

It Sucks to Be Single!

Marital Status and Redistribution of Social Security*

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Abstract

In this paper, we study the labor supply effects and the redistributive consequences of the U.S. social security system. We focus particularly on auxiliary benefits, where eligibility is linked to marital status. To this end, we develop a dynamic, structural life cycle model of singles and couples, featuring uncertain marital status and survival. We account for the socio-economic gradients to both marriage stability and life expectancy. We find that auxiliary benefits have a large depressing effect on married women's employment. Moreover, we show that a revenue neutral minimum benefit scheme would moderately reduce inequality relative to the current U.S. system.

JEL Classification: J12, J26, E62, D91, H55.

Keywords: Social Security, Spousal and Survivor Benefits, Marital Risk, Female Labor Supply, Redistribution

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1 Introduction

Social security is a strong source of intra-generational redistribution in the United States. At the individual level, benefits are progressive due to the concavity of the benefit formula. In addition to claiming benefits based on one's own earnings record, it is possible to claim benefits based on the spouse's entitlements. These so called auxiliary benefits top up benefits for married and widowed individuals with low lifetime earnings. Auxiliary benefits are an important source of retirement income for women. In 2010, almost 54% of women collecting social security in the U.S. were collecting spousal or survivor benefits.¹ Social security benefits in general constitute between 50 and 70% of retirement income for women, depending on educational attainment.

Eligibility for auxiliary benefits depends on marital status. This implies redistribution from singles to married households, and among married households from dual-earner couples to single-earner couples. Yet, never married and divorced individuals are at greatest risk for poverty in old age. Furthermore, poorer individuals have less stable marriages, and are therefore less likely to have the option of claiming auxiliary benefits than their richer counterparts. These features introduce a regressive element to social security. Auxiliary benefits also distort labor supply decisions. They disincentivize the labor supply of married women by awarding them larger benefits than they would be entitled to based on their own earnings record. In contrast, men are encouraged to postpone retirement due to auxiliary benefits, since by working longer the husband increases not only his own benefit but that of the wife as well.

In this paper, we quantify the labor supply effects and the redistributive consequences of auxiliary social security benefits. To this end, we develop a dynamic, structural life cycle model of singles and couples with marriage and divorce risk and uncertain survival. Our model lends itself to interesting policy analysis. We carry out two counterfactual experiments: (1) eliminate auxiliary benefits, and (2) replace auxiliary benefits with a minimum social security benefit which is means tested at the household level.

Auxiliary benefits were designed to support families where the wife stays at home and cares for the children, by granting these families higher benefits and supporting the widow after the spouse's death (see, e.g., [Nuschler and Shelton 2012](#)).

¹Numbers are taken from [SSA \(2017\)](#), Table 5.A14 for the year 2010. They include all women aged 62 or older receiving social security benefits.

When these benefits were first introduced in 1939, most families had a sole, male earner. Nowadays, such families are much less common. Increasing female labor force participation implies that families with two-earners are much more frequent. Declining marriage and increasing divorce rates also imply an increasing share of elderly singles over time. These changes call for re-evaluating the redistributive consequences of auxiliary benefits. This is particularly important, since poverty rates among divorced and never married elderly women exceed 20%, whereas less than 6% of married women fall below the official poverty line. Further, by redistributing from two-earner to one-earner married households, the auxiliary benefit system creates incentives for also highly educated women – potentially with high labor market productivity – to stay at home, resulting in efficiency losses. While these aspects have drawn some attention in public policy debates ([Butrica and Smith 2012](#), [Karamcheva et al. 2015](#), [Wu et al. 2013](#), [Nuschler and Shelton 2012](#)), the redistributive consequences of these policies have not been systematically analyzed. Moreover, the effect of auxiliary benefits on female labor supply, taking the relevant uncertainties with respect to marital status and survival into account, has not been studied.

Before turning to the results from our policy analysis, we analyze the redistribution built into the current U.S. social security system. To this end, we compute replacement rates. We find that the current system is progressive within marital status. Namely, for a given marital status, the replacement rate is declining in education. However, there is strong redistribution from never married and divorced (who we term non-eligible) to married and widowed females (who we term eligible), with replacement rates for married and widowed women up to three times larger than for singles. This introduces a regressive element to social security, implying greater replacement rates for eligible high-educated women than for non-eligible low-educated women. In addition, we find that the current system becomes highly regressive, i.e., redistributes from the bottom to the top, when we adjust the replacement rates for the fact that less educated individuals spend fewer years in retirement. Hence, we find that differences in longevity overturn the concavity of the social security system.

Our policy analysis reveals that auxiliary benefits significantly dampen female labor supply. We find a large employment effect of 12.6pp for married women from eliminating auxiliary benefits. This translates into an increase in aggregate hours of 2.4% for the whole economy. Abolishing auxiliary benefits heavily decreases the redistribution from singles to ever-married households. However, the elimination of

auxiliary benefits hurts the least educated, married females the most, which implies an increase in overall inequality in the economy. This is evidenced by large declines in the household replacement rates for social security income for couples with dropout wives, from 0.54 in the baseline to 0.45 in the counterfactual. Conversely, the corresponding rate declines only slightly for couples with a college educated wife, from 0.36 to 0.34. Remarkably, the major disincentive for labor supply stems from spousal benefits and not survivor benefits. Roughly two thirds of the employment effect for married women can be attributed to them. At the same time, the negative redistributive consequence from abolishing auxiliary benefits – again around two thirds – comes from survivor rather than spousal benefits.

If the objective of auxiliary benefits is to prevent poverty, an argument can be made that redistribution should depend on income, not marital status. To this end, we replace auxiliary benefits with a revenue neutral, minimum benefit system which is means tested on household income. To calculate the minimum benefit, we first compute benefits based on individual entitlements and then take the household average of them. If needed, this is then topped up to 30.3% of average income in the economy (both spouses awarded the same benefit). The model predicts a negligible decrease in married women’s employment relative to the benchmark, 0.2 pp to be exact. While there is a substantial increase in the employment of college educated wives, this is offset by a decline in employment among high school dropouts. Moreover, male employment declines. All in all, aggregate hours of work decline by roughly 1.0%. However, the minimum benefit introduces redistribution from richer to poorer households, resulting in less inequality of social security income. Notably, the average household replacement rate for social security income rises for couples with dropout wives and for all single women, with dropout singles benefitting the most (an increase from 0.47 to 0.66).

Our paper builds on several different strands of the literature. There is a large reduced form literature measuring the redistribution inherent to social security; see, e.g., [Coronado et al. \(2000\)](#) and [Gustman and Steinmeier \(2001\)](#). The first paper to study the labor supply implications of auxiliary benefits was [Blau \(1997\)](#). However, his approach is methodologically very different from ours. Our structural approach allows us to study the equity-efficiency trade-off. There is a broad literature studying the equity-efficiency trade-off of social security at the individual level. See, for example, [Conesa and Krueger \(1999\)](#), [Imrohorglu et al. \(1995\)](#), [Fuster et al. \(2007\)](#), and [French \(2005\)](#) for studies of the labor supply effects of social security. There is also a growing literature using structural life cycle models of couples to study

important issues related to the family, see [Greenwood et al. \(2017\)](#) and [Doepke and Tertilt \(2016\)](#) for recent overviews. Our paper contributes to the literature on the insurance value of marriage and marital status and social security (see, e.g., [Attanasio et al. \(2005\)](#), [Fehr et al. \(2017\)](#), [Kaygusuz \(2015\)](#), [Nishiyama \(2015\)](#) and [Bethencourt and Sánchez-Marcos \(2014\)](#)). Relative to this literature, our main contribution stems from quantifying the effect of auxiliary benefits over the life cycle and from shedding light on the role of auxiliary benefits as a redistributive instrument using an approach that is better suited to measuring the overall effect of said policies than previously employed in the literature. In particular, our framework captures the relevant risks for studying the interplay between marital status and redistribution of social security – marital transition, survival and income risk.

Our paper also relates to the literature studying the effect of divorce risk on female employment. See, for example, [Fernandez and Wong \(2014\)](#) and [Chakraborty et al. \(2015\)](#).

The remainder of the paper is structured as follows. Section 2 describes the institutional setting as well as a few stylized observations from the data. Section 3 presents the model. Section 4 describes the parametrization of the model, while Section 5 outlines the calibrated economy. Section 6 presents the results from the policy analysis, while Section 7 provides some sensitivity analysis. Section 8 concludes.

2 Social Security, Marital Status and Employment

Before analyzing how social security benefits influence labor supply and redistribution, it is necessary to understand how social security benefits are determined and how they interact with other tax and transfer policies. In the US, social security benefits are linked to both earnings and marital histories. Retired-worker benefits are a concave function of income from the best 35 years. However, in addition to the worker’s own benefit, social security provides benefits for qualified spouses of retired workers.² These benefits are not gender based, but in practice they are mostly claimed by women, since women typically have lower earnings than men. Auxiliary benefits are rather generous. The wife of a retired worker is entitled to a spousal benefit, which bridges the gap between her own benefit and 50% of the husband’s benefit. Widows are entitled to a survivor benefit which bridges the gap between her own benefit and 100% of the deceased husband’s benefit. Eligibility for these

²Auxiliary benefits are also paid to children and parents of retired, disabled and deceased workers. We abstract from this rather small group throughout the paper.

auxiliary benefits is based on marital status. To claim auxiliary benefits one must either be married (for at least a year) or divorced after a ten-year marriage.

Given that social security benefits depend on both earnings and marital histories, it is important to understand marital patterns as well as the patterns associated with female employment and earnings across the population. We document three important observations from the data: (1) marital stability is linked to socio-economic status, (2) survival risk is linked to socio-economic status and (3) female employment is linked to own and spousal income. In the presented data, we focus on the cohort born 1950-54. See the Appendix B.1 for a detailed description of the data.

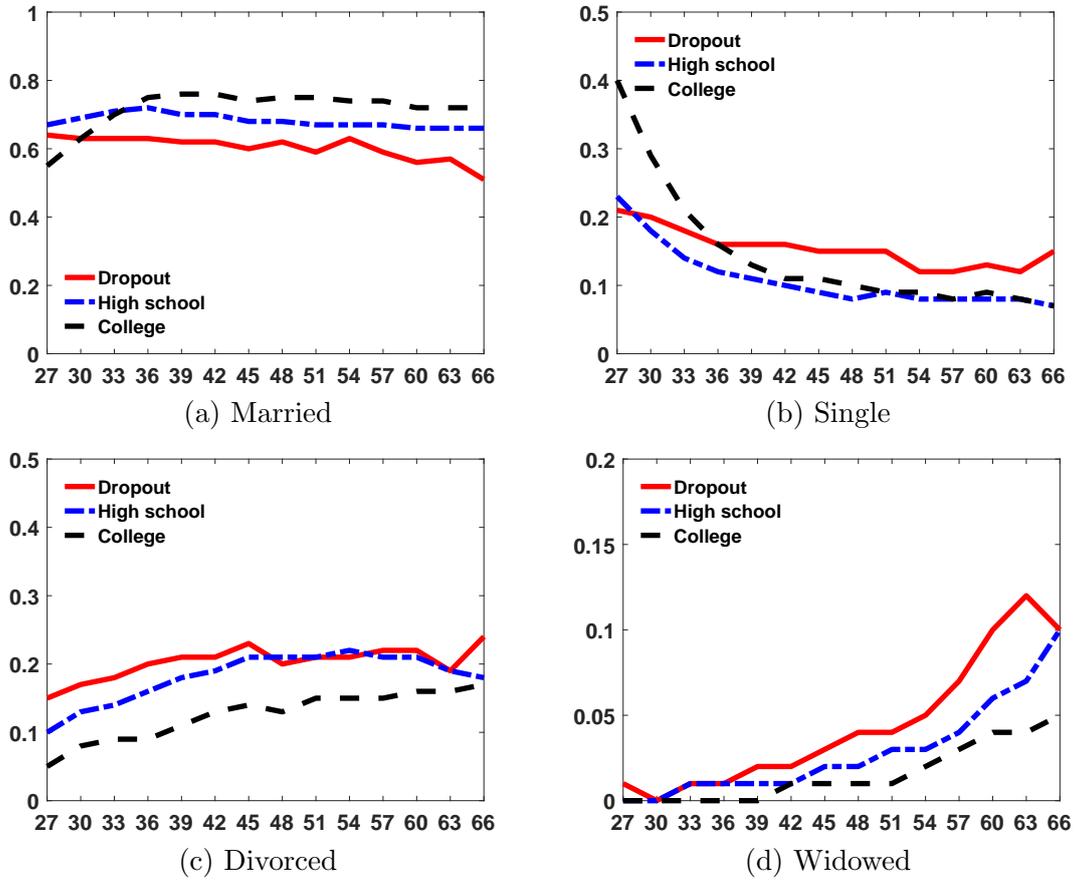
Figure 1 plots the share of individuals in each of four marital states, married, never married, divorced, and widowed over age and education. From the graphs it is apparent that more educated individuals marry later. However, marital stability increases with education. In other words, more educated individuals are more likely to be married and less likely to be divorced than their less educated counterparts. The share of people aged 45-64 who are currently married is 7pp higher for individuals with a college degree than for those with only a high school degree, and 14pp higher than for those who dropped out of high school. In the same age group, the share of people who are currently divorced is 6pp lower among college graduates compared to high school graduates and dropouts. See Isen and Stevenson (2010) for a more detailed discussion of marital status over education, controlling for cohort, gender and race.³

Given that poorer individuals are less likely to be married, they are also less likely to have the option of claiming auxiliary benefits. Auxiliary benefits imply redistribution from singles to married households. Yet, poverty rates are highest for divorced and never married individuals. Poverty rates among divorced and never married elderly women exceed 20%, whereas less than 6% of married women are below the official poverty line.

Life expectancy is strongly increasing in education. As seen from Table 1, life expectancy is 6.4 (7.5) years higher for college educated women (men) than for those who did not finish high school. There is also a substantial gender-difference in life expectancy, on average 4.3 years, in favor of women. The large differences in life expectancy over education have been previously noted by Pijoan-Mas and Ríos-Rull

³Figure 1 displays pure fractions of marital status over age. In our model, we instead use transition probabilities that allows us to keep track of the length of the marriage such that we can disentangle eligible (marriage lasted more than 10 years) and non-eligible (shorter than 10-year marriage) divorced, see also Appendix B.4.

Figure 1: Marital Status by Age and Education



Notes: Share of people in each marital state by age. Computed from CPS data for the cohort born 1950-54, and with a slightly extended cohort, 1946-1954, for ages 65+.

(2014).⁴

The concavity of the social security benefit formula implies that the replacement rates of retired-worker benefits are higher for less educated, low-earning individuals than for their more educated, higher earning counterparts. However, the large differences in life expectancy over education imply that more educated individuals are likely to collect social security benefits for more years. This, in turn, introduces a regressive element to social security.

⁴Our estimates are similar to theirs.

Table 1: Life Expectancy by Gender and Education (in years)

	Women	Men
Dropouts	73.9	69.5
High School	77.5	72.9
College	80.3	77.0
Total	78.3	74.0

Notes: Life expectancy at birth, computed by summing up over the yearly unconditional survival rates for ages 26-89 (the age-span in our model) and adding 25. *Source:* HRS, pooled waves 1992-2010.

