Gender, Marriage, and Portfolio Choice: Role of Income Risk

Pubali Chakraborty [*] Anand Chopra [†]

Abstract

This paper examines the source of gender and marital status differences in portfolio choices across U.S. households. Using the Panel Study of Income Dynamics (PSID) and the Survey of Consumer Finances (SCF), we find evidence that single female-headed households invest the least in risky assets, followed by single male-headed households. Further, married households invest the most in risky assets. Towards explaining these differences in portfolio allocations, we further document that women earn lower income and face higher individual income risk relative to men. To quantitatively investigate the importance of these gender differences in income profiles, we develop a two-asset incomplete market life-cycle model with heterogeneous households. Using the model, we show that the gender wage gap is important in explaining portfolio choice differences during the initial years of working life; however, higher income risk leads to lower risk-taking behavior by female-headed households in later working years. We also show that dual-earner households exhibit higher investment in risky assets compared to single-earning couples, consistent with our empirical findings, indicating a role for spousal insurance.

Keywords: Gender, Marriage, Risky Investment, Income Risk, Spousal Insurance

JEL Codes: D15, E21, G11, J16, J31

We thank Aaradhya Gupta and Roopal Jain for excellent research assistance.

[*] Department of Economics, Bates College, Email: pchakraborty@bates.edu

[†] Economics group, Management School, University of Liverpool, Email: achopra@liverpool.ac.uk

1 Introduction

Portfolio choices affect wealth accumulation. A conservative portfolio implies lower wealth holding given an equity premium. Single households[1] invest a lower fraction of their wealth in risky assets, as compared to married households in the US. Further, among single households, women undertake less risky investments relative to men. This same ranking holds for total wealth as well, with large differences across the three groups[2]. The distribution of wealth in an economy has implications for business cycle dynamics and economic policies (Benhabib, Bisin, & Zhu, 2011; Kaplan, Moll, & Violante, 2018; Krueger, Mitman, & Perri, 2017). This paper quantitatively investigates the reasons behind the asymmetry in portfolio holdings across gender and marital status through the lens of a lifecycle model. We analyze the role of differential income process across gender in explaining the differences in portfolio choices between single men and women. Further, we assess the role of spousal insurance on the risk-taking behavior of couples relative to singles.

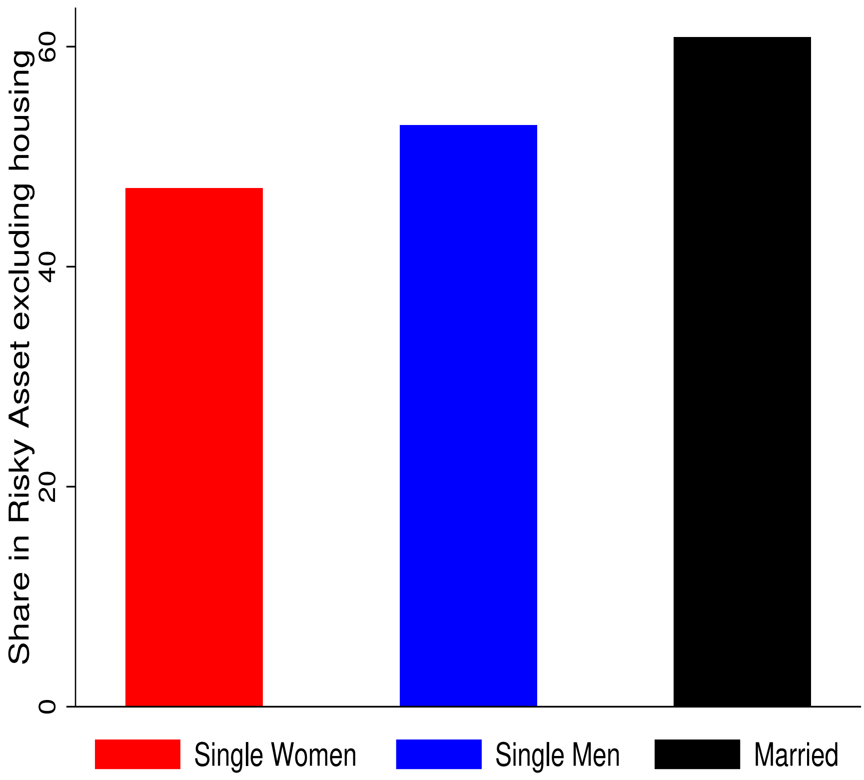


Figure 1: Share of risky asset holdings by couples, single men and single women

[1] "Single" includes household heads who have never married or are currently divorced, separated, or widowed.

[2] The median net worth of couples, single men and single women was $120,900, $23,384 and $12,532 respectively in 2019.

Figure 1 shows the unconditional average share of risky asset holdings of married, single men and single women using the Survey of Consumer Finances (SCF)[3]. Couples hold 61% of their total wealth, excluding housing in risky assets, whereas single men and single women hold 53% and 47%, respectively. In this paper, we first show that the ranking of portfolio holdings across the above demographic groups is robust to controlling for household characteristics and self-reported measures of individual risk aversion and financial knowledge. We verify our findings using the Panel Study of Income Dynamics (PSID), which is a panel dataset, unlike the SCF. The panel dimension allows us to account for household unobservable characteristics through lagged risky asset share.

We focus on two novel explanations motivated by data to rationalize the heterogeneity in portfolio choices: (i) women experience a riskier income process and a lower income level ("gender pay gap") than men, and (ii) the presence of a second earner in a household increases risky asset holdings. Using the PSID, we document that the variance of permanent income shocks for women is significantly higher than for men, whereas the variance of temporary income shocks is not significantly different by gender. We also find that men earn 43% more than women on average over the lifecycle. The differential income profile between men and women can be a candidate explanation for the higher risky asset share by single men compared to single women. Moreover, we highlight in the data that within married households, dual-earner households hold a higher risky asset share than single-earner households. Thus, the presence of a second earner might explain why couples invest more in risky assets than singles.

To quantitatively assess the role of income risk and spousal insurance, we develop an incomplete market life-cycle model with heterogeneous agents and allow for two asset choices (safe and risky). Households have to pay a fixed cost to adjust their risky asset holding. Households are risk averse, with the degree of risk aversion and the discount factor the same across the three groups. Households choose their consumption and investment in risky and safe assets over their lifetime. For married households, we use a unitary framework, where agents make joint decisions. Both individuals in married household work. In the model, single men and women differ with respect to income level, income risk, and initial wealth levels. Couples and singles differ with respect to income level, income risk, initial wealth levels, and the number of individuals who live and work in a household.

[3]Risky assets include stocks, business net worth, the net worth of real estate excluding primary residence and Individual Retirement Accounts (IRAs). Safe assets include checking or savings accounts, money market funds, certificates of deposit, governmental savings bonds, treasury bills, and cash value in a life insurance policy.

The model is parameterized using Simulated Methods of Moments to match the model average wealth-to-income ratio and risky asset share across all households as in the data. The model can exactly match the untargeted risky asset share for single men, single women, and couples. The differences in risky asset share exist throughout the working life of the households. The differences are less initially across the groups but become larger as households age until the end of their working life. We perform three counterfactual exercises to show the role of the different channels in explaining portfolio choices over the lifecycle.

First, the gender pay gap matters early in the lifecycle of households. A lower income implies fewer resources at hand to enter the risky asset market. When we remove differences in income levels, single women have a similar share of risky assets compared to single men for the first few years of the lifecycle, unlike the baseline model. Second, income risk asymmetry matters after the initial few years of working life. A higher income risk amplifies the precautionary saving motive of an individual leading to portfolio reallocation towards safe assets. In the counterfactual exercise where the income risk of men and women is equal, single women invest much more in risky assets than single men during the middle years of the lifecycle. In the baseline simulations, the risky asset share gap between single men and women is 4 percentage points (pp) averaged over the entire working life. In the counterfactual scenario with equal income risk, single women invest more than single men by 2.6pp over the working life. Moreover, single women accumulate wealth more slowly but consume more over the lifecycle in the counterfactual model compared to the baseline model. Finally, to understand the importance of the second earner, we perform a counterfactual exercise of a married household with a single earner. The risky asset share of a single-earner married household is 9pp lower than a dual-earner married household. Thus, spousal insurance through the presence of an additional earner increases the risk appetite of married households.

As family structures keep rapidly evolving in the US (Doepke & Tertilt, 2016), household differences in investment behavior by gender and marital status can have significant aggregate consequences through its impact on wealth holdings. Wealth is an important indicator of household well-being. Further, household wealth directly impacts access to education (Bartscher, Kuhn, & Schularick, 2020), and so, differences in wealth across households can exacerbate earnings and wealth inequality. Thus, understanding the determinants of difference in risky portfolio holdings along the gender and marital status dimension is a first-order policy question.

This paper is related to the literature studying differences in portfolio choices by gender

(Almenberg & Dreber, 2015; Huang & Kisgen, 2013; Hardies, Breesch, & Branson, 2013; Neelakantan, 2010; Sunden & Surette, 1998). These papers mostly use empirical methods to explore the role of differences in individual characteristics like risk aversion, confidence, or financial literacy. Bacher (2024) shows that the gender pay gap can help explain some of the asymmetry in the risky asset share holdings using a structural model. Income risk is a key determinant of portfolio choice behavior (Angerer & Lam, 2009; Catherine, Sodini, & Zhang, 2020; Chang, Hong, Karabarbounis, Wang, & Zhang, 2022; Lynch & Tan, 2011; Merton, 1969). This paper shows the importance of income risk asymmetry by gender through a quantitative model to explain the gap in risky asset shareholdings. The model shows income risk is a key channel since if income risk differences by gender were absent, single women would invest more in risky assets than single men.

Schmidt and Sevak (2006) and Borella, De Nardi, and Yang (2018) document significant differences between the wealth holdings of couples and singles. Bertocchi, Brunetti, and Torricelli (2011) shows using Italian data that male-headed married households participate more in risky assets than male-headed single households, and similarly, female-headed married households invest more in stocks than female-headed single households. Addoum, Kung, and Gonzalo (2016), Gu, Peng, and Zhang (2019) and Ke (2021) stress the role of intrahousehold bargaining due to differences in risk aversion, financial literacy, or education to explain the equity shares across the marital status. Spousal insurance has been shown to play an important role in household consumption smoothing (Bardóczy, 2020; Blundell, Pistaferri, & Saporta-Eksten, 2016; Halla, Schmieder, & Weber, 2020; Lundberg, 1985). This paper shows quantitatively the importance of a second earner in significantly affecting the risky asset share holdings within married households.

The rest of the paper is as follows: Section 2 discusses the empirical evidence, which guides the development of the theoretical framework in Section 3. Section 4 provides details of a quantitative analysis of our framework, Section 5 discusses the results from the quantitative exercises, and Section 6 concludes.

2 Empirical Evidence

2.1 Data and Sample Selection

The Panel Study of Income Dynamics is a longitudinal household survey that began in 1968. PSID collects data on household wealth and consumption, and individual level information on income, hours worked and other demographic characteristics of the household members. It started as an annual survey but became a bi-annual survey from 1999. From 1999 it started collecting much more detailed information on the various asset and consumption categories than before. But, the PSID underestimates wealth compared to the Survey of Consumer Finances (SCF) which is considered the gold standard for wealth measurement in the US (Pfeffer, Schoeni, Kennickell, & Andreski, 2016). Thus, to complement our empirical analysis we also employ SCF which is conducted by the Federal Reserve Board. The SCF is a cross-sectional household survey that collects very detailed information on the household balance sheet along with household demographic characteristics. This allows us to construct better measures of the fraction of wealth in risky and non-risky assets. The SCF survey design and implementation have been consistent starting from 1989 survey until the latest 2019 survey. The main drawback of the SCF is that we cannot follow households over time and thus, cannot control for household-specific characteristics through either fixed effects or lagged variables.

We define single households as the scenario where the reference individual of the household is either divorced or separated or never married.[4] We define the risky asset share as the ratio of risky assets to total wealth excluding housing. Risky assets include: stocks in publicly held corporations, mutual funds and investment trusts including private annuities or Individual Retirement Accounts (IRAs), business net worth and net worth of real estate excluding primary residence. Non-risky assets include checking or savings accounts, money market funds, certificates of deposit, governmental savings bonds, treasury bills and cash value in a life insurance policy. We show results using alternate definitions where we include housing or consider stocks as the sole risky asset and show that the results are similar to our baseline definition.

The sample selection performed on each of the datasets is fairly standard. We focus on households where the age of the interview respondent is between 25-64. We also drop those households where household income is less than \$100. This is done to retain individuals that have strong attachment to the labour force. As a robustness check, we include households where

[4]In the PSID, when the household structure changes because of members moving in or out then we treat such changes as a new household entering the sample.

the reference individual's age is between 65-70. We drop households with missing information on age, race, education and marital status of the reference individual. We control for outliers in total wealth and various wealth categories like stocks, bonds, IRA, etc. Additionally, we drop the Survey of Economic Opportunity (SEO), Latino and immigrant samples in the PSID. We focus on the years 1999-2019 in the PSID and 1995-2019 in the SCF. This leaves us with 35,943 and 27,483 households in the PSID and SCF respectively. We convert all nominal variables into real terms with 2006 as the base year.

