,s}_t$ are replaced by actual benefits ssb_t and ssb^s_t. The expectation is taken with respect to wage, employment, Social Security program belief, and health uncertainty.

Retirement phase At age 70, individuals who have not yet claimed automatically begin receiving their own benefits and, if the spouse is eligible, spousal benefits. Some younger spouses may not yet be eligible at that point; their spousal benefits begin once they reach age 62.

$$V^j_{e,q,t}(a_t, a^{ss}_t, a^{ss}_{st}, \mu_t) = \max_{c_t} \Bigg\{ U^{e,m,j}(c_t, l_t) + \beta^{e,m,j} \pi^s_t(e, m, j, \mu_t)\, E\left[V^j_{e,q,t+1}(a_{t+1}, a^{ss}_{t+1}, a^{ss}_{st+1}, \mu_{t+1})\right] + \beta^{e,m,j}\left(1 - \pi^s_t(e, m, j, \mu_t)\right) \Omega^{e,m,j}(A^q_{t+1}) \Bigg\} \quad \text{s.t.}$$

$$a_{t+1} = a_t + W\left(y_{st}, \bar{r}a_t, \tau^j_t\right) + ssb_t + \mathbb{I}\left\{t - \iota \geq 62\right\} \times ssb^s_t + tr_t + pb_t - c_t,$$
(1), (6), (13), (15), and (16).

In this phase, the expectation is taken with respect to health uncertainty only.

C Data: PSID, HRS, MEPS, and UAS

Panel Study of Income Dynamics (PSID) The description of the PSID data and collection methodology in this paper is based on material made publicly available by the study here: https://psidonline.isr.umich.edu/default.aspx.[21] The PSID is a nationally representative longitudinal survey in the United States that we use to estimate life-cycle profiles of labor force participation, hours, wealth, the wage process, and initial conditions. The original PSID sample was drawn from the nationally representative SRC sample and an oversample of the low-income SEO sample. We use a subsample of individuals from the SRC sample who were interviewed at least twice between 1968 and 2017. Our analytic sample consists of male household heads between ages 22 and 99, born between 1902 and 1965. The final sample includes 95,534 observations for 5,593 individuals. Table C.1 provides details on how we derive our sample.

Table C.1: Panel Study of Income Dynamics sample selection

	Observations	Individuals
Initial sample	3,385,493	82,573
SRC sample	1,429,096	34,856
1968-2017	1,359,384	34,856
Interviewed twice	1,010,175	33,725
Male household head (and wife, if applicable)	122,317	9,683
Ages 25-99	115,057	9,208
Born 1902-1965	95,534	5,593

[21]The collection of data used in this study was partly supported by the National Institutes of Health under grant number R01 HD069609 and R01 AG040213, and the National Science Foundation under award numbers SES 1157698 and 1623684.

Health and Retirement Study linked with SSA administrative records The Health and Retirement Study (HRS) is a longitudinal survey of Americans over age 50.[22]

In this work, we use HRS data (2016, v1) linked to SSA administrative records on benefits and earnings. This dataset is used to compute claiming age distributions and related statistics, spousal benefits within couples, and the evolution of spousal earnings and Average Indexed Monthly Earnings (AIME) of household heads and spouses over the life cycle.

We use three different samples: two derived from the Respondent Cross-Year Benefits file (male and spouse samples) and one from the Summary Earnings file (household earnings sample). The male sample, used to construct claiming behavior, consists of 2,296 men born between 1926 and 1939 who first claimed retirement benefits between ages 62 and 70 (refer to Table C.2 for details). We focus on this cohort to ensure a sufficiently large sample while including only individuals for whom Social Security was in place throughout their working lives and the normal retirement age was 65. The spouse sample includes 254 married couples in which the male household head was born between 1921 and 1939 and (i) claimed Social Security retirement benefits on his own earnings record between ages 62 and 70, and (ii) the spouse first claimed retirement benefits either solely on her own record, jointly on her own and her spouse's record, or exclusively as auxiliary benefits on her spouse's record (refer to Table C.3 for details).

The household earnings sample contains 72,545 observations for 1,270 households in which the male head was born between 1926 and 1940 and spousal earnings are non-missing (including zeros). Refer to Table C.4 for sample selection details.

Table C.2: Health and Retirement Study sample selection: male sample
(Respondent Cross-Year Benefits Files)

	Observations
Initial sample	43,559
Male household head	14,394
Received SS retirement benefits between age 62-70	5,097
Born 1926-1939	2,296

Medical Expenditure Panel Survey (MEPS) We use the Household Component of Medical Expenditure Panel Survey (MEPS-HC) to identify health and mortality related parameters. MEPS-HC is a nationally representative survey of the U.S. civilian noninstitutionalized population. The sampling frame is drawn from respondents to the National Health Interview Survey (NHIS), which is conducted by the National Center for Health Statistics. We use a pooled sample (between the years 1996 and 2014) of males between the ages of 20 and 90 which gives us a total sample size of 89,870 observations.

Understanding America Study (UAS) Our project relies on data from surveys administered by the Understanding America Study (UAS), maintained by the Center for Economic and Social

[22]The HRS (Health and Retirement Study) is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan.

Table C.3: Health and Retirement Study sample selection: spouse sample
(Respondent Cross-Year Benefits Files)

	Observations
Initial sample	10,384
Male household head	5,280
Head claims SS retirement, dual, or auxiliary benefits	3764
Born 1926-1940	1014
Head claims SS retirement benefits on his own record between ages 62-70	539
Spouse claims SS retirement, dual, or auxiliary benefits	254

Table C.4: Health and Retirement study sample selection
(Summary Earnings File)

	Observations	Individuals
Initial sample	889,627	43,558
Male household head	103,040	1,457
Born 1921-1939	89,810	1,270
Spouse earnings ≥ 0	72,545	1,270

Research (CESR) at the University of Southern California. The content of this paper is solely the responsibility of the authors and does not necessarily represent the official views of USC or UAS.

The UAS is a panel dataset of roughly 9,000 respondents per wave, designed to be nationally representative of the United States and administered in various modules. The panel is conducted online, allowing respondents to participate digitally at their convenience. We use this dataset to measure how well individuals understand the Social Security system. Specifically, we use a nationally representative sample of men ages 25–69 who are not currently receiving Social Security retirement benefits, drawn from two waves of the study: UAS94 and UAS231. This sample includes 3,663 observations for 2,347 individuals collected between 2017 and 2022. After further restricting the sample to respondents who answered the subjective program knowledge questions, our final sample contains 3,648 observations for 2,339 individuals. Details on the sample selection process are provided in Table C.5.

D First-step estimation

D.1 Health and objective survival

We estimate health transitions using the Household Component of Medical Expenditure Panel Survey on a population between the ages of 20 and 90. The coefficient estimates for these health transitions are provided in Table D.1.

To estimate objective survival probabilities, we use the HRS tracker files to obtain individuals' age at death, based either on the reported year of death or, when unavailable, the last known date

Table C.5: Understanding America Study sample selection

	Observations	Individuals
Initial sample	17,520	10,727
Nationally representative sample	12,899	7,975
Ages 25-69	10,593	6,651
Male	4,305	2,702
Not currently receiving SS retirement benefits	3,663	2,347
Answered misinformation questions	3,648	2,339

Table D.1: Ordered probit estimates of health transitions

	(1)
Health Lag=1	1.454***
Age	0.0213
$\text{Age}^2/10^2$	0.0186
$\text{Age}^3/10^3$	-0.00337*
College=0 $\times$ married=1	-0.149***
College=1 $\times$ married=0	-0.369***
College=1 $\times$ married=1	-0.623***
cut1	2.232***
Observations	85,853
Pseudo R^2	0.22

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

alive. Because the HRS is conducted biennially, we expand the dataset to account for intervening years. Marital and health status between waves are imputed using information from the preceding wave, while age is imputed by incrementing the prior value by one year. Education and birth cohort are treated as time-invariant. Using this expanded dataset and reported ages at death, we construct an indicator capturing the precise timing of death. Columns 2 and 3 of Table D.2 presents a comparison of life expectancies at ages 50, 60, and 70 between those constructed from HRS estimated objective survival probabilities and Social Security Administration life tables.

D.2 Subjective survival

Subjective mortality expectations are measured from the Health and Retirement Study (HRS). One module of the survey asks respondents what they believe is the probability they will live to certain ages: *(What is the percent chance) that you will live to be [X] or more?*[23]

[23]At the outset, respondents are prompted:*Next we would like to ask your opinion about how likely you think various events might be. When I ask a question, please give a number from 0 to 100, where "0" means you think there is absolutely no chance, and "100" means you think the event is absolutely sure to happen.*

Table D.2: Life expectancy comparisons (1931–1935): HRS vs. SSA Life Tables

Life expectancy at	HRS objective	Life Tables
age 50	28.0	27.1 - 28.1
age 60	20.3	20.0 - 21.0
age 70	13.2	13.1 - 14.1

Notes: life expectancy at ages 50, 60, and 70 from both the HRS and life tables is reported for men born between 1931 and 1935. The group-specific weights used to compute average life expectancy from the HRS are 17.4, 14.5, 24.3, and 43.7 for non-college single, college single, non-college married, and college married men, respectively. Because life expectancy from life tables can be calculated for each single birth cohort, we report a range spanning those born in 1931 through 1935.

The target age [X] varies by respondents' current age. Respondents under age 65 are asked about survival to age 75. If they report a positive probability, they are then asked about survival to age 80. Respondents aged 65–69 are asked about age 80, those 70–74 about age 85, 75–79 about age 90, 80–84 about age 95, and 85–89 about age 100. Respondents 90 and older are not asked these questions.

These questions yield subjective survival expectations to ages 75–100. To maximize usable reports, we impose four assumptions: (1) If a respondent reports a 0% probability of survival to a given age, we assume they believe they have a 0% chance of survival to all later ages; (2) If they report a 100% chance of survival to a given age, they also believe they have a 100% chance of survival to all prior ages; (3) If the same probability is reported for two non-consecutive ages, the same probability is assumed for all ages in between. (4) All respondents believe there is a 0% chance of survival to age 110. We drop respondents with inconsistent answers (e.g., higher survival chances to older ages) or who report 0% or 100% for all ages.[24]

The final sample includes men ages 45–89 born between 1926 and 1965.[25] This yields 60,308 observations for 12,851 individuals: 7,265 ages 45–54, 27,624 ages 55–64, 17,007 ages 65–74, and 8,412 ages 75–89. We compute the median subjective survival probability to each target age by reference (current) age, education, marital status, and health using HRS cross-sectional weights.