Female employment is increasing in own education/income, but decreasing in the husband's education/income. Table 2 shows that the employment rate of college educated, married women is 9pp (27pp) higher than that of married women with a high school degree (dropouts). However, married women with at least a high school degree are less likely to work if their husband is college educated relative to just high school educated; this difference is between 5 and 9pp.

Table 2: Employment Rate of Wives, Ages 26-69

	Husband Dropout	Husband High School	Husband College	Total
Wife Dropout	0.43	0.47	0.46	0.45
Wife High School	0.61	0.65	0.60	0.63
Wife College	0.78	0.78	0.69	0.72

Notes: Employment rate of married females aged 26-69 depending on own and husband's education. *Source:* CPS, cohort born 1950-1954 (data for age 65-69 for cohort born 1945-1949). Excludes those who do not work due to disability.

The differences in female labor supply are even more pronounced over income than over education. The table in Appendix A.1 shows the fraction of households where the husband is the sole earner. Strikingly, in 30% of families with a college educated woman and the husband in the highest income bracket, the husband is the sole earner.

Auxiliary social security benefits distort labor supply decisions. They depress the labor supply of married women by awarding them a larger social security benefit than

they would be entitled to based on their own earnings record. Despite the fact that highly educated women should have a strong incentive to work, there seems to be a counteracting force for staying out of the labor force, if the husband's earnings are sufficiently high. Auxiliary benefits, in conjunction with more stable marriages for high-income households, provide potential incentives for also more educated women to stay at home with children. Auxiliary benefits may, however, increase the labor supply of married men, since by working more the husband positively influences not only his own benefit but also that of the wife. The distortive effect of auxiliary benefits interacts with the distortion arising from joint taxation of labor income. Joint taxation implies high tax rates on secondary earners. When a married female enters the labor market, the first dollar of her earnings is taxed at her husband's current marginal rate.

Table 3: Female Per-Capita Benefits (in \$)

	Married and Widowed			Singles	
	AIME	Benefit Married	Benefit Widowed	AIME	Benefit
Male	4,000	1,721		-	-
Female	0	861		0	0
Per-capita		1,291	1,721		0
Male	3,500	1,561		-	-
Female	500	781		500	450
Per-capita		1,171	1,561		450
Male	3,000	1,401		-	-
Female	1,000	761		1,000	761
Per-capita		1,082	1,401		761
Male	2,000	1,081		-	-
Female	2,000	1,081		2,000	1,081
Per-capita		1,081	1,081		1,081

Notes: Social security benefits for different distributions of household earnings, holding household per-capita earnings fixed. Benefit married refers to the benefit when both spouses are alive, benefit widowed refers to the surviving wife's benefit.

It is worth noting that different distributions of earnings across spouses lead to different auxiliary benefits for the same total household earnings, and thereby

couples who have made essentially the same social security contributions. This is illustrated on the left-hand side of Table 3. When the husband is the sole earner, the couple's total social security benefit (when both spouses are alive) is maximized, as is the surviving spouse's benefit. The widow's benefit is smallest when the husband and wife have equal earnings. The right-hand side of this table highlights the role of auxiliary benefits.⁵ Single females earning the same amount as their married counterparts (i.e. having the same AIME) receive much lower per-capita benefits. The difference is particularly pronounced for females with a labor-market history that leads to relatively low AIME. Note that the per-capita benefit of widows is by far the largest compared to married or single females.

When auxiliary benefits were first introduced in 1939, most households were organized around a male bread-winner. Subsequently there have been large changes to female employment and earnings, as well as to marital patterns. These trends in turn have implications for women's social security benefits and the importance of auxiliary benefits. Between 1950 and 2010, the labor force participation rate of women aged 25-54 doubled, from 37% to 75% (according to BLS, 2011). The increase in employment has been particularly pronounced for married women. The gender wage gap in earnings has also declined substantially over this period. In 1950, median male earnings were twice that of women, whereas in 2010 male earnings exceeded female earnings by a factor of 1.4.⁶

In 2001, over three quarters of women aged 40-69 had marital histories that assured them the option of claiming auxiliary benefits in retirement. However, trends in marital patterns imply a downward shift in the share of women potentially eligible for spousal and survivor benefits in the future. The rise in the share of never married women is particularly striking. In 2001, roughly 10.5% of women aged 40-49 had never been married, a doubling relative to 1985. The share of women aged 40-49 in 2001 who were currently divorced was 35.5%, up from 29.1% in 1985. Moreover, 51.4% of those women were divorced before reaching 10 years of marriage, up from 32.7% in 1985. See [Tamborini and Whitman \(2007\)](#) for more details.

Historically, auxiliary social security benefits have been an important source of retirement income for older women. Table 4 depicts the fraction of females entitled to spousal and survivor benefit for the year 2010. The table disaggregates the total fraction into fully and dually entitled wives, where the former refers to women who

⁵For the benefit-calculations in Table 3, we do not take minimum benefits, the so-called Special Minimum PIA, into account. However, due to several reasons explained in [Meyerson \(2014\)](#), the Special Minimum PIA has virtually no effect on the benefits paid to retirees.

⁶Data from [SSA \(2017\)](#), Table 4.B3.

receive benefits based solely on the husband’s entitlements and the latter to women who receive a top up to their retired-worker benefit. The time series trends regarding the evolution of female employment, the gender wage gap and marital patterns outlined above might suggest that the overall importance of auxiliary benefits will decline in the future. However, there are several reasons why studying the impact of auxiliary benefits is also important for current and future generations. First, an increasing share of non-eligible elderly singles aggravates the redistributive consequences of these policies, as these groups have the highest poverty rates. Second, a relatively stable gender-wage gap implies a substantial top-up of married women’s benefits when the husband dies. Third, the negative incentive to work even for high-educated females if their husband is sufficiently rich will continue to be an inefficiency generated by the auxiliary benefit system. Moreover, despite increasing female employment, a shrinking gender earnings gap and changes in marital patterns, [Butrica and Smith \(2012\)](#) estimate that 37% of women born 1946-55 will receive auxiliary benefits when first claiming social security benefits (note that this number does not include women who are widowed after the start of benefit collection). Thus, auxiliary benefits continue to be an integral part of the US social security system.

Table 4: Percentage Distribution of Benefits for Females age 62+

<i>Benefits</i>	
Own entitlement only	46.4%
Spousal benefits, total	21.7%
entitled as wife only	9.6%
dually entitled	12.1%
Survivor benefits, total	31.9%
entitled as wife only	16.4%
dually entitled	15.5%

Notes: Data on benefits based on entitlement for all females aged 62 and older. Source: [SSA \(2017\)](#), Table 5.A14, for year 2010.

3 The Model

We develop a partial-equilibrium life-cycle model of singles and couples. Given that our goal is to study the labor supply effects and redistributionary consequences of social security in the US, this naturally necessitates a detailed modeling of the social security system, including auxiliary benefits. To capture heterogeneity in social security benefits, our model must generate heterogeneity in life cycle earnings histories and in auxiliary benefit eligibility. As such, the key ingredients of our framework are: (1) intensive and extensive margin labor supply choice for married women, (2) human capital accumulation in the form of learning by doing for married women, and (3) uncertainty with respect to marital status, survival and labor income. In the previous section we documented socio-economic gradients to marital stability and survival. In our model, we accommodate these facts by exogenously assuming different marriage and divorce rates over education and different survival probabilities over education. These linkages are important for capturing the differences in auxiliary benefit eligibility over the population, as well as the regressive elements built into the social security system.

Agents enter the model at age 26 and live until at most age 89.⁷ A model period corresponds to three years in the data, implying that we have 21 model periods.

3.1 Endowments

Households initially differ with respect to marital status, own and spousal education, own and spousal persistent income states, preferences for leisure and initial assets. Agents fall into one of four categories based on marital status: single, married, divorced or widowed. We model three education categories: high school dropouts, high school graduates and college graduates. Given that we allow the educational attainment of spouses to differ, we have nine educational types for married couples. We assume that assortative mating with respect to education is determined initially, and does not change in case of remarriage. We assume that spouses are identical with respect to age, asset holdings and the transitory income shock.

Over the life cycle, households' heterogeneity evolves with respect to female labor market experience, the income shock realization (persistent and transitory), asset holdings, the age at benefit claiming and the length of marriage.⁸

⁷We do not model educational choices, and therefore start the model after these decisions have been made.

⁸The length of marriage is necessary to determine auxiliary benefit eligibility, as divorced house-

3.2 Survival and Marital Transitions

Agents die stochastically. The survival rate depends on gender, age, and education, $\psi_{g,t,e}$. Survival risk is idiosyncratic and washes out at the aggregate level. Since we hold the number of newborn households constant, the population is stationary.

Marital transitions are exogenous to the model. The initial marital status of individuals is married m , never married, u , or divorced d . As agents get older, they can also become widowed, w . Marital status is then given by $s_t \in \{m, u, d, w\}$.

Singles face a marriage probability $\xi_{g,t,e}$, which depends on gender, age and education. Similarly, divorced agents face a remarriage probability $\nu_{g,t,e}$. Married couples, in turn, face a divorce probability $\mu_{g,t,e}$. We return to the assumption of exogenous marital transitions in Section 7.

To determine auxiliary benefit eligibility, we have to keep track of the length of the marriage, l_t .⁹ For simplicity, we only count the years of a marriage until the eligibility threshold for auxiliary benefits is reached. In addition, we assume that there is no divorce risk once a marriage has lasted for 10 years.¹⁰

3.3 Preferences and Economies of Scale

Husbands and wives derive utility from own consumption, $c_{g,t}$, and disutility from own labor supply, $L_{g,t}$, where gender is denoted by $g = 1, 2$ and 1 is female and 2 is male. Instantaneous utility is given by:

$$U(c_{g,t}, L_{g,t}) = \ln(c_{g,t}) - \Phi_{g,t,e,v} \frac{L_{g,t}^\gamma}{\gamma} + v_{e,esp,t} \quad (1)$$

Preferences are assumed to be separable and consistent with balanced growth, thereby dictating the $\ln(c)$ choice. The preference parameter γ governs the curvature on the disutility of work. $\Phi_{g,e,t,v}$ denotes disutility from work, which we allow to differ by gender, education, preference for leisure v (high or low disutility from work) and age. The utility term $v_{e,esp,t}$, which depends on own and spousal education and age, governs the disutility from joint work/utility from joint retirement of spouses.

holds can be eligible based on their ex-spouses' entitlements, if they were married for at least ten years.

⁹We approximate the threshold of 10 years by 4 model periods, implying $4 \times 3 = 12$ actual years.

¹⁰A person who is divorced with a marriage that lasted more than 10 years must also be currently unmarried to be eligible to claim spousal benefits based on the ex-spouse's earnings record. In the case of remarriage, benefits from the ex-spouse cannot be claimed unless the new marriage ends in divorce/death of the new spouse.

Singles face the same utility function as married individuals, with the exception of the utility term v .

Couples benefit from economies of scale in consumption. Consumption expenditure for the married household is given by:

$$c_t = [c_{1,t}^\varrho + c_{2,t}^\varrho]^{\frac{1}{\varrho}} \quad (2)$$

where $\varrho \geq 1$ implies that couples are able to consume more than the spouses living separately could, keeping expenditure fixed.

3.4 Life Cycle Income

Labor Income Women accumulate human capital, h_t , through work, according to the following learning by doing specification:

$$h_{t+1} = \begin{cases} h_t - \delta \cdot h_t & \text{if not working} \\ h_t + \iota \cdot \Delta t & \text{if working part-time} \\ h_t + \Delta t & \text{if working full-time} \end{cases} \quad (3)$$

Human capital is measured in years of experience, where Δt constitutes one model period, or three years. Human capital is subject to depreciation (at rate δ) if the woman does not work. We follow [Blundell et al. \(2016\)](#) and assume a part-time penalty, $\iota < 0.5$, implying that part-time work accumulates less than 50% of the human capital of full-time work.

Female earnings are modeled as a non-linear function of human capital h_t

$$y_{1,t,e} = \gamma_e + \alpha_e \cdot h_{t,e} + \bar{\alpha}_e \cdot h_{t,e}^2 + w_{t,e} \quad (4)$$

where γ_e , α_e , and $\bar{\alpha}_e$ are constants varying by educational type e . The stochastic component of earnings process, $w_{t,e}$, has a transitory and a persistent component. For couples, we assume a positive correlation between spousal persistent income shocks.

Since men are continuously employed until retirement, their earnings are simply a function of age. Given that even women working full-time have lower earnings than men, we exogenously impose an age- and education-specific gender wage gap. The details of the estimation of the income processes are described in the calibration section 4, where we also formally specify the gender-difference in income.

Social Security Benefits We model the US social security system in detail. Social security benefits, b_g , are paid out as an annuity and depend on past income, the claiming age, t^r , and marital status (due to auxiliary benefit payments). We assume that benefits are claimed when the agent stops working (after age 61).¹¹

Benefits based on one’s own earnings history are calculated as follows. First, the so called Average Indexed Monthly Earnings (AIME) is computed, by averaging over life-time earnings from the highest 35 years (including possible zeros). A concave benefit formula is then applied to AIME to get the Primary Insurance Amount (PIA), which is not allowed to exceed a maximum benefit value. Finally, benefits are adjusted according to actual claiming age. See Appendix B.3 for a detailed description of how social security benefits are computed.

Auxiliary benefits Auxiliary benefits top up social security benefits for individuals with low average lifetime earnings. These benefits are claimed based on the spouse’s earnings record, and as such they are dependent on marital status. Eligibility requires that the individual is either married (for at least a year) or divorced after a marriage that lasted at least 10 years. Given that men work continuously until retirement and we impose an exogenous gender wage gap, in our model, only women claim auxiliary benefits. With auxiliary benefits, the social security benefit of the wife is the higher of one’s own benefit and 50% of the spouse’s entitlement. If the spouse dies, the widow is eligible for survivor benefits equal to 100% of the deceased’s benefit. More formally:

$$b_{g,t} = \begin{cases} b_{g,t} & \text{if single or divorced and ineligible} \\ \max \{b_{g,t}; \frac{1}{2}b_{-g,t}\} & \text{if married or divorced and eligible} \\ \max \{b_{g,t}; b_{-g,t}\} & \text{if widowed} \end{cases} \quad (5)$$

where we denote the respective spouse of gender g by $\neg g$. A divorced spouse is eligible if her marriage lasted for at least ten years.

Contributions and earnings cap Social security benefits are funded by a payroll tax, τ_{ss} . Only earnings up to a cap of y_{max} are subject to the payroll tax. This introduces a regressive element to the U.S. social security system. Formally, income

¹¹For simplicity, we do not model benefit claiming as a separate choice. Given that adjustments for early and delayed claiming are roughly actuarially fair for an individual with average life expectancy, we would argue that this is not of first-order importance.

that is considered for social security taxes is given by:

$$\hat{y}_{g,t} = \min\{y_{g,t}, y_{max}\}. \quad (6)$$

3.5 Budget Sets of Households

The budget set of agents depends on marital and employment status. For a married couple with both spouses working, the budget constraint is given by:

$$(1 + \tau_c)c_t + a_{t+1}^s = a_t^m + (1 - \tau_y^m)(ra_t^m + y_t) - \tau_{ss}\hat{y}_t + 2T \quad (7)$$

where c_t is household consumption (see equation (2)), and y_t is household income ($y_{1,t} + y_{2,t}$).

