Revisiting Retirement and Social Security Claiming Decisions*

Neha Bairoliya†
Neha.Bairoliya@marshall.usc.edu

Kathleen McKiernan‡
kathleen.mckiernan@vanderbilt.edu

December 5, 2022

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 provide answers to this puzzle within the scope of an augmented, albeit standard, forward-looking life-cycle framework, in contrast to prior literature relying on behavioral channels. Toward this goal, we document *claiming frictions* that may prevent households from delaying benefit claims. 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 costs of these frictions. Counterfactual experiments show that the claiming frictions—SS marital rules, budgetary shocks, misbeliefs, and bequest motives—can explain 78 percent of the overall early claiming rates in the model. Policy experiments highlight the role of these frictions, in limiting the ability of households to augment their claiming ages, in response to changes 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 40 percent higher if the impact of claiming frictions on behavior 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

---

*We would like to thank Jim Poterba, Mariacristina De Nardi, Andrew Atkeson, Karen Kopecky, Eric French, Gary Hansen, Ayşe İmrohoroğlu, Selo İmrohoroğlu, Olivia Mitchell, Sita Slavov, David Weil, Dominic Smith, participants of the LAEF and NBER Social Security workshops, for their valuable comments.

†University of Southern California, Department of Finance and Business Economics, Los Angeles, CA 90089-1422, United States.

‡Vanderbilt University, Department of Economics, Nashville, TN 37235, United States.

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. For instance, our framework reveals that the aggregate lifetime benefit payouts after an increase in the normal retirement age can be up to 40 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 spousal benefits available to married individuals heighten the trade-off for this group as the percentage penalty or credit represents a nominally larger sum of money. For an average life span, these groups 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 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 and potential costs of these claiming frictions, 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 claiming frictions 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 64.3 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 work status, education, health, and marital status. The model also does well in out-of-sample predictions for the Social Security claiming behavior of a cohort with different Social Security rules.[1]

[1]Specifically we use the 1941-1945 birth cohort for our validation exercise. This cohort observed a normal retire-

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

1. Nearly 78 percent of all early claims (claims before the normal retirement age) and almost all of early claims for college educated and married individuals can be attributed to 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. 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 the married households. These benefits create large variations as well in early claiming rates across married households with different relative age gaps between spouses. Bequest motives heavily impact the claiming behavior of college graduates (both married and singles). While budgetary shocks, especially unemployment, mainly impact the claiming behavior of singles, misbeliefs play an important role for married households, particularly those with 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. Model predictions of raising the NRA to 70 are:

1. Claiming behavior shifts little, with most of the changes in claiming ages coming from married individuals. Behavior of singles, in contrast, remain mostly inelastic to policy change. As a result, the married group experiences relatively smaller losses in lifetime value of SS benefits as compared to singles.

2. Without claiming frictions, the same policy produces large rightward shifts in SS claiming, resulting in relatively lower losses in lifetime benefits for all groups.

3. Understanding how frictions impact claiming behavior has important implications for the government budget. Aggregate lifetime benefit payouts could be 40 percent higher under the increased NRA policy if the friction-less baseline 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

ment age of 66, no earnings test starting age 65 and higher delayed retirement credit.

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 (2005b, 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.[2]

Second, our paper is closely related to prior structural work studying the strong claiming peak at age 62 (Gustman and Steinmeier (2005b, 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 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

[2] 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.

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

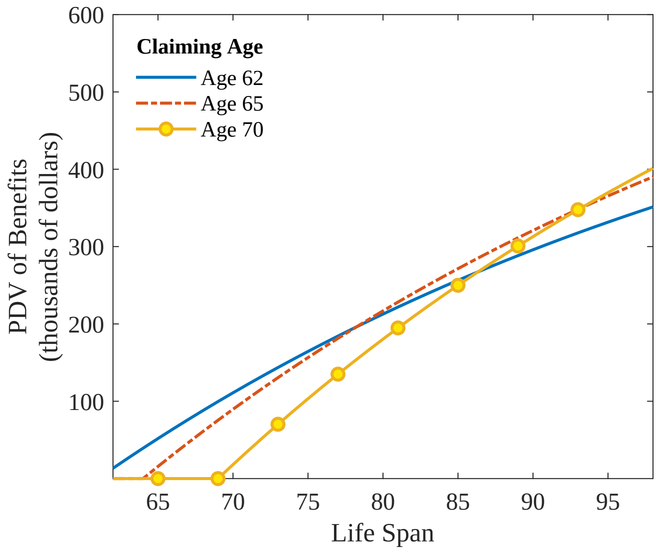
The United States Social Security system provides a flow of retirement income starting at the time of claiming and continuing until the death of the beneficiary. A worker's benefits are a progressive function of their average indexed monthly earnings. Up to a maximum taxable amount, higher income during 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 can claim *spousal benefits* on the earnings record of the primary earner.[3] 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, who in turn would receive these benefits until the end of their life.

Individuals first become eligible for benefits at the age of 62 and become eligible for full benefits at the normal retirement age. 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 somewhat shorter period of time. These penalties/credits for early/delayed claiming also apply to spousal benefits. Spouses who claim prior to the NRA incur a penalty while spouses who delay their claims up to age 70 receive a credit. The structure of the U.S. Social Security system, therefore, creates a trade-off between the number of years pension payments are received and their size.

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

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



Notes: Present value of benefits is calculated at age 62 using a 2 percent 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.

2.1 Present-Discounted Value Analysis

We highlight this trade-off in Figure 1 by constructing the present-discounted value (PDV) of total benefits, 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. 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 78 years, workers receive a higher present value of benefits by delaying claims from age 62 to 65. In order to receive more by delaying their claims to age 70, however, workers must live at least to the age of 94. As the average lifespan, conditional on living to age 62, of American men born between 1931 and 1935 is roughly 80 years, the average worker would receive more in PDV of total benefits by claiming at age 65 but less in PDV by pushing claims from age 65 until age 70.[4]

This PDV calculation further indicates that, for a given fixed life span, the strength of incentives

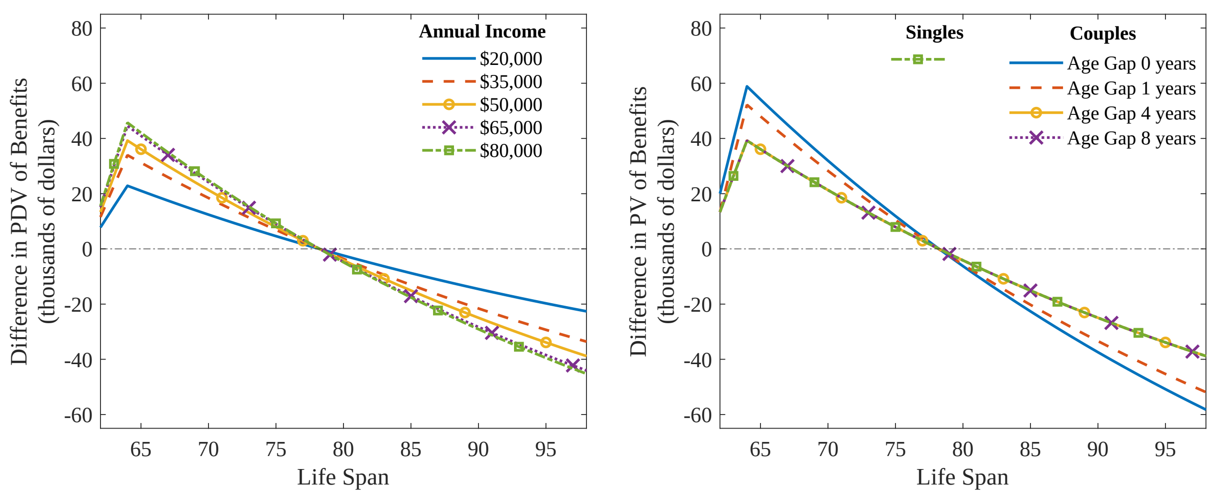
[4]This life expectancy is based on the Social Security Administration's actuarial life tables from 1993 to 1997 (when men of the 1931-1935 cohort were 62 years old). This table indicates that conditional on living to age 62, a male worker faces a 1.7% probability of dying within one year and a life expectancy of 17.45 years.

(in terms of the nominal size of benefits) to claim early or delay claims until the normal retirement age could vary by income level and marital status. Figure 2 shows the difference in the present value of benefits between claiming at age 62 and at 65 (the gap between the solid and dashed lines in Figure 1; referred to as PDV gap henceforth) and how it varies by income (Figure 2a) 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 age 79, with those who live shorter lives receiving more by claiming early, and those who live longer lives receiving more by claiming later. However, the level of how much more or less these individuals receive differs by income and spousal age gap (in the case of married households).

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

(a) By Income

(b) By Marital Status



Notes: Present value of benefits is calculated at age 62 using a 2 percent interest rate. All households in the comparison by marital status are shown with annual earnings of $50,000. Married couples are assumed to always claim together (if both are eligible) or as soon as eligible (if one is not eligible) and claim on the earnings record of the head of household. Spouses are also assumed to always outlive heads of household. Calculations includes only spousal benefits; survivors benefits are not part of the computation.

As shown in Figure 2a, depending on how long the beneficiary lives, the progressive nature of the benefit formula leads to a larger gap between present values of benefits for higher income individuals. For a life-span of 70 years, for example, the gap between the PDV of benefits ranges from $12,000 to $25,000 for incomes between $20,000 and $80,000. For a lifespan of 85 years, on the other hand, these beneficiaries give up between roughly $9,000 and $18,000 by claiming at 62 rather than age 65. This gap between present-discounted values of benefits received for claiming at age 62 and 65 increases in income up until the maximum taxable income cap. Therefore, for a given life span, the incentive to claim early or late is magnified for higher incomes below this cap but identical for all those above the cap. For the average lifespan, higher income individuals give up more by claiming at age 62 than lower income workers.

Figure 2b highlights that the additional benefits married individuals receive in the form of spousal 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, but decreasing in the spousal age gap. As spouses must have reached the age of 62 in order for the household to receive spousal benefits, workers with higher age gaps between themselves and their spouses do not experience higher benefits by claiming at age 62. For a life span of 70 years, singles (or those married couples with spousal age gaps of three years or more) receive roughly \$21,000 more in PDV of benefits by claiming at age 62. This number is roughly \$32,000 for married couples with no age gap and \$28,000 for couples with a one-year age gap. This result carries through to longer lifespans with married couples with lower age gaps seeing larger (negative) PDV gaps between age 62 and age 65 claims than their single and high spousal age gap married counterparts. For a lifespan of 85 years, married couples with no age gap receive around \$23,000 less by claiming at age 62 than at 65, while couples with one-year age gap receive \$20,000 less and singles receive only \$15,000 less.

The above calculations highlight two lessons. First, given the average life expectancy of roughly 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 the progressivity of the Social Security benefit formula or additional spousal benefits received by married beneficiaries leads to heightened incentives to delay claims to age 65 for higher income and married individuals.

2.2 Empirical Analysis

Given variations in mortality across the population 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 stark contrast to the predictions of the PDV calculations, 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

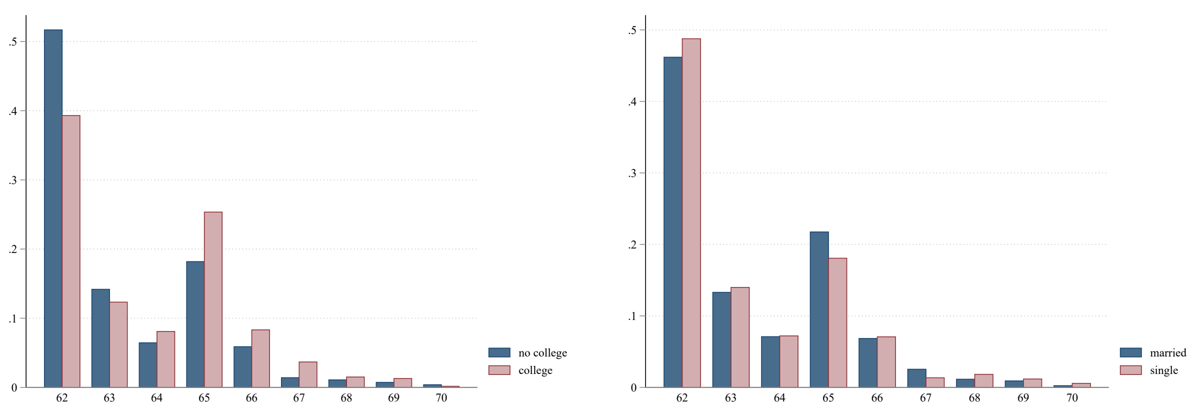
[5]Previous work has also identified that many household could gain from delaying claims Coile et al. (2002), Meyer and Reichenstein (2010), Shoven and Slavov (2014a), Shoven and Slavov (2014b), Sun and Webb (2009) Maurer et al. (2021) Maurer and Mitchell (2021)

percentages of delayed claims in this cohort with only slightly over 10 percent of men claiming at age 66 or later. Furthermore, as longer life expectancy and the structure of the U.S. Social Security program heightens the incentives for higher income and married individuals to delay claims, we would expect very low early claims among these groups. Early benefits claims, however, remain high among both college educated and married individuals.[6]

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.[7] More college educated men delayed claims past age 65, with around 15 percent of 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. More details on the sample are included in Appendix A

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.[8] 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

[6]In what follows we use education as a proxy for income levels. We also considered using occupation rather than education as the control, but there is a strong correlation between the two. Details on the inclusion of occupation are considered in Appendix C.1

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

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

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 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.[9,10] These facts highlight *claiming frictions* that may impact the ability of households to delay benefit claims: (1) mechanisms highlighting the importance of budgetary constraints that are missing from the PDV calculation, (2) those hindering an individual's ability to accurately perform the PDV calculation, and (3) mechanisms indicating objectives outside of maximizing the present discounted value of lifetime benefits.

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

   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 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.[11]

   Additionally, we document that many workers have already left the labor force prior to the decision to claim benefits–indicating that there is a link between the participation decision of a worker and the claiming decision of the worker. This decision is not restricted to occurring in the same period. We document in Figure 4b that many workers have chosen non-participation prior to choosing early claims. This results weakens as we consider lags further before the claiming age, but those individuals who are not working at during the same year of claiming, one to two years prior to claiming, and three to four years prior to claiming

[9]Details on the empirical strategy are contained in Appendix B

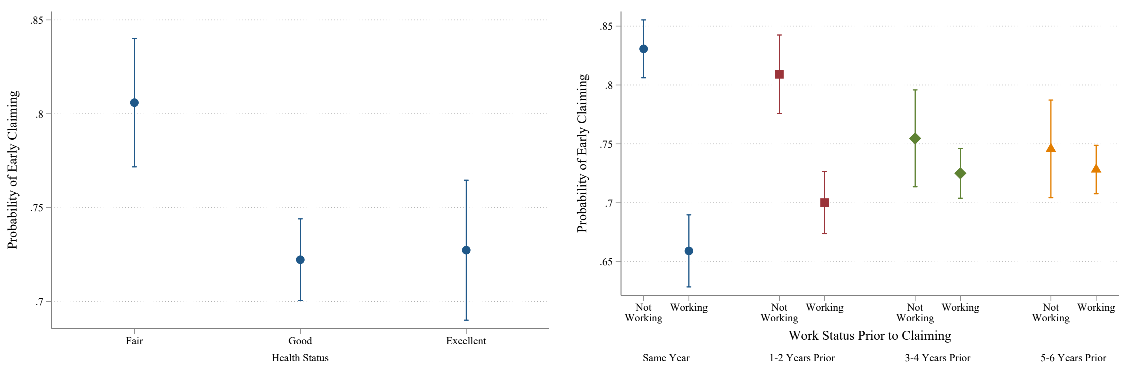
[10]In this empirical work, we focus only on all early claims rather than claims exactly at age 62 and claims for only men. However, some results including women and for claims at the early retirement age are shown in Appendix C.2 and Appendix C.3

[11]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

are more likely to claim Social Security benefits prior to the normal retirement age.[12] [13]

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

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.

   Tables 1 and 2 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 10 percent of workers with a college degree believe there is

[12]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.

[13]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.

Table 1: Program Misbelief

	Fraction of workers who believe pension 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 is they respond that the size of pension benefits received does no depend on the age at which benefits are claimed. 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

no penalty for early claims, while this fraction is over 20 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 1 percentage point higher probability of survival to age 75 than estimated, college educated workers underestimate this probability by around 6 percentage points. Among these education types, married workers overestimate mortality on average while singles underestimate mortality.

Figure 5 shows how the 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.[14,15,16] Figure 5b shows how early claims vary by beliefs of mortality. While those who underestimate and correctly estimate mortality claim

[14] These results comes from the Understanding America Survey. In an attempt to make clean comparisons between this and the results of the regression in the Health and Retirement Study, we include as many of the same control variables as possible. However, because UAS is not a panel, we cannot include controls for lagged work status. Rather, we include only work status in the year of observation. Additionally, we cannot control for the mortality misbelief or the expectation of leaving a bequest. More information is included in Appendix B.2.

[15] 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.

[16] 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).

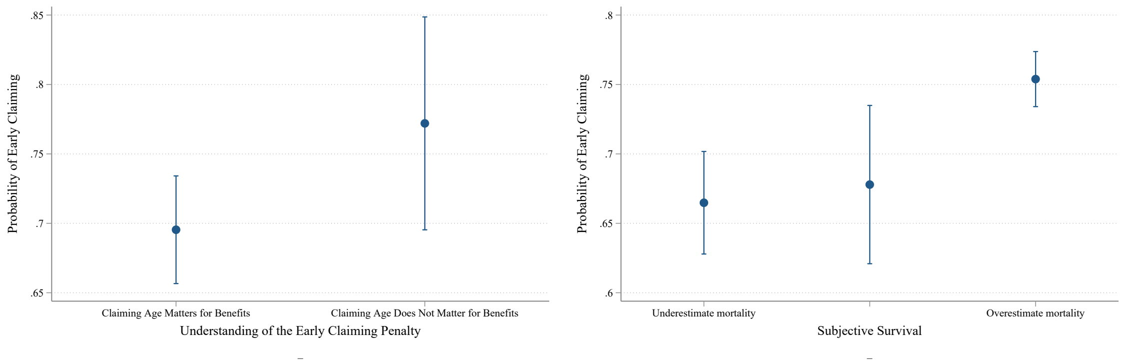
Table 2: Mortality Misbelief

	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 probability of survival to age 75 is larger than the estimated probability of survival to age 75; an individual overestimates mortality if the subjective survival is less than the estimated probability of survival. Average misbelief is measured as the difference between estimated and subjective survival probabilities; 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

(a) Program Rules (b) Subjective Mortality



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.

at roughly the same rate, those workers who underestimate mortality—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.[17]

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 total PDV of their 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. 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 cannot.[18] A desire to leave a bequest, therefore, may lead individuals to claim early.

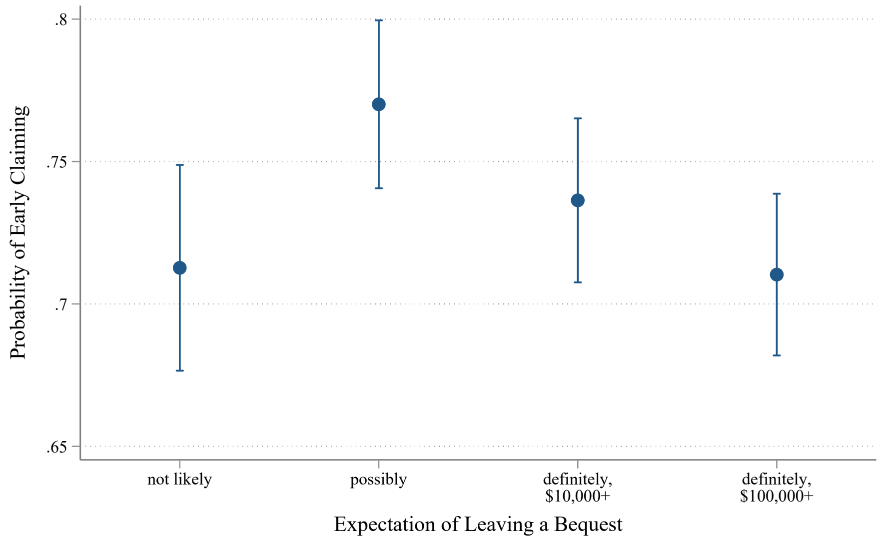
   Figure 6 demonstrates how the probability of early claiming varies depending on whether workers are likely to leave bequests and the size of these bequests.[19] There is evidence that those workers who have the possibility of leaving bequests are more likely to claim benefits early. There is a jump in 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.

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

[18]Social Security benefits can, however, be left to spouses in the form of Social Security spousal benefits.

[19]Additional details on the construction of this variable and the estimation are discussed in Appendix B.1.

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. Expectations of leaving a bequest are measured at age 60. More on the empirical strategy and construction of these results is included in Appendix B.

The above stylized facts help us identify channels driving the claiming behavior of older workers. Together with SS marital and survivors benefits (which as shown earlier can also interact with the incentives to claim at various ages), we refer to these channels as *claiming frictions*. Next, in order to quantify the role of these frictions in driving claiming behavior, we build a structural life-cycle model of consumption, savings and retirement that allows 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 Social Security are modeled in great detail to match that of the current U.S. system.

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, 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.[20]

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.[21]

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

Where $\rho^{e,m}$ is the coefficient of relative risk aversion and $\nu^{e,m}$ is the weight on consumption. $\zeta_t^{e,m}$ is the equivalent scale in consumption. Each of these parameters 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:

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

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 assume the following function form for both the time and health costs of working:

[20] Note that Social Security application is a one-time decision in the model which cannot be reversed.

[21] The paper follows French and Jones (2011), French (2005), Casanova (2010) and others in addressing the "retirement-consumption puzzle". A decline in consumption at retirement is caused by both- 1) unexpected health shocks to leisure causing unplanned retirement and 2) non separability of preferences between consumption and leisure.

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

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

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

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.[22] 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 and current health status as given below:

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

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).

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

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

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.[23]

$$\begin{aligned} w_t &= \xi(\lambda_t)\exp(\omega(e,t)+\eta_t) \\ \eta_t &= \rho^w \eta_{t-1} + \epsilon_t^w \\ \epsilon_t^w &\sim N(0, \sigma^2_{\epsilon^w}) \end{aligned} \tag{3}$$

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

The Social Security system in the U.S. provides retirement incentives at the time when these benefits become available. 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_t^{ss} be the Social Security wealth in the model (annualized measure of AIME). Then the Social Security wealth evolution is approximated in the model in the following simple way:

$$a_{t+1}^{ss} = \max\{[(1+g_{awi}\{t \leq 60\})a_t^{ss} + \max\{0, (w_t h_t - (1+g_{awi}\{t \leq 60\})a_t^{ss})/35\}], a^{\max}\} \tag{4}$$

Where $a^{\max}$ is the threshold at which the Social Security wealth is capped and g_{awi} captures the indexing of the Social Security benefits for real wage growth and $w_t h_t$ denotes annual earnings for period t.[24] Note that in equation 4, 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

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

[24] Note that in practice, a worker's annual nominal earnings each year are indexed to economy-wide earnings as of the year the worker turns age 60, which is accomplished by multiplying the annual nominal earnings by the ratio of the national Average Wage Index (AWI) in the year the worker turns 60 to the AWI in the year the nominal earnings were paid.

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

$$pia(a_t^{ss}) = 0.90 \times \min\{a_t^{ss}, b_0\} + 0.32 \times \min\{\max\{a_t^{ss} - b_0, 0\}, b_1 - b_0\} \\ +0.15 \times \max\{a_t^{ss} - b_1, 0\} \tag{5}$$

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 4). For instance, staying longer in the labor market by working fewer hours may not increase the benefits for the individuals in the model.[25] 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).

$$ssb_t = pia(a_t^{ss}) * \Gamma_t - \Upsilon_t \tag{6}$$

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}).[26] 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. It has been largely argued in the literature (Heiland and Yin, 2014; Gruber and Wise, 2005) that while the benefit reductions due to early claim are actuarially fair, the delayed claim benefit increase does not fully compensate the beneficiary for the loss in benefits in the previous periods. Hence, they are not actuarially fair. This structure of the Social Security system

[25] 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.

