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You Better Get Married! Marital Status and Intra-Generational Redistribution of Social Security

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You Better Get Married!
Marital Status and Intra-Generational Redistribution of Social Security

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Abstract

In this paper, we study the intra-generational redistribution of the U.S. social security system in a dynamic, structural life cycle model of couples with uncertain marital status and survival risk. We focus particularly on auxiliary benefits, namely spousal and survivor benefits, where eligibility is directly linked to marital status. We show that marital stability increases strongly with income, leading to redistribution from the bottom to the top. We evaluate the impact of auxiliary social security benefits on both the poverty rate of the elderly and on household labor supply.

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

Keywords: Spousal and Survivor Benefits, Marital Risk, Female Labor Supply, Old-Age Poverty

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1 Introduction

Social security is an important source of retirement income, especially for women. Auxiliary benefits, which are based on the spouse's eligibility, are an integral part of U.S. social security: about 34% of women collecting social security are collecting spousal or survivor benefits. In addition, almost a quarter of women are dually entitled, which means that they receive auxiliary benefits that top-up the benefit they are entitled to based on their own earnings record.[1]

Marital status is the main eligibility criterion for spousal and survivor benefits. A precondition for these benefits at the time of claiming is a current marriage or a divorce where the last marriage lasted for at least ten years. Spousal benefits are equal to 50% of a retired worker's Primary Insurance Amount (PIA). Surviving spouses may be eligible for survivor benefits that are equal to 100% of the deceased worker's PIA.[2] Both marital status and survival are uncertain and strongly linked to socio-economic status.

In this paper, we study the redistributional consequences and the labor supply effects of auxiliary social security benefits. To this end, we develop a dynamic, structural life cycle model of couples with marriage and divorce risk and uncertain survival. We also account for the education and income gradients of marital stability.

At an individual level, U.S. social security redistributes from higher earners to lower earners (often women), due to the concave nature of the pension formula. However, 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. Moreover, the income gradient in divorce risk introduces a regressive component to social security.

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 (spousal benefits) and supporting the widow after the spouse's death (survivor benefits), 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. By redistributing from two-earner to one-earner (married) households, the auxiliary benefit system creates incentives for –

[1] Nubers are calculated using data from *Benefits and Earnings* 2004 from the Social Security Administration. The sample consist of all individuals receiving Social Security benefits, excluding those receiving disability benefits.

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

potentially even well-educated – women to stay at home. 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. 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 redistributional consequences of these policies have not been systematically analyzed. Moreover, the effect of auxiliary benefits on female labor force participation, taking into account the relevant uncertainties with respect to marital status and survival, has not been analyzed.

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 beween marital stability and income is even more pronounced than the one between marital stability and education. In particular, the share of married individuals is 33 percentage points lower in the lowest income quintile compared to 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). These correlations might have strong redistributive consequences within the social security system.

There are a few recent studies that analyze the impact of auxiliary social security benefits on female labor supply in structural, life cycle models; see Kaygusuz (2015), Nishiyama (2015) and Bethencourt and Sànchez-Marcos (2014). The quantitative findings from these studies are a bit mixed. Kaygusuz (2015) predicts a large increase in female labor force participation (5.2%) from the elimination of spousal and survivor benefits, with the middle-class households experiencing the highest welfare-losses. Conversely, Nishiyama (2015) finds a much smaller increase in labor force participation (1.4%) from a similar counterfactual.[3] Bethencourt and Sànchez-Marcos (2014) find the largest response in female labor force participation (9 pp increase) from removing auxiliary benefits. We add to this literature by explicitly taking the uncertainty of marital status into account and by incorporating the strong link 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 labor supply effects (for men and women) of the current auxiliary benefit system.

[3]Nishiyama (2015) claims that his assumption of uncertain labor income attenuates labor supply effects, as future retirement benefits are also uncertain. [TBC: Check out differences more closely: What are the precise policy experiments, i.e., how do they balance the gov budget?].

Our paper is also related to Fernandez and Wong (2014), who study the effect of increased divorce risk on female labor supply decisions. They find that changes in the marital patterns between the 1935 and the 1955 cohorts account for a large share (42%) of the increase in female labor force participation between these cohorts. 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.

In the next Section we outline the main stylized facts that emerge from the data.

2 Stylized Facts

In this section we document four main facts: (1) marital stability is strongly linked to socio-economic status (while differences are also found over education, they are more pronounced over per capita household income), (2) survival risk is linked to education, (3) poverty is linked to marital status, and (4) female labour supply is linked to spousal income.

2.1 Marital Status and Socio-Economic Conditions

Table 1 shows the fraction of individuals who are married, divorced or never married by educational achievement (based on cross-section). Note that the share of people who are currently married is 5pp higher for individuals with a college degree than for those without, while the share of people who are currently divorced is 4pp lower. The share of never married is actually slightly higher among the more educated than the less educated, since more educated individuals marry later.

Table 1: Marital Status over Education, Cohort 1950-54

	Married	Divorced	Widowed	Never Married
Below College	0.68	0.18	0.05	0.08
College	0.73	0.14	0.02	0.10
Total	0.70	0.16	0.04	0.08

Source: SIPP 2009. Sample consists of cohort born 1950-54. We drop individuals with less than high school. College includes those with a B.Sc. or above.

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 10pp higher, and the fraction of currently married 33pp lower, in the lowest income quintile than in the highest. Appendix A.1 presents more statistics on the differences in marital status over socio-economic variables, including the same as the table below but for high- and low-educated individuals separately.

Table 2: Marital Status over Per Capita HH Income, Cohort 1950-54

HH Inc. Quintile	Married	Divorced	Widowed	Never Married
Q1	0.50	0.25	0.08	0.14
Q2	0.63	0.18	0.05	0.12
Q3	0.70	0.16	0.03	0.09
Q4	0.76	0.14	0.02	0.07
Q5	0.83	0.10	0.02	0.04
Total	0.69	0.16	0.04	0.09

Source: SIPP 2009. Sample consists of cohort born 1950-54. Quintiles are computed based on per-head, equivalence-scaled total monthly household income, pooled over age bins.

Discussion

The differences in marital status over education are much weaker than the differences over household income quintiles.[4]

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. Isen and Stevenson (2010) discuss marital status over education in more detail, showing results by cohort, gender and race. They find that the fraction of households who are ever married is actually lower for high-educated than low-educated individuals, since more educated individuals marry later. Divorce rates are higher for the low-educated than the high-educated, although there are two hump-shaped patterns. With three education bins – college, some college and high school or less – one observes that divorce rates are actually highest for 'some college' and lowest for 'college'. Isen and Stevenson (2010) argue that

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

those who are not able to finish college also have difficulties maintaining their marriage (see p.120). The second hump can be attributed to time effects. Divorce rates increased up until the 1970s and have been going down since.

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 the (estimated) death rate over age for different education groups. For all age groups, the fraction of deaths is lower for people with a college degree than for those without. Life-expectancy is 3.9 (4.2) years higher for college educated women (men) than for their less educated counterparts. The gender-difference in life-expectancy is on average 4.6 years, in favor of women.

Table 3: Life-Expectancy by Gender and Education

	Women	Men
College	75.2	70.8
High School	71.3	66.6

Source: HRS, pooled waves 1992-2010.