Using this sample, we estimate survival curves that vary by education, marital status, and self-reported health. Because many survival curves can rationalize the reported cumulative probabilities, we follow o2018subjective and assume subjective survival probabilities follow a Weibull distribution:

For example, no one can ever be sure about tomorrow's weather, but if you think rain is very unlikely tomorrow, you might say there is a 10 percent chance. If you think there is a very good chance it will rain, you might say there is an 80 percent chance.

[24] Papers such as bissonnette2017 treat 50% responses as "focal answers" reflecting rounding or guessing. We retain them because they remain informative for deviations from objective responses, especially in affecting the mean or median responses we use in estimation.

[25] We expand the cohort to ensure enough observations to estimate subjective survival curves at younger ages. Using only the 1931-1935 cohort would preclude estimation of subjective survival at reference ages 50 and 55. Additionally, using only this cohort would leave a small sample for which estimation of parameters as a function of demographics and health would not be feasible.

$$S_{\mu}^{e,m}(\alpha; X) = exp\left[-\left(\frac{X-\alpha}{\kappa_{\mu}^{e,m}}\right)^{\lambda_{\mu}^{e,m}}\right] \tag{18}$$

where $\kappa_{\mu}^{e,m}$ and $\lambda_{\mu}^{e,m}$ are the estimated parameters. This yields survival curves from age α to 110 for each education-marital-health combination.

To incorporate evolving health, we construct survival curves in two steps. First, for each reference age $\alpha = 50, ..., 70$, we estimate cumulative survival curves in rolling 10-year bins. For example, the curve for reference age 60 uses data from ages 55–65. This produces 21 curves per demographic-health group. Second, we compute average cumulative survival probabilities to each age, $\bar{S}_{\mu}^{e,m}(X = \alpha, ...; 110)$, by averaging across all curves that include that age:

$$\bar{S}_{\mu}^{e,m}(X = \alpha, ...; 110) = \begin{bmatrix} 1 \\ S_{\mu}^{e,m}(50; 51) \\ \vdots \\ \sum_{\alpha=50}^{X-1} \frac{1}{X-\alpha} S_{\mu}^{e,m}(\alpha; X) \end{bmatrix}$$

This method allows the cumulative probability of survival to vary by not only fixed education and marital status but also by healths shocks after age 50.[26]

Figures D.2 show estimated objective, $\bar{O}_{\mu}^{e,m}(X)$, and subjective survival curves, $\bar{S}_{\mu}^{e,m}(X)$. The solid lines on this graph represent the subjective cumulative probability of survival to various ages, conditional on survival to age 50, for individuals who vary based upon education, marital status, and self-reported health. The cumulative probability of survival to age X for someone in bad/good health represents the cumulative probability of survival for someone who received a bad/good health shock in each period from age 50 to age X. The dashed lines represent the objective cumulative probability of survival (as estimated from HRS using the process discussed in Section D.1) for these same groups. The gap between these lines captures deviations in subjective mortality from the mortality predicted by average objective survival probabilities.

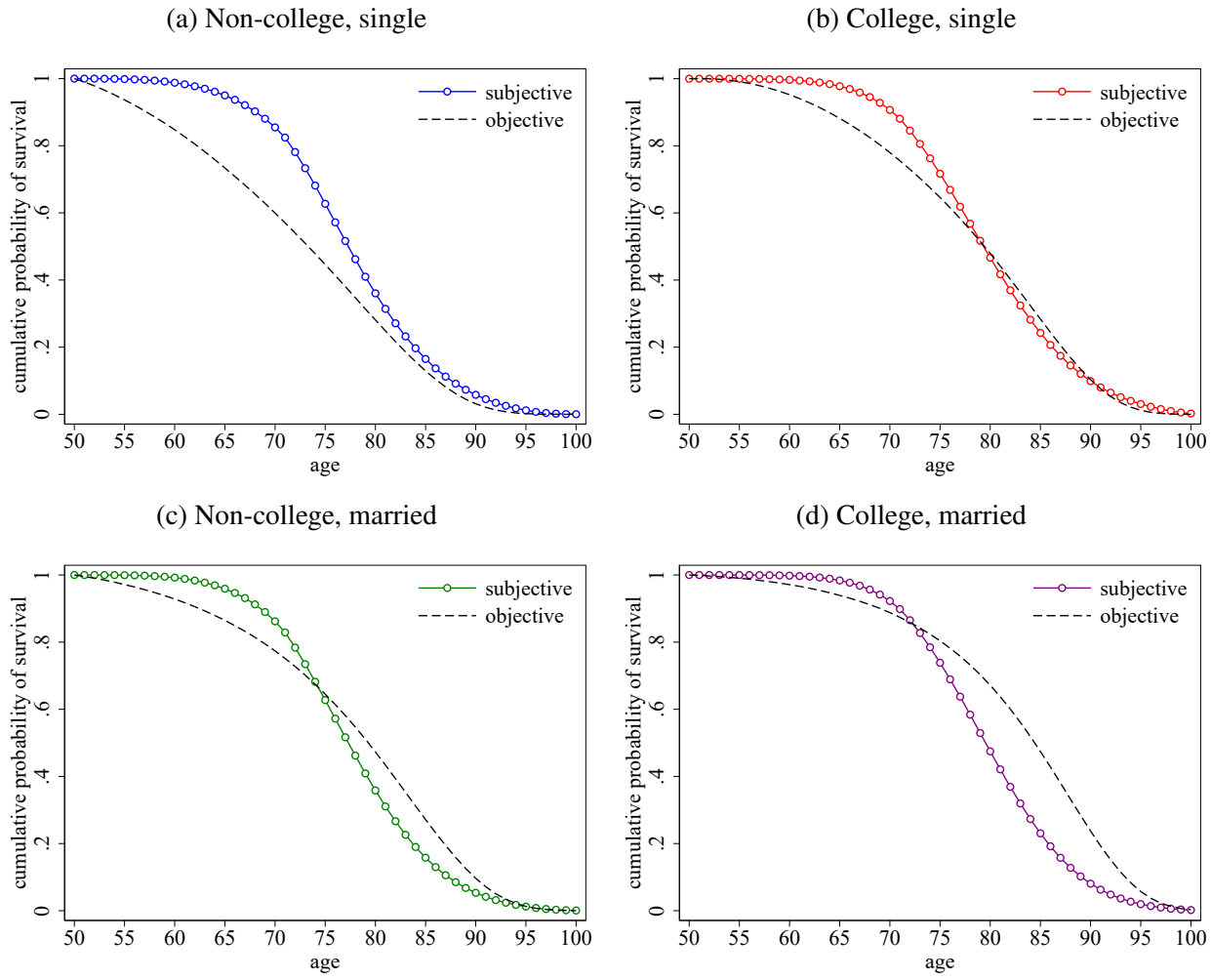
We use these survival curves to compute the annual survival probabilities that will be used as inputs into our model. One option would be to back out annual survival probabilities directly from these curves as the ratio of the cumulative probability of survival to age $t+1$ to the cumulative probability of survival to age t. Specifically, $\pi_{t+1}^{s}(e, m, \mu) = \bar{S}_{\mu}^{e,m}(t+1) / \bar{S}_{\mu}^{e,m}(t)$. However, there are many options of annual survival probabilities that can deliver the same cumulative survival curve. Thus, we choose to use the structure of the estimated objective survival probabilities to guide the shape of the probabilities. Specifically, we will construct a scale factor which will augment objective survival probabilities to make the dashed objective survival curves by health exactly match the estimated subjective survival curves.[27]

The objective cumulative probability of survival to age t, $\bar{O}_{\mu}^{e,m}(t)$, is equal to the product of the objective cumulative probability of survival to age $t-1$, $\bar{O}_{\mu}^{e,m}(t-1)$, and the probability of survival between ages $t-1$ and t. We compute a education, marital status, and health specific scale

[26]Due to data limitations, we only estimate the age specific curves up until age 70 (using data on individuals up to age 75). The assumption we make is that shocks after age 70 do not impact your subjective perceptions of survival to various ages differently than the health shocks realized up until age 70.

[27]Because annual probabilities of survival must be bounded above by 1, in some cases it may be impossible to find a scale factor that exactly matches objective and subjective probabilities.

Figure D.1: Objective $\left(\bar{O}_{\mu}^{e,m}\right)$ and subjective $\left(\bar{S}_{\mu}^{e,m}\right)$ cumulative survival curves by education, marital status, and self-reported health (1931–1935 cohort)



Source: Health and Retirement Study, authors' calculations

Notes: solid lines show the subjective survival curves of an individual of a given education-marital status group for bad (circle marked) and good (x marked) health. Dashed lines are the objective survival curves measured from HRS for the same education, marital status, and health groups.

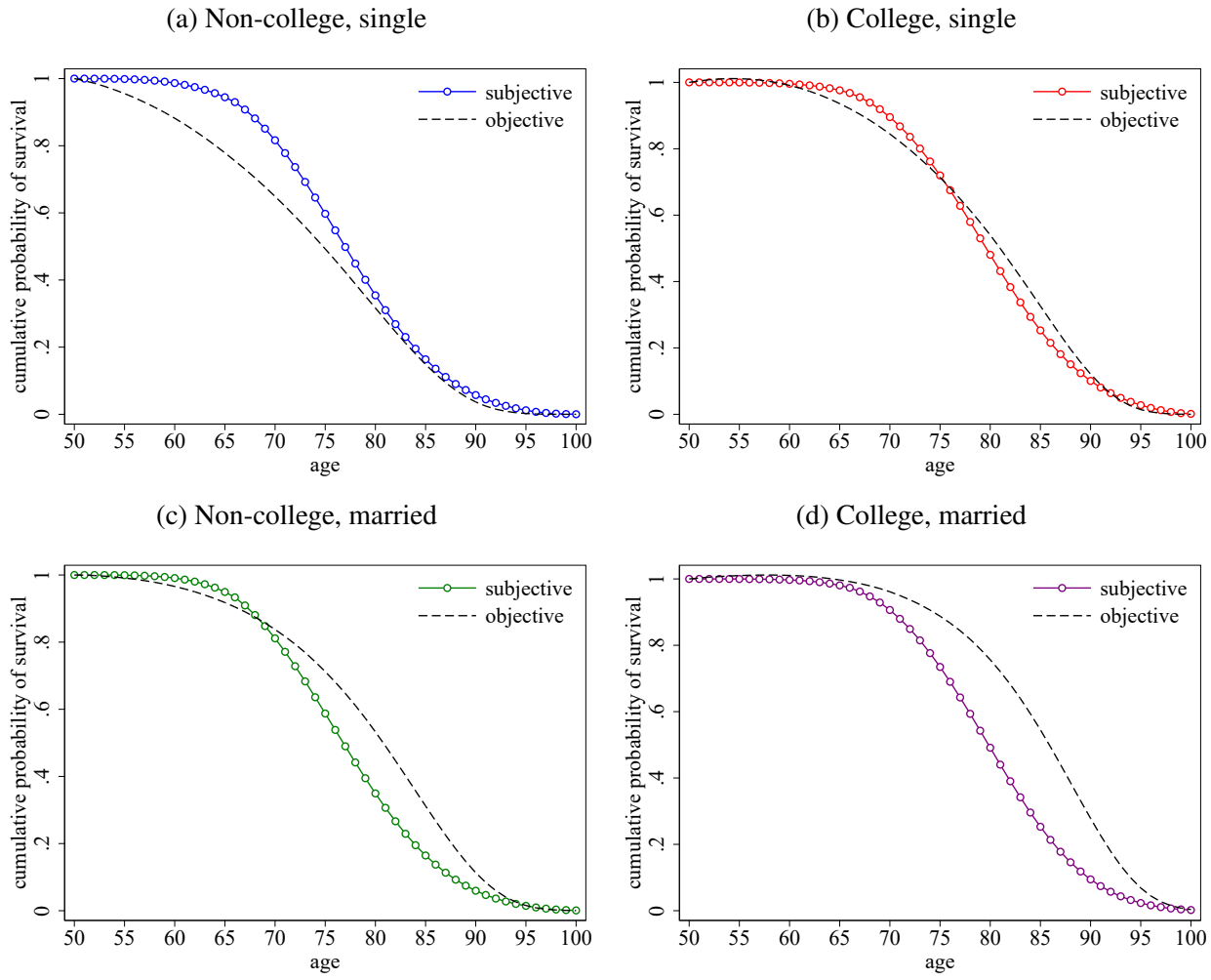
factor, $\gamma_t^{e,m,\mu}$, such that the cumulative objective probability of survival is equal to the cumulative subjective probability of survival estimated from HRS:

$$\bar{O}_{\mu}^{e,m}(t) = \left[\left(1+\gamma_j^{e,m,\mu}\right)\pi_t(e,m,\mu)\right] * \bar{O}_{\mu}^{e,m}(t-1) \text{ s.t. } \bar{O}_{\mu}^{e,m}(t) = \bar{S}_{\mu}^{e,m}(t)$$

This scale factor is shown in Figure D.3.

Comparison between subjective and objective survival We define the life expectancy gap as the difference between the subjective life expectancy (implied by the estimated subjective survival probabilities) and the measured life expectancy derived from education- and marital-status-specific

Figure D.2: Objective $\left(\bar{O}_{\mu}^{e,m}\right)$ and subjective $\left(\bar{S}_{\mu}^{e,m}\right)$ cumulative survival curves by education, marital status, and self-reported health (1945–1949 cohort)



Source: Health and Retirement Study, authors' calculations

Notes: solid lines show the subjective survival curves of an individual of a given education-marital status group for bad (circle marked) and good (x marked) health. Dashed lines are the objective survival curves measured from HRS for the same education, marital status, and health groups.

survival probabilities (and the SSA life tables):

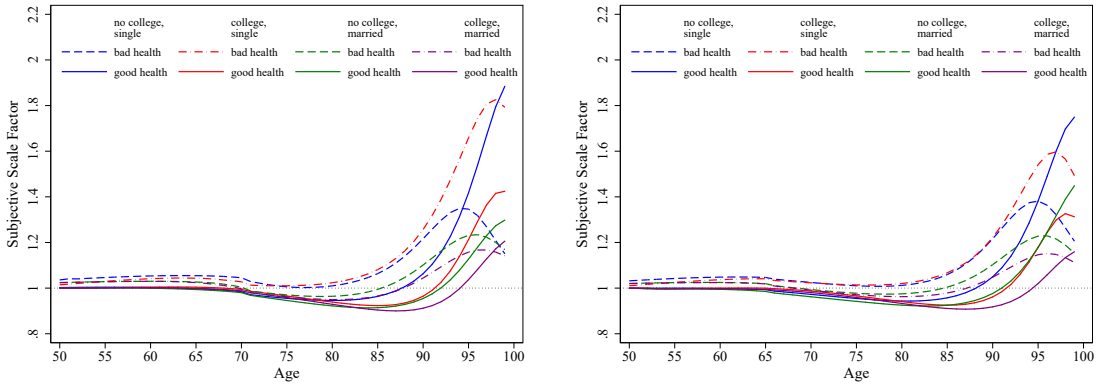
$$\text{life expectancy gap} = \text{subjective life expectancy} - \text{measured life expectancy}$$

As Table D.3 and Figure D.5 show, both subjective and objective annual survival probabilities and, thus, life expectancy vary across education-marital groups. Data on observed deaths reveal higher objective life expectancy among college-educated and married men, while subjective expectations are also higher for the college educated. Importantly, variation in these measures contributes to deviations between how long a worker expects to live and how long the average individual of his demographic group does.

This gap is shown in Figure D.6. There is substantial variation across demographic groups and

Figure D.3: Subjective scale factor for annual survival probabilities

(a) 1931–1935 (b) 1945–1949



Source: Health and Retirement Study, authors' calculations

Notes: shows the computed scale factor which equates objective and subjective cumulative probabilities of survival.

over the life cycle. At age 50, the average gap is about $+1$ year, meaning perceived life expectancy exceeds measured life expectancy by one year on average. However, across groups this ranges from nearly $+6$ years (for single men without a college degree) to about -2 years (for married college-educated men). By age 70, all demographic groups exhibit a negative gap, while by age 90 all have a positive gap.

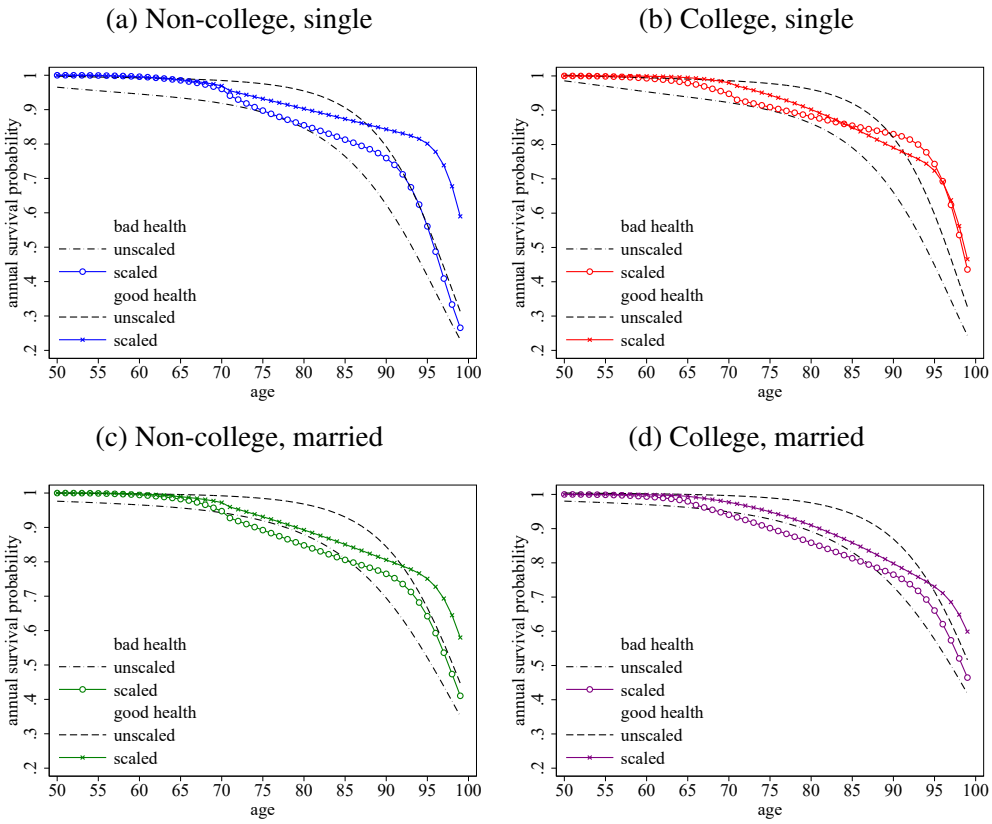
Note that when we do not allow subjective survival to vary by health, the average life expectancy gap by education-marital status remains similar to what is shown in Figure D.6. However, in that case there is no within-group variation in the gap due to realized health outcomes. The life cycle and demographic heterogeneity are thus not the only sources of variation: because we estimate subjective survival curves separately by health status for each education-marital group, there is additional variation attributable to health. Moreover, for each group, the distribution of subjective life expectancy relative to objective extends across zero, indicating that even when the group average is positive or negative, some individuals perceive themselves as living longer or shorter lives than predicted by life tables.

D.3 Family structure

Family structure in the model varies by education. For men born between 1931 and 1935, the share married or cohabiting is roughly stable over the life cycle. Accordingly, we model marriage as a fixed state determined at age 25, based on initial conditions drawn from the data. The married share is set to approximately 56 percent for non-college-educated individuals and about 74 percent for college-educated men.

Figure D.8a displays the number of children in the household over the life cycle by education of the household head. This measure includes all children age 17 and under living in the household at any point in time. The number of children follows a hump-shaped profile, peaking around age 35 (slightly earlier for non-college-educated heads) and declining to zero by age 65. Non-college-educated men reach a peak of about 2.5 children, while college-educated men peak slightly above

Figure D.4: Subjective and objective survival probabilities
by education, marital status, and health (1931–1935)



Source: Health and Retirement Study (2016, v1), authors' calculations.