2.2 Empirical Specification and Results

To estimate the gap in risky asset shares across the marital status and gender dimension after controlling for household characteristics, we consider the following OLS specification:

$$RS_{it} = \alpha + \beta_M M_{it} + \beta_{SM} SM_{it} + \beta_X X_{it} + u_{it} \tag{1}$$

where RS_{it} denotes risky asset share of household i at time t, M_{it} is a dummy variable with value 1 for married household and 0 otherwise, SM_{it} is a dummy variable with value 1 for single male household and 0 otherwise and single female household (SF) is the omitted category in the model. β_M and β_{SM} are the coefficients of interest and the point estimate married household dummy and single male-headed household dummy respectively. X_{it} contains controls like household income, household wealth, family size, number of children, state of residence, dummy for presence of children, five-year age bins, education, race and employment status of reference individual and year fixed effects. We restrict the ratio of risky asset share to be less than equal to 1.[5]

Table 1 shows the estimated coefficients of interest estimated using the PSID data. The unconditional difference in risky asset shares between single men and married households relative to single women is 2.7 percentage point (pp) and 17.5pp respectively. After controlling for household characteristics, the difference in risky asset shares are 3.3pp and 12.4pp for single men and married households respectively. The benefit of the PSID is that we can use the panel structure to account for household-specific unobservable characteristics using lagged values.[6] The difference in risky asset shares remains substantial at 1.8pp and 7.3pp for single men and

[5] Instead of dropping those observations with negative and greater than 1 risky asset shares, we consider a censored Tobit regression in Appendix Table 9 and show results are robust to this alternative specification.

[6] We cannot use individual fixed effects because of the sample design of PSID. PSID tracks only males across marital transitions and not females.

married households respectively relative to single women.

Table 1: Regressions for risky asset share in PSID

	(1)	(2)	(3)
Single Men	0.027***	0.027***	0.016**
	(0.007)	(0.006)	(0.008)
Married	0.175***	0.098***	0.059***
	(0.006)	(0.007)	(0.008)
Lagged Risky Share			0.462***
			(0.006)
Constant	0.259***	0.218***	0.189***
	(0.005)	(0.025)	(0.028)
Observations	35988	35943	24637
Household Controls	No	Yes	Yes
Single Men=Married	0	0	0

Standard errors in parentheses
Includes age-bins, income, wealth, family size, no. kids, self-employment
Includes year, state, race, education, employment and child present dummies
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Regressions for risky asset share in SCF

	(1)	(2)	(3)
Single Men	0.057***	0.063***	0.031***
	(0.010)	(0.010)	(0.010)
Married	0.137***	0.132***	0.104***
	(0.008)	(0.007)	(0.007)
Above Average Risk			0.019
			(0.014)
Average Risk			-0.060***
			(0.013)
No Risk			-0.222***
			(0.014)
Constant	0.471***	0.131***	0.292***
	(0.007)	(0.017)	(0.021)
Observations	27489	27489	27489
Household Controls	No	Yes	Yes
Single Men=Married	0	0	0

Standard errors in parentheses
Includes age-bins, income, wealth, family size, no. kids, self-employment
Includes year, race, education, child present and employment status dummies
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 shows the gap in risky asset shares in the SCF across the demographic groups. The unconditional difference in risky asset shares between single men and married households relative to single women is 5.7 percentage point (pp) and 13.7pp respectively. This difference remains almost the same after accounting for household characteristics. We use self-reported measures of risky behaviour in the SCF to account for the role of individual traits in portfolio choices. We include all the four self-reported risk taking behaviour categories: (1) take substantial financial risks expecting to earn substantial returns, (2) undertake above average financial risks expecting to earn above average returns, (3) take average financial risks expecting to earn average returns, and (4) Not willing to take any financial risks. The negative coefficients of "Average Risk" and "No Risk" show that individuals with lower self-reported risk taking behaviour invest less in risky assets compared to high risk lovers. More importantly, the gap in risky asset share between single men and married households compared to single women is 3.1pp and 10.4pp respectively. These differences are economically and statistically substantial as they amount to 6% and 21% higher risky asset share for single men and married households relative to single women respectively.

We further show in Appendix table 10 that the gap in risky asset shares across gender and marital status are prominent in early and middle working age. The difference between singles and married continues to be prominent near retirement age as well. The baseline definition of single households includes both never married and currently not married individuals. Appendix table 11 displays that never married single women hold less risky asset shares than never married men and never married men hold less in risky assets than married households. Appendix table 12 highlights that asymmetries in risky asset shares across demographic groups exist in the decision to participate in the risky asset market too. Single women participate least in the risky market and married households are more likely to invest in risky assets than single men. This is consistent with Bertocchi et al. (2011) who find for Italy that married households are more likely to invest in stocks than singles conditional on the same gender of the household head. Thus, the gap in risky asset holdings exist across the lifecycle and present in the extensive margin of portfolio choices.

2.2.1 Robustness Checks

We discuss that the ranking of demographic groups in the main empirical results are robust to alternative definitions of risky asset shares and present in European countries as well.

We consider three alternate definitions of risky asset share. In the first definition we include housing in risky asset and total wealth. We consider an alternate definition where we include stocks in IRA's as non-risky assets rather than risky assets as the returns from such investment might accrue much later in the lifecycle. Lastly, we consider only stocks as risky assets consistent with Angerer and Lam (2009) and Bacher (2024). Appendix tables 13 and 14 show the differences across the three groups in the PSID and SCF data respectively. Both tables show that across all the alternate definitions single women hold the least risky asset share followed by single men. The least difference between single men and single women in assets across the various measures is when housing is included as a risky asset which might be due to fertility or marital transitions (Chang et al., 2022) that we do not consider in this paper.

We show that the disparity in risky asset holdings across gender and marital status holds in European countries too. We use the Household Finance and Consumption Survey which collects information on household assets and income in a harmonized manner. It is a cross-sectional survey of with data available in three waves (2010, 2014 and 2017). Appendix Table 15 showing the number of observations in each wave for the 20 countries. Appendix table 16 shows that the risky asset share of single men and married households is 4pp and 5pp respectively greater than single women. The estimated gap in European countries is very similar for single men and women as estimated for US households but a bit smaller for married households relative to single women. The key message is that the gender and marriage portfolio gap is prevalent in US and Europe.

2.3 Role of Multiple Earners in Portfolio Allocations

One explanation for married households holding more risky assets than singles can be because the presence of dual earners in a married household provides insurance against shocks and increases the risk appetite of married households. To provide some suggestive evidence along this direction, we compare the portfolios of married households where both spouses are working versus one working. We construct two measures to determine the working status of an individual over the year: (1) annual hours worked > 480 and (2) individual labour income $> \$5,000$.[7]

Table 3 shows that risky asset share of dual working spouse is higher by at least 1pp compared to where both members are not working. The coefficient using the hours measure is 1.3pp whereas with the income definition is 1.5pp and both are statistically different from zero. We

[7] We do not use employment status as the question is about current status whereas asset and income information is of the past year.

show that these results are robust to using weaker definitions of labour market attachment. Appendix table 17 shows that we obtain similar results using a 20 hours or \$100 income cutoff. This is consistent with Inkmann, Michaelides, and Zhang (2021) who find using the SCF that dual income married households are more likely to participate in the stock market than single income married households. Thus, within-married household variation in working status might help explain heterogeneity in portfolio allocations between singles and married too.

Table 3: Regression for risky asset share by married working types

	Hours	Income
Both working	0.013**	0.015**
	(0.006)	(0.006)
Constant	0.193***	0.193***
	(0.034)	(0.034)
Observations	22686	22686

Standard errors in parentheses
Includes age-bins, income, wealth, family size, no. kids, self-employment
Includes year, state, child present dummies and race and education dummies for both husband and wife
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3 Model

3.1 Overview

In this paper, we use an incomplete markets life-cycle model with heterogeneous agents to study portfolio choices. Time is discrete. The economy is populated with men and women who work for the first J periods of their life, retire for another J_R periods, and then die. There are three types of households: (a) single female-headed, (b) single male-headed, and (c) married, which comprise one male and one female. We assume that there are no marriage or divorce shocks in this environment.

Agents derive utility only from consumption, c, and are assumed to exhibit Epstein-Zin preferences. Each period, households decide on their consumption and savings allocation, $a' \geq 0$. Further, households have the option of saving in two types of assets: one which yields a risk-free return, R_f, or a risky asset. With probability $(1 - p_{\text{tail}})$, each individual draws a realization of $R \sim N(\mu_R, \sigma_R)$, and experience a stock market crash with probability p_{tail} following Fagereng, Gottlieb, and Guiso (2017). Moreover, adjustment of the risky asset requires the household to incur a fixed cost, ϕ. In their last period of life, households leave bequests through which they derive utility. Their total wealth each period is denoted as ψ, and the law of motion is given by

$$\psi' = (R' - 1)s' + R_f f' \tag{2}$$

where s' and f' denote the amount invested in the risky and safe asset, respectively. Further, housing, h, is modeled as an age-dependent flow of expenditure.

3.2 Single Households

For single households, individual earnings, y, for each working period ($j \leq J$), comprise three components: (a) a deterministic age (or experience) component where α_1, α_2, and α_3 are the associated coefficients to be estimated later, (b) their permanent income, z, and (c) a transitory shock, ε, and is denoted by

$$y_{g,j} = \max\{\exp(\alpha_{1,g} + \alpha_{2,g} j + \alpha_{3,g} j^2 + z_{g,j} + \varepsilon_{g,j}), \underline{y}\} \tag{3}$$

where $\varepsilon \sim F_{g,j}(\varepsilon)$, which is both gender, $g \in \{m, f\}$, and age specific. $\underline{y}$ denotes some minimum level of income and can be perceived as benefits earned by unemployed individuals. The permanent income process is given by

$$z' = z + \eta' \tag{4}$$

where η represents shock to the permanent income process and $\eta' \sim G_{g,j}(\eta')$. The transitory and permanent income shocks are uncorrelated with each other and over time.[8] Individual earnings are subject to a progressive tax system, where τ measures the degree of progressivity in the economy. Their earnings net of taxes is given by $y^{1-\tau}$.

The optimization problem for a single working household at age j ($j < J$) of gender $g \in \{m, f\}$ is given by

$$V_g(j, z, \varepsilon, s, \psi) = \max_{c, s', f'} \left\{ c^\gamma + \beta \mathbb{E}_{z', \varepsilon', R'} \left[V_g \left(j+1, z', \varepsilon', s', \psi' \right)^\alpha \right]^{\frac{\gamma}{\alpha}} \right\}^{\frac{1}{\gamma}} \tag{5}$$

subject to

[8] This is a popular method to model the income process as it matches the lifecycle income profile quite well (Meghir & Pistaferri, 2004).

$$c + d + f' \leq y_{g,j}(z,\varepsilon)^{1-\tau}(1 - h(j)) + \psi - \mathbb{1}_{s \neq s'}\phi \tag{6}$$

$$\psi' = (R' - 1)s' + R_f f' \tag{7}$$

$$s' = s + d; \quad c, s', f' \geq 0; \tag{8}$$

where the coefficient of relative risk aversion is given by $1-\alpha$, and the elasticity of intertemporal substitution is given by $\frac{1}{1-\gamma}$; β is the discount factor, and $y_{g,j}$ is given by equation (3), as described above. d captures the withdrawal from or deposit into risky assets. Individuals pay a fixed cost ϕ if they choose to change their risky asset holdings. Otherwise, the stock of risky assets remains the same over time, but individuals enjoy the interest income every period.

Retired households, $(J < j \leq J+J_R)$, receive pension earnings, $b(z_J)$, which are a function of their permanent income level in the last working period, which is subject to the same progressive taxation system that was described above. We assume that they do not receive any transitory or permanent shocks to their income and derive utility from leaving bequests after they die (). Their optimization problem is described below

$$\begin{aligned} V_g(j, z_J, 0, s, \psi) = \max_{c,s',f'} \{ c^{\gamma} & + \beta \mathbb{1}_{j<J+J_R} \mathbb{E}_{R'} \left[V_g\left(j+1, z_J, 0, s', \psi'\right)^{\alpha} \right]^{\frac{\gamma}{\alpha}} \\ & + \beta \mathbb{1}_{j=J+J_R} \mathbb{E}_{R'} \left[B(\psi' + s')^{\alpha} \right]^{\frac{\gamma}{\alpha}} \Big\}^{\frac{1}{\gamma}} \end{aligned} \tag{9}$$

subject to

$$c + d + f' \leq b(z_J)^{1-\tau}(1 - h(j)) + \psi - \mathbb{1}_{s \neq s'}\phi \tag{10}$$

$$\psi' = (R' - 1)s' + R_f f' \tag{11}$$

$$B(x) = L\left(\Phi + x\right) \tag{12}$$

$$s' = s + d; \qquad c, s', f' \geq 0 \tag{13}$$

where $B(x)$ represents the bequest function. Here L measures the strength of the bequest motive and Φ reflects the luxuriousness of the bequest motive.