Asset holdings, a_t^s , are dependent on marital status $s_t \in \{m, u, d, w\}$ and yield a market return at rate r . Households are not allowed to borrow. Due to marital status risk, a_{t+1}^s is uncertain to the household in period t . We assume that assets are split evenly between spouses in the case of a divorce (i.e., $a_{t+1}^d = 0.5a_{t+1}^m$).¹² In case of widowhood, assets stay with the surviving spouse ($a_{t+1}^w = a_{t+1}^m$).

Total income, i.e., the sum of labor income of both spouses and the returns from assets, are subject to a progressive income tax, τ_y^s , which depends on marital status. We follow [Guner et al. \(2014\)](#) and assume a simple linear tax function:

$$\tau_y^s = \alpha_s + \beta_s \cdot \frac{(y_t + ra_t^s)}{\bar{y}} \quad (8)$$

where \bar{y} is average income in the economy. Households also pay a proportional social security payroll tax, τ_{ss} , on taxable earnings y_t (see equation (6)). Consumption expenditures are taxed at a proportional rate τ_c .

Finally, households receive a lump-sum transfer, T , per individual, the size of which is determined by the balancing of the government budget.

If both spouses are retired, the budget constraint of a married couple is given by

$$(1 + \tau_c)c_t + a_{t+1}^m = [1 + (1 - \tau_y^m)r] a_t^m + b_t + 2T \quad (9)$$

where, again, $b_t = b_{1,t} + b_{2,t}$ is the households' social security benefit.

¹²As it pertains to our cohort born in 1950, by then most U.S. states had shifted away from a division of property by title of ownership to either equal division or a division made by the court with certain discretionary power. See [Voena \(2015\)](#) for a study of the importance of differences in divorce laws for household decision making.

There are similar budget constraints for different combinations of marital and employment status. To conserve space, we omit them here.

3.6 Recursive Planning Problem

We assume a Markov-process for the stochastic wage uncertainty, which allows us to state the household problem recursively.

In every period, households make decisions regarding how much to save and how to allocate consumption between the household members. To facilitate the modeling of labor supply, we divide the recursive maximization problem into three stages: the pure working-age phase, the benefit claiming phase and the retirement phase.

In working age, between ages 26 and 61, married women can work full-time, part-time or not at all, $L_{1,t} = \{0, 0.5, 1\}$. We assume that married men work full-time. During the benefit claiming phase, between ages 62 and 70, households choose whether or not to stop working and claim benefits, separately for each member. The female labor supply choice is between $L_{1,t} = \{0, 0.5, 1\}$, where now retirement ($L_{1,t} = 0$) is assumed to be an absorbing state and coincides with benefit claiming. Male labor supply is a choice between full-time and no work, $L_{2,t} = \{0, 1\}$, where again stopping work coincides with benefit claiming and is an absorbing state. In the retirement phase, from age 71 on, everyone is assumed to be retired.

We assume single individuals work full-time until at least age 61, after which they face the decision of whether or not to stop work and claim social security benefits.

The choices are made based on a rich state space consisting of a total of 15 state variables for married individuals. Accordingly, we define the value function for each age t , marital status s , and gender g as $V_{g,t}^s(\Gamma_t)$, where:

$$\Gamma_t = \{e, e^{sp}, v, t^r, t^{rsp}, h, a, i, z, z^{sp}, \eta, l\}$$

The remaining state variables are own and spousal education (e and e^{sp} , respectively), the type determining work-disutility (v), the own claiming/stop work age (t^r) and that of the spouse (t^{rsp}), human capital (h), assets (a), AIME (i)¹³, persistent own and spousal income components (z and z^{sp} , respectively), transitory income states (η), and the length of marriage (l).

¹³Assets, human capital and AIME are continuous variables discretized on non-equally spaced grids. The AIME grid is only dependent on e and e_s , the human capital grid is age- and education specific, and the asset grid is dependent on age, education (own and spousal), disutility-type, and marital status. This very detailed grid-specification for assets is necessary to account for very different asset holdings across these states.

Below we outline the recursive maximization problems for married and non-married agents in the three different stages of life.

Married Households

The married household solves a constrained Pareto problem, where χ denotes the Pareto weight of the wife and $1 - \chi$ of the husband. For computational tractability, these weights are exogenously determined.¹⁴ The value function of a married household is given by the weighted sum of each spouse's value function.

During the working-age stage, agents face marital, wage and survival risk. Married households choose male and female consumption, savings and female labor supply. Married men always work. The planning problem for the married household is to maximize:

$$V_t^m(\Gamma_t) = \max_{c_{1,t}, c_{2,t}, L_{1,t}, a_{t+1}} [\chi V_{1,t}^m(\Gamma_t) + (1 - \chi)V_{2,t}^m(\Gamma_t)] \quad (10)$$

subject to the budget constraint given in (7), where each spouse's value function is given by:

$$\begin{aligned} V_{g,t}^m(\Gamma_t) = & \left[\ln(c_{g,t}) - \Phi_{g,t,e,v} \frac{L_{g,t}^\gamma}{\gamma} + v_{e,esp,t} \right] \\ & + \psi_{g,t,e} \psi_{-g,t,e} (1 - \mu_{t,e}) \beta E [V_{t+1}^m(\Gamma_{t+1} | \Gamma_t)] \\ & + \psi_{g,t,e} \psi_{-g,t,e} \mu_{g,t,e} \beta E [V_{g,t+1}^d(\Gamma_{t+1} | \Gamma_t)] \\ & + \psi_{g,t,e} (1 - \psi_{-g,t,e}) \beta V_{g,t+1}^w(\Gamma_{t+1} | \Gamma_t) \end{aligned} \quad (11)$$

We again denote the respective spouse of gender g by $-g$. $V_{g,t+1}^d$ is the continuation value of divorce, and $V_{g,t+1}^w$ is the continuation value of widowhood.

The planning problem in the retirement decision phase is the same as above, with the distinction that now also male labor supply is a choice. Recall that social security claiming and the decision to stop work coincide in our model. Retirement is an absorbing state. From age 71 onward all agents are retired, implying that the household only makes decisions about consumption and savings.

¹⁴We do, however, conduct sensitivity analyses with respect to these weights. See Section 7.

Non-married households

The planning problem for non-married households (singles, divorced and widows) involves maximizing individual consumption subject to exogenous (re-)marriage and survival probabilities. The only difference between the value functions of the single and divorced household $s = \{u, d\}$ are the marriage and remarriage probabilities, $\xi_{g,t,e}$ and $\nu_{g,t,e}$, respectively. Defining $\Pi = \{\xi, \nu\}$ we get:

$$\begin{aligned} V_{g,t}^s(\Gamma_t) = & \max_{c_{g,t}, a_{t+1}} \left[\ln(c_{g,t}) - \Phi_{g,t,e,v} \frac{L_{g,t}^\gamma}{\gamma} \right] \\ & + \psi_{g,t,e} (1 - \Pi_{g,t,e}) \beta E [V_{g,t+1}^s(\Gamma_{t+1} | \Gamma_t)] \\ & + \psi_{g,t,e} \Pi_{g,t,e} \beta E [V_{t+1}^m(\Gamma_{t+1} | \Gamma_t)] \end{aligned} \quad (12)$$

where V_{t+1}^m is the value function if the agent (re)marries. The maximization is subject to the budget constraint faced by a single agent. Note that our definition of divorced individuals includes only those who are not eligible for auxiliary benefits, since we assume no divorce risk after 10 years of marriage.

We assume widows face no probability of remarriage. Their recursive problem is simply given by:

$$V_{g,t}^w(\Gamma_t) = \max_{c_{g,t}, a_{t+1}} \left[\ln(c_{g,t}) - \Phi_{g,t,e,v} \frac{L_{g,t}^\gamma}{\gamma} \right] + \psi_{g,t,e} \beta V_{g,t+1}^w(\Gamma_{t+1} | \Gamma_t) \quad (13)$$

subject to the budget constraint. Again, the planning problem in the retirement decision stage (ages 62-70) also involves a decision to stop work for the man. From age 71 onward, all agents are retired, implying that the individuals only make decisions about consumption and savings.

3.7 Aggregation

To calculate averages over the life cycle we have to determine the distribution of agents over the state space. Denote the cross-sectional measure of households in period t in each state as $\Omega_t(s, g, t^r, t^{rs}, h, a, i, e, e^{sp}, z, z^{sp}, \eta, l, v)$ over the Cartesian product $\mathcal{Y} = \mathcal{S} \times \mathcal{G} \times \mathcal{T}^r \times \mathcal{T}^{rs} \times \mathcal{H} \times \mathcal{A} \times \mathcal{I} \times \mathcal{E} \times \mathcal{E}^{sp} \times \mathcal{Z} \times \mathcal{Z}^{sp} \times \Theta \times \mathcal{L} \times \mathcal{V}$, where each element is the set of all possible realizations. E.g., $\mathcal{A} = [0; \infty]$ is the set of all possible asset holdings (starting at zero due to our assumption of a no-borrowing constraint).

The initial measure of households, Ω_0 , is determined by the survival rate $\psi_{g,t,e}$,

which allows us to calculate the share of 26 year olds. From the data, we can then determine the initial distributions across marital states $s_{g,0,e}$ (which differ by gender and education), assets $a_{0,s,e}$ (which differ by marital status and husband's education)¹⁵, and persistent income states $z_{0,e}$ (which depend on education). The distribution of spousal income states $z_{0,g}^{sp}$ (depending on gender) is approximated using data on education for married couples.¹⁶ We also take the education shares, e and e^{sp} , from the data. Initial length of marriage is normalized to $l_0 = 1$.

The evolution of this measure for ages $t > 1$ is driven by the transitory and persistent income shocks, marital status transition probabilities, survival prospects, as well as the policy functions for consumption, labor supply and benefit claiming. The cross-sectional measure evolves according to

$$\begin{aligned} & \Omega_{t+1} (\mathcal{S} \times \mathcal{G} \times \mathcal{T}^r \times \mathcal{T}^{rs} \times \mathcal{H} \times \mathcal{A} \times \mathcal{I} \times \mathcal{E} \times \mathcal{E}^{sp} \times \mathcal{Z} \times \mathcal{Z}^{sp} \times \Theta \times \mathcal{L} \times \mathcal{V}) \\ = & \int \sum_{z_{t+1} \in \mathcal{Z}} \sum_{z_{t+1}^{sp} \in \mathcal{Z}^{sp}} \pi_{z,z^{sp}}(z_{t+1}, z_{t+1}^{sp} | z_t, z_t^{sp}) \cdot \sum_{\eta_{t+1} \in \Theta} \pi_{\eta}(\eta_{t+1} | \eta_t) \cdot \sum_{s_{t+1} \in \mathcal{S}} \pi_s(s_{t+1} | s_t) \cdot \psi_{g,t} \\ & \cdot \Omega_t (ds_t \times dg \times dt^r \times dt^{rs} \times dh_t \times da_t \times di_t \times de \times de^{sp} \times dz_t \times dz_t^{sp} \times d\eta_t \times dl_t \times dv) \end{aligned}$$

where $\pi_{z,z^{sp}}$ and π_{η} are Markov-transition probabilities for the persistent and transitory income shocks. For married couples the transition probabilities of the persistent income shocks are jointly determined, while we have only π_z if the agent is non-married. We use π_s as shorthand for the marital transition probability depending on current marital status s_t .¹⁷

¹⁵Due to small sample size, we cannot determine initial assets for each husband-wife-education type in a marriage, so we chose to evaluate initial assets only for husbands when married (and individually for non-married).

¹⁶We group the education variable into high school, some college, B.Sc., and M.Sc. and above and compute the fractions given the education of the spouse.

¹⁷ π_s is determined by the (re)marriage and divorce probabilities as well as the spousal survival rate and defined for an individual g with a spouse $\neg g$ as:

$$\pi_s(s_{t+1} | s_t) = \begin{cases} \pi_s(m_{t+1} | u_t) & = \xi_{g,t,e,z} \\ \pi_s(m_{t+1} | m_t) & = \psi_{\neg g,t,e}(1 - \mu_{g,t,e,z}) \\ \pi_s(m_{t+1} | d_t) & = \nu_{g,t,e,z} \\ \pi_s(d_{t+1} | m_t) & = \psi_{\neg g,t,e} \mu_{g,t,e,z} \\ \pi_s(w_{t+1} | m_t) & = 1 - \psi_{\neg g,t,e} \end{cases}$$

3.8 Government Budget Constraint

We define the working population by $\sum_{t=0}^{t^r-1} N_t$ and the retired population by $\sum_{t=t^r}^T N_t$, where t^r is chosen endogenously by the households. Recall that N_t denotes the age t population, governed by the survival rates ψ_t , where we normalize $\sum_t N_t = 1$.

The government budget constraint is given by:

$$\begin{aligned} \sum_{t=t^r}^T N_t b_t + T + C_t &= \sum_{t=0}^{t^r-1} N_t [\tau_y^s y_t + \tau_y^s R a_t^s] \\ &+ \sum_{t=0}^{t^r-1} N_t \tau_{ss} \hat{y}_t \\ &+ \tau_c C_t \end{aligned} \tag{14}$$

Note that consumption, assets and income are—by slight misuse of notation—life cycle aggregates in equation (14). Accidental bequests—arising because of missing annuity markets—are taxed away at a confiscatory rate of 100%. This revenue is included in government consumption C_t , which is otherwise neutral. We further specify a certain fraction of the tax revenue to be used for government consumption.

4 Parameterization

In what follows, we describe the parametrization of the model. We focus on the cohort born 1950-54 and characterize their marital status transitions, income processes, median asset holdings over the life cycle, and employment patterns over age.

The parameterization of our model is a two-stage process. In the first stage we assign values to parameters that can be estimated outside our model. There are also a few parameters which we take directly from the literature. In the second stage we calibrate further parameters by matching moments of our model to the data.

4.1 Estimation of First-Stage Parameters

The first-stage parameters, which can be estimated outside our model, are the marital status transition probabilities, the survival rates and the income process. We describe these estimation procedures in what follows.

4.1.1 Marital Status Transition Probabilities

To determine the remarriage and divorce probabilities, we employ data from the Survey of Income and Program Participation (SIPP) from the U.S. Census Bureau for year 2008. Due to the recursive nature of the SIPP marital history variable, we can elicit cohort specific values by only taking data from one year. For the marriage probabilities, we construct a synthetic panel from the CPS for years 1976-2015, because SIPP data cannot be used.

We compute marriage, divorce and remarriage probabilities by age, gender and education. They are reported in Appendix B.4, along with a more detailed description of how they were computed. All marital transition probabilities are smoothed over age. We also use the CPS for the initial distribution of marital status, see Table B.6 in the Appendix.

4.1.2 Survival Risk

Since data on survival rates from the life-tables only distinguishes between age and gender, we have to estimate these assuming a Logistic model for the survival rate. We use the Health and Retirement Study (HRS) to estimate survival probabilities over age, gender and education.

Following Pijoan-Mas and Ríos-Rull (2014), we estimate a Logistic regression of death rates on age, education and gender. We predict the conditional survival rates and compute the estimated life expectancy given in Table 1. Our estimates line up well with life-table data on life expectancy.¹⁸ Life cycle profiles of survival probabilities are shown in Appendix B.5. We make out-of-sample predictions for ages 49 and below.

4.1.3 Income Process

We assume that labor income is determined by age (men) or human capital (women), and differs by education. In addition to the deterministic component, we model an idiosyncratic component, $w_{t,e}$, which differs by education, and is correlated between spouses.