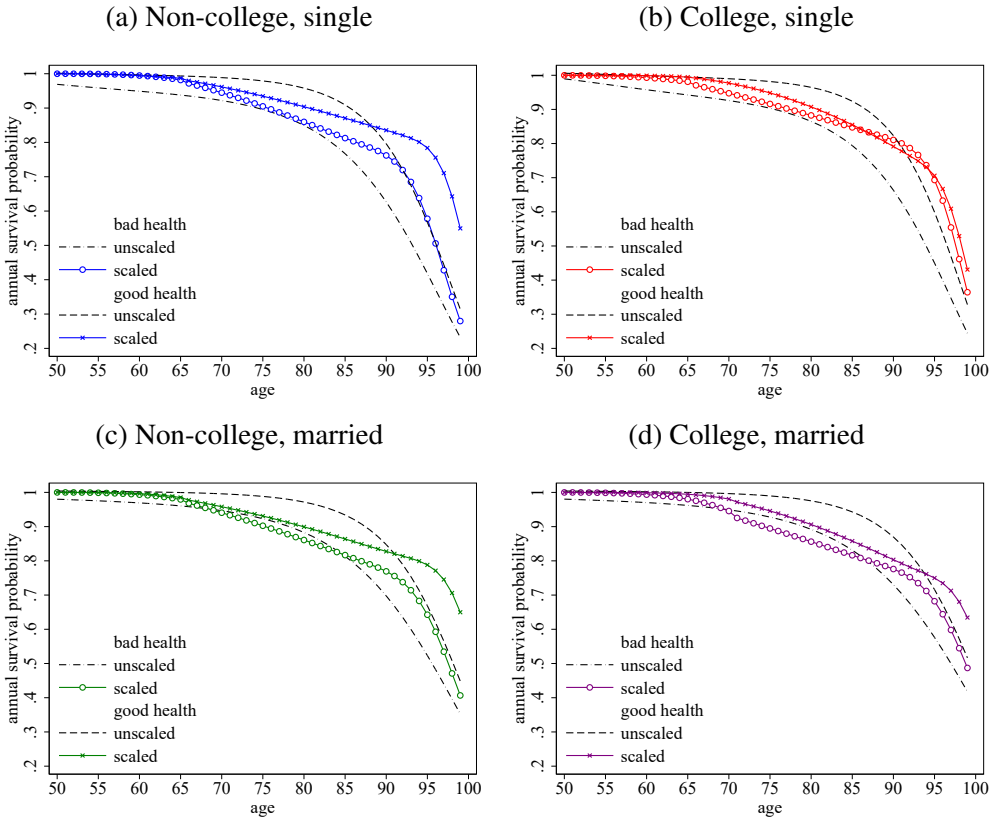
Notes: solid, colored lines in each figure show the annual survival probabilities multiplied by the computed scale factor for bad (circled marked) and good (x marked) health for each education-marital status group. Dashed lines are the unscaled, objective survival probabilities estimated from HRS.

2 children.

Married couples are eligible for Social Security spousal benefits, which depend on both the worker's age and the spouse's age. Consequently, the spousal age gap is an important determinant. Figure D.8b shows the distribution of this gap for married couples in the cohort. The average gap is approximately 4 years.

To focus on the central part of the distribution, we restrict attention to couples with an age gap between –1 (wife one year older) and +10 years, excluding the bottom 5 percent and top 10 percent. Even within this range, considerable variation remains. For computational tractability, we partition the distribution into four groups and assign each group the median gap within it. This approach captures both the prevalence of small gaps and the presence of larger ones. Estimated shares are as follows: 8.7 percent of couples have gaps of –1 to 0 years (median = 0), 26.2 percent have gaps of 1–2 years (median = 1), 46.1 percent have gaps of 3–6 years (median = 4), and 19 percent have gaps of 7–10 years (median = 8).

Figure D.5: Subjective and objective survival probabilities
by education, marital status, and health (1945–1949)



Source: Health and Retirement Study (2016, v1), authors' calculations.

Notes: solid, colored lines in each figure show the annual survival probabilities multiplied by the computed scale factor for bad (circled marked) and good (x marked) health for each education-marital status group. Dashed lines are the unscaled, objective survival probabilities estimated from HRS.

D.4 Spousal income

Spousal income enters the budget constraint of married workers. Accurately estimating this income is important both for capturing total household resources and for predicting whether a spouse claims Social Security benefits on her own record or the household head's record. We estimate spousal income in two steps. First, we regress spousal labor force participation (or having positive labor income) on the state variables and income of the household head: a fourth. Second, we estimate a regression of spousal labor income—conditional on participation—on the same set of controls.

$$1[y_{it}^s > 0] = X_{it}'\beta + \varepsilon_{it} \tag{19}$$

$$y_{it}^s = X_{it}'\beta + \varepsilon_{it} \tag{20}$$

where X_{it}' is a vector of controls, including a fourth-order polynomial in the age of the house-

Table D.3: Life expectancy comparisons: Objective and Subjective

Life expectancy at	All		Bad Health		Good health	
	Objective	Subjective	Objective	Subjective	Objective	Subjective
age 50						
Non-college singles	21.9	27.3	15.1	26.4	31.1	29.0
College singles	27.3	29.7	17.5	26.8	33.1	30.9
Non-college married	26.9	27.7	19.0	26.2	35.2	29.3
College married	31.7	29.9	19.4	25.9	36.0	31.2
age 60						
Non-college singles	15.4	17.5	11.3	16.6	23.2	19.3
College singles	19.1	19.8	12.0	17.2	24.3	20.9
Non-college married	19.2	17.9	14.2	16.4	26.4	19.4
College married	23.3	20.0	14.6	16.2	27.2	21.2
age 70						
Non-college singles	9.9	9.4	7.8	8.6	15.5	11.2
College singles	12.3	11.0	8.2	9.6	16.3	11.8
Non-college married	12.2	9.7	9.4	8.6	17.7	10.9
College married	15.3	11.1	9.9	8.4	18.4	12.1

Notes: objective and subjective life expectancy at ages 50, 60, and 70 from the HRS are reported for men born between 1931 and 1935, both for the overall population in this birth cohort and conditional on health status at the given ages. "Good health" refers to the top three categories of self-reported health, while "bad health" corresponds to the bottom two categories.

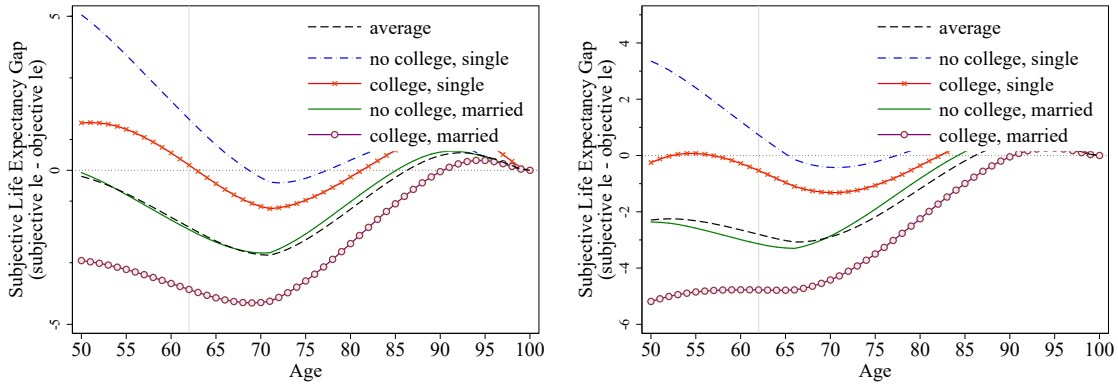
hold head; an indicator for whether the head attended college interacted with age; the head's labor income (in thousands) interacted with the fourth-order age polynomial; and the spousal age gap interacted with age.

$$1[\hat{y}^s_{it} > 0] = X'_{it}\hat{\beta}$$
$$\hat{y}^s_{it} = X'_{it}\hat{\beta}$$

These regressions are estimated using the household earnings sample from the HRS linked to the SSA Summary Earnings file. The sample includes 75,545 observations for 1,270 households with male household heads born between 1926 and 1940. We use the estimated coefficients to impute spousal labor force participation (setting income to zero if not participating) and spousal income in the model. The estimated coefficients are reported in Tables D.4 and D.5.

Figure D.6: Life expectancy gap by education, marital status
(subjective life expectancy - objective life expectancy)

(a) 1931–1935 (b) 1945–1949

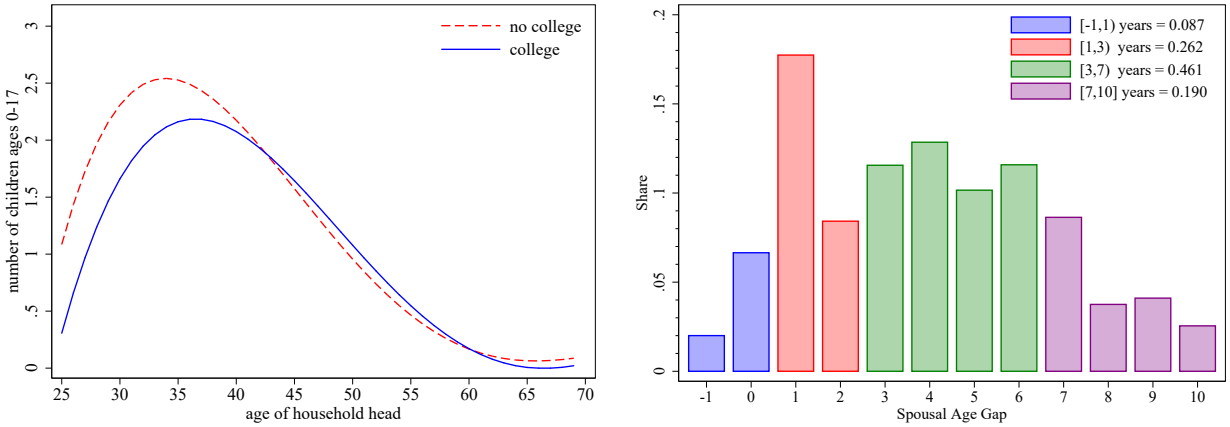


Source: Health and Retirement Study, authors' calculations

Notes: figure shows the difference between subjective and objective life expectancy by education-marital group. Life expectancies are calculated using the annual survival probabilities from Figure D.5 and the health status shares implied by MEPS health transitions. The dashed black line indicates the average life expectancy gap. Group-specific weights used to compute this average are 17.4, 14.5, 24.3, and 43.7 for non-college single; college single; non-college married; and college married men, respectively. The vertical grey line marks age 62—the first age of Social Security eligibility.

Figure D.7: Family statistics (1931–1935)

(a) Number of children (b) Spousal age gap

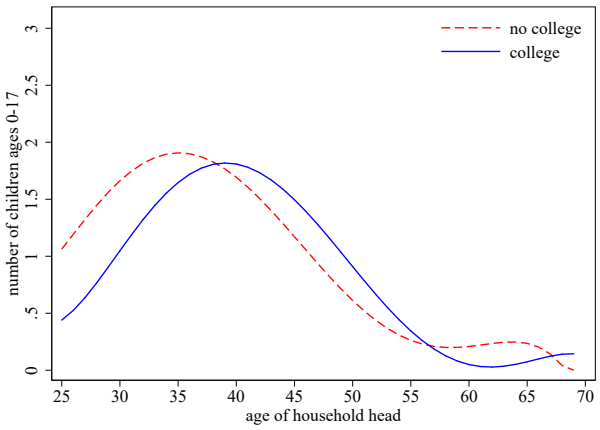


Source: Panel Study of Income Dynamics, authors' calculations

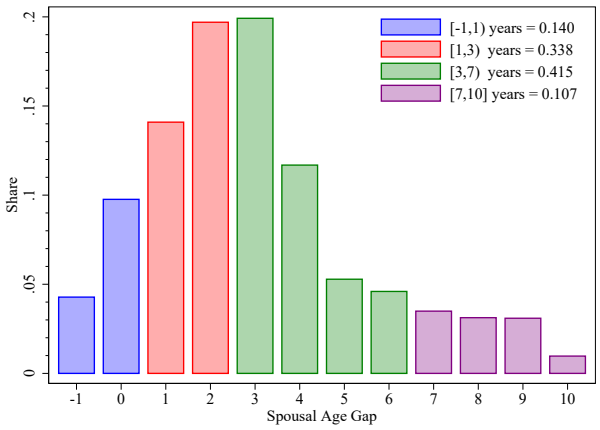
Notes: Panel (a) shows the number of children ages 0–17 in the household by education and age of the household head. Panel (b) displays the distribution of spousal age gaps. The color shading indicates the four groups used in the quantitative model.

