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It Sucks to Be Single! Marital Status and Redistribution of Social Security

Max Groneck ^a

Johanna Wallenius ^a

^aStockholm School of Economics
Department of Economics

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Max Groneck[†]

Johanna Wallenius[‡]

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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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[†]Max Groneck, Stockholm School of Economics and Netspar (max.groneck@hhs.se).

[‡]Johanna Wallenius, Stockholm School of Economics (johanna.wallenius@hhs.se)

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 especially important for women. Eligibility for these benefits depends on marital status, irrespective of education or income. This implies redistribution from singles to married households, and among married households from dual-earner couples to single-earner couples. Note that 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 be eligible for 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. We present stylized facts about the socio-economic gradients of marital stability and longevity, which we incorporate into our structural analysis. 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 are quite generous, with spousal benefits equal to 50% of a retired worker's Primary Insurance Amount (PIA) and survivor benefits equal to 100% of the deceased worker's PIA.¹ Auxiliary benefits are an important source of retirement income for women. About 54% of women collecting social security in the U.S. are collecting spousal or survivor benefits.² Moreover, social security

¹Auxiliary benefits are also paid to children and parents of retired, disabled and deceased workers. We abstract from this rather small group throughout the paper.

²Numbers are taken from SSA (2014), Table 5.A14 for the year 2010. They include all women

constitutes between 50 and 70% of retirement income for women, depending on educational attainment.

When studying the intra-generational redistribution and labor supply incentives of the social security system it is important to take note of two striking facts: both marital status and survival are uncertain and strongly linked to socio-economic status. Investigating marital patterns for different educational backgrounds, Isen and Stevenson (2010) and Stevenson and Wolfers (2007) find a positive correlation between marital stability and education. We find that the positive correlation between marital stability and income is even more pronounced than the one between marital stability and education. In particular, the share of married individuals is 31 percentage points lower in the lowest income quintile than in the highest quintile. In addition, it has long been recognized that bad health and mortality are more prevalent among the socioeconomically disadvantaged, see Lantz et al. (1998) and Sorlie et al. (1995). According to our estimates, high school dropout women can expect to live on average 6.4 years less than their college graduate counterparts. These correlations might have strong redistributive consequences within the social security system.

Our analysis of the auxiliary benefit system is partly motivated by the fact that both marital patterns and the composition of the workforce have changed dramatically since the introduction of auxiliary benefits. When auxiliary benefits were first introduced in 1939, most families were organized around a male-breadwinner. The law aimed at supporting families where the wife stayed at home and cared 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). Nowadays, families with a sole male breadwinner are much less common. Increasing female labor force participation implies that families with two-earners are much more common. There are also many more singles (and couples who do not marry), and divorce rates have gone up markedly. These patterns imply an increasing share of elderly singles over time, which calls for re-evaluating the redistributive consequences of auxiliary benefits. Divorced people with a short marriage duration, as well as never married individuals (potentially with children), are not eligible for auxiliary benefits, although poverty rates are highest for these population groups. Poverty rates among divorced and never married elderly women exceed 20%, whereas less than 6% of married women are below the official poverty line. Further, by redistributing from two-earner to one-earner married households, the auxiliary benefit system creates incentives for aged 62 or older receiving social security benefits.

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 6.4pp for married women from eliminating auxiliary benefits. This translates into an increase in aggregate hours of 1.8% 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.

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 by a 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 35% of average income in the economy (both spouses awarded the same benefit). While average employment of married women rises by only 1.8pp in a system with minimum benefits, the employment effects are most pronounced for college educated women (+3.7pp). More importantly, the

minimum benefit introduces redistribution from richer to poorer households. Specifically, low educated wives who are married to low educated men gain. Widows lose the most relative to the benchmark.

Our paper builds on several different strands of the literature. There is a broad literature studying the equity-efficiency trade-off of social security at the individual level.³ Our paper also contributes to the 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. Only a few studies analyze the impact of social security benefits on labor supply in structural models taking the family context explicitly into account; see Kaygusuz (2015), Nishiyama (2015) and Bethencourt and Sánchez-Marcos (2014). What distinguishes us from the aforementioned papers is that we explicitly take uncertainty over marital status into account. Moreover, we incorporate the strong links between socio-economic status and marital stability, and education and survival risk. Our framework also features endogenous retirement, which allows us to study, not only the distributional consequences, but also the retirement margin effects of the auxiliary benefit system for men and women.

Our framework is also related to Fernandez and Wong (2014) and Chakraborty et al. (2015), although the research questions are quite different. They study the effect of increased divorce risk on female labor supply decisions. As previously noted, our framework features endogenous retirement and survival risk, which allows us to also study the effect of marriage and divorce risk on retirement entry and retirement income.

Section 2 outlines the main stylized facts that emerge from the data and 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. Section 7 concludes.

2 Stylized Facts

In this section we document three main facts: (1) marital stability is strongly linked to socio-economic status, (2) survival risk is linked to education, and (3) female labor supply is linked to spousal education and income. Relating these facts to our model and analysis, note that the first two facts will be summarized by exogenous

³See, for example, Conesa and Krueger (1999), Imrohoroglu et al. (1995), Fuster et al. (2007), and French (2005) for studies of the labor supply effects of social security.

processes which are fed into our model. 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. The third fact, on the other hand, is something our framework will strive to account for.

For most of the data we focus on the cohort born 1950-54. 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 college), and those without a high school degree which we term dropouts. In our sample, 12% of people are high school dropouts, 66% have a high school degree and 22% have a college degree.⁴

2.1 Marital Status and Socio-Economic Conditions

As our first stylized fact we establish that marital stability is increasing in education, and even more so in income. Table 1 reveals that the share of people 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. The share of people who are currently divorced is 6pp lower among college graduates compared to their least educated counterparts. Marriage rates are lowest for high school dropouts. Thus, the fraction of agents who never married is 4pp higher for dropouts than for those with a college degree.⁵ There are slightly more widowed females among the less educated than among the more educated due to assortative matching and the lower survival rates of less educated husbands. These differences are, however, smaller than the ones we observe for married and divorced individuals.

⁴We assign respondents with 12th grade but 'unclear degree' to the high school category. The descriptive statistics for these groups are very similar.

⁵The share of never married is actually slightly higher among the college educated than the high school educated, since more educated individuals tend to marry later.

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

	Married	Divorced	Never Married	Widowed
Dropouts	0.60	0.21	0.13	0.06
High School	0.67	0.21	0.08	0.04
College	0.74	0.15	0.09	0.02
Total	0.68	0.19	0.09	0.04

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

Table 2 highlights an even stronger relationship between marital status and household income than the one observed between marital status and education. The fraction of divorced individuals is more than twice as large in the lowest income quintile than in the highest income quintile. Also, the fraction of never married individuals is 11pp higher, and the fraction of currently married 26pp lower, in the lowest income quintile than in the highest.⁶

As previously noted, the differences in marital status over education are much weaker than the differences over household income quintiles.⁷ With respect to education, it appears that there are counteracting effects. On the one hand, more educated individuals marry later, and thus have a higher probability of ending up not married. On the other hand, marriage stability increases with education. See Isen and Stevenson (2010) for a more detailed discussion of marital status over education, controlling for cohort, gender and race.

⁶There is of course the concern that divorce can result in lower income, especially for women. To alleviate this concern, here we focus on men. Appendix A.1 presents further statistics on the differences in marital status over socio-economic variables, including the same as the table below but for the three education types separately.

⁷For an overview of marital status over time, see <https://www.census.gov/prod/2011pubs/p70-125.pdf>.

Table 2: Marital Status over Per Capita HH Income, Men aged 50-60

HH Income Quintile	Married	Divorced	Never Married	Widowed
1st (lowest)	0.59	0.23	0.16	0.02
2nd	0.63	0.21	0.14	0.02
3rd	0.72	0.18	0.09	0.01
4th	0.80	0.14	0.05	0.01
5th (highest)	0.85	0.10	0.05	0.00

Notes: Fraction of men in each of the four marital states over per-capita household income. Quintiles are computed based on per-head, equivalence-scaled total annual household income, pooled over age bins. *Source:* CPS, cohort born 1950-54.

In our structural model, we accommodate these facts by exogenously assuming different marriage and divorce rates over education. In addition, we assume a correlation between negative income shocks and divorce and the probability to marry.

2.2 Survival Rate and Education

Table 3 shows estimated life expectancy for the different education groups. Life expectancy is increasing in education. Specifically, life expectancy is 6.4 (7.5) years higher for college educated women (men) than for those who did not finish high school. The gender-difference in life expectancy is 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 (2014); their estimates are similar to ours.

Table 3: Life Expectancy by Gender and Education

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

Notes: The table shows life expectancy at birth, which was 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.

In our model, we account for the gender and education differences in life expectancy by feeding in gender and education specific survival probabilities.