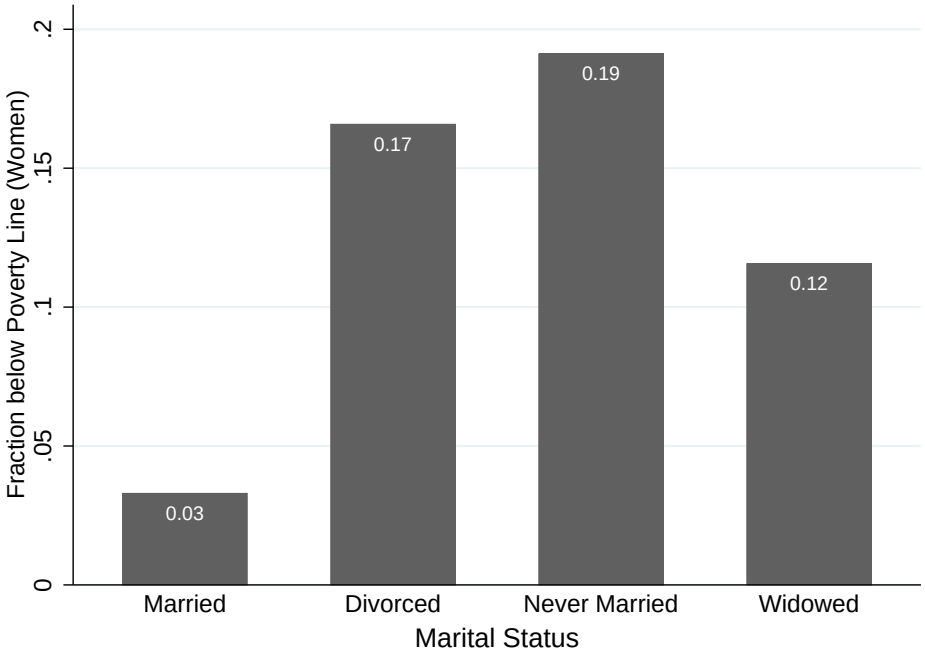
Note that our estimated life-expectancy matches up well with the life-table data.[5] Life expectancy at birth for the cohort born 1949-51 (i.e. a little earlier than our cohort) is 70.96 for women and 65.47 for men.

2.3 Marital Status and Poverty

Figure 1 shows that marriage seems to provide good insurance against poverty: only 3% of married women are below the poverty line. The table also shows that it is not widows who are in the most danger of being in poverty, but rather the divorced and never married women. Note that the figure focuses on women aged 60 and above. This implies that the samples of 'never married' and 'divorced and married for less than 10 years' are relatively small, 5% and 14%, respectively. The majority of women 60 and above are either still married (50%) or widowed (32%).

[5] See *www.cdc.gov/nchs/data/nvsr/nvsr*63/*nvsr*63$_0$7*.pdf*.

Figure 1: Share of Women Below Poverty Line by Marital Status



Notes: SIPP 2009, sample of women aged 60+. Calculated as the fraction of individuals where total household income is below the official CPS poverty threshold in 2009.

2.4 Labor Supply of Married Women

Table 8 shows the fraction of one-earner households over the *husband's* total income, for a sample of married households with at least one child. The table shows that one-earner households are more common when the husband earns more, irrespective of the education of the woman. It is less common to have only one-earner in families where the woman is more educated, relative to families where the woman is less educated. However, it is quite striking that in 37% of the families with a highly educated woman and the husband in the higest income bracket, the husband is the sole bread-winner. 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.

[TBC: Check out difference to CPS-data]

Table 4: One-Earner Families over Wife's Education and Husband's Income

	High-Educated Women		Low-Educated Women	
HH Inc. Quintile	HH Income	One-Earner Male	HH Income	One-Earner Male
Q1	797	0.13	879	0.22
Q2	2,464	0.13	2,405	0.31
Q3	3,853	0.16	3,702	0.28
Q4	5,684	0.22	5,383	0.32
Q5	12,130	0.37	10,262	0.43
Total	6,678	0.24	3,935	0.30

Source: SIPP 2009. Quintiles calculated based on the husband's total income for a sample of married couples with children, aged below 62.

3 The Model

Households initially differ by gender, marital status, and education. They are subject to income risk, (re)marriage and divorce risk and survival risk.

Households fall into one of four categories based on marital status: single, married, divorced or widowed. Single individuals get married with a certain probability and match with a spouse that has identical characteristics [TBC]. Married households face a probability of divorce and of becoming widowed. Divorced individuals face a probability of remarriage. 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. Education, e, is modeled as college (B.Sc. or above) and less than college.

Households enter the model at age 26; the terminal age is 89. A model period corresponds to three years in the data, implying that we have 21 model periods. The model is divied into three sub-periods, corresonding to ages 26-61, 62-70 and 71-89. Households make consumption-savings decisions in all periods. We assume that men work for sure until age 61. Conversely, in each of these periods women choose whether or not to work. If a woman works, she gains experience which positively affects her wage and future social security claims. Between ages 62 and 70 couples endogenously choose when to stop working (unless the women never worked/stopped working earlier, in which case the household chooses when the husband stops working). We assume that social security benefit claiming coincides with the husband's decision to stop working. Moreover, in our model a couple simultaneously claims benefits [TBC]. Social security payments are linked to marital status through auxiliary benefit payments, in particular spousal and survivor benefits. We assume that everyone is retired from age 71 onward.

3.1 Choices and Preferences

During ages 26-61, households (or individuals) decide on female labor force participation, conditional on asset holdings a_t, experience h_t, and the spouse's (male) earnings, if married. The instantaneous utility of an individual is given by

$$U(c_t, L_t) = \frac{c_t^{1-\theta}}{1-\theta} - \Phi_{e,t}^{v} \mathbf{I}_{L_t=1}, \tag{1}$$

where $\hat{c}_t$ is household consumption and $c_t = \hat{c}_t/q$ is consumption measured in adult equivalences, if the agent is married. $\mathbf{I}_{L_t=1}$ is in indicator function, which assumes the value one if the agent is working and zero otherwise. $\Phi_{e,t}^{v}$ represents disutility from working. We assume that only married women incur a utility cost from working. For these women we assume two different utility types $v = 1, 2$, i.e., women have ceteris paribus either higher or lower disutility from working based on their disutility type. This modeling choice is a shortcut for an explicit modelling of children. We assume that disutility also differs by education type, e and age t. Men and single women work full-time up until their endogenous retirement decision. The utility cost parameters are calibrated to match labor force participation of married women by education.

3.2 Marital Status

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

We distinguish between single and divorced households, since marriage and remarriage probabilities differ. Singles face a marriage probability $\pi(g, t, e, z)$, which depends on gender, age, education and the permanent income realization. Similarly, divorced agents face a re-marriage probability $\nu(g, t, e, z)$.

Married couples 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. To this end, we simply count the number of years of the marriage:[6]

$$l_{t+1} = \begin{cases} l_t + 1 & \text{if } s_t = m \text{ and } l_t < 4 \\ 0 & \text{if } s_t = d \text{ and } l_t < 4 \\ 4 & \text{if } l_t = 4 \end{cases} \tag{2}$$

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.[7]

As a first and most simple assumption, a potential spouse is equipped with the same characteristics as the individual, i.e., they have the same set of state variables, in particular education, assets and age. Upon divorce, assets are split evenly between spouses.

The probabilities determining marital status are fed exogenously into the model according to the data outlined in the calibration section. The probability of becoming widowed is determined by the survival probabilities.

3.3 Income Process

The wage process is uncertain, consisting of an idiosyncratic permanent component, z_t, and a transitory component, η_t. Since men are assumed to work full-time until retirement, their income is a a function of age. Income for women depends on experience, h_t. Following Fernandez and Wong (2014) we assume that income is subject to human capital depreciation if the agent did not work in the previous period. Finally, the income risk differs by gender and education, hence:

$$y_t = y(g, e, h_t, z_t, L_{t-1}) \tag{3}$$

Experience, h_t, is modeled as a learning-by doing technology that simply counts the number of years in the labor market:

$$h_{t+1} = h_t + \mathbf{I}_{L_t=1} \tag{4}$$

The divorce probability is assumed to be correlated with our permanent income com-

[6]Note, that we approximate the threshold of 10 years by 4 model periods implying 4*3=12 actual years.

[7]A 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.

ponent. Milosch (2014) and Weiss and Willis (1997) present evidence of a positive correlation between negative income shocks and divorce. We will determine the parameters governing the strength of this correlation such that our model can replicate the marital pattern over income that is shown in Tables A.1 and A.2. In particular, we assume a loading factor λ_z on the divorce and 1 minus the marriage and remarriage probabilities in case of low realizations of z. Details are described in the calibration section.