For men ($g = 2$), we assume that labor income for each age bin t is given by

$$y_{2,t,e} = \gamma_e + \alpha_e \cdot t + \bar{\alpha}_e \cdot t^2 + w_{t,e} \quad (15)$$

¹⁸Life expectancy for our cohort born 1950-54 is 74 for males and 79 for females, see <http://www.ssa.gov/oact/tr/2012/lr5a4.html>.

The deterministic wage-equation thus consists of a constant term, γ_e , and an age polynomial captured by the coefficients α_e and $\bar{\alpha}_e$. The regression is performed separately for the education groups.

To estimate this wage process, we use data on males in the Panel Study of Income Dynamics (PSID) for the years 1969-2013, so as to cover most of the life-cycle income process of our 1950-54 cohort. Details of the data are relegated to Appendix B.2.

Women’s income is modeled according to the following specification:

$$y_{1,t,e} = (1 - \zeta_{t,e}) \cdot \{ \gamma_e + \alpha_e \cdot h_{t,e} + \bar{\alpha}_e \cdot h_{t,e}^2 \} + w_{t,e} \quad (16)$$

The most notable difference to men is that women’s income depends on human capital, h_t , not age. Recall that women accumulate human capital by working. We assume depreciation of 2.5% per year from non-participation.¹⁹ Following [Blundell et al. \(2016\)](#), we assume low human capital accumulation from part-time work. We follow [Guner et al. \(2012\)](#) and assume that the coefficients γ_e , α_e , and $\bar{\alpha}_e$ are the same for women as for men (the spells of non-employment make estimating this equation separately for women challenging). In addition, since even women working full-time face lower wages than their male counterparts, we scale down women’s income in order to match the data on the gender wage gap. We follow an approach taken by [Jones et al. \(2015\)](#) who assume an age-specific wedge as a proxy for either direct wage discrimination or, e.g., a glass ceiling. We choose an age profile for $\zeta_{t,e}$ for each education type and match it to the CPS data on the gender-wage gap over age. The gender-wage gap for our cohort is quite substantial; female hourly wages are on average 73% of male wages.²⁰

The residuals from regressions (15) and (16) represent the stochastic part of wages, $w_{i,t,e}$, for each individual i . As is standard in the macroeconomic literature, we follow [Storesletten et al. \(2004\)](#) and assume that the idiosyncratic income component can be represented by a time-invariant process with a persistent and a transitory component. See Appendix B.2 for details. For married couples, we assume a positive correlation between the persistent income components of spouses, with a correlation coefficient of 0.25 as estimated by [Hyslop \(2001\)](#). The parameters are estimated with a GMM estimator. Results are given in Table B.4 in the

¹⁹This is in line with the literature estimating the human capital depreciation from one year away from the labor market, which ranges from 2-5%. See, e.g., [Attanasio et al. \(2008\)](#).

²⁰In the model we use the linear trend for the life cycle profile of the gender-wage gap, since the raw data is noisy. Note that the ratio of female to male wages differs over education with 69% for dropouts, 72% for high school graduates, and 78% for females with a college degree, on average.

Appendix. We assume the same shock process for high school dropouts and high school graduates due to sample size problems.

We discretize the persistent stochastic component with a 4-state Markov-process using Tauchen’s method. This yields the transition probability matrix $\pi_z(z_{t+1}|z_t)$ for singles. For married couples we apply Tauchen’s method to the multivariate case with non-diagonal covariance structure. The technique is described by [Terry and Knotek \(2011\)](#) and yields the transition probability matrix for a married household, $\pi_{z,z^{sp}}(z_{t+1}, z_{t+1}^{sp}|z_t, z_t^{sp})$.²¹ For the transitory shock we assume $\pi_\eta(\eta_{t+1}|\eta_t) = 0.5$.

4.1.4 Exogenous Parameters

The policy parameters are set to match the U.S. social security and tax systems. [Guner et al. \(2014\)](#) estimate a progressive tax function for married and single individuals. We use their estimated parameter values. The values for the proportional consumption and payroll taxes are taken from [McDaniel \(2007\)](#).²² All tax parameter values are reported in Appendix [B.6](#).

Recall that the lump sum transfer T is chosen to balance the budget. These transfers capture education and healthcare expenditures as well as social aid and disability insurance. In addition, we assume that a fraction of the government revenues are spent on consumption expenditures that are not explicitly modeled. To determine this fraction, we follow [Chakraborty et al. \(2015\)](#), who set this equal to the expenditures on defense, interest payments and protection in the U.S. government budget from 2000. This yields a fraction of 24%. Hence, we assume that the remainder, i.e., 76% of total government expenditures, is handed back to the households in the form of social security benefits and lump sum transfers.

We also set the following parameters exogenously from the literature:

The curvature parameter on the disutility from work is related to the labor supply elasticity and consistent with estimates from models incorporating human capital accumulation (see, e.g., [Imai and Keane 2004](#) and [Wallenius 2011](#)).²³ We assume a

²¹Note that while π_z is a four by four matrix depending on education, $\pi_{z,z^{sp}}$ is a 16 by 16 matrix determining each simultaneous transition of spousal incomes. Further note that there are in principal four different transition probability matrices depending on the educational attainments of the spouses. Given our symmetry assumption, the transition probabilities for a low-educated wife with a high-educated husband are equal to the ones for a high-educated wife with a low-educated husband.

²²We take her updated version, which can be downloaded at: http://www.caramcdaniel.com/tax-files/McDaniel_tax_update_12_15_14.xlsx.

²³We assume the same elasticity for men and women. In a recent paper, [Rogerson and Wallenius \(2018\)](#) use data on the time use of older Americans to show that the curvature parameters are in

Table 5: Exogenous Parameters

Parameters			Source
γ	Curvature on disutility from work	2.0	Wallenius (2011)
χ	Pareto weight	0.5	Fernandez and Wong (2014)
ϱ	McClement equivalence scaling	1.4023	Voena (2015)
ι	Return to experience from part-time	0.1	Blundell et al. (2016)

Pareto-weight of 0.5, implying equal bargaining power for both spouses. We conduct sensitivity with respect to the Pareto weights in Section 7. For equivalence scaling we use the McClement scale. The value for the accumulation of experience from part-time work is taken from Blundell et al. (2016).²⁴

4.2 Calibration of Second-Stage Parameters

The parameters that we calibrate using our model are the utility-cost of working parameters, $\Phi_{g,e,t,v}$, α , and $v_{e,esp,t}$, and the discount rate, ρ .

Discount Rate and Asset holdings

We set the interest rate equal to 4.2% (as in Siegel (2002)). We choose the discount rate to match median asset holdings over age. A discount rate of $\rho = 0.011$ gives the best fit to the data.

Disutility of Work

The parameters governing the disutility of work are critical for matching female employment, as well as the prevalence of part-time work, over the life cycle. We allow the disutility from work parameters to differ across utility-types, education and age. While this specification generates qualitatively the correct gradient to women’s employment over husband’s education or income, the effect is too strong. In order to improve the fit along this dimension, we add a fixed utility cost of joint work to the model, which we condition on the husband’s education. This is a common practice in this literature, see, e.g., Guner et al. (2012). All the disutility parameters, together with the fraction of females with high disutility, α , are calibrated to match employment over age, own education and spouse’s education.

fact very similar for men and women.

²⁴Note that this estimate is for the UK. However, a related study for the U.S., Blank (2012), also finds very low accumulation of experience from working part-time.

This degree of heterogeneity in preferences is necessary to simultaneously match the age profiles of overall employment and part-time work of married females, as well as average rates for the nine education types (i.e., considering the wife’s and the husband’s education). The preference heterogeneity can be viewed as capturing features that are not explicitly modeled here, such as children and health. For married males we assume the same profile for both utility types until age 62, which corresponds to the low disutility profile of married females. We then calibrate the high and low disutility parameters for ages 62-70 to match the male stop working ages. Table 6 lists the calibrated preference parameters and the respective data moments to which they were matched. The resulting estimated values are shown in Appendix B.7.

Table 6: Second-Stage Parameters and Data Moments

Preference Parameters		Matched Data Moments
$\Phi_{1,e,t,v}$	Female disutility from work	Total female employment and part-time by age and education in CPS
α_e	Share of high disutility women	Average female employment and part-time in CPS
$\Phi_{2,e,t,v}$	Male disutility from work ⁽¹⁾	Male employment at older ages in CPS
v_{e,esp,t_1}	Disutility of joint work at age $t_1 = [1, t^r - 1]$	Average female employment by own and spousal education in CPS
v_{e,esp,t_2}	Utility of joint retirement at age $t_2 = [t^r, T]$	Distribution of joint retirement in HRS
ρ	Discount rate	Median asset holdings over age in CPS

Notes: ⁽¹⁾ For working age males we assume the corresponding low-disutility value of females, an innocuous assumption as men always work full-time.

5 Calibrated Economy

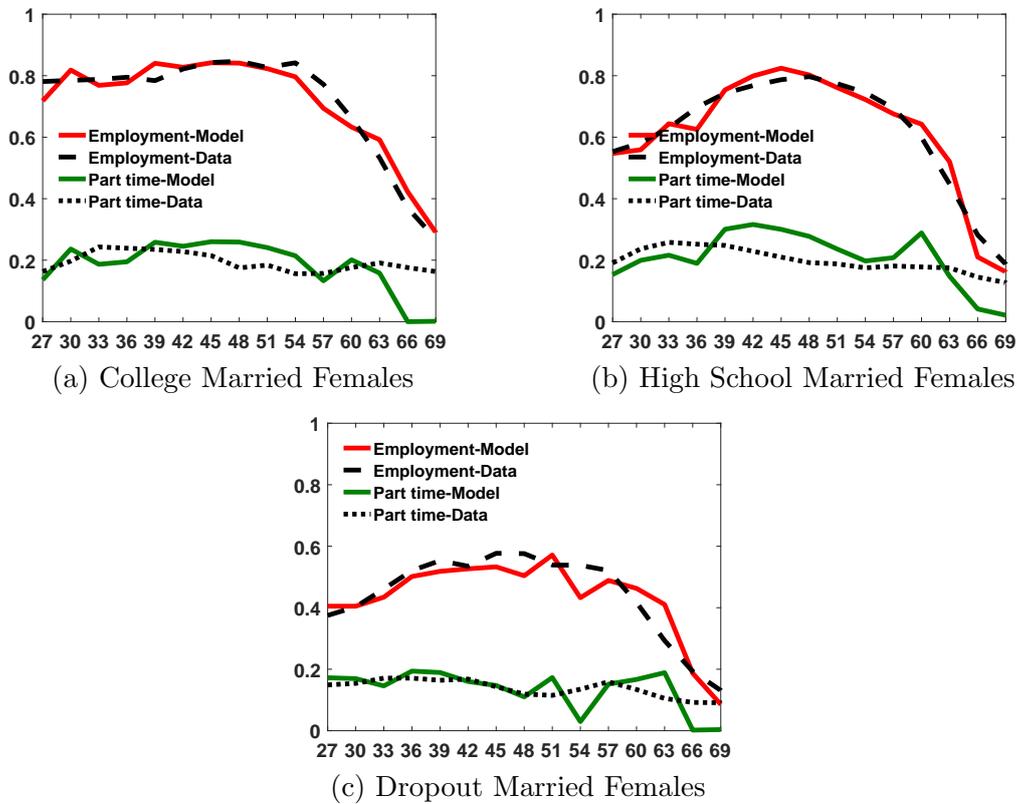
In this section we highlight the key properties of our calibrated benchmark economy and discuss the fit of the model to the data.

As a robustness check for our calibration, we feed in the marital and education patterns, as well as the gender wage gap, for the 1930 cohort. We then check whether we are able to match the much lower employment rates for the 1930 cohort with our calibrated model economy.

5.1 Employment

Figure 2 plots the model predicted overall employment rate, as well as the part-time employment rate, for married women over age and education, relative to the data. The model matches the hump-shaped pattern to life cycle employment well. The model does a decent job in generating a relatively flat profile for part-time employment over age, although it struggles a bit to match the prevalence of part-time employment at older ages.

Figure 2: Total Employment and Part-Time Work, Model vs. Data



Notes: Age-specific employment rate and rate of part-time work are computed from CPS data for the cohort born in 1950-54.

Not only does the model capture the differences in married women's employment over own education, but, as seen from Table 7, it matches the differences in married women's employment over spousal education as well. This is important for generating the correct distribution of auxiliary benefits in the model.

Table 7: Average Employment of Married Women over Own and Spousal Education

Wife-/Husband Education	Data	Model
Dropout/Dropout	0.43	0.43
Dropout/High School	0.47	0.47
Dropout/College	0.46	0.45
High School/Dropout	0.61	0.61
High School/High School	0.65	0.64
High School/College	0.60	0.60
College/Dropout	0.78	0.78
College/High School	0.78	0.77
College/College	0.69	0.69

Notes: Average employment of married women over own and spousal education, model outcomes relative to the data. *Source:* CPS, cohort born 1950-1954; females aged 26-69, data for age 65-69 for cohort born 1945-1949. Excludes those who do not work due to disability.

Table 8 shows the model fit with respect to employment of married men for ages 62 to 70. The model does very well in matching the male retirement patterns.

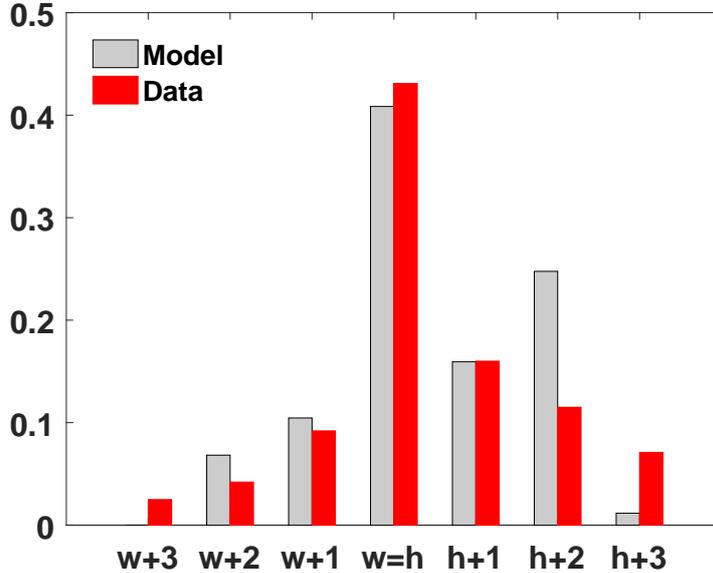
Table 8: Stop Work Decision of Married Men

Fraction stop working...	Dropouts		High School		College	
	Model	Data	Model	Data	Model	Data
...by 62-64	0.44	0.45	0.41	0.40	0.31	0.30
...by 65-67	0.65	0.65	0.60	0.60	0.45	0.45
...by 68-70	0.75	0.75	0.69	0.69	0.58	0.57

Notes: Data from CPS, cohort born 1950-54. Stop working is defined as 1 minus the age-specific employment rate of married males.

As evidenced by Figure 3, the model is also able to match the high prevalence of joint retirements across couples. Notably, more than 40% of couples retire within the same period. More generally, the model does a good job of matching the timing of retirement across spouses, with the exception of the extremes.

