Revisiting Retirement and Social Security Claiming Decisions*

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Abstract

The Social Security (SS) program structure presents a trade-off between the number of years the benefits are received and the size of those benefits. SS claiming behavior, especially of those Americans with high life expectancy, suggests that older workers place little value on the longer-term annuity of these benefits, preferring instead to start receiving benefits as early as they can, even though this option reduces the overall payout. We explain this puzzling phenomenon within the scope of an augmented, albeit standard, forward-looking life-cycle framework. This contrasts with prior literature that relies on behavioral channels for an explanation. Toward this goal, we document how policy rules and *claiming frictions* — budgetary shocks, misbeliefs, and bequest motives — may impact claiming behavior. We build a structural life-cycle model of consumption, savings, retirement and Social Security claiming, with rich heterogeneity in demographics and family structure, to quantify the role and potential impact of these mechanisms. Counterfactual experiments show that the marital benefits and claiming frictions can explain 53 percent of overall early claims. Policy experiments highlight the role of these mechanisms in limiting the ability of households to augment their claiming ages in response to an increase in the normal retirement age. This is found to be especially true for singles who lack insurance through their spouses. Aggregate lifetime benefit payouts after such a policy change are found to be up to 24 percent higher if the impact of these mechanisms is not taken into account.

Keywords: Labor supply, Social Security, annuity, misbeliefs, life cycle, health, marriage, spousal benefits, survivors benefits, bequest motive, preference heterogeneity.

JEL Classification Numbers: J14, J26, E21, H55

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1 Introduction

It is well known that an aging U.S. population is putting budgetary pressure on the Social Security system (De Nardi et al., 1999; Reznik et al., 2005; Kotlikoff et al., 2007; Attanasio et al., 2007). The current predicament with the Social Security Trust Fund insolvency requires an urgent discussion of policy reforms geared toward either increasing the tax revenue or decreasing the retirement benefits paid out by the Social Security system. The potential impact of any such policy, however, crucially depends on how individuals respond to these changes in terms of their labor supply and benefit-claiming decisions. This requires a thorough understanding of the mechanisms behind current decisions, especially if these decisions appear to be at odds with standard economic-theory predictions. In this work, we provide a comprehensive framework for understanding the drivers of Social Security claiming decisions and how the nature and strength of these drivers vary across different households in the socioeconomic spectrum. We view this study as a critical first step toward laying a robust groundwork for policy analysis in this direction. Along with providing numerous other insights, our framework reveals that the aggregate lifetime benefit payouts after an increase in the normal retirement age can be up to 24 percent higher if changes in claiming behavior are not accurately predicted.

Workers can claim Social Security benefits as early as age 62. However, claiming benefits prior to the normal retirement age is heavily penalized. Workers who claim early, receive a smaller fraction of benefits every year than if they had claimed at the normal retirement age; workers who delay claims past the normal retirement age, receive a larger fraction of benefits each year. Many Americans would receive a larger sum of benefits, in present-discounted value (PDV), by delaying their Social Security claims. Because there are penalties for claiming early, this present-value calculation entails a trade-off between the size of pension benefits and the number of years a pension is received — a calculation that depends critically on life expectancy. As life expectancy increases, incentives to claim early decrease, and beneficiaries receive more by delaying claims. Yet, surprisingly, over two-thirds of all beneficiaries claim benefits before the normal retirement age, and roughly half claim as soon as they reach age 62.

The mystery is further intensified by observing the actions of those in the top end of the socioeconomic spectrum — married household heads or those with a college degree. Larger pensions received by high income workers and additional SS marital benefits available to married individuals changes the PDV calculation for these groups. This heightens the trade-off between benefit size and length of time benefits are received as the percentage penalty or credit represents a nominally larger sum of money. For an average life span, college-educated and married men forego a larger amount (in present value) by claiming benefits early. Given variations in life-expectancy in retirement and stronger incentives to delay benefit claiming for both college-educated and married individuals, it is natural to hypothesize that there should also exist a stark contrast in early claiming rates for these groups, as compared to their less advantaged counterparts (singles or those without a college degree). However, we observe only a small gradient in early claiming rates by education and practically no difference across marital status.

To achieve a comprehensive understanding of the drivers of SS benefit claiming, this paper proceeds on four fronts. First, we document stylized facts on claiming behavior which support various *claiming frictions* that may induce workers' decisions to deviate from the predictions of the aforementioned PDV calculation: (1) individuals' behavior could be driven by budgetary considerations that are missing from the PDV calculation, (2) individuals might be operating under limited information which hinders their ability to accurately perform the PDV calculation, and (3) individuals' decisions might be driven by objectives outside of maximizing the present discounted value of lifetime benefits. Specifically, we empirically show that budgetary shocks (due to bad health and unemployment), misbeliefs about one's life span or SS program rules, and bequest motives can have important impacts on claiming behavior.

Second, to quantify the role of policy details related to marital status as well as these frictions in driving overall claiming behavior, we construct a life-cycle model of consumption, savings, labor supply, and Social Security application that includes rich details of the United States Social Security system, including spousal and survivors benefits available to married households. Agents in the model are heterogeneous with respect to education, marital status, knowledge of the Social Security program and the subjective perceptions of their life span. They face exogenous shocks to health and survival, labor productivity, and employment status.

We follow a two-step process to structurally estimate the model and identify the relative importance of each of the mechanisms we highlight. In the first step, we estimate the processes for the claiming frictions directly from the data. These include health status and subjective survival probabilities, labor productivity and employment status, and the shares of individuals misinformed about SS program rules. We allow these to vary by education and marital status. Next, we estimate the preference parameters of each group to match the evolution of wealth and labor supply over the life cycle for a cohort of men born between 1931 and 1935. Finally, initial conditions and policy parameters of this cohort are estimated directly from the data. By estimating the frictions directly from the data and leaving claiming behavior as an untargeted outcome of the model, a reasonably specified model should replicate observed claiming choices.

The estimated model is in fact able to replicate substantial early claims with 69.9 percent of workers claiming Social Security benefits prior to the normal retirement age. Additionally, we find that the model can replicate the variation in claiming behavior by education, and marital status, health, and work status.

Third, with confidence in the structural model, we perform several counterfactual experiments to quantify the role of Social Security marital benefits and the claiming frictions in driving overall claiming behavior. Our model offers several key insights:

1. Over 53 percent of all early claims (claims before the normal retirement age) and roughly two-thirds of early claims for college educated and married individuals can be attributed to either marital benefits or the claiming frictions. Consistent with the present-value calculations, the remaining early claims are concentrated within the group with the lowest life expectancy (non-college singles).

2. Frictions and marital benefits are largely responsible for equalizing claiming behavior across different socioeconomic groups. The benchmark model produces a 16.9 percentage points gap in early claiming rates of college vs. non-college groups. This gap increases to 22.3 p.p. in a counterfactual economy without claiming frictions and marital benefits. More importantly, the benchmark gap in early claiming rates between singles and married groups increases from 21 to 35.6 percentage points after eliminating the claiming frictions and marital benefits.

3. There is heterogeneity in the relative importance of these claiming frictions.

   Social Security marital benefits (spousal and survivors benefits) have the largest impact on the claiming behavior of college-educated, married households. Bequest motives heavily impact the claiming behavior of college graduates (both married and singles) and non-college married workers. While budgetary shocks, especially unemployment, mainly impact the claiming behavior of singles, misbeliefs play an important role for married households, particularly those without a college degree.

Fourth and finally, we use the model to understand the impact of raising the normal retirement age (NRA) on claiming behavior, both in the benchmark as well as the scenario without any of the claiming frictions and marital benefits. Model predictions of raising NRA to age 70 are:

1. Claiming behavior shifts little, with most of the changes in claiming ages coming from married individuals. Behavior of singles, in contrast, remains mostly inelastic to policy change. Average claiming age goes up from 63.4 in the benchmark to 66.3 under the policy.

2. Without claiming frictions, the same policy produces large rightward shifts in SS claiming. Average claiming age goes up from 65.3 in the friction less baseline to 68.7 under the policy conducted in the baseline without frictions and marital benefits.

3. Understanding how frictions impact claiming behavior has important implications for the government budget. Aggregate lifetime benefit payouts could be 24 percent higher under

the increased NRA policy if an economy without marital benefits or claiming frictions is assumed.

To summarize, this study identifies important claiming frictions that go a long way in rationalizing the extent of early claiming, especially among those with high life expectancy. In doing so, we highlight that an augmented, albeit standard, life-cycle model with rational forward-looking agents is sufficient to resolve much of the claiming puzzle. This is in stark contrast with prior literature which highlights behavioral channels to explain the same phenomenon (Brown et al. (2016); Gustman and Steinmeier (2005, 2012)). Policy experiments further reveal that accounting for the role of frictions in determining claiming behavior is extremely important, both from the point of understanding the household's ability to mitigate losses, as well as the true budgetary impacts for the government due to such a change.

Our paper makes important contributions to several strands of the existing literature. First, we contribute to a growing literature on using rich structural life-cycle models of retirement, Social Security, consumption and savings to understand important questions at the intersection of macroeconomics, labor economics, and public policy. Notable papers include Fan et al. (2022); Jones and Li (2020); Bairoliya (2019); Borella et al. (2019); De Nardi et al. (2010); Imrohoroglu and Kitao (2012); Yu (2022); French and Jones (2011); Hubener et al. (2016); Rust and Phelan (1997); Van der Klaauw and Wolpin (2008); French (2005); Hosseini et al. (2021); Scholz and Seshadri (2011). We add to this literature by modeling the important role of misbeliefs and family specific insurance and institutions in households' decision making.[1]

Second, our paper is closely related to prior structural work studying the strong claiming peak at age 62 (Gustman and Steinmeier (2005, 2015); Benitez-Silva et al. (2009); Pashchenko and Porapakkarm (2018)). Our work contributes to this literature in several ways. While many of these studies highlight the importance of discount rate estimates for matching the share of age 62 claims, we can generate close estimates of overall early claims without explicitly relying on discount rates. Additionally, while these studies also highlights the need for alternative frictions (such as expectations of not receiving benefits or bequest motives), including a rich set of these frictions allows us to rationalize early claiming behavior of not only the most disadvantaged groups but also those with the highest life expectancy and wealth at older ages. Finally, we bring to light how specific institutions like the SS spousal and survivors benefits interacts with claiming behavior of married households, creating sharp incentives to claim before the normal retirement age.

Third, we contribute to the literature studying annuitization decisions of households (Lockwood (2012); Finkelstein and Poterba (2004); Dushi and Webb (2004); Turra and Mitchell (2007); Hosseini (2015)). The Social Security program offers the largest public annuity in the U.S. Given

[1] Borella et al. (2019); De Nardi et al. (2021); Van der Klaauw and Wolpin (2008); Hubener et al. (2016); Scholz and Seshadri (2011) also include heterogeneity by marriage and family dynamics.

the trade-offs embedded in the system for claiming at various ages, studying claiming behavior is akin to studying annuitization decisions of older households. By focusing on the claiming behavior, we are able to bring new mechanisms to the table and provide insights which can be generalized toward understanding the broader puzzle. For instance, consistent with the findings of Lockwood (2012) and O'Dea and Sturrock (2018) in the case of private annuity markets, we show that bequest motives and subjective mortality expectations have significant impacts on claiming behavior.

Finally, we contribute to the literature studying the welfare implications of the Social Security program in a general equilibrium framework (İmrohoroglu et al., 1995; Conesa and Krueger, 1999; Fuster et al., 2003; Krueger and Kubler, 2006; Hong and Ríos-Rull, 2007; Huggett and Parra, 2010). By focusing on the benefit-claiming decisions of individuals, we contribute to an understanding of how this choice is distinct from, and at the same time, interacts with labor supply and savings decisions.

2 Motivation

The United States Social Security system provides a flow of retirement income starting at the time of claiming and continuing until the death of the beneficiary. A worker's benefits are a progressive function of their average indexed monthly earnings. Up to a maximum taxable amount, higher income during an individual's working life translates to higher benefits during retirement. However, the progressivity of the formula means that high income individuals receive lower replacement rates on their earnings than lower income workers.

Married households may receive two additional benefits offered by the Social Security program. First, spouses of primary earners are eligible to claim *spousal benefits* on the earnings record of the primary earner.[2] These benefits may be up to 50 percent of the benefits of the primary earner and are contingent on the primary earner also claiming Social Security benefits. Second, the primary earner can bequeath their Social Security benefits to their surviving spouse upon death (*survivors benefits*), who in turn would receive these benefits until the end of their life.

Individuals first become eligible for reduced benefits at the early retirement age (ERA) of 62 and eligible for full benefits at the normal retirement age (NRA). Claiming Social Security benefits before the NRA entails lower pension payments for a longer period of time. Delaying pension claims until beyond the normal retirement age (up until age 70) entitles workers to larger pension payments, albeit for a shorter period of time. The penalties for early claiming also apply to spousal benefits. Spouses who claim prior to the NRA incur a penalty. Spousal benefits, however, do no receive credits for delayed claims.

[2]Spouses may elect whether to claim benefits on their own earnings record or that of the primary earner.

Table 1: Life Expectancy at Age 62

Average	Education Status		Marital Status	
	Non-College	College	Singles	Married
80.5	78.6	82.0	78.4	81.8

Source: Medical Expenditure Panel Survey, authors' calculations.

Given the penalties associated with early claims, the structure of the U.S. Social Security system creates a trade-off between the number of years pension payments are received and the size of the benefits.

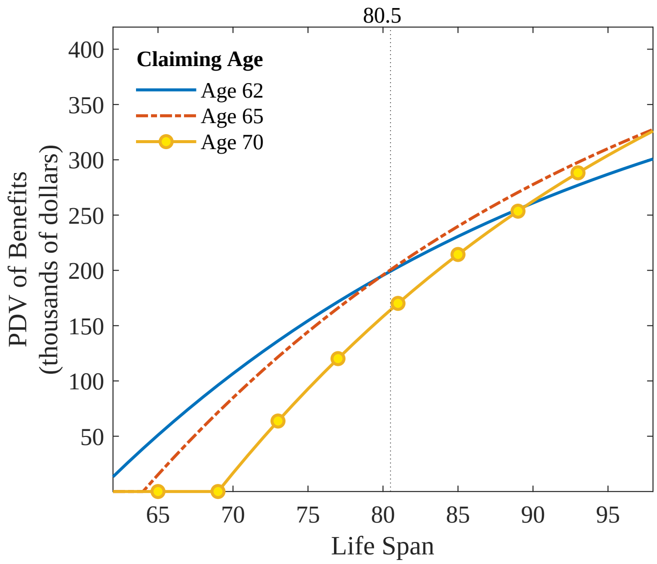
2.1 Present-Discounted Value Analysis

We highlight this trade-off in figure 1 by constructing the age 62 present-discounted value (PDV) of total benefits received, using the Social Security rules of the 1931-1935 birth cohort, for various claiming ages—62, 65 (the NRA), and 70—and life spans of the beneficiary.[3] Differing slopes across these PDV calculations for the three claiming ages reflect the early claiming penalty (for age 62 claims) of 6.67% per year and the delayed claiming credit (for age 70 claims) of 5.5% per year. The intersection between lines represents the age at which a worker would break even, in present-discounted value, between claiming at two different ages. The figure demonstrates that for life spans greater than around 79 years, workers receive a higher present value of benefits by delaying claims from age 62 to 65. As the average lifespan, conditional on living to age 62, of American men born between 1931 and 1935 is roughly 80.5 years, the average worker of this cohort would receive slightly more in PDV of total benefits by claiming at age 65 but less in PDV by pushing claims from age 65 until age 70. However, this calculation is very sensitive to the life-span of the beneficiary; the claiming decision that leads to the highest PDV of benefits will change as the length of life changes. Given variation in mortality across the population and differences in the average life-expectancy by demographic characteristics, as shown in table 1, this PDV calculation would predict claiming decisions that differ across the population.

This PDV calculation further indicates that, for a given fixed life-span, the strength of claiming incentives (in terms of the nominal size of benefits) induced by the policy rules of the Social Security system could vary by income level and marital status. Figure 2 shows the difference in the present value of benefits received between claiming at age 62 and at age 65 (the gap between the solid and dashed lines in figure 1; referred to as PDV gap henceforth) and how it varies by education

[3]As all PDV calculations are computed at age 62, computations for later claiming ages reflect the expected PDV of future benefits.

Figure 1: Present Value of Social Security Benefits by Claiming Age



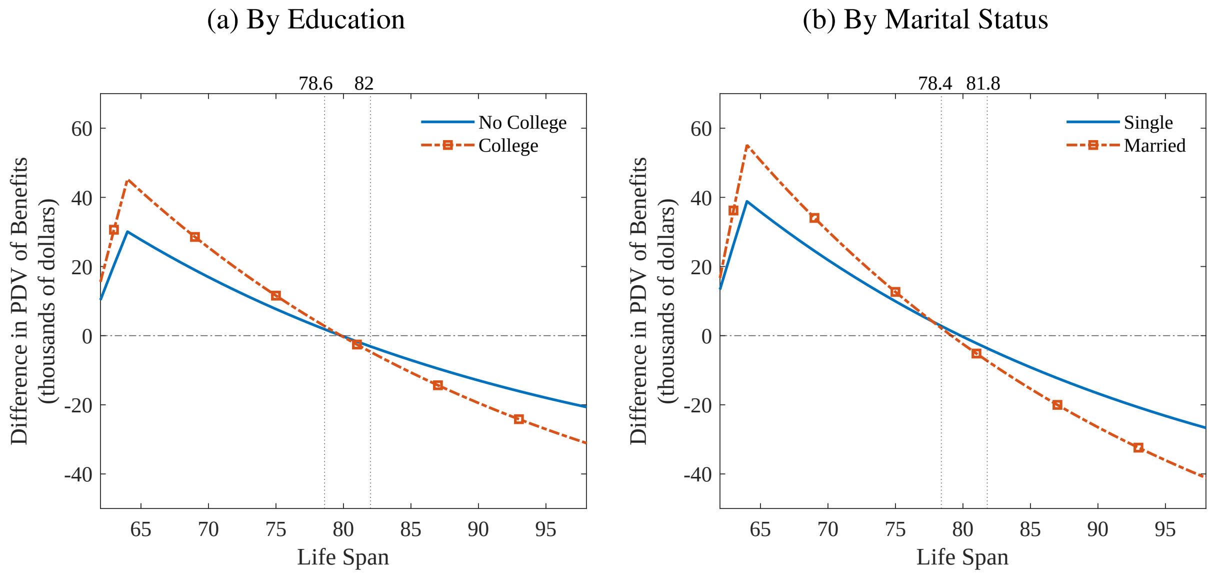
Notes: Present value of benefits is calculated at age 62 using a 3% interest rate. Calculation is done for an individual who has an annual income of $50,000. Social Security rules are for those born between 1931 and 1935; normal retirement age is 65, the early claiming penalty is 6.67% per year, and the delayed claiming credit is 5.5% per year. Vertical line at 80.5 represents the average life expectancy conditional on survival to age 62.

(figure 2a)–or income levels– and marital status (figure 2b). Both figures echo the previous result that in order to break even between age 62 and 65 claims, workers must live at least to roughly age 79, with those who live shorter lives receiving more by claiming early, and those who live longer lives receiving more by claiming later.[4] However, the level of how much more or less these individuals receive relative to other claiming ages differs by income and marital status due to both policy and life-expectancy differences between these groups.

As shown in figure 2a, depending on how long the beneficiary lives, the fact that Social Security benefits are increasing in income (up to a maximum cap) leads to a larger gap between present values of benefits (of age 62 and 65 claims) for higher income individuals. Given the differences in income and longevity between those with college education and those without, this feature will induce differences in the PDV gap by education. For the overall average life-span of 80.5 years, and non-college educated individual (assumed to earn $30,000 annually) would give up roughly $1,000 in PDV by choosing to claim at age 62 rather than age 65. This number for a college educated individual (earning $70,000 annually) increases to around $1,500. However, as college educated individuals also have higher average life-expectancy, the average life-span masks the

[4]In the presence of survivors benefits the break-even point between age 62 claims and age 65 claims moves earlier, although it remains between age 79 and age 80. Because the size of survivors benefits is also impacted by early claiming, the value of claiming early is decreased and the life span at which workers will receive more by claiming at age 65 is earlier.

Figure 2: Difference in Present Value of Benefits between Age 62 and Age 65 Claims



Notes: Present value of benefits is calculated at age 62 using a 3% interest rate. College educated households are assumed to have annual earnings of $70,000 while those without college education are assumed to have annual earnings of $30,000. All households in the comparison by marital status are shown with annual earnings of $50,000. Married couples are assumed to be the same age, always claim together, and claim on the earnings record of the head of household. Spouses are also assumed to always live until age 99. Calculations include both spousal benefits and survivors benefits. In panel (a), vertical lines at 78.6 and 82 years represent the average life expectancy of non-college and college education workers, respectively, conditional on survival to age 62. In panel (b), vertical lines at 78.4 and 81.8 years represent the average life expectancy of single and married workers, respectively, conditional on survival to age 62

variation in incentives across education levels. The PDV gaps for the average lower educated workers (with life-expectancy of 78.6 years) becomes positive; these individuals receive nearly $2,000 more by claiming at age 62 than at age 65. In contrast, college educated workers who have higher income and life-expectancy give up almost $5,000 in PDV by claiming at age 62.

Figure 2b highlights that the additional benefits married individuals receive in the form of spousal benefits and survivors benefits, increases the PDV gap between age 62 and 65 claims. For those with shorter lifespans, who receive more by claiming at age 62, the PDV gap is higher for married individuals. For the average life span of 80.5 years, singles receive roughly $1,200 less in PDV of benefits by claiming at age 62. This number is almost $4,000 for married couples. Variation in life-expectancy by marital status–as with education–induces differences in this calculation. Given the average life-span of 78.4, single workers receive around $2,500 more by claiming at age 62 than at age 65. By contrast, married individual, with average life-expectancy of 81.8 years, leave behind over $7,000 by choosing to claim at age 62.

The above calculations highlight three lessons. First, given the average life expectancy of slightly over 80 years for American men born between 1931 and 1935, delaying claims to age 70 is unlikely to result in a higher present-discounted value of benefits. However, for this average life-expectancy worker, claiming benefits at the normal retirement age rather than early leads to higher total benefits received (in PDV).[5] Second, holding this average life-span constant, variation in benefits received due to lifetime earnings differences or additional spousal benefits received by married beneficiaries leads to heightened incentives to delay claims to age 65 for higher educated and married individuals. Third, given that college educated and married individuals live longer (on average) than their lower educated and single counterparts, these workers have a stronger incentive to delay benefit claiming. For non-college educated and single workers, however, a lower life expectancy and lower nominal benefits sizes means these workers can receive more by claiming benefits at younger ages.

2.2 Empirical Analysis

Given variations in mortality across the population (as demonstrated in table 1) and the uncertainty related to life expectancy, it is likely that the claiming decisions of workers deviate from the predictions of the present-value calculation. However, in contrast to the predictions of the PDV calculations which would predict an average claiming age of around age 65[6], among a cohort of men born between 1931 and 1935, over 45 percent of men claimed benefits at age 62 while nearly 70 percent claimed prior to the normal retirement age of 65. Consistent with the low incentives to delay claims past the normal retirement age, though, we document small percentages of delayed claims in this cohort with only slightly over 10 percent of men claiming at age 66 or later. While this pattern may be more consistent with the PDV calculation for low education or single individuals, we would expect very low early claims among highly educated or married individuals. Early benefits claims, however, remain high among both these groups.[7]

In figure 3, we document the distribution of claiming ages for college versus non-college educated as well as married versus single men. The distributions by education are in figure 3a. Over 50 percent of those without a college degree claimed benefits at age 62, with over 70 percent claiming before age 65. These shares are roughly 40 percent and 60 percent for college educated men of this cohort.[8] More college educated men delayed claims past age 65, with around 15 percent of

[5] Previous work has also identified that many household could gain from delaying claims Coile et al. (2002) Meyer and Reichenstein (2010), Shoven and Slavov (2014a), Shoven and Slavov (2014b), Sun and Webb (2009) Maurer et al. (2018) Maurer et al. (2021) Maurer and Mitchell (2021).

[6] This claim is drive by the average life expectancy falling very close to the break even point between age 62 and age 65 claims

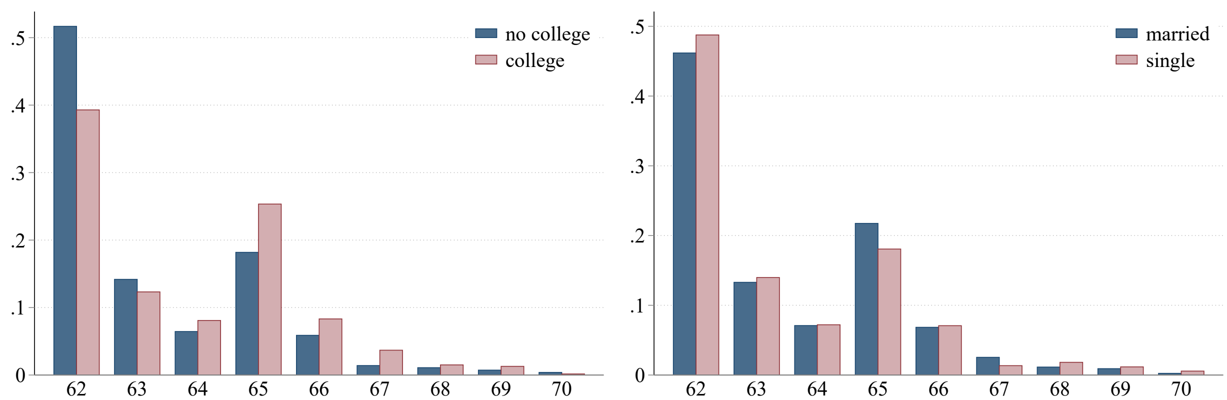
[7] We also considered using occupation rather than education as the proxy for income levels, but there is a strong correlation between the two. Details on the inclusion of occupation are considered in appendix C.1.