3.4 Survival Risk and Demographics

The survival rate depends on gender, age, and education:

$$\psi = \psi(g, t, e) \tag{5}$$

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.

3.5 Social Security Benefits

The pay-as-you-go (PAYG) social security system taxes labor earning and pays out benefits to the retired. Benefits, $b(g, e, h, t^r, s)$ depend on past income, and hence on gender, education and work experience (for women), as well as the claiming age, t^r, and marital status (due to auxiliary benefit payments).

Auxiliary benefits depend 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. Since only women decide on labor force participation this yields:

$$b_t^{spouse}(f, e, h, t^r, s) = \max\left\{b_t(f, e, h, t^r, s); \frac{1}{2}b_t(m, e, h, t^r, s))\right\} \tag{6}$$

if $s = m$ or if $s = d$ and $l = 4$.

If the husband dies, the eligible (ex-)wife gets survivor benefits equal to 100% of the deceased's benefits, assuming that the husband's benefits were higher than the wife's. The resulting survivor benefits are given by:

$$b_t^{surv}(f, e, h, t^r, s) = \max\left\{b_t(f, e, h, t^r, s); b_t(m, e, h, t^r, s)\right\} \tag{7}$$

3.6 Recursive Problem

3.6.1 State Space and Notation

The state space is given by the claiming/stop work age t^r (4 states), experience h (15 states), assets a (25 grid points), gender g (2 states), marital status s (3 states)[8], age (21 states), education e (2 states), length of marriage l (4 states), utility-types v (2 states) and the persistent z (5 states) and transitory q (2 states) income components.

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 $s = \{m, s, w\}$, and gender $g = \{f, m\}$ as $V^s_{g,t}(\Gamma_t)$, where

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

are the remaining state variables. Next period's income is uncertain, so we have to calculate the expected value tomorrow as $E\left[V^s_{g,t+1}\left(\Gamma_{t+1}|\,\Gamma_t\right)\right]$.

The model can be structured into three distinct stages: a pure working-age phase from age 26 to 61, a retirement decision phase between ages 62 and 70 and a retirement phase from age 71 onward. Both the set of decisions and uncertainties differ between these stages.

3.6.2 Working-age

During the working age stage, agents face marital, wage and survival risk. Agents decide about consumption and married women decide whether to work or stay home.

Married Households We assume that the household solves its maximization problem jointly, assuming Pareto-weights χ for each single utility function:

$$\begin{aligned} V^m_{g,t}\left(\Gamma_t\right) \;=\; & \max_{c_t, L_t, a_{t+1}} \chi\left[\frac{c_t^{1-\theta}}{1-\theta} - \Phi^v_{e,t}\mathbf{I}_{L_t=1}\right] + (1-\chi)\,\frac{c_t^{1-\theta}}{1-\theta} \\ & +\psi(f,t,e)\psi(m,t,e)(1-\mu(g,t,e,z))\beta E\left[V^m_{g,t+1}\left(\Gamma_{t+1}|\,\Gamma_t\right)\right] \\ & +\psi(f,t,e)\psi(m,t,e)\mu(f,t,e,z)\beta\chi E\left[V^d_{f,t+1}\left(\Gamma_{t+1}|\,\Gamma_t\right)\right] \\ & +\psi(f,t,e)\psi(m,t,e)\mu(m,t,e,z)\beta(1-\chi)E\left[V^d_{m,t+1}\left(\Gamma_{t+1}|\,\Gamma_t\right)\right] \\ & +\psi(f,t,e)(1-\psi(m,t,e))\beta\chi V^w_{f,t+1}\left(\Gamma_{t+1}|\,\Gamma_t\right) \\ & +\left[1-\psi\left(f,t,e\right)\right]\psi\left(m,t,e\right)\beta(1-\chi)V^w_{m,t+1}\left(\Gamma_{t+1}|\,\Gamma_t\right) \end{aligned} \tag{8}$$

[8] We have three instead of four states here because the divorced-state arises endogenously from the single agents with positive entries for the 'length-of-marriage'-states.

where $\mu(g,t,e,z)$ is the divorce probability and $\psi(g,t,e)$ the conditional probability of survival from age t to age $t+1$. $V^d_{g,t+1}$ is the continuation value of divorce (depending on gender g), and $V^w_{f,t+1}$ and $V^w_{m,t+1}$ are the continuation values of a widow and a widower, respectively.

The budget constraint of a married couple is given by:

$$\hat{c}_t + a^m_{t+1} = Ra^m_t + \mathbf{I}_{L_t=1} \cdot y_{f,t} + y_{m,t}$$

where a^s_t are asset holdings at age t for marital status s and $y_{g,t}$ is income at age t for gender $g = f, m$. [TBC: gender m and marital status m? Change!] Recall, that $\hat{c}_t$ is household consumption. Since we don't model children, it is given by $\hat{c}_t = 2c_t$ in a married household.

If a divorce occurs, assets are split evenly so that $a^d_{t+1} = \frac{1}{2}a^m_{t+1}$.

Single and Divorced Households We assume that non-married households always work, and normalize their utility cost of working to zero. The value functions of the single and divorced households $j = \{u, d\}$ only differ by the marriage and re-marriage probabilities, $\pi(g,t,e,z)$ and $\nu(g,t,e,z)$, respectively. Defining $\Pi = \{\pi, \nu\}$ we get:

$$\begin{aligned} V^j_{g,t}(\Gamma_t) &= \max_{c_t, a_{t+1}} \frac{c_t^{1-\theta}}{1-\theta} + \psi(g,t,e)\left(1 - \Pi(g,t,e,z)\right)\beta E\left[V^j_{g,t+1}(\Gamma_{t+1}|\,\Gamma_t)\right] \\ &\quad + \psi(g,t,e)\Pi(g,t,e)\,\beta E\left[V^m_{g,t+1}(\Gamma_{t+1}|\,\Gamma_t)\right] \end{aligned} \tag{9}$$

where V^m is the value function in case the agent (re-)marries.

The budget constraint of the household is given by:

$$c_t + a^j_{t+1} = Ra^j_t + y_{g,t} \tag{10}$$

Assets in $t+1$ depend on the marital shock. If the agent enters a marriage, assets from the spouse are added to one's own assets, so that $a^m_{t+1} = 2 \cdot a^j_{t+1}$.

Note, that although singles can be eligible for auxiliary benefits, there is no potential state of widowhood in equation (9). The reason for this is that we assume no divorce risk after 10 years of marriage. This implies that our definition of divorced individuals includes only those who are not eligible for auxiliary benefits.

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

$$V^w_{g,t}(\Gamma_t) = \max_{c_t, a_{t+1}} \frac{c_t^{1-\theta}}{1-\theta} + \psi(g,t,e)\beta V^w_{g,t+1}(\Gamma_{t+1}|\,\Gamma_t) \tag{11}$$

subject to the budget constraint (10).

3.6.3 Retirement Decision Phase

Between ages 62 and 70 the agent/couple can additionally decide about retirement. Social security claiming and the decision to stop working coincide in our model. In terms of notation, we define a dummy, $\mathbf{I}_{B_t}$, which assumes the value one if the household claims benefits and zero otherwise. For now, we assume that couples retire jointly.[TBC]

Married Households For a married couple the maximization problem is the same as in equation (8), with the addition that now the agent also maximizes with respect to the decision to retire, B_t.

We assume that couples retire jointly and that retirement is an absorbing state. The budget constraint of a potentially retired married couple is given by:

$$\begin{aligned} \hat{c}_t + a_{t+1}^m &= Ra_t^m + (1 - \mathbf{I}_{B_t=1}) \left(\mathbf{I}_{L_t=1} y_{f,t} + y_{m,t}\right) \\ &\quad + \mathbf{I}_{B_t=1}(b_{f,t} + b_{m,t}) \end{aligned}$$

where we suppressed all states in the notation for the benefits, b, other than age and gender. Recall, however, that benefits can also be spousal benefits, $b_t^{spous}(f, e, h, t^r, s)$. Again, note that $\hat{c}_t = 2 \cdot c_t$ in case of marriage. As above, assets in case of divorce are split, $a_{t+1}^d = 0.5 \cdot a_{t+1}^m$. Assets at widowhood do not change, $a_{t+1}^w = a_{t+1}^m$. In other words, the surviving spouse inherits all assets.