Figure 3: Difference in Retirement Age, Wife (w) and Husband (h)



Notes: The figure depicts the time-difference of retirement entry for married couples. $w = h$ denotes the fraction of couples that retires jointly, $h + 1$, $h + 2$, and $h + 3$ denote the fractions of couples where the husband retires 1, 2 and 3 periods after the wife, and vice versa for $w + 1$, $w + 2$, and $w + 3$, where one period is three years. Data from HRS.

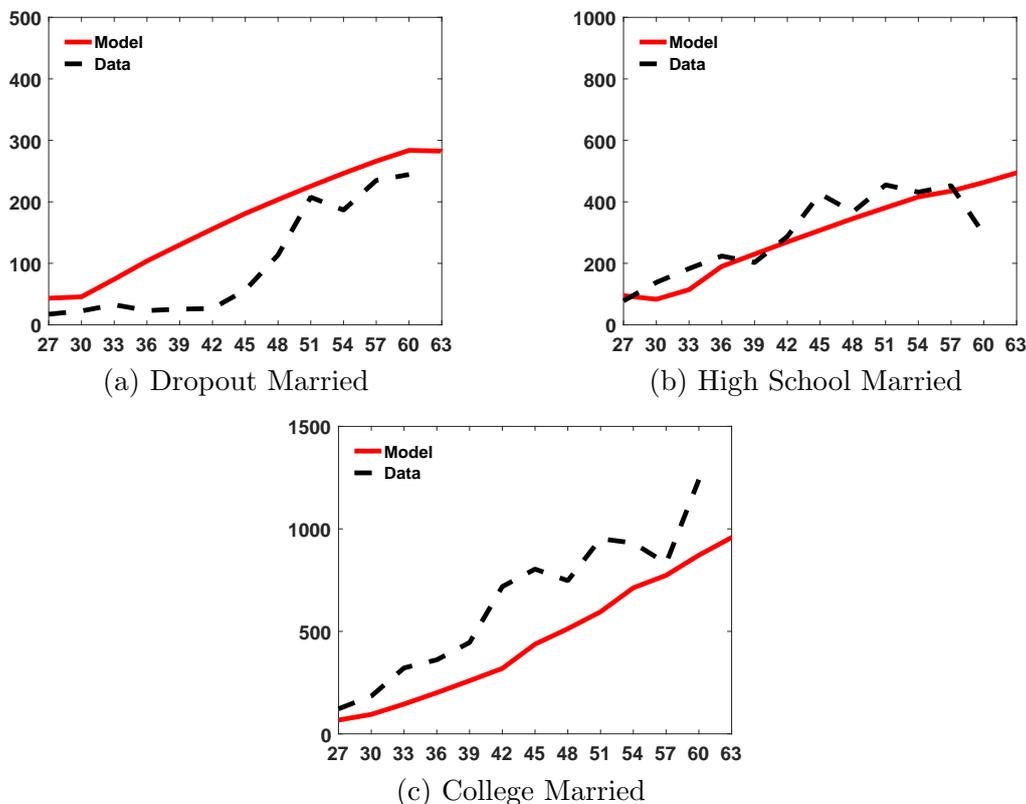
5.2 Distribution of Assets

As noted previously, the model matches the age-profile for the median asset holdings. In order to judge the model's ability to match the distribution of assets across the economy, Figure 4 plots median assets over age and education. Although, we do not directly target age-profiles over education, the overall model generated fit is decent. However, we overestimate asset holdings for high-school dropouts and underestimate them for college graduates, i.e., we do not fully match the education gradient in median asset holdings. For the low-educated this might be due to the fact that, since singles always work in our model, our framework does not include truly poor individuals. Conversely, for the highly educated we do not include inheritances, which account for a significant fraction of assets for this group.

5.3 Auxiliary Benefits

We do not directly target the fraction of women claiming auxiliary benefits, rather it is the result of various model elements which we feed in (marital transition probabilities and wages) or target (employment). Table 9 shows the fraction of married females who are claiming spousal and survivor benefits. Our model matches the

Figure 4: Median Asset Holdings, Model vs. Data



Notes: Age-specific median assets over education. Data from CPS for the cohort born 1950-54.

data well, although it somewhat over-predicts the prevalence of spousal benefits and under-predicts the prevalence of survivor benefits. Moreover, the share of women who are fully entitled to spousal benefits is overstated, 15.4% in the model compared with 9.6% in the data. Conversely, the share of women who are fully entitled to survivor benefits is only 7.3% in the model, compared with 16.4% in the data. Note, however, that the data on auxiliary benefit claiming is for 2010, and therefore includes women from older cohorts. This is the reason for the discrepancy in survivor benefit claiming. The data does not allow disaggregated statistics by educational type.

According to our predictions, survival benefit claiming is more prevalent among the less educated than the highly educated, due to assortative matching and the fact that the gender gap in life expectancy is larger for the less educated. In our model, 36% of high-school dropouts, 31% of high-school graduates and 20% of college graduates receive survivor benefits. Similarly, spousal benefit claiming is more prevalent among the less educated, with 31% of high-school dropouts, 28% of high-school

graduates and 19% of college graduates receiving spousal benefits. Although labor supply is increasing in own education and income, it is decreasing in spousal education and income. Since many college educated women are married to high earning husbands, even many highly educated women are eligible for spousal benefits.

Table 9: Auxiliary Benefits for Married Females

<i>Auxiliary Benefits</i>	Model	Data
Spousal benefits	26.6%	21.7%
fully entitled	15.4%	9.6%
dually entitled	11.2%	12.1%
Survivor benefits	29.2%	31.9%
fully entitled	7.3%	16.4%
dually entitled	21.9%	15.5%

Notes: Data on auxiliary benefits are taken from SSA (2017), Table 5.A14, for year 2010.

5.4 Redistribution through Social Security

To understand the nature of redistribution built into the current U.S. social security system, we use our benchmark economy to compare the replacement rates for different sub-populations. Here replacement rates are defined as the ratio of social security benefits to average life-time earnings, which we proxy using AIME (average indexed monthly earnings).

Due to the concavity of the social security formula in the U.S., there is redistribution from the rich to the poor. This is reflected in, for example, the differences in replacement rates of unmarried individuals.²⁵ The replacement rate is decreasing over education, from 0.47 for dropouts to 0.36 for college educated females. It is also evident from the higher replacement rates of single females compared to single males in the same education group, as women have lower earnings than men.

Auxiliary benefits break the link between social security benefits and one's own earnings record. This introduces redistribution from singles and dual-earner households to single-earner married households. This is reflected in much higher replacement rates for married and widowed females compared with unmarried females. The

²⁵We define unmarried as being never married or divorced with a marriage that lasted less than 10 years, i.e., these individuals are not eligible for auxiliary benefits. We use the terms unmarried and single interchangeably.

especially high replacement rates for widows is due to the generosity of survival benefits. However, the difference to singles is not solely due to auxiliary benefits, as ever married females work less than singles. Recall that, in our model, singles work until retirement by assumption. Thus, concavity of the benefit formula again contributes to the higher replacement rates for this group. It is nevertheless noteworthy that the replacement rate for ever married college women is slightly higher than the replacement rate of unmarried high school graduates. These numbers suggest strong redistribution from the bottom to the top, and from singles to married households. Within marital types the replacement rate is decreasing in education. This is due to several factors: the concavity of the benefit formula, assortative matching, and the fact that less educated women work less than their more educated counterparts.

Table 10: Replacement Rates - Baseline

	Females		Males	
	Married	Widowed	Unmarried	Unmarried
Dropouts	0.95	1.37	0.47	0.40
High School	0.62	0.92	0.43	0.38
College	0.44	0.61	0.36	0.32
<i>Total</i>	<i>0.56</i>	<i>0.86</i>	<i>0.41</i>	<i>0.36</i>

Notes: Ratio of average social security benefits to average indexed monthly earnings (AIME) conditional on being retired. Unmarried is defined as single or divorced and married less than 10 years, i.e., not eligible for auxiliary benefits.

It is not possible to directly compare these model generated numbers with the data. Relying on data from the HRS for years 1992-2012, [Khan et al. \(2017\)](#) estimate an average replacement rate of 0.39 for men and 0.50 for women. The corresponding values in our model are 0.40 and 0.60 for men and women, respectively. The over-prediction of the replacement rate for women likely stems from the fact that, in the model, single women always work, and benefit collection coincides with the stop work decision.

The model generated replacement rates in [Table 10](#) are conditional on being retired, and do not reflect differences in expected years in retirement. As a next step, we calculate a replacement rate that is adjusted for the difference in expected years in retirement. The latter is determined by our survival rate estimations and the endogenous benefit claiming decisions coming from our model.²⁶

²⁶The adjusted replacement rate is calculated by multiplying the ordinary replacement rate by

Table 11: Adjusted Replacement Rates - Baseline

	Females			Males
	Married	Widowed	Unmarried	Unmarried
Dropout	0.76	1.00	0.36	0.20
High School	0.64	0.98	0.45	0.38
College	0.52	0.73	0.42	0.48

Notes: Ratio of average social security benefits to average indexed monthly earnings (AIME) conditional on being retired. Adjusted for the difference in expected years in retirement. Unmarried is defined as single or divorced and married less than 10 years, i.e., not eligible for auxiliary benefits.

When adjusting the replacement rates for differences in expected years in retirement over education, it is striking that the concavity of the benefit formula for unmarried individuals is completely overturned by the differences in longevity (see Table 11). The adjusted replacement rate for single females is 6pp lower for dropouts compared to college graduates. This difference is even more pronounced for males. The difference is smaller when comparing college and high school graduates. Two counteracting forces are at work here: both the timing of benefit claiming and life-expectancy (own and spousal) differ over education. But even though women with a college degree retire almost two years later than high school dropouts, they live almost 6.5 years longer (men 7.5 years longer). Taken together, this means that college educated individuals spend substantially more years in retirement than high school dropouts. The effect of longevity differences is not as stark for married and widowed women as it is for singles. The reason is that less educated married women have considerably lower labor supply than their more educated counterparts. This results in lower lifetime earnings and higher replacement rates for less educated married women. Also, due to assortative matching, less educated wives typically have less educated husbands who die young, resulting in the claiming of survival benefits for more years.

the gender, education, and marital state specific deviation of expected years in retirement from the average (normalized to one). As an example, the time spent in retirement for a married college female is 18% higher than for the average woman (net effect of higher life-expectancy of high educated women and a smaller life expectancy difference between spouses for high-educated couples). We thus have $0.44 \cdot 1.18 = 0.52$, which corresponds to the value for the married college female in Table 11.

5.5 Robustness Check of Model Calibration

The labor supply responses to potential policy changes are at the heart of our analysis. In a model with a discrete labor supply choice, the mapping from the curvature parameter governing the disutility of work to the labor supply elasticity is weaker than in models with a continuous hours choice. As a validation exercise for our calibration, particularly the implied labor supply elasticity, we ask whether our model is able to generate the much lower employment rates for the 1930 cohort – holding preference parameters fixed – when feeding in differences in: (1) the gender wage gap, (2) educational attainment, (3) assortative matching and (4) marital transition probabilities.²⁷ This is very similar to the exercise carried out in [Fernandez and Wong \(2014\)](#).

From [Table 12](#) it is evident that by feeding in differences in gender wage gaps, education and marital transitions, our model is able to account for almost all of the difference in married women’s employment across the two cohorts. The fact that our model is able to generate the large employment variation across cohorts, and most importantly that it does not overstate said labor supply effects, lends credence to the calibration of the profiles governing the disutility of work.

Table 12: Employment of Married Females - Cohort Comparison

	1930 Cohort		1950 Cohort	
	Data	Model	Data	Model
Employment	0.439	0.469	0.636	0.632
Part-Time	0.181	0.176	0.197	0.199

Notes: Data from CPS for the cohorts born 1950-54 and 1930-34, respectively.

6 Policy Analysis

We consider two counterfactual experiments, abandoning auxiliary benefits altogether and replacing auxiliary benefits with a minimum benefit scheme. The motivation for the first exercise is that by abolishing auxiliary benefits we are able to quantify the negative labor supply effects of spousal and survivor benefits. The motivation for the second exercise is that, if the goal is to reduce poverty, a case can

²⁷Note, however, that we assume the same survival rates across cohorts. Due to sample size problems we cannot separately estimate cohort-specific survival rates.

be made that benefits should depend on income not marital status.

6.1 Abolishing Auxiliary Benefits

Let us now consider the labor supply implications for married women from abolishing auxiliary benefits. In our baseline specification, we assume that the additional revenue that is left over after auxiliary benefits are abolished is rebated lump-sum to all older individuals, specifically those aged 62 and above. Our model predicts a large increase in the average employment rate of married women, 12.6pp to be exact.²⁸

Table 13: Labor Supply Effects

	No Auxiliary Benefits	Only Survivor	Minimum Benefit
Married Females, Employment	12.6	8.7	-0.2
Dropout	22.4	13.8	-4.0
High school	13.5	9.9	-0.25
College	4.7	2.4	2.7
Married Males, Employment	-2.7	-0.8	-2.7
All Females, Employment	7.6	5.0	0.003
Part-Time	6.5	4.8	-0.7
All Males	-1.6	-0.5	-1.6
Aggregate Hours	2.36%	1.82%	-0.96%

Notes: Employment change from counterfactuals (in pp).

The employment effects are more pronounced for less educated women. This is intuitive, since less educated women rely more heavily on auxiliary benefits in the benchmark economy. See Table 13 for details. These employment effects are almost exclusively due to an increase in part-time work.

The employment effects for women are dampened by some men retiring earlier. With auxiliary benefits, there is an incentive for the husband to work longer in

²⁸For robustness, we also consider a scenario where the additional tax revenue is thrown in the ocean. This is equivalent to assuming that it is used for government consumption, as long as it does not affect the marginal utility of private consumption. As expected, the effect on married women's employment is even larger in this case, 13.7pp, (the effect for males is almost unchanged) implying an increase in aggregate hours of 2.85 percent.

order to increase his entitlements, which then leads to higher benefits for him and – through auxiliary benefits – for his wife. Hence, in the counterfactual, men tend to retire earlier. We find that male employment is reduced by 1.6pp. All in all, abolishing auxiliary benefits increases aggregate hours by 2.4%.²⁹

Table 14: Household Replacement Rates

	Married Household	Widowed Females	Unmarried Females
Baseline			
Dropout	0.54	1.37	0.47
High School	0.47	0.92	0.43
College	0.36	0.61	0.36
<i>Total</i>	<i>0.42</i>	<i>0.86</i>	<i>0.41</i>
No Auxiliary Benefits			
Dropout	0.45	0.57	0.47
High School	0.42	0.49	0.43
College	0.34	0.40	0.36
<i>Total</i>	<i>0.39</i>	<i>0.47</i>	<i>0.41</i>
Minimum Benefit			
Dropout	0.59	1.26	0.66
High School	0.46	0.68	0.53
College	0.34	0.45	0.38
<i>Total</i>	<i>0.42</i>	<i>0.65</i>	<i>0.49</i>

Notes: Value: Per-capita average replacement rate of the household depending on education. Unmarried is defined as single or divorced and married less than 10 years, i.e., not eligible for auxiliary benefits.