Figure D.8: Family statistics (1945–1949)

(a) Number of children



(b) Spousal age gap



Source: Panel Study of Income Dynamics, authors' calculations

Notes: Panel (a) shows the number of children ages 0–17 in the household by education and age of the household head. Panel (b) displays the distribution of spousal age gaps. The color shading indicates the four groups used in the quantitative model.

D.5 Wages

Data on wages is drawn from the PSID. Hourly wages are computed as annual earnings divided by annual hours worked. To address outliers and minimum wage distortions, we exclude observations with hourly wages below $3.50 or above $75 (in 1998 dollars), which trims approximately the bottom 1% and top 2% of the wage distribution. To ensure sufficient life-cycle coverage, the sample includes all workers aged 20 to 74 born between 1901 and 2000. Because wages are only observed for individuals who participate in the labor market, we estimate hourly wage profiles using a Heckman selection model.

In the first step, a probit regression estimates the probability of labor market participation and generates the inverse Mills ratio. This ratio is then included as a regressor in the second-stage wage regression. Labor market participation is modeled as a function of a quadratic in age, interacted with a college education indicator, as well as dummies for being married, having children, and being in good health—all interacted with age. We also control for cohort fixed effects. Table D.7 confirms the significance of the inverse Mills ratio, indicating that selection bias is present in the simple OLS estimates of wages.

In the second stage, we estimate wage profiles by regressing the natural logarithm of hourly wages on a second-order polynomial in age, its interaction with a college education indicator, and an interaction between age and a marital status indicator. The regression also includes cohort fixed effects. Table D.7 reports the estimated coefficients, and panel (a) of Figure D.9 displays the resulting wage profiles by age, education, and marital status.

These estimated wage profiles exhibit several interesting patterns. First, wages generally increase over the life cycle, with the rate of growth slowing at older ages. Consistent with rutledge2017does, we find that these profiles remain fairly flat as workers approach retirement rather than declining during these years. Second, in addition to a clear skill premium associated with

Table D.4: Regression results: spousal income estimation (cohort 1931-1935)

	Spousal LFP		Spousal Labor Earnings (thousands of 1998 dollars)	
age	0.0351**	(0.0136)	-2.081**	(0.918)
$age^2/10^2$	-0.0183	(0.0500)	8.241**	(3.316)
$age^3/10^4$	-0.0692	(0.0738)	-11.32**	(4.930)
$age^4/10^6$	0.0492	(0.0376)	4.619*	(2.595)
college*age	-0.000506	(0.000553)	0.131***	(0.0274)
labor income (thousands of 1998 $)*$age$	0.00130***	(0.000228)	0.0362***	(0.00738)
labor income *$age^2/10^2$	-0.00966***	(0.00139)	-0.226***	(0.0469)
labor income *$age^3/10^4$	0.0212***	(0.00279)	0.446***	(0.0974)
labor income *$age^4/10^6$	-0.0142***	(0.00184)	-0.278***	(0.0661)
spousal age gap (0,2] years*age	0.00272***	(0.00105)	0.0733	(0.0471)
spousal age gap (2,6] years*age	0.00554***	(0.000999)	0.123***	(0.0451)
spousal age gap (6,10) years*age	0.00967***	(0.00126)	0.304***	(0.0733)
constant	-0.398***	(0.119)	19.37**	(8.817)
N	61158		25848	
R^2	0.110		0.173	

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Health and Retirement Study (2016, v1) linked to SSA Administrative Records, authors' calculations.

Notes: regression coefficients from regressing spousal labor force participation (left columns) and real spousal labor income—conditional on positive labor income—in thousands of 1998 dollars (right columns) on a set of controls. All controls variable values are determined characteristics the head of household.

higher education levels, our results (aligned with BorellaDeNardiYang) also reveal a marriage premium: married men earn higher wages than their non-married counterparts across both education groups.

These estimated profiles are then used to compute predicted wages for individuals in the sample. The residuals—defined as the difference between observed and predicted hourly wages—are used to estimate the stochastic component of the wage process. Specifically, the parameters of the AR(1) income process are estimated using Method of Simulated Moments, with the identity matrix as the weighting matrix. This procedure yields an estimate of $\rho = 0.968$ for persistence and $\sigma^2 = 0.022$ for the variance of the wage innovation.

Unemployment shock and wage scarring

Two parameters govern employment shocks in the model: the probability of receiving a shock, λ, and the wage penalty associated with it, ξ.

We set λ equal to the annual involuntary separation rate. Since our model explicitly captures wage scarring from unemployment, we focus solely on separations due to involuntary job loss, excluding voluntary exits and job-to-job transitions.

The separation rate is computed in two steps. First, using CPS data from 1995–2005 for men

Table D.5: Regression results: spousal income estimation (cohort 1945-1949)

	Spousal LFP		Spousal Labor Earnings (thousands of 1998 dollars)	
age	0.0618***	(0.044)	0.226	(1.232)
$age^2/10^2$	-0.0113*	(0.0607)	-0.444	(4.714)
$age^3/10^4$	0.0859	(0.100)	1.920	(7.436)
$age^4/10^6$	-0.0436	(0.0564)	-2.437	(4.146)
college*age	-0.000653	(0.000698)	0.130***	(0.0397)
labor income (thousands of 1998 $)*$age$	0.00150***	(0.000256)	0.0422***	(0.0102)
labor income *$age^2/10^2$	-0.0104***	(0.00154)	-0.262***	(0.0638)
labor income *$age^3/10^4$	0.0222***	(0.00301)	0.526***	(0.131)
labor income *$age^4/10^6$	-0.0148***	(0.00192)	-0.337***	(0.0871)
spousal age gap (0,2] years*age	0.00170	(0.00140)	0.139**	(0.0597)
spousal age gap (2,6] years*age	0.00467***	(0.00137)	0.182***	(0.0571)
spousal age gap (6,10) years*age	0.00841***	(0.00167)	0.329***	(0.108)
constant	-0.644***	(0.110)	-2.696	(11.20)
N	33608		14630	
R^2	0.172		0.171	

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Health and Retirement Study (2016, v1) linked to SSA Administrative Records, authors' calculations.

Notes: regression coefficients from regressing spousal labor force participation (left columns) and real spousal labor income—conditional on positive labor income—in thousands of 1998 dollars (right columns) on a set of controls. All controls variable values are determined characteristics the head of household.

aged 25–69, we estimate the monthly separation rate among employed workers and annualize it, yielding a total separation rate of 19.9%. This rate ranges from 17.5% to 24.5% across education-marital groups and from 16.4% to 28.0% over the life cycle. Second, we adjust this figure to exclude voluntary separations. Based on simmons2023, who use SIPP data to classify separations, only 28.6% of separations are involuntary.[28] Applying this share yields an annual involuntary separation rate of 5.6%.

To construct the wage penalty from an unemployment shock, $\xi(\lambda)$, we follow the literature estimating the effect of job displacement on re-employment earnings. Specifically, we estimate the following regression:

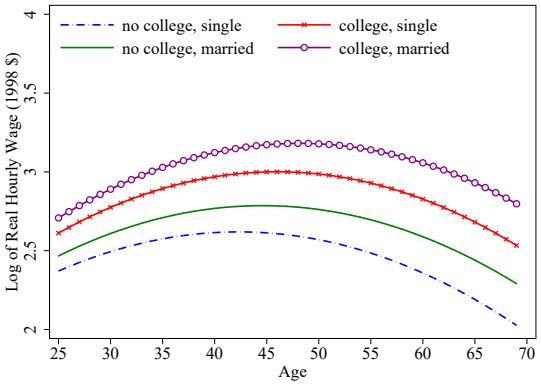
$$y_{it} = x_{it}'\beta + \sum_{k\geq -2}^{20} \delta^k D_{it}^k + \alpha_i + \gamma_t + \varepsilon_{it} \tag{21}$$

Here, y_{it} is the log wage of individual i at time t; x_{it} includes controls such as education and a quadratic in experience; D_{it}^k is a set of dummies indicating the k-th year relative to a displacement

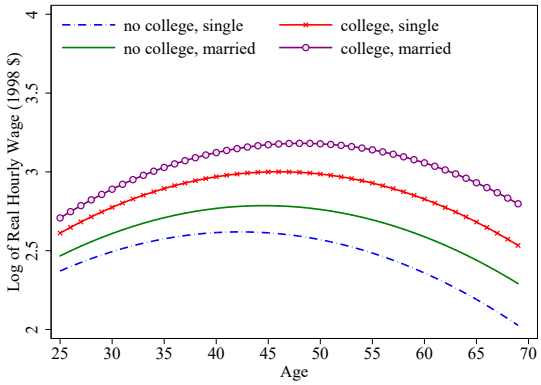
[28] simmons2023 uses the Survey of Income and Program Participation to classify separations as involuntary (due to lay-off, discharge/firing, employer bankruptcy or sale, or temporary employment ending) or voluntary (due to employer-to-employer transitions, dissatisfaction with the job, personal circumstances, or other reasons).

Figure D.9: Wage profiles by education and marital status

(a) 1931–1935



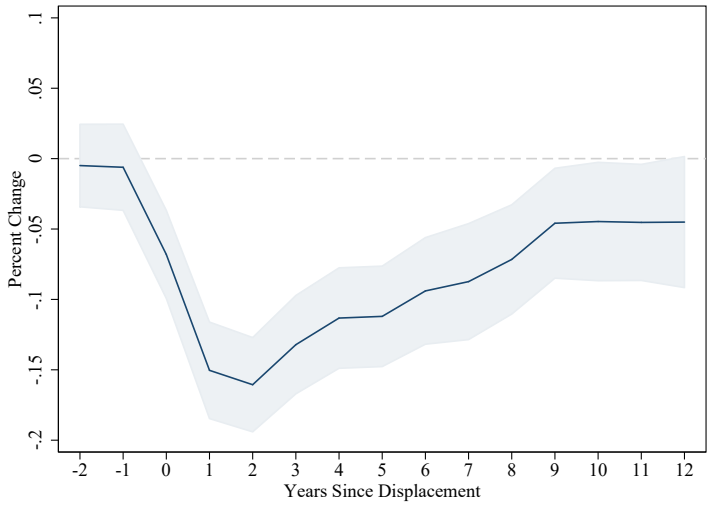
(b) 1945–1949



event; and α_i and γ_t are individual and time fixed effects.