Singles and Divorced Households Singles and divorced households, $j = \{u, d\}$, work full-time until retirement. The maximization problem at retirement is the same as in equation (9), with the additional argument of B_t in the maximization problem. The budget constraint is given by:

$$c_t + a_{t+1}^j = Ra_t^j + (1 - \mathbf{I}_{B_t=1})\, y_{g,t} + \mathbf{I}_{B_t=1} b_{g,t}$$

Assets a_{t+1}^j change with marital transitions as described above.

Widows For widows during this phase the recursive problem is given as in equation (11) while agents also decide about their retirement entry B_t. The budget constraint is given as:

$$c_t + a_{t+1}^w = Ra_t^w + (1 - \mathbf{I}_{B_t=1})\, y_{g,t} + \mathbf{I}_{B_t=1} b_{g,t}$$

3.6.4 Retirement

From age 71 onwards 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:

$$\begin{aligned} V_{g,t}^{m}\left(\Gamma_t\right) &= \max_{c_t, a_{t+1}} \chi \frac{c_t^{1-\theta}}{1-\theta} + \left(1-\chi\right) \frac{c_t^{1-\theta}}{1-\theta} \\ &+\psi\left(f,t,e\right)\psi\left(m,t,e\right)\beta V_{g,t+1}^{m}\left(\Gamma_{t+1}|\,\Gamma_t\right) \\ &+\psi\left(f,t,e\right)\left[1-\psi\left(m,t,e\right)\right]\beta\chi V_{f,t+1}^{w}\left(\Gamma_{t+1}|\,\Gamma_t\right) \\ &+\left[1-\psi\left(f,t,e\right)\right]\psi\left(m,t,e\right)\beta(1-\chi) V_{m,t+1}^{w}\left(\Gamma_{t+1}|\,\Gamma_t\right) \end{aligned}$$

where $V_{f,t+1}^{w}$ and $V_{m,t+1}^{w}$ are the continuation values of a widow and a widower, respectively.

The budget constraint of a retired married couple is given by:

$$\hat{c}_t + a_{t+1}^{m} = R a_{t+1}^{m} + b_{f,t} + b_{m,t}$$

Again, social security benefits can be auxiliary benefits; see 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:

$$V_{g,t}^{j}\left(\Gamma_t\right) = \max_{c_t, a_{t+1}} \frac{c_t^{1-\theta}}{1-\alpha} + \psi\left(g,t,e\right)\beta V_{g,t+1}^{j}\left(\Gamma_{t+1}|\,\Gamma_t\right)$$

subject to the budget constraint

$$c_t + a_{t+1}^{j} = R a_t^{j} + b_{g,t}$$

3.7 Aggregation

We denote the cross-sectional measure of households with characteristics $(t, s, g, t^r, h, a, e, z, q, l, v)$ by $\Omega(t, s, g, t^r, h, a, e, z, q, l, v)$. The evolution of this measure is driven by transitory and persistent income shocks, marital status transition probabilities, survival prospects, as well as the labor-force participation end edogenous retirement decisions.[TBC]

4 Calibration and Estimation

In what follows we describe the parametrisation of the model. We focus on the cohort born 1950-54 and characterize their marital status transitions, asset holdings [TBC], income process and labor force participation. For 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).

The parameter of relative risk aversion is set based on values found in the literature. In what follows, we start by describing the first-stage parameters that we can estimate outside our model. These include the marital status transition probabilities, the survival rates and the income process. We then describe the second-stage parameterization, where we use our model to calibrate: (i) the utility-costs of working for married women to match female labor force participation, and (ii) the correlation between marital status and the persistent income component in order to match the divorce rate over income quintiles.

4.1 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.[9] The survey is well suited for determining marital patterns. 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.

The recursive nature of the SIPP marital history variable, however, does not have information on the individuals who are not (yet) married, which is needed in order to compute the marriage rates. Ideally, we would use panel data to compute transition probabilities from never married into marriage. 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.[10]

The marriage, divorce and remarriage probabilities are reported in Tables A.3, A.4 and A.5 in Appendix A.2, along with a more detailed description of how they were computed.

We also use the CPS for the initial distribution of marital status. Table 5 shows that at age 25 (i.e., right before the start of our model), roughly half of the individuals in our cohort are already married. The fraction is higher for less educated individuals than for their more educated counterparts. Also, 8% of low-educated males are already divorced

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

[10] We accessed the data with IPUMS, cf. King et al. (2010).

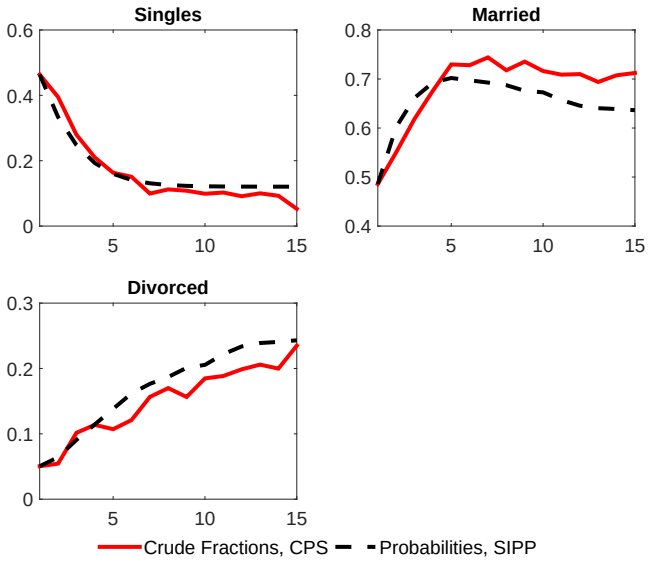
when they enter the model.

Table 5: Initial Marital Status

	Women		Men	
	College	High School	College	High School
Married	0.42	0.54	0.49	0.61
Single	0.56	0.41	0.46	0.31
Divorced	0.02	0.05	0.05	0.08

Source: CPS, 1976-2015. Initial marital status at age 25 of cohort born 1950-54.

Figure 2: Marital Status over Age, College



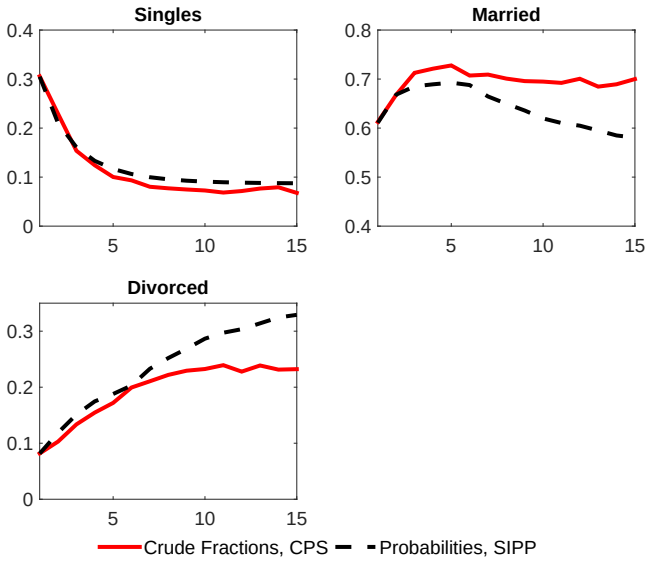
Source: CPS and SIPP. Note that age-bins are depicted at the abscissa where 1 is age 26-28 and 15 is age 62-64.

Figures 2 and 3 cross-validate the marital status probabilities used in the model by comparing the fractions of married, single and divorced over age implied by our probability profiles and initial marital states with those computed from the CPS.[11]

Note that the CPS statistics cannot to be interpreted as the 'true' profile. Although we report statistics for individuals born 1950-54 (and hence control for cohort effects), the CPS is a repeated cross-section. This implies that the CPS age-profiles employ data from

[11]Due to our choice of cohort the oldest individual is 64 in 2013 (which is the latest CPS wave that we use), hence we exclude widows from this cross check.