3.3 Married Households

For married households, family earnings for each working period $(j \leq J)$ comprise of four components: (a) male permanent income, z_m, (b) female permanent income, z_f, (c) a transitory shock to male income, ε_m, and (d) a transitory shock to female income, ε_f, and is equal to $y_m(z_m, \varepsilon_m) + y_f(z_f, \varepsilon_f)$. We assume that $\begin{bmatrix} \varepsilon_m \\ \varepsilon_f \end{bmatrix} \sim F_j^M(\varepsilon_m, \varepsilon_f)$ and $\begin{bmatrix} \eta'_m \\ \eta'_f \end{bmatrix} \sim G_j^M(\eta'_m, \eta'_f)$. The individual transitory and permanent income shocks are uncorrelated to each other and exhibit no serial correlation. However, we allow for the individual-specific income shocks of the spouses to be correlated. We specify this structure in more detail in Section 4.1. Retired households receive pension earnings, $b(z_{m,J}) + b(z_{f,J})$, which are a function of the permanent income level of each member of the household in their last working period. Family earnings are also subject to the same progressive tax system governed by τ.

Within married households, we assume that both members are of the same age; they pool their income and share consumption. The optimization problem for a married household of working age $j < J$ is given by

$$V(j, z_m, z_f, \varepsilon_m, \varepsilon_f, s, \psi) = \max_{c,s',f'} \left\{ \left(\frac{c}{1+\chi} \right)^{\gamma} + \beta \mathbb{E}_{z'_m, \varepsilon'_m, z'_f, \varepsilon'_f, R'} \left[V\left(j+1, z'_m, z'_f, \varepsilon'_m, \varepsilon'_f, s', \psi'\right)^{\alpha} \right]^{\frac{\gamma}{\alpha}} \right\}^{\frac{1}{\gamma}} \tag{14}$$

subject to

$$c + d + f' \leq \{y_m(z_m, \varepsilon_m) + y_f(z_f, \varepsilon_f)\}^{1-\tau} (1 - h(j)) + \psi - \mathbb{1}_{s \neq s'} \phi \tag{15}$$

$$\psi' = (R' - 1)s' + R_f f' \tag{16}$$

$$s' = s + d; \quad c, s', f' \geq 0; \tag{17}$$

where χ denotes the consumption equivalence scale.

Similarly for retired married households of age ($J < j \leq J + J_R$),

$$\begin{aligned} V(j, z_{m,J}, z_{f,J}, 0, 0, s, \psi) = \max_{c,s',f'} \Bigg\{ \left(\frac{c}{1+\chi} \right)^{\gamma} &+ \beta \mathbb{1}_{j<J+J_R} \mathbb{E}_{R'} \left[V\left(j+1, z_{m,J}, z_{f,J}, 0, 0, s', \psi'\right)^{\alpha} \right]^{\frac{\gamma}{\alpha}} \\ &+ \beta \mathbb{1}_{j=J+J_R} \mathbb{E}_{R'} \left[B(\psi' + s')^{\alpha} \right]^{\frac{\gamma}{\alpha}} \Bigg\}^{\frac{1}{\gamma}} \end{aligned} \tag{18}$$

subject to

$$c + d + f' \leq \{b(z_{m,J}) + b(z_{f,J})\}^{1-\tau} (1 - h(j)) + \psi - \mathbb{1}_{s \neq s'} \phi \tag{19}$$

$$\psi' = (R' - 1)s' + R_f f' \tag{20}$$

$$B(x) = L(\Phi + x) \tag{21}$$

$$s' = s + d; \quad c, s', f' \geq 0; \tag{22}$$

4 Solution Method and Parameterization

4.1 Estimation of the Income process

We parameterize the income shocks for single males and females in the following manner:

$$\varepsilon_{i,g,t} \sim \text{iid } N\left(0, \sigma^2_{\varepsilon,g}\right), \ \eta_{i,g,t} \sim \text{iid } N\left(0, \sigma^2_{\eta,g}\right) \tag{23}$$

where $\varepsilon_{i,g,t}$ and $\eta_{i,g,t}$ denote transitory and permanent income shock respectively to individual i and gender $g = \{m, f\}$ realized at time t[9]. Both the transitory and permanent income process are independently drawn from a Normal distribution with variances given by $\sigma^2_{\varepsilon,g}$ and $\sigma^2_{\eta,g}$ respectively. The important thing to note is that the expected values of the shocks do not change by gender but we allow for income risk to be gender asymmetric. The gender income gap is incorporated in the initial permanent income draw $\exp(z_0)$.

The income process for married males and females is shown below:

$$\begin{bmatrix} \varepsilon_{i,m,t} \\ \varepsilon_{i,f,t} \end{bmatrix} \sim \text{iid } N \left(0, \begin{bmatrix} \sigma^2_{\varepsilon,m} & \sigma_{\varepsilon,mf} \\ \sigma_{\varepsilon,mf} & \sigma^2_{\varepsilon,f} \end{bmatrix} \right) \tag{24}$$

$$\begin{bmatrix} \eta_{i,m,t} \\ \eta_{i,f,t} \end{bmatrix} \sim \text{iid } N \left(0, \begin{bmatrix} \sigma^2_{\eta,m} & \sigma_{\eta,mf} \\ \sigma_{\eta,mf} & \sigma^2_{\eta,f} \end{bmatrix} \right) \tag{25}$$

Similar to singles, we allow the variances of the spouses to be gender specific. But we allow the spouses permanent (transitory) shocks to be contemporaneously correlated with covariance denoted by $\sigma_{\eta,mf}\,(\sigma_{\varepsilon,mf})$. The sign and magnitude of this correlation is theoretically unclear. If spouses intentionally work in separate industries or occupations to share risk then this cor-

[9] Another common income process is MA(1) temporary shock process and a persistent rather than permanent income process. The MA(0) transitory-permanent income process implies autocovariances higher than 1 lag should be zero where as that is not the case with either the MA(1) temporary shock or persistent income process. We show in Appendix Table 18 that the data supports the MA(0) transitory-permanent income process as autocovariances higher than order 2 are insignificant from zero.

relation will be negative. In contrast, assortative matching on income and education lines will hint towards this correlation being positive.

The identification of these parameters follows Abowd and Card (1989) and relies on the cross-sectional variance and covariance of current and future income growth. Ignoring $\underline{y}$, log income and growth of log income of an individual using equations 3 and 4 can be written as:

$$\ln y_{i,g,t} = \alpha_{1,g} + \alpha_{2,g} * t + \alpha_{3,g} * t^2 + \varepsilon_{i,g,t} + z_{i,g,t} \tag{26}$$

$$\Delta \ln y_{i,g,t} = \chi_g + \varepsilon_{i,g,t} + \varepsilon_{i,g,t-1} + \eta_{i,g,t} \tag{27}$$

where $\chi_g = \alpha_2 + \alpha_{3,g} * (2t + 1)$. The variance of the transitory income shock can be computed as the negative covariance between current and future income growth. Permanent income is a random walk so, current and future income growth are linked only through the transitory shock as highlighted in equation 28. On the other hand, permanent income shock only shows up in long-term income growth (sum of current, past and future income growth). Thus, the cross-sectional covariance of current and long-term income growth can identify the variance of the permanent income shock.

$$\mathrm{Cov}\left(\Delta \ln y_{i,g,t}, \Delta \ln y_{i,g,t+1}\right) = -\sigma^2_{\varepsilon,g} \tag{28}$$

$$\mathrm{Cov}\left(\Delta \ln y_{i,g,t}, \Delta \ln y_{i,g,t} + \Delta \ln y_{i,g,t-1} + \Delta \ln y_{i,g,t+1}\right) = \sigma^2_{\eta,g} \tag{29}$$

The identification of the covariance parameters for husband and wife depend on the cross income growth and follows a similar intuition as above. Equation 30 displays the covariance between husband and wife transitory shocks that can be estimated through the cross-sectional covariance between a spouse's current income growth and the other spouse's future income growth. Similarly, the covariance between the permanent shock is computed using the covariance between a spouse's current income growth and the other spouse's long-term income growth (equation 31). In this case, clearly there exist overidentifying equations.

$$\mathrm{Cov}\left(\Delta \ln y_{i,m,t}, \Delta \ln y_{i,f,t+1}\right) = -\sigma_{\varepsilon,mf} \tag{30}$$

$$\mathrm{Cov}\left(\Delta \ln y_{i,m,t}, \Delta \ln y_{i,f,t} + \Delta \ln y_{i,f,t-1} + \Delta \ln y_{i,f,t+1}\right) = \sigma_{\eta,mf} \tag{31}$$

We use PSID from 1997 to 2019 to estimate the coefficients relating to age and variances and covariances of the income process. We implement a multi-step estimation strategy. First, we regress the income growth of men and women separately on observable characteristics to predict residuals. The observable variables we include in the regression are marital status dummy, cohort fixed effects, year interacted with education, race and employment status, fixed effects for mortgage, household size, number of children, additional earners, disability, child living outside house, state of residence, and change in employment status, mortgage, number of kids, household size and disability. Second, we use the second order moments of the residuals from the first step to estimate the parameters of interest. We employ an Equally-Weighted GMM instrumenting for marital status and gender and standard errors are clustered at the household level.

Figure 2 shows upward-sloping and concave income profiles of both men and women. The income profile is captured through the coefficients α_1, α_2, and α_3 as described above in the income process equation. Table 4 displays the estimated coefficients. We normalize the constant (α_1) to zero for men. The corresponding coefficient is -0.38 for women implying that women earn 38% lower than men when they enter the labour market. The coefficients (α_2, α_3) highlight that the rise in income is stronger for men than women in middle years but men's income declines faster than women as they approach retirement.

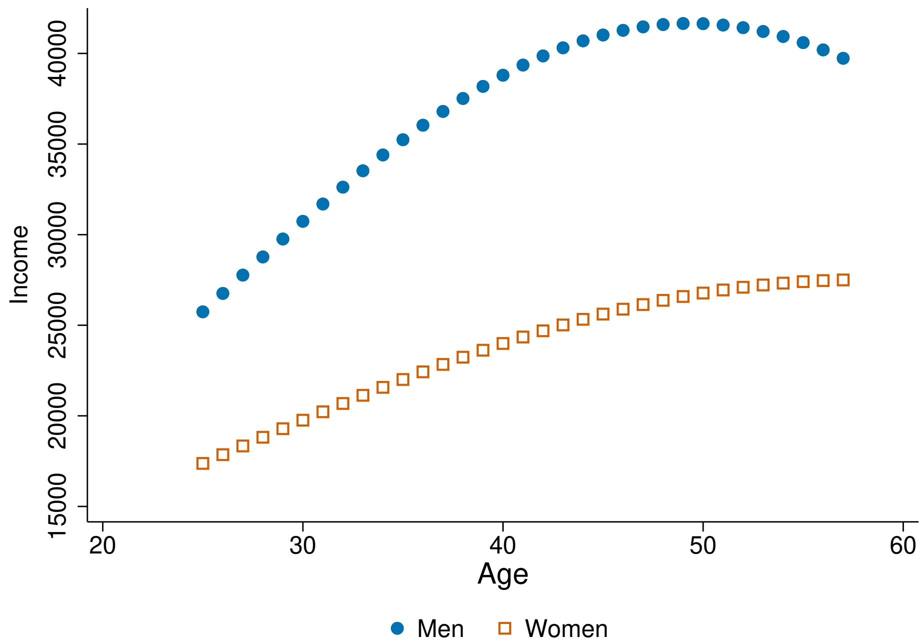


Figure 2: Income profiles by gender

The income risk parameters are presented in Table 4. The variance of permanent shock for men and women are 0.024 and 0.045 respectively. Permanent income variance for women is 88%

higher than men and this gap is statistically significant. On the other hand, the transitory shock variance is 0.035 and 0.028 for males and females respectively. This difference is not statistically significant at standard levels of significance. Blundell et al. (2016) also find that women have a higher permanent wage shock than men. Similar to Blundell et al. (2016), we also document that the covariance of permanent and transitory income shocks within married households is economically small and statistically insignificant. This implies, that the permanent (transitory) income process of men and women in a married households are virtually uncorrelated. Thus, merely the presence of additional earners in a household will provide insurance against income shock to a spouse (Krueger & Wu, 2021).

Table 4: Income Process Parameters

	Men	Women	P-value
Constant (α^0)	0	-0.381	
Age (α^1)	0.041	0.0287	
Age Squared (α^2)	-0.00081	-0.00042	
Variance Permanent	0.024***	0.045***	0
	(10.504)	(14.859)	
Variance Temporary	0.035***	0.028***	0.15
	(10.059)	(6.820)	
Covariance Permanent	-0.001		
	(-0.392)		
Covariance Temporary	0.001		
	(0.619)		

T-statistics in parentheses
The third column shows the test of equality across gender
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Borella, De Nardi, and Yang (2023) argues that changes in labour supply represent one of the most important variation in income of females. We argue that gender asymmetry in the variance of permanent income remains after accounting for labour supply participation. When considering currently full-time individuals, we show in Appendix Table 19 that women's permanent income variance falls to 0.036 compared to 0.045 in the baseline. The variance of permanent income of men remains the same, but is significantly smaller than females. Low, Meghir, and Pistaferri (2010) argue that incorporating employer transitions is important to isolate the importance of the permanent and transitory that an individual faces within a firm. We show in Appendix table 21 that the variance of employer transitions is same for men and women and thus, the variance of permanent shocks that women experience within a firm is greater than those for men.[10]

We explore heterogeneity by demographic and employment characteristics to shed light on some of the factors that can explain the difference in the permanent shock variance by gender. Appendix table 22 displays that conditional on marital status, women's variance of permanent income shocks is significantly higher than that of men. This asymmetry exists over the working life apart from a few years before retirement as shown in Appendix table 24. Motherhood penalty is an important explanation of the gender inequality in earnings (Kleven, Landais, & Søgaard, 2019). Appendix Table 23 shows that the gender asymmetry in the variance of permanent income is higher for individuals with kids than those without children.