[8] The fact that early claiming is decreasing in education is also documented in Venti and Wise (2014).

them delaying claims compared to 10 percent of those without college education. While higher education individuals do claim later than their lower education counterparts, early claims remain high, with more than half of the college population claiming prior to the NRA.

Figure 3: Claiming Behavior by Age, Education, and Marital Status

(a) By Education (b) By Marital Status



Notes: Histograms are constructed from the Health and Retirement Study (2016, v1) and shows the claiming ages of men born 1931-1935. We focus on individuals who claim benefits for the first time between the ages of 62 and 70 in order to eliminate those workers who may enter the Social Security system through the Disability Insurance program prior to the ERA.

Claiming age distributions for single and married individuals are documented in figure 3b. This result shows that while there are small differences in claiming behavior across marital status, these differences are minimal.[9] Single men are slightly more likely to claim at age 62 but less likely to claim at the normal retirement age. Delayed claiming looks very similar across these groups. Despite the lessons of the PDV analysis, which would indicate a stronger incentive for married men to delay claims, the claiming distribution does not largely vary by marital status.

Overall, across education and marital status groups, a salient feature of the data is high levels of benefit claims before the age of 65 — a result that conflicts with the simple present-discounted value calculation presented previously. We turn our attention, therefore, to other motivations for claiming decisions. Here we document some additional stylized facts related to early claiming.[10] These facts highlight *claiming frictions* which deviate claiming behavior from what the simple PDV calculation would predict: (1) mechanisms highlighting the importance of budgetary considerations that are missing from the PDV calculation, (2) mechanisms hindering an individual's

[9]Shoven and Slavov (2014a) and Shoven and Slavov (2014b) also find that claiming behavior does not vary by marital status.

[10]In this empirical work, we focus only on all early claims rather than claims exactly at age 62 and claims for only men. However, some results including women and for claims at the early retirement age are shown in appendix sections C.2 and C.3.

ability to accurately perform the PDV calculation, and (3) mechanisms indicating objectives outside of maximizing the present discounted value of lifetime benefits.

In order to disentangle these classes of mechanisms, we run two regressions.[11] The first regression, shown in Equation 1, uses data from the Health and Retirement Study (HRS).[12]

$$Pr[i\,\text{claims before NRA}] = x_i'\beta + \sum_{k=-3}^{0} \delta_k I_{ik}^p + \gamma M_i + \rho B_i + \mu M_i * B_i + \varepsilon \tag{1}$$

The dependent variable is an indicator which takes a value of 1 if an individual claims Social Security benefits prior to the full retirement age. This indicator is regressed on a set of control variables x_i which includes education, race, gender, marital status, number of children, and interaction between gender, marital status, number of children and race, and an interaction between education level and health status. Additionally, we regress the indicator of a series of dummy variables, I_{ik}^p, which represent whether a worker was working prior to claiming. We include dummies for participation in the year of claiming, one to two years prior, three to fours years prior, and five to six years prior.[13] We also include a categorical variable measuring how well a worker predicts his own mortality, M_i, a categorical variable for whether a worker expects to leave a bequest and the size of the expected bequest, B_i, and an interaction between these two beliefs.

In order to analyze how program knowledge determines claiming behavior we run an additional regression, shown in Equation 2, in the Understanding America Study (UAS)–a survey which contains information on individual perceptions of Social Security rules[14]:

$$Pr[i\,\text{claims before NRA}] = x_i'\beta + \delta_0 I_{i0}^p + \gamma K_i + \varepsilon \tag{2}$$

Once again, the dependent variable is an indicator which takes a value of 1 if an individual claims Social Security benefits prior to the full retirement age and x_i' is a vector of similar control variables as those included in Equation 1. As we have only two waves of UAS available, we are unable to control for lagged labor force participation. Rather, I_{i0}^p is an indicator for work status in the year of interview and K_i is an indicator variable which takes a value of one if the individual understands the penalty associated with early retirement claims.

The predicted early claiming rates which result from these regressions are detailed in the following empirical facts.

1. *The probability of early claiming varies by health and employment status.*

[11]More details on data and sample selection for these regressions are shown in appendix A.

[12]More information on this regression and details of how indicators are constructed is detailed in B.1.

[13]Because HRS is collectively biannually, we cannot include lags for every year. Additionally, we may not observe workers in the year they claim. Therefore, we consider a year after claiming age for these workers.

[14]More information on this regression and details of how indicators are constructed is detailed in appendix B.2.

Workers may choose to claim Social Security benefits early due to budgetary constraints that are not included in the PDV calculation above. The presence of these constraints may induce beneficiaries to accept lower benefit payments to smooth consumption into retirement. To highlight whether these motives may impact claiming behavior, we study how claiming varies with transitory features such as health status and employment status.

Figure 4a shows how the predicted probability of early claiming changes based upon self-reported health status. Those in bad health are more likely to claim prior to the normal retirement age. We also note that while there does not seem to be a significant difference in claiming behavior between those in fair and excellent health, there does seem to be a difference in claiming behavior between those in the top two health states and those in the worst health.[15]

Additionally, we document a strong a link between non-participation in the labor market and the timing of benefit claiming, even though these decisions are not restricted to be occurring in the same period. We document in figure 4b that many workers have chosen non-participation prior to choosing early claims. This result weakens as we consider lags further before the claiming age, but those individuals who are not working during the same year of claiming, one to two years prior to claiming, and three to four years prior to claiming are more likely to claim Social Security benefits prior to the normal retirement age.[16, 17]

2. *Those with misbeliefs about program rules and mortality are more likely to claim early.*

   In order to maximize the present-discounted value of Social Security benefits received, a worker must be able to clearly predict the key parts of the calculation. Workers must know how claiming age impacts the annual benefits received and must know how long they will live. To empirically document this class of mechanisms, we study how claiming behavior varies according to whether workers understand there is a penalty associated with claiming prior to the NRA and whether they underestimate, correctly predict, or overestimate their own mortality. An individual is measured as having misbelief with respect to program rules if he reports that benefits received are independent of claiming age; an individual is measured as having misbelief with respect to mortality if his reported subjective probability, at age 60, of survival to age 75 is more than 5 percentage points higher or lower than the objective

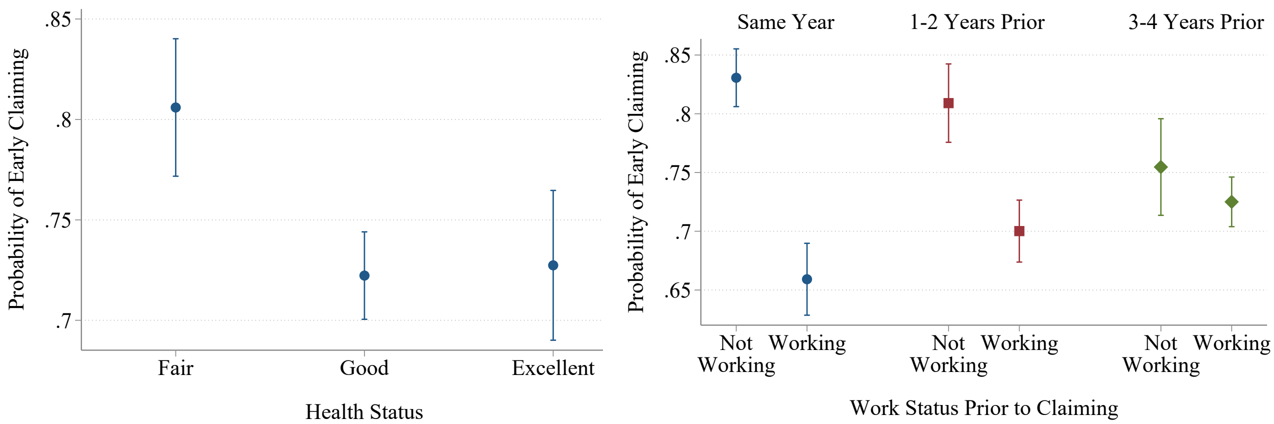
[15]We also experimented with studying how lagged values of self-reported health impact claiming. These results showed that health in various years prior to claiming does not have a significant impact on claiming.

[16]Chan and Huff Stevens (1999), Chan and Huff Stevens (2001), and Chan and Huff Stevens (2004), have demonstrated that unemployment spells among older workers may drive workers to earlier retirement and claiming.

[17]Bairoliya and Miller (2021) show parental long-term care needs can induce both early retirement and early claiming. However, given that parental care needs are largely met by women and given the focus of this study on male household heads, we abstract away from care needs in the study.

Figure 4: Claiming Behavior and Self-Reported Health, Work Status

(a) Health Status (b) Work Status



Notes: Results are constructed from the Health and Retirement Study (2016, v1) and shows the claiming ages of men born 1931-1935. More on the empirical strategy and construction of these results is included in appendix B

probability that an age 60 individual of his education, marital status, and self-reported health status will live to age 75.[18][19]

Tables 2 and 3 demonstrate that a significant fraction of people have misbeliefs about program rules and mortality. Approximately 10-20 percent of workers believe that benefits received are independent of the age at which a worker claims these benefits. Additionally, the vast majority of workers incorrectly predict their own probability of surviving to age 75. When asked at age 60, between 15 and 25 percent of workers expect to live to 75 with higher probability than they do, while between 70-80 percent believe they have a lower probability of survival to age 75.

The fraction of workers misbelieving and the extent of this misbelief vary across education levels and marital status. Nearly 6 percent of workers with a college degree believe there is no penalty for early claims, while this fraction is roughly 17 percent for non-college educated workers. There is less heterogeneity in mortality misbelief across education groups and marital status. However, the extent of this misbelief is significantly different. While non-college workers believe, on average, they have a 5 percentage points higher probability of survival to age 75 than estimated, college educated workers underestimate this probability by around 7 percentage points. Among these education types, married workers overesti-

[18]The Understanding America Study asks respondents a true/false question: *Social Security benefits are not affected by the age at which someone starts claiming*. We classify an individual as have misbelief if he answers *True* to this question.

[19]Objective probabilities of survival by age, education, marital status, and self-reported health status are estimated from the Medical Expenditure Panel Study. Details on this estimation are discussed in appendix section E.1.

Table 2: Program Misbelief

	Fraction of workers who believe SS benefit size is independent of claiming age
No College	16.8
Single	19.0
Married	15.5
College	5.5
Single	9.8
Married	4.5

Notes: Results are constructed from the Understanding America Study. An individual is classified as having misbelief related to program rules if they respond *True* to the statement "Social Security benefits are not affected by the age at which someone starts claiming". The share who have misbelief related to the program is defined over everyone ages 25-61. The share for various ages in shown in appendix C.4

mate mortality on average while singles underestimate mortality. As in Hurd and McGarry (1995) and Hurd and McGarry (2002), we find that the deviations of subjective and objective survival expectations are fairly small, indicating that individual do well at predicting their own survival. However, by connecting these expectations to claiming probability, we demonstrate that small deviations in cumulative probabilities of survival can translate into large differences in behavior. Figure 5 shows how the predicted probability of early claiming varies depending on this misbelief.

In figure 5a, the probability of early claiming is higher for those who believe claiming age has no impact on the size of benefits.[20,21] Figure 5b shows how early claims vary by beliefs of mortality. While those who are optimistic and accurate with regards to their own mortality claim at roughly the same rate, those workers who are pessimistic—or believe they have a lower probability of living to age 75 than they do—are more likely to claim Social Security benefits prior to the full retirement age.[22]

[20]While point estimates show a higher probability of early claims when workers misunderstand, these estimates are not statistically different. This is likely driven by the small sample size of the UAS and the small fraction of the sample who have misbeliefs about the program.

[21]Previous literature has identified this mechanism and has found conflicting results on the importance of it as a driving force of early claims. Papers in this literature include Greenwald et al. (2010) Liebman and Luttmer (2009) Liebman and Luttmer (2011) Coile et al. (2002) Benitez-Silva and Yin (2009) Diamond and Orszag (2004) Mastrobuoni (2010) Song and Manchester (2007).

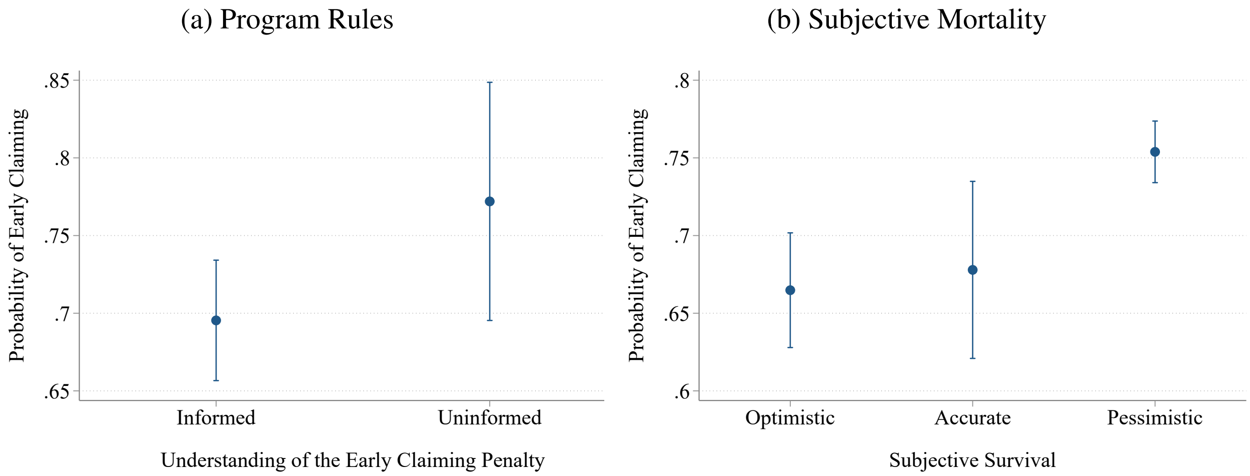
[22]Sun and Webb (2011) and Hurd et al. (2004) also look at the relationship between subjective survival rates and SS claiming.

Table 3: Mortality Misbelief

	Fraction of workers who		Average Misbelief
	Underestimate	*Overestimate*	*estimated - subjective*
No College	19.7	77.0	-4.9
			[-6.6, -3.3]
Single	21.8	70.4	-10.2
			[-14.0, -6.4]
Married	19.0	79.0	-3.2
			[-5.0, -1.4]
College	15.9	77.0	6.8
			[5.4, 8.3]
Single	24.2	72.0	0.6
			[-2.6, 3.8]
Married	13.0	78.7	9.2
			[7.6, 10.8]

Notes: Results are constructed from the Health and Retirement Study (2016, v1) and shown for men born 1931-1935. An individual underestimates mortality if, at age 60, the subjective cumulative probability of survival to age 75 (conditional on gender, education, marital status, and self-reported health status at age 60) is more the 5 pp larger than the estimated objective cumulative probability of survival to age 75 (once again, conditional on gender, education, marital status, and self-reported health status at age 60); an individual overestimates mortality if the subjective cumulative survival probability is more than 5 pp lower than the estimated cumulative probability of survival. Average misbelief is measured as the average difference between estimated and subjective survival probabilities across members of the group considered; a negative value indicates underestimation of mortality while a positive number suggests overestimation of mortality. 95% confidence intervals for averages are shown in brackets

Figure 5: Claiming Behavior and Misbelief



Notes: Results for misbelief of program rules are estimated from the Understanding America Study. Results for mortality misbelief are constructed from the Health and Retirement Study (2016, v1). Mortality misbelief is measured at age 60. More on the empirical strategy and construction of these results is included in appendix B.

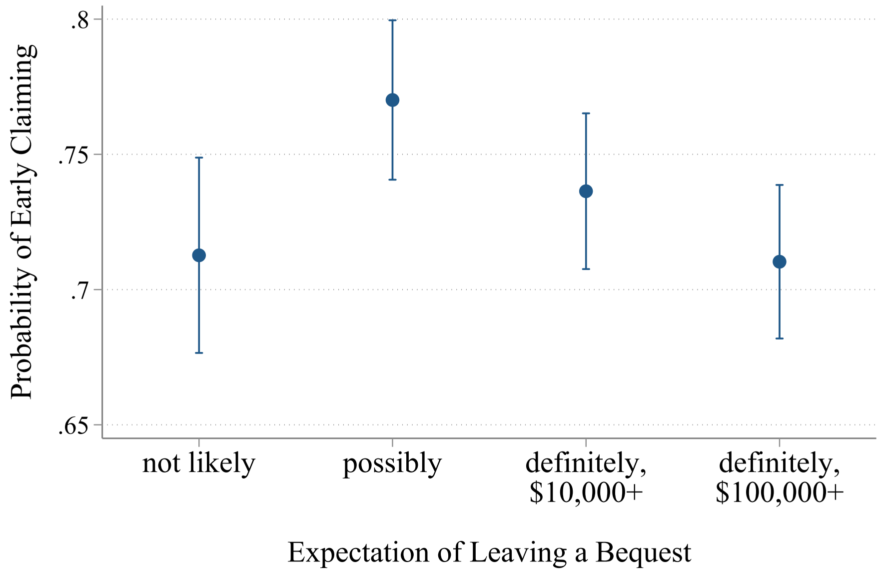
3. *A desire to leave bequests for the next generation may impact early claims.*

   The discussion of the present-discounted value calculation assumes that workers aim to maximize the PDV of their total lifetime Social Security benefits. If an individual has different goals, however, decisions on when to claim may not align with maximizing the PDV of what they receive. One such goal could be leaving wealth to future generations. Social Security benefits and private savings can both be used to finance consumption. However, while private savings can be bequeathed to the next generation, Social Security benefits–with the exception of survivors benefits to spouses–cannot. A desire to leave a bequest, therefore, may lead individuals to claim early in order to maximize bequeathable wealth.

   Figure 6 demonstrates how the predicted probability of early claiming varies depending on whether workers are likely to leave bequests and the size of these bequests. While estimates from our regression are not precisely estimated, our results indicate that those workers who have the possibility of leaving bequests are more likely to claim benefits early, even controlling for factors such as education and health status.[23] There is a jump in the probability of early claiming if a worker reports they will possibly leave a bequest rather than not likely to leave a bequest. However, once it becomes certain that the worker will leave a bequest of at least $10,000, this probability of claiming early decreases.

[23]Previous literature, such as Kopczuk and Lupton (2007) and Hurd and Smith (2022), provide evidence that bequests are a luxury good and wealthier individuals are more likely to leave bequests. As education and other control variables from Equation 1 are correlated with wealth, our result indicates this bequest motive may impact early claims even after controlling for wealth.

Figure 6: Claiming Behavior and Bequest Expectations



Notes: Results are constructed from the Health and Retirement Study (2016, v1) and shows the claiming ages of men born 1931-1935. Categories of expectations of leaving a bequest are measured based upon reported probabilities at age 60. More on the construction of these results is included in appendix B.1.

In summary, the PDV analysis highlights how income differences across education groups and policy differences for married individuals may change the trade-off between claiming benefits early versus delaying claims later in life. These may in-turn induce differences in claiming behavior across these groups. However, despite these differences, the distribution of claiming ages for workers born between 1931 and 1935 remains similar. Therefore, we study how other mechanisms–which we call *claiming frictions*–may lead workers' decisions to deviate from the predictions of the PDV analysis. In order to quantify the role of both policy (SS marital benefits) and these mechanisms in driving claiming behavior, we build a structural life-cycle model of consumption, savings, and retirement that allows for dynamic as well as non-linear interactions between these forces.

3 Structural Model

This section presents a dynamic programming model of retirement and Social Security. In order to capture the true nature of retirement incentives for older workers, retirement benefits from the current U.S. Social Security are modeled in great detail.

Labor supply (h_t), consumption (c_t), savings (a_{t+1}) and Social Security benefit application (b_t^{ss}) of a male household head is modeled. Individuals make these decisions in every time period

t and adjust their behavior in response to uncertainty pertaining to employment, wages, health status, and subjective survival.

Individuals' life cycle from ages $t = 25, 26, ..., 99$ is modeled. Individuals are heterogeneous with respect to both permanent and evolving states. Agents are permanently different with respect to their fixed education type (e), marriage (q), and SS program knowledge type (k). Marriage is summarized by a pair $q = (m, \iota)$ where m is a variable indicating if the agent is single or married and ι denotes the age gap between spouses if the individual is married. Evolving states include stochastic labor productivity (η_t), employment status (λ_t), health status (μ_t), assets (a_t), Social Security wealth (a_t^{ss}) and application status (b_{t-1}^{ss}). Given this vector of states $\left(e, q, k, \eta_t, \lambda_t, \mu_t, a_t, a_t^{ss}, b_{t-1}^{ss}\right)$, individuals choose optimal consumption, labor supply and make Social Security benefit application decisions (if eligible) to maximize the present discounted value of life-time utility.[24] The dynamic programming model has various components. The following sections describe each model ingredient in detail.

3.1 Preferences

Agents in period t derive utility from consumption c_t and leisure l_t. The within period utility is non-separable between the two and is given as follows.

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

Where ρ is the coefficient of relative risk aversion and ν is the weight on consumption. $\zeta_t^{e,m}$ is the equivalent scale in consumption which is permitted to vary by both education (e) and marital status (m). Note that that the utility of married households is also multiplied by two to account for spousal utility from consumption and leisure. The total amount of leisure in period t is given by:

$$l_t = \bar{l}^{e,m} - h_t - \phi_P^{e,m}(t)\mathbb{I}\{h_t > 0\} - \phi_H^{e,m}(\mu_t, t) \tag{3}$$

Where $\bar{l}^{e,m}$ is the total endowment of leisure each period, h_t is hours worked, function $\phi_H^{e,m}$ determines the amount of leisure lost due to a bad health shock and $\phi_P^{e,m}$ determines the participation cost incurred if hours worked h_t are positive. We fix the time cost of poor health from Jones and Li (2023) and assume the following functional form for the time costs of working:[25]

[24] Note that Social Security application is a one-time decision which cannot be reversed.

[25] The best health state in Jones and Li (2023) corresponds to our first two health states and our worst group directly maps into their fair/poor group. They allow the health costs to vary by education groups same as our. As such we use their age-education specific time cost of poor health for our worst health group. At age 25, this is roughly 15% of time endowment for non-college graduates and 40% for college graduates.

$$\phi_P^{e,m} = \frac{\exp(\phi_0^{e,m} + \phi_1^{e,m} t + \phi_2^{e,m} t^2)}{1 + \exp(\phi_0^{e,m} + \phi_1^{e,m} t + \phi_2^{e,m} t^2)} \tag{4}$$

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

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

Bequeathable wealth, A_t^q, is equal to any assets that remain, a_t, and Social Security survivors benefits, if eligible. Eligibility for survivors benefits depends on marriage (marital status and the age gap between spouses), q.[26] The coefficient $\theta_{beq}^{e,m}$ measures the strength of bequest motive and $\kappa_{beq}^{e,m}$ measures the curvature of the bequest function. Increase in $\theta_{beq}^{e,m}$ increases the marginal utility of a unit of bequest and increase in $\kappa_{beq}^{e,m}$ indicate that the bequest is valued more like a luxury good. These parameters are permitted to vary by education level, e, and marital status, m.

3.2 Health and Mortality

In every period, individuals are subject to an exogenous education-specific health shock. Health affects individuals in multiple ways–next period survival probability as well as the total time endowment. The transition probability for health depends on current health status, education level, and age in the next period. The transition between two possible health states i and j is given by:

$$\pi_{t+1}^{\mu_{ij}} = prob(\mu_{t+1} = j | \mu_t = i, e, t+1)$$

Individuals are also subject to mortality shocks in each period. The survival probability for the next period depends on age next period, education level, marital status, and current health status as given below:

$$\pi_{t+1}^{s} = prob(s_{t+1} = 1 | e, m, \mu_t, t+1)$$

[26]More details on survivors benefits is discussed in Section 3.5.3.

3.3 Employment

An individual experiences unemployment shocks with probability π^{λ}. Unemployment shocks lower labor productivity and create wage-scarring effects in the model (see section 3.4).

$$\pi^{\lambda}_{t+1} = prob(\lambda_{t+1} = 1)$$

3.4 Wages

Hourly wage in every time period is a function of an education and age-specific profile $\omega(e,t)$, unemployment status (λ_t) and an auto-regressive component η_t.[27]

$$\begin{aligned} w_t &= \xi(\lambda_t)\exp(\omega(e,t) + \eta_t) \\ \eta_t &= \rho^w \eta_{t-1} + \epsilon^w_t \\ \epsilon^w_t &\sim N(0, \sigma^2_{\epsilon^w}) \end{aligned} \tag{5}$$

If the individual experiences an unemployment shock $\lambda_t = 1$ then they may immediately re-enter the labor market but experiences a wage penalty, ξ.

3.5 Social Security

Social Security benefits are computed in several steps. First, the earnings of the 35 highest earning years are averaged into an index – Average Indexed Monthly Earnings (AIME). The AIME increases by working an additional year if earnings in that year are higher than the lowest earnings embedded in it and are also capped at a threshold.

