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

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February 15, 2023

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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 incomes 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 would like to thank seminar participants at Ashoka University, Asian Meeting of Econometric Society, ISI-Delhi, North American Meeting of Econometric Society and Shiv Nadar University. We thank Aaradhya Gupta and Roopal Jain for excellent research assistance. Pubali Chakraborty acknowledges financial assistance provided by the Department of Economics, Ashoka University.

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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.

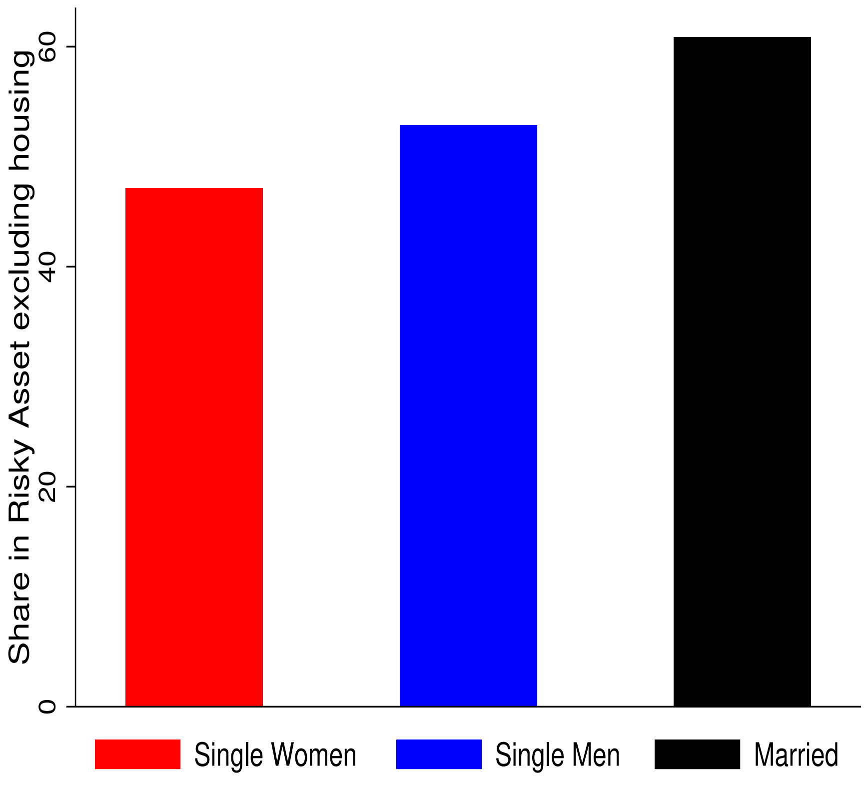


Figure 1: Share of risky asset holdings by couples, single men and single women

[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 (2021) 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; Y. 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 share holdings. The model shows income risk is a key channel as absent income risk differences by gender, single women will 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.

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 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 Risky Asset Share Definition

We consider predominantly two definitions of risky asset share: (1) the ratio of risky financial assets to total financial assets, and (2) the ratio of risky assets to total wealth excluding housing. Risky financial assets include stocks in publicly held corporations, mutual funds and investment trusts. It excludes stocks in employer-based pensions or Individual Retirement Accounts (IRAs). Safe financial 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. Total financial assets is a sum of risky and safe financial assets.

Risky assets in wealth include risky financial assets plus business net worth, net worth of real estate excluding primary residence and money in private annuities or Individual Retirement Accounts (IRAs). Non-risky assets in wealth comprises of safe financial assets. Total wealth excluding housing combines risky assets and non-risky assets in wealth as defined above.[4] The benefit of the financial asset measure is that it allows us to investigate both the intensive and extensive margin portfolio choice. Though while dealing with quantitative macro models, we usually think about total wealth rather than only financial wealth. Thus, to be more consistent with our model later, we will treat the ratio of risky assets to total wealth excluding housing as the baseline definition of "risky asset share".