[26] 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.

thus provides strong incentives to not delay benefit claims.[27]

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.

$$\Gamma_t = \begin{cases} (1-\gamma_t^{ss})^{(t_{NRA}-t)} & \text{if } t < t_{NRA} \\ 0 & \text{if } t = t_{NRA} \\ (1+\gamma_t^{ss})^{(t-t_{NRA})} & \text{if } t > t_{NRA} \end{cases} \tag{7}$$

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:[28]

$$\begin{aligned} ssb_{t+1} &= pia(a_{t+1}^{ss}) * \left[1 + \left(\frac{\Upsilon_t}{ssb_t}\right)\gamma_t^{ss}\right] \\ a_{t+1}^{ss*} &= pia^{-1}(ssb_{t+1}) \end{aligned} \tag{8}$$

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}.[29] 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.

[27]The actual incentives may also depend on a variety of other factors such as an individual's subjective mortality expectations, heterogeneous discount factors etc.

[28]Note that this is a simplification as in practice, the benefits are typically adjusted upon reaching the NRA.

[29]Note that the earnings test was removed for worker over the NRA starting in 2000.

3.5.2 Misbeliefs

In modeling SS program knowledge (k) regarding 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 either the early claiming penalty or 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.

$$\overline{ssb}_t = \begin{cases} ssb_t & \text{if } k = \text{informed} \\ pia\left(a_t^{ss}\right) - \Upsilon_t & \text{if } k = \text{uninformed} \end{cases} \tag{9}$$

In short, 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 though.[30] Note that 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 50 percent of head's benefits through Social Security, as soon as they reach the age of eligibility (62).[31] Specifically, spousal benefits received depend on marital status and spousal age where the latter is determined by the difference between the head's age t, 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:

$$\delta_t^q = \begin{cases} 1.0 & \text{if } m = \text{single or } m = \text{married}, t - \iota < t_{ERA} \\ 1.5 & \text{if } m = \text{married}, \ t - \iota \geq t_{ERA} \end{cases} \tag{10}$$

Singles and married individuals whose spouse is not yet eligible for benefits $(t - \iota < t_{ERA})$

[30] 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.

[31] Note that in practise, spouses can choose to delay benefit claim as well. However, this requires keeping spousal claiming decision distinct from the head's claiming. Given our focus on the household head's claiming decision, we allow spouses to receive benefits as soon as they reach 62. We also simplify any further penalties in spousal benefits due to spouses claiming before their normal retirement age.

receive no additional spousal benefits. Married individuals for whom the spouse's age is above the early retirement age, receive the additional 50 percent of benefits.[32]

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:

$$A_t^q = \begin{cases} a_t + \sum_{j=t-\iota}^{T} \frac{1}{1+r} \pi_{j+1}^s ssb_t & \text{if } m = \text{married}, \;\; b_t^{ss} = 1 \\ a_t & \text{otherwise} \end{cases} \tag{11}$$

In addition to any leftover assets, a_t, bequeathable wealth is a function of Social Security wealth if the individual is married and has already chosen to claim benefits, $b_t^{ss} = 1$.[33] 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 till the end of their own life. Therefore, this present value is a function of the household head's age t and the spousal age gap, ι.

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:

$$c_t + a_{t+1} = a_t + W\left(y_t, y_{st}, \bar{r}^e a_t, \tau\right) + \mathbb{I}\left\{b_t^{ss} = 1\right\} \times \delta_t^q \overline{ssb}_t + tr_t \tag{12}$$

An individual's disposable household income, $W(\cdot)$, consists of various components. They receive income through hours worked in the labor market $w_t h_t$, spousal income y_{st} if the individual is married, and an education-specific interest on assets $\bar{r}^e a_t$, meant to capture differences in returns on financial wealth by education. If eligible, individuals receive transfers from the government, tr_t as described in equation 17 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:

[32]Note that we abstract away from any spousal early application penalty and allow spouses to start receiving benefits upon reaching age 62 (conditional on the head having claimed his benefits).

[33]It is assumed that if an individual dies prior to claiming Social Security benefits, their spouse is not eligible for survivors benefits.

$$c_t + a_{t+1} = a_t + W\left(y_t, y_{st}, \bar{r}^e a_t, \tau\right) + \delta_t^q ssb_t + tr_t \tag{13}$$

Labor income, y_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, age, health status and labor income in the model, and is given as follows:

$$y_{st} = f\left(e, t, \mu_t, w_t h_t\right) \tag{14}$$

There is a standard borrowing constraint on assets given by:

$$a_{t+1} \geq 0 \ \forall t \tag{15}$$

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

$$c_t \geq \bar{c} \tag{16}$$

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. like Supplemental Nutritional Assistance Program (SNAP), Supplemental Security Income (SSI), Temporary Assistance for Needy Families (TANF), and other programs.

$$tr_t = \min\{0, \underline{c} - (a_t + W_t + \delta_t^q ssb_t)\} \tag{17}$$

Where W_t is the total disposable household income as defined in equation 13.

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.[34].The second is the *retirement choice* phase between ages 62 and 69 where individuals also make Social Security application decisions (b_t^{ss}). Finally there 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:

3.7.1 Employment phase

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

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

(1), (4-8), (15), and (16).

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:

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

[34]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.

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

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

(1), (4-8), (15), and (16).

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

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

(1), (4-8), (15), and (16).

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).

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

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

(1), (5), (15), and (16).

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.[35] 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 assets. 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 $\Theta = \{\beta^{e,m}, \rho^{e,m}, \nu^{e,m}, \theta^{e,m}_{beq}, \phi^{e,m}_{H}(t, \mu_t), \phi^{e,m}_{P}(t)\}$ using Method of Simulated Moments (MSM) by education and marital status.[36] 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 data from the self-reported health status variable.[37][38] Health transitions across these states are then estimated by running an ordered probit of self-reported health status on previous year health status, education, and a quadratic 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 the raw 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 quadratic, education, and marital status as mentioned earlier. Then, as MEPS does not sample the

[35] Details on the data and samples used for estimation are included in Appendix A

[36] The share of the population within each fixed education, marital status group are shown in Table D.1.

[37] The Medical Expenditure Panel Survey 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

[38] 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.

institutionalized population, we adjust these profiles to match life expectancy at age 65 for both education groups for our benchmark birth cohort (those born in between 1931 and 1935).[39]

Second, subjective survival probabilities are obtained by scaling the estimated 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 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

As shown, wages are assumed to be comprised of an age and education-specific profile and a persistent shock. This function of age and education as well as parameters of the AR(1) shock

[39] Data on LE : https://www.ssa.gov/policy/docs/workingpapers/wp108.html

[40] More details on the construction of these survival probabilities are contained in Appendix D.1

[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 D.2, D.3, D.4

[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.

process is estimated from PSID.[43]

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 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 3 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 3 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.

[43] Discussion of this estimation and the estimation of the parameters of the stochastic process are detailed in Appendix D.5.

[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 D.6

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

Table 3: 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.

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 birth cohort and estimate the following function from the PSID data:

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

We allow for the tax function to differ by education type to capture any differences in family size across these two 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 1, 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.

[47]Details of the estimation of parameters in the tax function are in Appendix D.7

4.1.8 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 point 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 point gap between the return of college and non-college education workers. This delivers a rate of return of 2.2 percent for non-college and 7.1 percent for college educated individuals.

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 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:

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

[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 D.8.

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:

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

where m_{it} is a vector of data moments

5 Results

5.1 Estimation

Table 4 shows our structural parameter estimates. Our model is estimated on data for male household heads who are born between 1931 and 1935. The estimated discount factor is higher for married men than singles and for college graduates than those without a college degree. It ranges between 0.95 to 1.0 where the lowest value is for singles without a college degree and highest for those who are married and have a college degree.[49] The coefficient of relative risk aversion ranges between 1.95 and 2.87 across individuals in these four permanent groups and the consumption weight between 0.38 and 0.63. Together these two parameters imply an inter-temporal elasticity of substitution for consumption $\frac{-1}{\nu(1-\rho)-1}$ which ranges between 0.73 and 0.46 for these four groups respectively. Note that our estimated discount rates imply a declining life-cycle consumption path for the singles and increasing consumption paths for the married individuals. [50]

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

[50]Note that $\tilde{\beta} < \frac{1}{1+r}$ for the singles, where $\tilde{\beta}$ is the effective discount factor after taking into account survival probability. This is especially true for those without a college degree as $r = 2.2\%$ for this group. By contrast,

Together, the bequest parameters θ_{beq} and κ_{beq} govern the strength of terminal bequest motive. Figure 7 plots the implied share of resources that would be left as bequests by households in different marital and education groups, if their probability of death next period was one. We find that bequest motives are strongest for the non-college groups. Consistent with De Nardi et al. (2021), we find that bequest motives are even more of a luxury good (higher wealth threshold for leaving any positive bequests) for the married groups than singles.

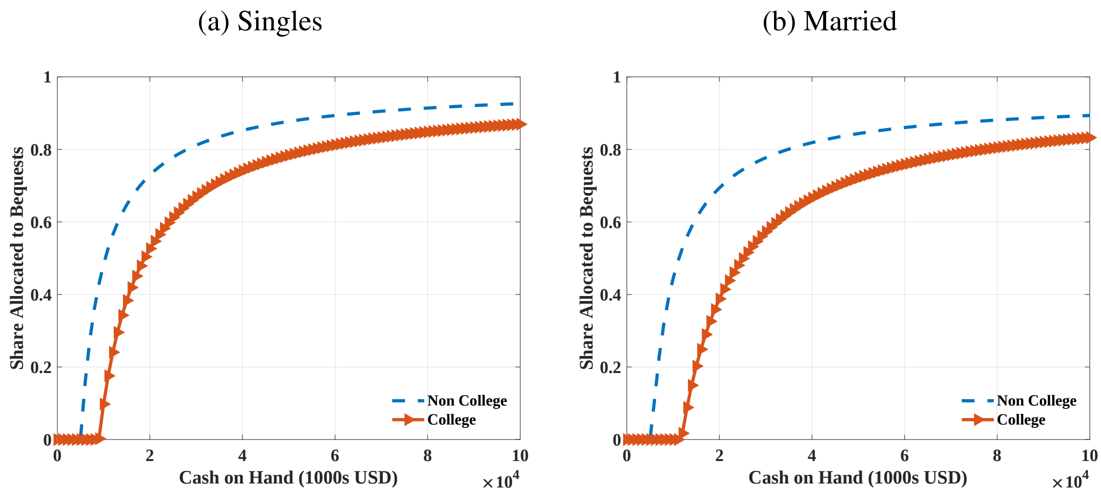
We allow the time cost parameters to vary by age, education and health. We estimate the coefficients of the function as described in equation 2 for each education and marital group in our model. Note that we only allow the bottom two health states to impact time endowment. Specifically, individuals in excellent health only incur a loss in their time endowment due to work. Our estimates indicate that the time cost of being in the worst health state is relatively high at younger ages. Also, while this cost remains high for all groups, the growth over the life cycle is the steepest for those with a college degree. Empirically, the college educated group is less likely to work at older ages, in the event of a bad health shock, than the non-college group. The structural model rationalizes this observation in terms of differences in bad-health time cost at older ages. Finally, time endowment parameter $\bar{l}$, in terms of annual hours, is estimated to be between 5,457 and 4,874 for these groups.

Table 4: Estimated Parameters

Parameter	Description	Singles		Married	
		Non-College	College	Non-College	College
β	discount factor	0.953	0.960	1.000	1.000
ρ	relative risk aversion	1.954	2.308	2.206	2.869
ν	consumption weight	0.381	0.539	0.500	0.632
θ_{beq}	bequest intensity	0.994	1.149	1.371	4.361
κ_{beq} (in 000s)	bequest curvature	2.021	1.917	0.882	1.976
$\bar{l}$	time endowment	5457	4909	4983	4874

$\tilde{\beta} > \frac{1}{1+r}$ for the married group, especially college graduate for whom $r = 7.1\%$

Figure 7: Estimated Bequest Motives



Notes: Estimated bequest motives for singles (panel a) and married households (panel b) with college degree (solid lines) and without college degree (dashed lines) are presented. Calculations are similar to those presented in De Nardi et al. (2021).

5.2 Benchmark Model

Appendix Figures D.4-D.6 show the benchmark model fit for average participation, hours worked and wealth over the life cycle for male household heads (born between 1931 and 1935) by marital status and education group. Our structural model performs well in matching these moments. We next check to see if the model is able to generate a reasonable prediction for moments that were not targeted explicitly in the structural estimation. We are particularly interested in seeing how the model performs in predicting the Social Security claiming behavior for our simulated cohort. Figure 9 shows the Social Security claiming behavior for all the simulated individuals in the model. We find that the estimated model generates substantial early claiming; however, it somewhat under predicts claiming at age 62. The inability of the model to generate large numbers of age 62 claims could be because these are explained by behavioral channels, some of which maybe outside the scope of a standard life-cycle model with rational forward-looking agents.[51] Yet, the model does surprisingly well in matching the overall claiming behavior along the three important dimensions–before age 65 (early claims), at age 65 (claims at NRA) and after age 65 (delayed claims).

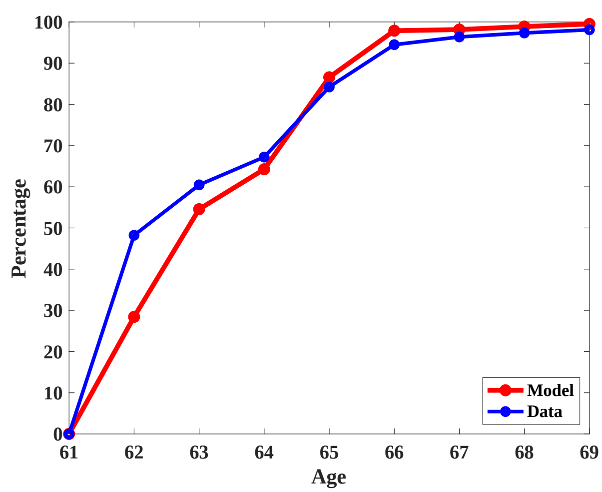
Apart from matching the overall Social Security claiming behavior well, the model is also able to predict several important characteristics of early Social Security claimers. For instance, the model generates the strong correlation between labor supply status and early claims as observed in

[51]Gustman and Steinmeier (2005a), Gustman and Steinmeier (2015), and Pashchenko and Porapakkarm (2018) attribute 62 claims to high time preference rates.

the data. First two rows of Table 6 show percent early claimers by labor force participation status at age 62. Specifically, 55.7 percent of men working at age 62 were seen claiming early in the data, the model predicts this to be 56.9 percent. Similarly, the model closely matches the early claiming rates of those who were in excellent or fair health at age 62. However, it over predicts the early claiming rates of those in the worst health state. For permanent states like marriage and education, it generates a reasonable match for the early claiming behavior of college graduates (60.4 data vs. 58.1 model) and those without a college degree (73.5 data vs. 72.8 model). The model qualitatively predicts the gradient in early claiming by marital status as observed in the data. However, it substantially over predicts the early claiming rates of singles.

The benchmark model generates a gradient in early claiming by wealth. Table 5 shows the percent of those claiming Social Security benefits before their normal retirement age in each wealth quintile for both the data and the model. The model somewhat over predicts early claims for those in the lowest quintiles and under predicts for those in the highest quintile.

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.

Table 5: Early Claiming by Wealth Quintiles

% Early Claimers	Lowest	Second	Third	Fourth	Highest
Data	74.0	73.1	70.5	68.7	60.6
Model	84.4	77.0	67.0	48.0	44.9

Notes: *Percent of those claiming before their normal retirement age is reported for each wealth quintile (at age 60) both in the data and the model. Data is for male household heads from the Health and Retirement Study.

Table 6: Heterogeneities in Early Claiming

% early claimers	Data	Model
*Work Status**		
Not Working	95.2	80.9
Working	55.7	56.9
*Health**		
Excellent	63.0	56.2
Fair	68.4	62.7
Poor	78.5	86.0
Education		
No College	73.5	72.8
College	60.4	58.1
Marital Status		
Singles	76.6	94.5
Married	65.2	50.1

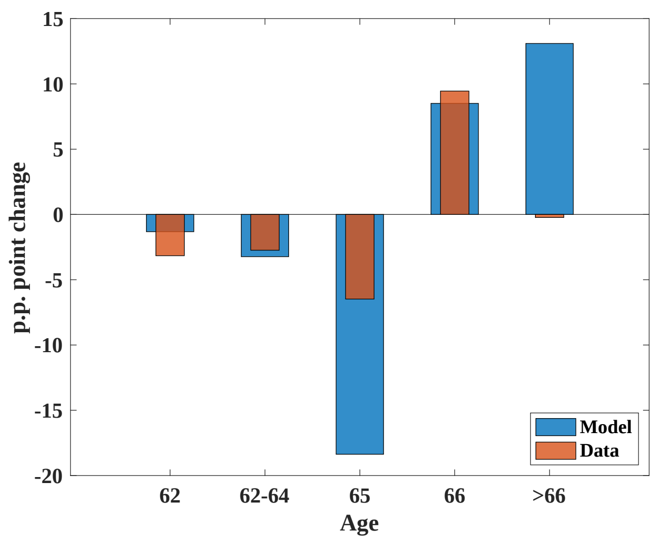
Notes: *For health and labor supply, which are not fixed over the life cycle, age 62 status is considered in both the data and the model to see it's impact on early claiming. Early claimers refer to those claiming before the NRA (age 65).

5.3 Model Validation

Even though we are not explicitly targeting the Social Security application moments in our structural estimation, part of the results could be driven by targeting the labor supply and wealth moments for our benchmark birth-cohort. In order to validate our benchmark model, we would like to test its predictions for the SS claiming behavior of a later birth cohort that experienced different Social Security rules. Specifically, those born in 1941-1945 observed a normal retirement age of 66. This cohort also experienced only part of the earnings test, because in the year 2000, it was removed for those 65 and older. At the same time, the later cohort experienced a higher delayed application credit of 7.5 percent. We feed these three important Social Security changes in the benchmark model while keeping all other parameters the same.

Figure 10 shows the percentage point change in SS claims between the two birth cohorts, both in the model and the data. The model is able to closely match three interesting features of the changes in claiming behavior observed across these two birth cohorts in the data. First, increasing the NRA and removing the earnings test past 65 did not have a big impact on age 62 claims. This illustrates the idea that perhaps most of these early claims are driven by behavioral or economic channels that are less responsive to policy. Second, overall claims before age 65 had a small decline both in the model and the data. Finally, claiming at age 66, the new normal retirement age, went up significantly both in the model and the data (8.5 p.p. model vs. 9.45 p.p. data). The model predicts a strong decline in claiming at age 65, which is also observed in the data, though to a lesser extent. The feature of the data that the model fails to predict is claiming past 66 (new delayed claims). While the model predicts a large increase in overall delayed claims, the data shows no noticeable effect. This could possibly mean that there were other countervailing forces at play between the two birth cohorts that adversely impacted delayed claims, such as growing uncertainty about the sustainability of the SS program.[52] The fact that our model is broadly able to capture well these SS claiming features of the data for a later birth cohort, one that was not used in the estimation, gives us further confidence that the model is well suited for understanding the drivers of Social Security claiming.

Figure 10: Model Validation: SS Claiming Behavior of 1931-1935 and 1941-45 Birth Cohorts



Notes: Percent point changes in claiming rates, at each of the given ages, between the 1941-1945 and 1931-1935 birth cohorts. Data is for male household heads from the Health and Retirement Study.

5.4 Counterfactual Experiments

In this section, we conduct experiments to understand the importance of the claiming frictions in explaining the Social Security claiming behavior of men. As discussed earlier, we think about these claiming frictions—SS marital benefits, precautionary motive caused by budgetary shocks,

[52]Concern about the insolvency of the Social Security system grew after President Clinton's 1998 State of the Union Address. In this speech, President Clinton stated that educating the American people about program finance was critical and brought public attention to the issue. While many workers in the 1931-1935 cohort were already claiming benefits in 1998, workers born between 1941 and 1945 may have been pushed to claim earlier by the increase scrutiny on the program.

misbeliefs about program rules or mortality, and the presence of a bequest motive—as impediments to delaying benefit claims. The first three rows of Table 7 show the early claiming rates in the benchmark model, after switching off frictions not related to policy, and after switching off all frictions together, respectively. We find that together the policy and non-policy frictions can explain almost all (over 99 percent) early claiming behavior of the college-educated singles and all married individuals in the model. This implies that these claiming frictions indeed explain why a majority of individuals (78 percent) in the model claim benefits before their normal retirement age. The only remaining group with high rates of early claiming is the non-college singles. However, their behavior is consistent with the PV calculations discussed in Section 2.1, given low life expectancies for this group.

In the following sections, 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 claiming frictions that affect both married as well as single households.

Table 7: Counterfactual Experiments
Changes in Early SS Claiming

Experiment	All	Singles		Married	
		Non-College	College	Non-College	College
Early claiming rates (%)					
Benchmark	64.3	93.8	95.3	57.8	45.8
No non-policy frictions	46.4	79.1	2.6	60.0	40.4
No frictions	14.2	79.1	2.6	0.0	0.0
*p.p. change**					
(1) Precautionary	-4.2	-4.2	-10.0	-1.7	-3.6
Unemployment	-1.9	-9.4	-16.5	5.1	2.1
Health	-0.7	2.8	1.0	-2.0	-1.9
(2) Misinformation	-3.7	1.5	-0.5	-4.4	-6.5
Mortality	-0.6	2.4	0.0	2.2	-3.6
SS Program	-3.2	-1.3	-0.5	-7.0	-2.7
(3) Bequest	-10.8	-3.2	-27.2	-5.5	-11.3

Notes: *percentage points changes for each experiment are relative to the benchmark. No non-policy frictions case refers to a scenario where we switch off the effect of (1)-(3) together. No frictions case additionally shuts off the SS marital benefits.

5.4.1 Social Security Marital Benefits

Social Security program rules are different for singles and married households in two important dimensions that could potentially impact the claiming behavior of the latter group. First, spouses can claim up to 50 percent of the household head's benefits. Second, spouses can receive survivors benefits upon the death of the 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 by the spousal age gap of the married households.[53]

The first row of Table 8 shows the benchmark levels of early claiming in the overall population as well as among married households with different spousal age gaps. The first striking observation is that households with similar aged spouses (age gap of 0 or 1) have much higher levels of early claiming (96 percent roughly) compared to the overall population (64.3 percent) and vice versa for households with younger spouses (households with spousal age gap of four or eight have early claiming rates of roughly 26 percent). The second row shows that switching off both spousal and survivors benefits for married households results in equalizing the early claiming rates across married households of different age-gap type. However, the changes work in different directions for different households, suggesting that these policies have large, and differential, impacts on behavior.

As discussed in Section 2.1, spousal benefits can either intensify the early claiming motives or delayed claiming gains, compared to singles, based on the life expectancy of the head as well as the age gap between spouses. Since the spousal age gap in our model is not correlated with any permanent feature of households (human capital, for instance), it is safe to assume that married households within each age-gap type have the same life expectancy of the household head. This means, ceteris paribus, individuals with similar aged spouses will generally have stronger incentives to claim early than those with younger spouses. The third row of Table 8 confirms this intuition as we see that those with similar aged spouses see a massive decline in early claiming compared to the benchmark–early claiming rates are roughly cut in half for this group. For households with younger spouses, spousal benefits are relatively less important in driving claiming behavior as compared to survivors benefits. Also, note that in terms of total resources directed towards bequests, survivors benefits are relatively more important for households with younger spouses. At the same time, the share of these benefits in terms of total bequeathable wealth goes down with increase in the non-SS wealth of the households (refer to Appendix Figure D.7). Thus, when we switch off spousal benefits, households with younger spouses accumulate higher life-cycle wealth to compensate for the loss in these post-retirement benefits. For instance, age 70

[53] Since spousal and survivors policy effects for married households are more strongly correlated with spousal age gap, and given that spousal age is not correlated with education status in our model, we focus the discussion of policy changes by the age gap of households rather than education.

wealth goes up by roughly 17 percent for households with a much younger spouse only 7 percent for households with similar aged spouses (refer to Appendix Figure D.8 for details). This makes the contribution of survivors benefits less important in their overall terminal bequest utility. This in turn drives up the early claiming rates a little for these households as survivors benefits generally work towards delaying benefit claims.

Survivors benefits affect claiming in different ways for different households. First, households with similar aged spouses react relatively less to changes in these benefits due to reasons discussed above. Second, households with younger spouses and lower levels of private wealth depend heavily on these benefits for their terminal bequest utility. These households are also relatively unhealthy and face significant mortality risk. As a result, the presence of survivors benefits for these households may initiate early claims. This is driven by fears of dying in the next period with zero survivors benefits in the event that the household head has not claimed benefits in the current period. Third, households with younger spouses but moderate to high levels of private wealth depend relatively less on these benefits. Particularly those in excellent health prefer delaying claims and leaving behind higher benefits (with delayed retirement credit) as bequests for their surviving spouses. The last row of Table 8 shows these countervailing mechanisms at play. We find that households with similar aged spouse have less of an effect, albeit a positive one, on their early claiming behavior. However, those with younger spouses experience much stronger negative effects on their early claiming rates. This indicates that the aforementioned second channel dominates the behavior of this group on average.