Let a^{ss}_t be Social Security wealth (annualized measure of AIME). The evolution of Social Security wealth is approximated in the model in the following simple way:

$$a^{ss}_{t+1} = \max\{[a^{ss}_t + \max\{0, (w_t h_t - a^{ss}_t)/35\}], a^{\max}\} \tag{6}$$

Where $a^{\max}$ is the threshold at which the Social Security wealth is capped and $w_t h_t$ denotes annual earnings for period t. Note that in equation 6, we assume that the high earnings year only replaces an average earnings year, as modeling the actual system would require keeping track of entire earnings history which is computationally infeasible.

Second, AIME is converted to obtain the Primary Insurance Amount (PIA), which determines

[27]This specification provides reasonable wage scarring effects of unemployment spells in the model.

the Social Security benefits using the following piece-wise linear function:

$$pia(a_t^{ss}) = 0.90 \times \min\{a_t^{ss}, b_0\} + 0.32 \times \min\{\max\{a_t^{ss} - b_0, 0\}, b_1 - b_0\} \\ +0.15 \times \max\{a_t^{ss} - b_1, 0\} \tag{7}$$

The Social Security system in the model provides several work disincentives at older ages. For instance, the Social Security wealth a_t^{ss} is recomputed upwards only if current earnings are greater than average past earnings (as shown in equation 6). For instance, staying longer in the labor market by working fewer hours may not increase the benefits for the individuals in the model.[28] Additionally, there are strong work disincentives due to penalty/reward system associated with the timing of SS application and earnings test as described below.

3.5.1 Adjustments

Social Security benefits, ssb_t, are a function of the PIA as discussed above and two possible adjustments: a penalty/credit for claiming early/late (Γ_t) and a decrease in benefits for those workers who continue working while also claiming benefits (Υ_t).

$$ssb_t = pia(a_t^{ss}) * \Gamma_t - \Upsilon_t \tag{8}$$

Each of these adjustments is discussed below.

Early/Late Claiming Penalty

SS benefits can be claimed without any penalty at the normal retirement age (t_{NRA}).[29] However, individuals can claim benefits with some penalty starting the Early Retirement Age (t_{ERA}) of age 62. For every year before the NRA that these benefits are claimed, the Social Security amount received is permanently reduced by the early claiming penalty. Individuals can also delay their benefit claim beyond NRA. In that case, future benefits are permanently increased by the delayed claiming credit.

This penalty or credit shows up at a percentage decrease, γ_t^{ss}, for each year prior to the normal retirement age that a worker claims or a percentage increase for each year after the normal retirement age that a worker delays claiming. The penalty or credit for a claiming age of t^{ss} is:

[28] In practice, the highest 35 years of covered earnings are used to compute AIME. If the individual has not yet worked for 35 years, some zeros are included in the average, and any positive earnings, including part-time work, will increase the AIME.

[29] The NRA is slightly different for different birth cohorts. For instance, the sample used in this analysis, observed an average NRA of 65. But later cohorts observed an NRA of 66 or 67.

$$\Gamma_t = \begin{cases} 1-(t_{NRA}-t^{ss})*\gamma_t^{ss} & \text{if } t^{ss}<t_{NRA} \\ 0 & \text{if } t^{ss}=t_{NRA} \\ 1+(t^{ss}-t_{NRA})*\gamma_t^{ss} & \text{if } t^{ss}>t_{NRA} \end{cases} \tag{9}$$

Earnings Test

Social Security earnings test taxes the labor income, above a certain threshold y_t^{ss}, of the Social Security beneficiaries at a rate τ_t^{ss}, until the age of 70. Specifically, for each additional dollar earned above the threshold, Social Security benefits are reduced by τ_t^{ss}, until all benefits are taxed away as shown below:

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

Υ_t denotes benefits lost through the earnings test. Taxed benefits are credited back through permanent increases in future benefits, which is implemented in the model through increases in the Social Security wealth as shown below:[30]

$$\begin{aligned} ssb_{t+1} = pia(a_{t+1}^{ss}) * \left[1+\left(\frac{\Upsilon_t}{ssb_t}\right)\gamma_t^{ss}\right] \\ a_{t+1}^{ss*} = pia^{-1}(ssb_{t+1}) \end{aligned} \tag{10}$$

where γ_t^{ss} is the same reduction/increment factor which is used for determining penalty/credit for early/late benefit application as discussed earlier. The net work incentives provided by the earnings test crucially depends on γ_t^{ss}.[31] As a result, the earnings test combined with the benefit application age structure may provide strong incentives to retire upon reaching the claiming age. Since the Social Security rules have been changing over time, the specific rules pertinent to the sample used in this analysis are taken from SSA.

3.5.2 Misbeliefs

To model SS program knowledge (k) regarding the penalty/credit for early/late application, we allow two groups of individuals–one group is fully informed about the rules and the other unaware of both the early claiming penalty and the delayed claiming benefit while making their decisions. We define perceived Social Security benefits, $\overline{ssb}_t$, based on whether an individual understands the rules or not.

[30]Note that this is a simplification as in practice, the benefits are typically adjusted upon reaching the NRA.
[31]Note that the earnings test was removed for worker over the NRA starting in 2000.

$$\overline{ssb}_t = \begin{cases} ssb_t & \text{if } k = \text{informed} \\ pia\left(a_t^{ss}\right) - \Upsilon_t & \text{if } k = \text{uninformed} \end{cases} \tag{11}$$

If the individual is informed, the Social Security benefits received are identical to those calculated by the system, or $\overline{ssb}_t = ssb_t$. However, if the individual is uninformed about the rules, the perceived benefits do not include the adjustments for the early or late claims. Note that we still allow the adjustment with respect to the earnings test.[32] This way of modeling misbeliefs is akin to agents operating under limited information with their actions resulting in irreversible mistakes in terms of claiming.

3.5.3 Marriage Related Benefits

Spousal Benefits

Married households receive additional income through Social Security spousal benefits. Spouses of household heads are entitled to up 50 percent of head's benefits depending upon the age benefits are claimed. We assume that all spouses claim together, and, thus, the size of the spousal benefits received is a function of the head's age at SS claiming, t^{ss}, and the age gap between spouses, ι. Total household Social Security benefits received by a household is given by $\delta_t^q ssb_t$ where δ_t^q is determined as follows:

$$\delta_t^q = \begin{cases} 1.0 & \text{if } m = \text{single or } m = \text{married}, t^{ss} - \iota < t_{ERA} \\ 1.5 * \left[1 - (t_{NRA} - (t^{ss} - \iota)) * \gamma_t^{ss})\right] & \text{if } m = \text{married}, \ t_{ERA} \leq t^{ss} - \iota < t_{NRA} \\ 1.5 & \text{if } m = \text{married}, \ t^{ss} - \iota \geq t_{NRA} \end{cases} \tag{12}$$

Singles and married individuals whose spouse is not yet eligible for benefits ($t^{ss} - \iota < t_{ERA}$) receive no additional spousal benefits. Married individuals for whom the spouse's age is above the normal retirement age, receive the additional 50 percent of benefits. Married individuals whose wives are between 62 and 65 at the time of claiming receive benefits penalized by the early retirement penalty.[33] Spousal benefits do not accrue delayed retirement credits, thus, are maximized at the spouse's normal retirement age.

[32] We model misbeliefs in such a way because it better maps with the survey question. However, even if we allow the misbeliefs related to the earnings test, it has very little impact on our results.

[33] Details of spousal penalty adjustments for early claiming are provided in appendix D.

Survivors Benefits

Married individuals may also leave their Social Security benefits to their spouses when they die. These survivors benefits enter into the bequeathable wealth of individuals, A_t^q, which takes the following form:

$$A_t^q = \begin{cases} a_t + \sum_{j=t-\iota}^{T} \frac{1}{1+r} \pi_{j+1}^s ssb_t & \text{if } m = \text{married}, t - \iota \geq 62 \\ a_t & \text{otherwise} \end{cases} \tag{13}$$

In addition to any leftover assets, a_t, bequeathable wealth is a function of Social Security wealth if the individual is married and the spouse is over the age of 62. These survivors benefits are calculated as the present value of the stream of benefits a spouse would receive from the time of the death of the household head until the end of her own life. Therefore, this present value is a function of the household head's age t and the spousal age gap, ι.[34]

3.6 Budget Constraint

Before claiming their Social Security benefits, individuals make their decisions based on a budget constraint that includes the perceived Social Security benefits. This budget constraint is given as follows:

$$c_t + a_{t+1} = a_t + W\left(y_t, y_{st}, ra_t, \tau\right) + \mathbb{I}\left\{b_t^{ss} = 1\right\} \times \delta_t^q \overline{ssb}_t + tr_t \tag{14}$$

An individual's disposable household income, $W\left(\cdot\right)$, consists of various components. He receives income through hours worked in the labor market y_t, spousal income y_{st} (if the individual is married), and return on assets ra_t. If eligible, individuals receive transfers from the government, tr_t as described in equation 19 below. Note that the decisions of the individuals are based on their perceived Social Security benefits $\delta_t^q \overline{ssb}_t$, that they would receive once they claim. However, once individuals claim their benefits (i.e. $b_t^{ss} = 1$), the true Social Security benefits are revealed to them. The budget constraint then is given as follows:

$$c_t + a_{t+1} = a_t + W\left(y_t, y_{st}, ra_t, \tau\right) + \delta_t^q ssb_t + tr_t \tag{15}$$

Labor income, $y_t = w_t h_t$, is a function of the hourly wage and work hours chosen by the individual. Spousal income for married households is determined as a function of the head's education,

[34] Details of survivors benefit calculations are provided in appendix D.

age, health status and labor income, and is given as follows:

$$y_{st} = f\left(e, t, \mu_t, w_t h_t\right) \tag{16}$$

There is a standard borrowing constraint on assets given by:

$$a_{t+1} \geq 0 \; \forall t \tag{17}$$

and a consumption floor which guarantees a minimum level of consumption (Hubbard et al., 1995).

$$c_t \geq \bar{c} \tag{18}$$

Government transfers, tr_t, bridge the gap between this minimum level of consumption and individual's liquid resources. This is a simple approximation to the federal safety net programs in the U.S. such as Supplemental Nutritional Assistance Program (SNAP), Supplemental Security Income (SSI), Temporary Assistance for Needy Families (TANF), and other programs.

$$tr_t = \min\{0, \underline{c} - (a_t + W_t + \delta_t^q ssb_t)\} \tag{19}$$

Where W_t is the total disposable household income as defined in equation 15.

3.7 Recursive Formulation

Let $z_t = \left(e, q, k, \eta_t, \lambda_t, \mu_t, a_t, a_t^{ss}, b_{t-1}^{ss}\right)$, be the period t state vector. Then individuals solve a finite-horizon Markovian decision problem where they choose a sequence of consumption $\{c(z_t)\}_{t=1}^{T}$, hours $\{h(z_t)\}_{t=1}^{T}$ and Social Security benefit application $\{b^{ss}(z_t)\}_{t=1}^{T}$ rules to maximize the expected discounted lifetime utility subject to the exogenous processes for health transition, employment shocks, survival, and wage determination, a set of budget, borrowing, and time constraints, government transfer rule, and policies for taxes and Social Security.

The life cycle of an individual between ages 25 and 99 is divided into three distinct phases. The first is the *employment* phase between ages 20 and 61 where individuals make consumption, savings, and employment decisions.[35].The second is the *retirement choice* phase between ages 62 and 69 where individuals also make Social Security application decisions (b_t^{ss}). The final stage is a *retired* phase where individuals make only consumption and savings decisions. The decision problem of a household head with education level e, marital status m, and Social Security belief type k for each phase is given below:

[35]We do not allow individuals to claim disability benefits in the model and only estimate the model for individuals who claim Social Security through the non-disability route.

3.7.1 Employment phase

$$
\begin{aligned}
V_{e,q,k}(a_t, a_t^{ss}, \eta_t, \lambda_t, \mu_t) = \max_{\{c_t, h_t\}} \Bigg\{ & U^{e,m}(c_t, l_t) \\
& + \beta^{e,m} \pi_{t+1}^{s} \Big[EV_{e,q,k}(a_{t+1}, a_{t+1}^{ss}, \eta_{t+1}, \lambda_{t+1}, \mu_{t+1}) \Big] \\
& + \beta^{e,m}(1 - \pi_{t+1}^{s}) beq^{e,m}(A_{t+1}^{q}) \Bigg\} \quad s.t.
\end{aligned}
$$

$$
a_{t+1} = a_t + W(y_t, y_{st}, \bar{r}a_t, \tau) + tr_t - c_t,
$$

(3), (6-10), (17), and (18).

where $y_t + y_{st} + \bar{r}^e a_t$ is the total pre-tax income and $W(., \tau)$ gives the level of post-tax income with the tax rate τ. Note that the expectation is taken with respect to wage, employment and health uncertainty.

3.7.2 Retirement choice phase

Starting age 62, individuals also make benefit-claiming decisions. Note that this is a one-time decision and benefits are based on the age at which the individuals choose to claim benefits for the first-time. During this phase, if an individual enters a period as a non-claimer, he faces the decision of whether to claim benefits this period or not as shown below:

$$
V_{e,q,k}(a_t, a_t^{ss}, \eta_t, \lambda_t, \mu_t, b_{t-1}^{ss} = 0) = \max \left\{ V_{e,q,k}^{b_t^{ss}=0}, V_{e,q,k}^{b_t^{ss}=1} \right\}
$$

$$
\begin{aligned}
V_{e,q,k}^{b_t^{ss}=0}(a_t, a_t^{ss}, \eta_t, \lambda_t, \mu_t, b_{t-1}^{ss} = 0) = \max_{\{c_t, h_t, b_t^{ss}\}} \Bigg\{ & U^{e,m}(c_t, l_t) \\
& + \beta^{e,m} \pi_{t+1}^{s} \Big[EV_{e,q,k}(a_{t+1}, a_{t+1}^{ss}, \eta_{t+1}, \lambda_{t+1}, \mu_{t+1}, b_t^{ss} = 0) \Big] \\
& + \beta^{e,m}(1 - \pi_{t+1}^{s}) beq^{e,m}(A_{t+1}^{q}) \Bigg\} \quad s.t.
\end{aligned}
$$

$$
a_{t+1} = a_t + W(y_t, y_{st}, \bar{r}a_t, \tau) + tr_t - c_t,
$$

(3), (6-10), (17), and (18).

$$V_{e,q,k}^{b_t^{ss}=1}(a_t, a_t^{ss}, \eta_t, \lambda_t, \mu_t, b_{t-1}^{ss} = 0) = \max_{\{c_t, h_t, b_t^{ss}\}} \Bigg\{ U^{e,m}(c_t, l_t) + \beta^{e,m}\pi_{t+1}^s \Big[EV_{e,q,k}(a_{t+1}, a_{t+1}^{ss}, \eta_{t+1}, \lambda_{t+1}, \mu_{t+1}, b_t^{ss} = 1) \Big] + \beta^{e,m}(1 - \pi_{t+1}^s) beq^{e,m}(A_{t+1}^q) \Bigg\} \quad s.t.$$

$$a_{t+1} = a_t + W(y_t, y_{st}, \bar{r}a_t, \tau) + tr_t + \delta_t^q ssb_t - c_t,$$

(3), (6-10), (17), and (18).

3.7.3 Retired phase

At age 70, if an individual has still not claimed their benefits, then they automatically start receiving both their own benefits as well as their spousal benefits (if applicable).

$$V_{e,q}(a_t, a_t^{ss}, \mu_t) = \max_{c_t} \Bigg\{ U^{e,m}(c_t, l_t) + \beta^{e,m}\pi_{t+1}^s EV_{e,q}(a_{t+1}, a_{t+1}^{ss}, \mu_{t+1}) + \beta^{e,m}(1 - \pi_{t+1}^s) beq^{e,m}(A_{t+1}^q) \Bigg\} \quad s.t.$$

$$a_{t+1} = a_t + W(y_{st}, \bar{r}a_t, \tau) + \delta_t^q ssb_t + tr_t - c_t,$$

(3), (7), (17), and (18).

4 Estimation

We estimate our model for male household heads born between 1931 and 1935 using a two-step estimation strategy following Gourinchas and Parker (2002). In the first step, we use several data sets—including the Panel Study of Income Dynamics (PSID), the Health and Retirement Study (HRS), the Household Component of the Medical Expenditure Panel Study (MEPS), and the Understanding America Study (UAS)—to estimate processes that can be identified without using the dynamic programming model.[36] We call this vector Φ which includes health transitions, subjective survival probabilities, family structure and spousal income, wages, unemployment probabilities, knowledge about Social Security rules, the tax function, and the exogenous rate of return on as-

[36]Details on the data and samples used for estimation are included in appendix A.

sets. In the second step, we use initial conditions drawn from data for the relevant cohort, our structural model, and the parameters from the first step to estimate the preference parameter vector $\Theta = \{\beta^{e,m}, \theta_{beq}^{e,m}, \kappa_{beq}^{e,m}, \phi_P^{e,m}(t), \bar{l}^{e,m}\}$ using Method of Simulated Moments (MSM) by education and marital status.[37] The following sections describe both the first and second steps in detail.

4.1 First Step Estimation

4.1.1 Health and Mortality

We allow health to take take three possible values, $\mu_t = \{\text{excellent}, \text{good}, \text{poor}\}$ in the model. We identify these health states in the Medical Expenditure Panel Survey (MEPS) as well as the Health and Retirement Study data from the self-reported health status variable.[38][39] Health transitions across these states are then estimated from MEPS by running an ordered probit of self-reported health status on previous year health status, education, and a cubic function of age.

The benchmark specification uses subjective mortality profiles. These subjective mortality profiles are estimated in two steps. First, objective survival probabilities are obtained from MEPS. We estimate an age-, education-, marital status-, and health-specific profiles from the MEPS data by running an ordered probit model of death indicator on self-reported health status, age cubic, education, and marital status. Refer to appendix E.1 for details on the estimation of both health transition as well as objective survival probabilities.

Second, subjective survival probabilities are obtained by scaling the estimated objective probabilities so that the cumulative probability of survival to age 75 conditional on survival to age 60 is equivalent to the subjective probability of survival to age 75 conditional on survival to age 60 as measured in the HRS. This scaling factor is assumed to be constant over age but differs by education and marital status.[40]

4.1.2 Family Structure

Family structure determines two parameters for married men: the equivalence scale in consumption, $\zeta_t^{e,m}$ and the gap between spouses, ι. In addition to these parameters, married men also

[37] The share of the population within each fixed education, marital status group are shown in table E.1.

[38] Both surveys asks respondents to self-report their health on a scale of 1 to 5 where 1 is "Excellent," 2 is "Very Good," 3 is "Good," 4 is "Fair,"and 5 is "Poor". For computational simplicity, the 5-point scale is converted into a 3 point scale by grouping individuals of "Very Good" and "Good" health into the good health category and those in "Fair" and "Poor" into the poor health category.

[39] An alternative would be to use a more objective measure of health such as frailty index along the lines of Hosseini et al. (2022). However, as discussed in Miller and Bairoliya (2021), self-rated health has been shown to be predictive of mortality in even after controlling for other health conditions, health behavior, which is indicative of people having private information about their health over and above objective measures.

[40] More details on the construction of these survival probabilities are contained in appendix E.2.

receive spousal income.[41]

We assume that the equivalence scale in consumption differs by education and marital status and is constructed based on family statistics calculated in PSID. Single households are assumed to have an equivalence scale of 1. The equivalence scale of married households, however, is based on the presence of a spouse and the average number of children living in the household for each age and education type. Given family size, values for $\zeta_t^{e,m}$ are set based on the OECD equivalence scale.[42]

Additionally for married couples, the age gap between the male household head and their spouse is determined based on the distribution of age gaps for the cohort at hand. We use four age gap options $(0, 1, 4, 8)$ to describe this distribution and assign the mass at each point from PSID data. Data indicates that 8.7 percent of married couples have no age gap, 26.2 percent have an age gap of one year, 46.1 percent have an age gap of four years, and 19 percent have an age gap between spouses of eight years.

Spousal income, y_{st}, is estimated from PSID and is assumed to be a function of the age, education level, health, and labor income of the household head.

4.1.3 Labor productivity

Wages are assumed to be comprised of an age and education-specific profile and a persistent shock.[43] This function of age and education as well as parameters of the AR(1) shock process is estimated from PSID in two steps. First, age-education specific profiles are estimated using Heckman two-step procedure. Second, persistence and standard deviation of the shock process is estimated through Method of Simulated Moments. Discussion of this estimation and the estimation of the parameters of the stochastic process are detailed in appendix E.6.

4.1.4 Employment Shock and Wage Scarring

The employment shock is the exogenous probability that a worker is separated from the labor market and is independent of education and marital status. We set this employment shock, λ, to match the separation rate measured in JOLTS and set at $\lambda = 0.1$.

The wage penalty associated with the employments shock, ξ, is modeled as a percentage of income. The penalty is estimated from PSID following the literature on the wage scarring and set

[41] More information on estimation of parameters related to family structure (details on marriage and children, the age gap between spouses, spousal income) is discussed in Appendices E.3, E.4, E.5.

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

[43] We experimented with estimating these profiles separately for married and single individuals. However, estimates were not statistically different by marital status once we controlled for education. Borella et al. (2019) also find that marital status is not statistically significant in determining wages once human capital is controlled for.

to $\xi = 0.86$.[44] To estimate the penalty of a displacement, the log of hourly wages is regressed on dummies representing years since a labor force displacement occur as well as a vector of control variables including a quadratic in age and a quadratic in experience. This penalty is set to be the percentage drop in annual wages that displaced workers experience.[45]

4.1.5 Social Security

Explicitly modeling the rich detail of the U.S. Social Security System (described in Section 3.5) requires us to define the parameters involved with these modeling choices. Table 4 shows these parameters based on the 1998 rules from the United States Social Security Administration.

The first group of parameters, b_0, b_1, and a^{max}, are related to the calculation of Social Security wealth and benefits. The maximum wealth at which benefits are capped is given by a^{max} and is set at $68,400. The parameters b_0 and b_1 define the bend points of the Social Security benefits formula, $g(\cdot)$. These points are set to $5,724 and $34,500. There is no variation in these parameters based on the claiming age of the worker.

The second group of parameters is based on the earnings test. Before the NRA, earnings above $9,120 are taxed at a rate of 50 percent. After the normal retirement age, earnings above $14,500 are taxed at 33 percent.[46]

The final parameter of table 4 defines the penalty for early claiming (or the benefit for delaying claiming). Benefits are decreased by 6.7 percent for each year prior to the NRA the worker claims. After the normal retirement age, benefits are increased by 5.5 percent for each year the worker delays benefit claims.

4.1.6 Taxes

Individuals in the model pay a proportional payroll tax, τ_t^{ss}, and labor income taxes, $\tau^{e,m}$. The proportional labor income tax τ_t^{ss} includes both the Social Security payroll tax as well as Medicare tax. The Social Security payroll tax is 6.2 percent on income up until the maximum taxable amount, a^{max}, while the Medicate tax is 1.45 percent on total labor income.

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). We allow the function to vary by education and marital status and estimate the following function from the PSID

[44] Papers in this literature include Jacobson et al. (1993), Huff Stevens (1997), and Huckfeldt (2016).

[45] Additional details on the estimation of the separation rate and the wage penalty for the employment shock are included in appendix E.7.

[46] This normal retirement age is dependent on birth cohort. It is age 65 for our benchmark birth cohort (born in 1931-1935).

Table 4: Social Security Benefit Formula

Parameter	Value*	
	before the NRA	after the NRA
a^{max}	68,400	68,400
b_0	5,724	5,724
b_1	34,500	34,500
Earnings Test		
y^{et}	9,120	14,500
τ^{et}	0.50	0.33
γ_t^{ss}	0.067	0.055

*1998 rules from the SSA and those pertaining to the 1931-1935 birth cohort.

data:

$$\tau^{e,m} = 1 - \lambda^{e,m} y^{-\xi^{e,m}}.$$

We allow for the tax function to differ by education type and marital status to capture any differences in family size across these groups.[47]

4.1.7 Misunderstanding of the Social Security System

We model misunderstanding of the Social Security system as a fixed type. We use the Understanding America Study to estimate the fraction of workers who believe that the age at which they begin claiming has no impact on the benefits received. As previously shown in table 2, we estimate that roughly 22 percent of non-college educated workers are misinformed while nearly 9 percent of college-educated individuals do not understand the policy.

4.2 Second Step Estimation

Given the vector of exogenous data generating processes Φ and the vector of preference parameters Θ as described above, the decision rules $c(z_t, \Phi, \Theta)$, $h(z_t, \Phi, \Theta)$, and $b^{ss}(z_t, \Phi, \Theta)$ are solved numerically using backward induction. The estimated Φ and initial conditions z_0 are then used to simulate the life-cycle profiles of hypothetical individuals. Finally, an MSM criterion function is used to find $\hat{\Theta}$ that minimizes the distance between aggregated simulated and data profiles.[48] The

[47]Details of the estimation of parameters in the tax function are in appendix E.8.

[48]Life-cycle profiles estimated by fitting a regression with fourth-order polynomial in age and controls for education and marital status (in levels plus interacted with each other and age) for the 1931-1935 cohort. This is done for participation, hours, and wealth. Data on the construction of wealth data is discussed in appendix E.9.

following moments are matched to estimate the elements of Θ by education (no college or college) and marital status groups (single or married):

1. Labor market participation of male household heads between ages 25 and 69 resulting in 180 moment conditions.

2. Log of hours worked, conditional on participation, of male household heads between ages 25 and 69 resulting in 180 moment conditions.