Figure 3: Marital Status over Age, High-School



Source: CPS and SIPP. Note that age-bins are depicted at the abscissa where 1 is age 26-28 and 15 is age 62-64.

different years and different samples of individuals. Nevertheless, the two time series are quite similar. The fraction of divorced (married) individuals implied by our probabilities is somewhat higher (lower) than that implied by the CPS data at older ages.

4.2 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.[12]

We estimate the folloging Logistic regression[13]

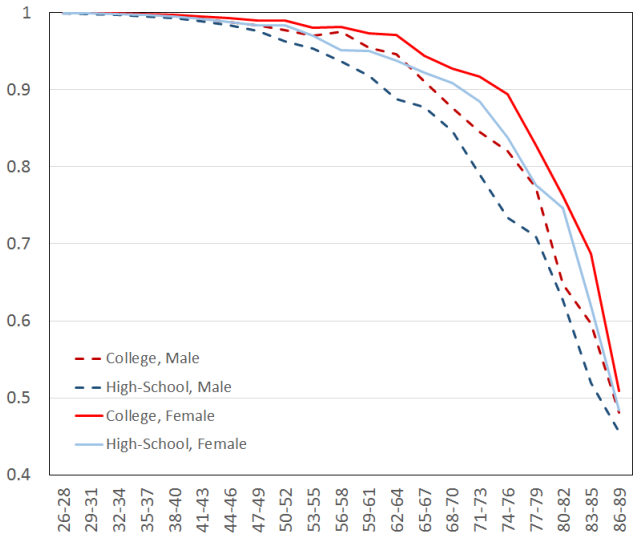
$$\begin{aligned}\text{Logit}(death) &= \alpha + \beta_1 edu + \beta_2 age + \beta_3 age \cdot edu \\ &\quad + \beta_4 age^2 + \beta_5 age^3 + \beta_6 sex + \beta_4 age \cdot sex\end{aligned}$$

[12]We cannot use the latest wave because of the recursive nature: the 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.

[13]We are using age-bins instead of the yearly age of the individuals as the explanatory variable. In addition, we have to take each estimate to the power of three in order to get a survival rate for one age bin (consisting of three years).

Predicted values are given in Figure 4. Note that we make out-of-sample predictions for ages 49 and below. It is clear from the Figure that there is a significant difference in survival rates over both education and gender, with high-school educated men having the lowest and college educated women the highest yearly survival rates. Figure 13 in Appendix A.4 confirms that our HRS estimates closely match the life-table data on survival.

Figure 4: Conditional Survival Probability



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

4.3 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 which is assumed to be the same for both genders.

Deterministic Wage Component

For men, we assume that labor income is given by

$$\ln y(m,t,e) = \gamma_{t,e} + \alpha_e \cdot t + \bar{\alpha}_e \cdot t^2 + w_{t,e} \tag{12}$$

The deterministic wage-equation thus depends on age-varying components, $\gamma_{t,e}$, and an age polynomial captured by the coefficients α_e and $\bar{\alpha}_e$. The regression is performed separately for the two education groups.

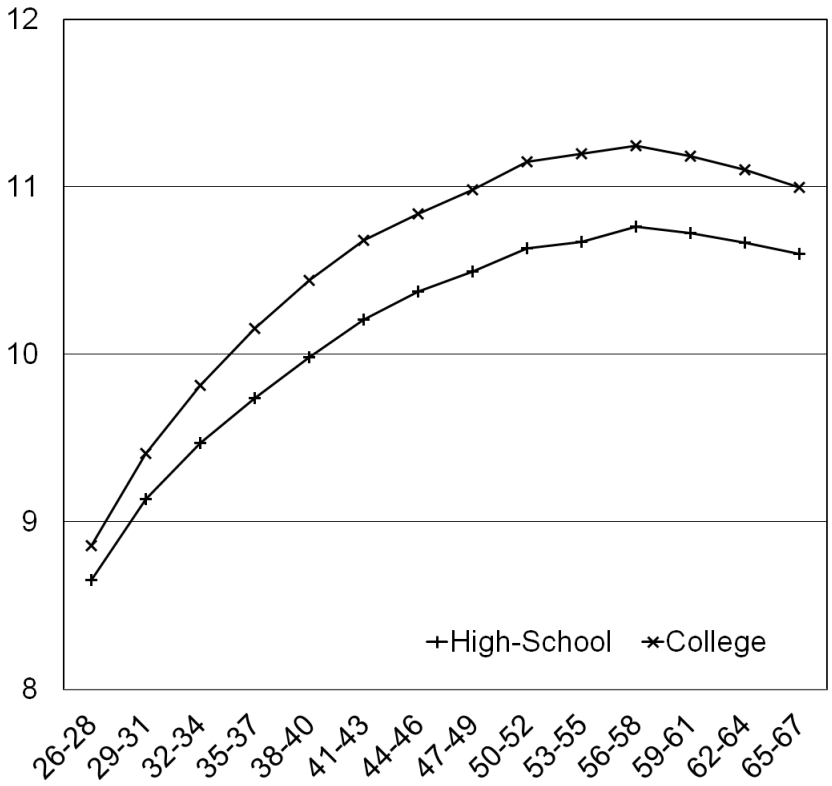
To estimate this wage process, we use data on male household heads aged 25-60 in the PSID for the years 1969-2013, so as to cover most of the life-cycle income process of

our 1950-54 cohort. Our variable is household head's wages and salaries, CPI-adjusted to 2000 prices. We focus on the SRC (Survey Research Center) sample. To eliminate outliers, we drop the top and botton 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 4,235 individuals in the 'low' education group and 2,152 in the 'high' education group. We use individual weights for the estimations.

To estimate the coefficients in equation (12) we regress log wages on age and age squared and a set of year dummies. We approximate the age-coefficient of our cohort by taking the average of the respective coefficients times the median age of each age-bin.[14]

The deterministic component of log-wages over age and education is depicted in Figure 5.

Figure 5: Deterministic Wage Component, Males



Source: Estimated deterministic component of log-wages using the age-specific intercepts and the coefficients for age and age squared from regression (12). The Figure depicts the profile for males who work every period.

Women's income depends on their work-experience, h_t, and their labor force participation in the previous period, L_{t-1}. The former captures human capital accumulation

[14]For example, to get the coefficient for the first age-bin at ages 26-28, $\gamma_{1,e}$, we use the coefficients of the 1976-1982 year-dummies which we multiply by 27.

in the form of learning, while the latter aims to account for human capital depreciation associated with non-employment spells. We assume the following specification:

$$\ln y(f,t,e) = (1-\tau_t) \cdot \left\{ \gamma_{t,e} + \alpha_e \cdot h_t + \bar{\alpha}_e \cdot h_t^2 - \delta(1 - \mathbf{I}_{L_{t-1}}) + w_{t,e} \right\} \tag{13}$$

We assume the same values for the coefficients $\gamma_{t,e}$, α_e, and $\bar{\alpha}_e$ that we estimated for men. 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. See Table A.6. We follow an approach taken by (Jones et al., 2015) who assume an age-specific wedge (τ_t) as a proxy for either direct wage discrimination or, e.g., a glass ceiling. For the depreciation rate of human capital δ we assume a value of 2% as estimated by XXX [TBC: depreciation not in the code yet, we need L_{t-1} as an additional state.].

Idiosyncratic Wage Component

The residual of regression (12) represents 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 the following time-invariant specification

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

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 parameters are estimated with a GMM estimator; details are described in Appendix A.3.

The estimated parameters are given in Table 6.

Table 6: Estimated Parameters for the Idiosyncratic Wage Component

	College	High School
Autocorrelation coefficient, ϱ	0.987	0.967
Variance of Persistence shock, σ_η^2	0.0176	0.0247
Variance of Transitory shock, σ_ϵ^2	0.1725	0.1529

Source: Parameters estimated using the GMM specified in (21).