Appendix table 25 highlights that the variance of permanent income shock of men is lower than women in both manufacturing and service industry but not agriculture. Appendix table 26 displays the asymmetry in the income process by gender and task content. We follow Jaimovich and Siu (2020) to group occupations into routine, non-routine manual and non-routine cognitive. Routine occupations are sales and office administrative support and "blue collar" jobs like machine operators and assemblers. Non-routine manual occupations include service jobs like janitors and personal care workers. Non-routine cognitive occupations are managerial, professional and technical workers. We find that gender disparities in permanent income variance exist in non-routine cognitive and routine occupations but not in non-routine manual occupations.

4.2 Parameterization

In order to quantitatively study the impact of differential income risk faced by men and women on portfolio choices across households, we solve this model using numerical methods. Table 5 lists the parameter values used.

This is an annual model and we assume the starting age to be 25 and a retirement age of 65. Therefore the number of working years, $J = 40$. Further, since the life expectancy in the US is 78.7 (World Bank, 2019), the number of years in the retired stage, $J_R = 14$. For the Epstein-Zin utility function, following Campanale, Fugazza, and Gomes (2015), γ is set to -3 and $\alpha = -4$. These values correspond to an elasticity of intertemporal substitution $\left(\frac{1}{1-\gamma}\right)$ of 0.25 and degree of risk aversion is 5 $(1-\alpha)$. The adult equivalence scale for married households $\chi = 0.7$

[10]We focus on income rather than wages as wages are not directly measured in the PSID. Hourly wage rate can be computed by dividing annual income by annual hours worked. Even using this imperfect measure, we show in Appendix table 20 that the variance of permanent income wage shock for women is higher than men.

is taken from the OECD tables corresponding to two-member households. Tax progressivity rate is assumed to be 18% (Heathcote, Storesletten, & Violante, 2017). The pension earnings function $b(z_J)$ is assumed to equal to $b_R \exp(z_J)$, where $b_R = 0.55$ (Low, 2005), that is, retirees receive 55% of their earnings when they retire. As discussed in Section 3, households receive utility from leaving bequests after they die which is given by:

$$B(\psi' + s') = \big[L(\Phi + \psi' + s')\big] \tag{32}$$

The values for L and Φ are set to 0.031 and 1.834 as per Cooper and Zhu (2016).

Table 5: Parameter Choices

Name	Source /Target	Value
α	Campanale et al. (2015)	-4
γ	Campanale et al. (2015)	-3
χ	OECD (n.d.)	0.7
τ	Heathcote et al. (2017)	0.18
b_R	Low (2005)	0.55
L	Cooper and Zhu (2016)	0.031
Φ	Cooper and Zhu (2016)	1.834
R_f	Krueger and Wu (2021)	1.02

We assume that the return on the risk-free asset is 2% annually (Krueger & Wu, 2021). All individuals face a disaster risk in the stock market with a $p_{\text{tail}} = 2\%$ probability where they experience a net risky asset return of 48.5% (Fagereng et al., 2017). With 98% probability, the risky asset returns for individuals follow a normal distribution with a mean of 7.3% and a standard deviation of 19.2. These measures are estimated using historical stock market and housing price data (Jordà, Schularick, Taylor, & Ward, 2019). The remaining parameters in the model have been calibrated using data moments as targets and discussed in Section 5.

We use numerical methods to solve this model. We discretize the total wealth that households have and allow ψ to take 50 values, and the risky asset grid s can take 20 values. Similarly, we discretize the income processes. At every age, permanent income level, z can take five values, whereas shocks to permanent income, η, and transitory income, ε, take three values each. The discretization of the transitory income shocks follows Tauchen (1986). Since this is a life-cycle model where death occurs deterministically, we solve the model backward and obtain the corresponding decision rules. Once we solve for the decision rules, we simulate the economy for 50,000 single females, 50,000 single males, and 1,00,000 married households and follow them over their lifetime.

5 Results

5.1 Aggregates

Table 6 shows the performance of the model with respect to its targeted moments in terms of population averages. The discount factor, β, and the fixed cost of adjusting risky assets, ϕ, have been calibrated to match the wealth-income ratio of 2.54 and the risky asset share of the entire population, which is approximately 57%, respectively. Unsurprisingly, the model performs well in terms of its targeted moments.

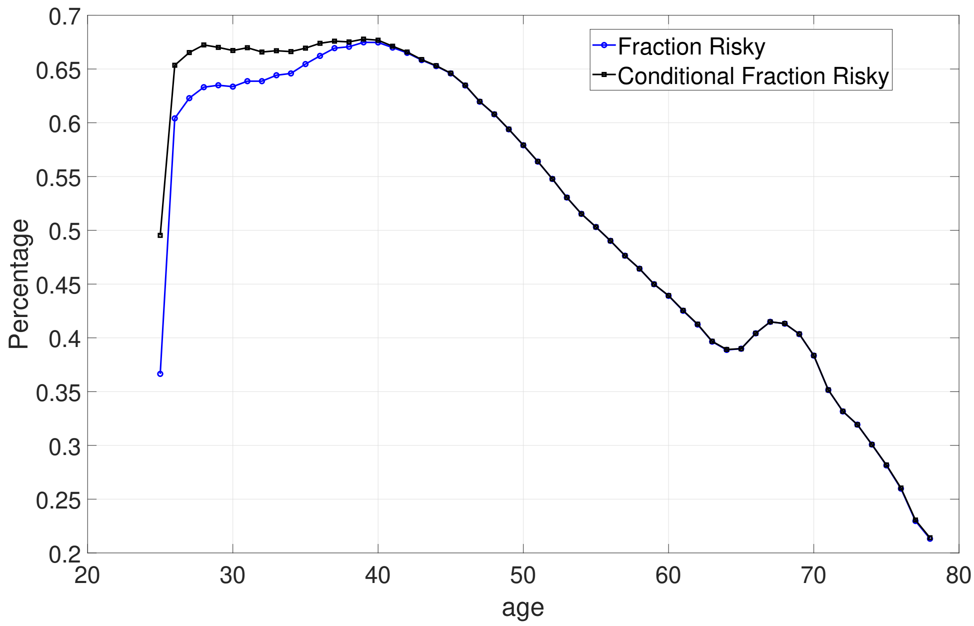
Table 6: Model Fit: Targeted Moments

Parameters	Values	Targets	Data	Model
ϕ	0.0601	Aggregate risky asset share	57.01	57.50
β	0.875	Wealth-income ratio	2.54	2.54

Figure 3 shows the model results for average risky asset share (both conditional and unconditional) over the lifecycle. Early on in their working life, individuals have a longer time horizon in the future to smooth their consumption. Thus, as soon as they accumulate enough wealth to overcome the fixed cost of participation, the higher expected return on risky assets incentivizes them to invest more in these assets. As they age, the ratio of expected future labor income to accumulated wealth falls; as a result, they diversify, which leads to lower risky asset share. In terms of life-cycle behavior, average consumption, income, and wealth show standard patterns and have been illustrated in Figure 11 in the Appendix.

5.2 Differences across gender and marital status

Table 7 demonstrates the model performance in terms of its untargeted moments. Even though only the aggregate risky asset share of the economy is targeted, the model is able to closely replicate the share of investment in risky assets by single female-headed, single male-headed, and married households, as seen in the data. The gender wage gap, gender differences in income risk, and inequality in terms of the initial wealth distribution across households result



Notes: The series in blue describes the unconditional share of wealth invested in risky assets for the entire population; the series in black illustrates the average risky asset share of the economy for those who invest in risky assets (conditional).

Figure 3: Life-cycle profile of risky asset share

in single female-headed households investing 4 pp. less in risky assets than single male-headed households, whereas married households invest approximately 10 pp. more than the single males.

Table 7: Model Fit: Untargeted Moments

Moment	Data	Model
Fraction Risky - Women	47.15	48.33
Fraction Risky - Men	52.87	52.35
Fraction Risky - Married	60.86	62.01

Figure 12 in the Appendix shows the simulated income profiles of single females, single males, and couples over the lifecycle. The gender wage gap faced by females and the dual-earner effect for married households can be seen through the differences in their household income profiles. Figure 4 illustrates the average fraction of wealth invested in risky assets by these different households over their lifetime. An initial rise followed by a gradual decline in the share of risky investment is consistent across all three types of households. As is observed in the figure, single female households invest a lower fraction of their wealth in risky assets for most of their working life, consistent with the empirical results. The empirical results also showed that single men hold 3-5 pp more risky assets than single women. Thus, our model can quantitatively produce similar results. Almost at every stage of life, married households invest more in risky assets than single households do. These differences can have significant effects on lifetime wealth accumulation and consumption profile.

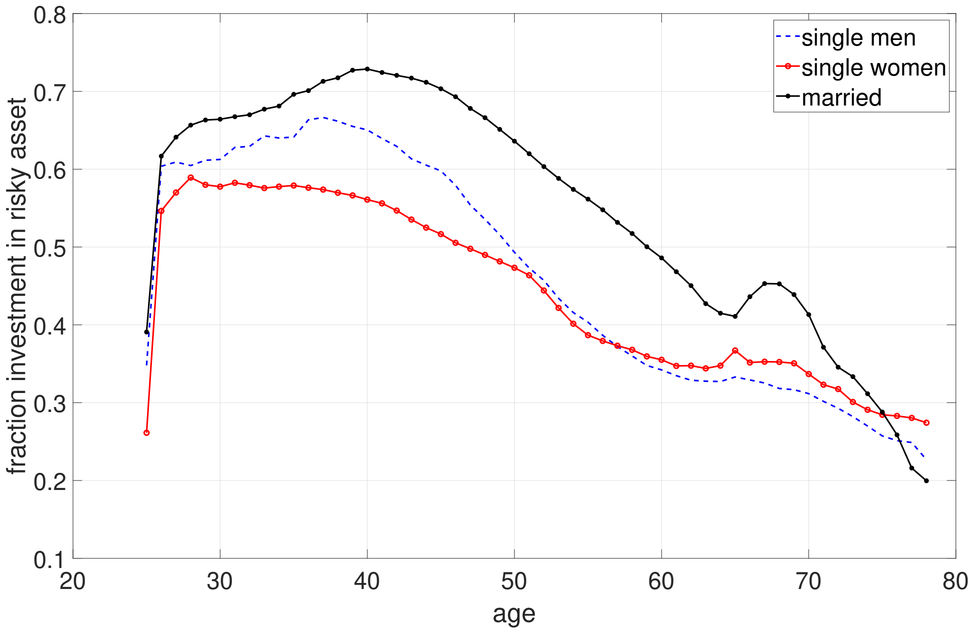


Figure 4: Risky asset share profile of single men, women, and couples

Figures 5 and 6 show the wealth accumulation and consumption profiles over the working life of the three groups, respectively. Households accumulate wealth and see an increase in their consumption levels over their working life. As they retire, their consumption levels decrease, but not as much as the decrease in their income levels since they consume out of their wealth. They die with positive wealth levels as they derive utility from leaving behind bequests.

Early in life, the wealth accumulated by single men and single women is similar. While the gender wage gap has a negative effect on the wealth accumulation of women, the higher income risk increases their precautionary saving incentive, thereby offsetting the effect of the gender wage gap. However, that leads to substantial consumption differences. Over their lifecycle, the gender wage gap is the dominant factor explaining differences in wealth accumulation among single households. For couples, total household income is higher than that of singles, but the precautionary saving motive is lower. Thus, their wealth accumulation early in life is not significantly different from that of single households. However, consumption differences exist, primarily due to the income effect.