2.3 Labor Supply of Married Women

The labor supply of married women is linked to own education and also that of the spouse. Table 4 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). Also, 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 4: Employment of Wives, Ages 26-49

	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: The table shows the employment rate of females aged 26-49 depending on own and husband's education. *Source:* CPS, cohort born 1950-1954, excludes those who do not work due to disability.

The differences in female labor supply are even more pronounced over income than over education. Table A.4 in Appendix A.2 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 breadwinner.

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.

3 The Model

We develop a partial-equilibrium life-cycle model of singles and couples who jointly make decisions regarding consumption, savings and labor supply. Households face uncertainty with respect to marital status, survival and labor income.

Agents enter the model at age 26; the terminal age is 89.⁸ A model period corresponds to three years in the data, implying that we have 21 model periods. The labor supply decision of married women includes an extensive and an intensive margin; they can work full-time, part-time or not at all. Through work, the woman gains experience, which positively affects future wages and social security claims. Married men (and singles) work full-time until at least age 62. For simplicity, we assume that the household claims social security benefits when the husband stops working. Moreover, in our model wives stop work either before or with their husband. Social security payments are linked to marital status through auxiliary benefit payments, in particular spousal and survivor benefits.

3.1 Demographics

Households initially differ by 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. The (re)marriage, divorce and survival probabilities differ by age, gender and education. In addition, the marital transition probabilities are affected by permanent income shock realizations. This correlation will be calibrated to match the stylized fact presented in Table 2.

Education, e , is classified as high school dropouts, high school degree and college. We allow the disutility from work to be dependent on education. Given that we allow the educational attainment of spouses to differ, we have $3 \times 3 = 9$ 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. Spousal incomes are assumed to be positively correlated. The initial matching of persistent income states of couples are approximated using educational data. 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

⁸We do not model educational choices, and therefore start the model after these decisions have been made.

market experience, the income shock realization (persistent and transitory), asset holdings, the age at benefit claiming and the length of marriage.⁹

Households die stochastically. Survival risk is idiosyncratic and washes out at the aggregate level. Since we hold the number of newborn households constant, the population is stationary. The number of age t households is defined as N_t and the total population normalized to unity, $\sum_{t=0}^T N_t = 1$. We denote objective survival probabilities by ψ_t . The dynamics of the population are given by $N_{t+1} = \psi_t N_t$, for a given N_0 .

3.2 Choices and Preferences

Households make decisions regarding consumption, c_t , savings, a_{t+1} , and labor supply, $L_{g,t}$. We assume that married couples make decisions jointly. Households have preferences over consumption and work as given by:

$$U(c_t, L_t) = \chi \left[\ln(\hat{c}_t) - \Phi_{1,t,e}^v \frac{L_{1,t}^\gamma}{\gamma} \right] + (1 - \chi) \left[\ln(\hat{c}_t) - \Phi_{2,t,e}^v \frac{L_{2,t}^\gamma}{\gamma} \right] \quad (1)$$

where χ is the weight on the wife's utility and $1 - \chi$ on the husband's. $\hat{c} = \frac{2c_t}{eq}$ is equivalence scaled household consumption. Preferences are assumed to be separable and consistent with balanced growth, thereby dictating the $\ln(c)$ choice. The Frisch elasticity of labor supply is given by $\frac{1}{\gamma-1}$. $L_{g,t}$ denotes labor supply in period t depending on gender, $g = 1, 2$, where 1 is female and 2 is male. The female labor supply choice is given by $L_{1,t} = \{0, \frac{1}{2}, 1\}$, until age 71 (retired for sure after that). The husband is assumed to work full-time until age 61. Thereafter the male labor supply choice is given by $L_{2,t} = \{0, 1\}$. If $L_{2,t} = 0$, we assume that benefits are claimed. In that case the wife also has to stop working. $\Phi_{g,e}^v$ denotes disutility from work, where $v = h, l$ denotes two different disutility types, high and low. In addition, we allow the disutility from work to differ by gender and education so as to match data on female part-time and full-time employment over the life-cycle as well as male employment at older ages over education.

The instantaneous utility of an unmarried individual is given by:

$$U(c_t, L_t) = \ln(c_t) - \Phi_{g,t,e}^v \frac{L_{g,t}^\gamma}{\gamma}, \quad (2)$$

⁹The length of marriage is necessary to determine auxiliary benefit eligibility. Divorced households can be eligible based on their ex-spouses' entitlements, if they were married for at least ten years.

where $L_{g,t} = \{0, 1\}$ is the decision to stop working, which is made between ages 62 and 70. Benefit collection coincides with the decision to stop working.

3.3 Survival and Marital Transitions

The survival rate depends on gender, age, and education, $\psi_t = \psi_{g,t,e}$. 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.

Marriage, divorce and widowhood occur exogenously in the model. The initial marital status of individuals is married m , unmarried/single, u , or divorced d . As agents get older, they can also become widowed, w . Marital status is thus given by $s_t \in \{m, u, d, w\}$.

Singles face a marriage probability $\xi_{g,t,e,z}$, which depends on gender, age, education and the permanent income realization, z . Similarly, divorced agents face a remarriage probability $\nu_{g,t,e,z}$. Married couples, in turn, face a divorce probability $\mu_{g,t,e,z}$. The persistent income component, z , in all of these probabilities aims to account for the fact that (persistent) negative income shocks are associated with higher divorce risk and a higher fraction of individuals being never married.

To determine auxiliary benefit eligibility, we have to keep track of the length of the marriage.¹⁰ The length of marriage in the next period, l_{t+1} , increases by one from the previous period if the agent was married in t , and resets to zero if the agent got divorced in t . 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.¹¹

The assumption of exogenous marital transitions is made for tractability. Changing certain aspects of the social security system influences the economic value of marriage, and as such could influence marriage and divorce behavior. In our context, for example, shutting down auxiliary benefits reduces the value of being married, which could lead to an increase in divorce. However, numerous empirical 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).¹² We

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

¹¹A 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.

¹²These papers use the 10-year eligibility threshold for spousal benefits as an identifying feature

would also argue that our estimate of the employment effects from shutting down auxiliary benefits in our model with exogenous marital transitions is a lower-bound estimate. The reason is that shutting down auxiliary benefits decreases the value of marriage and thereby potentially also divorce, if it were endogenous. This, in turn, would increase employment, as single females have higher employment rates than married women.

3.4 Income Process

The wage process is uncertain, consisting of an idiosyncratic permanent component, z_t , and a transitory component, η_t . For couples, we assume a positive correlation between spousal persistent income shocks. Since men are assumed to work full-time until retirement, their income is a function of age. Income for women depends on experience, h_t . We allow for human capital depreciation by assuming that income is lower if the agent did not work in the previous period. Income risk differs by gender and education. To ease notation, we define $y_{g,t}$ as shorthand for:

$$y_{g,t} = y(g, t, e, e^s, h_t, z_t, z_t^s, \eta_t) \quad (3)$$

Experience accumulation is modeled as a learning-by-doing technology that counts the number of years of work for the woman:

$$h_{t+1} = \begin{cases} h_t + 1 & \text{if } L_t = 1 \\ h_t + \iota & \text{if } L_t = 0.5 \\ h_t & \text{if } L_t = 0, \end{cases} \quad (4)$$

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. In our model, this is essentially the probability of gaining a full year of experience, implying an expected gain in experience of ι from part-time work.¹³

The divorce probability is assumed to be correlated with the permanent income component. Milosch (2014) and Weiss and Willis (1997) present evidence of a positive correlation between negative income shocks and divorce. We set the parameters governing the strength of this correlation so that our model replicates the marital patterns over income shown in Tables A.1-A.3. In particular, we assume a loading

to study whether there is a spike in divorce after the 10-year threshold has been met.

¹³To save on the state space, and thereby ease the computational burden, we do not add experience of ι as a state.

factor λ_z on the divorce probability and on 1 minus the marriage and remarriage probabilities in case of low realizations of z . Details are described in the calibration section.

3.5 Social Security

Social security benefits, b_g , are paid out as an annuity and depend on past income, and hence on gender, education (own and spousal), work experience (for women), the claiming age, t^r , and marital status (due to auxiliary benefit payments).

AIME and PIA To determine benefits based on one's own work history one must first compute the so called Average Indexed Monthly Earning (AIME), which is computed by averaging over life-time earnings from the highest 35 years (including possible zeros).¹⁴ For computational reasons, we want to avoid adding AIME and spousal AIME as (continuous) state variables. We therefore approximate AIME as follows. For each permanent income state in the last working period we take the expected value of income from the last 35 years recursively, making use of the Markov transition probability. We adjust the 35 years to $12 \times 3 = 36$ years, because a period is three years in our model.

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

$$B(\bar{y}_t) = \begin{cases} \lambda_1 \bar{y}_t & \text{if } \bar{y}_t < \kappa_1 \\ \lambda_1 \kappa_1 + \lambda_2 (\bar{y}_t - \kappa_1) & \text{if } \kappa_2 \geq \bar{y}_t \geq \kappa_1 \\ \lambda_1 \kappa_1 + \lambda_2 (\kappa_2 - \kappa_1) + \lambda_3 (\bar{y}_t - \kappa_2) & \text{if } \bar{y}_t > \kappa_2 \end{cases} \quad (5)$$

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 redistributional element in favor of low earners.