Finally, we can discretize the persistent stochastic component with a 5-state Markov-process using Tauchen's method.

4.4 Social Security Benefits, AIME and PIA

The Primary Insurance Amount (PIA), $B(\bar{y}_t)$, is calculated using an approximation of Average Indexed Monthly Earnings (AIME), $\bar{y}_t$.

AIME is based on average life-time earnings from the highest 35 years of earnings (including possble zeros).[15] Translated into our setting (with 3 year age bins) we assume that AIME is determined by the following equation:

$$\bar{y}_{t+1} = \bar{y}_t + \cdot \frac{\mathbf{I}_{L_t} E[y_{g,t}]}{11} \tag{14}$$

where we slightly adjust the 35 years to 11*3=33 years because our model starts at age 26. For ages 59+ (=our model age 12) AIME only increases if earnings exceed average earnings, i.e.:

$$\bar{y}_{t+1} = \bar{y}_t + \cdot \max\left\{0; \frac{\mathbf{I}_{L_t} E[y_{g,t}] - \bar{y}_t}{11}\right\} \tag{15}$$

The Primary Insurance Amount (PIA) is a piece-wise linear function of AIME:

$$B(\bar{y}_t) = \begin{cases} \lambda_1 \bar{y}_t & \text{if } \bar{y}_t < \kappa_1 \\ \lambda_1 \kappa_1 + \lambda_2 (\bar{y}_t - \kappa_1) & \text{if } \kappa_2 \geq \bar{y}_t \geq \kappa_1 \\ \lambda_1 \kappa_1 + \lambda_2 (\kappa_2 - \kappa_1) + \lambda_3 (\bar{y}_t - \kappa_2) & \text{if } \bar{y}_t > \kappa_2 \end{cases} \tag{16}$$

λ_i are replacement rates which differ by average income such that $\lambda_1 > \lambda_2 > \lambda_3$ and κ_1 and κ_2 are bend points at which the replacement rates change. This ensures a redistributional element in favor of low earners.

The actual retirement benefit depends on the age of climing as defined here:[16]

$$b_t(g,e) = \begin{cases} (1 - 0.201) & \text{if } t^r = 62 \\ 1.0 & \text{if } t^r = 65 \\ 1.24 & \text{if } t^r = 68 \\ 1.48 & \text{if } t^r = 71 \end{cases} \tag{17}$$

where t^r is claiming age.

4.5 Exogenous Parameters

For now [TBC] we assume the following parameters exogenously (where some of them will be estimated in future versions):

[15] Note that this 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.

[16] See *www.ssa.gov/oact/quickcalc/earlylate.html* for details.

Table 7: Exogenous Parameters

Rel.Risk Aversion, θ	2.0
Pareto-Weight, χ	0.5
Discount rate (yearly), ϱ	0.02
Interest rate (yearly), r	0.04

Source: xxx.

4.6 Simulation procedure for the Second-Stage Parameters

The main parameters we need to calibrate within the model are the female utility-costs of working, $\Phi^v_{e,t}$, and the factor λ_z governing the strength of the correlation between marital transition probabilities and income.

Marital Probabilities and Income

To calibrate the correlation between marital probabilities and income, we assume that the probabilities of remaining never married, remaining divorced and of becoming divorced are given by:

$$1 - \pi(g,t,e,z) = \lambda_z \cdot (1 - \pi(g,t,e)) \quad (18)$$

$$1 - \nu(g,t,e,z) = \lambda_z \cdot (1 - \nu(g,t,e)) \quad (19)$$

$$\mu(g,t,e,z) = \lambda_z \cdot \mu(g,t,e) \quad (20)$$

For λ_z we assume a simple linear functional form over the permanent income states, i.e., $\lambda_z = (1/\mu_{\lambda_z}) \cdot (a - b \cdot z)$ ensuring that $\sum_z \lambda_z = 1$.

Labor Force Participation

The parameters governing the disutility of work are critical for matching female labor force participation over the life cycle. We allow the disutility parameters to differ across utility-types, education and age. We assume a linear spline in age with four kinks. We assume that the low disutility type's age-profile is a scaled down version of the high disutility type's profile. Altogether this procedure requires us to calibrate 14 disutility parameter values to match the labor force participation rates of high- and low-educated women over age (30 data moments): six parameter values over age (an initial value, four bend-points and an end value) and the scale parameter, per education type.

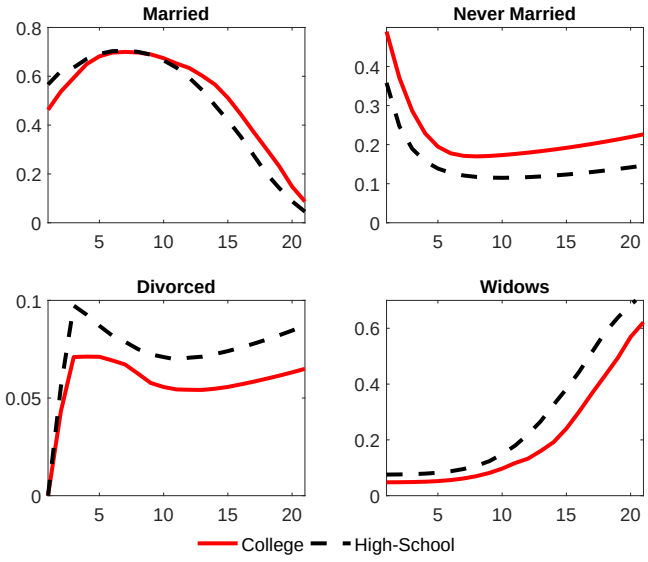
5 Calibrated Economy

5.1 Marital Transitions and Education

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. Let us first turn to marital status, as this is the main eligibility criterion for spousal benefits.

Figure 6 depicts the shares of married, divorced, widowed and never married individuals over age, for the two education categories separately. 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.

Figure 6: Marital Status over Age, Model



Notes: Age-bins are depicted at the abscissa where 1 is age 26-28 and 15 is age 62-64.

Comparing the two education types, we observe that although the low-educated have higher initial marriage rates, the fraction of married people is higher for college graduates from age 50 onward. Also, the fraction of divorced individuals and widows is higher for high-school graduates, since they face a higher risk of divorce and a lower survival probability. The fraction of never married, however, is higher for college graduates throughout the life-cycle. [TBC: include initial divorce rates]

5.2 Marital Transitions over Income

As described in Section 2, the differences in marriage and divorce rates are even more pronounced over income than over education. The loading factor λ_z is calibrated to

match the differences in the prevalence of marriage and divorce over income quintiles.[17]

Table 8: Marital Status over Income

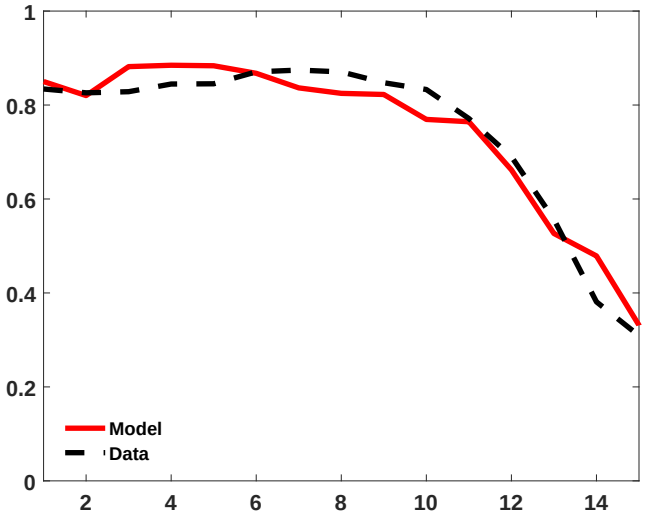
	Divorced		Never Married	
HH Inc. Quintile	Model	Data	Model	Data
Q1	0.22	0.25	0.09	0.14
Q2	0.18	0.18	0.07	0.12
Q3	0.14	0.16	0.06	0.09
Q4	0.10	0.14	0.05	0.07
Q5	0.08	0.10	0.04	0.04

Notes: Data taken from SIPP 2009. The numbers report fractions.