Average social security income for ever married households declines in response to the abolishment of auxiliary benefits, irrespective of education. The decline is evident from the replacement rates, see Table 14. This illustrates that both spousal and survivor benefits are important elements that boost replacement rates – for all

²⁹Joint taxation has a similarly dampening effect on married women’s employment as auxiliary benefits. Gumer et al. (2012) analyze this and find a substantial increase in aggregate hours of work, 2.6%, from moving from joint taxation to separate taxation.

education types – in our baseline scenario. The decline in social security income is most pronounced for the least educated households. The average household replacement rate for couples with a dropout wife falls from 0.54 to 0.45, whereas the corresponding decline for households with a college educated wife is only from 0.36 to 0.34. The change is even starker for widows, with the replacement rate declining from 1.37 to 0.57 for dropouts and from 0.61 to 0.40 for college graduates. These changes reflect the fact that households with low educated women rely most heavily on auxiliary benefits in the benchmark. Hence, abolishing auxiliary benefits decreases progressivity *within* marital states. At the same time, however, regressivity *between* marital states is diminished since non-eligible singles are hardly effected by the reform and, hence, gain in relative terms. Note that the increase in employment mitigates the decline in social security income resulting from abolishing auxiliary benefits.

Table 15: Asset-to-Income Ratio: Baseline vs. Counterfactuals

	Baseline	No Auxiliary Benefits	Only Survivor	Minimum Benefit
Dropout	1.57	1.57	1.56	1.55
High School	2.20	2.28	2.24	2.23
College	2.63	2.71	2.71	2.72

Notes: Median asset-to-income ratio for all households.

Households also adjust private savings in response to the changes in social security. Table 15 shows the median asset-to-income ratio over education for the baseline economy and for the counterfactual. The results demonstrate increased savings when eliminating auxiliary benefits. The largest increase is for high-school graduates and, to a lesser extent, for high-school dropouts. These groups lose the most when eliminating auxiliary benefits. Conversely, college graduates hardly increase their private savings.

We observe a relatively strong increase in the inequality of social security income from abolishing auxiliary benefits (see Table 16). The Gini-index of social security benefits rises from 0.146 in the baseline to 0.175 in the counterfactual without auxiliary benefits. Note that the numbers reported here are at the household level. The increase in inequality is more pronounced at the individual level than at the household level. We would argue that the household is the correct unit of study, since marriage provides substantial insurance against poverty.

Table 16: Distribution of Average Household Benefits

Pop.Frac.	Baseline		w/o Spousal		w/o Aux.Ben.		Min.Ben.	
	%	acc	%	acc	%	acc	%	acc
lower 20%	0.09	0.09	0.11	0.11	0.10	0.10	0.12	0.12
21 – 40%	0.18	0.27	0.15	0.26	0.14	0.24	0.16	0.28
41 – 60%	0.18	0.45	0.19	0.45	0.18	0.42	0.19	0.47
61 – 80%	0.25	0.70	0.22	0.67	0.25	0.67	0.23	0.70
81 – 100%	0.30	1.00	0.33	1.00	0.33	1.00	0.29	1.00
Gini-Index	0.146		0.157		0.175		0.135	

Notes: Fraction of household social security benefits in each population quintile.

Given that survivor benefits are intended to smooth the consumption of the widow, they differ somewhat from spousal benefits. It is, therefore, of interest to consider the implications of spousal and survivor benefits separately. We find that the employment effects from eliminating spousal benefits but keeping survivor benefits at the level of the current U.S. system are quite large. Specifically, the employment of married women rises by on average 8.7pp. This exercise illustrates that the depressing effect on labor supply of the auxiliary benefit system arises in large part – around two thirds – from spousal benefits. As one would expect, savings among high school dropouts and high school graduates increase when spousal benefits are abolished. Conversely, the increase in inequality relative to the baseline is much more modest when only abolishing spousal benefits: only about one third can be attributed to abandoning spousal benefits. Hence, our results show that abolishing spousal benefits, while keeping survivor benefits, is a policy measure that would eliminate most of the disincentives to labor supply, while only modestly increasing inequality.

6.2 Replacing Auxiliary Benefits with Minimum Benefit

If the objective of auxiliary benefits is to prevent poverty, an argument can be made that redistribution should depend on income, not marital status. A minimum social security benefit is an alternative to auxiliary benefits that would provide insurance against poverty in old age. Many countries have opted for minimum benefits, instead

of spousal benefits.³⁰

We consider an equivalence-scaled minimum benefit which is means tested on household income. To calculate the minimum benefit, we first compute benefits based on individual entitlements and then take the household average of these. If this average is below a certain threshold of average income in the economy we top up the benefits of both spouses to this level. We determine this threshold by requiring that the policy reform be revenue-neutral. This gives a threshold of 30.3% of average income in the economy. If income falls below this value, the household is eligible for minimum benefits. We equivalence-scale the minimum benefit by granting singles 0.61 of the benefit of a married individual.³¹

We find that replacing the auxiliary benefit scheme with such a minimum benefit results in a negligible employment effect of married women in our model, a decrease of 0.2pp to be precise. While the employment of college educated wives rises, this is offset by a decline in employment for dropout wives. The reason for this is that the minimum benefit is more generous than the old spousal benefit for the majority of low educated women. Male employment declines by 1.6pp in response to the minimum benefit. Consequently, aggregate hours decline by 0.96% relative to the baseline.

The minimum benefit does, however, increase the progressivity of the social security scheme, as evidenced by the replacement rates in Table 14. The household replacement rate for married couples where the wife is a high school dropout rises from 0.54 in the baseline to 0.59 with the minimum benefit. Conversely the household replacement rate for couples where the wife is a college graduate declines modestly from 0.36 to 0.34. The average replacement rate for unmarried women rises for all education types, with the dropouts experiencing the most dramatic increase – from 0.47 to 0.66. Widows lose out relative to the benchmark, albeit the reduction is lower for the high school dropouts.

Note that savings are hardly increased when replacing auxiliary benefits with a minimum benefit system. Again, this is because the poorest individuals receive a larger benefit under the minimum benefit scheme than in the baseline.

The redistribution from richer to poorer households implied by a minimum benefit system is also confirmed by the Gini index, see Table 16. The Gini-index of social security benefits declines from 0.146 in the baseline to 0.135 with the mini-

³⁰For a discussion of survival benefits across countries, see James (2009).

³¹According to the McClements scale, a person living alone spends 61 percent of what a childless couple spends to consume the same amount.

mum benefit scheme.

7 Robustness

In this section we discuss the limitations of our framework along with the implications of some of our main modeling assumptions. We devote particular attention to the exogeneity of marital status and the constancy of bargaining weights across spouses.

There are two models of household decision making, the unitary household model and the collective household model. The former is a cooperative solution that is efficient and requires binding commitments. The latter implies a non-cooperative self-enforcing outcome. As is common in macroeconomic models of household economics, our modeling approach resembles the unitary approach, implying constant bargaining power of spouses. However, there is a growing literature showing that the cooperative model seems to fit data on consumption and work behavior of married couples much better, see [Browning and Chiappori \(1998\)](#) for parametric, and [Cherchye et al. \(2009\)](#) for non-parametric evidence. The difference between the models arises from the idea that events that alter the family budget constraint can also influence the relative bargaining power of spouses. For a discussion of the unitary versus the collective model, see, for example, [Vermeulen \(2002\)](#).

Ours is already a rich model environment, and introducing a full marriage market is beyond the scope of this paper. While we treat marital transitions as exogenous, and hence keep bargaining power constant, here we discuss the implications of these assumptions in more detail.

7.1 Varying the Relative Bargaining Power of Spouses

It has been found that the bargaining power within a marriage is not equal. Typically, the husband has higher bargaining power than the wife, see, e.g., [Voena \(2015\)](#). For robustness, we start by altering the bargaining power across spouses. Specifically, we consider a scenario where we assign a higher bargaining weight to the husband, 0.7 to be exact, and a lower weight to the wife, 0.3. These are the weights estimated by [Voena \(2015\)](#). This change in bargaining power necessitates a recalibration of our model.

The parameters for the disutility of work, which we calibrate to match female employment and part-time work, need to be much higher than in our baseline spec-

ification. This is intuitive, as lower female bargaining power per-se would imply a higher employment rate for married women.

As a result of our recalibration, the overall model fit is very similar to our baseline specification with equal bargaining weights.³² The results are also very similar to the benchmark specification. The increase in aggregate hours resulting from abolishing auxiliary benefits is similar to the baseline, 2.1% (vs. 2.4%). The effect on aggregate hours of abolishing spousal benefits while keeping survivor benefits is somewhat higher, 2.0% compared to 1.8% in the baseline. The negative effect on aggregate hours of replacing auxiliary benefits with a revenue neutral minimum benefit is also similar to the baseline value, -1.0% .

The results concerning the redistributive consequences are also virtually unchanged with a Gini of 0.146 in the baseline, 0.177 without auxiliary benefits, and 0.135 with a minimum benefit system. Our results are in line with [Fernandez and Wong \(2014\)](#) who also do not find a significant difference in their main results when altering the bargaining power of spouses.

7.2 Policy Reform and the Value of Marriage

A key concern with our assumption of exogenous marital transitions is that large changes to social security, such as abolishing auxiliary benefits, alter the value of marriage. What is our model missing by assuming exogenous marital transitions?

Abolishing auxiliary benefits might affect both marital transition probabilities and the bargaining power of wives. Auxiliary benefits are tied to marital status, since they are only granted to (ever) married individuals. Abolishing them implies a decrease in the value of a marriage, relative to the value of staying single. In other words, the relative value of the outside option increases. The potential impact on marital decisions is twofold: (1) single females are less likely to enter a marriage to begin with (lower marriage probability), and (2) some women might decide to leave a marriage (higher divorce probability).

Hence, endogenizing marital transitions in our model would lead to a higher fraction of singles in the economy. This in turn would imply an increase in female employment, since singles have on average higher employment rates.

Empirically, it is not obvious that abolishing auxiliary benefits would actually lead to a significant increase in divorce. The empirical literature studying the effect of a change in the wife's income relative to the husband's income on marital

³²Detailed results for this exercise are available from the authors upon request.

dissolution is mixed. For example, [Weiss and Willis \(1997\)](#), and [Jalovaara \(2003\)](#) find that the wife’s earning capacity raises the divorce hazard, while [Hoffman and Duncan \(1995\)](#) and [Hankins and Hoekstra \(2011\)](#) do not find significant effects of female income on divorce. More closely related to our setting, studies find little or no change in divorce rates in response to social security reform, see [Dillender \(2016\)](#), [Goda et al. \(2007\)](#), and [Dickert-Conlin and Meghea \(2004\)](#).³³

The above mentioned change in the value of the outside option to marriage, due to the policy reform that we study, also impacts female bargaining power. On the one hand, it might be that single women need to be compensated with a higher bargaining weight in order to enter into marriage. At the same time, the bargaining power of wives’ remaining married might rise due to selection effects, cf. [Berniell et al. \(2017\)](#). On the other hand, for married women who would have been eligible for spousal benefits, the reform – *ceteris paribus* – implies a drop in lifetime income if they stay married. This could theoretically have a *negative* effect on female bargaining power, although this latter effect might be of second order.

To conclude, even if we abstract from the potential effects of the studied policy reforms on marital transition probabilities, we might expect a positive effect on the intra-household bargaining power of females; [Mazzocco \(2007\)](#) and [Voena \(2015\)](#) provide evidence of that. To analyze this effect, we conduct the following experiment. We continue to assume that divorce is exogenous. However, we take into account that the bargaining power changes after a large change to social security. If the threat of divorce exists, the wife would need to be compensated with a higher bargaining weight in order to stay in the marriage. Using our model, we attempt to quantify this effect in a stylized way. We compare the average welfare of a married female relative to one who is divorced (and not eligible for auxiliary benefits), before and after the counterfactual. We find that this fraction is lower in the counterfactual. We then increase the Pareto-weight of the female such that the average welfare ratio of married versus non-married is equal between the baseline and the counterfactual.

³³These papers use the 10-year eligibility threshold for spousal benefits for identification. However, see [Berniell et al. \(2017\)](#) for a study that does report positive effects on divorce analyzing a social security reform in Argentina.

Table 17: Labor Supply Effects - Robustness

	No Auxiliary Benefits
Married Females, Employment	9.0
Dropout	18.1
High school	10.1
College	1.2
Married Males, Employment	-1.9
All Females, Employment	5.6
Part-Time	5.8
All Males	-1.1
Aggregate Hours	1.36%

Notes: Employment change from counterfactual with no auxiliary benefits (in pp) with increased bargaining power for married females.

The Pareto weight increases from 0.5 in the baseline to 0.516 after auxiliary benefits are abolished. Note that all other parameters are kept fixed. Table 17 summarizes the labor supply effects from abolishing auxiliary benefits with exogenously changing bargaining weights. Although the employment effects are slightly dampened relative to the baseline, they are still sizable. Moreover, we should stress that this is assuming no increase in divorce. Given that some of these couples would likely choose to divorce, there would be a further increase in female employment.

While abolishing auxiliary benefits lowers the value of marriage, thereby potentially leading to decreased stability of marriages, a possible counteracting force arises due to the positive labor supply effects. Recall that we documented a positive correlation between education and marital stability. If this stems from the fact that educated women are more attached to the labor market and bring more income to the households, women staying at home – partly because of the negative incentive to work provided by auxiliary benefits – could make their marriage less stable. Newman and Olivetti (2015) document a negative correlation between divorce and the rate of married female labor force participation.

8 Conclusion

In the U.S., social security is a strong source of redistribution. Due to the concavity of the pension formula, at an individual level U.S. social security redistributes from higher earners to lower earners. However, differences in survival rates create a counteracting force due to the socio-economic gradient to survival. Moreover, given that it is also possible to claim social security benefits based on a spouse's earnings record, at the household level U.S. social security redistributes from two-earner households and singles to one-earner married households. The education gradient in divorce risk introduces an additional regressive element to social security.

In this paper we study the labor supply effects and the redistributive consequences of the U.S. social security system, with a particular focus on auxiliary benefits. To this end, we develop a dynamic, structural life cycle model of singles and couples with marriage and divorce risk and uncertain survival. We also account for the fact that both marital status and survival are strongly linked to socio-economic status, as these correlations may have strong redistributive consequences within the social security system.

We calibrate our model to match data for the cohort born 1950-54. Having developed and parameterized the model, we conduct two policy exercises: (1) abolish auxiliary benefits, (2) replace auxiliary benefits with a minimum social security benefit that is means tested on household income.

We find a large employment effect for married women from eliminating auxiliary benefits. Specifically, our model predicts an increase in the average employment rate of married women of 12.6pp. These large employment effects are almost exclusively due to an increase in part-time work. There is a counteracting effect from a reduction in male employment. All in all, our model predicts an increase in aggregate hours of 2.4%. However, the elimination of auxiliary benefits hurts the least educated, married females the most, which implies an increase in overall inequality in the economy.

We consider a minimum benefit scheme financed by the additional resources gained from shutting down auxiliary benefits. With a minimum benefit redistribution depends on income, not marital status. Replacing the auxiliary benefit scheme with this minimum benefit has a negligible effect on the employment of married women and a negative effect on male employment. Aggregate hours of work are 1.0% lower than in the benchmark economy. However, the minimum benefit implies redistribution from richer to poorer households. In particular, the minimum benefit

implies higher benefits for singles and couples with high school dropout wives. The biggest losers are the widows who are no longer entitled to very generous survivor benefits.