The PIA is not allowed to exceed a maximum, which corresponds to the earnings cap, see below. Finally, benefits are adjusted according to age at benefit claiming.

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

¹⁴This 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.

introduces a regressive element to the U.S. social security system. Formally, income that is considered for social security taxes is given by:

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

Auxiliary benefits Spousal and survivor benefits are claimed based on the spouses earnings record. As such, they are dependent on marital status. Spousal benefits are granted to married persons (if married for at least one year) and consist of the higher of one's own benefit and 50% of the spouse's entitlement. Divorced individuals are also eligible, if their marriage lasted for at least 10 years. In our model, only women ($g = 1$) decide on labor supply (prior to the retirement decision), so this yields:

$$b_1^{spouse} = \max\left\{b_1; \frac{1}{2}b_2\right\} \quad (7)$$

if $s_t = m_t$, or if $s_t = d_t$ and $l_t = 4_t$.

If the spouse dies, the widow is eligible for survivor benefits equal to 100% of the deceased's benefit. The resulting survivor benefits are thus given by:

$$b_g^{surv} = \max\{b_1; b_2\} \quad (8)$$

3.6 Budget Sets of Households

A married couple faces the budget constraint given by:

$$\begin{aligned} (1 + \tau_c)2c_t + a_{t+1}^s &= (1 - \tau_y^s) \cdot [Ra_t^m + (L_{1,t}y_{1,t} + y_{2,t}) \cdot L_{2,t}] \\ &\quad - \tau_{ss}(\hat{y}_{1,t} + \hat{y}_{2,t}) \cdot L_{2,t} \\ &\quad + (1 - L_{2,t})(b_{1,t} + b_{2,t}) \\ &\quad + 2T. \end{aligned} \quad (9)$$

Asset holdings at age t are denoted by a_t^s and dependent on marital status s . 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., $a_{t+1}^d = 0.5a_{t+1}^m$).¹⁵ In case of widowhood, assets stay with the surviving spouse ($a_{t+1}^w = a_{t+1}^m$).

¹⁵As 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.

Similarly, the budget constraint of a single agent is given by:

$$(1 + \tau_c)c_t + a_{t+1}^s = (1 - \tau_y^s) \cdot (Ra_t^s + L_{g,t}y_{g,t}) - \tau_{ss}\hat{y}_{g,t} + (1 - L_{g,t})b_{g,t} + T. \quad (10)$$

Again, assets depend on marital status, and we assume that assets are doubled in the case of (re)marriage ($a_{t+1}^m = 2a_{t+1}^d = 2a_{t+1}^u$).

Since we are interested in labor supply incentives, it is important to model the details of the tax schedule. Our model includes a proportional consumption tax, τ_c , a proportional social security payroll tax, τ_{ss} , and a progressive income tax, τ_y^s , which is levied on total income and dependent on marital status. We follow Guner et al. (2014) and assume that the tax function is of the form given by:

$$\tau_y^s = \alpha_s + \beta_s \cdot \frac{(y_{g,t} + Ra_t^s)}{\bar{y}} \quad (11)$$

where \bar{y} is average income. Household receive a lump-sum transfer per individual, T , the size of which is determined by the balancing of the government budget.

3.7 Recursive Problem

In what follows, we lay out the recursive maximization problem for each of the three stages in our model: the pure working-age phase between ages 26 to 61, the benefit claiming phase between ages 62 and 70 and the retirement phase from age 71 onward. Both the choices and the uncertainties faced by agents differ across these stages.

3.7.1 State Space and Notation

We assume a Markov-process for the stochastic wage uncertainty so that we can state the household problem recursively. In terms of notation, we define the value function for each age t , marital status $s = \{m, u, d, w\}$, and gender $g = 1, 2$ as $V_{g,t}^s(\Gamma_t)$, where

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

are the remaining state variables given by the claiming/stop work age t^r , experience h , assets a , education e (own and spouse), persistent income components z (own and spouse), length of marriage l , utility-type v and an indicator i whether the women worked last period.

3.7.2 Working-age

During the working-age stage, agents face marital, wage and survival risk. All households choose consumption and saving, and married households also choose female labor supply.

Married Households We assume that the household maximizes joint utility, applying Pareto-weights of χ and $1 - \chi$:

$$\begin{aligned}
V_{g,t}^m(\Gamma_t) = & \max_{c_t, L_{1,t}, a_{t+1}} \chi \left[\ln(\hat{c}) - \Phi_{1,t,e}^v \frac{L_{1,t}^\gamma}{\gamma} \right] + (1 - \chi) \left[\ln(\hat{c}) - \Phi_{2,t,e}^v \frac{L_{2,t}^\gamma}{\gamma} \right] \\
& + \psi_{1,t,e} \psi_{2,t,e} (1 - \mu_{g,t,e,z}) \beta E [V_{g,t+1}^m(\Gamma_{t+1} | \Gamma_t)] \\
& + \psi_{1,t,e} \psi_{2,t,e} \mu_{1,t,e,z} \beta \chi E [V_{1,t+1}^d(\Gamma_{t+1} | \Gamma_t)] \\
& + \psi_{1,t,e} \psi_{2,t,e} \mu_{2,t,e,z} \beta (1 - \chi) E [V_{2,t+1}^d(\Gamma_{t+1} | \Gamma_t)] \\
& + \psi_{1,t,e} (1 - \psi_{2,t,e}) \beta \chi V_{1,t+1}^w(\Gamma_{t+1} | \Gamma_t) \\
& + (1 - \psi_{1,t,e}) \psi_{2,t,e} \beta (1 - \chi) V_{2,t+1}^w(\Gamma_{t+1} | \Gamma_t)
\end{aligned} \tag{12}$$

subject to the budget constraint given by equation (9). There is no male stop work/benefit claiming decision yet, so $L_{2,t} = 1$. Recall that $\mu_{g,t,e,z}$ is the divorce probability and $\psi_{g,t,e}$ the conditional probability of survival from age t to age $t + 1$. $V_{g,t+1}^d$ is the continuation value of divorce (depending on gender g), and $V_{g,t+1}^w$ is the continuation value of a widowhood (again depending on gender g).

Single and Divorced Households We assume that non-married households always work until (at least) age 61, such that $L_{g,t} = 1$. However, they still incur disutility from working. The only difference between the value functions of the single and divorced household $j = \{u, d\}$ is the marriage and remarriage probabilities, $\xi_{g,t,e,z}$ and $\nu_{g,t,e,z}$, respectively. Defining $\Pi = \{\xi, \nu\}$ we get:

$$\begin{aligned}
V_{g,t}^j(\Gamma_t) = & \max_{c_t, a_{t+1}} \left[\ln(c_t) - \Phi_{g,t,e}^v \frac{L_{g,t}^\gamma}{\gamma} \right] + \psi_{g,t,e} (1 - \Pi_{g,t,e,z}) \beta E [V_{g,t+1}^j(\Gamma_{t+1} | \Gamma_t)] \\
& + \psi_{g,t,e} \Pi_{g,t,e,z} \beta E [V_{g,t+1}^m(\Gamma_{t+1} | \Gamma_t)]
\end{aligned} \tag{13}$$

where V^m is the value function if the agent (re)marries. The maximization is subject to the budget constraint (10).

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.

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

$$V_{g,t}^w(\Gamma_t) = \max_{c_t, a_{t+1}} \left[\ln(c_t) - \Phi_{g,t,e}^v \frac{L_{g,t}^\gamma}{\gamma} \right] + \psi_{g,t,e} \beta V_{g,t+1}^w(\Gamma_{t+1} | \Gamma_t) \quad (14)$$

subject to the budget constraint (10), where again $L_{g,t} = 1$.

3.7.3 Retirement Decision Phase

Between ages 62 and 70, married men and single agents also face a labor supply decision. Social security claiming and the decision to stop work coincide in our model. Hence, married couples now maximize equation (12), with respect to c_t , a_{t+1} , $L_{1,t}$, and in addition $L_{2,t}$. Analogously, singles/divorced and widows maximize (13) and (14), respectively, with respect to c_t , a_{t+1} , and $L_{g,t}$, where $L_{g,t} = \{1, 0\}$. Retirement (the decision to stop work and claim benefits) is an absorbing state.

3.7.4 Retirement

From age 71 onward all agents are retired and the household is left with a consumption-saving decision. Moreover, there are no marital status transitions other than widowhood.