So far, we have shown that quantitatively the differences in risky portfolio shares across households are similar in magnitude to our empirical estimates, even though the risk preferences

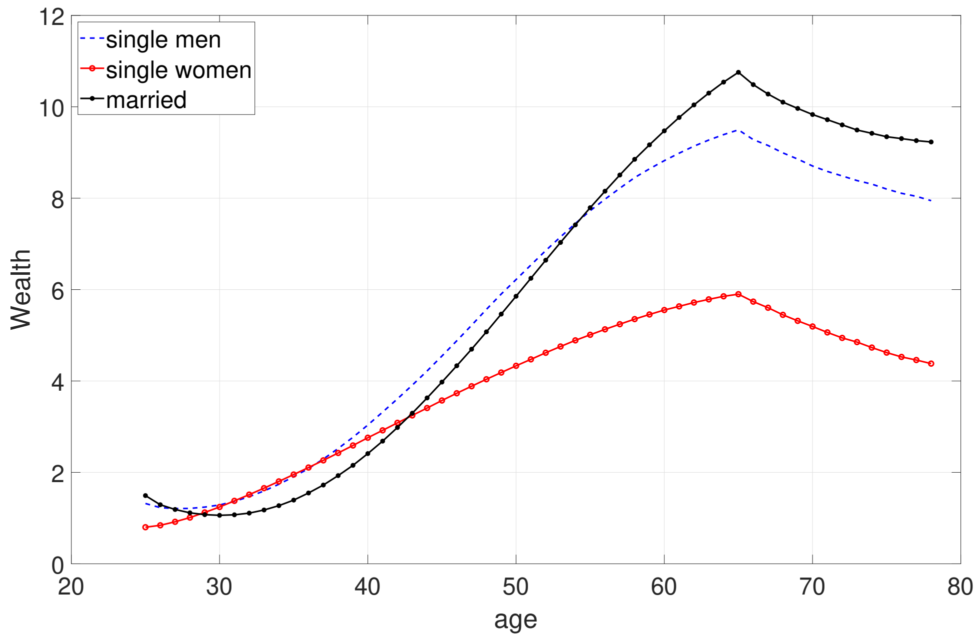


Figure 5: Wealth profile of single men, women, and couples

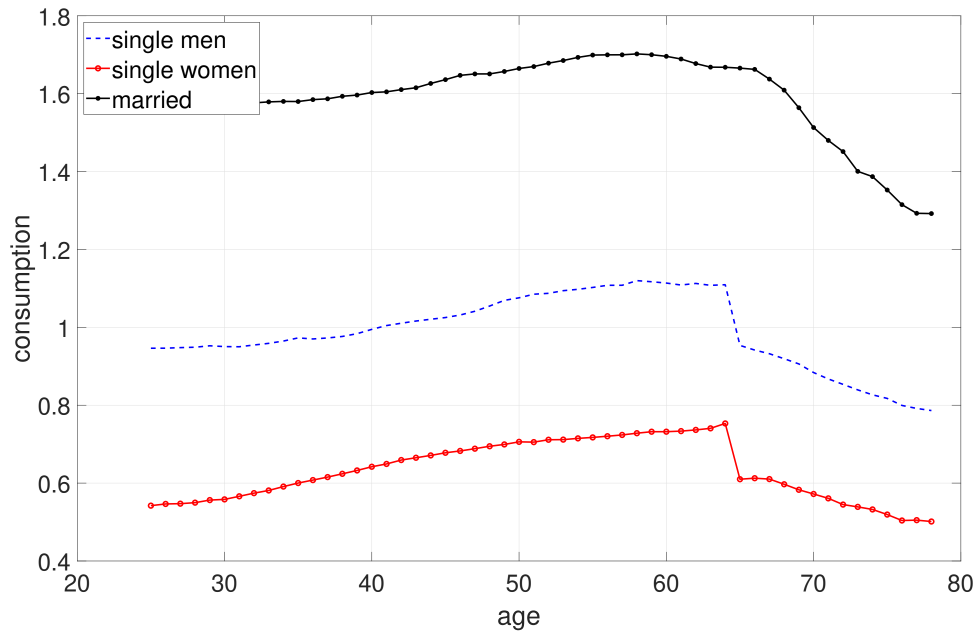
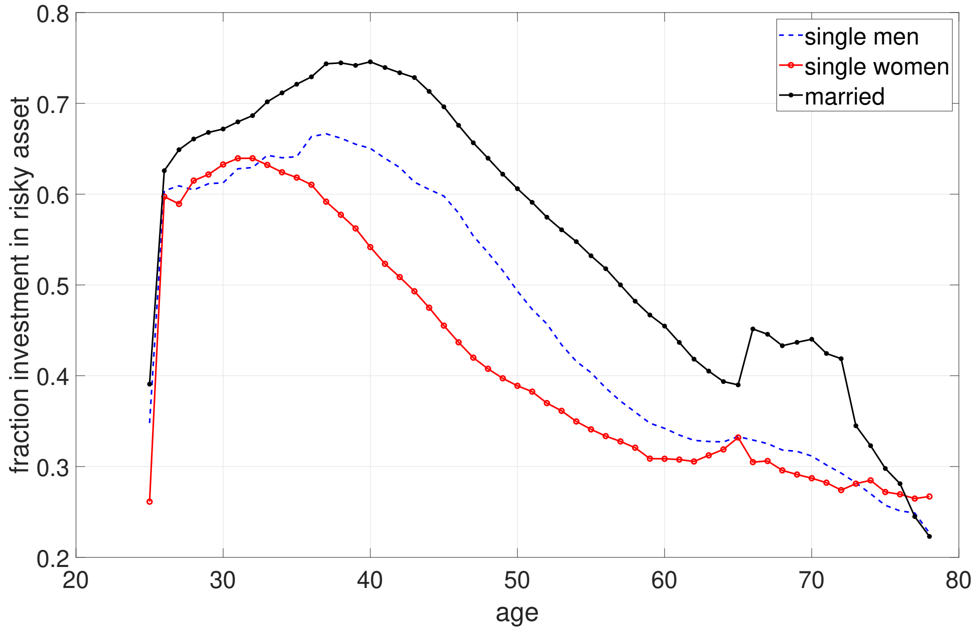


Figure 6: Consumption profile of single men, women, and couples

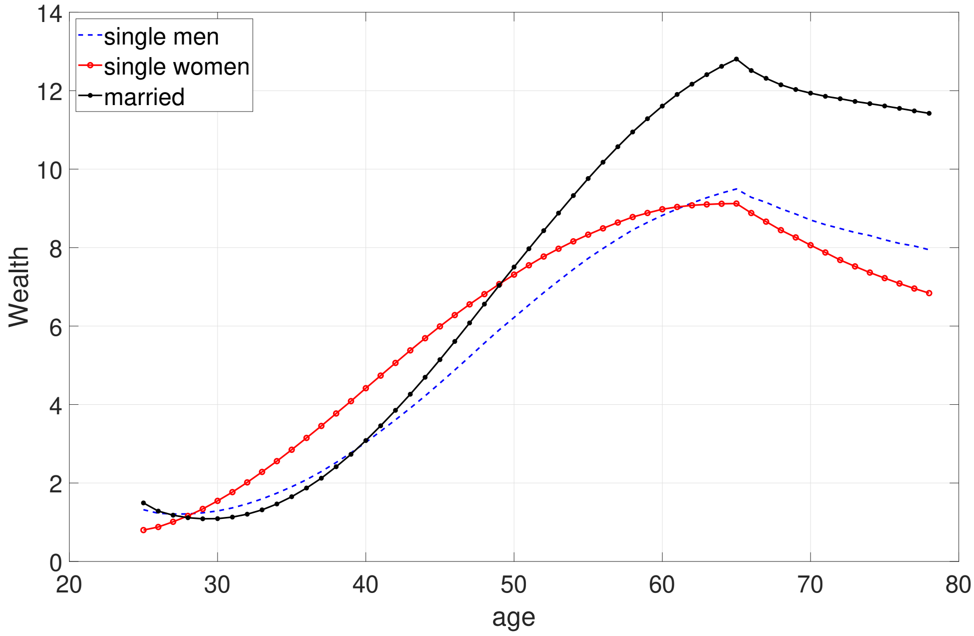
across households have been assumed to be the same, unlike (Neelakantan & Chang, 2010). Our next step involves quantifying the relative importance of the two major channels, that is, the gender wage gap and the difference in income risk on the savings behavior of households. To achieve this, we conduct counterfactual exercises where we (i) first assume that the gender wage gap is zero while the income risk differences are present, and (ii) next assume that the income risk faced by men and women are the same, while the gender wage gap exists. The results are discussed below.

5.3 Role of Gender Wage gap

Figure 13 in the Appendix shows the new income profiles where the gender differences at the start of the working age in terms of permanent income level between men and women are removed. This leads to women earning the same as men in their early working years; however, the gap widens as they age due to the higher variance in income faced by women. Figure 7a illustrates the risky portfolio shares, whereas 7b shows the wealth accumulation in this environment.



(a) Risky asset share across gender and marital status without gender wage gap



(b) Wealth profile across gender and marital status without gender wage gap

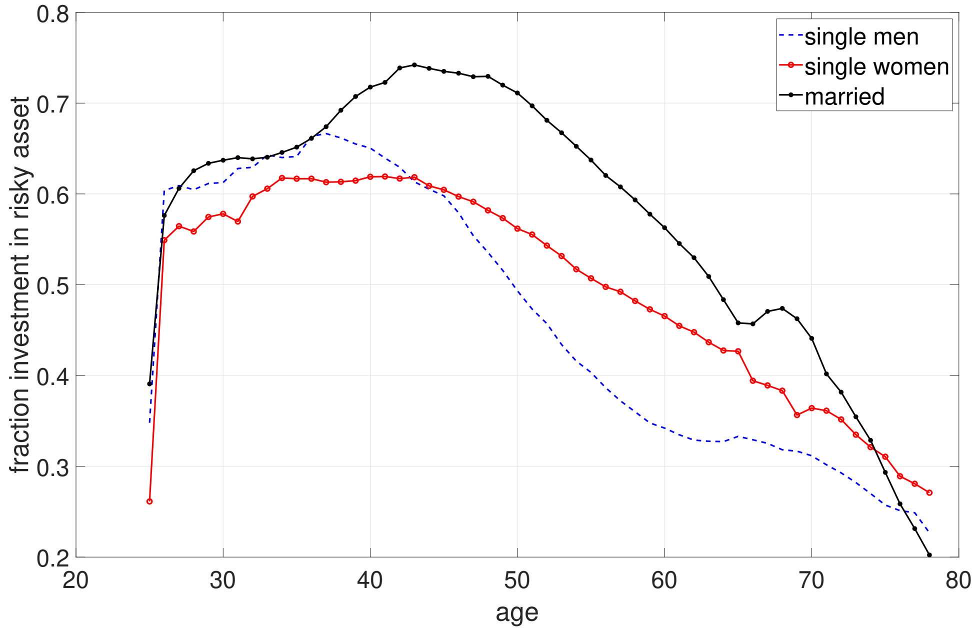
As the gender gap is removed, the delayed entry into the risky asset market by single women relative to men is no longer observed. As the income risk differences still exist, the gap in risky asset share is again observed as agents age. The higher precautionary motive for single women, coupled with an absence of the wage gap, results in them accumulating more wealth than their male counterparts and married households (for a large part of their working life, after which the income effect for couples dominates). Similarly, wealth accumulated by married households increases relative to single men. The higher wealth generates stronger portfolio diversification in middle-aged households, and single females hold a lesser equity share than males in this counterfactual compared to the baseline simulation. Similarly, the equity share gap shrinks between married and single male households. The net effect is that overall there is a fall in the risky asset share gap between single males and couples by 0.6pp. and a rise between single males and single females by 2 pp., as illustrated by Table 8 later. As shown in Figure 15 in the Appendix, higher wealth also translates into higher consumption for single females and couples than before.

5.4 Role of Income Risk

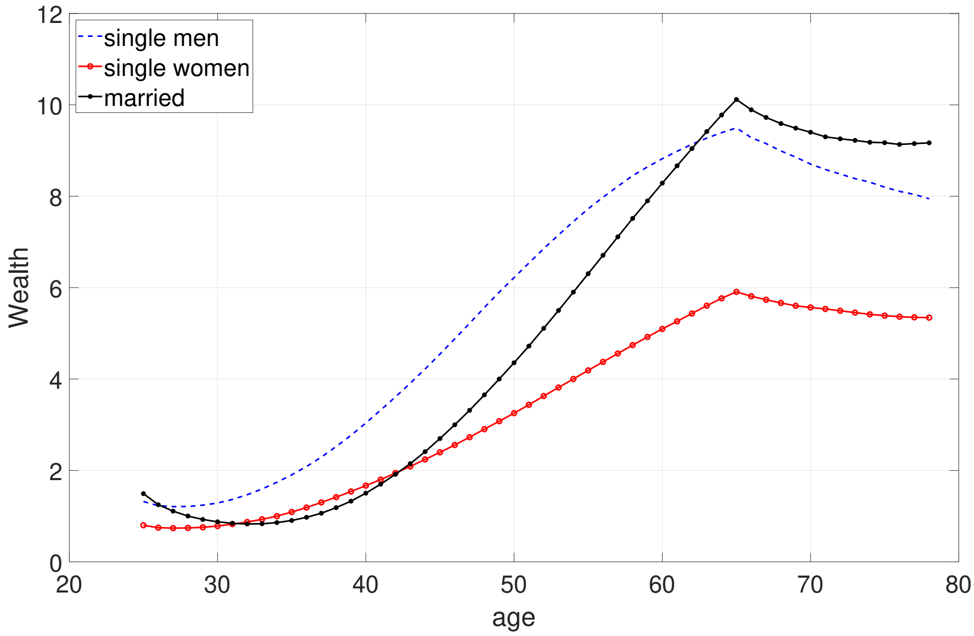
Figure 14 in the Appendix shows the income profiles when men and women experience the same variance in permanent income [11]; however, the gender wage gap remains. Figures 8a and 8b illustrate the risky portfolio shares and wealth accumulation across households in this environment, respectively.