5.3 LFP and Utility Cost of Working

Married women's utility costs of working are calibrated to match their labor force participation. Our model matches the data quite well, see Figures 7 and 8. The calibrated parameter values for the disutility of working, $\Phi^v_{t,e}$, are depicted in Figure 14 in Appendix A.5.

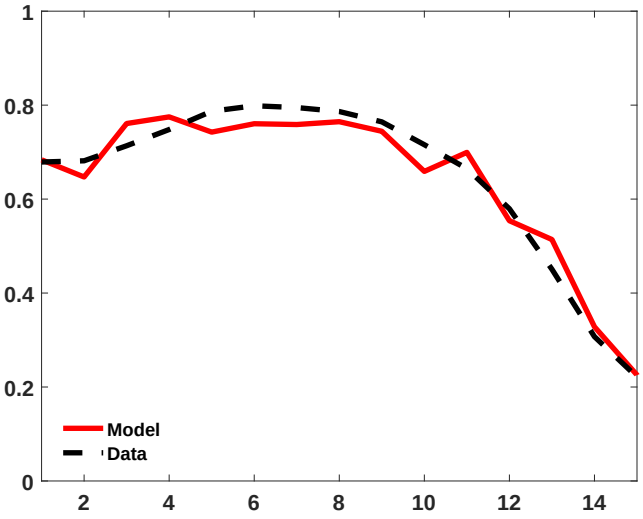
Figure 7: College Female Labor Force Participation, Model vs. Data



Notes: Age-bins are depicted at the abscissa where 1 is age 26-28 and 15 is age 62-64.

[17]We approximate income quintiles in our model with the five discretized permanent income states.

Figure 8: High-School Female Labor Force Participation, Model vs. Data



Notes: Age-bins are depicted at the abscissa where 1 is age 26-28 and 15 is age 62-64.

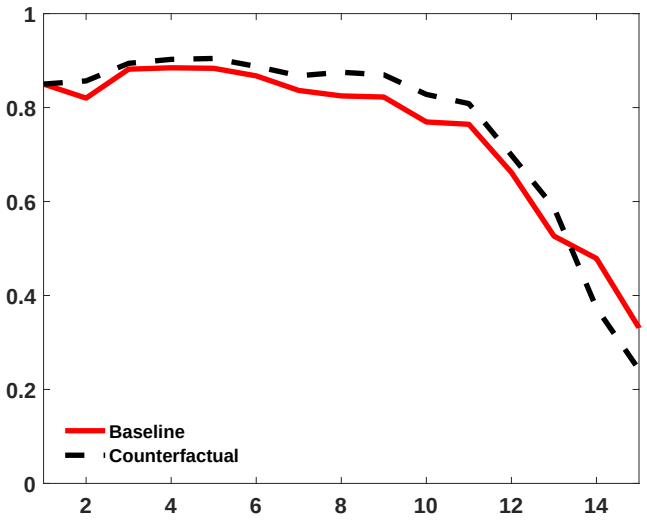
6 A Simple Counterfactual

Having established that our model does a good job of matching the salient features of household labor supply, we turn to the policy analysis. We start by considering the counterfactual experiment of abandoning auxiliary benefits altogether.

Figures 9 and 10 plot female labor force participation over the life cycle for this counterfactual and for our benchmark economy, for college and non-college educated women respectively. The resulting increase in female labor force participation is more pronounced for less educated women, than for their more educated counterparts. The endogeous retirement margin is important for accurately gauging the aggregate labor supply effects, as the high school educated women in particular reduce labor supply at older ages when they increase it earlier in the life cycle.

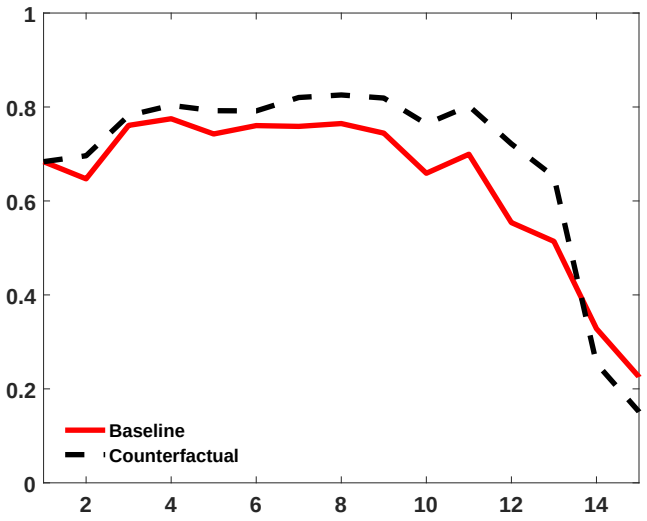
We are currently analyzing the distributional consequences and the labor supply effects (for men and women) of the current auxiliary benefit system.

Figure 9: College Female Labor Force Participation, Counterfactual vs. Baseline



Notes: Age-bins are depicted at the abscissa where 1 is age 26-28 and 15 is age 62-64.

Figure 10: High-School Female Labor Force Participation, Counterfactual vs. Baseline



Notes: Age-bins are depicted at the abscissa where 1 is age 26-28 and 15 is age 62-64.

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A Appendix

A.1 Marital Status over Income for both Education Groups

Table A.1: Marital Status over HH Income per Head, Low-Education

HH Inc. Quintile	Married	Divorced	Widowed	Never Married
Q1	0.48	0.27	0.08	0.13
Q2	0.60	0.21	0.06	0.11
Q3	0.71	0.16	0.04	0.07
Q4	0.76	0.14	0.02	0.06
Q5	0.83	0.10	0.02	0.03
Total	0.68	0.18	0.05	0.08

Source: SIPP 2009. Sample consists of cohort born 1950-54. Quintiles are computed with per-head equivalence-scaled total monthly household income, pooled over age bins.

Table A.2: Marital Status over HH Income per Head, High-Education

HH Inc. Quintile	Married	Divorced	Widowed	Never Married
Q1	0.60	0.21	0.02	0.16
Q2	0.65	0.17	0.02	0.13
Q3	0.75	0.14	0.01	0.08
Q4	0.79	0.13	0.02	0.05
Q5	0.83	0.08	0.02	0.06
Total	0.73	0.14	0.02	0.10

Source: SIPP 2009. Sample consists of cohort born 1950-54. Quintiles are computed with per-head equivalence-scaled total monthly household income, pooled over age bins.

A.2 Marital Transition Probabilities

In what follows we explain how the marriage probabilities shown in Table A.3 are determined. We calculate the fraction of never married households at a specific age for our cohort (e.g., for the 26 year olds we use the 1976 wave in order to have the cohort born in 1950). The marriage probability for our cohort born between 1950-54 is then approximated by the percentage change in the share of people never married between age-groups. We employ this approximation because the populations across different ages in our cohort are not the same, as the CPS is a repeated cross-section. Hence, computing the growth rate using absolute values often leads to negative values. Even with this approximation we encounter quite volatile values. Since we believe that marriage rates decline monotonically over age, we smooth the data using a logistic curve fit.[18]. The comparison of the real fractions with the fitted data is depicted in Figures 11 and 12.

Table A.3: Marriage Rates

	Women		Men	
Age	College	High School	College	High School
26-28	0.28	0.32	0.30	0.24
29-31	0.26	0.22	0.25	0.23
32-34	0.22	0.16	0.21	0.20
35-37	0.17	0.12	0.18	0.15
38-40	0.12	0.09	0.15	0.09
41-43	0.07	0.07	0.12	0.05
44-46	0.04	0.05	0.10	0.02
47-49	0.02	0.03	0.09	0.01

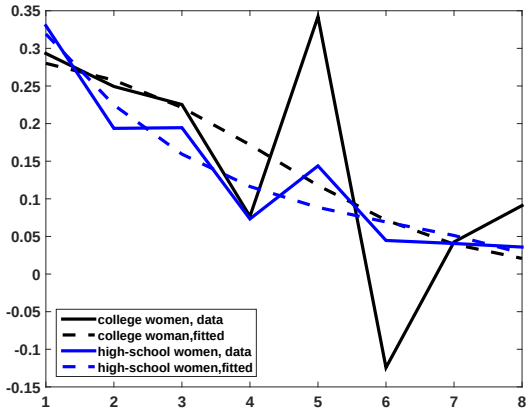
Source: CPS, 1976-2015. The marriage rate is approximated as the growth rate of the fraction of people reporting to be never married between age-bins. The values are smoothed using a Logistic model.