Married Households For a married couple the maximization problem is given by:

$$\begin{aligned} V_{g,t}^m(\Gamma_t) = & \max_{c_t, a_{t+1}} \chi \ln(\hat{c}) + (1 - \chi) \ln(\hat{c}) \\ & + \psi_{1,t,e} \psi_{2,t,e} \beta V_{g,t+1}^m(\Gamma_{t+1} | \Gamma_t) \\ & + \psi_{1,t,e} (1 - \psi_{2,t,e}) \beta \chi V_{1,t+1}^w(\Gamma_{t+1} | \Gamma_t) \\ & + (1 - \psi_{1,t,e}) \psi_{2,t,e} \beta (1 - \chi) V_{2,t+1}^w(\Gamma_{t+1} | \Gamma_t) \end{aligned}$$

subject to the budget constraint, which is now given by:

$$(1 + \tau_c)2c_t + a_{t+1}^m = (1 - \tau_y^s)Ra_{t+1}^m + b_{1,t} + b_{2,t} + 2T$$

Again, social security benefits can be auxiliary benefits as outlined above.

Singles, Divorced Agents and Widows For singles, divorced and widowed agents, $j = \{u, d, w\}$, the maximization problem at retirement is simply given by:

$$V_{g,t}^j(\Gamma_t) = \max_{c_t, a_{t+1}} \ln(c_t) + \psi_{g,t,e} \beta V_{g,t+1}^j(\Gamma_{t+1} | \Gamma_t)$$

subject to the budget constraint

$$(1 + \tau_c)c_t + a_{t+1}^j = (1 - \tau_y)Ra_t^j + b_{g,t} + T$$

3.8 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 with characteristics $(s, g, t^r, h, a, e, e^s, z, z^s, q, l, v)$ in period t by $\Omega_t(s, g, t^r, h, a, e, e^s, z, \eta, l, v)$ over the Cartesian product $\mathcal{Y} = \mathcal{S} \times \mathcal{G} \times \mathcal{T}^r \times \mathcal{H} \times \mathcal{A} \times \mathcal{E} \times \mathcal{E}^s \times \mathcal{Z} \times \mathcal{Z}^s \times \Theta \times \mathcal{L} \times \mathcal{V}$.

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 education), assets a_0^j (which differ by marital status, j)¹⁶, and persistent income states $z_{0,e}$ (which depend on education). The distribution of spousal income states $z_{0,g}^s$ (depending on gender) is approximated using data on education for married couples.¹⁷ We also take the education shares, e and e^s , from the data. The share of agents with high disutility of working, α , is a parameter pinned down by the calibration. Initial experience and length of marriage are normalized to $h_0 = l_0 = 1$.

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

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

¹⁶We cannot determine initial assets by education and marital status, as there are too few observations for this. The differences over marital status are more pronounced than the differences over education at this early age.

¹⁷We 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.

where π_{z,z^s} and π_η are Markov-transition probabilities for the persistent and transitory income shocks. Note that 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 .¹⁸

3.9 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.

The government budget constraint is given by

$$\begin{aligned} \sum_{t=t_r}^T N_t(b_{1,t} + b_{2,t}) + T + C_t &= \sum_{t=0}^{t_r-1} N_t \tau_y^s (L_{1,t} y_{1,t} + y_{2,t}) + \tau_y^s Ra_t^s \\ &\quad + \sum_{t=0}^{t_r-1} N_t \tau_{ss} (L_{1,t} y_{1,t} + y_{2,t}) \\ &\quad + \tau_c \cdot C_t \end{aligned} \quad (15)$$

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

¹⁸ π_s is determined by the (re)marriage and divorce rates as well as the spousal survival rate and defined for an individual with a spouse $g = j$ as:

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

age.¹⁹

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. In the second stage we use our model to calibrate some parameters. There are also a number of parameters which we take directly from the literature.

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 2008.²⁰ 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 1976-2015 surveys from the March supplement of the Current Population Survey (CPS) and use this to compute the marriage probabilities.²¹

The marriage, divorce and remarriage probabilities are reported in Appendix A.3, along with a more detailed description of how they were computed. All marital

¹⁹For the survival rate estimations we do not focus on a specific cohort due to sample size (and simply because the cohort under study has not reached old-age yet).

²⁰We use the marital history topical module for 2008, panel wave 2. This covers the year 2009.

²¹We accessed the data with IPUMS, cf. King et al. (2010).

transition probabilities are smoothed over age. We also use the CPS for the initial distribution of marital status, see Table A.5 in Appendix A.3.

4.1.2 Survival Risk

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.

To predict survival rates we use the waves from 1992 to 2010, and compute the number of age-specific deaths in each wave.²²

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

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

We predict the conditional survival rates and compute the estimated life expectancy given in Table 3. Our estimates line up well with life-table data on life expectancy.²³ Life cycle profiles of survival probabilities are depicted in Figure 6 in Appendix A.8. Note that 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 work experience (women), and differs by education. In addition to the deterministic component, we model an idiosyncratic component, $w_{t,e}$, which is assumed to be the same for both genders, and correlated between spouses.

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

$$y_{2,t,e} = \gamma_e + \alpha_e \cdot \text{age}_{t,e} + \bar{\alpha}_e \cdot \text{age}_{t,e}^2 + w_{t,e} \quad (16)$$

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

²²We 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.

²³Life expectancy for our cohort born 1950-54 is 74 for males and 79 for females, see <https://www.ssa.gov/oact/tr/2012/lr5a4.html>.

separately for the education groups.

To estimate this wage process, we use data on male household heads in the 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.²⁴ 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 us with 1,665 high school dropouts, 4,927 high school graduates, and 2,272 college graduates. We use individual weights.

The estimated coefficients are depicted in Table 5.

Table 5: Estimated Deterministic Wage Component

	Dropout	High School	College
Constant, γ_e	113.6	141.9	158.4
Coefficient for age , α_e	2.011	1.846	7.552
Coefficient for age^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 (22).

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

$$y_{1,t,e} = (1 - \zeta_{t,e}) \cdot \{ \gamma_e + \alpha_e \cdot h_{t,e} + \bar{\alpha}_e \cdot h_{t,e}^2 - d \cdot (1 - P_{t-1,e}) \cdot h_{t,e} \} + w_{t,e} \quad (17)$$

The most notable difference to men is that women's income depends on experience, h_t , not age. We use the coefficients $\gamma_{t,e}$, α_e , and $\bar{\alpha}_e$ that we estimated 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.²⁵ Finally, we introduce a penalty for time away from work. The indicator

²⁴In case there are less than three wage observations per id and age-bin we multiply the average existing values by three.

²⁵In the model we use the linear trend for the life cycle profile of the gender-wage gap, since the

P_{t-1} is one if the woman worked full-time in the last period, implying depreciation at rate d if the woman worked part-time or stayed at home.²⁶

The residuals from regressions (16) and (17) 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 this process can be represented by a time-invariant process with a persistent and a transitory component. See Appendix A.4 for details. For married couples, we assume a positive correlation between the persistent income components of spouses. We assume a correlation coefficient of 0.25 as estimated by Hyslop (2001). The parameters are estimated with a GMM estimator. Results are given in Table 6. We assume the same shock process for high school dropouts and high school graduates.

Table 6: Estimated Parameters for the Idiosyncratic Wage Component

	College	High School
Autocorrelation coefficient, ϱ	0.954	0.923
SD of Persistent shock, σ_ϵ	0.048	0.056
Covariance of Spousal Persistent shock, $\sigma_{\epsilon_e^s, \epsilon_e}$		
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 (22). SD is standard deviation.

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, $\pi_{z,z^s}(z_{t+1}, z_{t+1}^s|z_t, z_t^s)$.²⁷ For the transitory shock we assume $\pi_\eta(\eta_{t+1}|\eta_t) = 0.5$.

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.

²⁶The value of $d = 0.025$ 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).

²⁷Note that while π_z is a four by four matrix depending on education, π_{z,z^s} 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.

4.2 Calibration of Second-Stage Parameters

The parameters that we calibrate using our model are the utility-cost of working parameters, $\Phi_{g,e,t}^v$, the factor governing the strength of the correlation between marital transition probabilities and income, λ_z , 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 the median asset-to-income ratio of 2.6 computed from the PSID. A discount rate of $\varrho = 0.019$ yields a median value of 2.6 in our model.

Correlation of Marital Probabilities and Income

We calibrate the correlation between marital probabilities and income to match the income gradient of marital transitions. We assume that the probabilities of remaining never married, remaining divorced and of becoming divorced are given by:

$$1 - \xi_{g,t,e,z} = \lambda_i \cdot (1 - \xi_{g,t,e}) \quad (18)$$

$$1 - \nu_{g,t,e,z} = \lambda_i \cdot (1 - \nu_{g,t,e}) \quad (19)$$

$$\mu_{g,t,e,z} = \lambda_i \cdot \mu_{g,t,e} \quad (20)$$

for each persistent income state. We assume a simple linear functional form for λ_i over the (discretized) persistent income states: $\lambda_i = a - b \cdot i$, where i is a counter of the income states. We calibrate b and define $a \equiv 1 + b \cdot i_{med}$, where i_{med} is the median persistent income state. This normalization ensures that $\sum_i \lambda_i = 1$.