Table 8: No SS Marital Benefits
Changes in Early SS Claiming Behavior

Experiment	All	Age Gap			
		0	1	4	8
Benchmark	64.3	96.3	95.7	25.4	26.2
Both	77.2	68.2	69.5	68.8	69.6
p.p. change					
Spousal	-4.9	-41.7	-43.9	15.2	4.5
Survivior	-3.7	3.7	4.3	-12.5	-6.1

Notes: For each experiment, percentage point change in early claiming (claims before age 65) as compared to benchmark is reported for each sub-group as well as all individuals in the simulated sample.

5.4.2 Precautionary Motive

In order to explore the effect of budgetary shocks on claiming, we first switch off both health and unemployment shocks, and then switch these off one at a time. Comparing 2-4 rows of Table 7 with benchmark levels (first row) shows that there are noticeable non-linear interactions between the two shocks because the combined effect of these budgetary shocks is much larger on claiming (early claiming rates go down by 4.2 p.p.). We find that the largest effects are in turn for singles, especially those with a college degree.

Unemployment Shocks: Next we conduct an experiment where we switch off only unemployment shocks for all individuals in the model. In the model, switching off the unemployment shocks implies that unemployed individuals experience no wage-scarring effects if they choose to go back to work right away resulting in much higher life-cycle wage profiles (see Appendix Figure D.9).

We find that unemployment shocks have a relatively small effect on the extensive margin of labor supply at younger ages, especially for singles, and somewhat larger effects later in the life cycle for all subgroups (refer to Appendix Figure D.10). Average participation increases by roughly 6 to 14 percentage points between ages 60 and 65. Steep Earnings Test for SS beneficiaries between ages 62 and 65 and, declining health, combined with wage scarring effects of unemployment spells make individuals' labor supply particularly sensitive to shocks at these ages. As a result, in the model without unemployment shocks, individuals stay in the labor market longer and claim SS benefits closer to their normal retirement age. This is demonstrated by the fact that claiming before the normal retirement age (65) in the entire population goes down by 1.9 p.p.

A closer look reveals significant heterogeneity across households, in response to the absence of these shocks, due to the presence of countervailing mechanisms. The first row of Table 9 shows that the largest response comes from singles. We find that early claiming rates go down by roughly 9 (non-college) and 17 p.p. (college) for singles. This is not surprising given that the response of this group is purely driven by budgetary considerations. Large increases in both private and Social Security wealth for this group (refer to Appendix Figures D.12 and D.13) improve their ability to delay SS claims and enjoy higher future SS benefits. While this is certainly the case for the married group as well, there are other mechanisms that dominate the actions of this group. Both spousal and survivors benefits interact in important ways with the impact of these unemployment shocks. For instance, higher Social Security wealth heightens the incentives to claim early due to the presence of spousal benefits as discussed in the previous section. At the same time, the increase in life-cycle wealth reduces the relative importance of survivors benefits in terminal bequest utility, which may initiate early claims. We see that these channels certainly dominate; switching off unemployment shocks results in only small increases in early claiming for this group. However, when we analyze the effect of unemployment shocks in a world without any spousal and survivors benefits for the married group (both benchmark and counterfactual worlds have no marital SS benefits), we find the effects on early claiming are indeed negative (second row of Table 9).

Table 9: No Unemployment Shocks
Changes in Early SS Claiming Behavior

Experiment	All	Singles		Married	
		Non-College	College	Non-College	College
Unemployment	-1.9	-9.4	-16.5	5.1	2.1
No marital SS Benefits					
Both	-21.2	-9.4	-16.5	-5.1	-36.5
Spousal	-11.7	-9.4	-16.5	1.5	-18.3
Survivor	-2.6	-9.4	-16.5	-2.2	4.4

Notes: For each experiment, percentage point change in early claiming (claims before age 65) as compared to benchmark is reported for each sub-group as well as all individuals in the simulated sample.

Health Shocks: We next conduct an experiment where we switch off the effect of bad health on time endowment and spousal income for all individuals in the model.[54] Changes in life expectancy have a distinct effect on early claiming. So, in order to disentangle that channel from effects operating through the budget constraint, we keep life expectancy the same as benchmark. 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 the third row of Table 7, early claiming rates go down by only 0.7 p.p. where most of this effect now comes from the married group. Note that health shocks are fundamentally different from unemployment shocks in the sense that both the intensity and the likelihood of these shocks go up significantly over the life cycle. As a result, these shocks in the benchmark model generate significant precautionary savings over the life cycle. This is evident from Appendix Figure D.18, which shows that life-cycle evolution of wealth is much slower and lower for all groups, particularly singles.

Married individuals respond to these shocks by working longer and delaying their benefit claims as compared to the benchmark (refer to Appendix Figures D.15 and D.19 for the detailed impacts on labor supply and claiming). As earlier, we do find modest interactions with the spousal and survivors benefits. The response to these shocks for the married group is even stronger (at least for the non-college group) in the absence of these marital SS benefits (refer to the second

[54] 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).

row of appendix table D.5). However, with much smaller changes in both wealth and AIME, these effects are not large enough to wash away the main impact of health shocks–delaying SS claims by working longer in the labor market.

The singles group shows an interesting behavioral response. There is an overall tendency to delay benefit claims. For instance, the first two panels in Appendix Figure D.19 show at there is an important shift away from age 62 claims for both college and non-college singles. However, a small fraction of singles also shift their claiming from age 65 to between ages 63 and 64. This is the reason why overall early claims for singles go up by 1 to 3 p.p. after we switch off the health shocks in the model. The reason is evident by examining the labor supply response close to age 65 for this group. Note that the earnings test threshold is more generous starting at age 65. As a result some individuals (especially those with relatively low earnings) might find it optimal to quit work, claim just before their normal retirement age, and re-enter the labor market starting at age 65. In the benchmark, we observe this phenomenon only for the non-college singles. This is due to the steep labor market participation cost of bad health for the college group at these ages. However, once we remove these costs of bad health on labor supply, we find that this phenomenon is exacerbated for singles across both education groups. Some of these individuals now choose to quit the labor market, claim just before age 65 and re-enter later (note that age 65 labor supply now exhibits a much stronger kink for singles–see in Appendix Figure D.15).

5.4.3 No Misbeliefs

No Mortality Misbeliefs: Individuals may underestimate or overestimate their chances of survival, which can have a direct impact on their claiming behavior. 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 go down by 0.6 p.p.). However, a closer look at different subgroups reveals that this is because the mortality bias goes in different directions for different subgroups. Our empirical estimates suggest that all except the married college graduates are optimistic to varying degrees about their old-age survival chances (college singles have almost zero bias). As a result, when we give the true survival probabilities, we find increases in early claiming by the optimistic group and declines by the pessimistic group (married college graduates).

Appendix Figures D.20 to D.22 reveal that correcting the life-span bias does not result in any significant changes in the life-cycle profiles of labor supply or wealth. The only noticeable difference is in the wealth evolution of non-college singles. As discussed earlier, this group has the strongest bequest motive. As a result of a somewhat reduced life span, they care relatively more about the terminal bequests. Hence they modestly increase their asset holding towards the later part of their life cycle. Appendix Figure D.23 highlights further, interesting differences in overall claiming behavior of these different sub-groups. The biggest changes are for the most optimistic (non-college singles) and pessimistic groups (married college graduates). However, for the former group, the claiming at age 62 goes up significantly, while for the latter, claiming past 65 (delayed claims) experience the biggest increase.

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. Figure D.24 shows that this does not have any impact on the labor supply margin of any of the education-marital groups. In fact, other life-cycle profiles such as wealth, hours worked, and the evolution of Social Security wealth remain almost identical to the benchmark (see Appendix Figures D.25 and D.26). This shows that the informed and uninformed individuals behave in the same way regarding their labor supply and savings decisions.

As expected, the claiming behavior is significantly different. There is a 3.2 percentage points decline in overall early claims where most of this change is driven by married individuals. However, a closer look at the overall claiming distribution change reveals some interesting insights (refer to Appendix Figure D.27). For the non-married group, the biggest shift happens from age 62 claiming to a year or two later. So even though their early claiming rates do not change much, misinformation does impact their overall claiming behavior. Given all else, even without the program misbeliefs, it is not economically meaningful for them to further delay claims to the normal retirement age or beyond. As for the married group, we find that the entire claiming distribution shifts to the right. Specifically, age 62 claims go down and some of those claims shift all the way past age 65. These are individuals who should have delayed their claims and program misinformation is the only way to rationalize their early claiming behavior in the benchmark.

5.4.4 No Bequest Motive

We next explore the importance of bequest motive in generating early Social Security claiming. We do this by setting the end-of-life flow utility to zero for all individuals. Note that for married individuals, 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 may want to maximize the amount of their bequeathable wealth by applying early and accumulating the cash flows over a longer time. This channel may be particularly important for those who are facing higher longevity risk.

Table 7 shows that this is indeed the case. Removal of bequest motive results in a roughly 11 p.p reduction in overall early claims. At the same time, there is a roughly 19 p.p increase in delayed claims. We also find significant heterogeneity in changes in the claiming behavior, in response to this experiment, across different marital and education groups. While the married non-college group experiences the smallest decrease (3.2 p.p.) in early claims, the college singles observe a drastic 27.2 p.p reduction in their early claims. At the same time, almost the entire increase in delayed claims is attributable to the married college educated group.

In order to understand such a large variation in response to these bequest motives, it is important to recall the salient differences in estimated preferences for these groups. Recall that the estimated preference heterogeneity implies that non-college graduates in general have the strongest bequest motive. This is evident in Appendix D.30, which shows that the wealth evolution in a world without bequest motives is drastically different for non-college groups in either marital status. In the absence of any terminal bequest utility (especially for singles), these households completely draw down their wealth close to retirement years. Additionally, our preferences imply a declining life-cycle consumption path for the non-college singles group (the group with the lowest discount factor). This group also has the lowest weight on consumption relative to leisure compared to other permanent groups in our model. Together these factors imply that without any terminal bequest utility, the single non-college households shift consumption and leisure early on in their life cycle (refer to first panels in Appendix Figures D.30 and D.32). They consequently enter retirement with close to zero levels of wealth, which further initiates benefit claiming as soon as they become eligible. So, even though the absence of bequest motive implies less early claiming due to the aforementioned channel, for this group, the countervailing channel due to preferences imply more early claiming. The net decline in early claiming, therefore, is the lowest for this group. The college singles, by contrast, with a less intense bequest motive, do not fully draw down their wealth and thus represent the biggest declines in early claims. Note that for singles in general, the bequest motive does not change incentives to delay claims past age 65 (see first two panels of Appendix Figure D.33).

Married individuals in general have the highest discount rate implying an increasing life-cycle profile of consumption. As a result, these households prefer delaying benefit claim in light of higher future benefits. This indicates that the bequest motive in general has a relatively lesser role to play in governing their claiming behavior as compared to singles.

5.5 Policy Experiments

Both our benchmark model and the data suggest there are high levels of early claiming across both college and non-college workers, the two groups with very different life expectancy in retirement. The counterfactual experiments in the preceding section indicate that claiming frictions can fully account for the early claiming rates of the former group. At the same time, marital benefits can also account for the early claiming rates of the non-college married group.

What is not clear from the above experiments is how elastic households' behavior is to changes in policy. Does this degree of responsiveness to policy also depend on the household's relative position in the socioeconomic spectrum? What is the role of claiming frictions in determining this? In order to answer these questions, we analyze the impact of changes in Social Security normal retirement age on claiming behavior – both in the benchmark model and in a scenario without any claiming frictions. We raise the normal retirement age of claiming all the way to age 70 (we call this policy NRA 70 henceforth). This means that we wipe away any delayed retirement credit and any claiming before age 70 entails a penalty (refer to Appendix Figure D.34 for details on the changes in benefit structure).[55]

Table 10 shows the result of this policy change on the claiming distribution of the overall simulated population as well as different permanent groups in the model. Table 11 shows the changes in the present discounted value of lifetime benefits received with NRA 70 policy change. Row 1 and 3 show the change in the PV of lifetime benefits in the benchmark model and in a scenario without claiming frictions, respectively. Rows 2 and 4 of Table 11 further show these losses in both scenarios if we kept the claiming behavior fixed at their respective baseline levels. These experiments provide several interesting insights which we summarize below:

Role of frictions: In the benchmark model, even an extreme policy change such as NRA 70 results in little change in claiming behavior; overall claiming rates before age 65 go down only by a tenth. This is because the largest changes (relative to benchmark levels) are coming from the married group; the behavior of the singles remains largely unchanged. A majority of singles continue claiming benefits before the age of 65, with some shifts in claiming to age 65 and almost no changes after age 65. In comparison, the married group is more responsive, with important shifts in behavior after age 65. Claiming past age 65 goes up by 14 and 44 p.p. for the non-college and college married households respectively.

However, when we conduct the same policy experiment in an environment with no claiming frictions, 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. The role of frictions in curbing households' responsiveness to policy is further illustrated in Table 11. With NRA 70, the losses in PV of lifetime benefits received are significantly larger in the benchmark model, than the scenario with no frictions (compare rows 1 and 3 of Table 11).

These experiments indicate that the average age of claiming under NRA 70 policy is substan-

[55]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.

Table 10: NRA 70: Changes in Social Security Claiming Behavior

Experiment	All	Singles		Married	
		Non-College	College	Non-College	College
Early Claiming Rates					
Benchmark	64.3	93.8	95.3	57.8	45.8
p.p change	-8.4	-9.6	-12.1	-10.4	-5.5
No frictions baseline	14.2	79.1	2.6	0.0	0.0
p.p. change	-11.7	-65.2	-2.1	0.0	-0.0
Age 65 Claiming Rates					
Benchmark	22.3	6.2	4.7	8.5	42.3
p.p change	-14.6	9.4	11.7	-3.4	-39.1
No frictions baseline	73.5	20.9	97.4	49.1	100.0
p.p. change	-61.8	38.6	-88.2	-49.1	-100.0
After 65 Claiming Rates					
Benchmark	13.4	0.0	0.0	33.7	12.0
p.p change	22.9	0.2	0.4	13.8	44.6
No frictions baseline	12.4	-0.0	0.0	50.9	0.0
p.p. change	73.4	26.6	90.2	49.1	100.0

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).

tially different depending on the baseline: age 65 in the benchmark versus age 67 in the friction-less scenario. Additionally, while the claiming frictions affect all household's responsiveness to policy, the gaps in accurately predicting claiming ages are the largest for college-graduate singles. The average claiming age for this group due to NRA 70 policy goes from 63 to 68 if the underlying baseline assumption goes from benchmark to the no frictions case. This difference in predicted average claiming age has direct implications for the government budget. Aggregate lifetime benefit payouts will be 40 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. Since households increase their claiming ages more in response to policy in the friction-less model, these households receive relatively larger pensions (with smaller early claiming penalties) which lead to increased aggregate payouts.

Role of behavior: As discussed above, claiming frictions can be quite costly because they limit the ability of the households to mitigate losses in retirement benefits when there are policy changes. We find that this is particularly true for singles. Comparing the first two rows of Table 11 reveals that in the benchmark model, singles are mostly unable to mitigate the losses through changes in behavior. The NRA 70 policy's changes in PV of lifetime SS benefits remain similar to the case when we hold their labor supply and claiming behavior fixed at the benchmark levels. This is not the case in the scenario without claiming frictions. We find that the singles group is relatively better poised to mitigate losses in their lifetime retirement benefits in the absence of claiming frictions.

Table 11: Raising the Normal Retirement Age to 70
Changes in PV of Lifetime SS Benefits

	Singles		Married	
	Non-College	College	Non-College	College
Benchmark	-25.95	-26.20	-20.70	-22.57
Fixed behavior	-28.46	-27.91	-26.99	-27.67
No frictions baseline	-19.70	-17.43	-10.95	-12.14
Fixed behavior	-28.50	-25.25	-24.70	-25.20

Notes: Percentage changes in present discounted value of lifetime Social Security benefits (from the time of claiming till the end of life) is reported between the NRA 70 policy and the respective baseline (benchmark vs. no frictions scenario). Group specific life expectancy is used to in all PV calculations. Fixed behavior refers to a scenario when we change policy but keep all behavior (claiming and labor supply) fixed at the respective baseline level.

6 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. In this work, we have provided answers to this puzzle within the scope of an augmented, albeit standard, forward-looking life-cycle framework, in contrast to prior literature relying on behavioral channels. Toward this goal, we have identified four sets of *claiming frictions* — SS marital rules, precautionary motives due to budgetary shocks, misbeliefs about the SS program and mortality, and bequest motives—which could potentially limit the ability of the households to delay benefit claim. To quantify the role and potential costs of these frictions, 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, by some of these sources of heterogeneities and claiming frictions.

Counterfactual experiments using the model highlights the important role played by claiming frictions. Together these frictions are found to account for 78 percent of the early claiming rates in the model and practically all early claiming for the college and the married groups. By quantifying the important role played by 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 frictions, in terms of lifetime value of benefits received, by curbing the household's ability to respond effectively to the policy changes. These frictions 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 40 percent higher if the frictions 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.

References

Attanasio, O., Kitao, S., and Violante, G. L. (2007). Global demographic trends and social security reform. *Journal of monetary Economics*, 54(1):144–198.

Bairoliya, N. (2019). Pension plan heterogeneity and retirement behavior. *European Economic Review*, 116:28–59.

Bairoliya, N. and Miller, R. (2021). Informal care shocks and social security claiming behavior. *Available at SSRN 3951576*.

Becker, G. S. and Mulligan, C. B. (1997). The endogenous determination of time preference. *Quarterly Journal of Economics*, 112(3):729–758.

Benitez-Silva, H., Dwyer, D. S., Heiland, F., and Sanderson, W. C. (2009). Retirement and social security reform expectations: A solution to the new early retirement puzzle. *mimeo*.

Benitez-Silva, H. and Yin, N. (2009). An empirical study of the effects of social security reforms on benefit claiming behavior and receipt using public-use administrative microdata. *Social Security Bulletin*, 69(3):77–95.

Borella, M., Nardi, M. D., and Yang, F. (2019). Are marriage-related taxes and social security benefits holding back female labor supply? *NBER Working Paper No. w26097*.

Brown, J. R., Kapteyn, A., and Mitchell, O. S. (2016). Framing and claiming: How information-framing affects expected social security claiming behavior. *Journal of Risk and Insurance*, 83(1):139–162.

Casanova, M. (2010). Happy together: A structural model of couples' joint retirement choices. *Unpublished Manuscript, Department of Economics, UCLA, Los Angeles*.

Chan, S. and Huff Stevens, A. (1999). Employment and retirement following a late-career job loss. *American Economic Review*, 89(2).

Chan, S. and Huff Stevens, A. (2001). Job loss and the employment patterns of older workers. *Journal of Labor Economics*, 19(2):484–521.

Chan, S. and Huff Stevens, A. (2004). How does job loss affect the timing of retirement. *Contributions to Economic Analysis and Policy*, 3(1).

Coile, C., Diamond, P., Gruber, J., and Jousten, A. (2002). Delays in claiming social security benefits. *Journal of Public Economics*, 84:357–385.

Conesa, J. C. and Krueger, D. (1999). Social security reform with heterogeneous agents. *Review of Economic dynamics*, 2(4):757–795.

De Nardi, M. (2004). Wealth inequality and intergenerational links. *The Review of Economic Studies*, 71(3):743–768.

De Nardi, M., French, E., Jones, J. B., and McGee, R. (2021). Why do couples and singles save during retirement? Technical report, National Bureau of Economic Research.

De Nardi, M., Imrohoroğlu, S., and Sargent, T. J. (1999). Projected us demographics and social security. *Review of Economic dynamics*, 2(3):575–615.

De Nardi, M., Jones, J., and French, E. (2010). Why do the elderly save? *Journal of Political Economy*, 118(1):39–75.

Diamond, P. and Orszag, P. (2004). Saving social security: A balanced approach. Technical report, Brookings Institute.

Doepke, M. and Zilibotti, F. (2008). Occupational choice and the spirit of capitalism. *The Quarterly Journal of Economics*, 123(2):747–793.

Dushi, I. and Webb, A. (2004). Household annuitization decisions: Simulations and empirical analyses. *Journal of Pension Economics & Finance*, 3(2):109–143.

Fagereng, A., Guiso, L., Malacrino, D., and Pistaferri, L. (2018). Heterogeneity and persistence in returns to wealth. IMF Working Paper WP/18/171, International Monetary Fund.

Fan, X., Seshadri, A., and Taber, C. R. (2022). Estimation of a life-cycle model with human capital, labor supply and retirement. Technical report, National Bureau of Economic Research.

Finkelstein, A. and Poterba, J. (2004). Adverse selection in insurance markets: Policyholder evidence from the uk annuity market. *Journal of political economy*, 112(1):183–208.

French, E. (2005). The effects of health, wealth, and wages on labor supply and retirement behavior. *The Review of Economic Studies*, 72(2):395–427.

French, E. and Jones, J. B. (2011). The effects of health insurance and self-insurance on retirement behavior. *Econometrica*, 79(3):693–732.

Fuster, L., İmrohoroğlu, A., and İmrohoroğlu, S. (2003). A welfare analysis of social security in a dynastic framework. *International Economic Review*, 44(4):1247–1274.

Gourinchas, P.-O. and Parker, J. A. (2002). Consumption over the life cycle. *Econometrica*, 70(1):47–89.

Greenwald, M., Kapteyn, A., Mitchell, O. S., and Schneider, L. (2010). What do people know about social security? Technical report, RAND Report to the FLC/SSA.

Gruber, J. and Wise, D. (2005). Social security programs and retirement around the world: Fiscal implications, introduction and summary. Technical report, National Bureau of Economic Research.

Gustman, A. and Steinmeier, T. L. (2005a). The social security early retirement age in a structural model of retirement and wealth. *Journal of Public Economics*, 89(2-3):441–63.

Gustman, A. and Steinmeier, T. L. (2015). Effects of social security policies on benefit claiming, retirement and saving. *Journal of Public Economics*, 129(C):51–62.

Gustman, A. L. and Steinmeier, T. L. (2005b). The social security early entitlement age in a structural model of retirement and wealth. *Journal of public Economics*, 89(2):441–463.

Gustman, A. L. and Steinmeier, T. L. (2012). Policy effects in hyperbolic vs. exponential models of consumption and retirement. *Journal of Public Economics*, 96(5-6):465–473.

Heiland, F. and Yin, N. (2014). Have we finally achieved actuarial fairness of social security retirement benefits and will it last?

Hong, J. H. and Ríos-Rull, J.-V. (2007). Social security, life insurance and annuities for families. *Journal of Monetary Economics*, 54(1):118–140.

Hosseini, R. (2015). Adverse selection in the annuity market and the role for social security. *Journal of Political Economy*, 123(4):941–984.

Hosseini, R., Kopecky, K. A., and Zhao, K. (2021). How important is health inequality for lifetime earnings inequality?

Hosseini, R., Kopecky, K. A., and Zhao, K. (2022). The evolution of health over the life cycle. *Review of Economic Dynamics*, 45:237–263.

Hubbard, R. G., Skinner, J., and Zeldes, S. P. (1995). Precautionary saving and social insurance. Technical report, National Bureau of Economic Research.

Hubener, A., Maurer, R., and Mitchell, O. S. (2016). How family status and social security claiming options shape optimal life cycle portfolios. *The Review of Financial Studies*, 29(4):937–978.

Huckfeldt, C. (2016). Understanding the scarring effect of recessions. *Working Paper*.

Huff Stevens, A. (1997). Persistent effects of job displacement: The importance of multiple job losses. *Journal of Labor Economics*, 15:165–188.

Huggett, M. and Parra, J. C. (2010). How well does the us social insurance system provide social insurance? *Journal of Political Economy*, 118(1):76–112.

Hurd, M. D., Smith, J. P., and Zissimopoulos, J. M. (2004). The effects of subjective survival on retirement and social security claiming. *Journal of Applied Econometrics*, 19:761–775.

İmrohoroglu, A., Imrohoroglu, S., and Joines, D. H. (1995). A life cycle analysis of social security. *Economic theory*, 6(1):83–114.

Imrohoroglu, S. and Kitao, S. (2012). Social security reforms: Benefit claiming, labor force participation, and long-run sustainability. *American Economic Journal: Macroeconomics*, 4(3):96–127.

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). Earnings losses of displaced workers. *The American Economic Review*, 83:685–709.