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Appendix A Descriptive Statistics

A.1 Fraction of Male Bread-Winner Families over Husband's Income

Table A.1

HH Inc. Quintile	Wife Dropout	Wife High School	Wife College
1st (lowest)	0.41	0.23	0.10
2nd	0.45	0.24	0.10
3rd	0.48	0.27	0.13
4th	0.52	0.31	0.16
5th (highest)	0.59	0.45	0.30
Total	0.45	0.30	0.19

Notes: The table shows the fraction of married couples where only the husband is working. Quintiles are calculated based on the husband's total income for a sample of married couples with children, aged below 63. Computed from CPS data.

Appendix B Parameterization

B.1 Sample and Main Data Source

In our analysis, we focus on the cohort born in 1950-1954. However, for statistics on individuals aged 65+, we extend our cohort to individuals born 1946-1954, because the maximum age for our cohort in 2015 is age 65.

For most descriptive statistics (employment profiles, asset holdings, initial marital state, and for the calculation of marital transition probabilities) we use the 1975-2015 surveys from the March Supplement of the Current Population Survey (CPS).³⁴

The CPS is a large sample leaving us with 467,472 observations in total. This allows us to compute statistics by age, education, and marital status.

For the majority of statistics we split the sample into three educational groups: college graduates (B.Sc. or above), people with a high school degree (includes some

³⁴We accessed the data with IPUMS, cf. King et al. (2010).

college), and those without a high school degree which we term dropouts.³⁵

The share of individuals across educational types are given in Tables B.1 and B.2.

Table B.1: Share of Individuals Across Education Types

	Observations	Percent
Dropout	56,655	12.12%
High-school	308,180	65.92%
College	102,637	21.96%

Source: Cohort 1950-54, CPS.

Table B.2: Share of Married Couples Across Education Types

	Husband Dropout	Husband High School	Husband College
Wife Dropout	6.1%	4.5%	0.24%
Wife High School	5.1%	52.0%	11.5%
Wife College	0.26%	6.3%	14.1%

Notes: Share of married couples over spouses' education. Cohort 1950-54, CPS.

B.2 Estimation of Income Process

The PSID

To estimate the wage process, we use data on male household heads in the Panel Study of Income Dynamics (PSID) for the years 1969-2013, so as to cover most of the life-cycle income process of our 1950-54 cohort. Our variable is household head's wages and salaries, CPI-adjusted to 2010 prices where we take the aggregate of three years for each of the age bins in our model.³⁶ We focus on the SRC (Survey Research Center) sample. To eliminate outliers, we drop the top and bottom 1% of the income distribution in each year, as well as individuals with less than 1,000 annual hours worked. We also drop all individuals with imputed wages. This leaves

³⁵We assign respondents with 12th grade but 'unclear degree' to the high school category. The descriptive statistics for these groups are very similar.

³⁶In case there are less than three wage observations per id and age-bin we multiply the average existing values by three.

us with 1,665 high school dropouts, 4,927 high school graduates, and 2,272 college graduates. We use individual weights.

Deterministic wage component

The deterministic wage component is estimated with equation (15). The estimated coefficients are depicted in Table B.3.

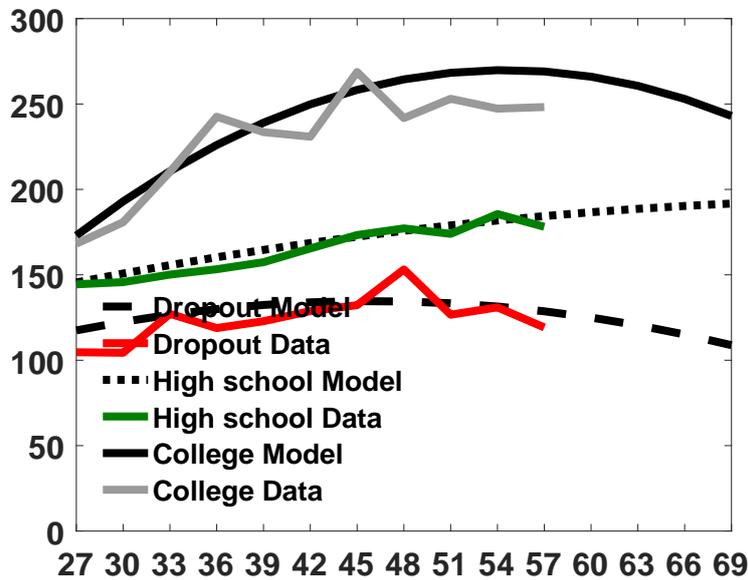
Table B.3: Estimated Deterministic Wage Component

	Dropout	High School	College
Constant, γ_e	113.6	141.9	158.4
Coefficient for t , α_e	2.011	1.846	7.552
Coefficient for t^2 , $\bar{\alpha}_e$	-0.0482	-0.0162	-0.1279
Depreciation rate (annual), d	2.5%	2.5%	2.5%

Source: Parameter estimates for earnings (in \$1,000) from regression (15). Depreciation rate taken from literature, cf. Attanasio et al. (2008).

The estimated deterministic wage profiles compared to the data are depicted in Figure B.1.

Figure B.1: Deterministic Wage Component



Notes: Wage profiles for full-time working males, data from PSID.

Idiosyncratic Component of the Wage Process

For singles, we assume a standard process given by:

$$\begin{aligned} w_{i,t,e} &= z_{i,t,e} + \eta_{i,t,e} \\ z_{i,t,e} &= \vartheta z_{i,t-1,e} + \varepsilon_{i,t,e} \end{aligned}$$

where $\eta_e \sim \mathcal{N}(0, \sigma_{\eta_e})$ and $\varepsilon_e \sim \mathcal{N}(0, \sigma_{\varepsilon_e})$. Note, that the variances do not depend on age. The persistent income component for married couples, however, is assumed to be (positively) correlated. In particular, we assume

$$z_{i,t,e}^{sp} = \vartheta^{sp} z_{i,t-1,e}^{sp} + \varepsilon_{i,t,e}^{sp}$$

where the superscript sp denotes the spousal values. The stochastic components for both spouses are assumed to be jointly normally distributed with a covariance matrix given by:

$$\Sigma_{\varepsilon} = \begin{bmatrix} \sigma_{\varepsilon_e} & \sigma_{\varepsilon_e, \varepsilon_e^{sp}} \\ \sigma_{\varepsilon_e^{sp}, \varepsilon_e} & \sigma_{\varepsilon_e^{sp}} \end{bmatrix} \quad (17)$$

where $\sigma_{\varepsilon_e, \varepsilon_e^{sp}}$ is the covariance between the persistent income shocks. We assume a correlation coefficient of 0.25 as estimated by [Hyslop \(2001\)](#).

Next, we describe the GMM estimation. We leave out the subscript e for convenience. Rewrite the process for $z_{i,t}$ as $MA(T)$, i.e., over all ages, $0, \dots, T$:

$$\begin{aligned} z_{i,t} &= \vartheta z_{i,t-1} + \varepsilon_{i,t} \\ z_{i,t} &= \vartheta^2 z_{i,t-2} + \vartheta \varepsilon_{i,t-1} + \varepsilon_{i,t} \\ &\dots \\ z_{i,t} &= \sum_{s=0}^T \vartheta^s \varepsilon_{i,t-s} \end{aligned}$$

The moments are then given by

$$E(z_{i,t}) = E \left[\sum_{s=0}^T \vartheta^s \varepsilon_{i,t-s} \right] = \sum_{s=0}^T \vartheta^s E[\varepsilon_{i,t-s}] = 0$$

$$\begin{aligned}
Var(z_{i,t}) &= Var\left[\sum_{s=0}^T \vartheta^s \varepsilon_{i,t-s}\right] = \sum_{s=0}^T \vartheta^{2s} Var[\varepsilon_{i,t-s}] \\
&= \sum_{s=0}^T \vartheta^{2s} \sigma_\varepsilon^2
\end{aligned}$$

The variance of w is given by

$$\begin{aligned}
Var_i(w_{i,t}) &= Var_i(z_{i,t} + \eta_{i,t}) \\
&= Var_i(z_{i,t}) + \sigma_\varepsilon^2
\end{aligned}$$

and the covariance of w at age t and age $t + 1$ is

$$Cov(w_{i,t}, w_{i,t+n}) = \vartheta^n Var_i(z_{i,t})$$

The summarized theoretical autocovariances are hence:

$$\begin{aligned}
Var(z_{i,t}) &= \sum_{s=0}^T \vartheta^{2sj} \sigma_\varepsilon^2 \\
Var_i(w_{i,t}) &= Var_i(z_{i,t}) + \sigma_\varepsilon^2 \\
Cov(w_{i,t}, w_{i,t+n}) &= \vartheta^n Var_i(z_{i,t})
\end{aligned}$$

Define a parameter vector $\theta = (\vartheta, \sigma_\eta^2, \sigma_\varepsilon^2)$ which is to be estimated.

Using the saved residuals $w_{i,t,e}$ from regression (15) we determine the empirical autocovariances which we calculate over years, j , using the fact that we can decompose the yearly variance, $Var(z_{i,j})$ and covariances, $Cov(w_{i,j}, w_{i,j+n})$ into their age-specific forms as:

$$\begin{aligned}
Var(z_{i,j}) &= \sum_{s=0}^T f_{t,j} \cdot Var(z_{i,t}) \\
Cov(w_{i,j}, w_{i,j+n}) &= \sum_{s=0}^T f_{t,j} \cdot Cov(w_{i,t}, w_{i,t+n})
\end{aligned}$$

where $f_{t,j}$ is the fraction of individuals who are at age t in year t . This weighting of each age-specific moment by the fraction of individuals is crucial for the estimation

results. The covariance matrix is then given by

$$C(X) = \text{vec} \begin{bmatrix} \text{Var}(w_{i,1}) & & & & & \\ \dots & \text{Var}(w_{i,2}) & & & & \\ \dots & \dots & \dots & \dots & & \\ \text{Cov}(w_{i,1}, w_{i,j}) & \text{Cov}(w_{i,2}, w_{i,j}) & \dots & \text{Var}(w_{i,j}) & & \\ \dots & & & \dots & \dots & \\ \text{Cov}(w_{i,1}, w_{i,j}) & & & \dots & & \text{Var}(w_{i,j}) \end{bmatrix}$$

To determine the parameter vector θ by GMM estimation:

$$\hat{\theta} = \arg \min_{\theta} [(C(\theta) - C(X))' \times W \times (C(\theta) - C(X))], \quad (18)$$

where W is a weighting matrix. We use the identity matrix here.

Lastly, the parameters estimated on yearly data must be transformed to our three-year age bins.

Table B.4: Estimated Parameters for the Idiosyncratic Wage Component

	College	High School
Autocorrelation coefficient, ϑ	0.954	0.923
SD of Persistent shock, σ_{ϵ}	0.048	0.056
Covariance of Spousal Persistent shock, $\sigma_{\epsilon_e^{sp}, \epsilon_e}$		
Spouse same education	0.012	0.014
Spouse different education	0.013	0.013
SD of Transitory shock, σ_{η}	0.041	0.034

Source: Parameters for 3-year adjusted data estimated using the GMM specified in (18). SD is standard deviation.

B.3 Social Security

To determine benefits based on one's own work history one must first compute the so called Average Indexed Monthly Earnings (AIME), \bar{y}_t , which is computed by averaging over life-time earnings from the highest 35 years (including possible zeros).³⁷

³⁷This is an approximation of the AIME calculation which abstracts from indexing past earnings, see <https://www.socialsecurity.gov/policy/docs/statcomps/supplement/2004/apnd.html> for details.

A concave benefit formula is then applied to AIME to get the Primary Insurance Amount (PIA):

$$B(\bar{y}_t) = \begin{cases} \lambda_1 \bar{y}_t & \text{if } \bar{y}_t < \kappa_1 \\ \lambda_1 \kappa_1 + \lambda_2 (\bar{y}_t - \kappa_1) & \text{if } \kappa_2 \geq \bar{y}_t \geq \kappa_1 \\ \lambda_1 \kappa_1 + \lambda_2 (\kappa_2 - \kappa_1) + \lambda_3 (\bar{y}_t - \kappa_2) & \text{if } \bar{y}_t > \kappa_2 \end{cases} \quad (19)$$

λ_i are replacement rates that differ by average income such that $\lambda_1 > \lambda_2 > \lambda_3$; κ_1 and κ_2 are bend points at which the replacement rate changes. This ensures a redistributive element in favor of low earners. Table B.5 shows the values for the benefit formula for the year 2010 that we use in our model.

Table B.5: Parameters for the PIA Formula

κ_1	First bend point of AIME	\$761
κ_2	Second bend point of AIME	\$4,586
λ_1	PIA formula slope parameter 1	0.9
λ_2	PIA formula slope parameter 2	0.32
λ_3	PIA formula slope parameter 3	15

Notes: Values taken from www.ssa.gov for the year 2010. Bend point values are adjusted to 3-year aggregates in our model.

Benefits are adjusted by \varkappa according to age at benefit claiming:³⁸

$$\varkappa = \begin{cases} (1 - 0.201) & \text{if } t^r = 62 \\ 1.0 & \text{if } t^r = 65 \\ 1.24 & \text{if } t^r = 68 \\ 1.48 & \text{if } t^r = 71 \end{cases} \quad (20)$$

where t^r is claiming age.

The benefit is not allowed to exceed a maximum \bar{b}^{cap} , which corresponds to the earnings cap. The total benefit for an individual is thus given by:

$$b_g = \min\{\varkappa B(\bar{y}_{g,t}), \bar{b}^{cap}\}. \quad (21)$$

³⁸See www.ssa.gov/oact/quickcalc/early_late.html for details.

B.4 Marital Transition Probabilities

Data

To determine the remarriage and divorce probabilities, we employ data from the Survey of Income and Program Participation (SIPP) from the U.S. Census Bureau for year 2008. We use the marital history topical module for 2008, panel wave 2. This covers the year 2009. The survey is well suited for determining marital patterns as it includes a question about marital history, which allows us to use only one wave and still compute probabilities for a specific cohort. Focusing on our 1950-54 cohort yields 5,722 observations, allowing us to reliably study also small sub-populations, such as cohort-specific, young male/female college graduates. However, for ages past 58 we increase the cohort to agents born 1940-54 due to small or missing sample sizes for our cohort (note that the maximum age for our cohort in 2009 is 59).

Due to the recursive nature of the SIPP marital history variable, it does not contain information on individuals who are not (yet) married, which is needed in order to compute marriage rates. Ideally, we would use panel data to compute transition probabilities from never married into married. However, the PSID, for example, is much too small to determine these probabilities, as the share of never married becomes low after age 30. We therefore construct a synthetic panel using the CPS from 1976-2015.

Transition Probabilities

Table B.6 shows the initial marital status at age 25 (i.e., right before the start of our model). Note, that more than half of the individuals in our cohort are already married. The fraction is higher for less educated individuals than for their more educated counterparts. Strikingly, 19% of woman without a high-school degree are already divorced when they enter the model.

Table B.6: Initial Marital Status

	Women			Men		
	College	High School	Dropout	College	High School	Dropout
Married	0.49	0.67	0.64	0.43	0.58	0.63
Single	0.46	0.24	0.17	0.56	0.35	0.30
Divorced	0.05	0.09	0.19	0.02	0.06	0.06

Source: CPS. Initial marital status at age 25 for cohort born 1950-54.