3. Mean assets of male household heads between ages 25 and 69 resulting in 180 moment conditions.

This gives a total of 540 moment conditions. Formally the MSM estimate $\hat{\Theta}_{MSM}$ is one that solves:

$$\hat{\Theta}_{MSM} = \text{argmin } \tilde{g}(\Theta, \Phi) W_T \tilde{g}(\Theta, \Phi)$$

where

$$\tilde{g}(\Theta, \Phi) = \begin{bmatrix} \frac{1}{N} \sum_{i=1}^{N} \{p_{it} - \tilde{p}_t^{e,m}(z_{it}, \Theta, \Phi)\} \\ \frac{1}{N} \sum_{i=1}^{N} \{\log h_{it|p_{it}>0} - \log \tilde{h}_{t|p_t>0}^{e,m}(z_{it}, \Theta, \Phi)\} \\ \frac{1}{N} \sum_{i=1}^{N} \{a_{it} - \tilde{a}_t^{e,m}(z_{it}, \Theta, \Phi)\} \end{bmatrix}$$

$$t = \{1, ..., T\},\ e \in \{non - college, college\}, m \in \{single, married\}$$

W_T could be an optimal weighting matrix given by the inverse of a consistent estimate of the covariance matrix of data moments. However, efficient choice of weighting matrix could introduce finite sample bias. Hence the following non-optimal weighting matrix is used for the structural estimation in this paper:

$$W_T = \left[diag\Big(var\big(\frac{1}{\sqrt{N}} \sum_{i=1}^{N} m_{it} \big) \Big) \right]^{-1}$$

where m_{it} is a vector of data moments.

5 Results

5.1 Estimation and Identification of Structural Parameters

As the analysis in this paper focuses on explaining savings, labor supply and claiming behavior, of workers who are heterogeneous with respect to marital status and education, we allow a limited set of structural parameters to vary across these groups while fix others. Specifically, we allow the discount rate, bequest motives, and parameters related to time endowment and time costs to vary across marital and education groups while we fix consumption weight and risk aversion parameter to be same across all. This allows us to match differences in wealth evolution and labor supply for individuals of different education-marital type in a parsimonious way. Discount rate heterogeneity allows for differences in the growth in wealth early in the life cycle while heterogeneous bequest motives help capture differential rates of dis-saving later on in life for these fixed groups. Time endowments and the time cost of working are permitted to vary across groups to match differences in extensive and intensive margins of labor supply. In Section 6, we test the robustness of our key findings to fixing both discount rates as well as bequest motives across groups.

In our benchmark specification, we fix the interest rate, r, to 0.03, consumption weight, ν, to 0.578, and relative risk aversion parameter, ρ, to 3.340 for all groups.[49,50] Together, these two parameters imply an inter-temporal elasticity of substitution for consumption, $\frac{-1}{\nu(1-\rho)-1}$, which equals 0.425. Table 5 shows our structural parameter estimates for $(\beta^{e,m}, \theta_{beq}^{e,m}, \kappa_{beq}^{e,m}, \bar{l}^{e,m})$. The estimated discount factor is higher for married men than singles and for college graduates than those without a college degree. It ranges between 0.904 for single, non-college educated men to 1.007 for married, college graduates.[51] Note that our estimated discount rates imply a declining life-cycle consumption path for the non-college singles and increasing consumption paths for the married individuals.[52]

Together, the bequest parameters $\theta_{beq}^{e,m}$ and $\kappa_{beq}^{e,m}$ govern the strength of terminal bequest motive. While our estimates indicate variation in $\theta_{beq}^{e,m}$ and $\kappa_{beq}^{e,m}$ across groups, it is important to note that both the marginal propensity to bequeath out of wealth and the wealth thresholds for individuals to leave positive bequests are non-linear function of the parameters $(\nu, \rho, \beta^{e,m}, \bar{l}^{e,m}, \theta_{beq}^{e,m}, \kappa_{beq}^{e,m})$.[53] For ease of interpretation, figure 8a plots the implied share of resources that would be left as bequests by households in different marital and education groups if their probabilities of death next period

[49]We also test the robustness of our results to allowing heterogeneous return across education groups in section 6.

[50]Parameter values for consumption weight, ν, and relative risk aversion, ρ, are taken from French (2005) which also estimates a life-cycle model of retirement and Social Security claiming.

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

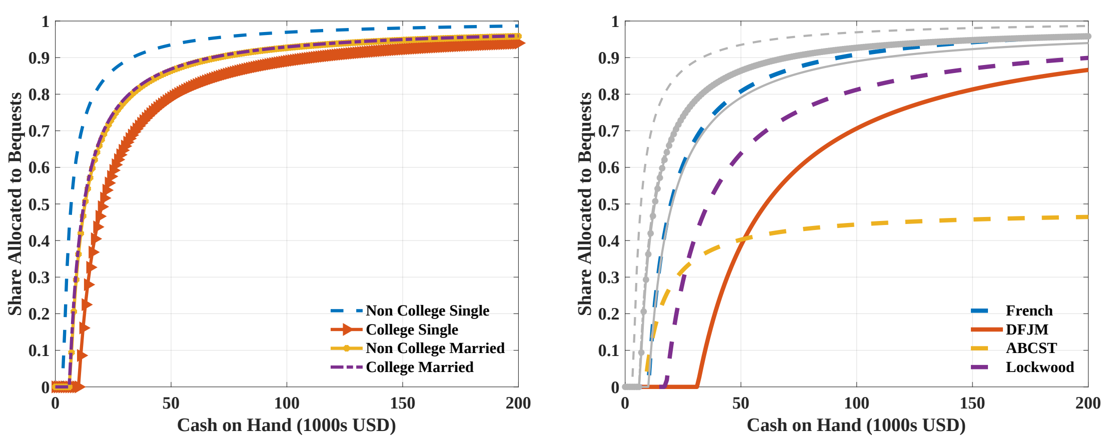
[52]Note that $\tilde{\beta} < \frac{1}{1+r}$ for the non-college singles, where $\tilde{\beta}$ is the effective discount factor after taking into account survival probability and $r = 0.03$. By contrast, $\tilde{\beta} > \frac{1}{1+r}$ for the married group.

[53]Refer to appendix F for a derivation of these.

were one. Figure 8b, provides a comparison with the literature on estimated bequest motives. Our benchmark model indicates that for all groups, estimated bequest motives are less of a luxury good (the wealth threshold for leaving any positive bequests is lower) than in papers such (Lockwood, 2012; De Nardi et al., 2010, 2021) but closer to others, including French (2005); Ameriks et al. (2020).

The time endowment, $\bar{l}^{e,m}$, is estimated to be between 4,531 hours annually (or 87 hours a week) for married college graduates and 7,259 hours (or 139 hours a week) annually for non-college singles. These estimates pick-up two features of the data. First, with respect to marital status, married individuals may have child-care responsibilities and engage in home production which would indicate lower time endowment towards work and leisure activities. Second, despite variation in wages across educational groups, levels of hours worked conditional on working does not largely vary for non-college and college educated men–conditional on marital status. This higher endowment helps to match the hours worked for non-college educated men despite the lower cost of leisure among these workers.[54] Finally, we also estimate the time cost of working using the structural model. Specifically, we estimate the coefficients of the function as described in equation 4 for each education and marital group in the model. appendix figure H.1 provides implied costs, as a fraction of time endowment, for each groups.

Figure 7: Estimated Bequest Motives



(a) (b)

Notes: Panel (a) presents expenditure share allocated to bequests for different education and marital groups facing certain death in the next period (refer to appendix F for calculation details). Panel (b) provides comparison with the literature. Grayed lines refer to groups in panel (a) and colored lines: (French) French (2005); (DFJM) De Nardi et al. (2021) for singles; (ABCST) Ameriks et al. (2020); and (Lockwood) Lockwood (2012).

[54]Aguiar and Hurst (2008) show that lower educated individuals consume more leisure that those of higher education, even conditional on working. A higher time endowment for lower education men supports this despite small differences in hours worked.

Table 5: Preference Parameters

Parameter	Description	Singles		Married	
		Non-College	College	Non-College	College
Fixed					
ρ	relative risk aversion	3.340	3.340	3.340	3.340
ν	consumption weight	0.578	0.578	0.578	0.578
Group-specific					
β	discount factor	0.904	0.978	0.993	1.007
θ_{beq}	bequest intensity	0.927	0.421	1.198	1.631
κ_{beq} (in 000s)	bequest curvature	1.343	2.525	1.598	1.544
$\bar{l}$	time endowment	7259	5174	6251	4531

5.2 Benchmark Model Fit

Appendix figures H.2-H.4 show the benchmark model fit for average labor force participation, hours worked, conditional on participation, and wealth over the life cycle for male household heads (born between 1931 and 1935) by marital status and education groups. With the exception of hours worked (close to retirement years) for the college-married group, our structural model mostly performs well in matching these targeted moments. Note that the benchmark model only allows a limited set of parameters to vary across groups and it is still able to achieve a near-perfect fit for wealth evolution for all groups, as well as reasonable fits for labor supply.

Next, we check to see if the model is able to generate a reasonable prediction for moments that were not targeted explicitly in the structural estimation — particularly Social Security claiming behavior. Figure 9 shows the cumulative Social Security claims for all the simulated individuals in the model economy. Specifically, the point corresponding to age 64 shows total share of all early claims (all claims prior to the normal retirement age of 65) in the data and the model. We find that the estimated model performs exceedingly well in matching all four important features of the claiming behavior – 1) age 62 claims (earliest age of eligibility), 2) claims before the age of 65 (early claims), 3) claims at age 65 (normal retirement age) and 4) claims after age 65 (delayed claims).

Apart from matching the overall Social Security claiming behavior extremely well, the model is also able to predict several important characteristics of early Social Security claimers discussed above in the empirical motivation (Section 2.2). These statistics are shown in table 6. For permanent states such as education and marital status (rows 1-4 of table 6), the model generates a reasonable match for the early claiming behavior of college graduates (61.1 data vs. 62.8 model) and those without a college degree (73.6 data vs. 79.7 model). The model also qualitatively predicts the gradient in early claiming by marital status as observed in the data. However, it somewhat over predicts the early claiming rates of singles. With regards to characteristics which evolve over the life cycle, the model predicts the relationships between health status and work status (rows 5-9 of table 6). The model closely matches the early claiming rates of those who were in excellent or fair health at age 62. However, it under predicts the early claiming rates of those in the worst health state. The model also generates the strong correlation between labor supply status and early claims as observed in the data; 61.9 percent of men working at age 62 were seen claiming early in the data, the model predicts this to be 66.1 percent.

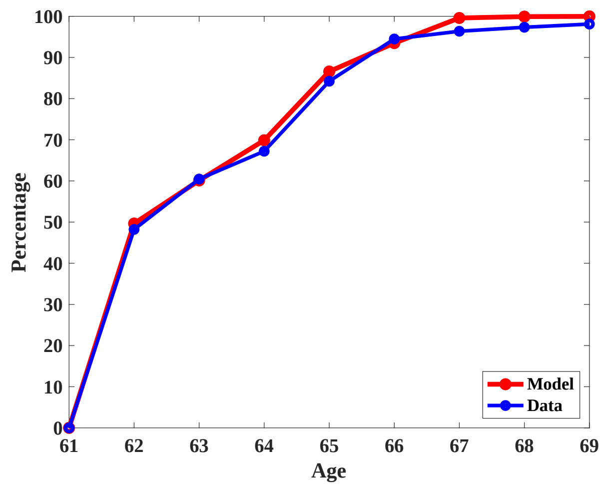
Finally, we examine how early claiming varies by wealth. Figure 10 shows the percent of those claiming Social Security benefits before the normal retirement age in each wealth decile (at age 62) for both the data and the model. While the data does not exhibit a strong pattern of how early claiming varies by wealth, the model generates a non-monotonocity in early claims with those in the lowest and highest deciles claiming early at higher rates than those in the middle of the age 62 wealth distribution. Importantly, however, the model is able to replicate that the share of workers claiming benefits early remains high across the wealth distribution.

Note that these comparisons of model and data statistics puts the model to a considerably strong test. Our benchmark model, with limited preference heterogeneity, is only explicitly designed to fit the life-cycle labor supply and wealth moments of these different groups of individuals. The fact that it is able to nearly perfectly fit overall Social Security claiming behavior and qualitatively fit several dimensions of heterogeneity in early claims is a testament to its strength as an approximation of the true data generating process. These tests demonstrate that the mechanisms incorporated in the structural model, along with the detailed policy features, are potentially driving claiming decisions in important ways.

5.3 Counterfactual Experiments

In this section, we conduct experiments to understand the importance of Social Security marital benefits and our claiming frictions in explaining the Social Security claiming behavior of men. As discussed, we view Social Security marital benefits as impacting claiming behavior by augmenting the calculation of the presented discounted value of benefits received, thus, changing the trade-off between the size of the benefits and the number of years for which these benefits are received. By

Figure 9: Benchmark: Social Security Claiming Behavior



Notes: The figure reports cumulative Social Security benefit claims at each age, both in the model and the data. Data is for male household heads, born between 1931 and 1935, from the Health and Retirement Study and excludes those receiving disability benefits.

contrast, claiming frictions — precautionary motive caused by budgetary shocks, misbeliefs about program rules or mortality, and the presence of a bequest motive — are mechanisms which impact claiming behavior by leading individuals to deviate from the predictions of the PDV calculation.

Rows 1-4 of table 7 show the early claiming rates (share of claims before the age of 65) in the benchmark model (row 1), after switching off only SS marital benefits (row 2), after switching off claiming frictions (row 3), and after switching off both claiming frictions and marital benefits (row 4). There are three key observations that we make from these experiments. First, we find that switching off marital benefits alone cuts the overall early claims by little less than a quarter (the share of all early claimers goes down from 69.9 to 54.1 percent), an effect coming solely from college-educated married households. The resulting early claims among married households are 79.7 and 17.8 percent for non-college and college groups, respectively. Note that while early claims go down a lot for the college educated married men, they go up a little for the non-college graduates as compared to benchmark. Second, we find that switching off the claiming frictions alone results in a nearly 40 percentage points decline in early claiming rates. The effects are coming from both singles and married households this time, albeit more from college and married groups. Third, switching off frictions and spousal benefits together reduces early claiming by roughly two-thirds for all groups except the non-college single men for whom early claiming rates remain high (80.4%).

These observations lead us to three important conclusions: 1) claiming frictions and SS marital benefits together explain why a majority of individuals (69.9 percent) in the model claim benefits

Table 6: Heterogeneities in Early Claiming

% early claimers	Data	Model
Education		
No College	73.6	79.7
College	61.1	62.8
Marital Status		
Singles	71.5	84.2
Married	67.6	63.2
*Health**		
Excellent	60.5	67.9
Fair	69.7	69.4
Poor	83.6	75.3
*Work Status**		
Not Working	90.8	79.2
Working	61.9	66.1

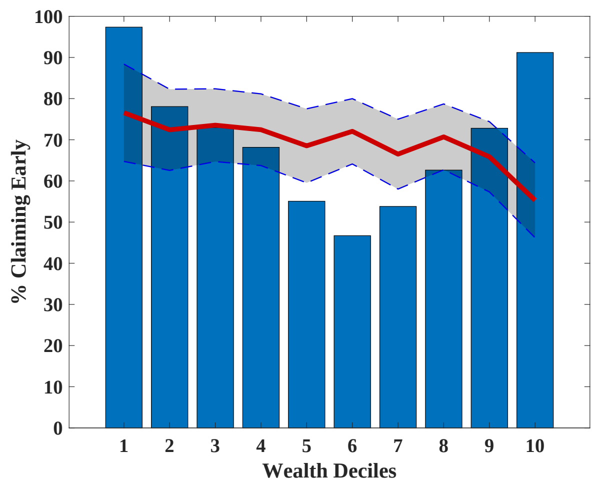
Notes: *For health and labor supply, which are not fixed over the life cycle, age 62 status is considered in both the data and the model to see it's impact on early claiming. Early claimers refer to those claiming before the NRA (age 65). Data is for male household heads, born between 1931 and 1935, from the Health and Retirement Study and excludes those receiving disability benefits.

before their normal retirement age, 2) Frictions and marital benefits are largely responsible for equalizing claiming behavior across different socioeconomic groups. For instance, in the benchmark model there is a 16.9 percentage points gap in early claiming rates of college vs. non-college groups. This gap increases to 22.3 percentage points when we consider a counterfactual economy without these claiming frictions and marital benefits. More importantly, the benchmark gap in early claiming rates between singles and married groups increases from 21 to 35.6 percentage points after eliminating the claiming frictions and marital benefits.[55] 3) The only significant remaining early claims after switching off frictions is for non-college singles — behavior which is consistent with the present value calculations discussed in Section 2.1 given the low life expectancy of this group.

Next, we explore the role of each channel separately. We first discuss the role of SS marital benefits in determining claiming behavior of married households and then we discuss the claiming frictions that affect married as well as single households.

[55]Note that these gaps are not directly present in table 7 but can be computed using the marriage-education specific gradients observed in rows 1 and 4 of the table and using education and marital shares from appendix table E.1.

Figure 10: Early Claiming by Wealth Deciles



Notes: Percent of those claiming before their normal retirement age is reported for each wealth decile (at age 62) both in the data and the model. Data is for male household heads, born between 1931 and 1935, from the Health and Retirement Study and excludes those receiving disability benefits.

5.3.1 Social Security Marital Benefits

Social Security program rules are different for singles and married men in two important dimensions that could potentially impact the claiming behavior of the latter group. First, spouses are eligible to claim spousal benefits up to an additional 50 percent of the household head's benefits. Second, spouses can receive survivors benefits upon the death of the household head. In this section, we explore the effect of these two rules for married individuals on claiming behavior. Table 8 shows the impact of these policies on claiming behavior of all men in our birth cohort (column 2), all married men (column 3), and by the education status of the married household head (columns 4 and 5).

The first and second rows of table 8 show the benchmark levels of early claiming and the levels of early claiming after switching off both spousal and survivors benefits for married households. These are the same as shown above in table 7. The third and the fourth rows however, show the percentage point change in early claiming rates, as compared to benchmark, when spousal and survivors benefits are switched off individually. As discussed in Section 2.1, spousal benefits can intensify either the early claiming motives or delayed claiming gains, compared to singles, based on the life expectancy of the head. Given survival pessimism of married men, we find that spousal benefits do indeed heighten early claiming incentives. Once we switch off these benefits in the model, there is a roughly 50 percentage points decline in early claiming rates for married men. As married men represent 66 percent of the economy, this response translates into a 34 percentage points drop in aggregate early claims. Survivors benefits, on the other hand, work in the opposite

Table 7: Counterfactual Experiments
Changes in Early SS Claiming

Experiment	All	Singles		Married	
		Non-College	College	Non-College	College
Early claiming rates (%)					
Benchmark	69.9	92.2	74.6	70.8	58.9
No marital benefits (MB)	54.1	92.2	74.6	79.7	17.8
No frictions	30.2	80.4	28.9	27.8	12.1
No frictions & MB	32.8	80.4	28.9	20.9	21.7
*p.p. change**					
(1) Precautionary	5.9	-6.0	-9.6	1.5	18.3
Unemployment	7.5	-5.6	-7.9	5.0	19.2
Health	-1.0	-0.7	-0.8	-2.6	-0.3
(2) Misinformation	-2.6	-0.2	-2.6	-8.2	-0.4
Mortality	0.3	1.1	0.0	-2.5	1.5
SS Program	-2.9	-1.7	-2.6	-5.4	-2.0
(3) Bequest	-31.0	1.3	-24.8	-25.1	-49.2

Notes: *percentage points changes for each experiment are relative to the benchmark. No frictions case refers to a scenario where we switch off the effect of (1)-(3) together. No frictions & MB case additionally shuts off both the Social Security spousal and survivors benefits.

direction by increasing incentives for men to delay benefit claims. These benefits are also affected by early claiming penalties or credits based on the head's claiming age, thus, early claims are associated with smaller survivors benefits. Warm glow utility over bequeathing these benefits to one's spouse results in delayed claims on part of these men. In an economy with spousal benefits but no survivors benefits, married men would have very strong incentives to claim early — over 90 percent of all married men in the model would claim early.

While these two benefits work in opposite directions in terms of their impact on early claims, their interaction effect can be substantially non-linear. Note that for both education groups of married men, spousal benefits reduce early claims by 50 percentage points and survivors benefits increases early claims by roughly 30 percentage points. The second row of table 8 demonstrates the the overall impact of marital benefits differs by education. For non-college men, eliminating both spousal and survivors benefits slightly increases early claims while for college educated men eliminating these marital benefits leads to substantially lower early claims. This result highlights that while survivors benefits are relatively more important to understand the claiming behavior of married college educated men, spousal benefits play a larger role for those without college education. However, while the joint impact of these marital benefits on the claiming behavior of non-college is quantitatively small (early claims increase only from 70.8 percent to 79.7 percent when spousal and survivors benefits are eliminated), these marital benefit play a quantitatively large role for college educated men. The share of college-married men who claim SS benefits prior to the NRA decline from 58.9 percent to merely 17.8 percent.

Table 8: Marital Benefits
Changes in Early SS Claiming Behavior

Experiment	All	Married		
		All Married	Non-College	College
Benchmark	69.9	63.2	70.8	58.9
Both	54.1	40.0	79.7	17.8
*p.p. change**				
Spousal	-34.3	-50.4	-51.4	-49.8
Survivor	21.5	31.6	28.4	33.3

Notes: *percentage points changes for each experiment are relative to the benchmark. Spousal case refers to where we switch off SS spousal benefits, Survivor refers to where we switch off survivors benefits and both refers to scenario where we switch off both SS marital benefits.

5.3.2 Precautionary Motive

In order to explore the effect of budgetary shocks on claiming, we first switch off both health and unemployment shocks (row 5 of table 7), and then switch these off one at a time (rows 6 and 7 of table 7). There is significant heterogeneity across education and marital status groups in how these channels impact claiming behavior. While the precautionary channels together suppress early claiming behavior of married-college educated men, they incentivize early claiming for singles. This is evident from row 5, where switching these off result in an 18.3 p.p. increase in early claiming for married college men and a 6 to 9.6 p.p. decline for singles depending on the education status. In the following sections we explore these heterogeneities in more detail.

Unemployment Shocks: Switching off the unemployment shocks implies that unemployed individuals experience no wage-scarring effects if they choose to immediately re-enter the labor market. This results in much higher life-cycle wage profiles (see appendix figure H.5) in the no-unemployment shocks counterfactual than in the baseline economy. Large increases in both private and Social Security wealth due to higher earnings provides strong incentives to individuals to stay in the labor market longer, delay SS claims, and receive higher future SS benefits. This is indeed the case for singles. We find their early claiming rates go down by 5.6 and 7.9 p.p. for non-college and college groups respectively. At the same time, their labor force participation rates between ages 62 and 70 increases by 6.7 and 4.7 p.p., respectively.

Married individuals, however, experience an increase in early claiming rates due to the presence of countervailing mechanisms; early claims increase by 5 p.p and 19.2 p.p for non-college and college educated men, respectively. While the above mechanisms are certainly at play, both spousal and survivors benefits interact in important ways with the impact of these unemployment shocks. Rows 1 and 2 of table 9 show the impact of this interaction by conducting the unemployment experiment in two different baseline scenarios — benchmark with marital benefits (row 1 of table 9), baseline without marital benefits (row 2). Note that when we switch off the impact of unemployment shocks in the benchmark, higher Social Security wealth (due to higher earnings) heightens the incentives to claim early due to the presence of spousal benefits; size of spousal benefits also increases as a function of the Social Security wealth of the household head. At the same time, increases in life-cycle wealth reduces the relative importance of survivors benefits in terminal bequest utility, thus, alleviates the incentive to delay induced by the survivors benefits. We see that these channels certainly dominate and lead to higher early claiming rates among married individuals; Row 2 of table 9 shows that when the interaction with marital benefits is eliminated, shutting down unemployment shocks lead to a 4.5 p.p.decrease in overall early claims and a 3.5 p.p. decrease in early claims among married men.

Health Shocks: We next conduct an experiment where we switch off the effect of bad health on the time endowment and spousal income for all individuals in the model.[56] As changes in life expectancy have a distinct effect on early claiming, we do not eliminate the impact of health on mortality. In other words, we still allow for the bottom two health states to affect survival probabilities. We find that bad health shocks, without their mortality impacts, have a relatively small effect on early claiming behavior. As shown in row 7 of table 7, early claiming rates go down by only 1 p.p. where most of this effect now comes from the non-college, married group.

Once again, for married individuals, we do find modest interactions with the spousal and survivors benefits. The response to these shocks for the married group is somewhat stronger (at least for the college group) in the absence of these marital SS benefits (refer to row 4 of table 9).However, with much smaller changes in both wealth and AIME as compared to the unemployment shocks counterfactual, these effects are not large enough to wash away the main impact of switching off health shocks–delaying SS claims by working longer in the labor market.

[56]In our model solution, individuals with the bottom two health states observe time endowment and spousal income of those in excellent health (within their age-education group).