In the benchmark case, the precautionary savings motive induces risk-averse households to hold more safe assets when they are faced with higher income risk. As the income risk faced by women falls, they hold a lower share in safe assets than before and accumulate less wealth. As expected, similar behavior is observed among married households too. Thus, portfolio share allocated to risky assets increases than before by both single female-headed households as well as married households once they are able to overcome the delay in entry due to the gender wage gap. Specifically, as documented in Table 8, there is a 6pp. increase in risky asset share holdings of single women and a corresponding 2pp. increase for couples. In this case, however, even though the wealth accumulation is lower for couples and single female households than in the benchmark, consumption levels improve for both these households, as shown in Figure 9.

[11] In particular, we assume that women face a lower income risk than before



(a) Risky asset share across gender and marital status without asymmetric income risk



(b) Wealth profile across gender and marital status without asymmetric income risk

5.5 Other Mechanisms

Table 8 shows portfolio share across different counterfactual experiments. Columns (1) and (2) show the average risky asset share when the wage gap and variance differences are removed, respectively (as already discussed). Column (3) shows the portfolio risky share when $\chi = 1$, which captures the role of economies of scale. In this case, the equity shares are almost unchanged from the benchmark. The higher equivalence share implies that households save less than before, but the fall in savings is not large and leads to portfolio shares similar to the

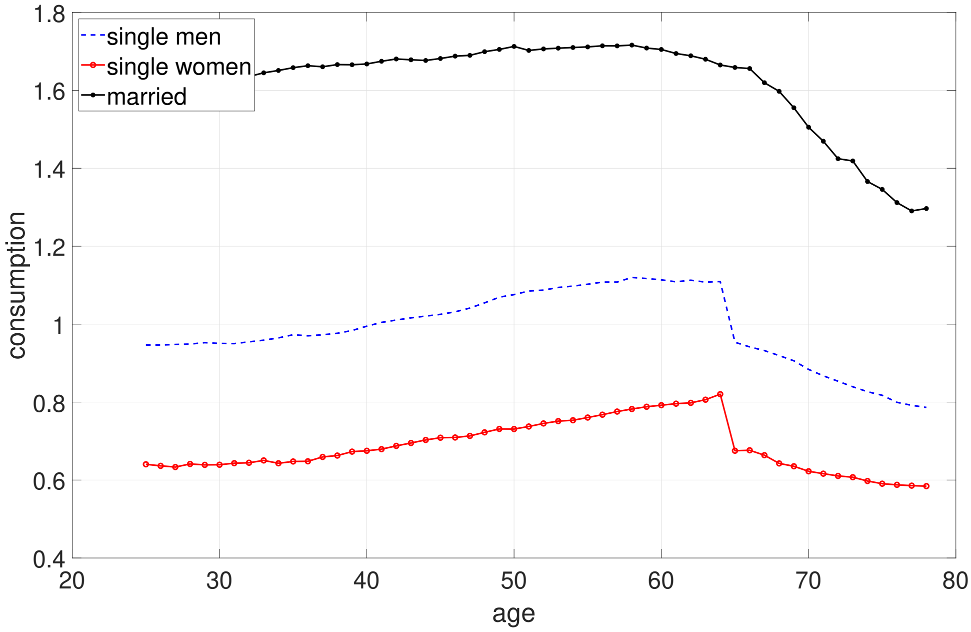


Figure 9: Consumption across gender and marital status without asymmetric income risk

benchmark.

Column (4) shows the share of investment in risky assets when disaster risk is removed, that is, $p_{\text{tail}} = 0$. Firstly, this results in all households holding a higher equity share than the benchmark, as the probability of a large negative return does not exist anymore. Secondly, the portfolio gap between single males and females rises as single males accumulate more risky assets as background risk falls, and they undertake less precautionary savings. Similarly, the portfolio gap between married and single men falls. Though, one thing to note is that the model with disaster risk produces risky asset shares closer to that observed in the data as seen in Figure 1 that shows the risky asset share across gender and marital groups. Column (5) shows the model results when the initial wealth distribution across households is eliminated. The numbers are similar to the ones obtained in the benchmark, indicating that this is not the dominant factor that explains the differences in risk-taking investment behavior across households.

Table 8: Risky Asset Share across various parameter values

Household type	Benchmark	(1)	(2)	(3)	(4)	(5)
Single Women	48.33	46.27	54.93	48.33	59.58	47.25
Single Men	52.35	52.35	52.35	52.35	64.88	52.35
Married	62.01	61.41	64.51	62.25	72.17	61.68

(1): No wage gap; (2): No variance gap; (3): No economies of scale; (4): No disaster risk; (5): Same initial wealth distribution

5.6 Spousal insurance

In this section of the paper, we discuss the role of spousal income for married households. While married households have higher household incomes than their single counterparts, their consumption needs are also higher. To understand the role of the additional source of income in the risk-taking behavior of married households, we now conduct a counterfactual exercise where we compare the risky asset share of married households where both members are working versus where only one member is working (in this case, the male member). The results are shown in Figure 10. We find that even though the female higher income risk is eliminated for single earners, they end up investing less in risky assets and behave similarly to the single male households. These results are consistent with the empirical estimates obtained in Table 3 before.

6 Conclusion

In this paper, we study the role of gender and marital status differences in portfolio allocations across US households. We document using the PSID and SCF that, even after controlling for observable and unobservable characteristics, married households invest a larger share of their wealth in risky assets as compared to single households. Further, single female-headed households hold a lower share of risky investments relative to single men. Next, to assess the role of income risk and spousal insurance in explaining portfolio allocation differences across these households, we develop an incomplete market two-asset life-cycle model with heterogeneous agents. We estimate the income process for men and women using the panel structure in PSID

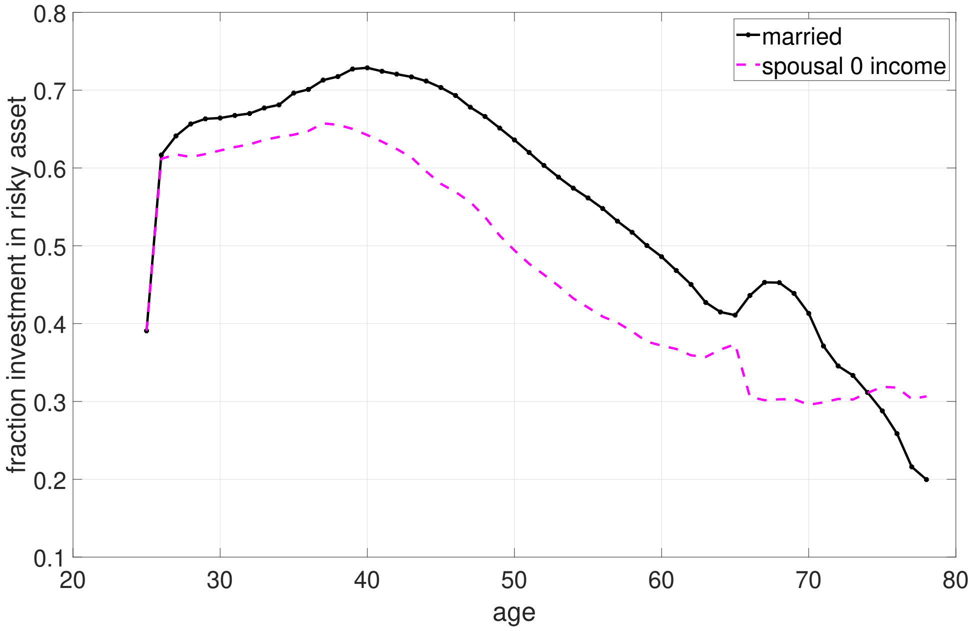


Figure 10: Risky asset share for single-earner versus dual-earner couples

and find evidence that women face a higher risk to their permanent income than men. We incorporate this in our framework along with the gender wage gap and quantitatively assess the impact on portfolio allocations across households. Model simulations show that the higher permanent income risk for women leads to significantly lower investment in the risky asset as compared to single male households. The gender wage gap has an important role only in early working life when individuals have not built up sufficient wealth to pay for adjusting their risky asset holding.

References

Abowd, J. M., & Card, D. (1989). On the Covariance Structure of Earnings and Hours Changes. *Econometrica*, *57*(2), 411–445.

Addoum, J. M., Kung, H., & Gonzalo, M. (2016). Limited marital commitment and household portfolios. *Working Paper*.

Almenberg, J., & Dreber, A. (2015). Gender, stock market participation and financial literacy. *Economics Letters*, *137*, 140–142.

Angerer, X., & Lam, P.-S. (2009). Income risk and portfolio choice: An empirical study. *The Journal of Finance*, *64*(2), 1037–1055.

Bacher, A. (2024). The gender investment gap over the life-cycle. *The Review of Financial Studies*, hhae068.

Bardóczy, B. (2020). Spousal insurance and the amplification of business cycles. *Unpublished Manuscript, Northwestern University*.

Bartscher, A. K., Kuhn, M., & Schularick, M. (2020). The college wealth divide: Education and inequality in america, 1956-2016. *Available at SSRN 3587685*.

Benhabib, J., Bisin, A., & Zhu, S. (2011). The distribution of wealth and fiscal policy in economies with finitely lived agents. *Econometrica*, *79*(1), 123–157.

Bertocchi, G., Brunetti, M., & Torricelli, C. (2011). Marriage and other risky assets: A portfolio approach. *Journal of Banking & Finance*, *35*(11), 2902–2915.

Blundell, R., Pistaferri, L., & Saporta-Eksten, I. (2016). Consumption Inequality and Family Labor Supply. *American Economic Review*, *106*(2), 387–435.

Borella, M., De Nardi, M., & Yang, F. (2018). The aggregate implications of gender and marriage. *The Journal of the Economics of Ageing*, *11*, 6–26.

Borella, M., De Nardi, M., & Yang, F. (2023). Are marriage-related taxes and social security benefits holding back female labour supply? *The Review of Economic Studies*, *90*(1), 102–131.

Campanale, C., Fugazza, C., & Gomes, F. (2015). Life-cycle portfolio choice with liquid and illiquid financial assets. *Journal of Monetary Economics*, *71*, 67–83.

Catherine, S., Sodini, P., & Zhang, Y. (2020). Countercyclical income risk and portfolio choices: Evidence from sweden. *Swedish House of Finance Research Paper*(20-20).

Chang, Y., Hong, J. H., Karabarbounis, M., Wang, Y., & Zhang, T. (2022). Income volatility and portfolio choices. *Review of Economic Dynamics*, *44*, 65–90.

Cooper, R., & Zhu, G. (2016). Household finance over the life-cycle: What does education contribute? *Review of Economic Dynamics*, *20*, 63–89.

Doepke, M., & Tertilt, M. (2016). Families in macroeconomics. In *Handbook of macroeconomics* (Vol. 2, pp. 1789–1891). Elsevier.

Fagereng, A., Gottlieb, C., & Guiso, L. (2017). Asset market participation and portfolio choice over the life-cycle. *Journal of Finance*, *72*(2), 705–750.

Gu, R., Peng, C., & Zhang, W. (2019). Risk attitude and portfolio choice: An intra-household perspective. *Working Paper*.

Halla, M., Schmieder, J., & Weber, A. (2020). Job Displacement, Family Dynamics, and Household Labor Supply. *American Economic Journal: Applied Economics*, *12*(4), 253–87.

Hardies, K., Breesch, D., & Branson, J. (2013). Gender differences in overconfidence and risk taking: Do self-selection and socialization matter? *Economics Letters*, *118*(3), 442–444.

Heathcote, J., Storesletten, K., & Violante, G. L. (2017). Optimal tax progressivity: An analytical framework. *Quarterly Journal of Economics*, *132*(4), 1693–1754.

Huang, J., & Kisgen, D. J. (2013). Gender and corporate finance: Are male executives overconfident relative to female executives? *Journal of financial Economics*, *108*(3), 822–839.

Inkmann, J., Michaelides, A., & Zhang, Y. (2021). Family portfolio choice over the life cycle. *Available at SSRN 3965481*.

Jaimovich, N., & Siu, H. E. (2020). Job Polarization and Jobless Recoveries. *Review of Economics and Statistics*, *102*(1), 129–147.

Jordà, Ò., Schularick, M., Taylor, A. M., & Ward, F. (2019). Global financial cycles and risk premiums. *IMF Economic Review*, *67*(1), 109–150.

Kaplan, G., Moll, B., & Violante, G. L. (2018). Monetary Policy According to HANK. *American Economic Review*, *108*(3), 697–743.

Ke, D. (2021). Who wears the pants? gender identity norms and intrahousehold financial decision-making. *The Journal of Finance*, *76*(3), 1389–1425.

Kleven, H., Landais, C., & Søgaard, J. E. (2019). Children and gender inequality: Evidence from denmark. *American Economic Journal: Applied Economics*, *11*(4), 181–209.

Krueger, D., Mitman, K., & Perri, F. (2017). Macroeconomics and Heterogeneity. In John B. Taylor & Harald Uhlig (Eds.), *Handbook of macroeconomics* (Vol 2B ed., pp. 843–921).

Krueger, D., & Wu, C. (2021). Consumption insurance against wage risk: Family labor supply and optimal progressive income taxation. *American Economic Journal: Macroeconomics*, *13*(1), 79–113.

Low, H. (2005). Self-insurance in a life-cycle model of labour supply and savings. *Review of Economic Dynamics*, *8*(4), 945–975.