Jones, J. B. and Li, Y. (2020). Social security reform with heterogeneous mortality. *FRB Richmond Working Paper No. 20-09*.

Kotlikoff, L. J., Smetters, K., and Walliser, J. (2007). Mitigating america's demographic dilemma by pre-funding social security. *Journal of monetary Economics*, 54(2):247–266.

Krueger, D. and Kubler, F. (2006). Pareto-improving social security reform when financial markets are incomplete!? *American Economic Review*, 96(3):737–755.

Liebman, J. B. and Luttmer, E. F. (2009). The perceptoin of social security incentives for labor supply and retirement: The median voter knows more than you think.

Liebman, J. B. and Luttmer, E. F. (2011). Would people behave differently if they better understood social security? evidence from a field experiment.

Lockwood, L. M. (2012). Bequest motives and the annuity puzzle. *Review of economic dynamics*, 15(2):226–243.

Mastrobuoni, G. (2010). The role of information for retirement behavior: Evidence based on the stepwise introduction of the social security statement.

Maurer, R. and Mitchell, O. S. (2021). Older peoples' willingness to delay social security claiming. *Journal of Pension Economics and Finance*, 20:410–425.

Maurer, R., Mitchell, O. S., Rogalla, R., and Schimetschek, T. (2021). Optimal social security claiming behavior under lump sum incentives: Theory and evidence. *The Journal of Risk and Insurance*, 88(1):5–27.

Meyer, W. and Reichenstein, W. (2010). Social security: When to start benefits and how to minimize longevity risk. *Journal of Financial Planning*, 23(3):49–59.

Miller, R. and Bairoliya, N. (2021). Health, longevity, and welfare inequality of older americans. *The Review of Economics and Statistics*, pages 1–45.

O'Dea, C. and Sturrock, D. (2018). Subjective expectations of survival and economic behaviour. Technical report, IFS Working Papers.

Pashchenko, S. and Porapakkarm, P. (2018). Accounting for social security claiming behavior. *Working Paper*.

Reznik, G. L., Shoffner, D., and Weaver, D. A. (2005). Coping with the demographic challenge: Fewer children and living longer. *Soc. Sec. Bull.*, 66:37.

Rust, J. and Phelan, C. (1997). How social security and medicare affect retirement behavior in a world of incomplete markets. *Econometrica: Journal of the Econometric Society*, pages 781–831.

Scholz, J. K. and Seshadri, A. (2011). Health and wealth in a life cycle model. *Michigan Retirement Research Center Research Paper*, (2010-224).

Shoven, J. B. and Slavov, S. N. (2014a). Does if pay to delay social security? *Journal of Pension Economics and Finance*, 13(2):121–144.

Shoven, J. B. and Slavov, S. N. (2014b). Recent changes in the gains from delaying social security. *Journal of Pension Economics and Finance*, 27(3):32–41.

Song, J. G. and Manchester, J. (2007). New evidence on earnings and benefit claims following changes in the retirement earnings test in 2000. *Journal of Public Economics*, 91:669–700.

Sun, W. and Webb, A. (2009). How much do household really lose by claiming social security at age 62? *CRR Working Paper*.

Sun, W. and Webb, A. (2011). How do subjective mortality beliefs affect the value of social security and the optimal claiming age? *CRR Working Paper 2011-22*.

Turra, C. M. and Mitchell, O. S. (2007). The impact of health status and out-of-pocket medical expenditures on annuity valuation.

Van der Klaauw, W. and Wolpin, K. I. (2008). Social security and the retirement and savings behavior of low-income households. *Journal of Econometrics*, 145(1):21–42.

Venti, S. and Wise, D. A. (2014). The long reach of education: Early retirement. *NBER Working Paper No. 20740*.

Yu, Z. (2022). Why are older men working more? the role of social security. Technical report, mimeo.

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

Because many workers choose early benefit claims in spite of lower payments, we run the following regression to understand how claiming behavior varies:

$$Pr[i \text{ claims before NRA}] = x_i'\beta + \sum_{k=-3}^{0} \delta_k I_{ik}^p + \gamma M_i + \rho B_i + \mu M_i * B_i + \varepsilon_i \tag{18}$$

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.[56] 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.[57] 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.[58]

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 definitey leaving a bequest is he has a 100 percent chance of leaving \$10,000 or \$100,000.[59]

[56] 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

[57] 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.

[58] More details on data and sample selection are show in Appendix A

[59] 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.

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 18). However, there are some differences to be noted. The regression run in UAS is shown in Equation 19.

$$Pr[i \text{ claims before NRA}] = x_i'\beta + \delta_0 I_{i0}^p + \gamma K_i + \varepsilon_i \tag{19}$$

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.

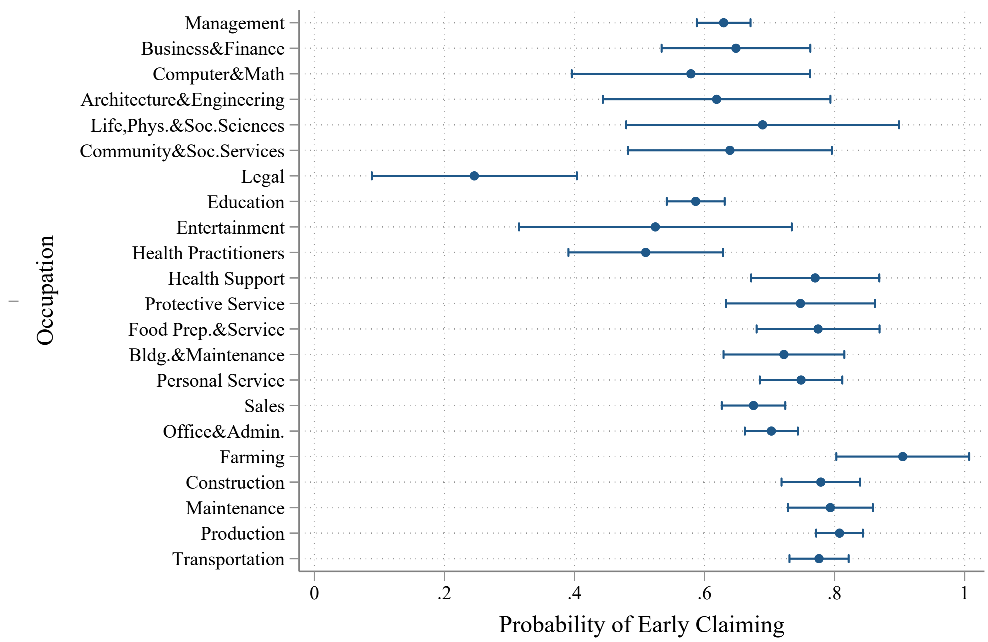
C Additional Details on Empirical Facts

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

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 18 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

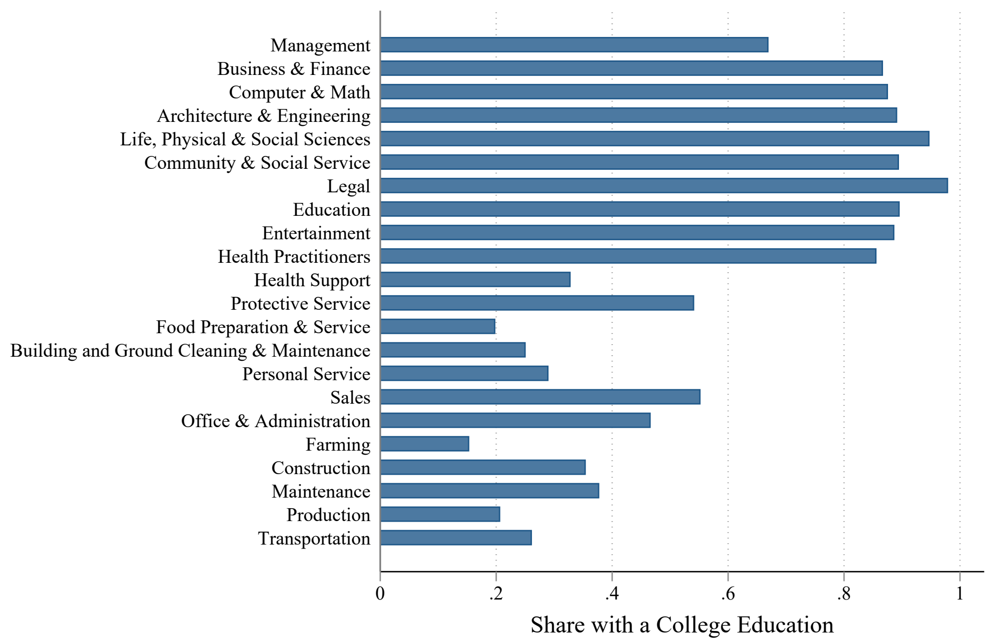


Figure C.3: Probability of Claiming at Age 62 by Work Status

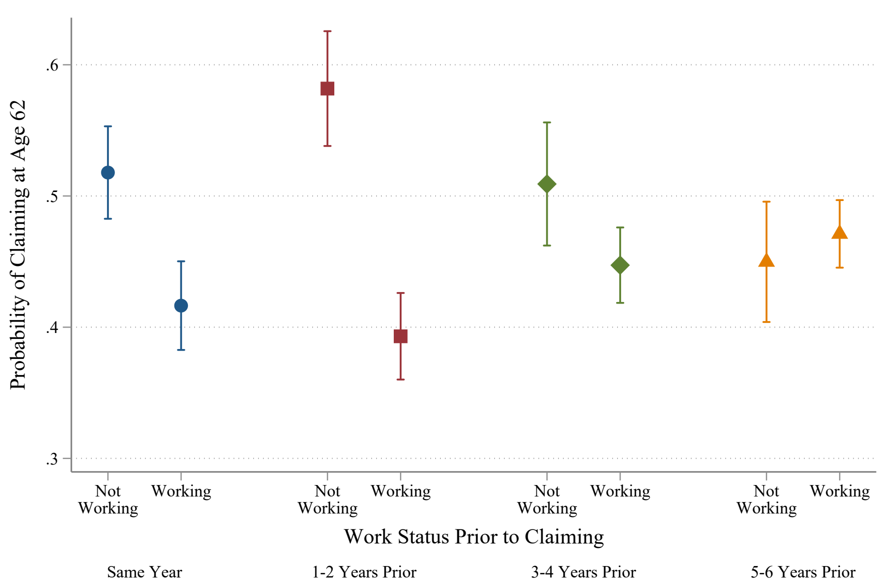
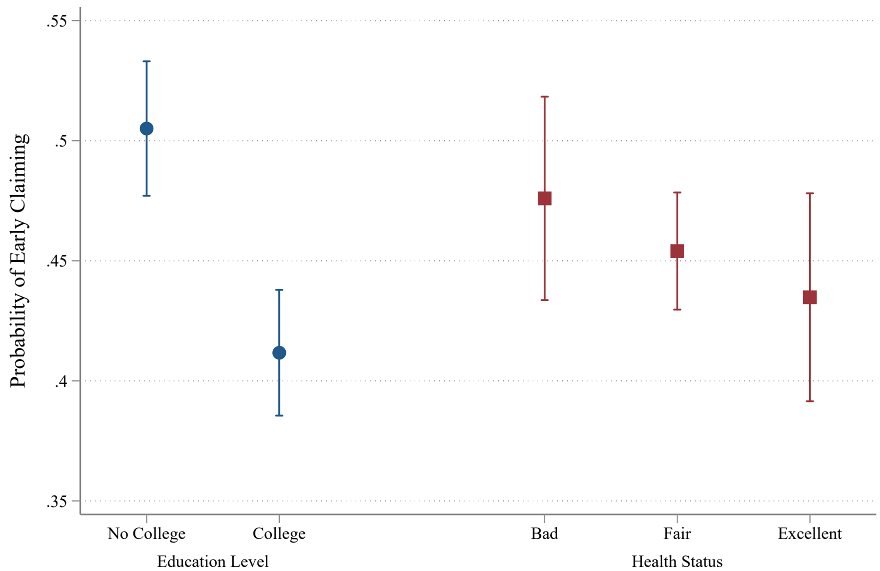


Figure C.4: Probability of Claiming at Age 62 by Education and Health



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.

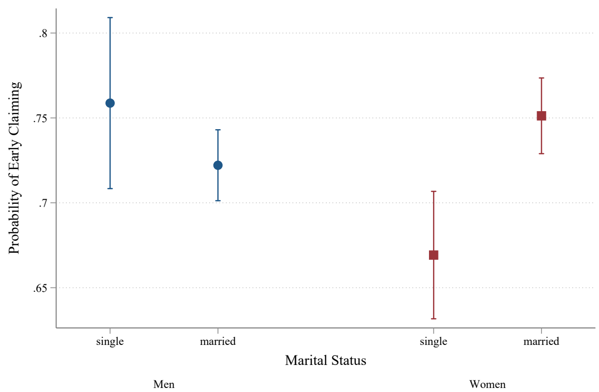
C.4 Misunderstanding of Social Security Rules

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

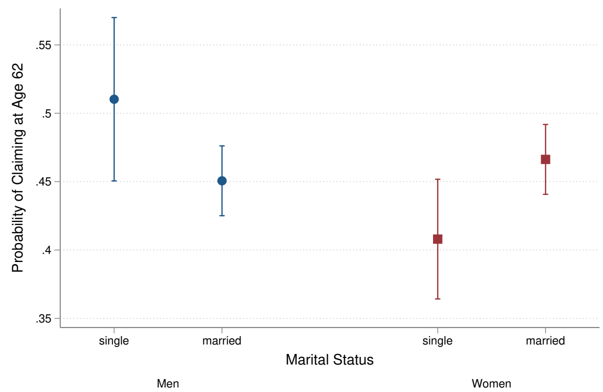


Table C.1: Program Misbelief by Age

	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

Table D.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.

D 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 D.1 shows the share of the population within each fixed type.

D.1 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. This scaling factor is calibrated so that the cumulative estimated probabilities of survival for each education marital status group match cumulative subjective probabilities of survival. This 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 D.2 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 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 D.2.

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 D.2. We assume that subjective survival is the same as estimated survival for all ages younger than 60. Probabilities from ages 60 to 99 are

Table D.2: 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

scaled to match the cumulative probabilities. The calibrated scale factors are shown in the final column of Table D.2.

D.2 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 across 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.

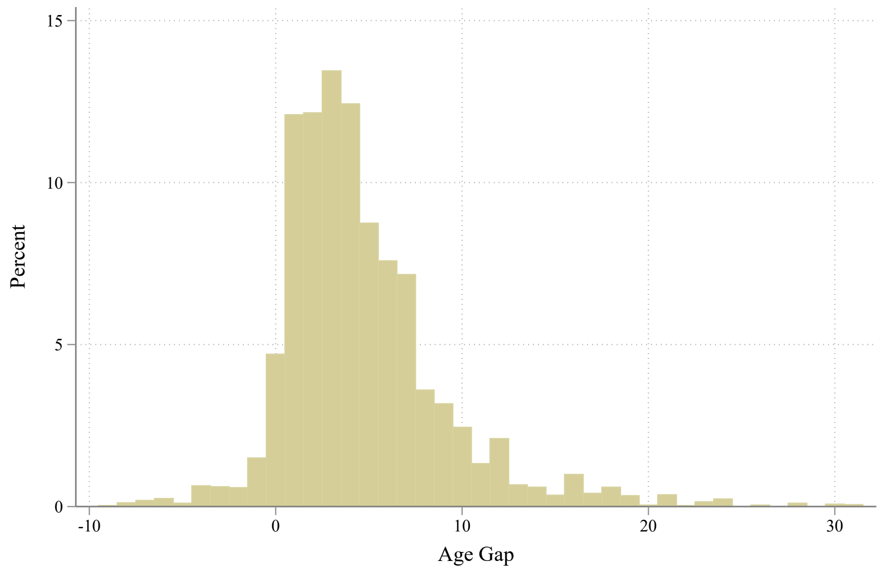
Figure D.2 shows the measure of children used in the model to estimate the household consumption equivalence scale. The figure shows how the number of children living in the household varies across the life cycle, and by education of the household head. This measure takes into account all children ages 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 slightly above 1.5 children.

D.3 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 D.1 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

Figure D.1: Distribution of Age Gap between Spouses



gaps (0 years, 1 year, 4 years, and 8 years) in the model. This allows us to capture that while 57 percent of 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.

D.4 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:

$$y^s_{it} = X'_{it}\beta + \varepsilon_{it} \tag{20}$$

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.

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

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

Figure D.2: Children by Age, Education and Marital Status

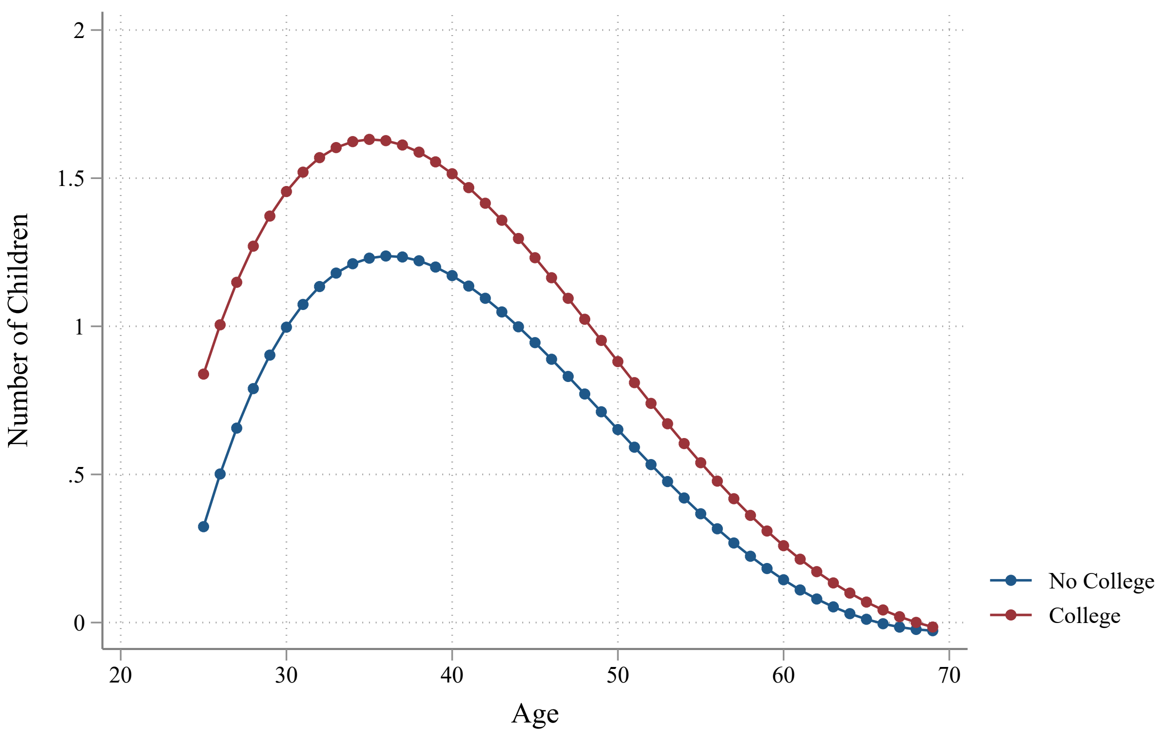


Table D.3: Coefficient of Spousal Income Regression

	Coefficient $\left(\hat{\beta}\right)$
age	-1.581 (1.369)
age*age	0.080 (0.057)
age*age*age	-0.001 (0.001)
age*age*age*age	0.000 (0.000)
college	17.071 (7.951)
college*age	-0.193 (0.092)
poor health	4.842 (23.379)
poor health*age	-0.024 (0.284)
labor income	0.098 (0.052)

levels and health status. The estimated coefficients are included in Table D.3.

D.5 Wages

Wage data is used in the calculation of the initial conditions as well as in the estimation of the wage profiles and shocks. Data on wage is taken from PSID. In PSID, the hourly wage is calculated as annual earnings divided the annual hours worked. In order to perform this estimation, we proceed in three steps described below.

Step 1 Impute potential wages for missing observations

For obvious reasons, we only observe wages for those workers who participate in the labor market. In order to deal with this we impute a potential wages, $\ln \hat{w}_{it}$, for those workers who have a missing wage.

First, we run the regression in Equation 22 to estimate how the wage varies based upon characteristics. The dependent variable is the natural log of the hourly wage for individual i in year t. γ_i is an individual fixed effect and X'_{it} is a set of explanatory variables including a fifth-order polynomial in age, education level, and self-reported health status. We estimate the regression including interaction terms between these explanatory variables.

$$\ln w_{it} = X_{it}'\beta + \gamma_i + \varepsilon_{it} \tag{22}$$

Using the results from Equation 22, we impute the wage for those workers with a missing observation. Specifically, the potential wage, $\ln \hat{w}_{it}$, is constructed as shown in Equation 23. The data observation for the wage is used for those workers with a wage. In this value is missing, the potential wage is imputed using the estimated parameter values from Equation 22.

$$\ln \hat{w}_{it} = \begin{cases} \ln w_{it} & \text{if } w_{it} \neq . \\ X_{it}'\hat{\beta} + \hat{\gamma}_i & \text{if } w_{it} = . \end{cases} \tag{23}$$

The advantage of the procedure above is allowing us to deal with issues of selection related to who participates in the labor market and receives a wage. However, this method also requires an assumption that the choice of participation is not driven by wage offers that are correlated with these explanatory variables. For example, we must assume that the participation decision of workers who report low self-reported health are not driven by being offered lower wages than their healthy peers of the same education level.

Given that we now have wage observations for our sample, the wage profiles can be estimated from the wage data.

Step 2 Estimate wage profiles $\omega^e(j)$, as a function of age and education

The wage profiles are estimated using the regression in Equation 24 where f_i is an individual-specific fixed effect and $g_e(t)$ is an education polynomial in age.

$$\ln \hat{w}_{it} = f_i + g_e(t) + u_{it} \tag{24}$$

Note that we do not control for birth-year cohort in this wage estimation. Because birth-year cohort is fixed throughout a worker's life, the impact of this, as well as other time invariant characteristics are absorbed into the fixed effect. The estimated profiles are shown in Figure D.9.

Step 3 Estimate the persistence, ρ, and variance, σ_ε^2, of the stochastic portion of the wage

The persistence and variance of the AR(1) process for the stochastic wage shocks are estimated by minimum distance estimation using the identity matrix as weighting matrix. We estimate these parameters as $\rho^w = 0.979$ and $\sigma_{\varepsilon^w} = 0.019$.

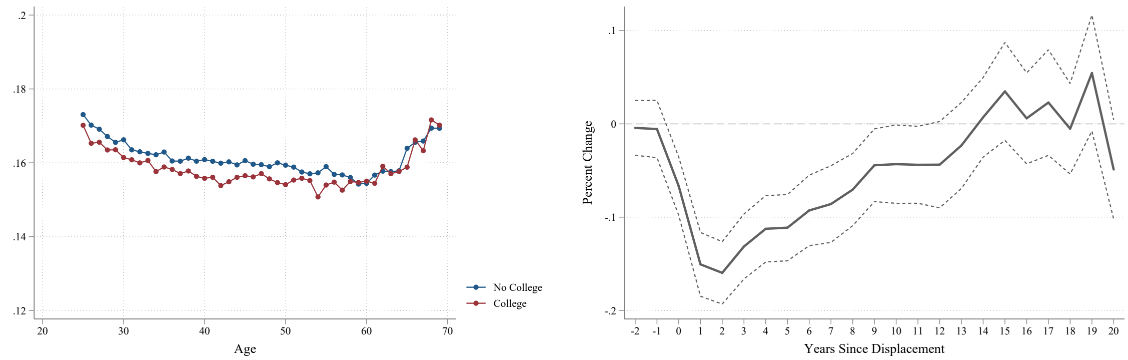
D.6 Employment Shocks and Wage Cost of Unemployment

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 D.3 shows the estimation of these parameters.

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)

Figure D.3: Unemployment Probabilities and Wage Impact of Unemployment

(a) Unemployment Probabilities (b) Wage Scarring



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 D.3a.

These separation rates are not only similar across education groups but also stable over the life cycle. 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 25.

$$y_{it} = x_{it}'\beta + \sum_{k\geq -2}^{20} \delta^k D_{it}^k + \alpha_i + \gamma_t + \varepsilon_{it} \tag{25}$$

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.

The results of this regression are shown in Figure D.3b. 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 $\xi(\lambda) = 0.86$.

Table D.4: Parameters of the Tax Function

	λ	ξ
No College		
single	1.35	0.041
married	1.32	0.043
College		
single	1.36	0.040
married	1.35	0.043

D.7 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 D.4.