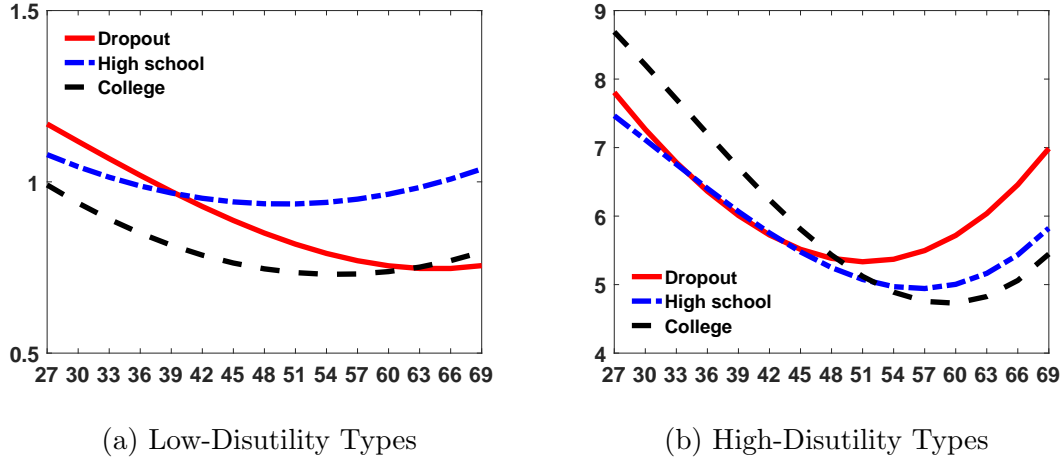
Table 7: Scaling Parameters for Marital Transition Probabilities

a	level	1.375
b	slope	0.15
Parameter estimates for $\lambda_i = a - b \cdot i$.		

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 parameters to differ across utility-types, education and age. For each

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



utility and education type we assume a third-order polynomial for the life cycle profiles of work-disutility. The parameters of these functions, together with the fraction of females with high disutility, α , are calibrated to match employment over age and education. This degree of heterogeneity in preferences is necessary to simultaneously match the age profile 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. The resulting profiles, plotted in Figure 1, are U-shaped. This is intuitive, as disutility from work is likely to be higher when children are young and when health starts to deteriorate.

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, see Table 8.

4.3 Exogenous Parameters

The policy parameters are set to match the U.S. social security and tax systems. The bend-point values in the social security formula, as well as the adjustments for early and delayed claiming can be found in Appendix A.5.

Guner et al. (2014) estimate a progressive tax function for married and single individuals. We use their estimated parameter values. The values for the propor-

Table 8: Disutility of Work for Married Males, $\Phi_{2,t,e}^v$

		Dropouts	High school	College
<i>Age</i> $t_1 = 26 - 52$	$\Phi_{2,t_2,e}^v$	$\Phi_{1,t_1,e}^1$	$\Phi_{1,t_1,e}^1$	$\Phi_{1,t_1,e}^1$
<i>Age</i> $t_2 = 62 - 70$				
high disutility	$\Phi_{2,t_2,e}^1$	2.00	2.65	2.80
low disutility	$\Phi_{2,t_2,e}^2$	0.63	1.17	0.93
Fraction high-disutility types	α	0.57	0.52	0.40

tional consumption and payroll taxes are taken from McDaniel (2007).²⁸ All tax parameter values are reported in Appendix A.5.

Recall that the lump sum transfer T is chosen to balance the budget. Note that 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., 74% 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:

Table 9: Exogenous Parameters

$1/(\gamma - 1)$	Frisch elasticity	0.7
χ	Pareto weight	0.5
eq	Consumption equivalence scaling	1.5
ι	Return of experience from part-time	0.1

The Frisch elasticity is set to 0.7, which is consistent with estimates from models incorporating human capital accumulation (see, e.g., Imai and Keane (2004) and Wallenius (2011)). We assume a pareto-weight of 0.5, implying equal bargaining power for both spouses. This is a common practice in the literature. The value for the accumulation of experience from part-time work is taken from Blundell et al. (2016).²⁹

²⁸We take her updated version, which can be downloaded at: http://www.caramcdaniel.com/tax-files/McDaniel_tax_update_12_15_14.xlsx.

²⁹Note that this estimate is for the UK. However, a related study for the U.S., Blank (2012),

5 Calibrated Economy

In this section we highlight some of the key properties of our calibrated benchmark economy and discuss the fit of the model to the data. We begin by comparing the model generated outcome for marital status over income quintiles with the data. Next, we show the fit of our model to the data along the key moments: overall employment and part-time employment by age and education. Lastly, we show the model fit along dimensions we did not directly target. In particular, we compare auxiliary benefit claiming predicted by our model relative 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 hold all other parameters, including the disutility from work parameters, fixed at their benchmark values. We check whether we are able to match the much lower employment rates for the 1930 cohort with our calibrated model economy.

5.1 Marital Transitions

As is evident from Table 10, by allowing for a correlation between income shocks and marital transition probabilities, our model replicates the higher prevalence of divorce among households at the bottom of the income distribution. Our model also generates more never married individuals at the low end of the income distribution.

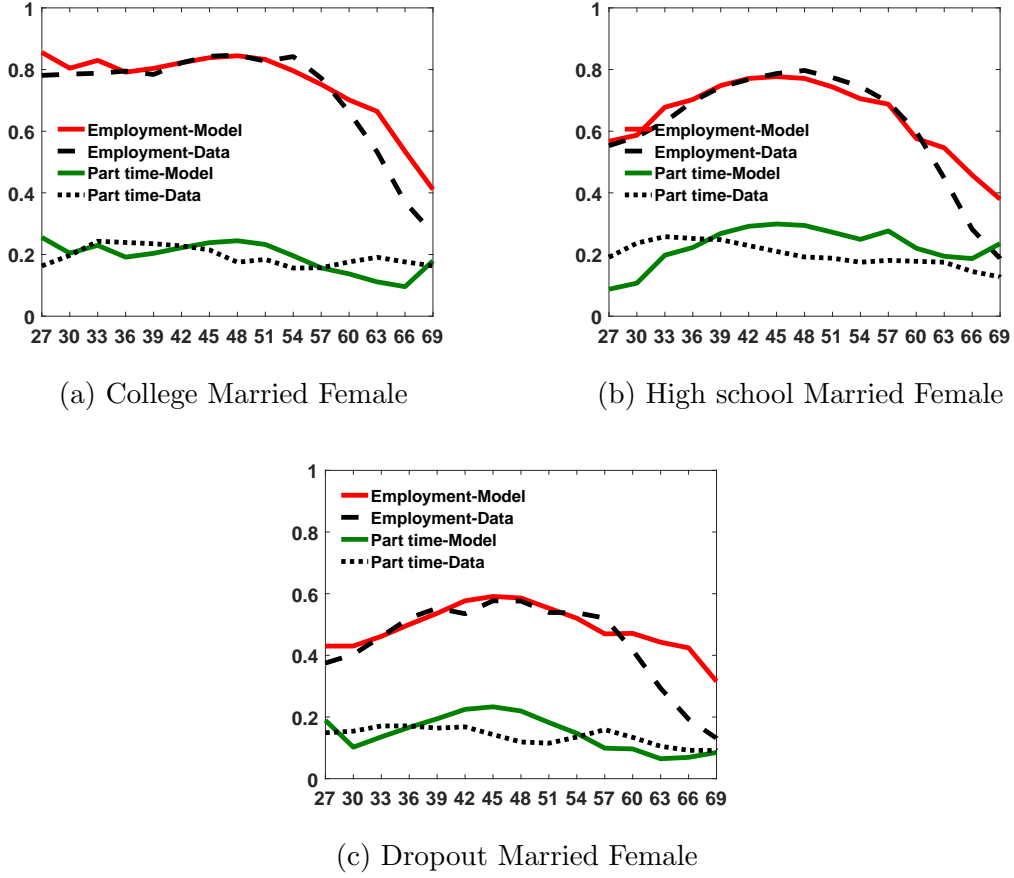
Table 10: Marital Status over Income

HH Inc. Quintile	Never Married		Divorced	
	Model	Data	Model	Data
1st (lowest)	0.15	0.19	0.06	0.11
2nd	0.17	0.12	0.09	0.08
3rd	0.08	0.11	0.05	0.07
4th	0.07	0.06	0.03	0.04
5th (highest)	0.09	0.05	0.03	0.04

Notes: Data taken from SIPP 2009. The reported numbers are fractions. Note that 'divorced' is defined only for marriages that lasted for less than 10 years.

also finds very low accumulation of experience from working part-time.

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.

5.2 Life Cycle 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.

Table 11 shows the model fit with respect to employment of married men for ages 62 to 70. We do quite well in matching the male retirement patterns. The fit to the data is decent for both employment and part-time work for married women. Employment is rather flat until age 62 and decreasing thereafter, while part-time work is roughly constant over age. We somewhat over-predict employment of married women at older ages. This is likely due to the fact that, in our model, we force married couples to start collecting retirement benefits at the same time.