Low, H., Meghir, C., & Pistaferri, L. (2010). Wage Risk and Employment Risk over the Life Cycle. *American Economic Review*, *100*(4), 1432–1467.

Lundberg, S. (1985). The added worker effect. *Journal of Labor Economics*, *3*(1), 11–37.

Lynch, A. W., & Tan, S. (2011). Labor income dynamics at business-cycle frequencies: Implications for portfolio choice. *Journal of Financial Economics*, *101*(2), 333–359.

Meghir, C., & Pistaferri, L. (2004). Income Variance Dynamics and Heterogeneity. *Econometrica*, *72*(1), 1–32.

Merton, R. C. (1969). Lifetime portfolio selection under uncertainty: The continuous-time case. *Review of Economics and Statistics*, *51*(3), 247–257.

Neelakantan, U. (2010). Estimation and impact of gender differences in risk tolerance. *Economic inquiry*, *48*(1), 228–233.

Neelakantan, U., & Chang, Y. (2010). Gender differences in wealth at retirement. *American Economic Review*, *100*(2), 362–67.

OECD. (n.d.). *What are equivalence scales?*

Pfeffer, F., Schoeni, R. F., Kennickell, A., & Andreski, P. (2016). Measuring wealth and wealth inequality. *Journal of Economic and Social Measurement*, *41*(2), 103–120.

Schmidt, L., & Sevak, P. (2006). Gender, marriage, and asset accumulation in the united states. *Feminist Economics*, *12*(1-2), 139–166.

Sunden, A. E., & Surette, B. J. (1998). Gender differences in the allocation of assets in retirement savings plans. *The American Economic Review*, *88*(2), 207–211.

Tauchen, G. (1986). Finite state markov-chain approximations to univariate and vector autoregressions. *Economics Letters*, *20*(2), 177-181.

Appendix

A Empirical Evidence

We consider a Censored Tobit regression to account for such two-sided censoring more explicitly in the following way:

$$RS^*_{it} = \alpha + \beta_M M_{it} + \beta_{SM} SM_{it} + \beta_X X_{it} + u_{it} \tag{33}$$

where u_{it} is the error term and RS^*_{it} is the desired risky share. Moreover, observed risky portfolio can be defined as:

$$RS_{it} = \begin{cases} 1, \text{ if } RS^*_{it} \geq 1 \\ RS^*_{it}, \text{ if } 0 < RS^*_{it} < 1 \\ 0, \text{ if } RS^*_{it} \leq 0 \end{cases} \tag{34}$$

Table 9: Tobit regressions for risky asset share

	PSID	SCF
Single Men	0.073***	0.069***
	(0.015)	(0.013)
Married	0.286***	0.16***
	(0.015)	(0.012)
Constant	-0.289***	-0.035***
	(0.051)	(0.024)
Observations	36002	27533
Single Men=Married	0	0

Standard errors in parentheses

Includes age-bins, income, wealth, family size, no. kids, self-employment

Includes year, state, race, education, employment and child present dummies

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Regressions for risky asset shares over lifecycle

	PSID	SCF
Single Men [25-29]	0.045***	0.044*
	(0.012)	(0.026)
Married [25-29]	0.062***	0.097***
	(0.012)	(0.021)
Single Men [30-34]	0.043***	0.113***
	(0.015)	(0.028)
Married [30-34]	0.088***	0.140***
	(0.013)	(0.021)
Single Men[35-39]	0.014	0.066**
	(0.017)	(0.028)
Married [35-39]	0.112***	0.148***
	(0.015)	(0.020)
Single Men [40-44]	0.046**	0.078***
	(0.019)	(0.028)
Married [40-44]	0.153***	0.164***
	(0.015)	(0.019)
Single Men [45-49]	0.006	0.039
	(0.020)	(0.028)
Married [45-49]	0.101***	0.150***
	(0.016)	(0.020)
Single Men [50-54]	0.002	0.048*
	(0.022)	(0.026)
Married [50-54]	0.106***	0.097***
	(0.016)	(0.019)
Single Men [55-59]	0.027	0.040
	(0.023)	(0.030)
Married [55-59]	0.092***	0.111***
	(0.017)	(0.020)
Single Men [60-64]	-0.027	0.065*
	(0.024)	(0.039)
Married [60-64]	0.076***	0.147***
	(0.018)	(0.025)
Constant	0.232***	0.155***
	(0.026)	(0.023)
Observations	35943	27489
Household controls	Yes	Yes
Single Men=Married [25-29]	.131	.021
Single Men=Married [30-34]	0	.24
Single Men=Married [35-39]	0	.001
Single Men=Married [40-44]	0	0
Single Men=Married [45-49]	0	0
Single Men=Married [50-54]	0	.027
Single Men=Married [55-59]	.001	.005
Single Men=Married [60-64]	0	.014

Standard errors in parentheses

Includes age-bins, income, wealth, family size, no. kids, self-employment

Includes year, state, race, education, employment and child present dummies

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Regressions with finer categories of singles

	PSID	SCF
Never Married Women	0.022**	0.021
	(0.009)	(0.013)
Never Married Men	0.074***	0.064***
	(0.009)	(0.014)
Separated Men	0.007	0.055***
	(0.009)	(0.014)
Married	0.131***	0.126***
	(0.008)	(0.011)
Constant	0.187***	0.125***
	(0.025)	(0.019)
Observations	35943	27489
Household Controls	Yes	Yes
Never Married Female=Never Married Male	0	.003
Never Married Female=Married	0	0
Never Married Male=Married	0	0
Separated Male=Married	0	0

Standard errors in parentheses
Includes age-bins, income, wealth, family size, no. kids, self-employment
Includes year, state, race, education, employment and child present dummies
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Regressions for risky asset extensive margin

	PSID	SCF
Single Men	0.026***	0.058***
	(0.008)	(0.012)
Married	0.138***	0.158***
	(0.008)	(0.008)
Constant	0.291***	0.326***
	(0.029)	(0.02)
Observations	35943	27489
Single Men=Married	0	0

Standard errors in parentheses
Includes age-bins, income, wealth, family size, no. kids, self-employment
Includes year, state, race, education, employment and child present dummies
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Regression with alternative definitions of risky asset share in PSID

	(1) Baseline	(2) With Housing	(3) IRA as Non-Risky	(4) Stocks
Single Men	0.033***	0.012*	0.047***	0.029***
	(0.006)	(0.007)	(0.005)	(0.004)
Married	0.124***	0.156***	0.069***	0.046***
	(0.007)	(0.007)	(0.005)	(0.004)
Constant	0.199***	0.366***	0.141***	0.133***
	(0.025)	(0.021)	(0.021)	(0.020)
Observations	35943	37723	35964	34318
Single Men=Married	0	0	0	0

Standard errors in parentheses

Includes age-bins, income, wealth, family size, no. kids, self-employment

Includes year, state, race, education, employment and child present dummies

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Regression with alternative definitions of risky asset share in SCF

	(1) Baseline	(2) With Housing	(3) IRA as Non-Risky	(4) Stocks
Single Men	0.051***	0.030***	0.052***	0.036***
	(0.010)	(0.009)	(0.007)	(0.007)
Married	0.119***	0.096***	0.075***	0.051***
	(0.009)	(0.008)	(0.006)	(0.005)
Constant	0.135***	0.371***	0.046***	0.003
	(0.018)	(0.017)	(0.013)	(0.010)
Observations	27489	27221	27459	27245
Single Men=Married	0	0	.004	.03

Standard errors in parentheses

Includes age-bins, income, wealth, family size, no. kids, self-employment and risk dummies

Includes year, race, education, child present and employment status dummies

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Observations for each country by waves in HFCS

	Year			
Country	2010	2014	2017	**Total**
Austria	1610	1821	1969	5400
Belgium	1491	1365	1436	4292
Cyprus	958	851	816	2625
Germany	2222	2720	2850	7792
Estonia	0	1554	1827	3381
Spain	3229	3262	3526	10017
Finland	7536	7208	6416	21160
France	9781	8092	9275	27148
Greece	1807	1685	1800	5292
Croatia	0	0	615	615
Hungary	0	0	3279	3279
Italy	4233	3752	3248	11233
Lithuania	0	0	976	976
Luxembourg	737	1260	1263	3260
Latvia	0	806	837	1643
Netherlands	834	779	1457	3070
Poland	0	0	3669	3669
Portugal	2653	4062	3633	10348
Slovenia	224	1612	1189	3025
Slovakia	1648	1201	1243	4092
Total	38963	42030	51324	132317

Table 16: Regression for risky asset share in HFCS

	(1)	(2)	(3)
Single Male	0.049***	0.033***	0.038***
	(0.006)	(0.006)	(0.006)
Married	0.134***	0.049***	0.050***
	(0.005)	(0.005)	(0.006)
Constant	0.180***	0.017*	-0.068***
	(0.004)	(0.010)	(0.011)
Observations	132319	132317	118754
Household Controls	No	Yes	Yes
Country FE	No	No	Yes
Single Male=Married	0	.004	.045

Standard errors in parentheses

Includes age dummies, income, wealth, family size, no. kids and self-employment

Includes year, education, child present and employment status dummies

Last column includes those countries with data for all the waves

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Regression for risky asset share by married working types

	Hours	Income
Both working	0.016**	0.014**
	(0.007)	(0.007)
Constant	0.191***	0.192***
	(0.034)	(0.034)
Observations	22686	22686

Standard errors in parentheses
Includes age-bins, income, wealth, family size, no. kids, self-employment
Includes year, state, child present dummies and race and education dummies for both husband and wife
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Higher Order Autocovariances

	Men			Women		
Year\Lags	2	4	6	2	4	6
1998	.0359***	-.0043	.0057	.0217**	4.3e-04	.0116
	(.0081)	(.0044)	(.006)	(.0101)	(.0061)	(.0094)
2000	.0421***	.009	8.2e-04	.0405***	-.0064	.0165*
	(.009)	(.0079)	(.0065)	(.0088)	(.0077)	(.009)
2002	.104***	-.003	-.0147	.0626***	.016*	.0035
	(.0163)	(.0051)	(.0101)	(.0169)	(.0094)	(.0056)
2004	.0713***	.0046	-9.6e-04	.0644***	-.0014	-.0086
	(.0135)	(.0085)	(.0065)	(.0159)	(.0069)	(.0076)
2006	.0391***	-.0027	.0018	.0625***	.024**	-.0078
	(.0082)	(.0056)	(.0064)	(.0139)	(.0121)	(.009)
2008	.0448***	-.0058	.0073	.0222**	.0167*	.0071
	(.0089)	(.0062)	(.0065)	(.0093)	(.0096)	(.0087)
2010	.0616***	-.0067	-6.5e-04	.0496***	.0031	-.0066
	(.0115)	(.006)	(.0057)	(.0123)	(.0082)	(.0073)
2012	.053***	.0045	-.0049	.0253**	.0211**	.0015
	(.0104)	(.007)	(.006)	(.0095)	(.0092)	(.0075)
2014	.0307***	.0081		.021**	.0281	
	(.0083)	(.0067)		(.0086)	(.0172)	
2016	.0229***			.0461***		
	(.0064)			(.0134)		
Chi-Square	209	7.51	5.71	131	20.1	8.86
Degrees of freedom	10	9	8	10	9	8
P-value	0	.58	.68	0	.02	.35

Household Clustered standard errors in parentheses
In this table we present tests for zero autocovariance of order 2,4 and 6. We provide the test statistic for the hypothesis that the respective autocovariance is zero in all time periods.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Variance of income shocks for full-time workers

	Men	Women	P-value
Variance Permanent	0.024***	0.036***	0
	(11.510)	(19.112)	
Variance Temporary	0.023***	0.008***	0
	(8.571)	(3.894)	

T-statistics in parentheses
The third column shows the test of equality across gender
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Variance of wage shocks

	Men	Women	P-value
Variance Permanent	0.013***	0.017***	0.027
	(14.227)	(13.217)	
Variance Temporary	0.026***	0.021***	0.032
	(16.464)	(12.235)	

T-statistics in parentheses
The third column shows the test of equality across gender
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Variance of income shocks incorporating employer transitions

	Men	Women	P-value
Variance Permanent	0.03***	0.052***	0
	(11.915)	(14.533)	
Variance Temporary	0.022***	0.012***	0.091
	(5.461)	(2.861)	
Variance Employer change	0.009***	0.009***	0.661
	(7.076)	(6.069)	

T-statistics in parentheses
The third column shows the test of equality across gender
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Variance of income shocks by gender and marital status

	MS	FS	MM	FM	Pv MS-FS	Pv MS-MM	Pv MS-FM	Pv FS-MM	Pv FS-FM	Pv MM-FM
Var Permanent	0.032***	0.054***	0.023***	0.044***	0.045	0.293	0.145	0	0.239	0
	(4.124)	(6.405)	(10.269)	(13.301)						
Var Temporary	0.081***	0.033***	0.034***	0.027***	0.002	0.001	0	0.921	0.525	0.217
	(6.147)	(3.815)	(9.022)	(6.419)						

T-statistics in parentheses
MS = Male Single, FS = Female Single, MM = Male Married and FM = Female Married
Columns 5 – 11 include p values of test of equality across gender and marital status
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Variance of income shocks for with and without child