D.8 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.

$$\ln\left(W_{it}+\delta\right) = x_{it}'\beta + \gamma_i + \varepsilon_{it} \tag{26}$$

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.[60] Additionally, γ_i is an individual fixed effect. This

[60]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,

$$\hat{W}_{it} = \begin{cases} W_{it} & \text{if } W_{it} \neq . \\ \exp\left(x'_{it}\hat{\beta} + \hat{\gamma}_i\right) - \delta & \text{if } W_{it} = . \end{cases} \tag{27}$$

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.

Figure D.4: Benchmark: Participation by Education and Marriage
Men born in 1931-1935

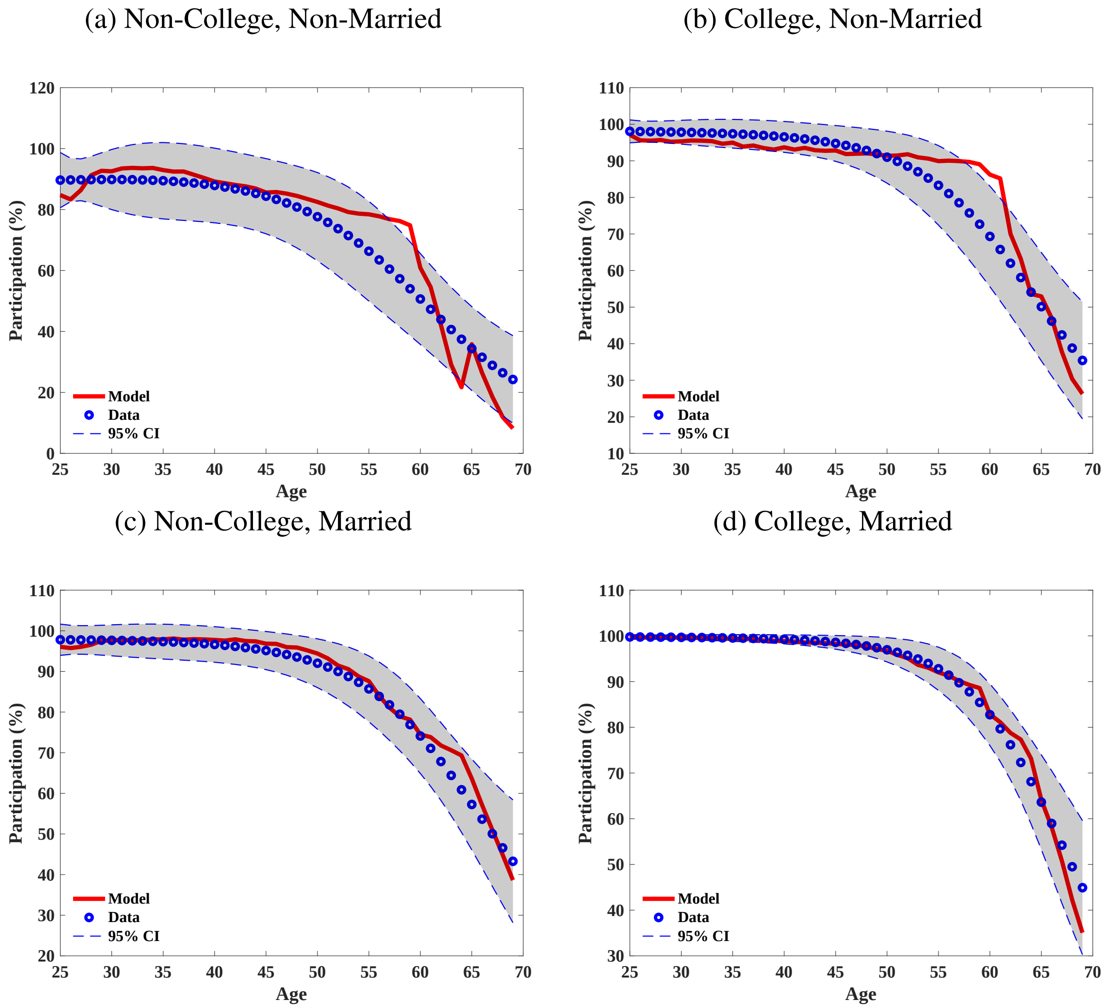
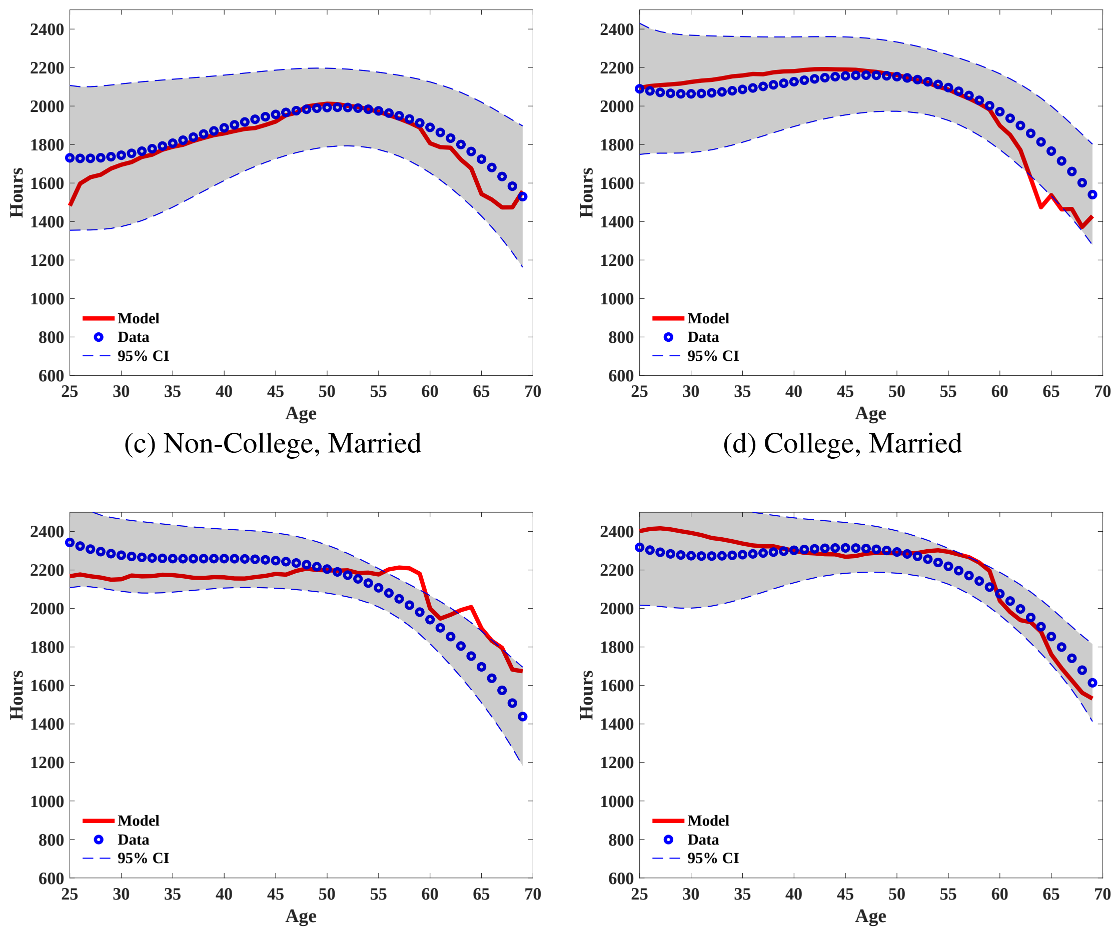


Figure D.5: Benchmark: Hours by Education and Marriage
Men born in 1931-1935



(a) Non-College, Non-Married
(b) College, Non-Married
(c) Non-College, Married
(d) College, Married

Table D.5: No Health Shocks
Changes in Early SS Claiming Behavior

Experiment	All	Singles		Married	
		Non-College	College	Non-College	College
Health	-0.7	2.8	1.0	-2.0	-1.9
No marital SS Benefits					
Both	-1.4	2.8	1.0	-7.7	-0.4
Spousal	-0.6	2.8	1.0	-4.6	-0.3
Survivor	-1.9	2.8	1.0	-7.7	-1.4

Notes: for each experiment, percentage point change in early claiming (claims before age 65) as compared to benchmark is reported for each sub-group as well as all individuals in the simulated sample.

Figure D.6: Benchmark: Wealth by Education and Marriage

(a) Non-College, Non-Married

(b) College, Non-Married

(c) Non-College, Married

(d) College, Married

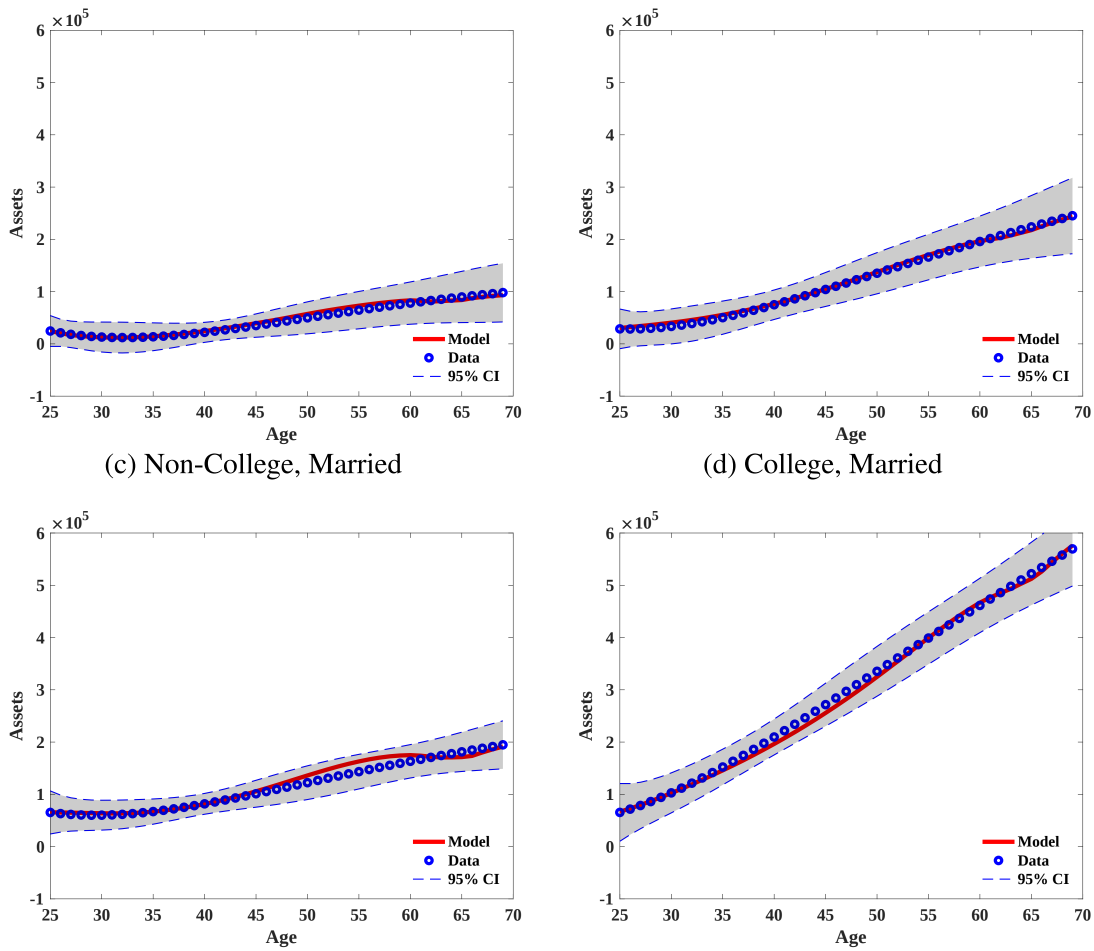
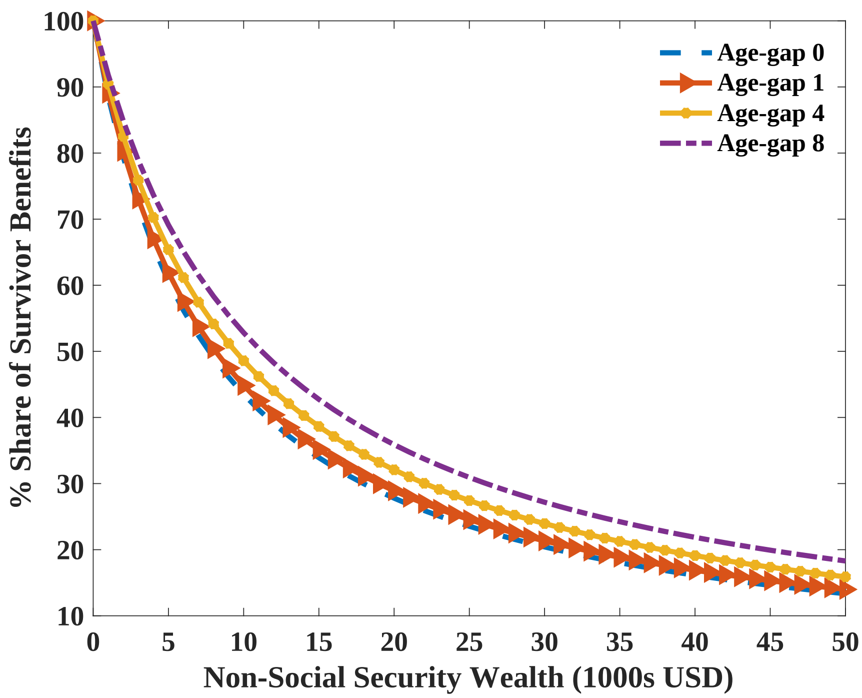


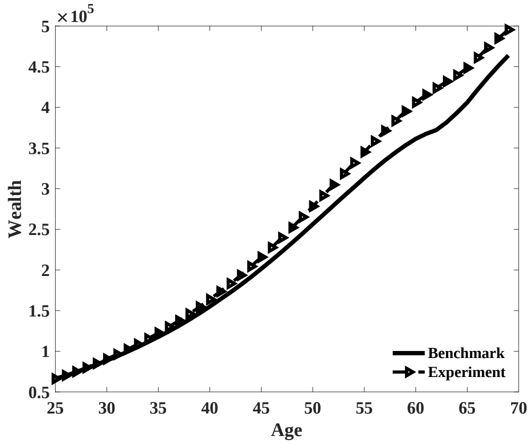
Figure D.7: survivors Benefits and Bequeathable Wealth



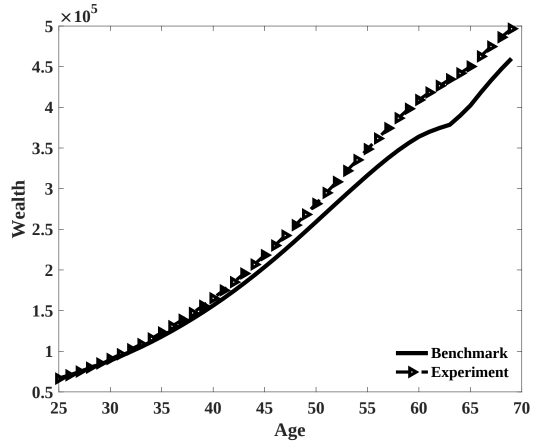
Notes: The figure plots the percentage share of survivors benefits in total bequeathable wealth for married households with different spousal age gaps. survivors benefits are computed as present value of Social Security benefits at the time of death. Spousal survival estimates of the non-college group and risk free rate of 3% is used in the present value calculations. Household head's death at age 80 and annual SS benefits of $1000 is used in all calculations.

Figure D.8: No Spousal Benefits: Asset by Age-Gap
Men born in 1931-1935

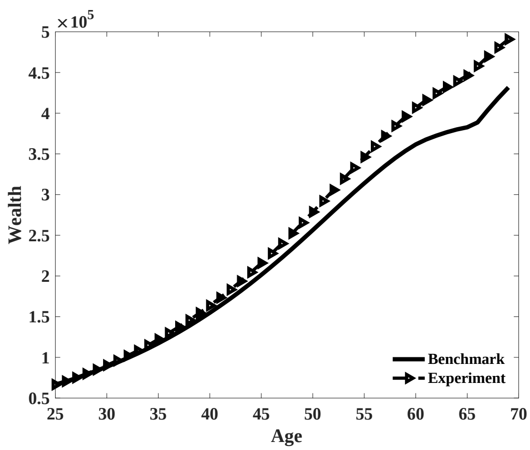
(a) 0 Age-Gap



(b) 1 Age-Gap



(c) 4 Age-Gap



(d) 8 Age-Gap

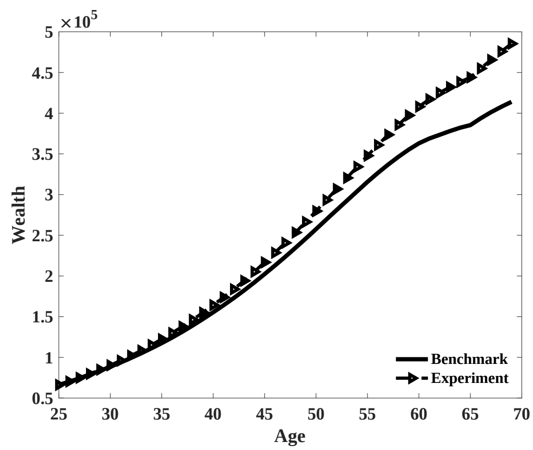
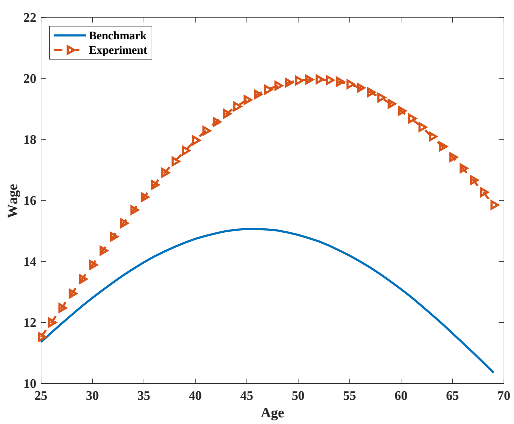


Figure D.9: Life-cycle Wage
Benchmark vs. No Unemployment Shocks Model

(a) Non-College



(b) College

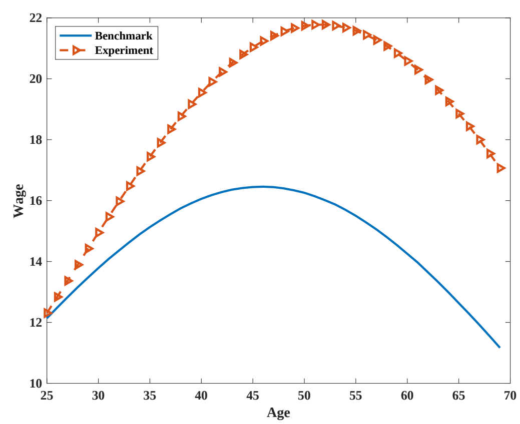
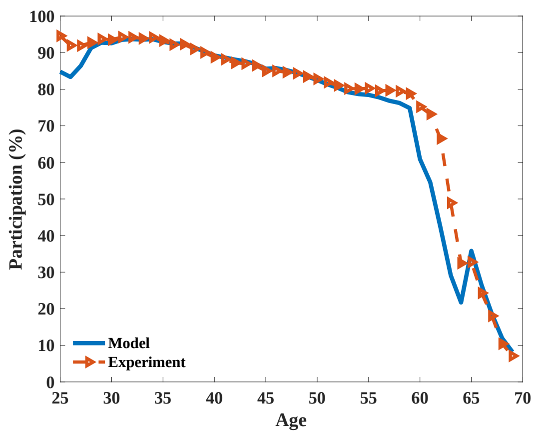
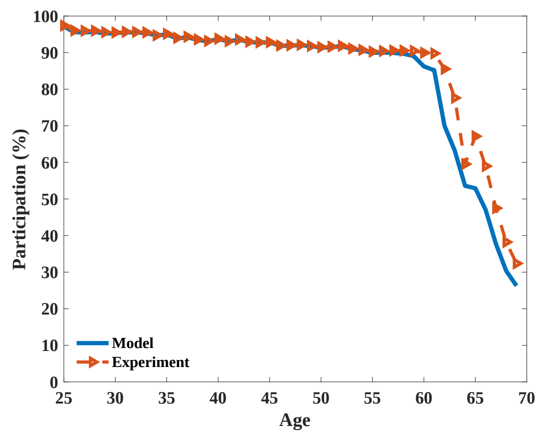


Figure D.10: No Unemployment Shocks: Participation by Education and Marriage
Men born in 1931-1935

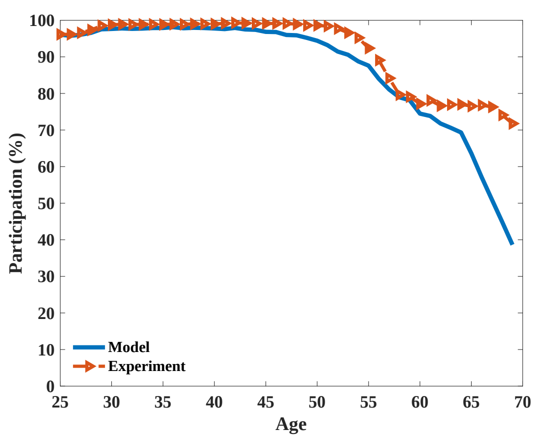
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

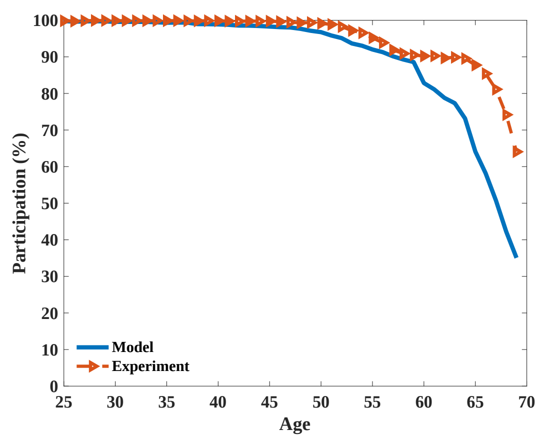
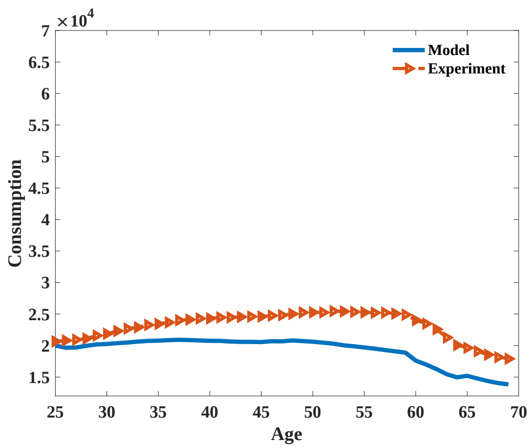
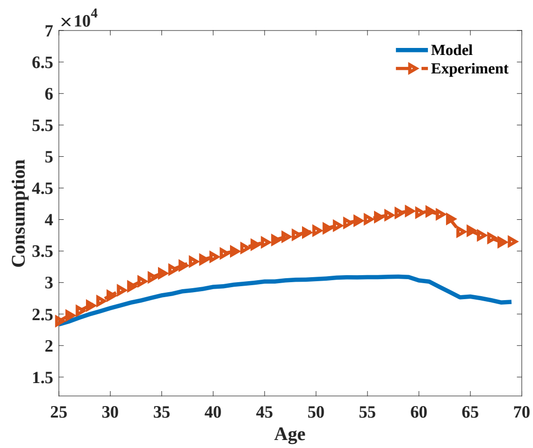


Figure D.11: No Unemployment Shocks: Consumption by Education and Marriage
Men born in 1931-1935

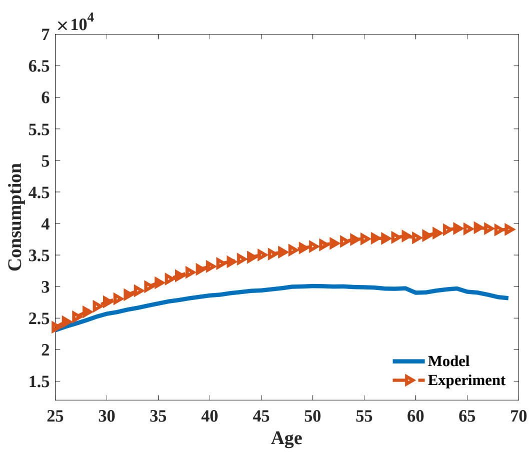
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