Table 11: Stop Work Decision of Married Men

Fraction stop working...	Dropouts		High School		College	
	Model	Data	Model	Data	Model	Data
...by 62-64	0.45	0.45	0.45	0.40	0.35	0.30
...by 65-67	0.60	0.65	0.58	0.60	0.43	0.45
...by 68-69	0.77	0.75	0.67	0.69	0.51	0.57

Notes: Data taken from CPS. Stop working is defined as 1 minus the age-specific employment rate of married males.

5.3 Non-Targeted Moments: Auxiliary Benefit Claiming

Table 12 shows the fraction of married females who are claiming spousal and survivor benefits. Our model matches the data closely, although it somewhat over-predicts the prevalence of spousal benefits. Note that the fraction of auxiliary benefit claimants in our model is the result of various model elements, most notably employment (full- and part-time) and incomes of males and females. Note also that the data on auxiliary benefit claiming is for 2005, and therefore includes women from older cohorts. 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 differences in life expectancy. In our model, 45% of high-school dropouts, 38% of high-school graduates and 25% of college graduates receive survivor benefits. Spousal benefit claiming is similar across education types. Although labor supply is increasing in own education and income, it is decreasing in spousal education and income. Due to assortative matching, even many highly educated women have low enough lifetime earnings to be eligible for spousal benefits.

Table 12: Auxiliary Benefits for Married Females

<i>Auxiliary Benefits</i>	Model	Data
Spousal benefits	27.0%	23.4%
Survivor benefits	35.6%	35.3%

Notes: Data on auxiliary benefits are taken from SSA (2014), Table 5.A14, for year 2005.

5.4 Robustness Check: The Time-Series Angle

As a validation exercise for our calibration, 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. Note, however, that we assume the same survival rates across cohorts.³⁰

From Table 13 it is evident that by feeding in differences in gender wage gaps, education and marital transitions, our model is able to account for a large share – in fact, about 74% – of the difference in married women’s employment across the two cohorts. This is similar to what Fernandez and Wong (2014) find.

Table 13: Employment of Married Females - Cohort Comparison

	1930 Cohort		1950 Cohort	
	Data	Model	Data	Model
Employment	0.44	0.51	0.64	0.66
Part-Time	0.18	0.13	0.20	0.21

6 Policy Analysis

Having established that our model does a good job of matching the salient features of household labor supply, we turn to the policy analysis. As a first step, we endeavor to understand the nature of redistribution built into the current U.S. social security system. To this end, we 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). We then consider two counterfactual experiments, abandoning auxiliary benefits altogether and replacing auxiliary benefits with a minimum benefit scheme.

6.1 Redistribution in Benchmark Economy

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

³⁰Due to sample size problems we cannot separately estimate cohort-specific survival rates.

replacement rates of unmarried individuals.³¹ The replacement rate is decreasing over education, from 0.45 for dropouts to 0.37 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 households. This is reflected in much higher replacement rates for married and widowed females compared with unmarried females. The especially high replacement rates for widows is due to the generosity of survival benefits. Note, however, that 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 striking to note that the replacement rate for ever married college women is much higher than the replacement rate of unmarried high-school dropouts. These numbers suggest strong redistribution from the bottom to the top, and from singles to married households. Note that 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 14: Replacement Rates - Baseline

	Females		Males	
	Married	Widowed	Unmarried	Unmarried
Dropouts	1.07	1.31	0.45	0.41
High School	0.82	1.02	0.42	0.38
College	0.56	0.66	0.37	0.32
<i>Total</i>	<i>0.72</i>	<i>0.94</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.

The replacement rates in Table 14 are conditional on being retired, and do not

³¹We 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.

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.

Table 15: Adjusted Replacement Rates - Baseline

	Females		Males	
	Married	Widowed	Unmarried	Unmarried
Dropout	0.78	0.98	0.33	0.20
High School	0.85	1.08	0.44	0.38
College	0.69	0.79	0.46	0.49

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 15). The adjusted replacement rate for single females is 12pp lower for dropouts compared to college graduates. This difference is even more pronounced for males. This 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 differ over education. But even though women with a college degree retire more than 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 quite 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.

Table 16: Labor Supply Effects

	No Auxiliary Benefits	Only Survivor	Minimum Benefit
Married Females, Employment	6.4	4.6	1.8
Dropout	4.4	2.5	-1.1
High school	6.8	4.8	1.7
College	6.2	4.9	3.7
All Females, Employment	5.1	3.5	1.4
Part-Time	4.5	3.5	1.0
All Males	-0.1	0.0	-0.3
Aggregate Hours	1.8%	1.2%	0.4%

Notes: Employment change from counterfactuals (in pp).

6.2 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 sizable increase in the average employment rate of married women, 6.4pp to be exact.³²

The employment effects are largest for women who are matched with a man with the same level of education. This is intuitive, as in couples where the man is more educated than the woman there is less incentive for the woman to work, even in the absence of auxiliary benefits. Also, in couples where the woman is more educated than the man, women are less likely to rely on auxiliary benefits to begin with. The employment effects are largest for high school educated women. See Table 16 for details. These large employment effects are almost exclusively due to an increase in part-time work.

The large employment effects for women are slightly dampened by some men retiring a bit earlier. With auxiliary benefits, there is an incentive for the husband

³²For 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 employment effect is even larger in this case, 7.8pp, implying an increase in aggregate hours of 2.2 percent.

to work longer in 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. However, the effect is quantitatively small: overall employment of men is reduced by 0.1pp. All in all, abolishing auxiliary benefits increases aggregate hours by 1.8%.

Table 17: Household Replacement Rates Relative to Baseline

	No Auxiliary Benefits			Minimum Benefit		
	Married	Widowed	Unmarried	Married	Widowed	Unmarried
Dropout	-16.1%	-38.7%	-1.2%	21.5%	-10.5%	10.4%
High School	-12.6%	-33.9%	-0.1%	9.5%	-15.1%	3.0%
College	-5.6%	-18.8%	-0.0%	-0.4%	-12.8%	-0.0%

Notes: Value: Per-capita average replacement rate of the household depending on education. Relative difference with respect to the baseline scenario with auxiliary benefits. 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 left-hand side of Table 17. This illustrates that both spousal and survivor benefits are important elements that boost replacement rates – for all education types – in our baseline scenario. The decline in social security income is most pronounced for the least educated households: replacement rates fall by 16.1% (38.7%) for married (widowed) dropout individuals compared to only 5.6% (18.8%) for college graduates. This is due to the fact that the least educated households rely most heavily on auxiliary benefits in the benchmark and also the fact that the employment response to abolishing said benefits is the smallest for this group. 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.

We observe a strong increase in the inequality of social security income from abolishing auxiliary benefits (see Table 18). The Gini-index of social security benefits rises from 0.13 in the baseline to 0.2 in the counterfactual without auxiliary benefits. Note that the numbers reported here are at the household level.

Table 18: Distribution of Average Household Benefits

	Baseline		w/o Spousal		w/o Aux.Ben.		Min.Ben.	
Pop.Frac.	%	acc	%	acc	%	acc	%	acc
lower 20%	0.12	0.12	0.13	0.13	0.09	0.09	0.16	0.16
20 – 40%	0.19	0.31	0.16	0.29	0.16	0.25	0.16	0.31
40 – 60%	0.19	0.50	0.20	0.48	0.21	0.46	0.18	0.50
60 – 80%	0.22	0.72	0.23	0.71	0.23	0.68	0.22	0.71
80 – 100%	0.28	1.00	0.29	1.00	0.32	1.00	0.29	1.00
Gini-Index	0.13		0.15		0.20		0.12	

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 4.6pp. This exercise illustrates that the depressing effect on labor supply of the auxiliary benefit system arises in large part from the spousal benefits. Moreover, abolishing spousal benefits increases inequality only moderately relative to the benchmark.

6.3 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.³³

We consider a 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 35% of average income in the economy – which corresponds to a revenue-neutral policy reform – we top up the benefits of both spouses to this level.

³³For a discussion of survival benefits across countries, see James et al. (2009).

Replacing the auxiliary benefit scheme with such a minimum benefit has a positive effect on the average employment of married women in our model, 1.8pp to be precise. Employment of married dropout women actually declines, since for this group the minimum benefit is more generous than the previous spousal benefit. However, college educated married women, who were eligible for auxiliary benefits, are not entitled to means-tested minimum benefits. The employment effect for college educated married women is large and positive, 3.7pp. The minimum benefit increases progressivity of social security income, as evidenced by the replacement rates in Table 17. Household replacement rates rise substantially for married couples where the wife is a high school dropout (21.5%), whereas they decline slightly for couples where the wife is a college graduate (-0.4%). Note also that unmarried individuals without a high school degree experience an increase in the replacement rate (10.4%), while it remains essentially unchanged for the unmarried college graduate. Widows lose out relative to the benchmark, albeit the reduction is higher for the highly educated.