2.3 Empirical Specification and Results

We define single households as the scenario where the reference individual of the household is either divorced or separated or never married.[5] To show that the ranking across the marital status and gender dimension is consistent with Figure **??** even after controlling for household characteristics, we consider the following linear model:

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

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 is the omitted category in the model. β_M

[4] We exclude residential investment while defining risky asset share in wealth since it has been shown that marital transitions and divorce have significant effect on housing choices (M. Chang, 2020) rather than income risk and insurance. But we check the robustness of our results by incorporating primary residential housing in the definition of risky assets in Section 2.4.2.

[5] 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.

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 and greater than equal to 0 and use a OLS model for most of the empirical analysis. The benefit of using OLS is the ease of interpreting the coefficients due to the large number of fixed effects. We also consider an alternate specification of a censored Tobit regression rather than dropping the negative and greater than 1 risky asset shares in our robustness checks (Section 2.4.1).

The benefit of the PSID is that we can use the panel structure to account for household-specific unobservable characteristics. We use the lagged risky asset share to control for household-specific characteristics that affect portfolio allocation between risky and safe assets in some regression specifications.[6] The lack of panel structure in the SCF does not allow us to include lagged or individual fixed effects as controls. Jianakoplos and Bernasek (1998) show that females are more risk-averse than men in the SCF and they argue that this fact can explain differences in portfolio allocations across single men and women. Gu et al. (2019) find financial knowledge an important factor in understanding gender asymmetric portfolio decisions. We use self-reported measures of risky behaviour and financial knowledge as additional controls in some regression specifications to partly account for individual traits.

The SCF asks the respondent to classify their risk taking behaviour in four 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. We include all the four categories in our analysis. SCF also asks the respondent about their knowledge on personal finance with 0 being "Not at all knowledgeable about personal finance" and 10 being "Very knowledgeable about personal finance". We create four categories as following: (1) High knowledge is defined as belonging to category 9 and 10, (2) Moderate knowledge being categories 7 and 8, (3) Limited knowledge is categories 4-6, and (4) No knowledge are those who reported categories 0-3. But, household financial knowledge is only available for the last two years of the data so we include it in only some regression 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.

Table 1 displays the main coefficients of interest using the PSID sample, β_M and β_{SM}, coefficients of some of the control variables and the p-value of the null hypothesis that $\beta_M = \beta_{SM}$. The definition of Risky asset share corresponding to total wealth excluding housing is used in this regression. Column (1) corresponds to the baseline regression specification. In column (2), we include household income and wealth squared as the change in risky asset share might not be linear in income and wealth (Fagereng, Gottlieb, & Guiso, 2017). In column (3), we include in the sample those households whose reference individual's age is between 65-70. In column (4), we use weights as provided by PSID in the regression equation whereas the baseline regression model does not use weights since the PSID is considered a nationally representative sample. In Column (5) we include lagged share of risky asset as an additional control.

We see from Column (1) that single male and married households hold 3.3 percentage points (pp) and 12.4pp higher share of risky assets than single female households. These estimates are statistically significant and the null hypothesis that the single male and married household coefficients are equal is rejected at the standard levels of significance. The mean dependent variable is 38.6% so, these coefficients imply that single males and married households have 8.5% and 32% relative increase in risky asset share compared to single female-headed household, which are sizeable differences.

These numbers reduce slightly to 2.4pp and 9.7pp in Column (2) when we include wealth and income squared but, the coefficients continue to be statistically significant from zero and each other. The results do not change much when we include older households or introduce weights in the baseline regression in Column (3) and Column (4) respectively. The coefficient of single male and married household falls a bit more when we include lagged share of risky asset. The coefficient of lagged share of risky asset is quite large and positive and so, explains a large variation of the risky asset share. But, the fall in the estimates to 1.8pp and 7.3pp is not substantial enough to alter the statistical significance of our results. Thus, singles household consistently less risky share than married households and single females invest less in risky investment than single males.