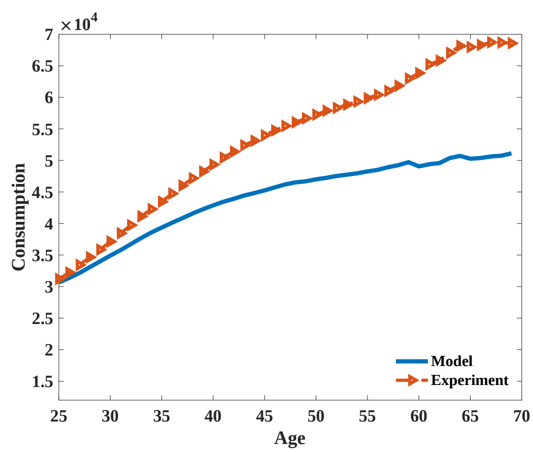
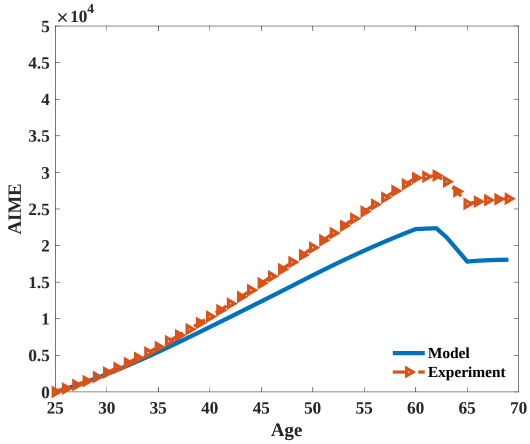
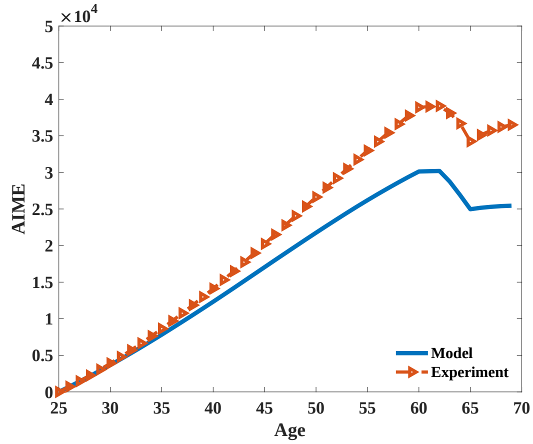


Figure D.12: No Unemployment Shocks: Social Security Wealth by Education and Marriage
Men born in 1931-1935

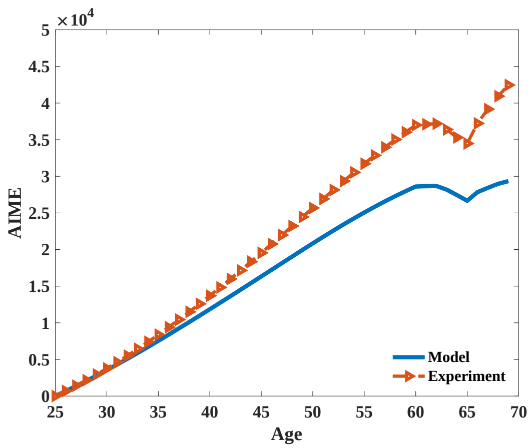
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

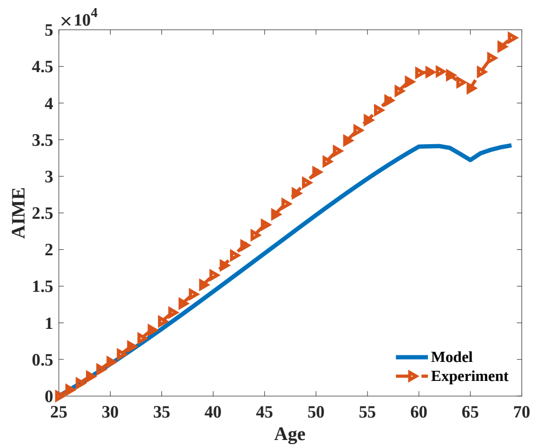
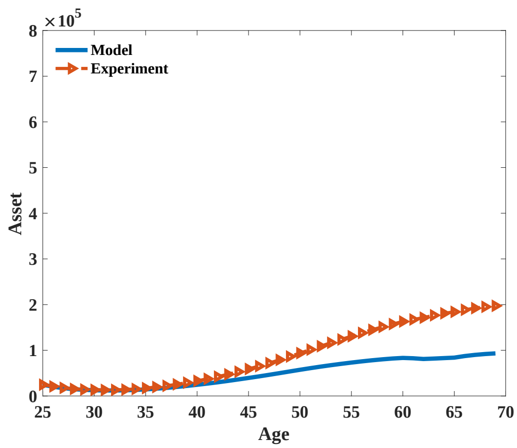
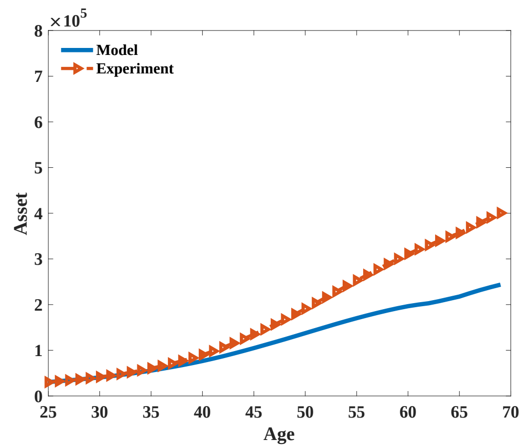


Figure D.13: No Unemployment Shocks: Wealth by Education and Marriage
Men born in 1931-1935

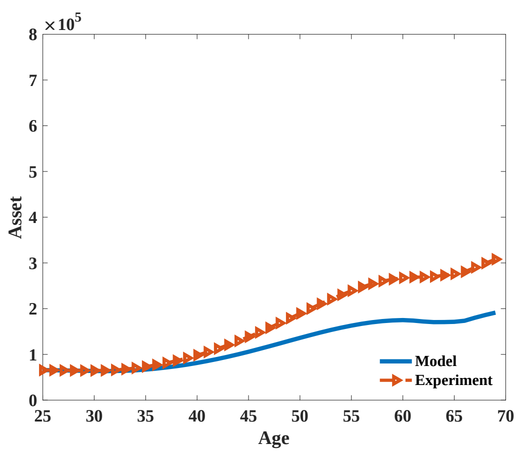
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

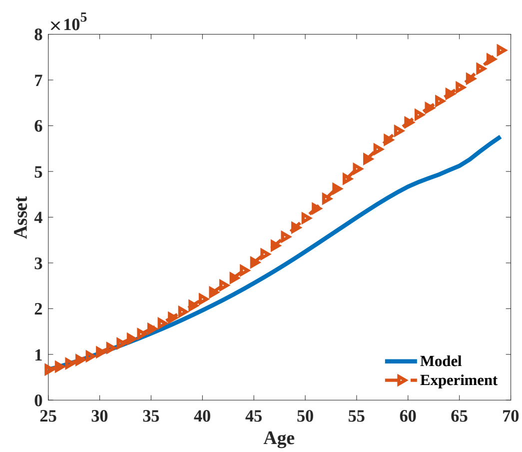
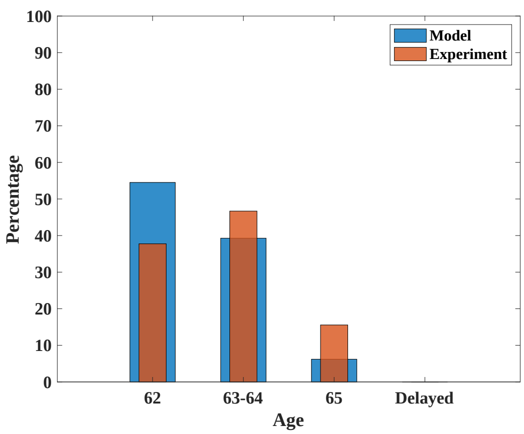
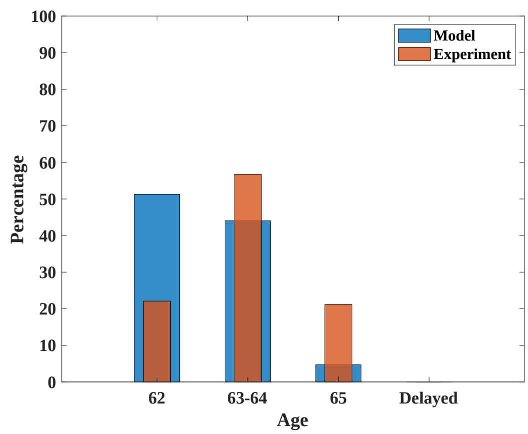


Figure D.14: No Unemployment Shocks: Claiming by Education and Marriage
Men born in 1931-1935

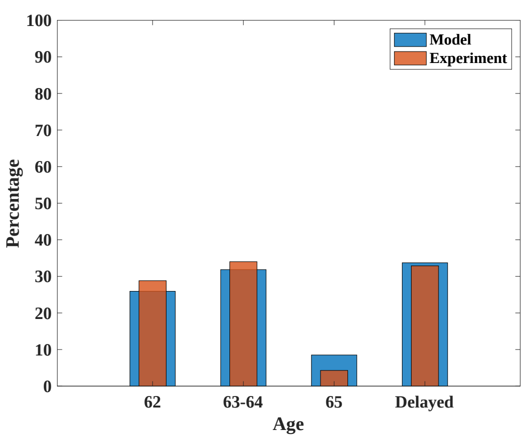
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

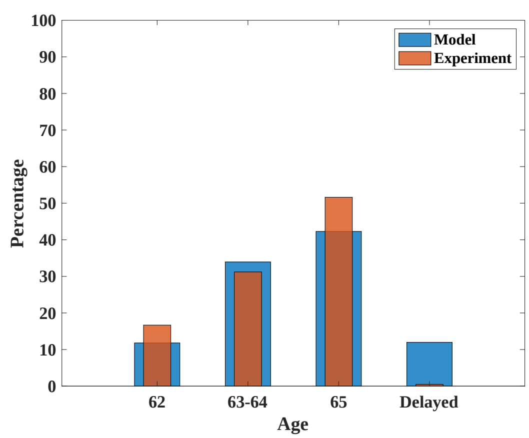
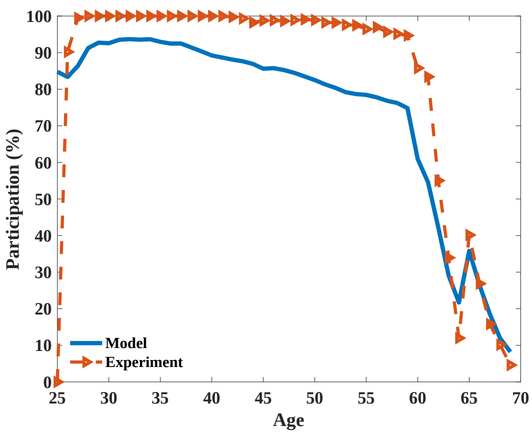
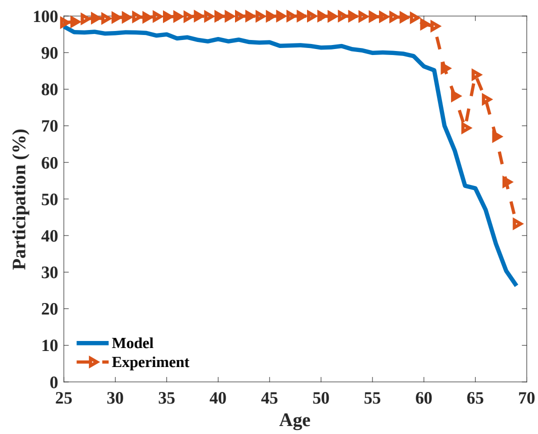


Figure D.15: No Bad Health Shocks: Participation by Education and Marriage
Men born in 1931-1935

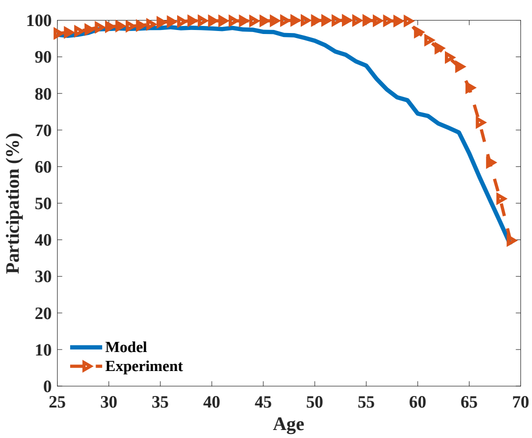
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

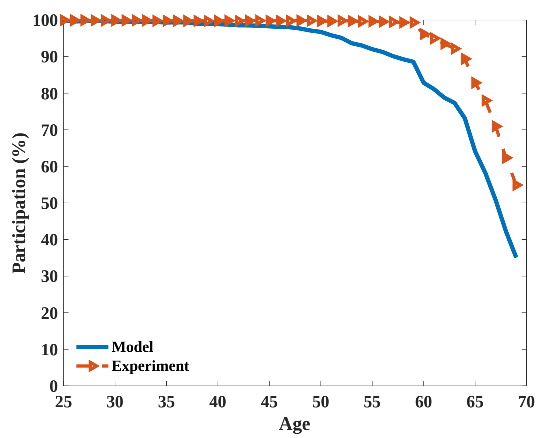


Figure D.16: No Bad Health Shocks: Consumption by Education and Marriage
Men born in 1931-1935

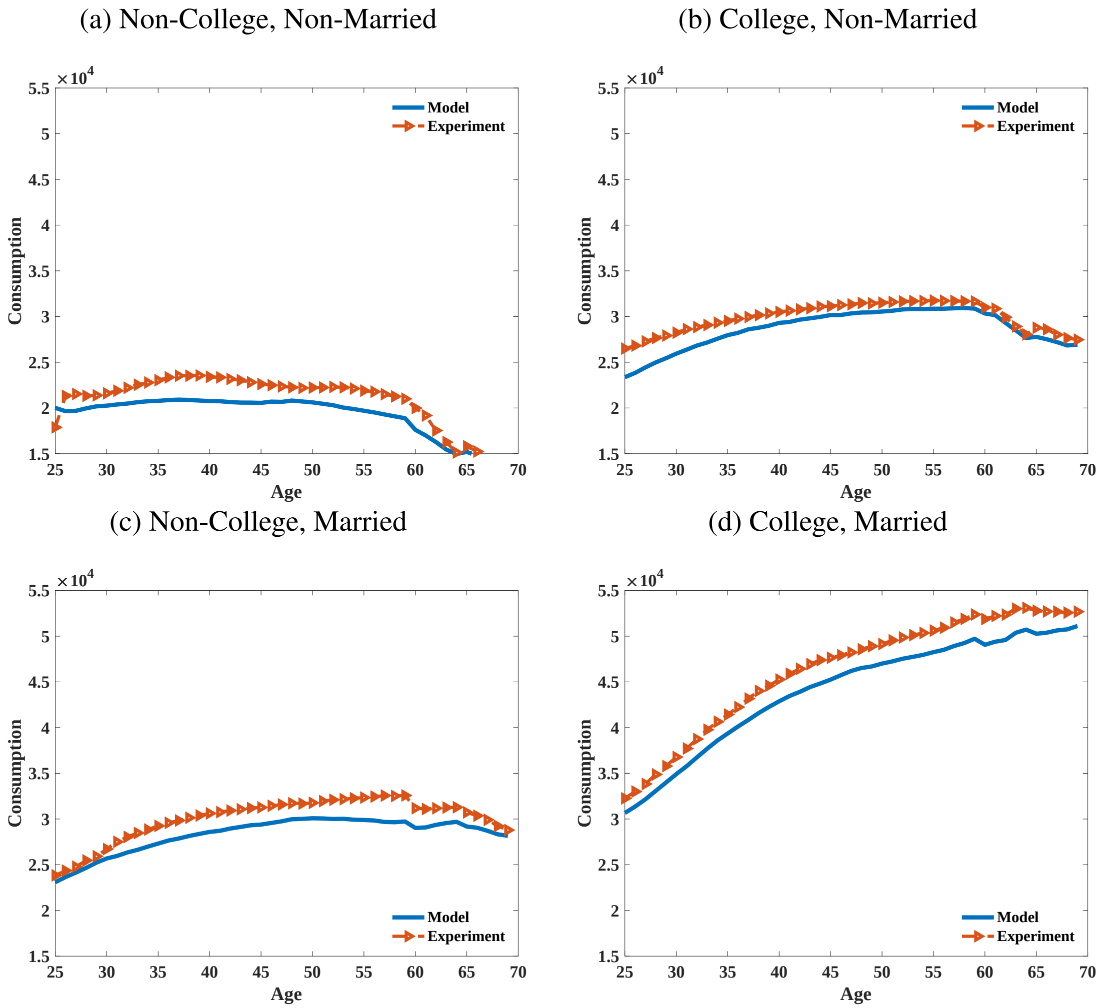
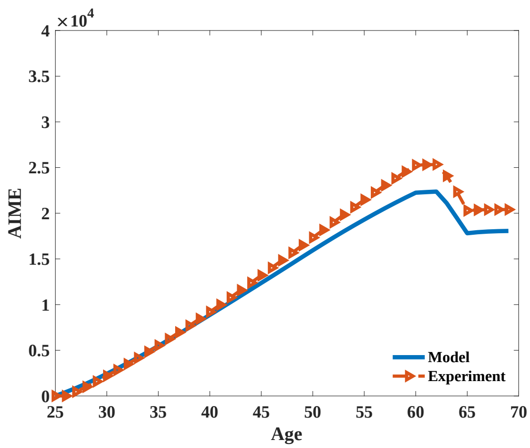
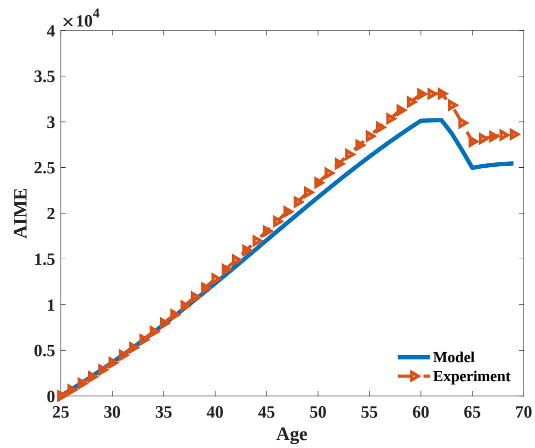


Figure D.17: No Bad Health Shocks: Social Security Wealth by Education and Marriage
Men born in 1931-1935

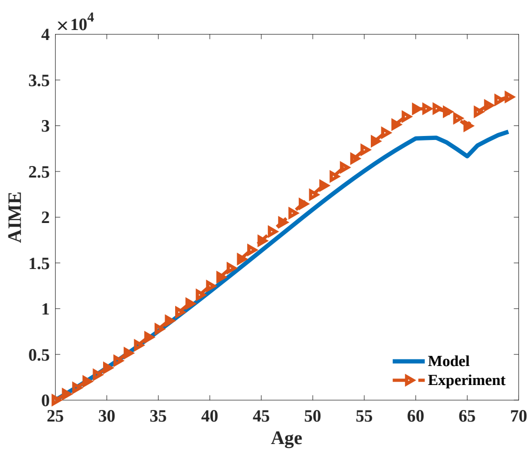
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

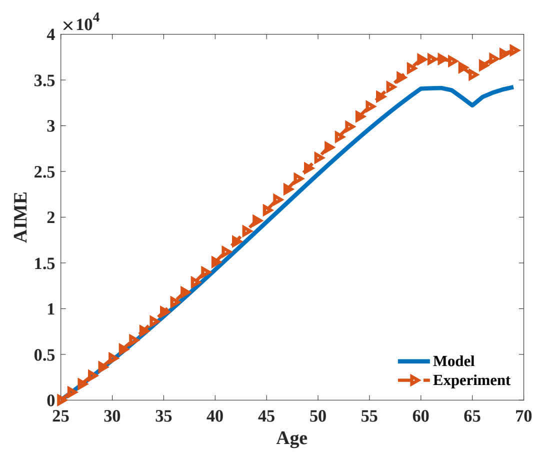
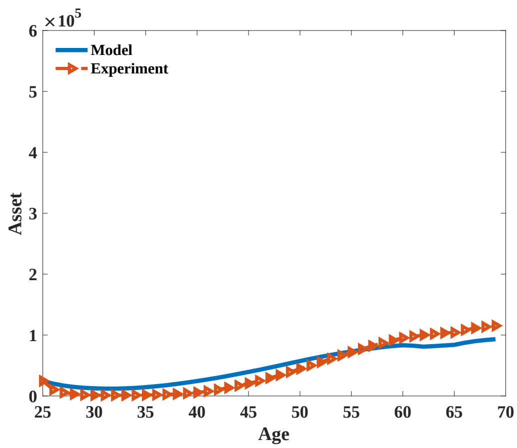
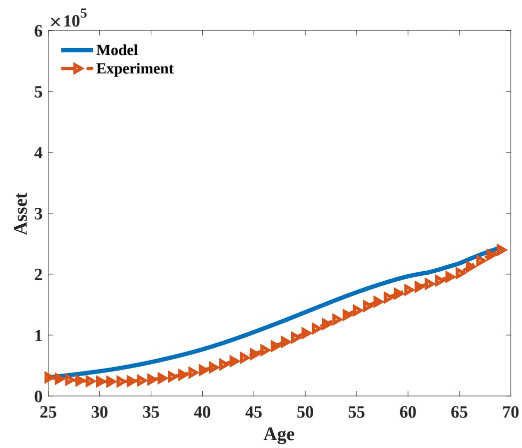


Figure D.18: No Bad Health Shocks: Wealth by Education and Marriage
Men born in 1931-1935

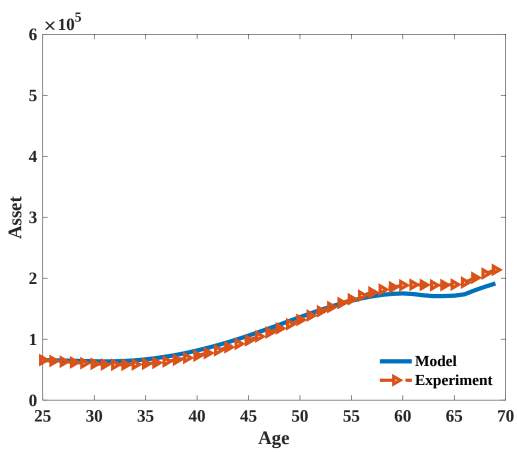
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

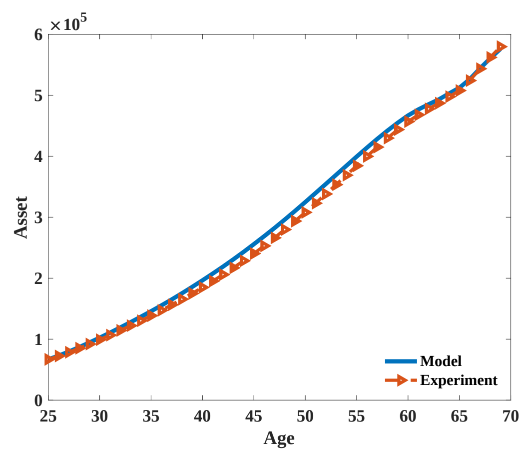
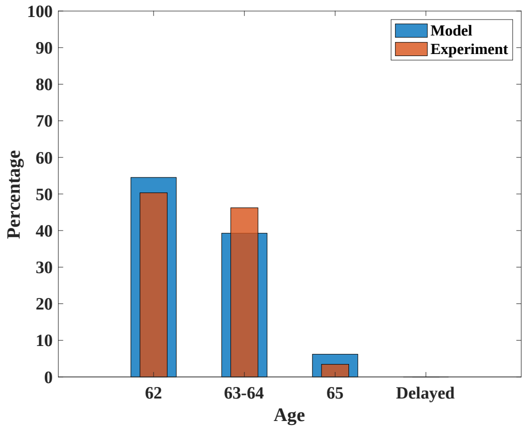
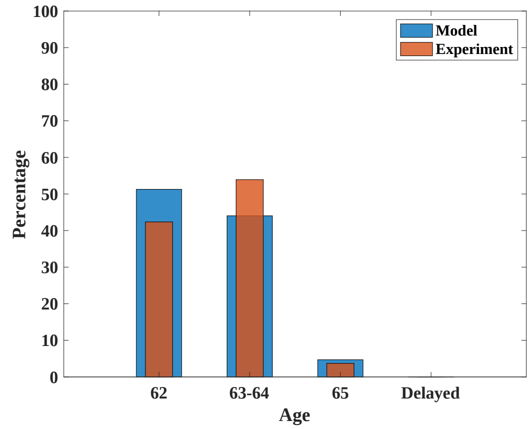