The estimated coefficients δ^k are plotted in Figure D.10. Consistent with previous work, we find that displaced workers earn roughly 14–20 percent less than non-displaced workers, with these losses persisting for 5 to 10 years post-displacement. Based on these estimates, we set the wage penalty from an unemployment shock at 14 percent, i.e., $\xi(\lambda) = 0.86$. Additional analysis by education level reveals similar displacement effects across educational groups.

Figure D.10: Wage scarring due to unemployment



Source: Panel Study of Income Dynamics, authors' calculations

Notes: figure is the graphical presentation of the estimated β coefficients from Equation 21. Solid line shows the impact of an unemployment spell on hourly wages (relative to the wages of an employed individual) for 2 years prior to and 12 year after such a spell. 90 percent confidence intervals shown.

D.6 Pensions

Following French, we model private pensions as a regressive function of individuals' Primary Insurance Amount, pia_t, specified as:

$$pb(pia_t) = \gamma_0(\gamma_1 + \gamma_2 pia_t + \gamma_3 \max\{0, pia_t - 5000\})$$

The parameters γ_1, γ_2, and γ_3 are taken from gustman1999, consistent with both our model and French. The scale parameter γ_0 is calibrated separately for each education and marital group to match the average pension benefits received by these groups at older ages in the HRS data. Specifically, we set γ_0 to 0 for non-college singles, 0.20 for college singles, 0.18 for non-college married, and 0.25 for college married individuals. A scale of zero implies that non-college single individuals receive no pension benefits in the model, reflecting both their low pension coverage and low benefit amounts conditional on coverage. Age-specific pension accrual rates are taken from gustman1998evaluating. The adjustment ϵ_t^p accounts for the difference in accrual patterns between pension and Social Security wealth at various ages, which tends to be negative at younger ages and positive at older ages.

D.7 Taxes

Taxes are modeled using a smooth function as in heathcote2010macroeconomic. Specifically, total taxes, $T(y_t)$, paid on income y_t is given by the following equation:

$$T(y_t) = y_t - \lambda_t y_t^{1-\xi_t}.$$

where λ_t determines the average level of taxes in the economy in year t and ξ_t captures the level of progressivity in year t. This function sets a relationship between pre-tax and after-tax income that we exploit in our estimation.

$$\underbrace{\overbrace{y_t}^{\text{pre-tax income}} \quad -T(y_t)}_{\text{after-tax income}} = \lambda_t y_t^{1-\xi_t}.$$

$$\ln(y_t - T(y_t)) = \ln(\lambda_t) + (1-\xi_t)\ln(y_t)$$

To estimate λ_t and ξ_t we regress the logarithm of after-tax household income on a constant and the logarithm of pre-tax household income.

PSID includes information on taxes paid up until 1991 and covers tax years up through 1990. Total taxable income of the family is measured as the sum of labor and Social Security income of the household head and the spouse and other family members (if present). Federal tax liability is constructed based upon the taxable income of the family as well as exemptions and the tax table used. We use this information to estimate parameters of the tax function which vary based upon tax year, marital status (single or married), and, if married, number of children (none, 1 child, 2 chil-

dren, more than two children). Our sample consists of 40,202 taxpayers born between 1921 and 1950 who are between the ages of 20 and 75 who also had non-missing tax information. We drop households whose taxable income is below $500 (1998 dollars) or overs $300,000 as well as those who report paying taxes that would imply an average tax rate above the maximum marginal tax rate for that year.[29] In order to maximize the sample available to estimate tax year specific functions which incorporate changes in taxes over time, we follow the procedure in BorellaDeNardiYang and estimate these time specific parameters in rolling 5-year bins.

We map these tax year and family structure specific parameters into the inputs for our structural model in two steps:

First, because we follow a single cohort in our analysis, time and age are equivalent in our setup. Therefore, we compute age- and family-structure-specific parameters based on the time-specific parameters. Specifically, parameters for tax year 1967 are used for ages 25 to 32. For ages 33 to 58, parameters are computed as the average of the parameters for the tax years during which our cohort would have been at each respective age.[30] Parameters for tax year 1990 are used for all ages 59 and above.

Second, we map these age- and family-structure-specific parameters into age, education and marital status specific parameters using the observed variation in the number of children over the life cycle. Single individuals (regardless of education level) are assigned the age-specific parameters for singles. Married individuals are assigned the profiles corresponding to the average number of children that households of their education level have at each age (see Figure D.8a). This approach allows the tax parameters to vary by education, reflecting differences in the number of dependents across groups.

D.8 Subjective social security program beliefs

We model program beliefs by including uncertainty over the adjustment factor for early claiming, $\widetilde{\gamma}_1^{ss}$. Perceived Social Security benefits (given by Equation 22) are a function of the primary insurance amount for an individual of a given SS wealth, $pia\left(a_t^{ss}\right)$, the uncertain total penalty (the accumulated annual penalties), $\widetilde{\Gamma}(t^{ss})$, and the retirement earnings test, Υ.

$$\widetilde{ssb}_t = pia\left(a_t^{ss}\right) * \widetilde{\Gamma}(t^{ss}) - \Upsilon_t \tag{22}$$

To estimate the belief distribution this uncertain penalty is drawn from, we use a question which asks respondents about the increase in benefits from delaying claims from age 63 to 64. The question asks:

Imagine an individual, Mr. Spencer Wills, who is retired from work and turning 63 today. Spencer expects his monthly Social Security retirement benefit to be about $2,000 if he claims now. How much should he expect his monthly benefit to be if he decides to wait another year and claim when he is 64?

(a) it would stay the same

[29] These restrictions drop only 639 observations.

[30] For example, the parameters for age 40 are the average of the parameters for tax years 1971–1975, as these are the years when the 1931–1935 cohort would be age 40.

(b) approximately $2,120 (6% higher)

(c) approximately $2,020 (1% higher)

(d) approximately $2,300 (15% higher)

The answer to this question allows us to determine not only whether workers have correct information about the penalty, but also what they believe if they are misinformed. Respondents who answer (b) are classified as correctly informed, while those who answer (a), (c), or (d) are considered misinformed and assigned to the corresponding categories. Because we do not have a comparable survey question regarding the value of the delayed retirement credit, we assume that individuals are informed about this parameter.

We also use a question about how knowledgeable the respondent is about this penalty to determine confidence in the response. The question used reads:

Below is a list of aspects of the Social Security system. For each one do you feel you are very, somewhat, not too, or not at all knowledgeable about that aspect?
How Social Security retirement benefits change based on how old you are when you claim.

Responses to this categorical variable are converted to a numerical scale in the following way: If an agent reports the are knowledgeable we set the confidence share to 1; if somewhat knowledgeable the CS is set to 0.75; if not too knowledgeable the CS is set to 0.25; if not at all knowledgeable the CS is equal to 0. The the average of this confidence share (ACS) by education-marital status and belief type is also shown in Table 5.

E Second-step estimation

We estimate the model by matching moments that vary by age, education, and marital status. We set the population shares for these groups based on the shares observed at age 25 in the PSID. Table E.1 shows the share of the population within each fixed type.

E.1 Target profiles

The target life-cycle profiles of participation, hours, and assets are estimated from the Panel Study of Income Dynamics (PSID) covering the years 1968–2016 (annually from 1968–1995 and biennially from 1996–2016), using the method described in French (2005).

In each year t, PSID respondents report their labor market variables for year $t-1$. Participation is measured as a binary variable equal to 1 if the respondent worked at least 300 hours (25 hours per month) in the previous year. Hours are measured as a continuous, self-reported variable capturing total annual hours worked. When constructing hours profiles, we restrict the sample to respondents reporting more than 1,000 hours worked annually.

We use wealth data from the 1984, 1989, 1994, 1999, 2001, 2003, 2005, and 2007 PSID wealth surveys, as well as the 2010–2016 PSID family files. Household assets are measured as the net value of farm and business equity, vehicles, checking and savings accounts, real estate, stocks,

mutual funds, IRAs, Keoghs, and investment trusts, after subtracting debts. We drop observations with household wealth above $1 million (in 1998 dollars).[31]

To measure mean life cycle profiles, we estimate the following fixed effect regression:

$$Y_{it} = f_i + \sum_{c\in\{0,1\}} \sum_{m\in\{0,1\}} \left(\sum_{k=1}^{J} \beta_c^m \mathbb{I}\left[age_{it} = k\right] \times \mathbb{I}\left[married_i = m\right] \times \mathbb{I}\left[college_i = c\right] \right) + \sum_{f=1}^{F} \beta_f \mathbb{I}\left[family\ \ size_{it} = f\right] + \beta_u u_t + \varepsilon_{it}$$

where Y_{it} represents an observation of the outcome variable (labor force participation, hours worked, or assets) for individual i in time period t; f_i is an individual fixed effect;

$$\mathbb{I}\big[\text{age} = k\big] \times \mathbb{I}\big[\text{married}_i = m\big] \times \mathbb{I}\big[\text{college}_i = c\big]$$

are education- and marital-status-specific age-group dummies[32];

$$\mathbb{I}\big[\text{family size}_{it} = f\big]$$

are family size dummies; and u_t is the unemployment rate in period t. The estimated parameters are

$$\{\beta_{nc}^{nm}, \beta_c^{nm}, \beta_{nc}^m, \beta_c^m, \beta_f, \beta_u\}.$$

In constructing these profiles, we make three adjustments to control for year, family size, and cohort effects: (1) we set the unemployment rate to 6.5%; (2) we fix family size at 1 for single individuals and 4 for married individuals; and (3) for each education and marital status group, we use the individual-specific effect of those born in 1930 and aged 45–49.

For the wealth moments, we report median in addition to the mean, computed by estimating a quantile regression on the set of education- and marital-status-specific age dummies.

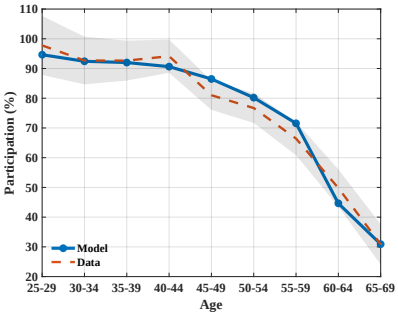
F Additional figures and tables

[31] This restriction removes only 1,302 observations and leaves a sample of 93,232 observations. We also experimented with dropping the 1,723 observations with negative wealth, since the model does not allow borrowing. The estimated wealth profiles are not overly sensitive to including these cases. Among households with negative wealth, average debt is slightly over $29,000, and median debt is roughly $9,000.