Table 1: Regression for Risky Asset Share in Total Wealth Excluding Housing in PSID

	(1)	(2)	(3)	(4)	(5)
Single Male	0.033***	0.024***	0.033***	0.030***	0.018**
	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
Married	0.124***	0.097***	0.123***	0.135***	0.073***
	(0.007)	(0.006)	(0.006)	(0.008)	(0.007)
30-34	0.061***	0.055***	0.061***	0.062***	0.016*
	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)
35-39	0.102***	0.088***	0.103***	0.105***	0.034***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.010)
40-44	0.141***	0.120***	0.142***	0.132***	0.046***
	(0.008)	(0.007)	(0.008)	(0.009)	(0.010)
45-49	0.163***	0.135***	0.165***	0.155***	0.051***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
50-54	0.192***	0.157***	0.194***	0.183***	0.079***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
55-59	0.230***	0.186***	0.231***	0.229***	0.088***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
60-64	0.234***	0.182***	0.234***	0.230***	0.091***
	(0.010)	(0.009)	(0.009)	(0.011)	(0.011)
Income (00,000)	0.020***	0.042***	0.021***	0.017***	0.005*
	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)
Wealth (00,000)	0.009***	0.023***	0.008***	0.009***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Family Size	−0.022***	−0.024***	−0.022***	−0.024***	−0.015***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of children	0.018***	0.020***	0.018***	0.020***	0.014***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Self-Employed	0.172***	0.143***	0.165***	0.173***	0.094***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Income squared		−0.001***			
		(0.000)			
Wealth squared		−0.000***			
		(0.000)			
65-70			0.227***		
			(0.011)		
Lagged Fraction Risky					0.465***
					(0.006)
Constant	0.199***	0.230***	0.179***	0.193***	0.177***
	(0.025)	(0.024)	(0.024)	(0.031)	(0.028)
Observations	35943	35943	38993	35632	24637
Single Male=Married	0	0	0	0	0

Robust Standard errors in parentheses

Includes year, state, race, education and child present fixed effects

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

Regarding other controls, the risky asset share is increasing in the age-group bins, income and wealth which is consistent with the literature (Jianakoplos and Bernasek (1998) and Wachter and Yogo (2010)). The share of risky asset increases with a fall in family size, increase in number of children and if reference individual is self-employed. We also find that the risky asset share is negatively related to income squared and wealth squared. Thus, there is some degree of diversification towards safer asset that occurs as wealth and income increase.

Table 2: Regression for Risky Asset Share in Wealth Excluding Housing in SCF

	(1)	(2)	(3)	(4)
Single Male	0.049***	0.048***	0.020**	0.022
	(0.010)	(0.010)	(0.010)	(0.020)
Married	0.121***	0.118***	0.092***	0.090***
	(0.009)	(0.009)	(0.009)	(0.018)
Income squared		−0.000**		
		(0.000)		
Wealth squared		−0.000***		
		(0.000)		
Above Average Risk			0.027**	0.052*
			(0.014)	(0.027)
Average Risk			−0.045***	0.006
			(0.013)	(0.026)
No Risk			−0.204***	−0.140***
			(0.014)	(0.028)
Moderate Knowledge				0.012
				(0.013)
Limited Knowledge				−0.042***
				(0.015)
No Knowledge				−0.128***
				(0.029)
Constant	0.145***	0.150***	0.285***	0.247***
	(0.018)	(0.018)	(0.022)	(0.045)
Observations	27483	27483	27483	6817
Single Male=Married	0	0	0	.001

Robust Standard errors in parentheses
Includes age-bins, income, wealth, family size, number of children, self-employment dummy and year, state, race, education and child present fixed effects as controls in all columns
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 shows the regression results from the SCF sample where we have used weights in all the regressions to account for the multiple imputed data structure. Single male-headed and married households hold 4.9pp and 12.1pp respectively more risky asset share than single female-headed households as shown in Column (1). Moreover, married households invest 7.2pp more in riskier assets than single males. All of these differences are highly significant. The PSID estimates are also similar to those from SCF which is quite reassuring. These magnitudes hardly change post inclusion of income squared and wealth squared in the OLS estimation. After controlling for risky attitudes that are different across gender in Column (3), single male and married households still possess higher fraction of risky investments by 2pp and 9.2pp respectively. Moreover, households with no or little risk appetite invest less in risky assets compared to households with very high risk appetite, consistent with economic intuition. The magnitudes of the key coefficients do not change much after including self-reported financial knowledge measures as displayed in Column (4). We also see that households who report no or little knowledge about personal finance hold much lower proportion of wealth in risky assets than those who report high level of financial literacy. Thus, the SCF results further strengthen the empirical patterns observed in the PSID data.