Table 9: Interaction of Frictions with Marital Benefits
Changes in Early SS Claiming Behavior

Experiment	All	Married		
		All	Non-College	College
Unemployment	7.5	14.1	5.0	19.2
No SS marital Benefits	-4.5	-3.5	-12.7	1.6
Health	-1.0	-1.1	-2.6	-0.3
No SS marital Benefits	-1.3	-1.5	-0.9	-1.8
Mortality Misinformation	0.3	0.1	-2.5	1.5
No SS marital Benefits	-1.6	-2.7	1.4	-4.9
Program Misinformation	-2.9	-3.2	-5.4	-2.0
No SS marital Benefits	-3.2	-3.7	-3.3	-4.0
Bequest Motive	-31.0	-40.6	-25.1	-49.2
No SS marital Benefits	-13.4	-14.7	-37.1	-2.2

Notes: For each experiment, the first row refers to the percentage point difference in early claiming rates between the benchmark and the case where we switch off that particular friction. The second row labeled "No SS marital Benefits" refers to the percentage point difference in early claiming rates between the baseline without any marital benefits and the case where we switch off that particular friction in a world without MB.

5.3.3 No Misbeliefs

We perform a similar exercise as above to understand the impact of two forms of misbelief on claiming behavior. Row 8 of table 7 shows early claiming rates when both mortality and Social Security program knowledge misbeliefs are eliminated; Rows 9 and 10 show these rates when each form of misbelief is switched off independently. Misinformation, overall, decreases early claiming by 2.6 percentage points. However, this varies by both the type of information and the education and marital status group. First, eliminating mortality misinformation increases early claims by 0.3 p.p. while switching off misinformation related to the SS program decreases early claims by 2.9 p.p. Early claims among non-college married men decline by 8.2 p.p. in the counterfactual economy without these misbeliefs; early claims among non-college singles decline by only 0.2 p.p. We explore these heterogeneities in the following sections.

No Mortality Misbeliefs: In the baseline model, individuals may underestimate or overestimate their chances of survival. In order to understand the impact of life-span misbeliefs on Social

Security claiming behavior, we conduct an experiment where we give individuals their objective survival probabilities instead of the ones based on their subjective evaluations. We find that correcting for mortality misinformation alone does not change claiming behavior in the overall population (early claiming rates in fact go up a little by 0.3 p.p.). However, this is largely due to variation in this bias across different subgroups. Our empirical estimates suggest that while married college graduates are pessimistic about their own survival, all other groups are optimistic, albeit to difference degrees. As a result, when we feed the objective survival probabilities into the model, we expect to find increases in early claiming for the singles and non-college married individuals and declines for the college educated, married individuals. This is the case for singles where there is small (1 p.p.) increase in early claiming for the non-college group and no change in claiming for the college group.

For married individuals, however, interaction between mortality misbelief and marital benefits — specifically survivors benefits — changes the result. In the counterfactual economy without mortality misbelief, we observe early claims among non-college married decrease by 2.5 p.p. while the early claims of college educated, married men increases by 1.5 p.p. A change in perceived life-span changes the value of the Social Security survivors benefits to married workers. For non-college educated, married workers, removing mortality misbelief decreases their expected longevity and increases the value of the survivors benefits for these individuals. As survivors benefits incentivize delayed claims (as discussed in Section 5.3.1), this leads to a decline in early claims for this workers. This logic works in the opposite direction for college educated, married individuals. For these workers, removing the mortality misbelief increases their expected lifetime, decreases the value of the survivors benefits, thus, leads to an increase in early claims. Row 6 of table 9 demonstrates this result; in the baseline without marital benefits, eliminating mortality misinformation leads to 1.4 p.p. higher early claims among non-college married men and a 4.9 p.p. decrease in early claims among college educated, married workers.

No Program Misbeliefs: Next, we explore the importance of the knowledge about the early application penalty in generating early claiming behavior. For this, we allow all our simulated individuals to be perfectly informed about the early/late SS application penalty/credit. We find that this results in a 2.9 percentage points decline in overall early claims with the lowest declines in early claims for non-college singles (1.7 p.p.) and highest declines for the non-college married groups (5.4 p.p.). We find that among singles, college educated men experience a larger decline than non-college individuals. This highlights that while a smaller share of college educated workers do not understand the penalty (6 percent versus 17 percent of non-college workers), this mechanism is more likely to be the driver of early claims among college-educated workers who do not understand the penalty than non-college educated, misinformed workers. While this mechanism interacts similarly with spousal and survivors benefits, row 8 of table 9 shows that the quantitative impact of this interaction is relatively small.

5.3.4 No Bequest Motive

To explore the importance of the bequest motive in generating early Social Security claiming, we explore a counterfactual in which the end-of-life flow utility from positive liquid assets is set to zero for all individuals. For married individuals, however, we still allow end-of-life utility from bequeathing their Social Security benefits to their spouses as survivors benefits. As Social Security benefits are not bequeathable otherwise, individuals facing mortality risk may want to claim early and maximize the amount of their liquid wealth by accumulating the cash flows over a longer time period.

Removal of bequest motive results in a roughly 31 percentage points reduction in overall early claims. At the same time, there is a roughly 35.6 percentage points increase in delayed claims. While the single, non-college group experiences the smallest change (1.3 p.p. increase) in early claims, the married-college group observes a drastic 49.2 percentage points reduction in their early claims. The college singles and non-college married groups both experience a roughly 25 percentage points decline in early claims. At the same time, the entire increase in delayed claims is attributable to the married group (refer to appendix figure H.6).

While both non-college and college married groups have very similar bequest motives, they differ in their discount rates where the latter group has $\beta > 1$. Given such a high discount factor, the presence of bequest motive is largely responsible for why this group does not delay benefit claiming. Consequently, we see a much larger impact of bequest motives on early claims for the college educated, married group. Additionally, the effect of bequest motive is magnified in the presence of marital benefits for this group. When we eliminate the bequest motive in an economy without these SS marital benefits, as shown in row 10 of table 9, early claims for this group (those whose behavior was shown in Section 5.3.1 to be strongly impacted by marital benefits) drop by only 2.2 p.p.

6 Robustness

In this section, we test the robustness of our results to various assumptions about preferences, particularly fixing discount rate and bequest motives across groups, and to incorporating other features into the model (i.e. uncertain medical expenditures and heterogeneous returns on wealth). We test the robustness of four key findings: 1) the level of baseline overall early claims, 2) the impact of claiming frictions and marital benefits on overall early claims 3) the heterogeneity in early claims by education and marital groups and 4) the importance of the claiming frictions and marital benefits on early claiming behavior for each education-marital status group. Table 10 summarizes the results from these robustness tests. The estimated structural parameters for these tests and other details are provided in appendix G.

Table 10: Robustness Tests
Changes in Early SS Claiming

Experiment	All	Singles		Married	
		Non-College	College	Non-College	College
*Early claiming rates (%)**					
Benchmark	69.9	92.2	74.6	70.8	58.9
No frictions & MB	32.8	80.4	28.9	20.9	21.7
(1) Fixed Beta Baseline	70.0	90.2	72.8	71.0	60.4
No frictions & MB	23.5	30.4	23.5	21.4	21.9
(2) Fixed Bequest Baseline	75.4	93.7	74.6	92.2	59.1
No frictions & MB	29.0	58.2	30.0	20.9	21.7
(3) Het. Return	66.5	91.7	56.0	67.2	59.5
No frictions & MB	26.3	76.4	14.7	8.4	20.2
(4) Medical Expenditures	68.8	89.2	88.6	68.8	54.0
No frictions & MB	31.3	89.0	47.0	26.7	5.6

Notes: *Percent claims before the age of 65 are reported for various cases. No frictions & MB case refers to scenario where we switch off all frictions and marital benefits in the respective baseline case for all groups (1) β is fixed to 0.992. (2) $\kappa_{beq} = 24,6200, \theta_{beq} = 0.335$ for all groups (3) rate of return for non-college and college are 1.2 and 6.1% and respectively. Return heterogeneity and medical expenditures estimation details are discussed in appendix section G.

Column 2 of table 10 shows the robustness of our first and second findings across different specifications. We find that these are consistently similar in magnitude no matter the specification. The only notable exception is for the baseline where we fix the discount rate to 0.999 for all groups. In this case, the effect of frictions and marital benefits are somewhat larger. This is understandable given that discount rate heterogeneity does drive some early claiming behavior in the benchmark model.

Columns 3-6 shows how our 3rd and 4th findings vary across specifications. These also appear mostly robust with a few exceptions. First, fixing discount rate only impacts claiming behavior of the non-married singles group. This group has the lowest discount rate in the benchmark (0.904) which is responsible for driving some of the claiming behavior for this group. When we assign a much higher β to this group, we attribute much of the early claiming behavior to the claiming frictions. However, now the baseline model fails to match the wealth evolution of this group with $\beta = 0.999$. Second, when we allow either heterogeneous rates of return on wealth across education groups or out-of-pocket medical expenditures, we find that the role of claiming frictions for married non-college and college groups, respectively, are somewhat overstated as compared to benchmark. For instance, when the model allows for college and non-college groups to have heterogeneous returns on wealth (6.1 and 1.2 % respectively), we find that frictions and marital benefits play a much larger role for the married non-college group. These now account for 58.8 p.p. (67.2-8.4) of early claiming as compared to roughly 50 p.p. (70.8-20.9) in the benchmark. This is also the case for married college graduates when we allow for medical expenditures. In the case of heterogeneous rates of return, we are assigning a lower return on wealth to the non-college group (1.2% as compared to 3% in the benchmark), hence attributing more of the life-cycle wealth evolution to bequest motives. As a result bequest motive (as part of the frictions) account for more of the early claiming. Finally, in the medical expenditures case, we attribute part of the steep wealth profiles at older ages to high growth in medical spending for this group (refer to appendix figure G.1). Now, in the health experiment, when we switch off the effect of the worst health state, we also switch off high medical expenditures in these cases — resulting in a somewhat larger role of frictions.

7 Policy Experiments

Both our benchmark model and the data suggest there are high levels of early claiming across both college and non-college workers as well as married and single individuals — socioeconomic groups with very different life expectancy in retirement. The counterfactual experiments in the preceding section indicate that claiming frictions as well as marital benefits can largely explain high early claiming rates among groups with high life-expectancy at older ages.

What is not clear from the above experiments is how elastic households' behavior is to changes in policy. In order to study the impact of policy change, we analyze the impact of changes in the Social Security normal retirement age on claiming behavior — both in the benchmark model and in a scenario without any claiming frictions or marital benefits. We raise the normal retirement age to age 70 (henceforth, NRA 70) — eliminating any delayed retirement credit and imposing that claiming at any age before age 70 entails a penalty (refer to appendix figure H.7 for details on the changes in benefit structure).[57] Note that this change in the early claiming penalty does not apply to spousal benefits. Spouses can still receive the full 50% of the heads benefits if they are age 65 and older at the time of head's benefit claiming.

Table 11: NRA 70: Changes in Social Security Claiming Behavior

Experiment	All	Singles		Married	
		Non-College	College	Non-College	College
Before 65 Claiming Rates					
Benchmark	69.9	92.2	74.6	70.8	58.9
p.p change	-42.2	-8.1	-26.5	-54.5	-54.2
No frictions & MB	32.8	80.4	28.9	20.9	21.7
p.p. change	-23.2	-29.4	-26.4	-19.6	-21.7
At 65 Claiming Rates					
Benchmark	16.7	5.4	22.1	26.6	13.9
p.p change	-7.9	3.0	-1.1	-18.8	-8.5
No frictions & MB	44.4	16.0	69.0	69.5	33.5
p.p. change	-40.3	2.5	-66.0	-67.7	-33.5
After 65 Claiming Rates					
Benchmark	13.4	2.4	3.3	2.6	27.2
p.p change	50.1	5.1	27.7	73.3	62.7
No frictions & MB	22.9	3.6	2.2	9.6	44.9
p.p. change	63.5	26.9	92.4	87.3	55.1

Notes: p.p. change refers to percentage point change in claiming rates (before 65, at 65 and after 65) between policy and the respective baseline (benchmark vs. no frictions scenario).

Table 11 shows the result of this policy change on the claiming distribution of the overall simulated population as well as on different permanent groups in the model. In the benchmark model, even an extreme policy change such as NRA 70 results in relatively smaller changes in claiming behavior than in an economy without marital benefits or claiming frictions. Overall claiming rates before age 65 go down by a little over half versus a roughly 70% drop in pre-65 claims in the model without these features. The largest changes (relative to benchmark levels)

[57] Note that in this experiment we do not change the parameters pertaining to the earnings test. In other words, individuals still qualify for a more generous earnings test threshold starting age 65 as in the benchmark case.

are among the married group with pre-65 claims dropping roughly 54 p.p. for this group; the behavior of the singles remains largely unchanged, especially the behavior of non-college singles whose claiming rates before age 65 drop only 8.1 p.p. The majority of singles continue claiming benefits before the age of 65, with some shifts in claiming to age 65 and after (especially for college educated singles). In comparison, married men are more responsive; claims after age 65 increase by 73.3 and 62.7 p.p. for the non-college and college educated married men, respectively.

However, when we conduct the same policy experiment in an environment with no claiming frictions and no marital benefits, the results are starkly different. We find that in this scenario, claiming for all groups, with the exception of non-college singles, shifts to past age 65. These experiments indicate that the average age of claiming under NRA 70 policy is substantially different depending on the baseline: age 66.3 in the benchmark versus age 68.7 in the environment without frictions and marital benefits. The gaps in accurately predicting claiming ages are the largest for college singles — group for whom the claiming frictions are strongest. The average claiming age for this group under the NRA 70 policy is 64.9 in the benchmark while it is 69.1 if marital benefits and claiming frictions are eliminated.

This difference in predicted average claiming age under NRA 70 policy, between benchmark and the baseline without claiming frictions or marital benefits, has direct implications for the impact of the policy reform on the government budget. Aggregate lifetime benefit payouts are 24.4 percent higher under the increased NRA policy if the friction-less baseline is assumed — one where households are significantly more responsive to policy — than the benchmark. At the same time, the errors in predicting aggregate benefit payouts under such a policy change would be even larger for singles (44.4%) than for married men (16.9%). Since individuals (particularly singles) increase their claiming ages more in response to policy in the friction-less model, these men receive relatively larger pensions (with smaller early claiming penalties) which lead to increased aggregate payouts.

8 Conclusion

The Social Security claiming behavior of older Americans presents a puzzle by implying a low annuity valuation of the benefits by these workers. Simple present-value calculations indicate that a majority of older individuals should be delaying benefit claims at least to the normal retirement age. This is especially true for college-educated and married individuals who not only have longer life-expectancies but also larger benefits due to higher income or SS marital benefits. In this work, we have explained this puzzling phenomenon using an augmented, albeit standard, forward-looking life-cycle framework, in contrast to prior literature relying on behavioral channels. Toward this goal, we have identified three sets of *claiming frictions* — precautionary motives due to budgetary shocks, misbeliefs about the SS program and mortality, and bequest motives — which along with different SS policy rules for married households, largely explain the observed claiming behavior. To quantify the role of these channels, we have built a structural life-cycle model of consumption, savings, retirement and Social Security claiming, with rich heterogeneity in demographics and family structure. The deep parameters of the structural model are estimated using the Method of Simulated moments, targeting moments related to labor supply and wealth evolution over the life cycle by education and marital status. We have shown that our estimated model closely matches the overall claiming behavior of the cohort of men born between 1931 and 1935. Additionally, it generates similar gradients in early claiming rates, as observed in the data, across several heterogeneous groups.

Counterfactual experiments using the model highlight the important role played by claiming frictions and marital benefits. Together, these account for over 53 percent of the early claiming rates in the model and two-thirds of all early claims for college educated and married men. Additionally, we find that these mechanisms are responsible for equalizing early claiming rates across different socioeconomic groups — married vs. singles, college vs. non-college. For instance, gradient in early claiming for married vs. singles goes up from 21 to 35.6 percentage points after eliminating the claiming frictions and marital benefits. We find that these results are quite robust to different assumptions about preferences — fixed discount rates and bequest motives across groups, as well as allowing for additional modeling features like rate of return heterogeneity on wealth and medical expenditures.

By quantifying the important role played by marital benefits and frictions in determining claiming behavior, especially for groups with high life expectancy, we are able to provide answers to the claiming puzzle within the scope of a rational forward-looking framework. Policy experiments further serve to highlight the significant costs of these mechanisms, in terms of lifetime value of benefits received, by curbing households' ability to respond effectively to policy changes. They also have important implications for the government budget: aggregate lifetime benefit payouts, after an increase in the normal retirement age, are shown to be up to 24 percent higher if the claiming frictions and policy rules for married households are not accounted for.

Overall, this work provides a robust framework to understand claiming behavior of male household heads and opens up many future paths of research. For instance, further investigation is needed to understand the incentives that the Social Security program presents to women, both married and single. In the present analysis, we have simplified our set-up by assuming that the claiming decisions of married couples are linked and that women claim benefits on their spouse's earnings record. While this is largely true for the birth cohort being considered in this paper, it is likely not the case for cohorts born later. Additionally, our work is unable to address the impacts of policy on the government budget in its entirety, or comment on the future sustainability of the Social

Security system. Embedding the rich household dynamics developed in this paper into a general equilibrium framework would allow for a more comprehensive policy analysis.

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Appendix

A Data: PSID, HRS, MEPS, and UAS

The Panel Study of Income Dynamics (PSID) is used to estimates life-cycle profiles of labor force participation, hours, and wealth; the wage process; and the initial conditions. PSID is a nationally representative longitudinal survey in the United States. The original PSID sample was drawn from the nationally representative SRC sample and an oversample of the low-income SEO sample. We use the a sample of individual from the SRC sample who were interviewed twice or more between 1968 and 2017. Our sample consists of only male household heads between the ages of 22 and 74 who were born between 1926 and 1970. Our final sample consists of 103,423 observations for 7,516 individuals. When we consider the wealth profiles, we consider workers up to age 84 and born up until 1990. This sample consists of 149,059 observations for 13,172 individuals.

The Health and Retirement Study (HRS) is a longitudinal study of Americans over the age of 50. 2016 Version 1 is used in this work. Importantly, the survey contains questions related to retirement and Social Security claiming decisions. This data set is used for understanding the distribution of claiming ages as well as for the estimation of the impact of various factors on the probability of claiming early. The estimation sample includes all workers born between 1926 and 1970 who report an age for their Social Security claiming between 62 and 70 (9,255 individuals). Results are predicted for a cohort born between 1931 and 1935 (2,727 individuals).

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.

The Understanding America Survey (UAS) is used to study what percentage of workers understanding the Social Security rule and the penalty associated with early benefit claims. UAS is a panel dataset of roughly 9,000 respondent representing the United States. The panel is an internet study where respondent can respond digitally whenever they choose. This dataset is used to measure the degree to which individuals understand the Social Security system. We use a sample of individuals between the age of 25 and 61; the final sample contains 3,710 observations.

B Data Work for Empirical Analysis

B.1 Health and Retirement Survey

As detailed in the main text, we run the following regression to understand how claiming behavior varies:

$$Pr[i \text{ claims before NRA}] = x_i'\beta + \sum_{k=-3}^{0} \delta_k I_{ik}^p + \gamma M_i + \rho B_i + \mu M_i * B_i + \varepsilon_i$$

The dependent variable is an indicator which takes a value of 1 if an individual claims Social

Security benefits prior to the full retirement age.[58] This indicator is regressed on a set of control variables x_i which includes education, race, gender, marital status, number of children, an interaction between gender, marital status, number of children and race, and an interaction between education level and health status. Additionally, we regress the indicator of a series of dummy variables, I^p_{ik}, which represent whether a worker was working prior to claiming. We include dummies for participation in the year of claiming, one to two years prior, three to fours years prior, and five to six years prior.[59] We also include an categorical variable measuring how well worker predicts his own mortality, M_i, a categorical variable for whether a worker expects to leave a bequest and the size of the expected bequest, B_i, and an interaction between these two beliefs. Results of this regression are detailed in the following empirical facts. This regression is estimated on data from the Health and Retirement Study.[60]

Prediction of mortality are constructed based on how a worker's subjective perception of his own probability of survival to age 75 differs from the probability estimated for his education-marital status group. More specifically, education and marital status specific probabilities of survival are estimated from MEPS. From these series the cumulative probability of survival to age 75 conditional on being alive at age 60 are constructed. This is compared to what an age 60 worker in HRS reports he believes is his probability of survival to age 75. This perceived survival is subtracted from the constructed cumulative probability of survival from MEPS; a negative gap indicates survival optimism while a positive gap signals survival pessimism. The variable M_i is constructed from this gap. Those workers with a gap between -0.05 and 0.05 are described as accurately predicting mortality. Those with gaps less than -0.05 underestimate mortality while those with gaps over 0.05 overestimate mortality.

In a similar way, the categorical variable related to bequest expectations, B_i, are constructed based on how an age 60 HRS respondent answers questions about how likely he is to leave a bequest. In HRS, respondents are asked about the probability he will leave a bequest of \$10,000. If he reports a positive probability of leaving a \$10,000 bequest, he is asked how likely he is to leave a \$100,000 bequest. If, on the other hand he reports 0 probability of leaving \$10,000 he is asked the probability of leaving any bequest. The categorical variable is constructed from how a respondent answers these questions at age 60. The respondent is classified as not likely to leave a bequest if he has less than a 50 percent chance of leaving anything. He is classified as possibly leaving a bequest is he reports between 50 and 99 percent chance of leaving a bequest. Workers are classified as definitely leaving a bequest is he has a 100 percent chance of leaving \$10,000 or \$100,000.[61]

Table B.1 shows the estimated coefficients of this regression equation.

[58] We also consider a case where rather than the indicator being for all claims prior to the normal retirement age we have an indicator for claims at the early retirement age of 62. These results are shown in appendix C.2.

[59] Because HRS is collectively biannually, we cannot include lags for every year. Additionally, we may not observe workers in the year they claim. Therefore, we consider a year after claiming age for these workers.

[60] More details on data and sample selection are show in appendix A.

[61] The reported probabilities of leaving a bequest in HRS are very high. At age 60, the average probability of leaving a bequest is 82 percent while the median is 100 percent. Over 50 percent of the sample is classified as definitely leaving a bequest of either \$10,000+ or \$100,000+ while only around 20 percent of the sample are unlikely to leave a bequest.

Table B.1: Coefficients of Early Claims Regressions (Health and Retirement Study)

	coefficient	standard error
working (lag 0)	-1.000***	(0.116)
working (lag 1)	-0.657***	(0.139)
working (lag 2)	-0.178	(0.137)
working (lag 3)	-0.105	(0.134)
good health	-0.188	(0.149)
excellent health	0.302	(0.223)
college	0.113	(0.226)
good health*college	-0.597**	(0.243)
excellent health*college	-1.331***	(0.314)
female	-0.275	(0.399)
married	0.114	(0.392)
female*married	-0.050	(0.520)
kids	0.128	(0.367)
female*kids	-0.285	(0.461)
married*kids	-0.344	(0.442)
female*married*kids	0.867	(0.576)
race	-1.095*	(0.631)
female*race	0.682	(1.080)
married*race	0.109	(1.057)
female*married*race	1.882	(1.777)
kids*race	1.491**	(0.741)
female*kids*race	-0.619	(1.169)
married*kids*race	-0.475	(1.145)
female*married*kids*race	-2.270	(1.860)
bequest (possibly)	1.028***	(0.272)
bequest (definitely $10,000+)	0.321	(0.249)
bequest (definitely $100,000+)	0.546**	(0.252)
mortality (accurate)	1.337***	(0.377)
mortality (pessimistic)	0.934***	(0.222)
bequest (possibly)*mortality (accurate)	-2.241***	(0.535)
bequest (possibly)*mortality (pessimistic)	-0.741**	(0.308)
bequest ($10,000+)*mortality (accurate)	-1.259**	(0.510)
bequest ($10,000)*mortality (pessimistic)	-0.142	(0.286)
bequest ($100,000+)*mortality (accurate)	-1.190**	(0.484)
bequest ($100,000)*mortality (pessimistic)	-0.679**	(0.284)
constant	1.873***	(0.389)
N	5,328	
R-squared	0.1359	

Source: Health and Retirement Study, authors' calculations

Notes: Dependent variable is an indicator for whether the individual claimed SS benefits prior to the normal retirement age. Standard errors are in parentheses.

*p<0.10, **p<0.0.5, ***p<0.01

B.2 Understanding America Survey

As mentioned in the text, the HRS does not contain details on knowledge of the Social Security program. Therefore, the impact of program knowledge on early claiming is estimated using the Understanding America Survey (UAS). UAS asks workers the following true or false question: "Social Security benefits are not affected by the age at which someone starts claiming". If the individual responds "True" to this question, we classify the worker as having misbelief regarding the rules of the Social Security program.

We aim to run a similar regression in UAS as we did in HRS (Equation 1). However, there are some differences to be noted. The regression run in UAS is shown in Equation 2.

$$Pr[i \text{ claims before NRA}] = x_i'\beta + \delta_0 I_{i0}^p + \gamma K_i + \varepsilon_i \tag{20}$$

where, as in the HRS regression, x_i is a vector of control variables. Because we have a small sample size in UAS, we include those who are an age, rather than focusing only on those near retirement. Therefore in addition to the controls from the original regression, we also control for age. Additionally, since UAS is not a panel study, we cannot control for lagged values of participation. Therefore, we include only a dummy variable for whether a worker is currently working, I_{i0}^p. Finally, since we are focused on the impact of program knowledge on claiming, we include a variable, K_i, which measures whether a worker knows that claiming age will impact benefit size. As UAS does not include information on bequests or subjective mortality, we do not include this variables. Results of the regression are included in table B.2.