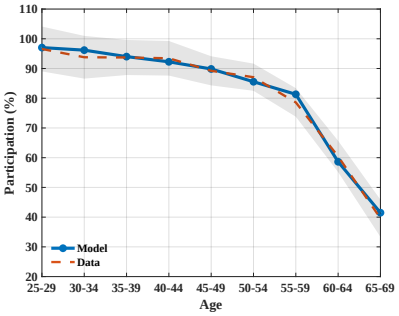
[32] We could have alternatively used age dummies for each year. We choose five-year age-group dummies to reduce noise in the estimated profiles.

Figure F.1: Model Fit: Labor force participation rates
Men born 1931-1935

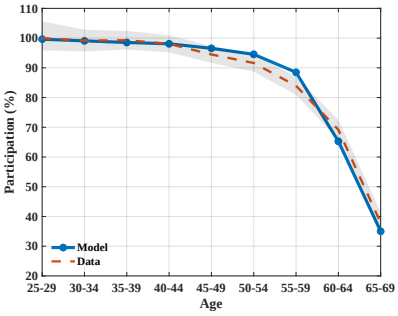
(a) Non-College, Non Married



(b) College, Non Married



(c) Non-College, Married



(d) College, Married

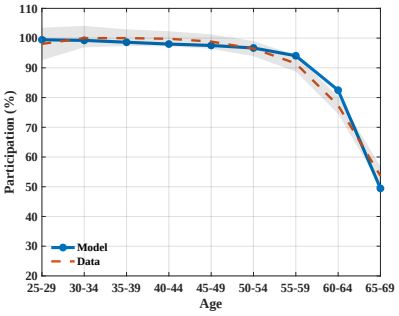


Table D.6: Estimated coefficients from logarithm of hourly wages (1931–1935)

	(1)	
	log_real_wage	
log_real_wage		
age	0.0703***	(0.00246)
age2	-0.0831***	(0.00372)
collage	0.0109***	(0.000354)
collage2	-0.00520***	(0.000745)
marage	0.00383***	(0.000200)
cc1	-0.129***	(0.0109)
cc2	-0.0440***	(0.0112)
cc3	-0.0453***	(0.0108)
cc4	-0.0515***	(0.0108)
cc5	-0.00698	(0.0112)
cc6	-0.0254**	(0.0123)
cc8	0.0338***	(0.0129)
cc9	0.0438***	(0.0123)
_cons	1.134***	(0.0496)
lfp		
age	0.0894***	(0.00294)
age2	-0.151***	(0.00324)
collage	0.0111***	(0.000986)
collage2	-0.00892***	(0.00175)
marage	0.00887***	(0.000314)
fsage	-0.000353	(0.000293)
cc1	-0.179***	(0.0287)
cc2	-0.152***	(0.0299)
cc3	-0.130***	(0.0283)
cc4	-0.0901***	(0.0280)
cc5	-0.00601	(0.0296)
cc6	-0.0195	(0.0319)
cc8	0.0765**	(0.0312)
cc9	0.0839***	(0.0280)
_cons	0.000141	(0.0696)
mills		
lambda	0.145***	(0.0466)
N	96768	

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Panel Study of Income Dynamics, authors' calculation

Notes: dependent variable of the wage equation: natural logarithm of the real hourly wage (1998 dollars); dependent variable of the selection equation: labor force participation. Standard errors in parentheses.

*p< 0.1, **p< 0.05, ***p< 0.01

Table D.7: Estimated coefficients from logarithm of hourly wages (1945–1949)

	(1) log_real_wage	
log_real_wage		
age	0.0665***	(0.00239)
age2	-0.0770***	(0.00358)
collage	0.0112***	(0.000353)
collage2	-0.00627***	(0.000728)
marage	0.00378***	(0.000203)
cc1	-0.0935***	(0.00627)
cc2	-0.0112	(0.00715)
cc3	-0.0134**	(0.00661)
cc5	0.0201***	(0.00767)
cc6	-0.00155	(0.00924)
cc7	0.0193*	(0.00999)
cc8	0.0471***	(0.0102)
_cons	1.161***	(0.0489)
lfp		
age	0.0855***	(0.00289)
age2	-0.145***	(0.00311)
collage	0.0114***	(0.000985)
collage2	-0.0102***	(0.00174)
marage	0.00895***	(0.000313)
fsage	-0.000292	(0.000292)
cc1	-0.141***	(0.0194)
cc2	-0.120***	(0.0216)
cc3	-0.101***	(0.0195)
cc5	0.00770	(0.0217)
cc6	-0.0113	(0.0247)
cc7	0.00173	(0.0251)
cc8	0.0700***	(0.0236)
_cons	0.0173	(0.0643)
mills		
lambda	0.114**	(0.0472)
N	96768	

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Panel Study of Income Dynamics, authors' calculation

Notes: dependent variable of the wage equation: natural logarithm of the real hourly wage (1998 dollars); dependent variable of the selection equation: labor force participation. Standard errors in parentheses.

*p< 0.1, **p< 0.05, ***p< 0.01

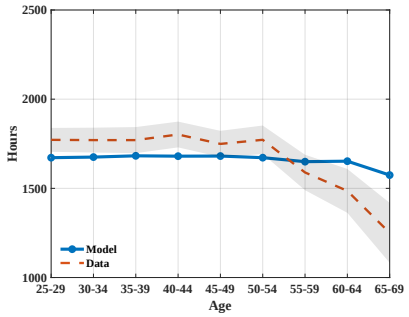
Table E.1: Shares by fixed-type

	Non-college, single	College, single	Non-college, married	College, married
1931–1935	0.17	0.06	0.35	0.42
1945–1949	0.09	0.17	0.25	0.50

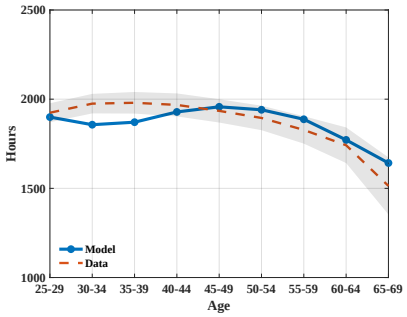
Notes:The share within each fixed type is calculated from the PSID based on education and marital status for individuals between ages 25 and 30 in each birth cohort. The numbers may not add up to one due to rounding.

Figure F.2: Model Fit: Hours Worked
Men born 1931-1935

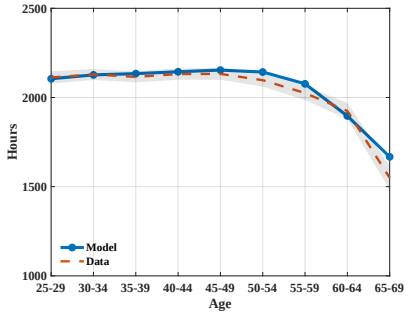
(a) Non-College, Non Married



(b) College, Non Married



(c) Non-College, Married



(d) College, Married

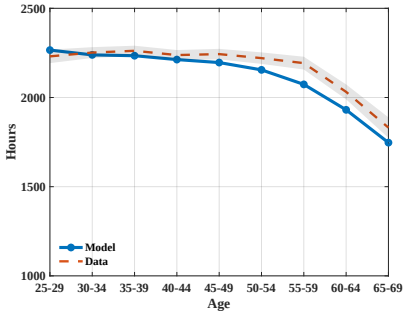
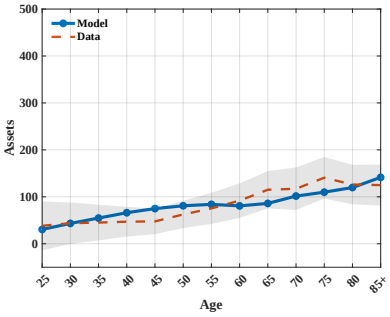
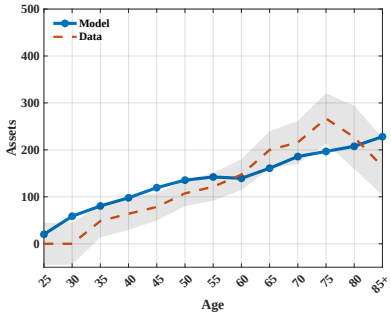


Figure F.3: Model Fit: Assets
Men born 1931-1935

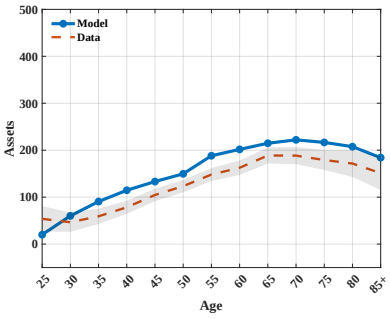
(a) Non-College, Non Married



(b) College, Non Married



(c) Non-College, Married



(d) College, Married

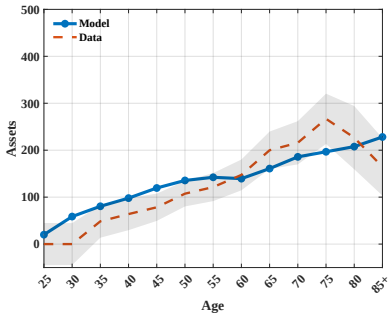
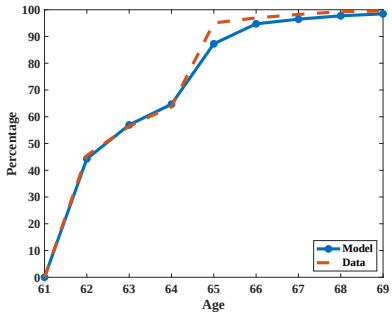


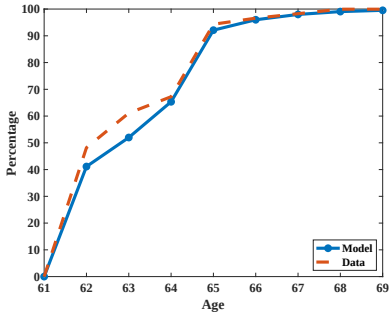
Figure F.4: Model Fit: Social Security Benefit Claiming
Men born 1931-1935