To compute the divorce rates depicted in Table A.4 we use the latest SIPP wave from 2009. Since the maximum age for our cohort in 2009 is 59 (for people born in 1950), we expand our sample to individuals born 1940-1954, when computing probabilities for ages above 58. The divorce probability for a certain 3-year age bin is calculated as the fraction of people who report being married at the beginning of the age-bin and who undergo at least one divorce during the subsequent three years.

The remarriage rates shown in Table A.5 are calculated analogously to the divorce

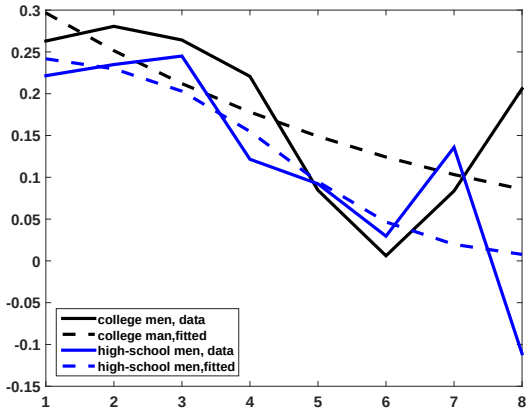
[18]We did not use a higher order polynomial to fit the data, because the fitted data exhibited negative probabilities at higher ages. Hence, we employed the logistic model that – albeit restricting a certain distribution – is bounded by zero and one.

Figure 11: Logistic Fitting of the Marriage Probabilities, Women



Source: CPS and own calculations. Note that age-bins are depicted at the abscissa where 1 is age 26-28 and 8 is age 47-49

Figure 12: Logistic Fitting of the Marriage Probabilities, Men



Source: CPS and own calculations

Table A.4: Divorce Rates

	Women		Men	
Age	College	High School	College	High School
26-28	0.07	0.10	0.05	0.09
29-31	0.07	0.09	0.06	0.07
32-34	0.06	0.07	0.05	0.07
35-37	0.05	0.05	0.06	0.07
38-40	0.06	0.05	0.03	0.06
41-43	0.04	0.07	0.04	0.05
44-46	0.03	0.06	0.04	0.06
47-49	0.04	0.05	0.04	0.05
50-52	0.02	0.05	0.02	0.04
53-55	0.03	0.04	0.03	0.03
56-58	0.02	0.01	0.00	0.01
59-61	0.015	0.024	0.010	0.014
62-64	0.006	0.020	0.008	0.009
65-67	0.004	0.009	0.006	0.007
68-70	0.001	0.002	0.001	0.000

Source: SIPP 2009. Fraction reporting to be divorced at specific age using recursive question.

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.

Table A.5: Remarriage Rates

	Women		Men	
Age	College	High School	College	High School
26-28	0.393	0.283	0.244	0.327
29-31	0.250	0.210	0.329	0.238
32-34	0.157	0.180	0.260	0.199
35-37	0.099	0.129	0.181	0.160
38-40	0.120	0.110	0.143	0.127
41-43	0.089	0.090	0.150	0.091
44-46	0.062	0.083	0.062	0.112
47-49	0.065	0.065	0.100	0.106
50-52	0.058	0.045	0.078	0.060
53-55	0.023	0.040	0.050	0.043
56-58	0.006	0.007	0.022	0.021
59-61	0.019	0.014	0.033	0.021
62-64	0.009	0.004	0.017	0.009
65-67	0.000	0.002	0.010	0.005
68-70	0.000	0.000	0.003	0.000

Source: SIPP 2009. Fraction reporting remarriage across age-bins, conditional on having a divorce in the past.

A.3 Estimation of the Income Process

Rewrite the process for $z_{i,t}$ as $MA(T)$, i.e. over all ages, $0, ..., T$

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

The moments are then given by

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

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

The Variance of w is given by

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

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

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

The summarized theoretical autocovariances are hence:

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

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

Using the saved residuals $w_{i,t,e}$ from regression (12) we determine the empirical autocovariances which we calculate over years, j using the fact that we can decompose the yearly variance, $Var\left(z_{i,j}\right)$ and covariances, $Cov\left(w_{i,j}, w_{i,j+n}\right)$ into their age-specific forms as:

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

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

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

To determine the parameter vector θ by GMM estimation:

$$\hat{\theta} = \arg\min_{\theta} \left[(C(\theta) - C(X))' \times W \times (C(\theta) - C(X)) \right], \tag{21}$$

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

Table A.6: Gender Gap and College Premium

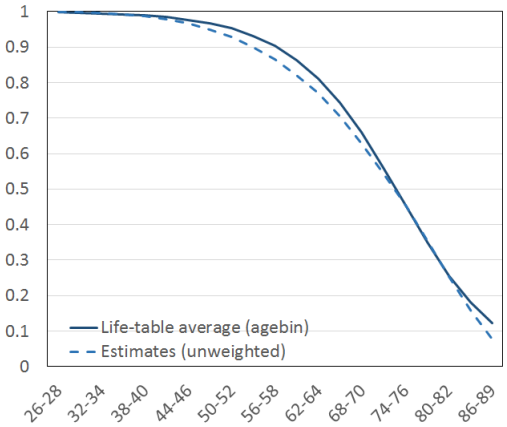
Age	Gender Wage Gap	College Premium
26-28	0.77	1.19
29-31	0.75	1.29
32-34	0.76	1.41
35-37	0.72	1.34
38-40	0.74	1.47
41-43	0.72	1.56
44-46	0.64	1.60
47-49	0.60	1.61
50-52	0.77	1.56
53-55	0.71	1.51
56-58	0.74	1.71
59-61	0.71	1.69
62-64	0.69	1.70
65-67	0.65	1.60
68-70	0.50	2.16

Source: CPS 1976-2015.

[TBC: Center the table header!]

A.4 Survival Estimations vs. Life-Table Data

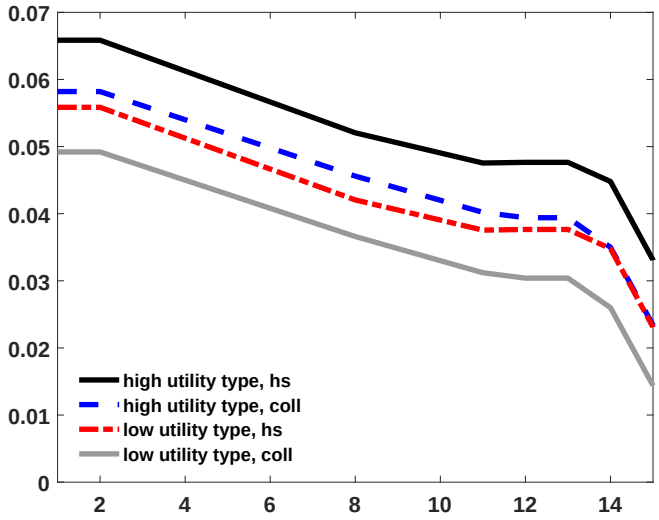
Figure 13: Unconditionsl Survival Probabilities, Estimates vs. Data



Notes: Predicted survival rates using HRS data from 1992-2010. Life-table data is taken from the Human Mortality Database (HMD).

A.5 Calibrated Utility-costs from Working

Figure 14: Calibrated Parameters



Notes: Age-bins are depicted at the abscissa where 1 is age 26-28 and 15 is age 62-64. Parameters are shown for high- and low utility types and for high-school (hs) and College (coll) graduates.