Table 3: Regression for Risky Asset Share in Financial Wealth in PSID

	(1)	(2)	(3)	(4)	(5)
Single Male	0.028***	0.023***	0.024***	0.027***	0.014***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Married	0.046***	0.030***	0.045***	0.051***	0.023***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Constant	0.132***	0.152***	0.126***	0.127***	0.083***
	(0.020)	(0.020)	(0.020)	(0.023)	(0.020)
Observations	34323	34323	37189	34041	22723
Single Male=Married	0	.081	0	0	.076

Robust Standard errors in parentheses

Includes age-bins, income, wealth, family size, number of children, self-employment dummy and year, state, race, education and child present fixed effects as controls in all columns

Compared to Column (1), Column (2) additionally includes income and wealth squared, Column (3) includes household where reference individual age is 65-70, Column (4) includes regression weights and Column (5) includes lagged risky asset share

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

Table 3 highlights the coefficients of single male and married households in the PSID sample using the risky asset share in financial wealth. We again find that married households have a significantly higher equity share than single males, and single males in turn hold a significantly higher risky portfolio than single females. The differences across the gender and marital status categories are a bit smaller in absolute terms using financial wealth than total wealth excluding housing. But in relative terms the differences are 21% and 34% for single males and married households respectively, which are a bit higher than considering estimates using net wealth.

Table 4 shows that the ranking of risky wealth share in financial wealth is preserved in the SCF too. The differences are statistically significant everywhere except between married and single males when we add both financial knowledge and risk aversion dummies. One possible reason is that financial knowledge is only available for two years so we lose a lot of observations when we include it as an explanatory variable.

Table 4: Regression for Risky Asset Share in Financial Wealth in SCF

	(1)	(2)	(3)	(4)
Single Male	0.036***	0.035***	0.018***	0.034***
	(0.007)	(0.007)	(0.007)	(0.011)
Married	0.053***	0.050***	0.037***	0.038***
	(0.006)	(0.006)	(0.005)	(0.009)
Constant	0.003	0.009	0.096***	0.110***
	(0.011)	(0.011)	(0.015)	(0.026)
Observations	27382	27382	27382	6787
Single Male=Married	.013	.026	.007	.785

Robust Standard errors in parentheses
Includes age-bins, income, wealth, family size, number of children, self-employment dummy and year, state, race, education and child present fixed effects as controls in all columns
Compared to Column (1), Column (2) additionally includes income and wealth squared, Column (3) includes risky behaviour categorical dummies and Column (4) includes dummies for financial knowledge
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The benefit of using the financial wealth definition of risky asset share is that it also allows us to look into the participation choice of investing in stocks. This helps to understand whether the observed asymmetries across demographic groups arise only from the participation decision or the risky investment share conditional on participation. Column (1) of Table 5 shows that married and single male-headed households are likely to invest 8.1pp and 2.7pp respectively more than single females. Married households on average own stocks 5.4pp more than single males, with all the differences being statistically significant. These results are quite robust to adding additional controls like income and wealth squared and lagged dummy of holding a risky asset as seen in Columns (2) and (5) respectively. While controlling for previous period stock market participation, the coefficient of single male reduces compared to the baseline regression but is

Table 5: Regression to invest in Risky Asset or not in PSID

	(1)	(2)	(3)	(4)	(5)
Single Male	0.027***	0.019***	0.022***	0.023***	0.007
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
Married	0.081***	0.054***	0.079***	0.089***	0.039***
	(0.006)	(0.005)	(0.006)	(0.007)	(0.005)
Constant	0.148***	0.170***	0.144***	0.138***	0.099***
	(0.021)	(0.021)	(0.020)	(0.022)	(0.021)
Observations	41702	41702	45001	41314	29976
Single Male=Married	0	0	0	0	0