The redistribution from richer to poorer households implied by a minimum benefit system is also confirmed by the Gini index, see Table 18. The decline in the average Gini is small, but the minimum benefit implies a move toward a more equal distribution of social security income, particularly at the lower end of the income distribution.

7 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 income 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 6.4pp. These large employment effects are almost exclusively due to an increase in part-time work. There is a small counteracting effect from a reduction in male employment. All in all, our model predicts an increase in aggregate hours of 1.8%.

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 less of an effect on employment than simply abolishing auxiliary benefits. Specifically, the employment rate of married women rises by 1.8pp relative to the benchmark with auxiliary benefits. However, the minimum benefit implies redistribution from richer to poorer households. In particular, the minimum benefit implies higher benefits for high school dropout wives whose husbands do not have a college education. The biggest losers are the widows who are no longer entitled to hugely generous survivor benefits.

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A Appendix

A.1 Marital Status over Income for both Education Groups

Table A.1: Marital Status over Per Capita HH Income, Dropout Men Age 45-60

HH Income Quintile	Married	Divorced	Never Married	Widowed
1st (lowest)	0.59	0.23	0.16	0.02
2nd	0.63	0.21	0.14	0.02
3rd	0.72	0.18	0.09	0.01
4th	0.80	0.14	0.05	0.01
5th (highest)	0.85	0.10	0.05	0.00
Total	0.72	0.17	0.10	0.01

Notes: Fraction of dropout men in each of the four marital states over per-capital household income. Quintiles are computed based on per-head, equivalence-scaled total annual household income, pooled over age bins. *Source:* CPS. Sample consists of cohort born 1950-54.

Table A.2: Marital Status over Per Capita HH Income, High School Men Age 45-60

HH Income Quintile	Married	Divorced	Never Married	Widowed
1st (lowest)	0.57	0.25	0.15	0.02
2nd	0.60	0.23	0.15	0.02
3rd	0.70	0.20	0.08	0.01
4th	0.77	0.16	0.06	0.01
5th (highest)	0.83	0.13	0.04	0.01
Total	0.69	0.20	0.10	0.02

Notes: Fraction of high school men in each of the four marital states over per-capital household income. Quintiles are computed based on per-head, equivalence-scaled total annual household income, pooled over age bins. *Source:* CPS. Sample consists of cohort born 1950-54.

Table A.3: Marital Status over Per Capita HH Income, College Men Age 45-60

HH Income Quintile	Married	Divorced	Never Married	Widowed
1st (lowest)	0.68	0.17	0.13	0.02
2nd	0.73	0.14	0.12	0.01
3rd	0.81	0.12	0.07	0.01
4th	0.83	0.10	0.07	0.01
5th (highest)	0.88	0.08	0.04	0.00
Total	0.78	0.12	0.09	0.01

Notes: Fraction of College men in each of the four marital states over per-capital household income. Quintiles are computed based on per-head, equivalence-scaled total annual household income, pooled over age bins. *Source:* CPS. Sample consists of cohort born 1950-54.

A.2 Stay-at-Home-Wives over Husband's Income

Table A.4: Fraction of Male Bread-Winner Families over Husband's Income

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.

A.3 Marital Transition Probabilities

Table A.5 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 A.5: 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

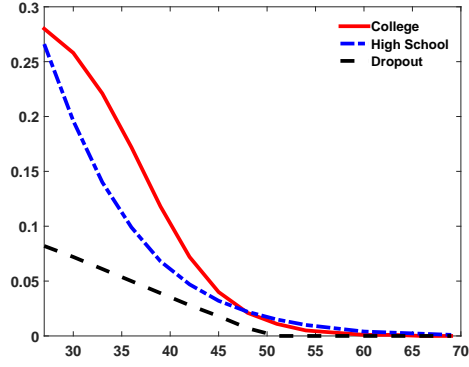
Source: CPS. Initial marital status at age 25 for cohort born 1950-54.

The marriage probabilities shown in the first two panels in Figure 3a and 3b 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 old 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 zero³⁴. For ages 50 to 68 we extrapolate the fitted data.

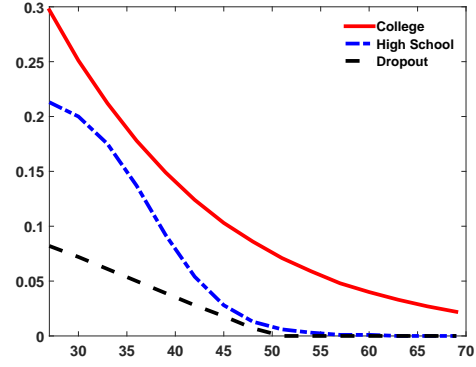
To compute the divorce rates depicted in panels 3c and 3d we use the latest SIPP wave from 2009. Since the maximum age for our cohort in 2009 is 59, we expand our sample to individuals born 1940-1954, when computing probabilities for ages above 58. The data are linear-fitted values. The divorce probability 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.

³⁴We 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.

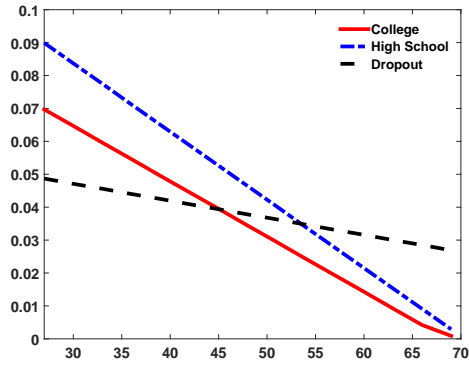
Figure 3: Marital Transition Probabilities, Fitted Values



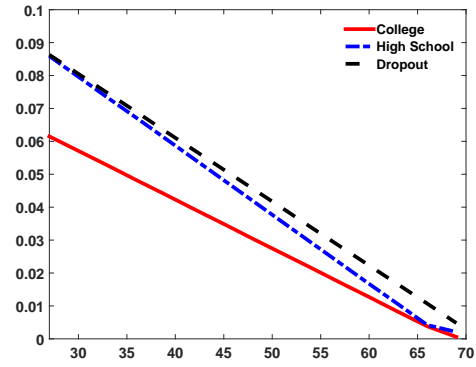
(a) Marriage Probabilities, Females



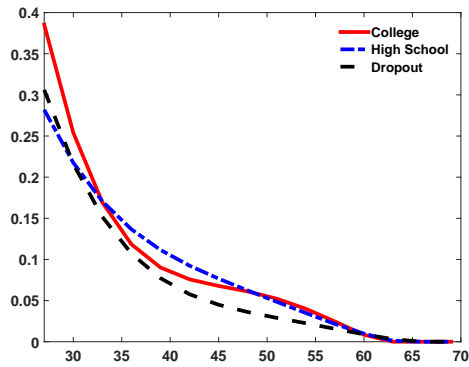
(b) Marriage Probabilities, Males



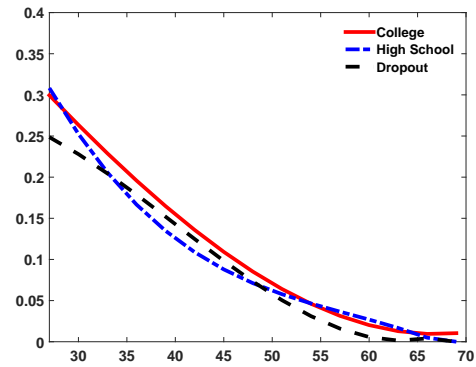
(c) Divorce Probabilities, Females



(d) Divorce Probabilities, Males



(e) Remarriage Probabilities, Females



(f) Remarriage Probabilities, Males

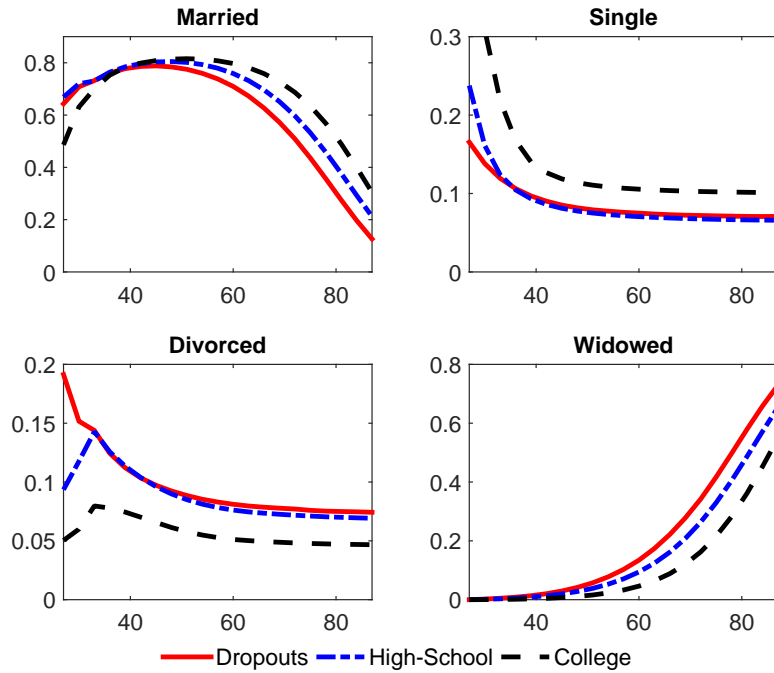
Source: CPS and own calculations. Logistic or linear fitting of raw probabilities.