Figure D.19: No Health Shocks: Claiming by Education and Marriage
Men born in 1931-1935

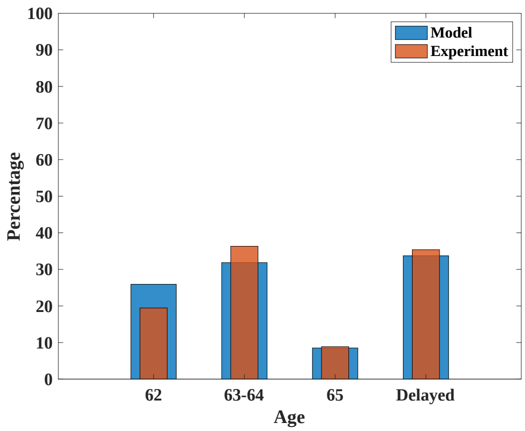
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

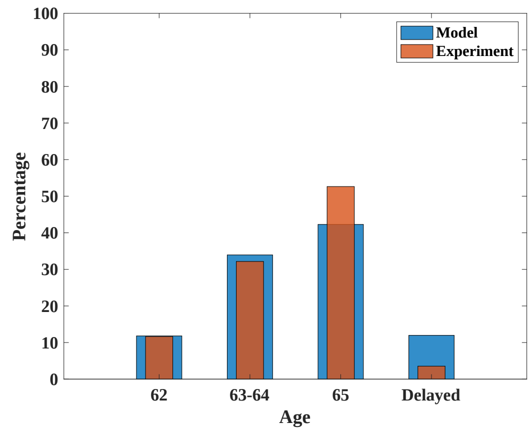
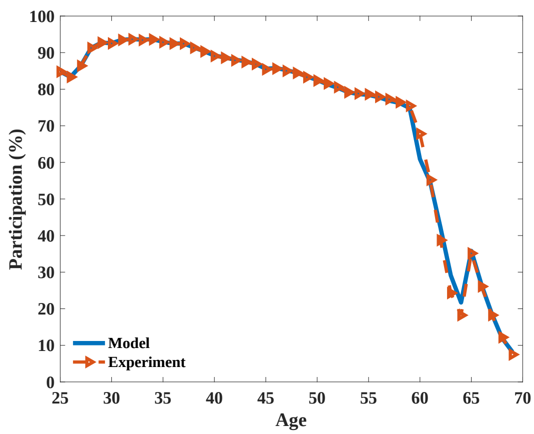
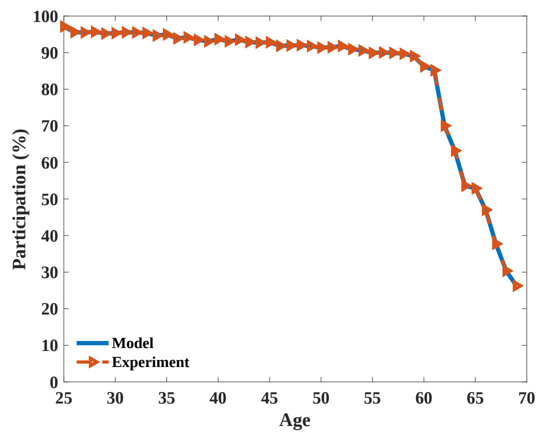


Figure D.20: No Mortality Misbeliefs: Participation by Education and Marriage
Men born in 1931-1935

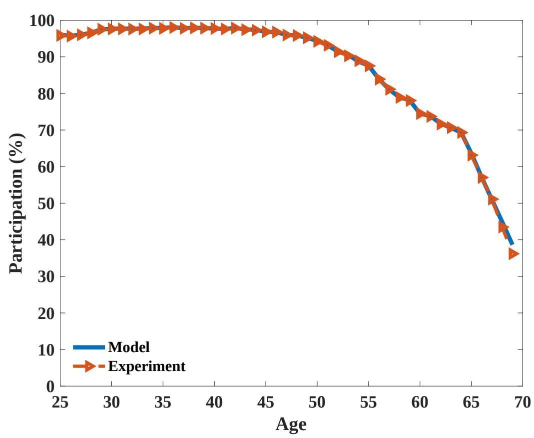
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

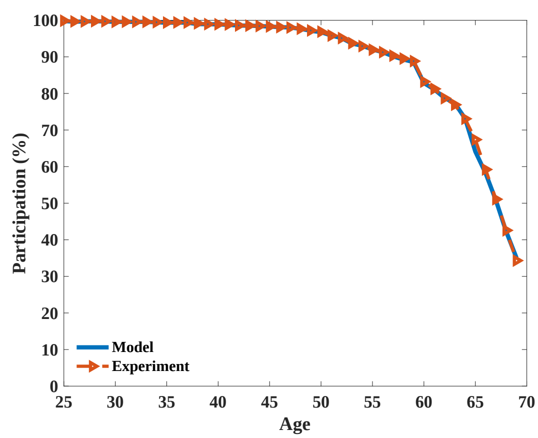
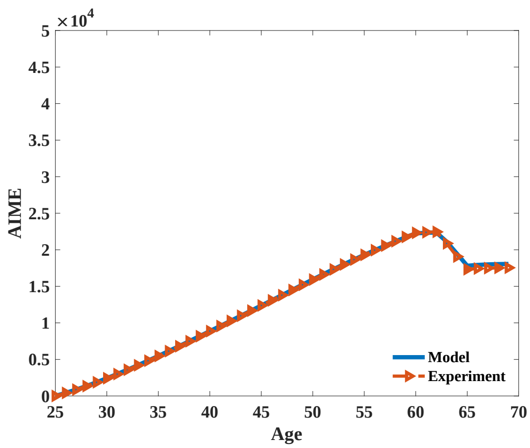
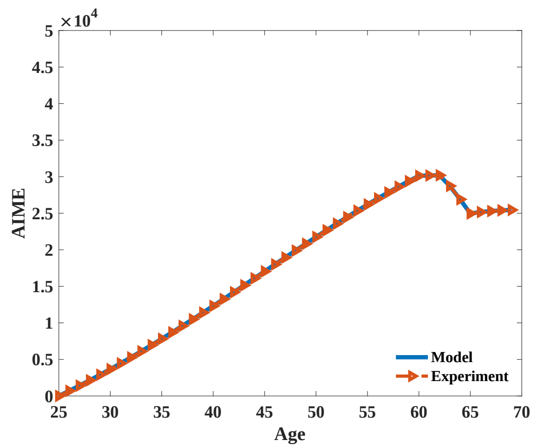


Figure D.21: No Mortality Misbeliefs: Social Security Wealth by Education and Marriage
Men born in 1931-1935

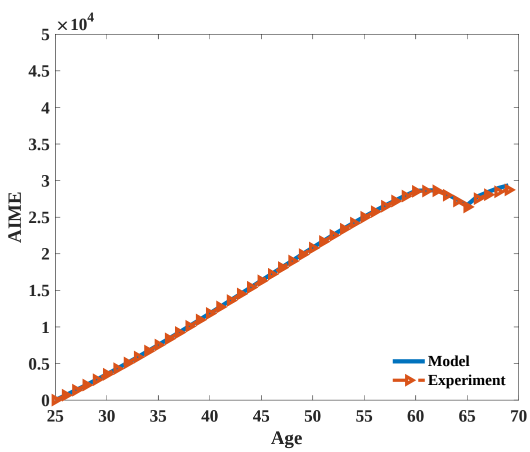
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

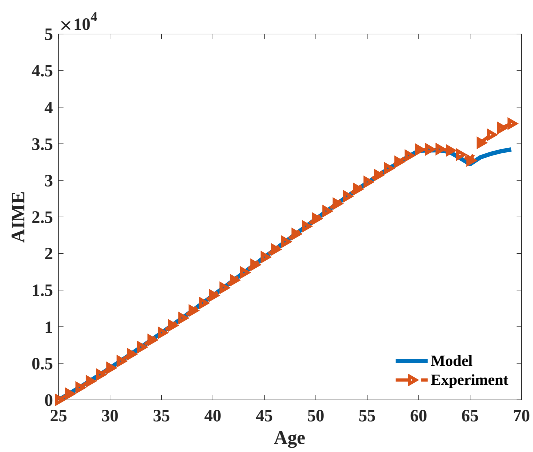
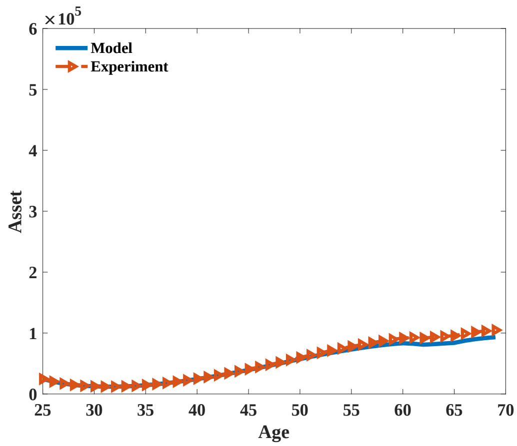
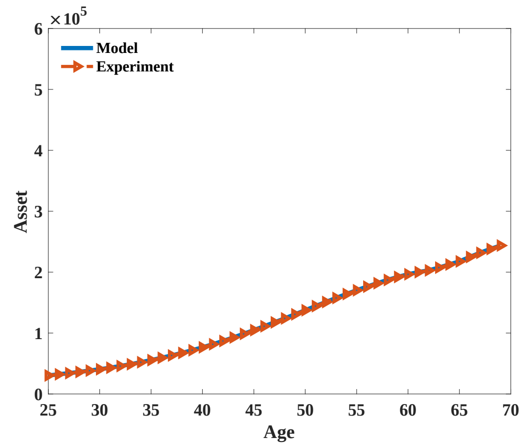


Figure D.22: No Mortality Misbeliefs: Wealth by Education and Marriage
Men born in 1931-1935

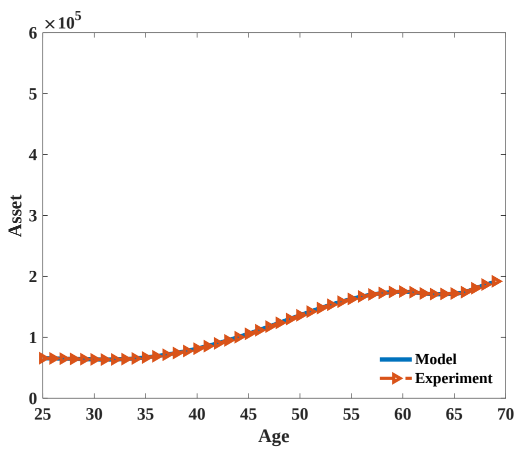
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

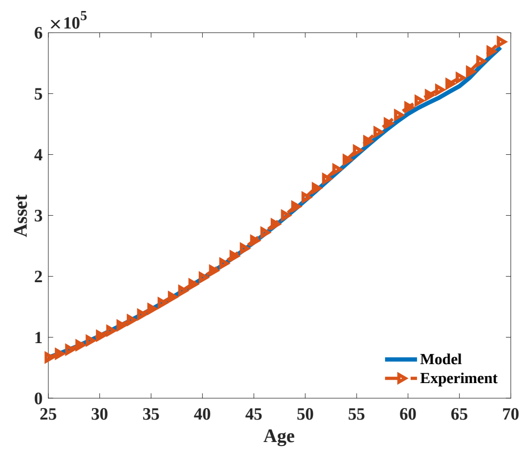
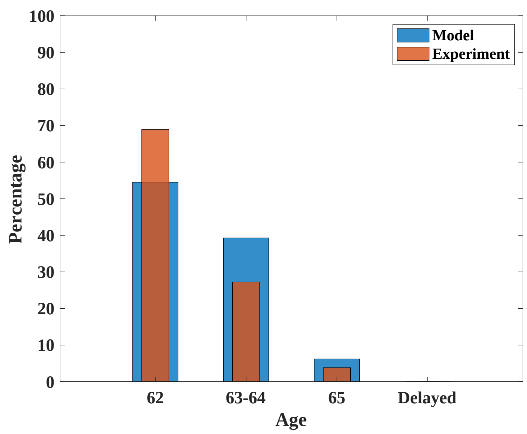
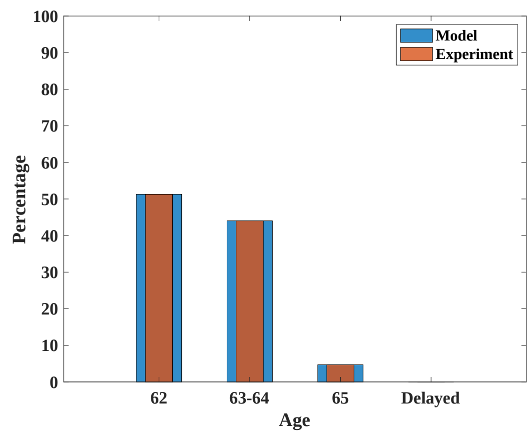


Figure D.23: No Mortality Misbeliefs: Claiming by Education and Marriage
Men born in 1931-1935

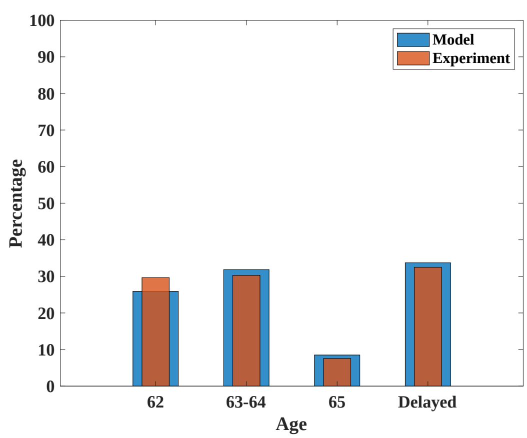
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

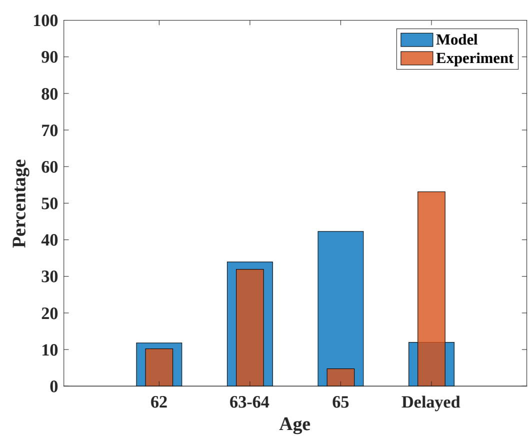
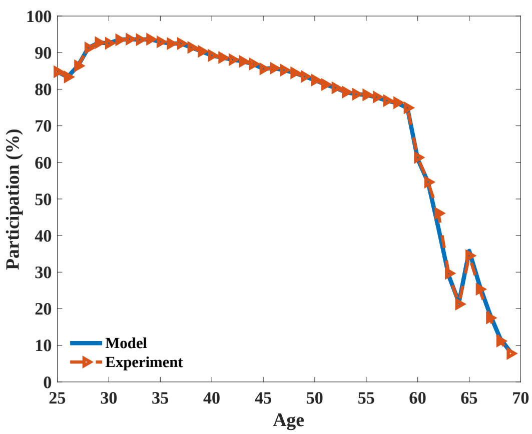
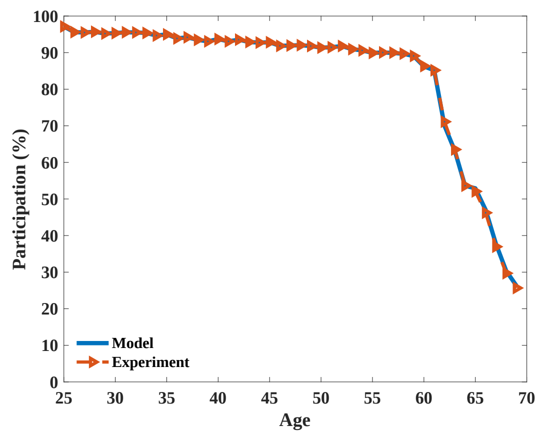


Figure D.24: No Program Misbeliefs: Participation by Education and Marriage
Men born in 1931-1935

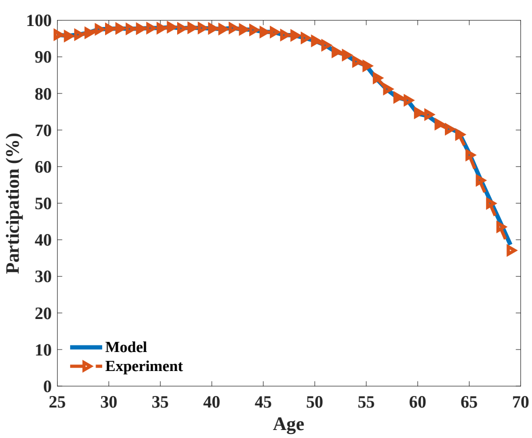
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

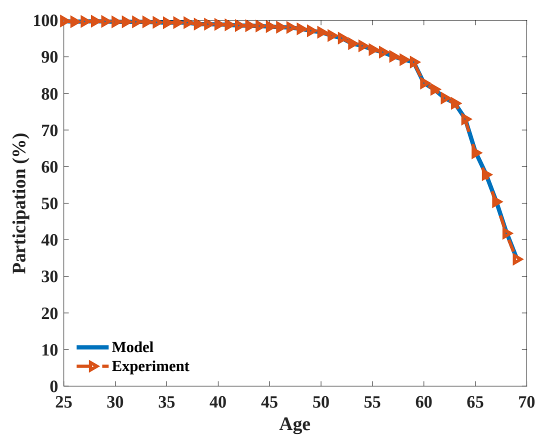
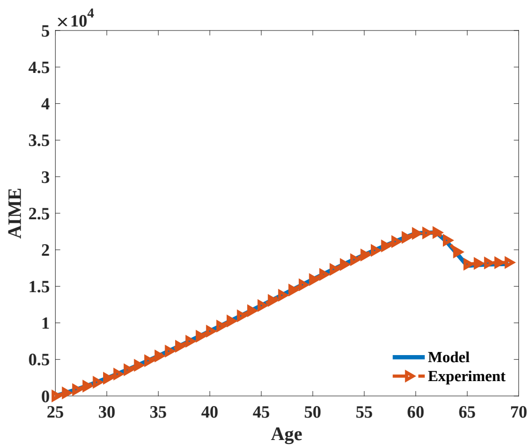
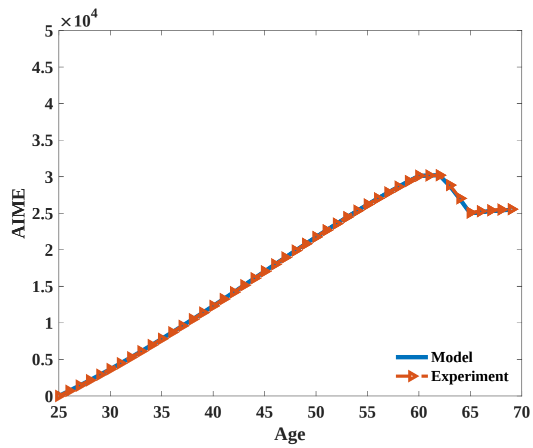


Figure D.25: No Program Misbeliefs: Social Security Wealth by Education and Marriage
Men born in 1931-1935

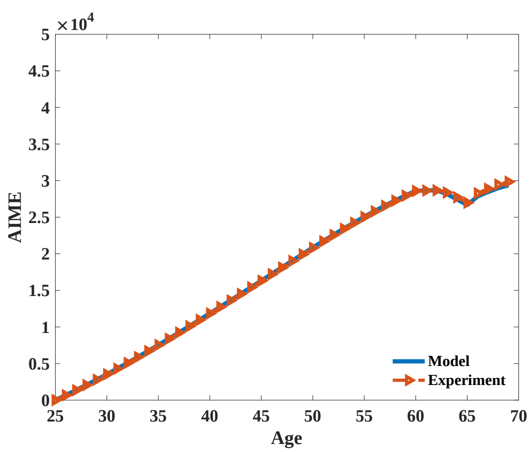
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

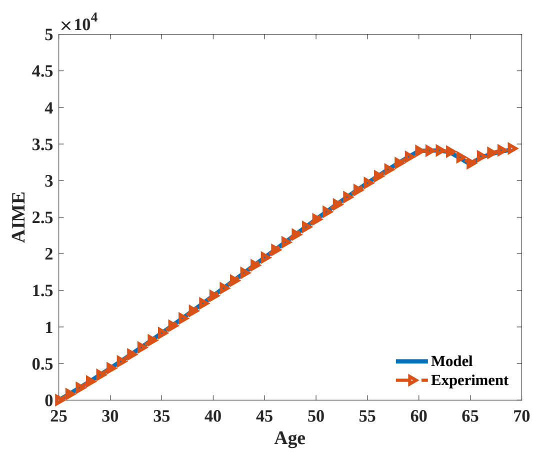
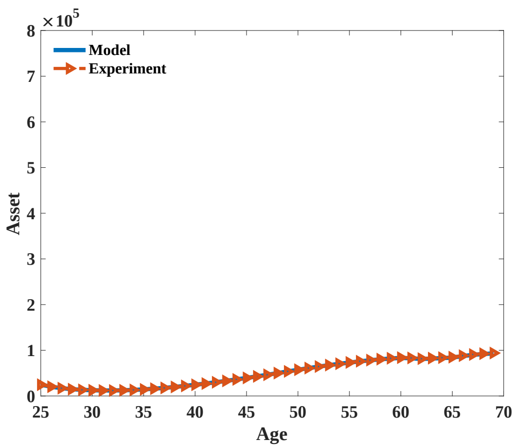
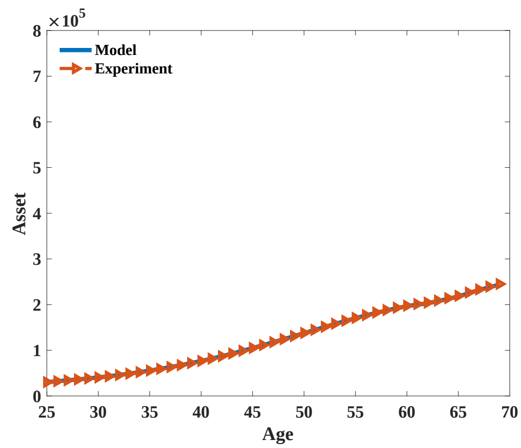


Figure D.26: No Program Misbeliefs: Wealth by Education and Marriage
Men born in 1931-1935

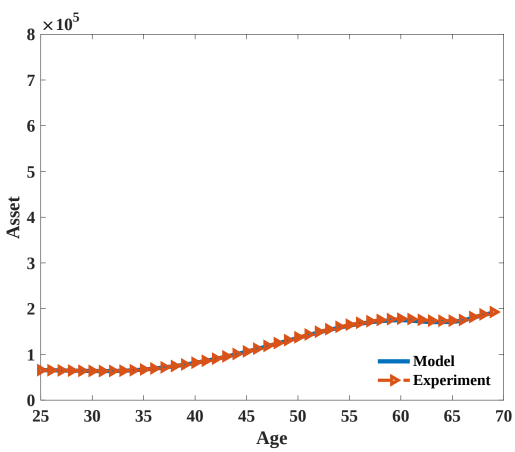
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

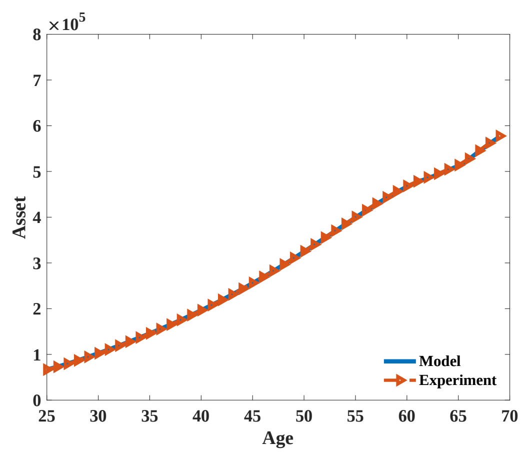
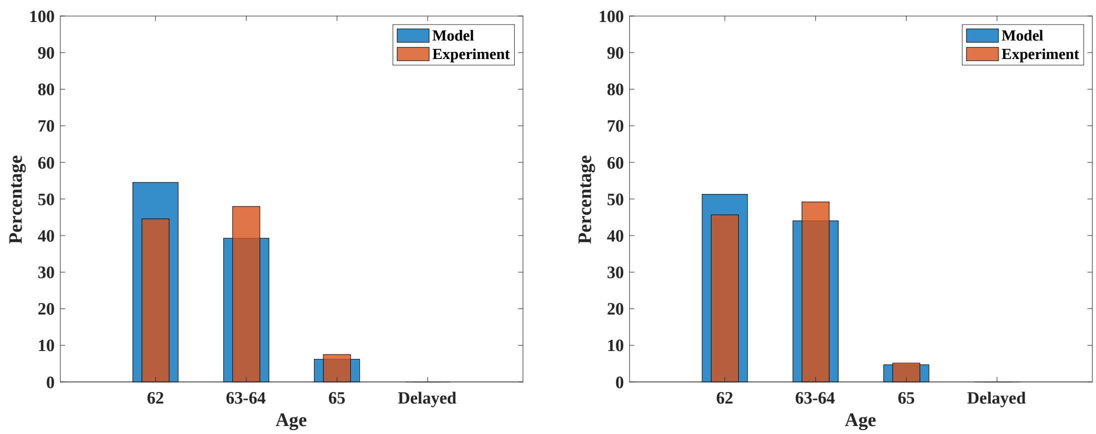