	Men	Women	P-value
Variance Permanent: Child Absent	0.031***	0.043***	0.173
	(5.307)	(6.983)	
Variance Temporary: Child Absent	0.047***	0.019***	0.006
	(5.638)	(2.832)	
Variance Permanent: Child Present	0.025***	0.046***	0
	(9.883)	(13.223)	
Variance Temporary: Child Present	0.033***	0.028***	0.452
	(8.624)	(6.675)	

T-statistics in parentheses
The third column shows the test of equality across gender
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Variance of income shocks by age

	Men	Women	P-value
Variance Permanent 25-33	0.043***	0.069***	0.029
	(5.863)	(7.844)	
Variance Temporary 25-33	0.048***	0.035***	0.33
	(6.119)	(3.669)	
Variance Permanent 34-39	0.022***	0.042***	0.01
	(4.720)	(7.297)	
Variance Temporary 34-39	0.036***	0.034***	0.911
	(4.400)	(3.698)	
Variance Permanent 40-45	0.019***	0.046***	0
	(3.804)	(7.432)	
Variance Temporary 40-45	0.031***	0.023***	0.431
	(4.963)	(3.091)	
Variance Permanent 46-51	0.017***	0.033***	0.042
	(2.781)	(6.365)	
Variance Temporary 46-51	0.037***	0.019***	0.091
	(4.210)	(3.084)	
Variance Permanent 52-57	0.041***	0.037***	0.748
	(6.022)	(4.014)	
Variance Temporary 52-57	0.012*	0.021**	0.399
	(1.911)	(2.226)	

T-statistics in parentheses
The third column shows the test of equality across gender
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25: Variance of income shocks by industry

	Men	Women	P-value
Variance Permanent Agriculture	0.021***	0.045	0.484
	(2.418)	(1.430)	
Variance Temporary Agriculture	0.057***	0.031	0.467
	(4.410)	(0.950)	
Variance Permanent Manufacturing	0.022***	0.036***	0.108
	(4.687)	(4.534)	
Variance Temporary Manufacturing	0.029***	0.004	0.012
	(4.602)	(0.474)	
Variance Permanent Service	0.028***	0.046***	0
	(9.303)	(14.513)	
Variance Temporary Service	0.032***	0.03***	0.624
	(9.094)	(6.998)	

T-statistics in parentheses
The third column shows the test of equality across gender
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: Variance of income shocks by task

	Men	Women	P-value
Variance Permanent Non-Routine Cognitive	0.021***	0.048***	0
	(6.267)	(11.636)	
Variance Temporary Non-Routine Cognitive	0.035***	0.01***	0
	(6.119)	(2.494)	
Variance Permanent Non-Routine Manual	0.04***	0.045***	0.74
	(5.583)	(3.883)	
Variance Temporary Non-Routine Manual	0.023***	0.073***	0.004
	(3.489)	(4.521)	
Variance Permanent Routine	0.024***	0.04***	0.045
	(6.445)	(5.744)	
Variance Temporary Routine	0.039***	0.038***	0.978
	(7.268)	(4.824)	

T-statistics in parentheses
The third column shows the test of equality across gender
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Additional Figures

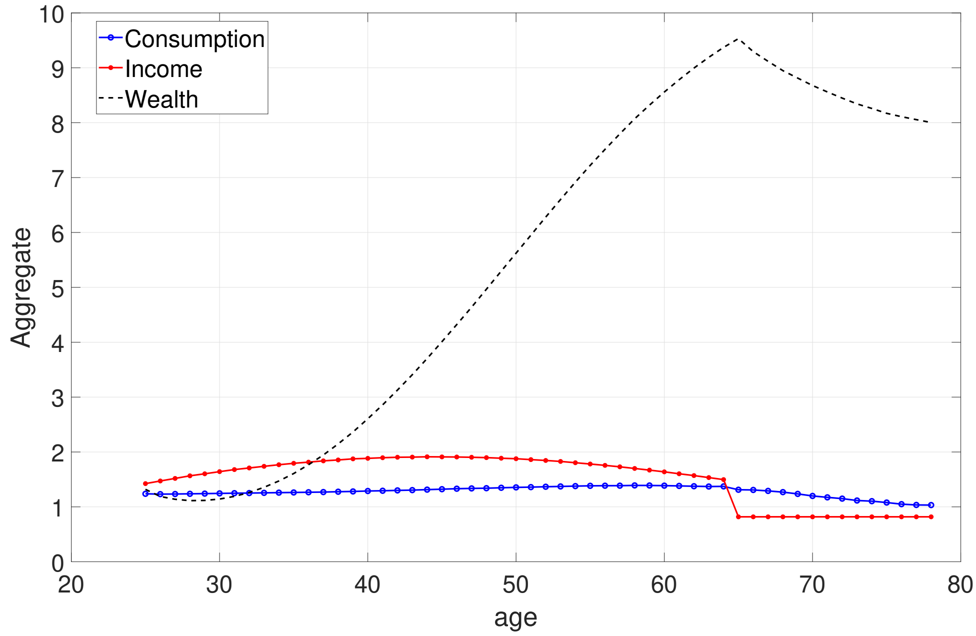


Figure 11: Lifecycle profile of aggregates

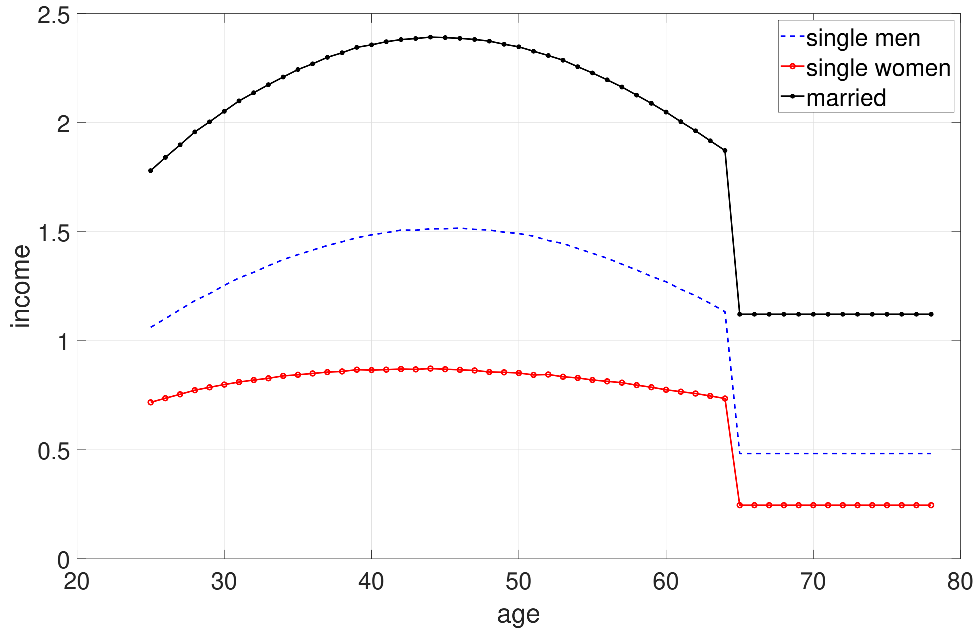


Figure 12: Differences in income profile across gender and marital status

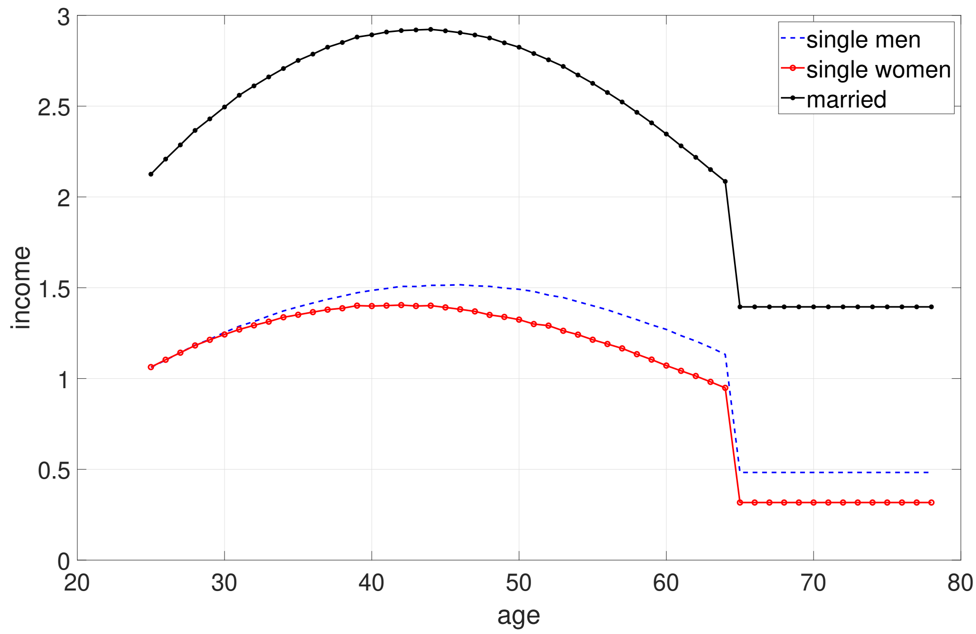


Figure 13: Income profile across gender and marital status with no gender wage gap

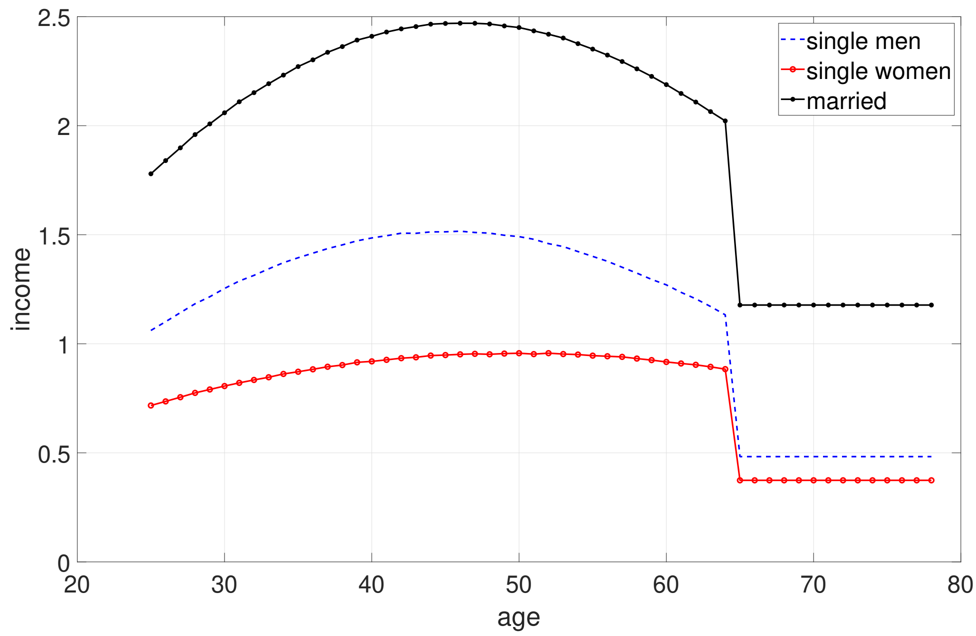


Figure 14: Income profile across gender and marital status with same income risk

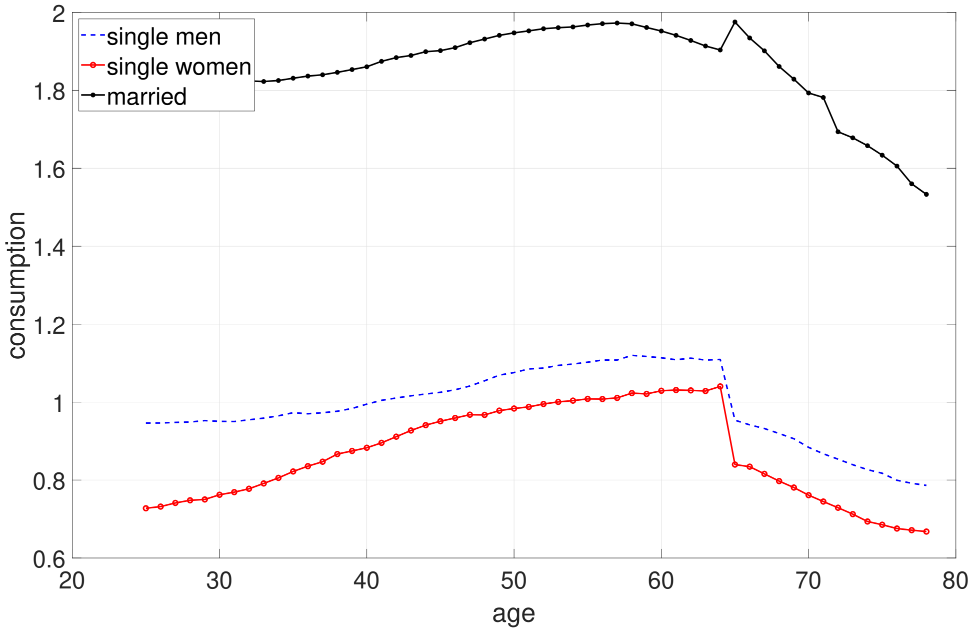


Figure 15: Consumption profile across gender and marital status with no gender wage gap