The remarriage rates shown in panels 3e and 3f 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.

Marital Patterns over the Life Cycle

Figure 4 depicts the shares of married, divorced, widowed and never married individuals over age, for the three education categories separately. The shares are directly implied by the marital transition probabilities above. Note that we cannot compare the shares with the data as our cohort has not reached old age. In addition, recall that our definition of divorced individuals is limited to individuals who were married for less than ten years, as this is the fraction of people who are not eligible for auxiliary benefits. Analogously, the share of married households includes divorced agents who were married for more than ten years, and are, hence, eligible for auxiliary benefits.

Figure 4: Marital Status over Age, Model



Notes: Model outcome of marital status. Age-bins are depicted at the abscissa. 'Divorced' is defined as being divorced and married less than 10 years.

Comparing the education types, we observe that although the initial marriage rates are lower for college graduates than their less educated counterparts, the fraction of married people is higher for college graduates from age 50 onward. This is largely due to the fact that less educated individuals die younger, so widowhood is more prevalent among the less educated. Also, the fraction of divorced (single) individuals is higher (lower) for high school graduates and dropouts than for college graduates.

A.4 Income Process and Estimation

For singles, we assume a standard process given as:

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

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

$$z_{i,t,e}^s = \varrho^s z_{i,t-1,e}^s + \varepsilon_{i,t,e}^s$$

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

$$\Sigma_{\varepsilon} = \begin{bmatrix} \sigma_{\varepsilon_e} & \sigma_{\varepsilon_e, \varepsilon_e^s} \\ \sigma_{\varepsilon_e^s, \varepsilon_e} & \sigma_{\varepsilon_e^s} \end{bmatrix} \quad (21)$$

where $\sigma_{\varepsilon_e, \varepsilon_e^s}$ 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. Note, that we leave out the subscript e for convenience. Rewrite the process for $z_{i,t}$ as $MA(T)$, i.e. over all ages, $0, \dots, T$

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

The moments are then given by

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

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

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

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

The summarized theoretical autocovariances are hence:

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

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

Using the saved residuals $w_{i,t,e}$ from regression (16) 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 . Note, that 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:

$$\hat{\theta} = \arg \min_{\theta} [(C(\theta) - C(X))' \times W \times (C(\theta) - C(X))], \quad (22)$$

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

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

A.5 Policy Parameters

Table A.6: 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 aggregate in our model.

Adjustments for early and delayed claiming of retirement benefits:³⁵

$$b_{t,g,e} = \begin{cases} (1 - 0.201) & \text{if } t^r = 62 \\ 1.0 & \text{if } t^r = 65 \\ 1.24 & \text{if } t^r = 68 \\ 1.48 & \text{if } t^r = 71 \end{cases} \quad (23)$$

³⁵See www.ssa.gov/oact/quickcalc/early_late.html for details.

where t^r is claiming age.

Table A.7: Tax Parameters

τ_c	Consumption tax	7.5%
τ_{ss}	Payroll tax	15.3%
y_{max}	Earnings cap for payroll tax in 2010	\$106,800
α_s	Coefficient in τ_y^s (married/single)	0.105/0.085
β_s	Coefficient in τ_y^s (married/single)	0.034/0.0058
\bar{y}	Average earnings in 2010	\$53,063
	Government Consumption Ratio	24%

The consumption tax rate is from McDaniel (2007). The payroll tax is the statutory rate (including the 2.9% for Medicare). The coefficients for the income tax function (as well as average earnings in 2010) are taken from Guner et al. (2014). The government consumption ratio is taken from Chakraborty et al. (2015).

A.6 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 A.8 shows the difference in marital status over education for both cohorts.

Table A.8: 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 Table shows 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.

Note that 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 A.9. 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 A.9: 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

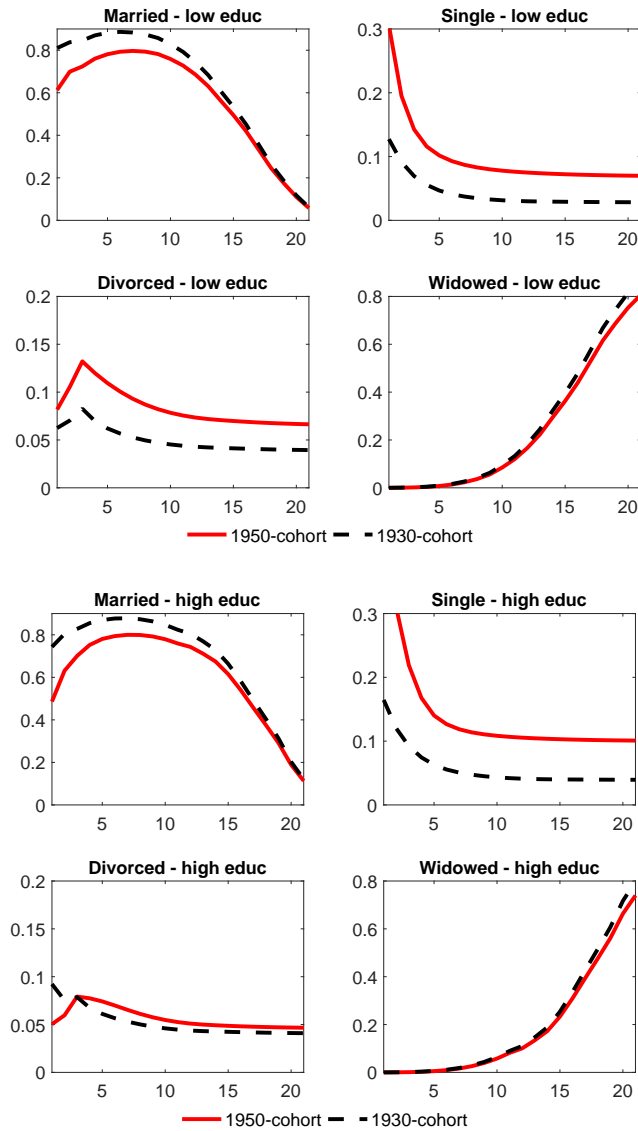
Notes: The Table shows the fraction of individuals in each marital state at initial age 25 (27 for the 1930 cohort). *Source:* CPS. Sample consists of cohort born 1950-54 and the cohort born 1930-36 (extended slightly to get data on individuals aged 27).

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.

A.7 Marital Transitions Between Cohorts

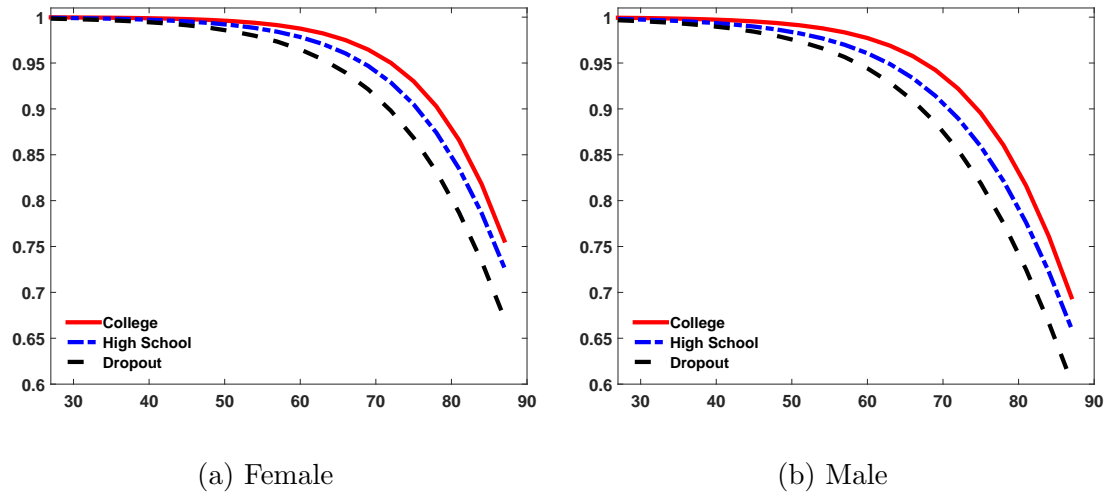
Figure 5: Marital Status over Age, Model



Notes: Model outcome of marital status for the 1950 and the 1930 cohort. Age-bins are depicted at the abscissa. 'Divorced' is defined as being divorced and married less than 10 years.

A.8 Unconditional Survival Rates over the Life cycle

Figure 6: Survival Rates



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