Robust Standard errors in parentheses
Includes age-bins, income, wealth, family size, number of children, self-employment dummy and year, state, race, education and child present fixed effects as controls in all columns
Compared to Column (1), Column (2) additionally includes income and wealth squared, Column (3) includes household where reference individual age is 65-70, Column (4) includes regression weights and Column (5) includes lagged investing in risky asset or not dummy
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

significant at 15% level of significance. Table 16 in the Appendix shows the same asymmetry in the extensive margin of risky asset as in the PSID with the estimates being a bit higher than the PSID. This is not surprising since the SCF oversamples richer households who are more likely to acquire risky assets.

The panel structure of the PSID also enables us to study entry and exit of households from the stock market. This will serve to better highlight the extent of asymmetries in portfolio allocations across the various household groups. Entry into the stock market is defined as stock market investment in the current period but not in the previous period. Exit from the stock market is defined as household investing in the stock market in the previous period but not in the current period.

Married households enter the risky asset market by 2.6pp more than single females and exit it by 10pp less, as seen in Table 6. This is true for married households with regards to single males as well and the differences are statistically significant. Thus, married households are more likely to buy a risky asset and continue to hold it for longer than single female-headed and male-headed households. Single male-headed households are equally likely to purchase a risky asset but are 5pp less likely to relinquish it than single female-headed households. Thus, the gender asymmetry in stock market participation that we saw in Table 5 can be explained by single males continuing to participate in the stock market for longer duration than single females.

Table 6: Regression for Exit and Entry in Risky Asset Investment

	(1) Entry	(2) Exit
Single Male	0.000	-0.050^{*}
	(0.004)	(0.027)
Married	0.026^{***}	-0.100^{***}
	(0.006)	(0.025)
Constant	0.082^{***}	0.310^{***}
	(0.019)	(0.087)
Observations	23996	5980
Single Male=Married	0	.035

Robust Standard errors in parentheses
Includes age-bins, income, wealth, family size, number of children, self-employment dummy and year, state, race, education and child present fixed effects as controls in all columns
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.4 Robustness Checks

In this subsection, we discuss how sensitive our results to an alternate empirical specification and alternate measurement of risky asset share.

2.4.1 Censored Tobit Regression

In the baseline regression specification, we assume that all risky shares have to be greater than equal to zero and less than equal to one. We consider another empirical specification which accounts for such two-sided censoring. The empirical model is as follows:

$$RS_{it}^{*} = \alpha + \beta_M M_{it} + \beta_{SM} SM_{it} + \beta_X X_{it} + u_{it} \tag{2}$$

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

$$RS_{it} = \begin{cases} 1, \text{ if } RS_{it}^{*} \geq 1 \\ RS_{it}^{*}, \text{ if } 0 < RS_{it}^{*} < 1 \\ 0, \text{ if } RS_{it}^{*} \leq 0 \end{cases} \tag{3}$$

Table 7 shows the results from the two-sided censored Tobit regression for both the definitions of the risky portfolio share using the PSID data. Single male-headed and married households own 14.8pp and 30.2pp respectively higher fraction of risky asset share in financial

Table 7: Tobit Regression for investment in Risky Assets in PSID

	(1) Financial Wealth	(2) Total Wealth excluding housing
Single Male	0.148^{***}	0.073^{***}
	(0.022)	(0.015)
Married	0.302^{***}	0.286^{***}
	(0.022)	(0.015)
Constant	-0.833^{***}	-0.289^{***}
	(0.078)	(0.051)
Observations	34323	36002
Single Male=Married	0	0

Robust Standard errors in parentheses
Includes age-bins, income, wealth, family size, number of children, self-employment dummy and year, state, race, education and child present fixed effects as controls in all columns
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

wealth than single females. The estimate for single males and married households is 7.3pp and 28.6pp respectively for risky asset share in total wealth excluding housing. Moreover, in each of the case married households also hold significantly more risky portfolio than single males.[7] Thus, the empirical facts that we have highlighted are robust to the treatment of the negative and greater than unity values of risky asset shares.