(a) Average

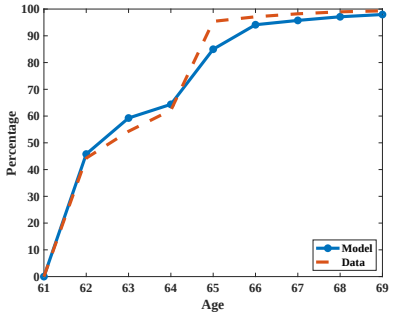


(b) Singles

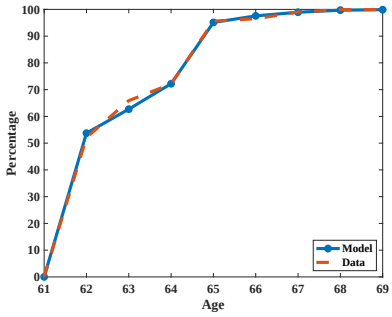
(c) Married



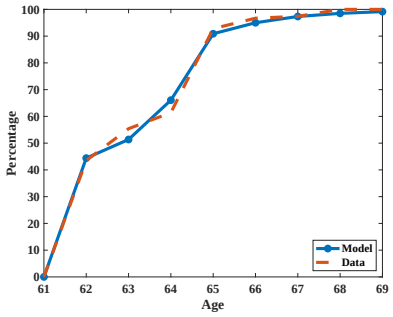
(d) Non-College, Non Married



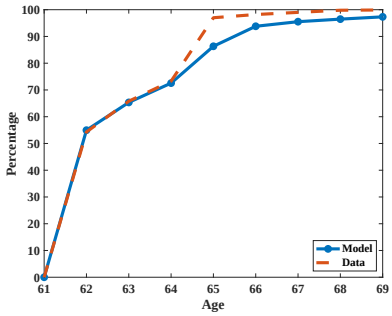
(e) College, Non Married



(f) Non-College, Married



(g) College, Married



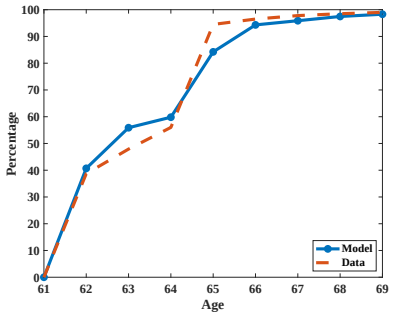
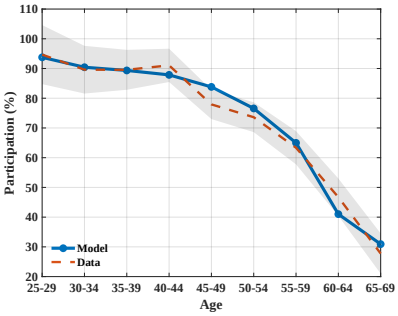
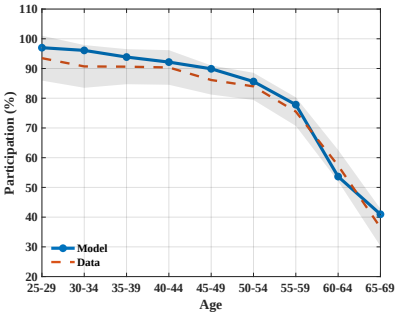


Figure F.5: Model Fit: Labor force participation rates
Men born 1941-1945

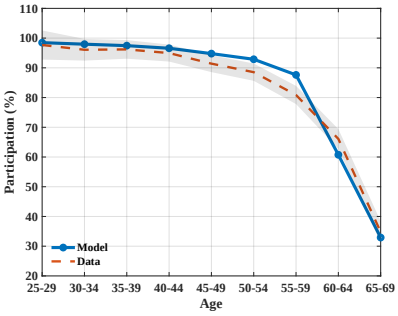
(a) Non-College, Non Married



(b) College, Non Married



(c) Non-College, Married



(d) College, Married

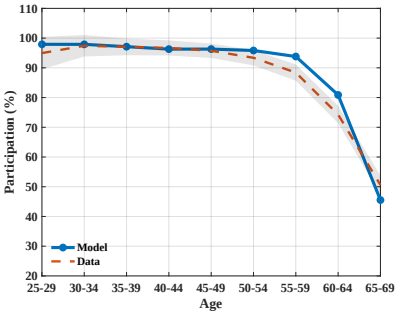
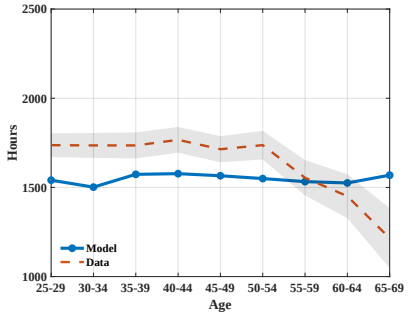
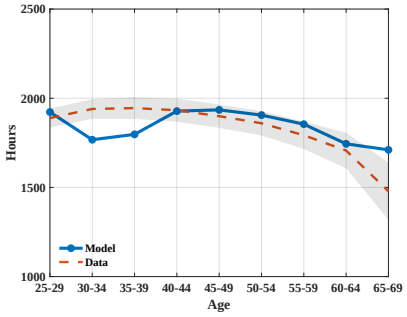


Figure F.6: Model Fit: Hours Worked
Men born 1941-1945

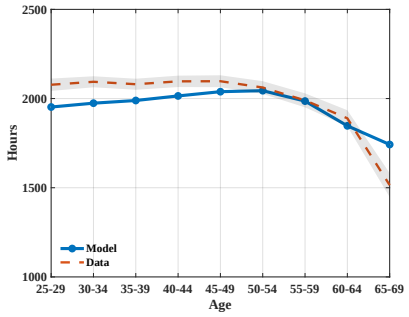
(a) Non-College, Non Married



(b) College, Non Married



(c) Non-College, Married



(d) College, Married

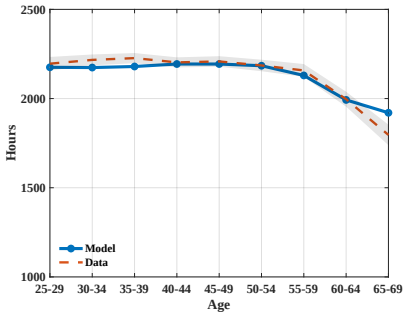
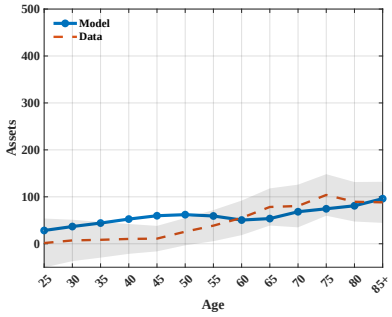
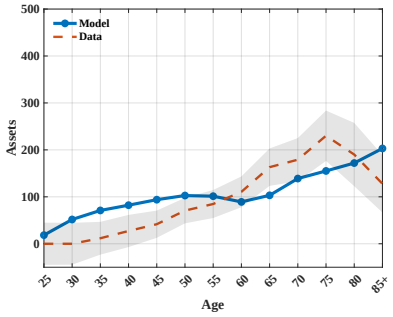


Figure F.7: Model Fit: Assets
Men born 1941-1945

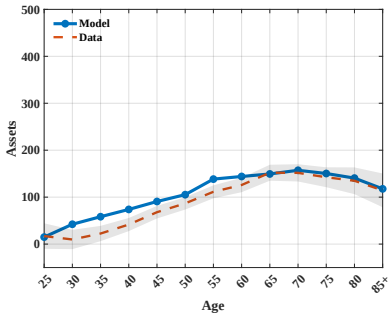
(a) Non-College, Non Married



(b) College, Non Married



(c) Non-College, Married



(d) College, Married

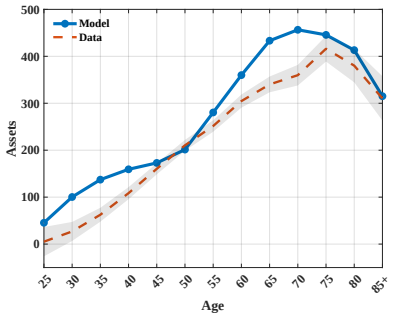
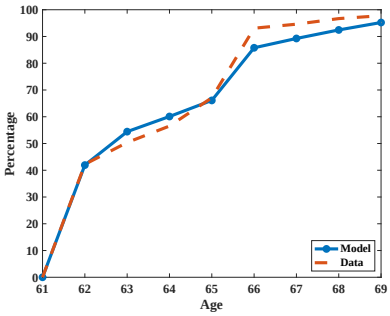


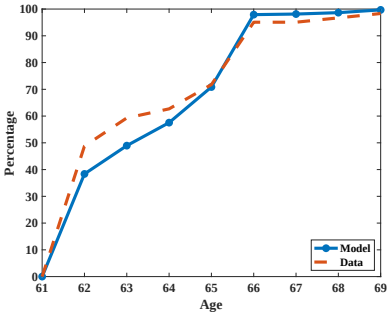
Figure F.8: Model Fit: Social Security Benefit Claiming
Men born 1941-1945

(a) Average

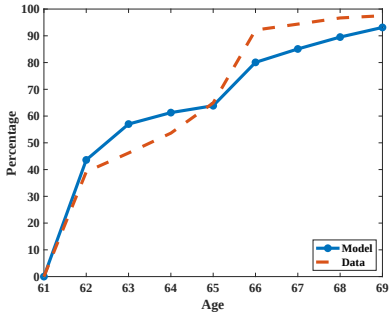


(b) Singles

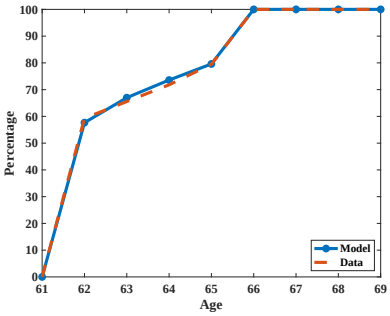
(c) Married



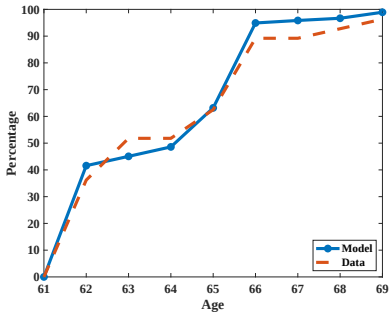
(d) Non-College, Non Married



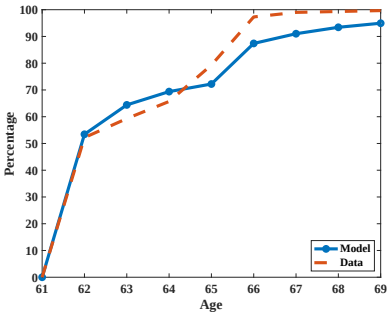
(e) College, Non Married



(f) Non-College, Married



(g) College, Married



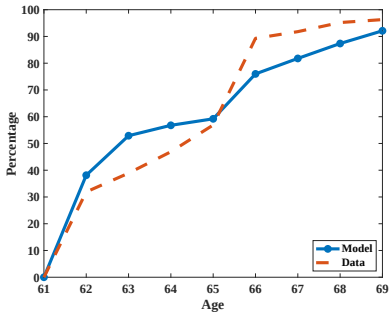


Figure F.9: Social Security Benefit Claiming Across Cohorts