C Additional Details on Empirical Facts

C.1 Impact of Occupation on Early Claiming

In most of the work, we document differences in early claiming behavior based upon education level. It is possible, however, that occupation is an important margin to consider. Figure C.1 shows how the probability of claiming prior to the normal retirement age varies by occupation. There is notable variation in early claiming probabilities across occupations. Specifically, occupations seems to fall into two groups: (1) those with a roughly 50 - 60 percent probability of claiming prior to the normal retirement, age and (2) those with roughly a 70 percent probability of claiming Social Security benefits early. The first group includes occupations such as management; business and financial; computer and math; architecture and engineering; life, physical, and social sciences; community and social services; legal; education; entertainment; and health practitioners. The second group includes health support; protective service; food preparation and service; building management and maintenance; personal service; sales; office and administration; farming; construction; maintenance; production; and transportation.

There is a strong correlation between these occupational groups and education level. Specifically, those occupations in the first groups (with lower probability of early claiming) are much more likely to have a college education. The share of those workers in these occupations with lower levels of claiming who have a college degree is 76 percent. This share is 32 percent for those occupations with higher probability of claiming early. Figure C.2 shows a more detailed breakdown on how the share of college graduates varies by occupation. The two groups mentioned prior

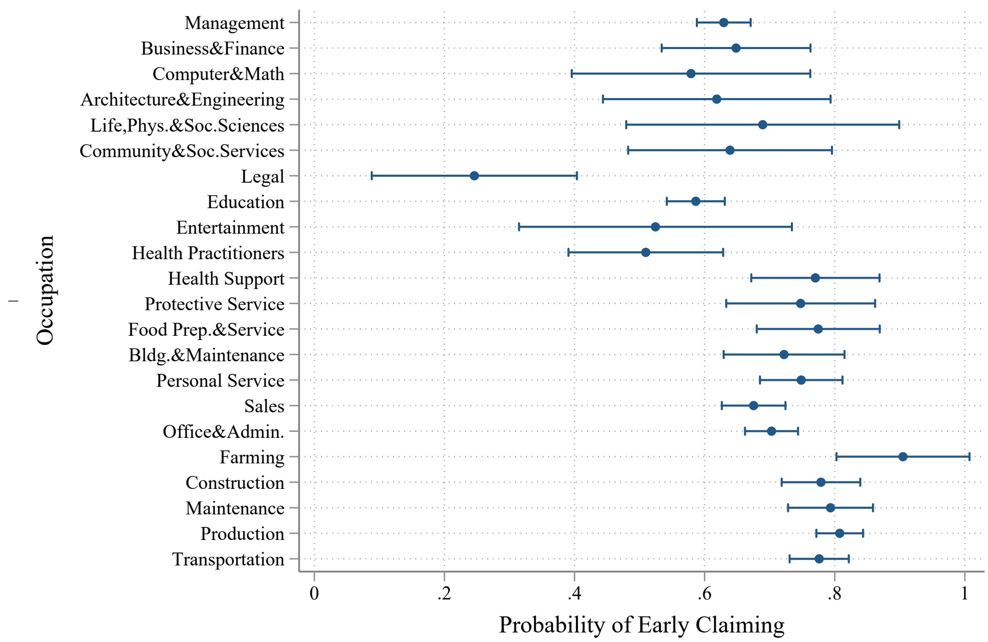
Table B.2: Coefficients of Early Claims Regressions (Understanding America Study)

	coefficient	standard error
no penalty	0.448*	(0.256)
work (lag 0)	-1.059***	(0.230)
good health	-0.710**	(0.337)
excellent health	-0.660	(0.467)
college	-1.070**	(0.529)
good health*college	0.392	(0.546)
excellent health*college	0.270	(0.647)
married	-0.156	(0.288)
male	-0.209	(0.319)
married*male	-0.247	(0.415)
kids (2-3)	-0.265	(0.395)
kids (4+)	-0.038	(0.487)
married*kids (2-3)	-0.060	(0.510)
married*kids (4+)	0.086	(0.668)
male*kids (2-3)	0.148	(0.725)
male*kids (4+)	1.901**	(0.854)
married*male*kids (2-3)	-0.069	(0.838)
married*male*kids (4+)	-2.286**	(1.059)
race	-0.091	(0.398)
married*race	0.121	(0.633)
gender*race	0.176	(0.681)
married*gender*race	0.668	(1.010)
kids (2-3)*race	0.731	(0.763)
kids (4+)*race	-0.172	(0.837)
married*kids (2-3)*race	-0.673	(1.224)
married*kids (4+)*race	-0.852	(1.299)
gender*kids (2-3)*race	-1.031	(1.312)
gender*kids (4+)*race	-1.153	(1.596)
married*gender*kids (2-3)*race	-1.266	(1.881)
married*gender*kids (4+)*race	3.943*	(2.268)
age	-0.326***	(0.008)
constant	4.253***	(0.661)
N	2,235	
R-squared	0.1023	

Source: Understanding America Study, authors' calculations
Notes: Dependent variable is an indicator for whether the individual claimed SS benefits prior to the normal retirement age. Standard errors are in parentheses.

*p<0.10, **p<0.0.5, ***p<0.01

Figure C.1: Probability of Early Claiming by Occupation



are clear in this figure.

C.2 Claims at the Early Retirement Age

In Section 2.2, we define early claiming at any claims prior to age 65, the normal retirement age for the cohort born between 1931 and 1935. Many workers, however, claim immediately when they become eligible at age 62. Therefore, figures C.3 and C.4 show the results of Equation 1 where the dependent variable is an indicator for whether the worked claimed Social Security benefits at age 62.

Figure C.3 shows how age 62 claims are impacted by work status. The results show, similar to the case of all early claims, that work status significantly impacts at 62 claims with those workers who are not working at claiming age and at various lags are more likely to claim Social Security benefits that those who continue to work. Contrary to the case of early claims where work status in the year of claiming has the largest impact, for age 62 claims, work status 1 to 2 years prior to claiming has the most significant impact.

Figure C.4 shows how age 62 claims vary by education level and health status. With respect to education level, we document that those workers who do not have a college degree are more likely to claim Social Security benefits at age 62. However, with respect to self-reported health status, we find that the impact of health does not significantly impact whether a worker claims at age 62.

Figure C.2: Share of Workers with a College Education by Occupation

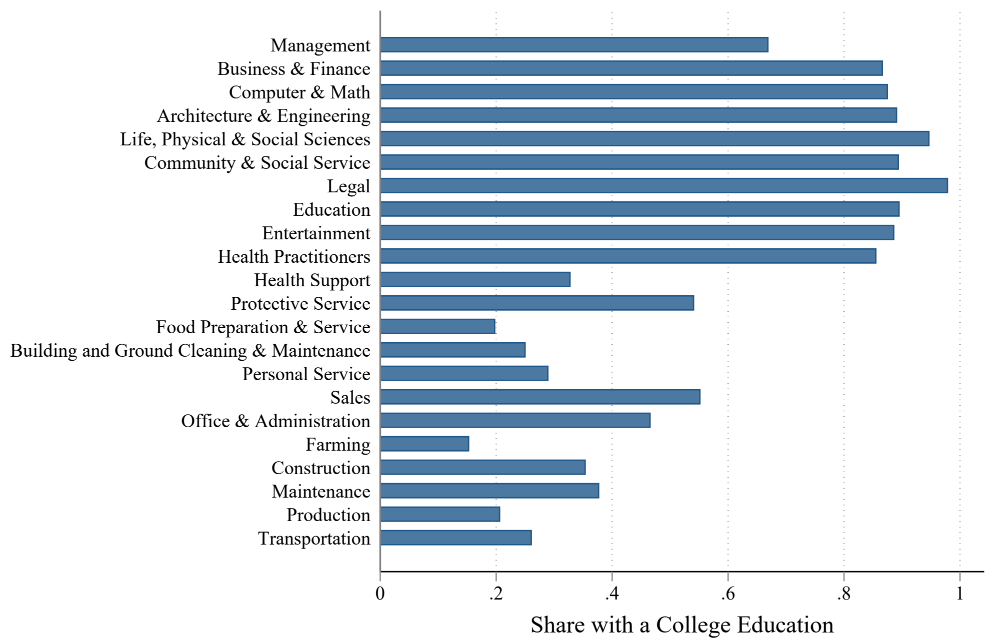


Figure C.3: Probability of Claiming at Age 62 by Work Status

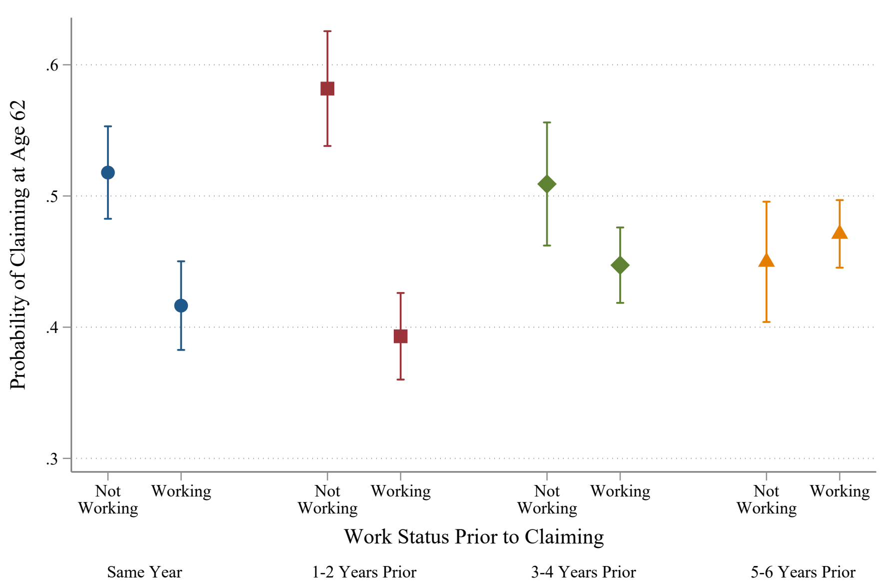
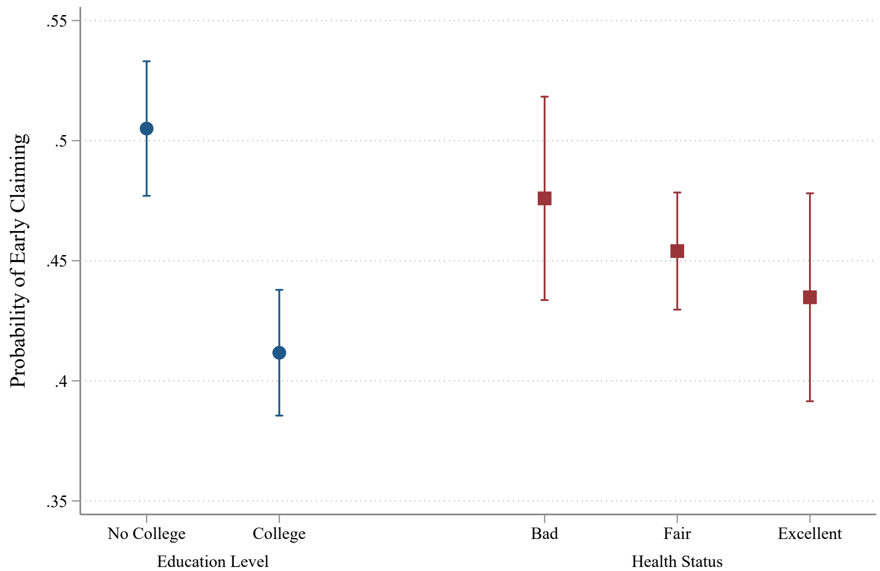


Figure C.4: Probability of Claiming at Age 62 by Education and Health



C.3 Impact of Gender on Early Claiming

An interesting feature of the results in Section 2.2 is that while marital status impacts the point estimate of the probability of early claiming, these point estimates are not statistically significantly difference. Figures C.5a and C.5b show how the probability of early claims and the probability of claims at age 62 vary by both marital status and gender.

This result indicates that marital status impacts claiming behavior differently for men and women. As discussed in the text, being married is associated with a lower point estimate in the probability of claiming prior to age 65 or of claiming at age 62. However, these differences are not statistically significant. For women, on the other hand, being married increases the probability of early claiming and claiming at age 62. The difference in the probability of early claiming is statistically significant. The economics behind this result are left to future research.

C.4 Misunderstanding of Social Security Rules

Given the complicated nature of the United States Social Security system, we allow an individual's claiming decision to, possibly, be impacted by whether or not they know about the system. Given that Social Security is a program aimed to older workers, it is possible that workers learn about the system as they age. Table C.1 shows how the fraction of workers who believe there is no penalty for early claims varies by age. Three age groups are shown: everyone over the age of 25, everyone over the age of 50, and everyone over the age of 60.

As expected, there is some variation in the fraction who do not understand the program by age. Interestingly, the pattern of the change in the share of misunderstanding differs based on education level. For non-college educated workers, the share with misbelief decreased by from nearly 15 percent to roughly 10 percent. For college workers, the share remains fair constant (even slightly increases) from around 6 percent of workers to 8 percent of workers.

Figure C.5: Probability of Early Claiming by Marital Status, Gender

(a) Early Claims (b) Age 62 Claims

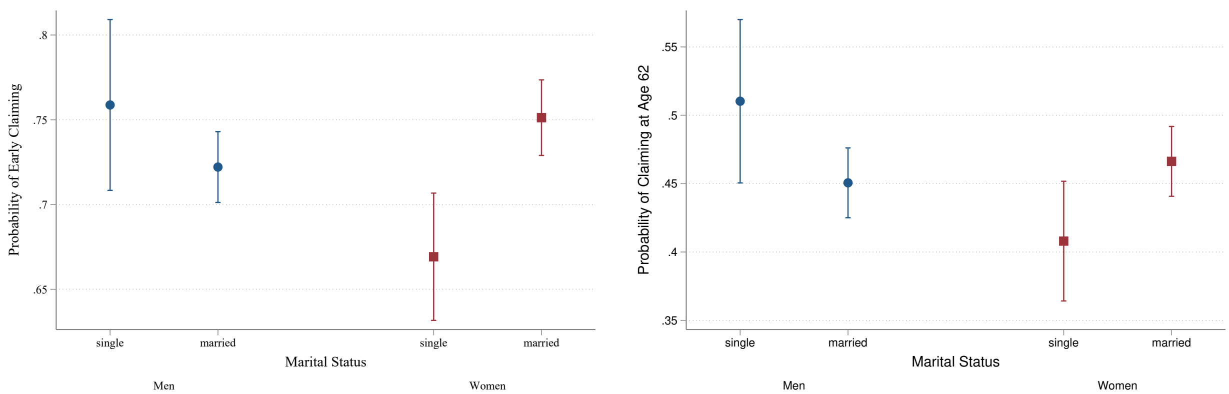


Table C.1: Program Misbelief by Age

	Fraction who believe there is no penalty for early claims		
	Ages 25-61	*Ages 50-61*	*Ages 60-61*
No College	16.8	15.8	18.8
Single	19.0	17.2	29.7
Married	15.5	15.2	12.9
College	5.5	5.5	2.9
Single	9.8	1.3	0.0
Married	4.5	6.3	4.2

D Spousal and Survivors Benefits

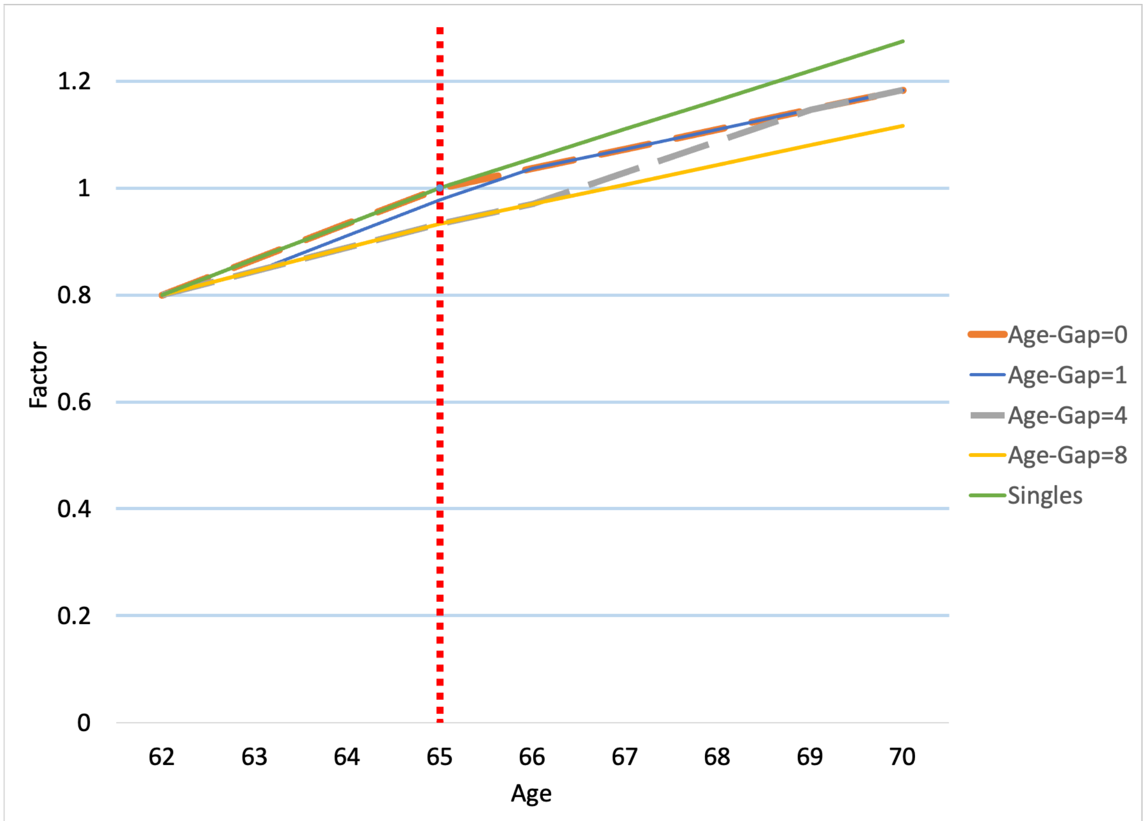
D.1 Spousal Benefits

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. The calculation of total household benefits involves a careful construction of how these penalties/credits differ across claiming ages and age gaps. Table D.1 shows the early/late application penalty/credit calculations for a household with zero age-gap. Columns 3 and 4 present the head's as well as spouse's penalty and credit for various claiming age combinations. Column 5 shows the joint benefits received. For instance, if a man whose wife is the same age claims his benefits at age 62, she automatically claims her spousal benefits at age 62 and the household will take the 20 percent penalty on both old-age and spousal benefits. Specifically, they will receive $0.80 * pia + 50\% * 0.80 * pia = 1.2 * pia$, where pia represents the primary insurance amount of the head of household. Had the head of household (and, therefore, also his wife) delayed claims to age 65, the household benefits would have been $pia + 50\% * pia = 1.5 * pia$ as neither the old-age benefits of the head nor the spousal benefits would have been penalized. Subsequent rows of table D.1 show the calculation for other claiming ages of a zero age-gap household. The calculation becomes more complex with positive spousal age gaps as old-age benefits and spousal benefits will be penalized to different degrees but uses the same approach. Figure D.1 shows the reduction/increment factor (the analog of column 6 in table D.1) for married households with different age gaps and compares them to singles.

Table D.1: Spousal Early Application Penalty
Zero Spousal Age Gap

Claiming Age		Penalty/Credit		Joint Benefits	Factor
Head	Spouse	Head	Spouse		
62	62	0.80	0.80	1.20	0.80
63	63	0.87	0.87	1.30	0.87
64	64	0.93	0.93	1.40	0.93
65	65	1.00	1.00	1.50	1.00
66	66	1.05	1.00	1.56	1.04
67	67	1.11	1.00	1.61	1.07
68	68	1.16	1.00	1.66	1.11
69	69	1.22	1.00	1.72	1.15
70	70	1.27	1.00	1.77	1.18

Figure D.1: SS Benefit Reduction/Increment Factor for Various Claiming Ages
By Spousal Age Gap



D.2 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.

E Estimation Details

We estimate the model by education and marital status. We set population shares for these groups based upon population shares at age 25. Table E.1 shows the share of the population within

Table E.1: Shares by Fixed-Type

	No College	College
Single	0.18	0.15
Married	0.23	0.43

Notes: The share within each fixed type is calculated from PSID based upon education and marital status for those between ages 25 and 30 for the 1931-1935 birth cohort. The numbers maynot add up to one due to rounding errors.

each fixed type.

E.1 Health and Objective Survival

We estimate health transitions using Household Component of Medical Expenditure Panel Survey on a population between the ages of 20 and 90. The coefficient estimates are provided in table E.2. We estimate the objective survival probabilities from MEPS by running an ordered probit regression of death indicator on self rated health interacted with a third order age polynomial as well as interactions of college and married indicators on the same population. Figure E.1 provides the estimated objective survival probabilities.

Table E.2: Ordered Probit Estimates of Health Transitions

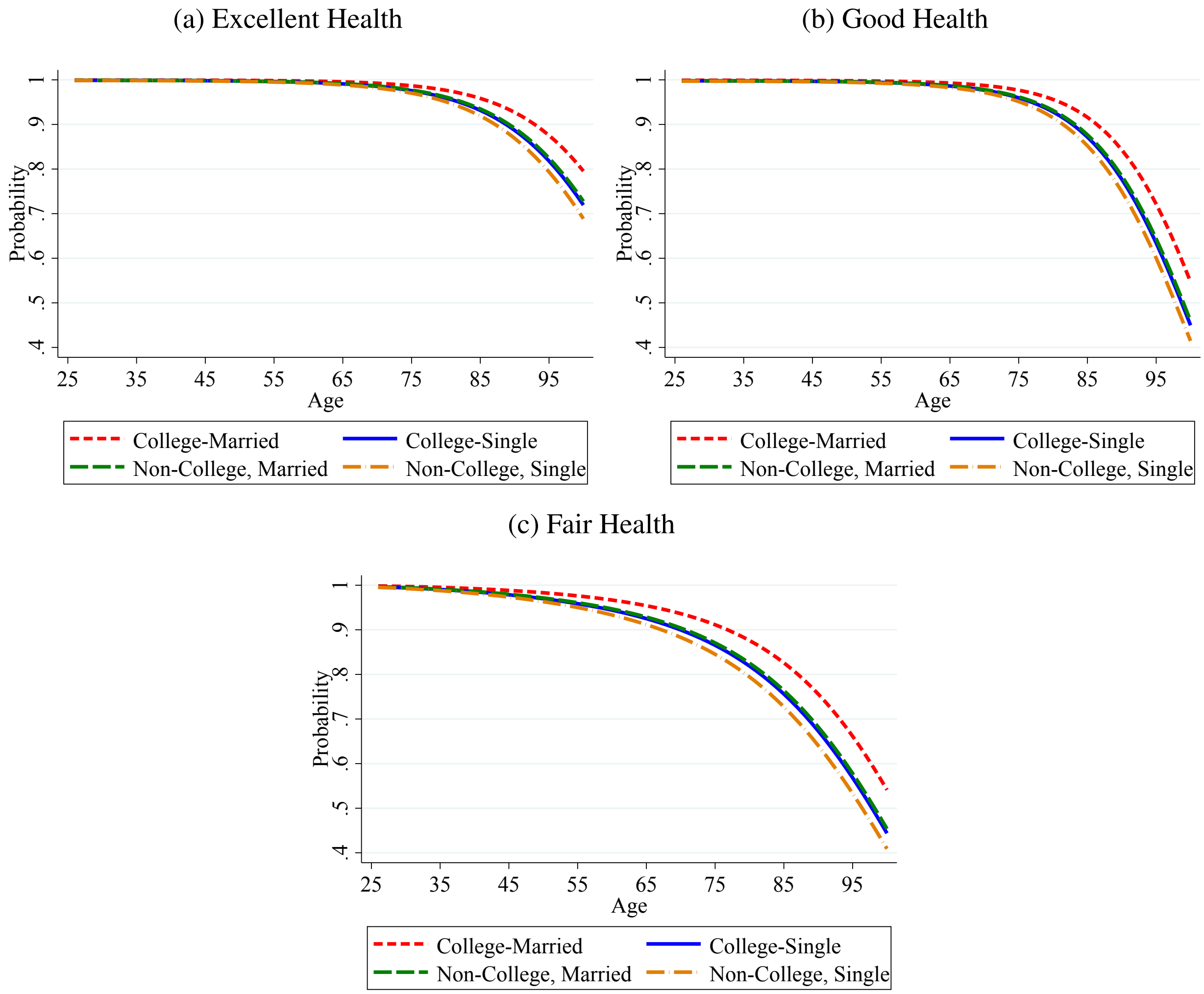
	Coefficient Estimates
Health Lag=2	0.924***
Health Lag=3	2.118***
Age	0.0200***
$Age^2/10^2$	-0.00939
$Age^3/10^3$	-0.000500
College=1	-0.329***
cut1	0.635***
cut2	2.613***
Observations	188,226
Pseudo R^2	0.1622

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

E.2 Subjective Survival Probabilities

As mentioned in the text, the baseline model uses subjective survival probabilities as an input. These subjective survival probabilities are constructed by scaling education, marital status, and health-specific survival probabilities estimated from MEPS as discussed above. This scaling factor

Figure E.1: Objective Survival Probabilities by Health, Education and Marital Status



is calibrated so that the cumulative estimated probabilities of survival for each education marital status group match cumulative subjective probabilities of survival. This calibration process occurs in three steps.