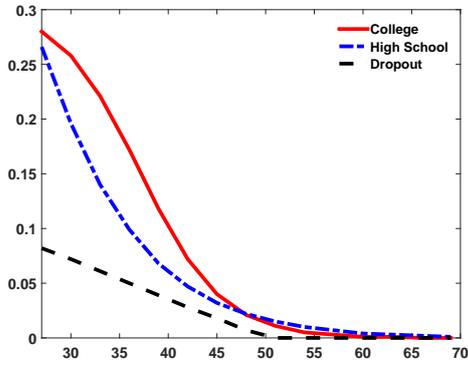
The marriage probabilities shown in the first two panels in Figure B.2a and B.2b are determined as follows. We calculate the fraction of never married households at a specific age for our cohort (e.g., for the 26 year olds we use the 1976 wave in order to have the cohort born in 1950). The marriage probability for our cohort born between 1950-54 is then approximated by the percentage change in the share of people never married between age-groups. We employ this approximation because the populations across different ages in our cohort are not the same, as the CPS is a repeated cross-section. Hence, computing the growth rate using absolute values often leads to negative values. Even with this approximation we encounter quite volatile values. Since we believe that marriage rates decline monotonically over age, we smooth the data using a logistic curve fit. In case of no convergence we chose to simply employ linear interpolation until zero³⁹. For ages 50 to 68 we extrapolate the fitted data.

To compute the divorce rates depicted in panels B.2c and B.2d we use the latest SIPP wave from 2009. Since the maximum age for our cohort in 2009 is 59, we expand our sample to individuals born 1940-1954, when computing probabilities for ages above 58. The data are linear-fitted values. The divorce probability for a certain 3-year age bin is calculated as the fraction of people who report being married at the beginning of the age-bin and who undergo at least one divorce during the subsequent three years.

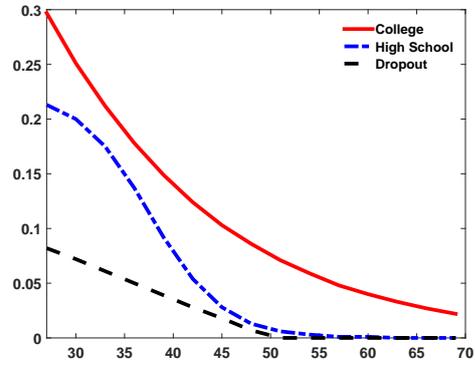
The remarriage rates shown in panels B.2e and B.2f are calculated analogously to the divorce rates. We determine the fraction who report being divorced at the first age of each age-bin and undergo at least one marriage during the 3-year bin.

³⁹We did not use a higher order polynomial to fit the data, because the fitted data exhibited negative probabilities at higher ages. Hence, we employed the logistic model that – albeit restricting us to a certain distribution – is bounded by zero and one.

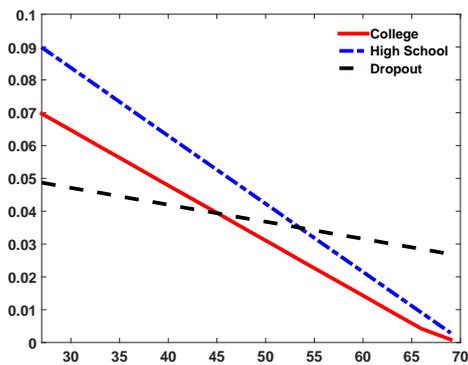
Figure B.2: Marital Transition Probabilities, Fitted Values



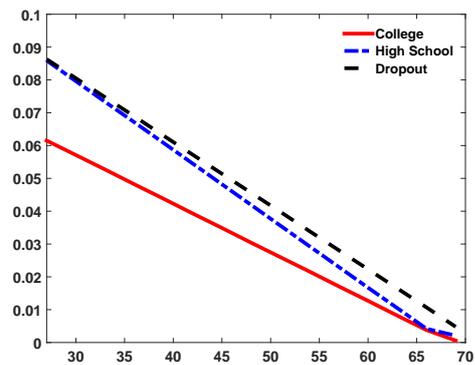
(a) Marriage Probabilities, Females



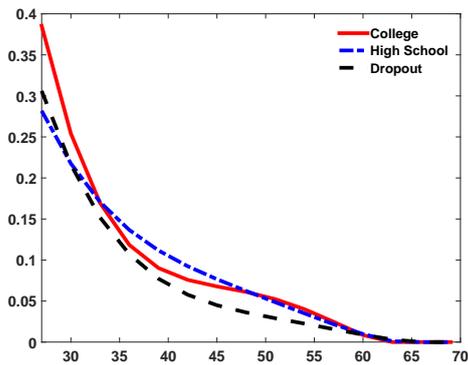
(b) Marriage Probabilities, Males



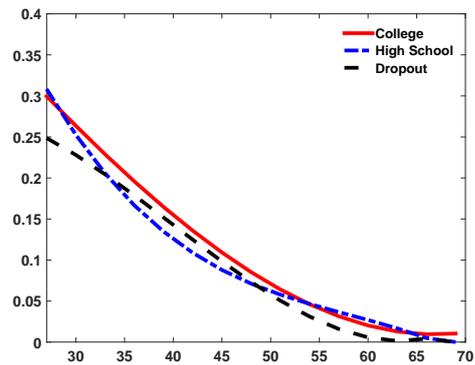
(c) Divorce Probabilities, Females



(d) Divorce Probabilities, Males



(e) Remarriage Probabilities, Females



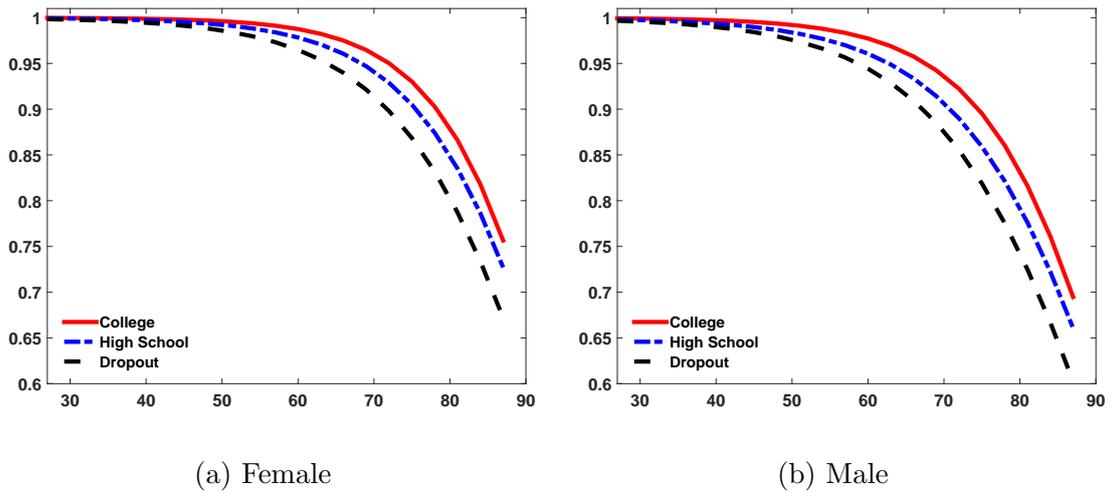
(f) Remarriage Probabilities, Males

Source: CPS and own calculations. Logistic or linear fitting of raw probabilities.

B.5 Unconditional Survival Rates over the Life cycle

We use the Health and Retirement Study (HRS), a longitudinal panel that surveys a representative sample of approximately 20,000 Americans over the age of 50 every two years, to estimate survival probabilities over age, gender and education.

Figure B.3: Survival Rates



Notes: Predicted survival rates using HRS data from 1992-2010.

To predict survival rates we use the waves from 1992 to 2010, and compute the number of age-specific deaths in each wave.⁴⁰

Following Pijoan-Mas and Ríos-Rull (2014), we estimate a Logistic regression, restricting our sample to ages 49-94:

$$\begin{aligned} \text{Logit}(\text{death}_{t+2}) = & \alpha_0 + \beta_1 \text{age}_t + \beta_2 \text{edu} + \beta_3 \text{sex} \\ & + \beta_4 \text{age}_t \times \text{edu} + \beta_5 \text{age}_t \times \text{sex} \end{aligned}$$

B.6 Policy Parameters

B.7 Second Stage Parameter: Disutility of Work

We allow the disutility from work parameters to differ across utility-types, education and age. For each utility and education type we assume a piece-wise linear profile

⁴⁰We cannot use the latest wave because of the recursive nature of the survey: a death stated in one wave implies that the respondent died between the current and the last wave, such that variables from the previous wave are used as covariates.

Table B.7: Tax Parameters

Parameter		Source	
τ_c	Consumption tax	7.5%	McDaniel (2007)
τ_{ss}	Payroll tax	15.3%	statutory rate
y_{max}	Earnings cap for payroll tax in 2010	\$106,800	statutory value
α_s	Coefficient in τ_y^s (single/married)	0.105/0.085	Guner et al. (2014)
β_s	Coefficient in τ_y^s (single/married)	0.034/0.058	Guner et al. (2014)
\bar{y}	Average earnings in 2010	\$53,063	Guner et al. (2014)
	Government Consumption Ratio	24%	Chakraborty et al. (2015)

The payroll tax and the earnings cap is the statutory value where the tax rate is including the 2.9% for Medicare.

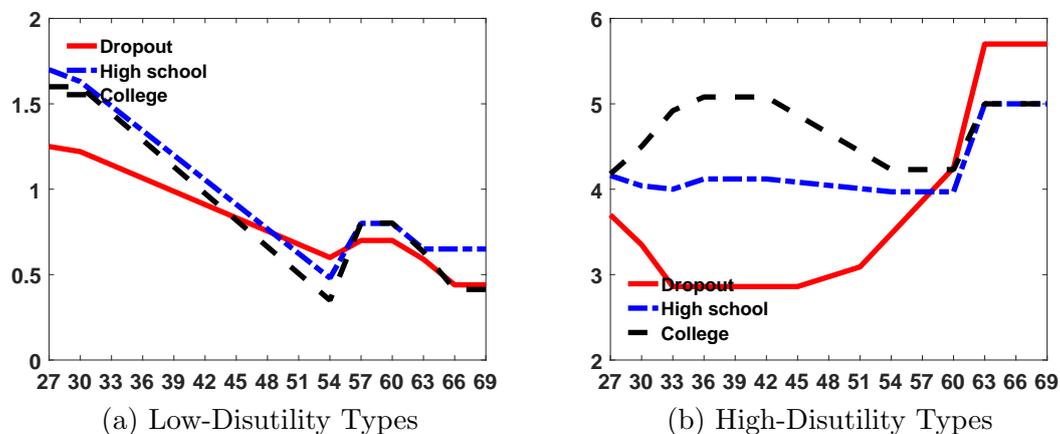
for disutility over age. Figure B.4 plots the age profile of the disutility of work parameter.

The overall fraction of high-disutility types, α , is calibrated to match the overall level of the age-profiles of both total employment and part-time work, see Table B.8.

Table B.8: Fraction of High-Disutility Types

	α_e
Dropout	0.595
High School	0.475
College	0.418

Figure B.4: Disutility of Work for Married Females, $\Phi_{1,e,t,v}$



As described in the main text, we need an additional utility parameter of joint work/retirement, $v_{e,e^{sp},t}$ in order to match both female employment over husband's education, cf. Table 2, as well as the distribution of joint retirement, cf. Figure 3. Table B.9 depicts the utility cost parameters for joint work, which are calibrated to match average employment of wives depending on husband's education. It turns out that by calibrating the stop-working decision of married females and males correctly (with the $\Phi_{g,e,t,v}$) we already match the distribution of joint retirement as depicted in Figure 3. Hence, we set $v_{e,e^{sp},t} = 0$ for ages 62+.

Table B.9: Utility Cost of Joint Work, $v_{e,e^{sp},t}$

	Husband Dropout	Husband High School	Husband College
Wife Dropout	-0.128	-0.0118	0.0576
Wife High School	-0.0887	0.0033	0.1155
Wife College	-0.186	-0.045	0.0182

Table B.10 depicts the disutility values for men. These values are calibrated to match male employment at ages 62-69, cf. Table 8.

Table B.10: Disutility of Work for Married Males, $\Phi_{2,t,e,v}$

Age	Dropouts		High school		College	
	$\Phi_{2,t,e,1}$	$\Phi_{2,t,e,2}$	$\Phi_{2,t,e,1}$	$\Phi_{2,t,e,2}$	$\Phi_{2,t,e,1}$	$\Phi_{2,t,e,2}$
62-64	3.08	0.0	3.934	0.0	3.8505	0.0
65-67	3.08	0.465	3.934	0.852	3.8505	0.831
68-70	3.08	0.3752	3.934	0.7857	3.8505	0.6867

We assign males below age 62 (no labor supply choice by assumption) the disutility value of low-disutility females with the same education.

Appendix C Additional Results

C.1 Cohort Comparison: 1950 vs. 1930

There have been sizable changes in marital patterns over the last couple decades. This has been accompanied by a decline in the gender wage gap. Here, we contrast our baseline cohort, those born 1950-1954, with an older cohort born 1930-34.

Table C.1 shows the difference in marital status over education for both cohorts.

Table C.1: Marital Status over Education, Ages 45-64

	Married		Divorced		Never Married		Widowed	
	1930	1950	1930	1950	1930	1950	1930	1950
Dropouts	0.70	0.60	0.14	0.21	0.06	0.13	0.09	0.06
High school	0.79	0.67	0.11	0.21	0.04	0.08	0.06	0.04
College	0.78	0.74	0.10	0.15	0.07	0.09	0.04	0.02
Total	0.77	0.68	0.12	0.19	0.05	0.09	0.07	0.04

Notes: The fraction of individuals in each of the four marital states. *Source:* CPS. Sample consists of cohort born 1950-54 and the cohort born 1930-34.

The differences over education are less pronounced for the 1930 cohort. In fact, the share of married individuals is slightly higher for high school compared to college graduates for the 1930 cohort. The difference in the prevalence of marriage between high school dropouts and college graduates is 8pp for the 1930 cohort and 14pp for the 1950 cohort.

In terms of marital transitions, the main difference is in the initials at age 25 (or 27 for the 1930 cohort), which are shown in Table C.2.⁴¹ Observe that, with the exception of college educated females, marriage rates for the 1930 cohort are already very high at the initial age, with values as high as 86%.

Table C.2: Initial Marital Status, Females

	Dropouts		High School		College	
	1930	1950	1930	1950	1930	1950
Married	0.80	0.64	0.86	0.67	0.65	0.49
Never Married	0.09	0.17	0.09	0.24	0.35	0.46
Divorced	0.11	0.19	0.05	0.09	0.00	0.05

Notes: The fraction of individuals in each marital state at initial age 25 (27 for the 1930 cohort). *Source:* CPS. Sample consists of cohort born 1950-54 and the cohort born 1930-36 (extended slightly to get data on individuals aged 27).

⁴¹The differences in marital transitions between cohorts are also taken into account and they are available from the authors on request.

The second important difference between the cohorts is the gender wage gap, i.e., the ratio of average female hourly wages to average male hourly wages. Comparing the two cohorts, we see that this ratio has risen from 0.55 to 0.69 for dropouts, from 0.54 to 0.71 for high school graduates and from 0.71 to 0.78 for college graduates, implying a significant narrowing of the gender wage gap across these two cohorts.

Lastly, there has been a rise in assortative mating over time. This implies that there is an increasing number of couples where the husband and wife have the same level of educational attainment. More importantly, however, the general level of female educational attainment has increased. The fraction of couples where neither has a high school degree has decreased by 12.7pp, while the share of couples where both have a college degree has increased by almost the same amount.