Figure D.27: No Program Misbeliefs: Claiming by Education and Marriage
Men born in 1931-1935

(a) Non-College, Non-Married

(b) College, Non-Married



(c) Non-College, Married

(d) College, Married

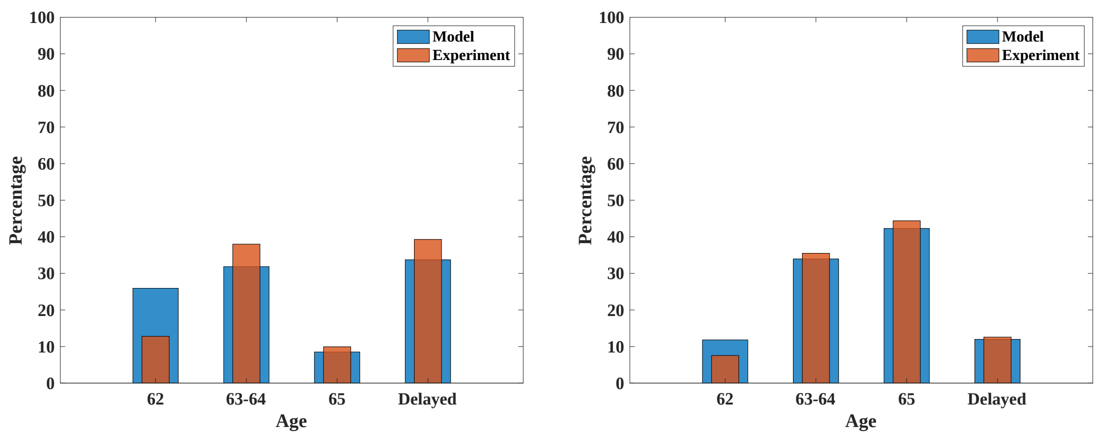
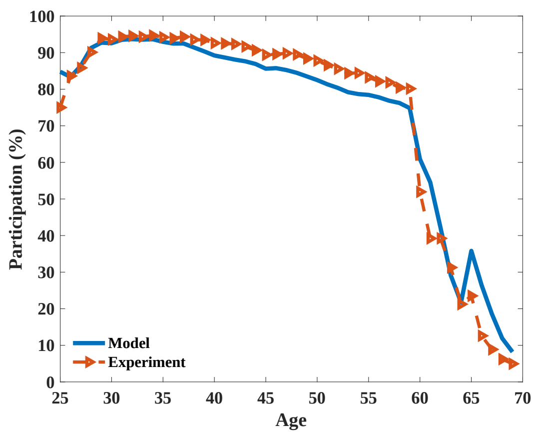
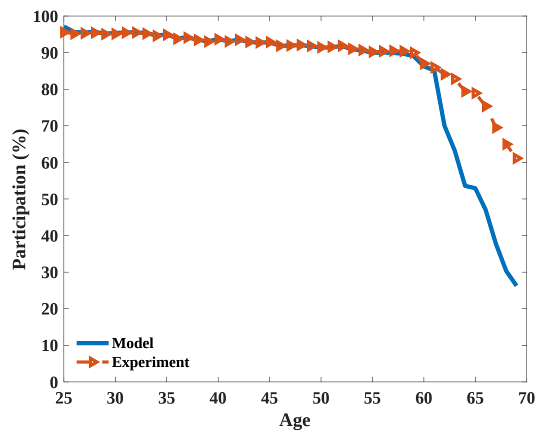


Figure D.28: No Bequest Motive: Participation by Education and Marriage
Men born in 1931-1935

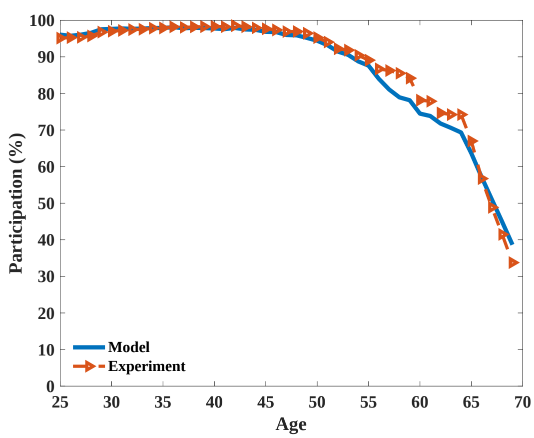
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

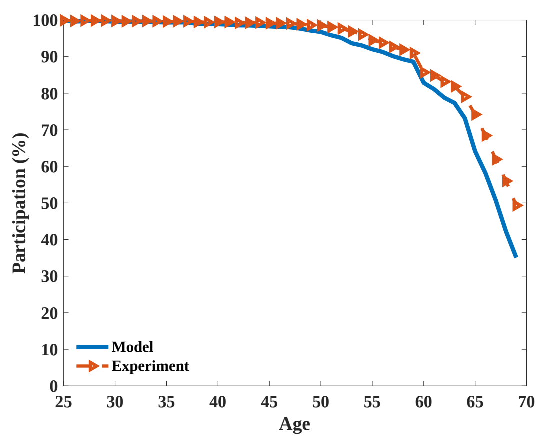
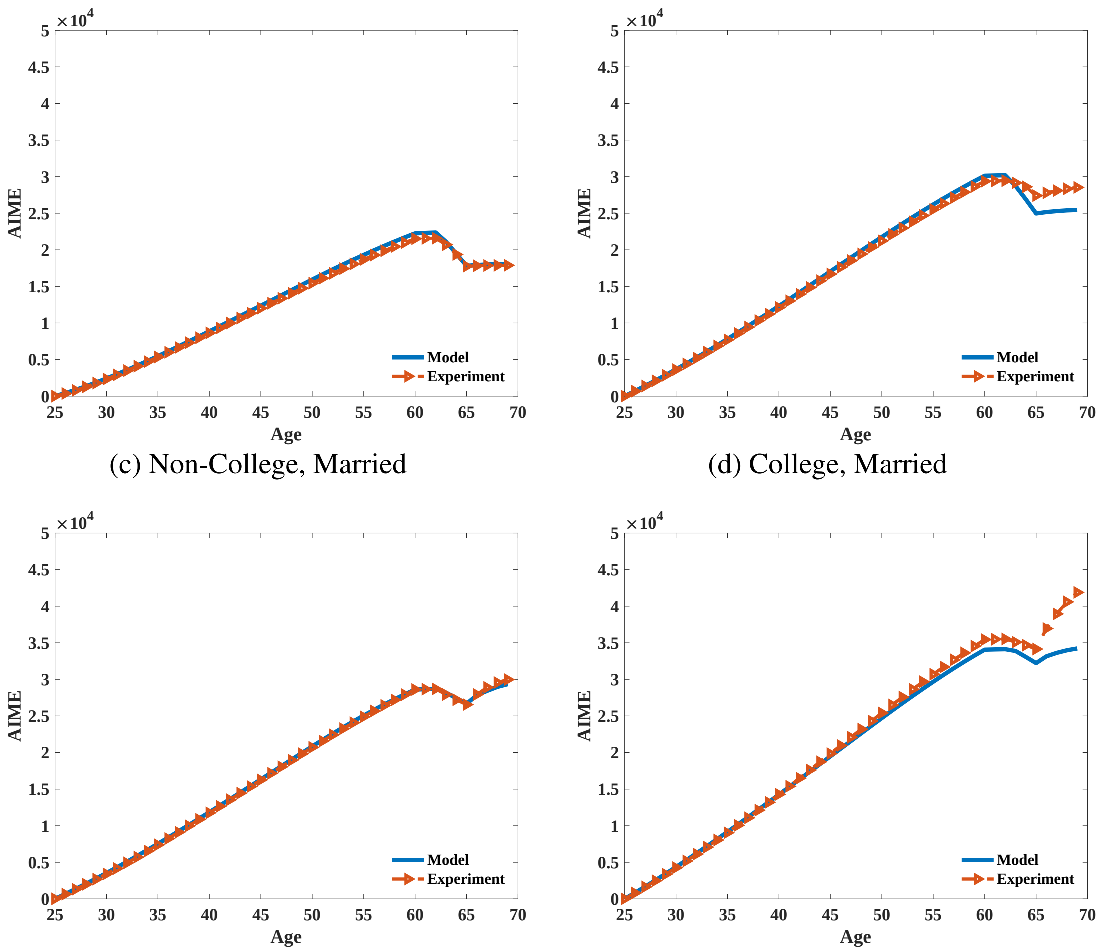


Figure D.29: No Bequest Motive: Social Security Wealth by Education and Marriage
Men born in 1931-1935

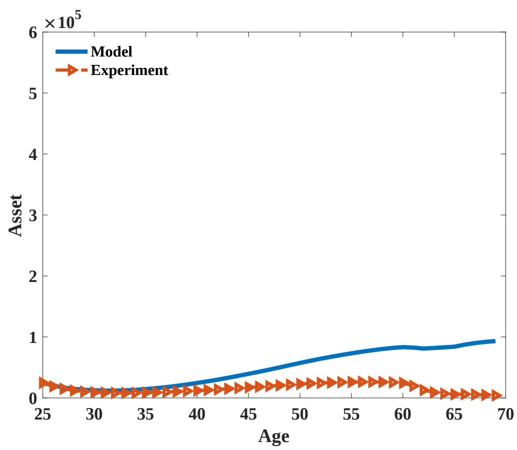
(a) Non-College, Non-Married (b) College, Non-Married



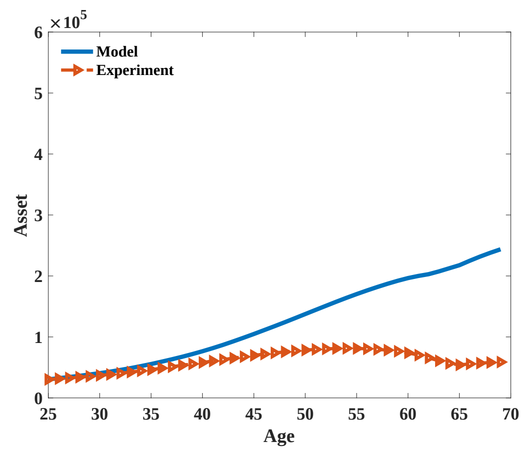
(c) Non-College, Married (d) College, Married

Figure D.30: No Bequest Motive: Wealth by Education and Marriage
Men born in 1931-1935

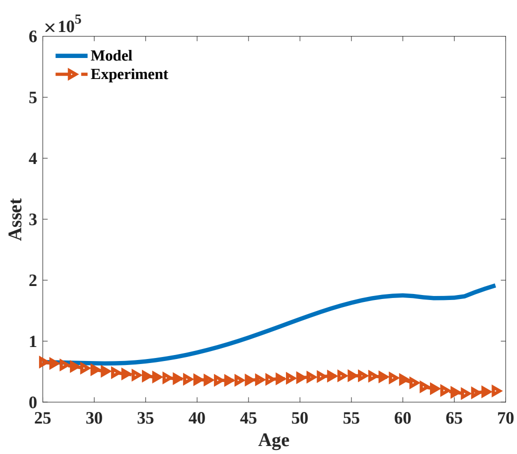
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

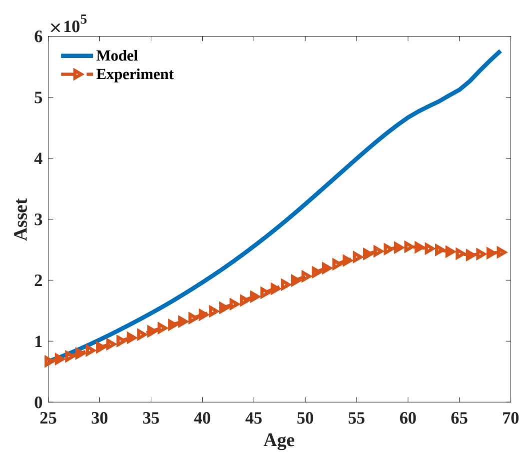
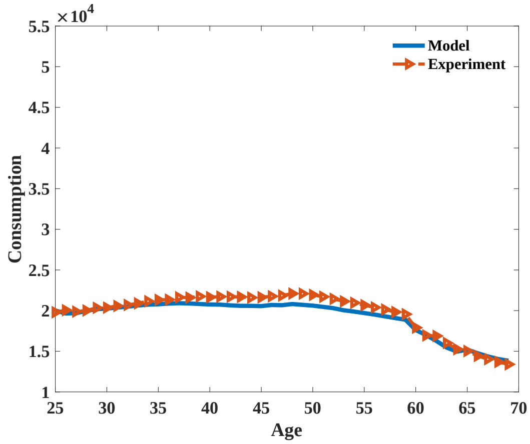
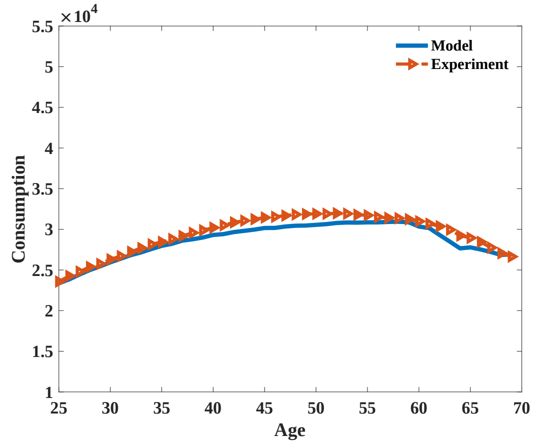


Figure D.31: No Bequest Motive: Consumption by Education and Marriage
Men born in 1931-1935

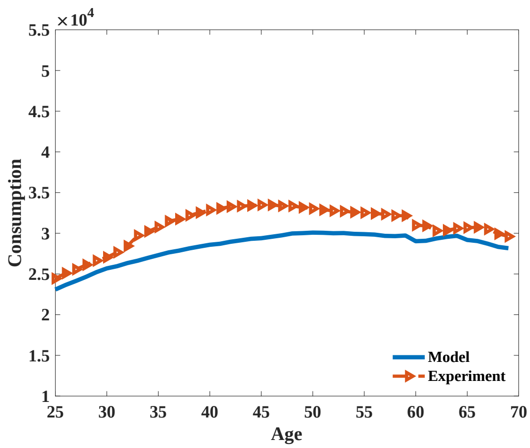
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

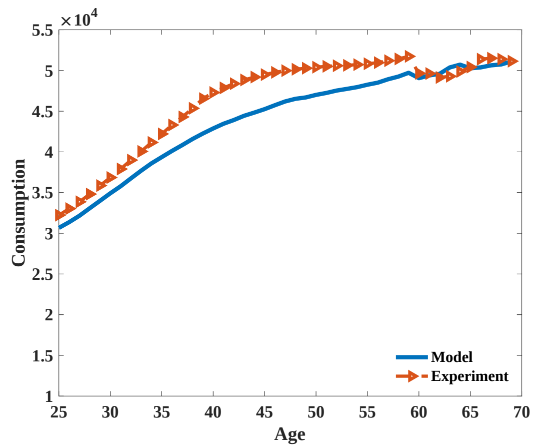
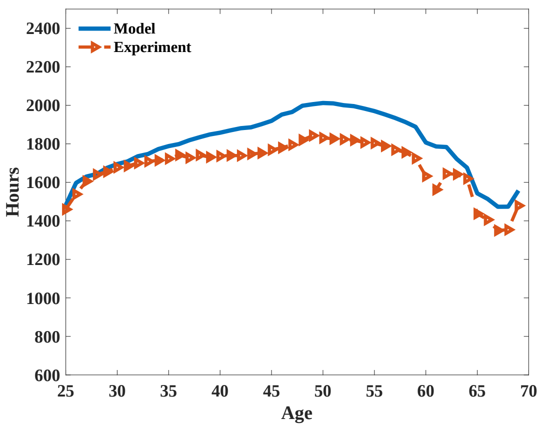
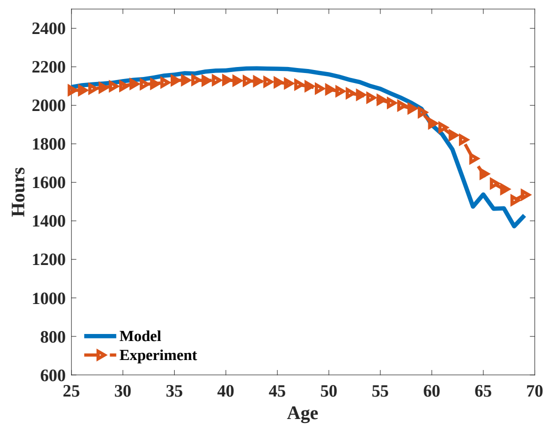


Figure D.32: No Bequest Motive: Hours by Education and Marriage
Men born in 1931-1935

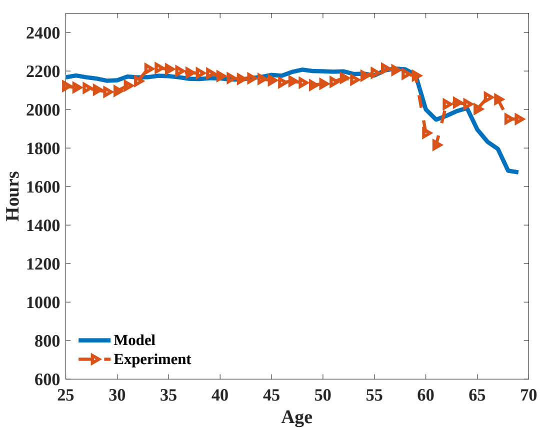
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

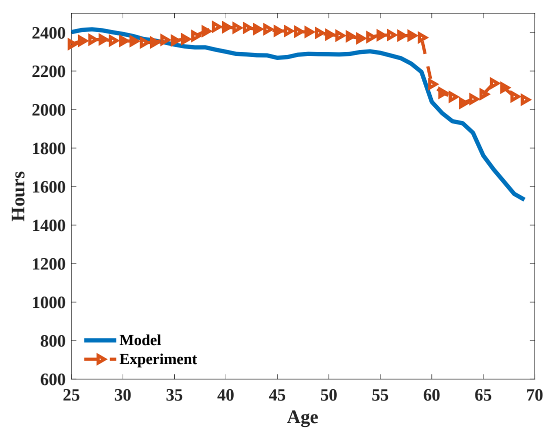
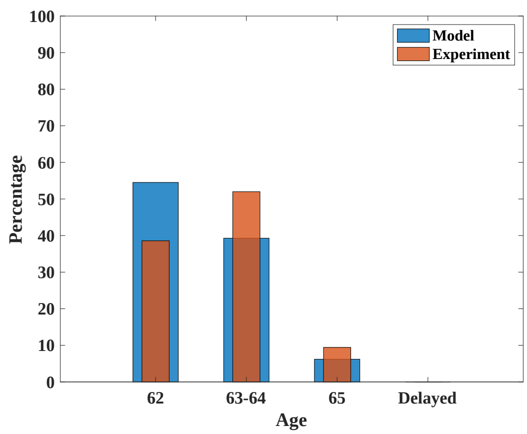
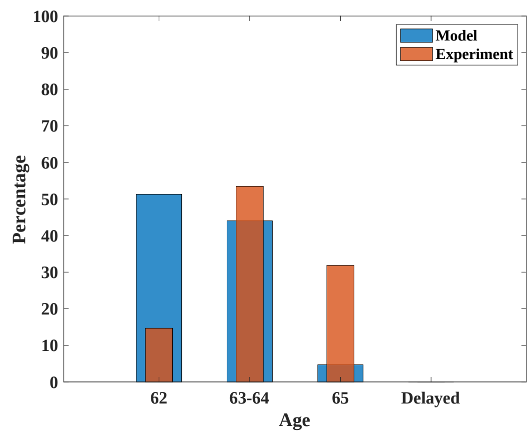


Figure D.33: No Bequest Motive: Claiming by Education and Marriage
Men born in 1931-1935

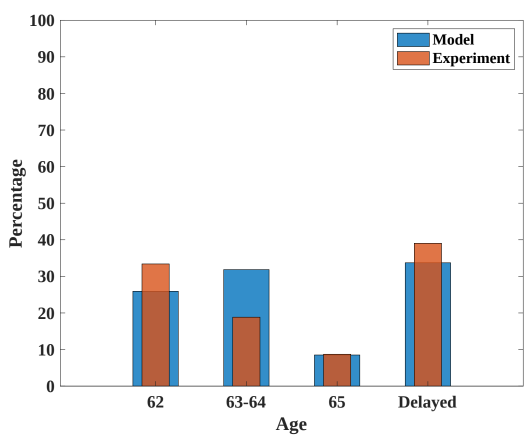
(a) Non-College, Non-Married



(b) College, Non-Married



(c) Non-College, Married



(d) College, Married

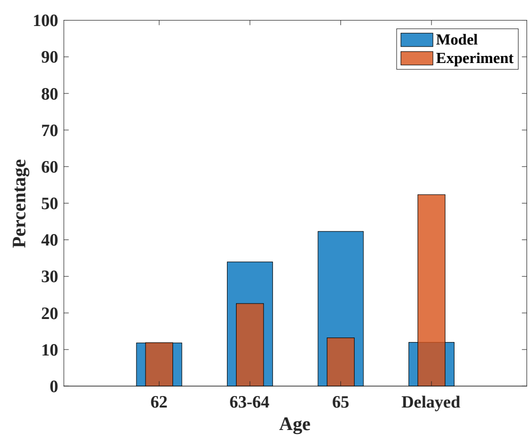
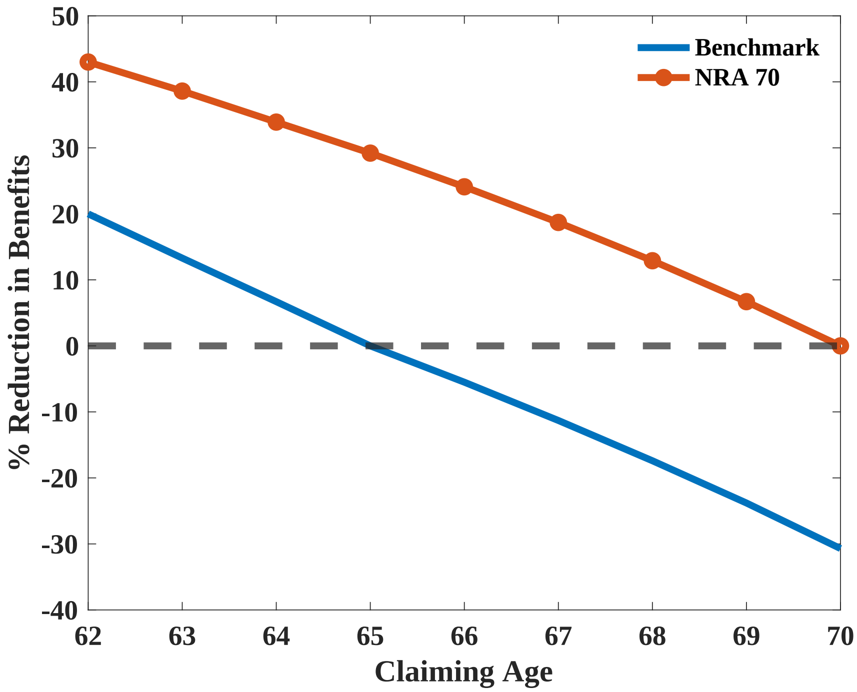


Figure D.34: Social Security NRA 70 Policy Parameters



Notes: The figure reports % permanent reduction in annual benefits by claiming age for both the benchmark and the NRA 70 policy scenarios. Negative numbers on the vertical axis indicate credits for delayed application in the benchmark.