First, average subjective probability of survival to age 75 conditional on living to age 60 is calculated from HRS. This is done for each education and marital status group. Table E.3 shows the average subjective cumulative probability of survival to age 75 for each of these groups. For each of these groups this average is taken at age 60. Values range from a subjective probability of 0.627 for married, non-college graduates to 0.710 for married, college graduates.

Second, an estimated cumulative probability of survival to age 75 at age 60 for each group is constructed from education, marital status, and health status specific survival probabilities. For each education and marriage state, this process requires information on health transition probabilities at each age and health status as well as the share of individuals in each health state at each age. We start with health specific probabilities which give the probability from survival from age j to $j + 1$ given the health state at age j. We then construct augmented series which incorporate expected future health transitions. This gives us series which show the probability of survival from

Table E.3: Cumulative Probability of Survival to Age 75 Conditional on Survival to Age 60

	Estimated	Subjective	Scale Factor
No College	0.579	0.628	–
Single	0.529	0.631	-0.01323
Married	0.595	0.627	0
College	0.771	0.702	–
Single	0.688	0.682	-0.00361
Married	0.801	0.710	0.008229

age j to $j+1$ conditional on health at some age j_0 where j_0 is age 60 in our analysis. Final survival probabilities for each education and marital status group are constructed by weighting these augmented series by the share of individuals in each health state by group. Using these final probabilities, we construct the cumulative probability of survival to age 75 given living to age 60. These probabilities are also shown in table E.3.

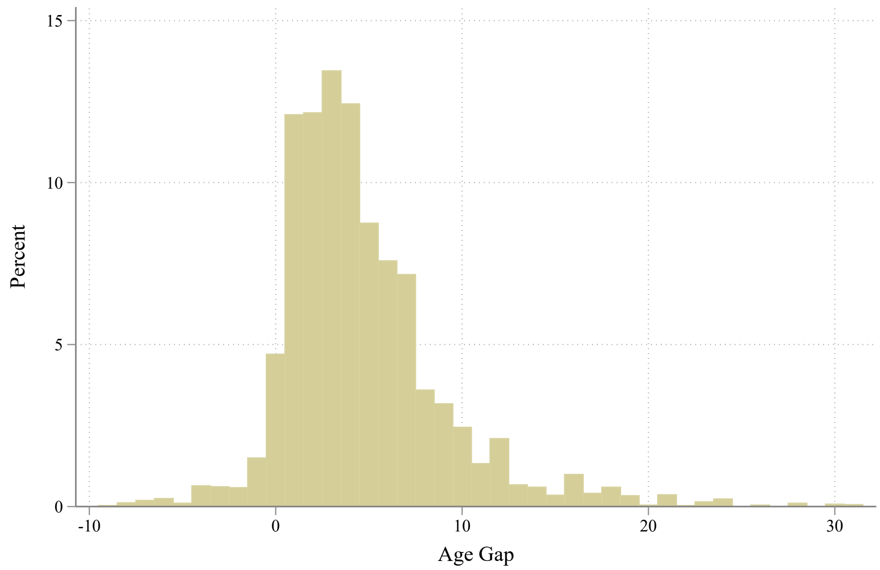
Finally, subjective probabilities of survival are constructed by scaling the estimated probabilities of survival so the cumulative probability of survival to age 75 conditional on being age 60 match the subjective survival moments in table E.3. We assume that subjective survival is the same as estimated survival for all ages younger than 60. Probabilities from ages 60 to 99 are scaled to match the cumulative probabilities. The calibrated scale factors are shown in the final column of table E.3. This scale factor is negative for no college singles and college singles who are optimistic about their own survival while it is positive for college, married men who are pessimistic. As college singles are fair accurate with their own predictions of survival, we do not scale these probabilities.

E.3 Marriage and Kids

Family structure in the model differs by education type. For the cohort of men born between 1931 and 1935, the share of the population in a married or co-habitating relationship is roughly stable over the life cycle. For this reason, we keep marriage a fixed state in the model, determined at age 25, based on the initial condition draws from the data and the married share is set to about 60 percent for non-college educated individuals and roughly 76 percent for college educated men.

Figure E.3 shows the measure of children used in the model to estimate the household consumption equivalence scale. The figure shows how the number of children living in the household varies across the life cycle, and by education of the household head. This measure takes into account all children ages 17 and under who are in the household at any point in time. The number of children is hump-shaped over the life cycle; the number of children peaks between the ages of 30 and 40 and then declines to 0 by age 60. Second, the profiles differ across education. Those without a college degree peak at around 1.2 children while those with a college degree peak at

Figure E.2: Distribution of Age Gap between Spouses



slightly above 1.5 children.

E.4 Age Gap between Spouses

Married couples have access to spousal benefits through the Social Security system; these benefits depend not only on the age of the worker but also on the age of the spouse. Therefore, the gap between the ages of the spouses is very important. Figure E.2 shows the distribution of this age gap for married couples born between 1926 and 1940. The average gap for this group is roughly 4 years.

The distribution shows 95 percent of the married couples have a positive age gap – meaning the male head is often older than their spouse. However, this age gap varies largely across the distribution. To represent this distribution in a computationally feasible way, we include four age gaps (0 years, 1 year, 4 years, and 8 years) in the model. This allows us to capture that while most couples have age gaps between 0 and 4 years, there are also many couples with large age gaps. Estimated shares show that 8.7 percent of married couples have no age gap, 26.2 percent have an age gap of one year, 46.1 percent have an age gap of four years, and 19 percent have an age gap between spouses of eight years.

E.5 Spousal Income

We include spousal income in the budget constraint of the married worker since we model only male household heads. Because of the high fraction of married household heads, the estimation of spousal income is important to understand the budget constraints faced by individuals. We first estimate how spousal income varies based upon characteristics of the head of household:

Figure E.3: Children by Age, Education and Marital Status

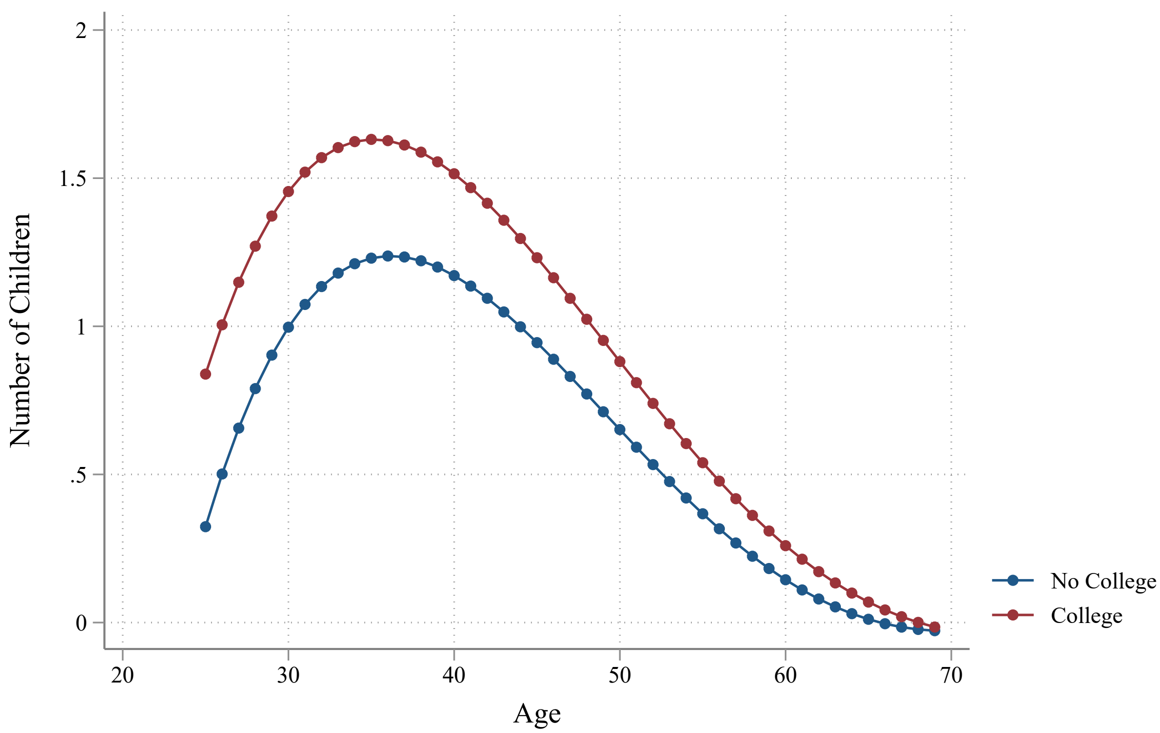


Table E.4: Coefficients of Spousal Income Regression

	coefficient	standard error
age	-1.581	(1.369)
age*age/(10^2)	8.024	(5.730)
age*age*age/(10^4)	-12.265	(7.859)
age*age*age*age/(10^6)	5.900	(3.540)
college	17.071**	(7.951)
college*age/(10^2)	-19.268**	(9.199)
poor health	4.842	(23.379)
poor health*age/(10^2)	-2.369	(28.361)
labor income (thousands)/(10^2)	9.842*	(5.211)
N	59,491	
R^2	0.165	

Source: Panel Study of Income Dynamics, authors' calculations
Notes: Dependent variable is labor income received by spouse (thousands). Standard errors are in parentheses.
*p<0.10, **p<0.0.5, ***p<0.01

$$y^s_{it} = X'_{it}\beta + \varepsilon_{it} \tag{21}$$

where X'_{it} is a vector of control variables including a fourth order polynomial in the age of the household head, and indicator for whether the head of household is in poor health (both in levels and interacted with age), an indicator for whether the head of household attended college (both in levels and interacted with age), and the labor income of the head of household (in thousands). This regression is run for a sample of married individuals born between 1926 and 1940. We then use the estimated coefficients to impute spousal income in the model.

$$\hat{y}^s_{it} = X'_{it}\hat{\beta} \tag{22}$$

By estimating how spousal income varies based on characteristics of the household head, we capture impact of assortative matching and differing probabilities of marriage across education levels and health status. The estimated coefficients are included in table E.4.

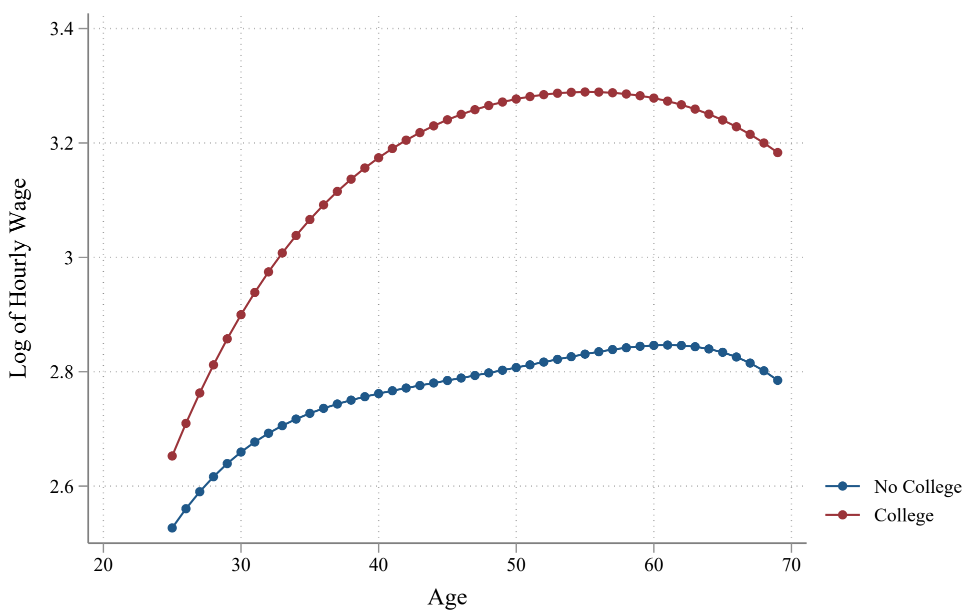
E.6 Wages

Data on wages is taken from PSID. In PSID, the hourly wage is calculated as annual earnings divided the annual hours worked. Observations less than 50 percent of the minimum wage or over $500 (1998 dollars) are dropped to control for minimum wage and high wage outliers. The sample is increased to include all workers born between 1901 and 2000 in order to have sufficient observations through the life cycle. Because wages are only observed for those who participate in the labor market, we use a Heckman selection model to estimate hourly wage profiles.

In the first step, a probit regression estimates the probability of labor market participation and computes the inverse mills ratio. This ratio is then used as an additional regressor in the regression of wages. In our approach, labor market participation is explained by number of children fully interacted with a dummy for a college education, marital status, and cohort dummies. A fourth-order age polynomial as well as this polynomial interacted with the college education dummy are included as independent variables in the selection equation. Table E.5 shows that in this estimation, the Mills ratio is statistically significant, indicating the presence of selection in OLS estimates.

In the second stage, wage profiles are estimated by regressing the natural log of the hourly wage on a fourth-order polynomial in age, the interaction of this polynomial with the college indicator, and dummies for cohorts. We experimented with including marital status in this regression, but estimates were statistically insignificant once we controlled for education. Therefore, we focus on estimates for age profiles which vary only by age. Table E.5 includes the coefficients of this regression; figure E.4 shows the age and education specific profiles.

Figure E.4: Productivity Profiles by Age and Education



These estimates are used to compute predicted wages for individuals in the sample. Residuals between hourly wages in the data and these predicted wages are used to estimate the AR(1) process governing the income risk. Specifically, using these residuals, the parameters of the income process are estimated using Method of Simulated Moments with the identity matrix as the weighting matrix. this process delivers estimates of $\rho = 0.987$ and $\sigma^2 = 0.018$ for the persistence and standard deviation, respectively.

E.7 Employment Shocks and Wage Cost of Unemployment

There are two main parameters which govern the employment shocks in the model: the probability of receiving the shock, λ, and the wage penalty associated with receiving the shock, ξ. Figure E.5 shows the estimation of these parameters.

Table E.5: Coefficients of Wage Estimation Equation

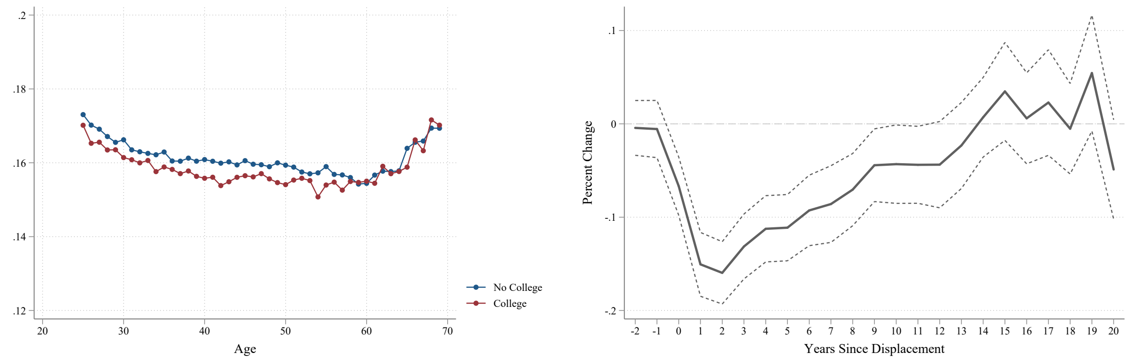
	coefficient	standard error
age	0.302***	(0.027)
age*age/(10^2)	-0.9383***	(0.096)
age*age*age/(10^4)	1.309***	(0.145)
age*age*age*age/(10^6)	-0.681***	(0.080)
college*age	-0.038***	(0.005)
college*age*age/(10^2)	0.289***	(0.031)
college*age*age*age/(10^4)	-0.552***	(0.066)
college*age*age*age*age/(10^6)	0.326***	(0.045)
cohort 1911-1920	-0.016	(0.027)
cohort 1921-1930	0.042*	(0.026)
cohort 1931-1940	-0.013	(0.026)
cohort 1941-1950	-0.026	(0.026)
cohort 1951-1960	-0.035	(0.026)
cohort 1961-1970	-0.094***	(0.026)
cohort 1971-1980	-0.114***	(0.027)
cohort 1981-1990	-0.184***	(0.028)
cohort 1991-2000	-0.234***	(0.046)
constant	-0.925***	(0.280)
Inverse Mills Ratio	-0.297***	(0.046)
N	97,896	

Source: Panel Study of Income Dynamics, authors' calculations
Notes: Estimated coefficients of Heckman two-step model. Dependent variable of wage equation: natural log of the hourly wage. Dependent variable of selection equation: labor force participation. Standard errors are in parentheses.

*p<0.10, **p<0.0.5, ***p<0.01

Figure E.5: Unemployment Probabilities and Wage Impact of Unemployment

(a) Unemployment Probabilities (b) Wage Scarring



We set the probability of receiving the unemployment shock based upon the annual separation rate. We use a combination of data from the Job Openings and Labor Turnover Survey (JOLTS) and the Current Population Survey (CPS) to construct education and age-specific separation rates. Specifically, we use JOLTS to construct industry level separation rates as the ratio of total separations to total employment within the industry. Education and age specific rates are calculated as the weighted average of these industry separation rates. We weight them by using the employment share of industries for each age-education pair. This calculation is shown in figure E.5a.

These separation rates are not only similar across education groups but also stable over the life cycle. For this reason, we choose to model the employment shock as independent of age, education, and marital status. While the youngest and oldest workers experience slightly higher separation rates, this increase in only 1-2 percentage points. The annual separation rates is roughly 15-16 percent. Similar literature often uses an annual separation rate of 10 percent. In order to remain consistent with previous literature, and since our estimate is only slightly higher, we use a value of $\lambda = 0.1$ in this work.

To construct the wage impact of receiving the unemployment shock, $\xi(\lambda)$, we follow the labor literature which estimates the impact of a displacement on the re-employment earnings of individuals. To measure this, we run the regression in Equation 23.

$$y_{it} = x_{it}'\beta + \sum_{k \geq -2}^{20} \delta^k D_{it}^k + \alpha_i + \gamma_t + \varepsilon_{it} \tag{23}$$

where y_{it} represents the log wages of individual i in time t, x_{it} is a vector of control variables including education and a quadratic term in experience, D_{it}^k is a series of dummies which identify displaced workers the k-th years relative to displacement and α_i, γ_t represent individual and time fixed effects. coefficients, δ^k, results of this regression are shown in figure E.5b. Similar to other literature, these results show that wages drop roughly 14-20 percent for those who experienced a displacement relative to those who did not experience a displacement. This impact of displacement is persistent with wages only recovering (relative to the non-displaced) between 5 to 10 years after displacement. We take a value of 14 percent drop in wages due to an unemployment spell, or $\xi(\lambda) = 0.86$. We, additionally estimated these wage scarring by education and found the impact

Table E.6: Parameters of the Tax Function

	λ	ξ
Single	1.333	0.042
no college	1.351	0.041
college	1.325	0.043
Married	1.370	0.043
nocollege	1.363	0.040
college	1.352	0.043

of displacement to be similar across education.

E.8 Taxes

PSID includes information on taxes paid up until 1991 and cover tax years up through 1990. In order to have individuals throughout the life cycle, we extend the sample to those workers between the ages of 1916 and 1945. In order to estimate the parameters of the taxation function, we regress the natural log of total family income net of income on a constant and the natural log of family pre-tax income for each education level and marital status. 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.

In order to maximize the sample size for measurement at each education level and marital status, we focus on estimating these parameters independently from age. The estimated parameters are shown in table E.6.

E.9 Wealth

PSID gather information on family wealth in 1984, 1989, 1994, and biannually from 1999 to 2019. The measure of wealth used includes home equity, farm/ business value, checking and savings wealth, value of other real estate, stocks, vehicles, and other assets net any debts.

We impute potential wealth for the years that observations are missing using a fixed effect regression.

$$\ln\left(W_{it}+\delta\right) = x_{it}'\beta + \gamma_i + \varepsilon_{it} \tag{24}$$

where δ is a shifter that is set equal to the minimum value of wealth in the sample to ensure that logs are taken of only positive values and W_{it} is the wealth of individual i at age t. x_{it}' is a set of controls which includes a quadratic polynomial in age, fully interacted with a dummy for education level and self-reported health status.[62] Additionally, γ_i is an individual fixed effect. This

[62] Self-reported health status is available only after 1984. For observations prior to 1984, the regression equation does not include a control for health.

regression equation is estimated separately for single men, single women, and married individual. Then,

$$\hat{W}_{it} = \begin{cases} W_{it} & \text{if } W_{it} \neq . \\ \exp\left(x'_{it}\hat{\beta} + \hat{\gamma}_i\right) - \delta & \text{if } W_{it} = . \end{cases} \tag{25}$$

Wealth is used to construct the lifetime wealth profiles. These profiles are constructed for a sample of male household heads born between 1926 and 1990 and between the ages of 20 and 84. Additionally, we drop individuals with negative wealth.

F Bequest Motive

The decision problem in the last period of the life cycle, with certain death in the next period, is given as follows:

$$\max_c \frac{\eta}{1-\rho}\left(\left(\frac{c}{\zeta}\right)^{\nu}\bar{l}^{1-\nu}\right)^{1-\rho} + \beta\frac{\theta_{beq}}{1-\rho}\left[(1+r)(a-c)+\kappa_{beq}\right]^{\nu(1-\rho)}$$

Where η is the scaling of utility for married household heads ($\eta = 2$) and equals one for singles, c denotes consumption, $\bar{l}$ full endowment of time to be consumed as leisure (assuming excellent health), and a denotes beginning-of-period resources (assets, SS benefits etc) that can be allocated either towards current consumption or bequeathed next period.

The first order conditions for an interior solution is given as:

$$\phi c^{\nu(1-\rho)-1} = \beta\theta_{beq}(1+r)\left[(1+r)(a-c)+\kappa_{beq}\right]^{\nu(1-\rho)-1}$$

where $\phi = \frac{\eta\bar{l}^{(1-\nu)(1-\rho)}}{\zeta^{\nu(1-\rho)}}$

$$c = \left[\frac{\beta\theta_{beq}(1+r)}{\phi}\right]^{\frac{1}{\nu(1-\rho)-1}}\left[(1+r)(a-c)+\kappa_{beq}\right]$$

Define:

$$\Gamma = \left[\frac{\beta\theta_{beq}(1+r)}{\phi}\right]^{\frac{1}{1-\nu(1-\rho)}}$$

Then we can solve for c as:

$$c = \frac{1}{\Gamma}\left[(1+r)(a-c)+\kappa_{beq}\right]$$

And bequest $B = (1+r)(a-c)$ as:

$$\Gamma\left[a - \frac{B}{1+r}\right] = B + \kappa_{beq}$$

$$\implies B = \frac{\Gamma a - \kappa_{beq}}{1+\frac{\Gamma}{1+r}}$$

Marginal propensity to bequeath out of last period resources $\frac{\partial}{\partial a}(\frac{B}{1+r})$ is then given as :

$$MPB = \frac{\Gamma}{1 + r + \Gamma}$$

And resource threshold for leaving positive bequests $(B > 0)$ as:

$$\underline{a} = \frac{\kappa_{beq}}{\Gamma}$$

G Robustness Test

G.1 Fixed Discount Rates

We fix discount rate to 0.992 for all groups and re-estimate the model to match the wealth and labor supply moments using the bequest and time-cost parameters alone. The estimated second-step parameters for this baseline are provided in table G.1 below:

Table G.1: Fixed Discount Rate: Preference Parameters

Parameter	Description	Singles		Married	
		Non-College	College	Non-College	College
Fixed					
ρ	relative risk aversion	3.340	3.340	3.340	3.340
ν	consumption weight	0.578	0.578	0.578	0.578
β	discount factor	0.992	0.992	0.992	0.992
Group-specific					
θ_{beq}	bequest intensity	0.366	0.284	2.408	1.743
κ_{beq} (in 000s)	bequest curvature	3.101	2.632	1.708	0.482
$\bar{l}$	time endowment	6157	4204	5789	4637

G.2 Fixed Bequest Motives

We fix bequest motives for all groups and re-estimate the model to match the wealth and labor supply moments using the discount rate and time-cost parameters alone. The estimated second-step parameters for this baseline are provided in table G.2 below:

Table G.2: Fixed Bequest Motives: Preference Parameters

Parameter	Description	Singles		Married	
		Non-College	College	Non-College	College
Fixed					
ρ	relative risk aversion	3.340	3.340	3.340	3.340
ν	consumption weight	0.578	0.578	0.578	0.578
θ_{beq}	bequest intensity	0.335	0.335	0.335	0.335
κ_{beq} (in 000s)	bequest curvature	2.462	2.462	2.462	2.462
Group-specific					
β	discount factor	0.958	0.974	1.027	1.030
$\bar{l}$	time endowment	5518	4440	5918	4647

G.3 Rate of Return Heterogeneity

We assume that college-educated workers receive a higher return on their financial assets than those individuals without a college degree. Fagereng et al. (2018) finds that the mean return on financial wealth is 4.2 percent with a 1.6 percentage points increase in the return per year of education above high school. We assume that those with some college education have, on average, three more years of schooling than those without college. We then choose the rates of return to match a mean return of 4.2 percent and a 4.9 percentage points gap between the return of college and non-college education workers. This delivers a rate of return of 1.2 percent for non-college and 6.1 percent for college educated individuals. The estimated second-step parameters for this baseline are provided in table G.3 below:

G.4 Medical Expenditures

We estimate annual out-of-pocket medical expenditures from the Health and Retirement Study data using all years from 1992-2018, following the same approach as detailed in Borella et al. (2019). We use their approach to medical expenditures for each education and marital groups. We allow these expenditures to vary health. However, using the approach in Borella et al. (2019), we allow expenditures to vary by excellent/good and poor health only. In other words, we combine the first two groups into one. There are two key details in the estimation of these profiles from the data. First, it is important to include medical expenses in the last year of life. This comes from the HRS exit interviews. Second, expenses covered by public or private insurance are not included in the measure, because they are not directly incurred by the individual. Figure G.1 reports the

Table G.3: Heterogenous Rate of Return: Preference Parameters

Parameter	Description	Singles		Married	
		Non-College	College	Non-College	College
Fixed					
ρ	relative risk aversion	3.340	3.340	3.340	3.340
ν	consumption weight	0.578	0.578	0.578	0.578
Group-specific					
β	discount factor	0.730	0.885	0.979	0.972
θ_{beq}	bequest intensity	1.439	1.476	1.610	4.210
κ_{beq} (in 000s)	bequest curvature	0.428	1.935	0.882	2.548
$\bar{l}$	time endowment	6537	4362	4317	4743

estimated expenditures for male household heads, born between 1931-1935, by age and health, for different education and marital status. The estimated second-step parameters for this baseline are provided in table G.4 below:

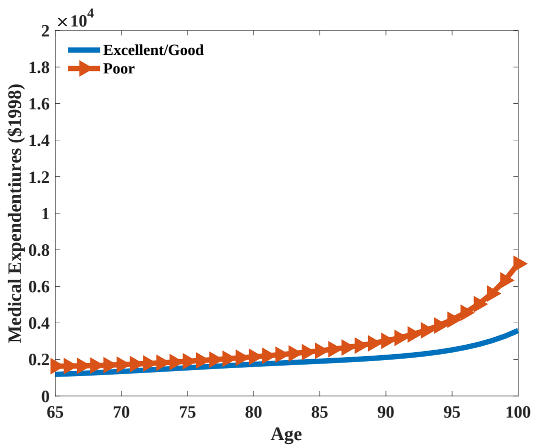
H Additional Figures and Tables

Table G.4: Medical Expenditures: Preference Parameters

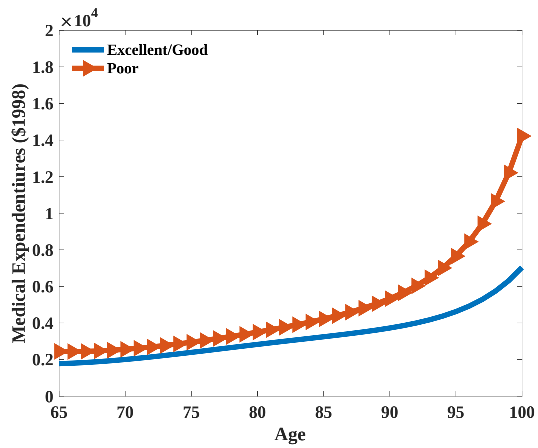
Parameter	Description	Singles		Married	
		Non-College	College	Non-College	College
Fixed					
ρ	relative risk aversion	3.340	3.340	3.340	3.340
ν	consumption weight	0.578	0.578	0.578	0.578
Group-specific					
β	discount factor	0.906	0.979	0.992	1.008
θ_{beq}	bequest intensity	0.928	0.441	1.223	1.650
κ_{beq} (in 000s)	bequest curvature	1.335	2.523	1.565	1.561
$\bar{l}$	time endowment	7269	5100	6323	4418

Figure G.1: Annual Medical Expenditures by Health, Education and Marriage
Men born in 1931-1935

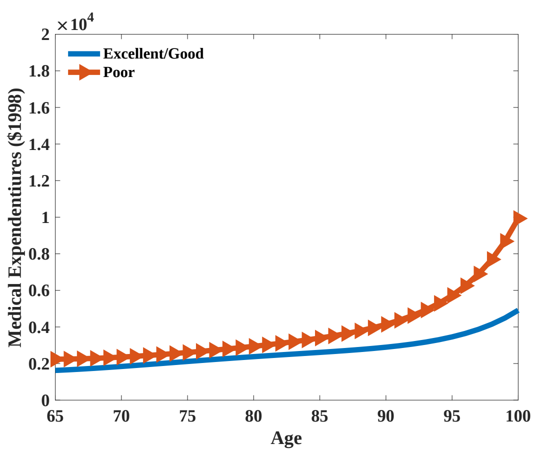
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

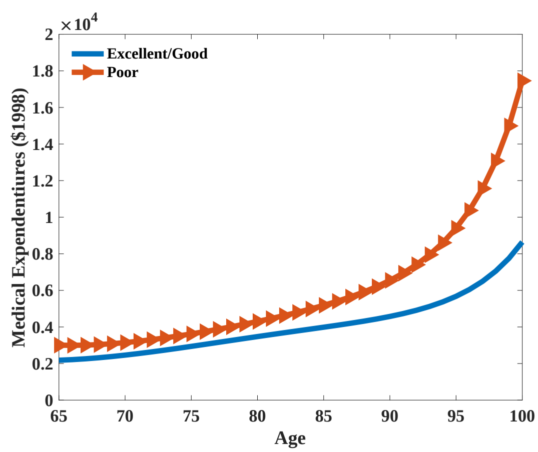
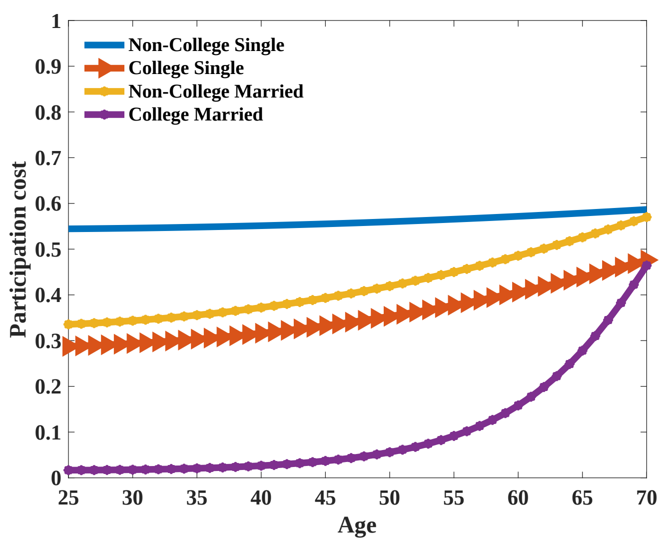


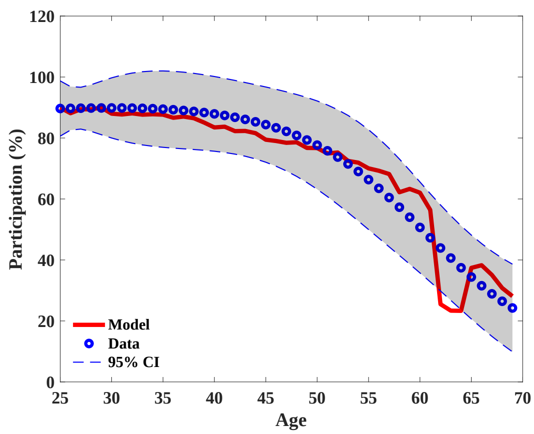
Figure H.1: Time Cost of Working



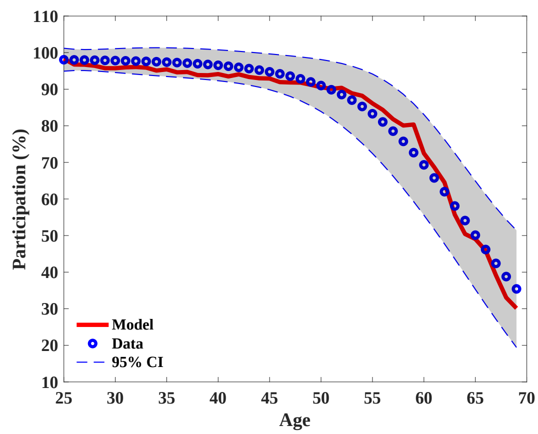
Notes: Time costs of labor market participation estimated from the structural model, expressed as a fraction of the time endowment, is reported for all college and marital groups.

Figure H.2: Benchmark: Participation by Education and Marriage
Men born in 1931-1935

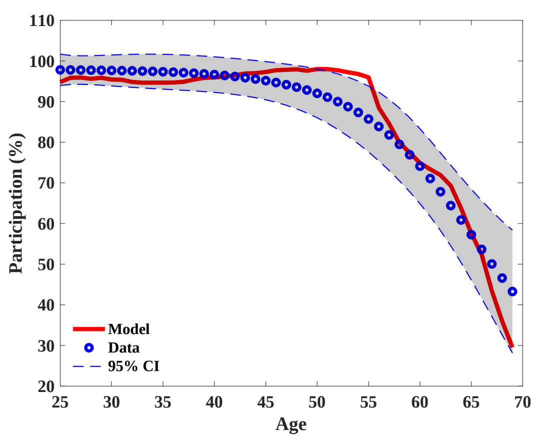
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

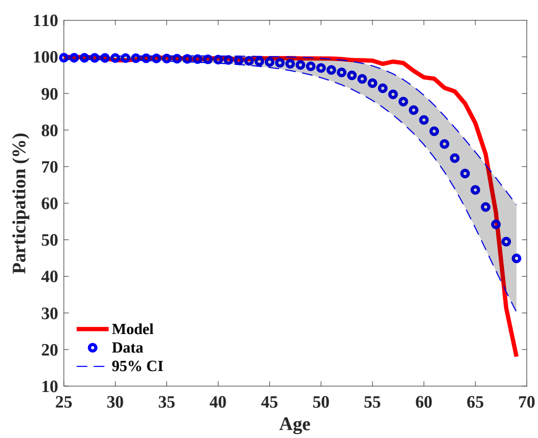
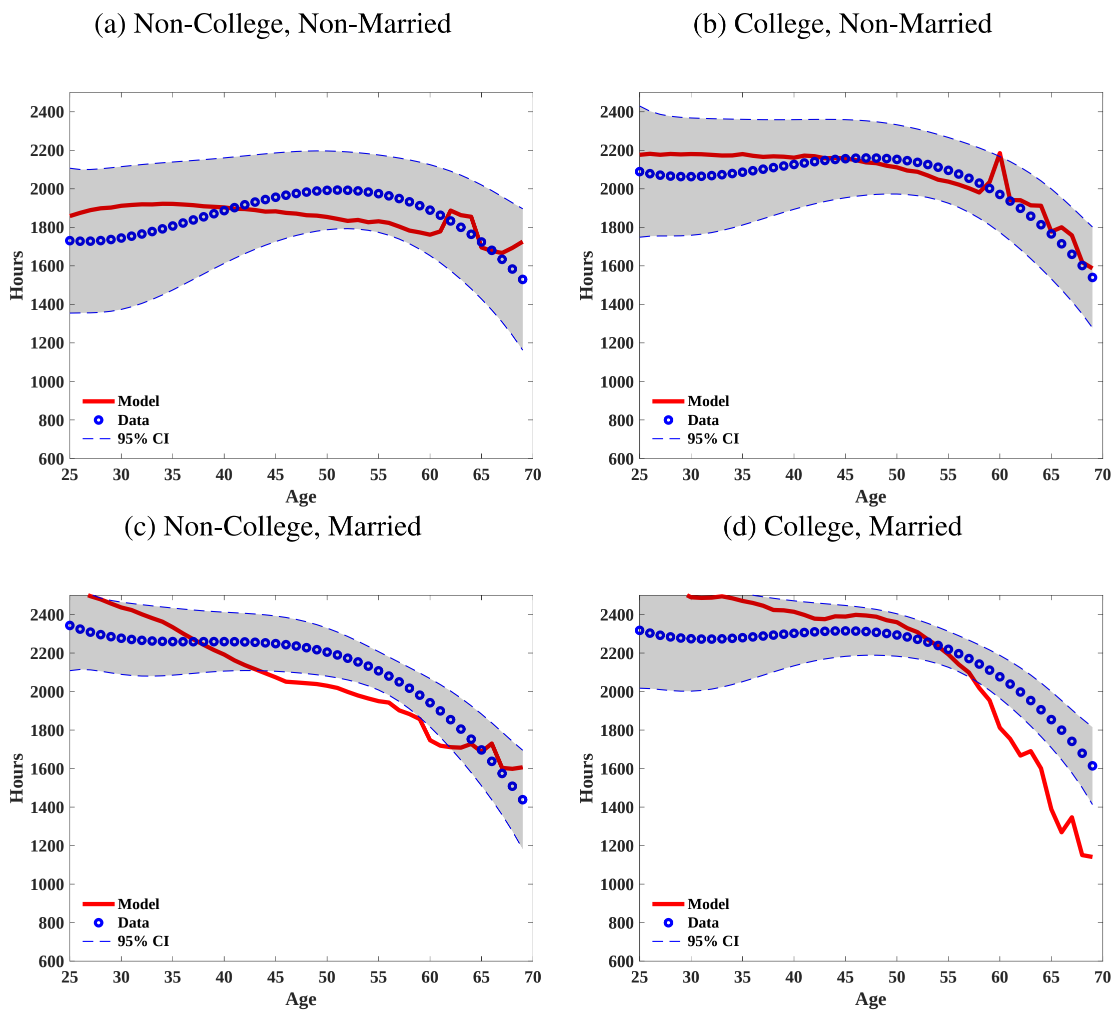


Figure H.3: Benchmark: Hours by Education and Marriage
Men born in 1931-1935



(a) Non-College, Non-Married

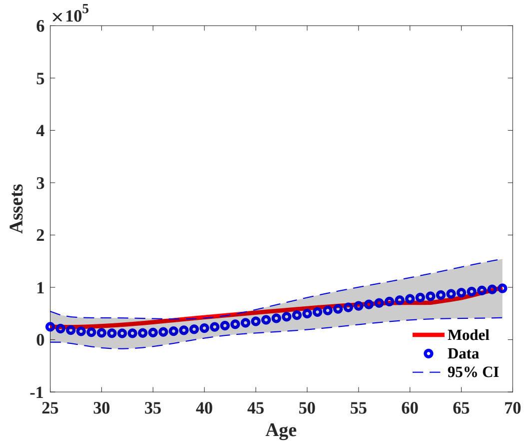
(b) College, Non-Married

(c) Non-College, Married

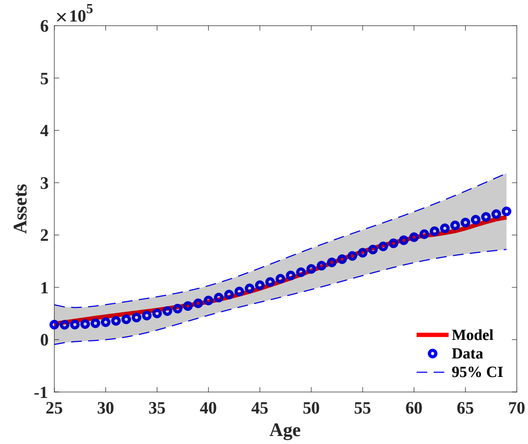
(d) College, Married

Figure H.4: Benchmark: Wealth by Education and Marriage

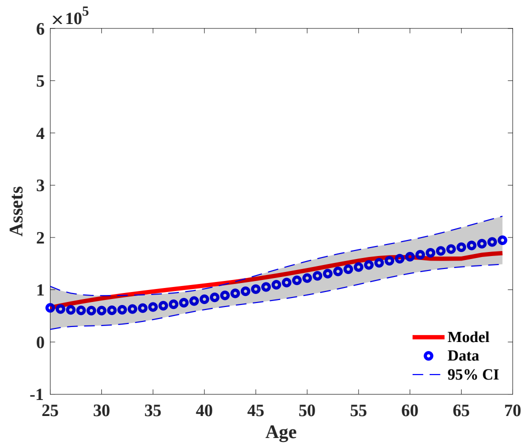
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

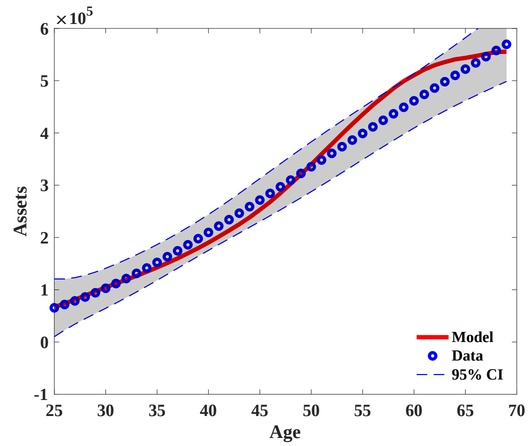
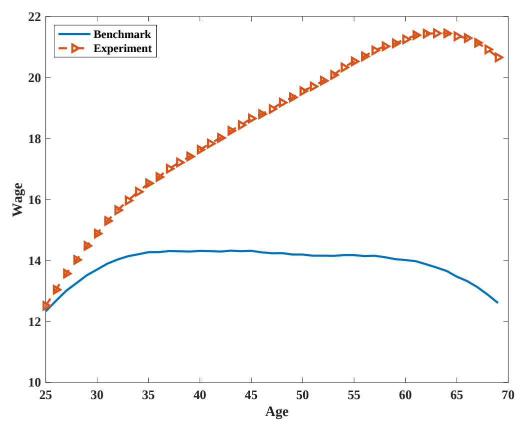


Figure H.5: Life-cycle Wage
Benchmark vs. No Unemployment Shocks Model

(a) Non-College



(b) College

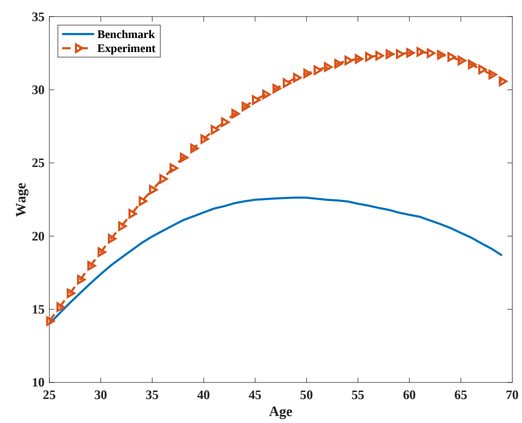
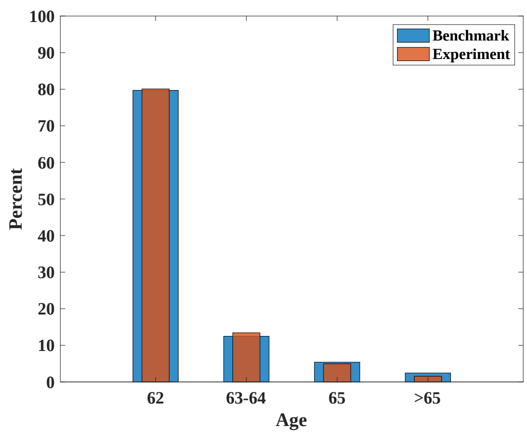
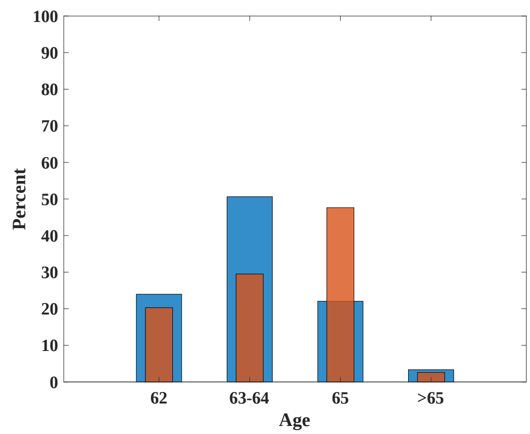


Figure H.6: No Bequest Motive: Claiming by Education and Marriage
Men born in 1931-1935

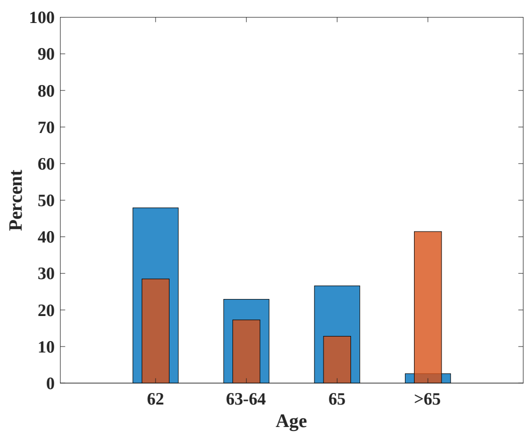
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

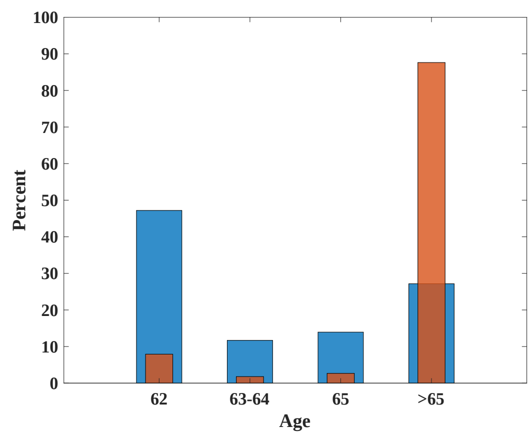
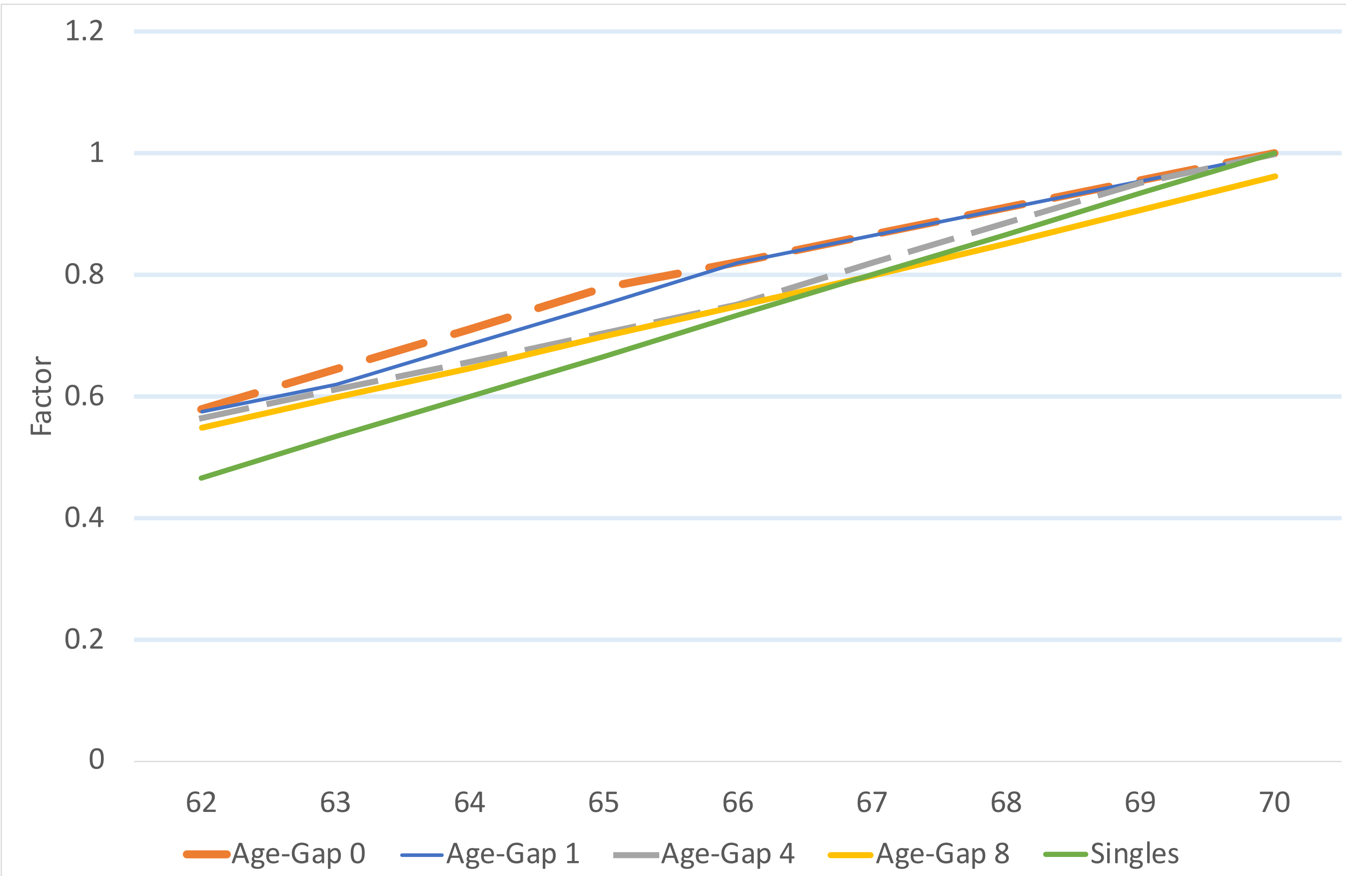


Figure H.7: Social Security NRA 70 Policy Benefit Reduction Factor



Notes: The figure presents analog of figure D.1 for the NRA 70 policy case. Note that for married individuals, reduction factors take into account joint benefits (primary earner benefit and spousal benefit). In this experiment, change in NRA does not impact spousal penalties. As a result, the reduction factor for joint benefits for married individuals are somewhat smaller than singles. For instance, age 62 claiming under NRA 70 policy entails a roughly 54% penalty for singles and only about 43% for married men.