2.4.2 Alternate Definitions of Risky Asset

Risky asset share in total wealth excluding housing includes stocks, net business worth, IRA and non-primary residential investment as risky assets. Housing is a risky investment that constitutes a large share of wealth for most households even if they only periodically invest in housing. We consider an alternate definition of risky asset share with housing. Moreover, one can argue that individuals do not face the same risk from equity investment in IRA's versus those unrelated to the pension system. To address this concern, we consider another definition of risky asset share where we exclude IRA's from risky assets and instead label them as safe assets.

The first column of Table 8 shows the risky asset share in total wealth excluding housing which is the same as the first column in Table 1. Single males hold a higher risky asset share by 1.2pp than single females when we consider housing as a risky asset. This estimate is much smaller than the baseline estimate but still significantly different from zero. This is not the case

[7] Our results are robust to only left or right side censoring as well.

for married households. The difference between married and singles becomes much more stark when housing is included as married households are far more likely to own a house than single households (M. Chang, 2020). When we include IRA's as a non-risky asset, single males and married households own 4.7pp and 6.9pp respectively, larger fraction of risky portfolio compared to single females. For both the definition, it continues to be the case that married households possess significantly larger fraction of risky assets than single males. Very similar estimates are obtained from the SCF data too as shown in Table 17 in the Appendix. Thus, the ranking over gender and marital status groups is preserved across various definitions of risky asset shares.

Table 8: Regression for investing in Risky Assets with Alternative Definitions in PSID

	(1) Excluding Housing	(2) With Housing	(3) IRA Safe
Single Male	0.033***	0.012*	0.047***
	(0.006)	(0.007)	(0.005)
Married	0.124***	0.156***	0.069***
	(0.007)	(0.007)	(0.005)
Constant	0.199***	0.366***	0.141***
	(0.025)	(0.021)	(0.021)
Observations	35943	37723	35964
Single Male=Married	0	0	0

Robust Standard errors in parentheses
Includes age-bins, income, wealth, family size, number of children, self-employment dummy and year, state, race, education and child present fixed effects as controls in all columns
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.5 Role of Multiple Earners in Portfolio Allocations

One of the hypothesis we propose to explain the marital status asymmetries is that the presence of multiple earners in a household provides insurance against income risk and facilitates greater risk appetite of married households. To provide some suggestive evidence along this direction, we consider the risky asset shares for married households where both spouses are working versus one spouse versus none are working. PSID asks each spouse about their current employment status on their main job in the survey but information on income and wealth is for the previous year. We construct two measures of working status due to this timing discrepancy: (1) use the lagged employment status, and (2) consider as not working if annual hours worked in the

Table 9: Regression for Risky Asset Share in total wealth among married working types

	(1) Work status	(2) Work status	(3) Hours	(4) Hours
Both working Lag	0.092***	0.055***		
	(0.016)	(0.014)		
One working Lag	0.042***	0.029**		
	(0.016)	(0.015)		
Both working Today			0.077***	0.054***
			(0.019)	(0.018)
One working Today			0.027	0.024
			(0.020)	(0.018)
Fraction Risky Lag		0.459***		0.459***
		(0.008)		(0.008)
Constant	0.307***	0.223***	0.262***	0.222***
	(0.039)	(0.038)	(0.037)	(0.039)
Observations	18287	17218	22889	17243
One Working=Both Working	0	0	0	0

Robust Standard errors in parentheses
Includes age-bins, income, wealth, family size, number of children, self-employment dummy and year, state, race, education and child present fixed effects as controls in all columns
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

previous period is less than 20 hours.[8] We do not make a distinction between unemployed and out of the labour force in these regressions as there are insufficient observations in these categories for inference.

Table 9 shows the coefficient of both spouses, one spouse and neither working in an OLS regression for married households with the risky asset share in total wealth without housing as the dependent variable. The first two columns consider the lagged employment status to compute working status, whereas the last two columns regard an hours-based measure of employment status. Lagged risky portfolio fraction is included in the regression specification in the second and fourth columns to account for the household-specific properties. Risky asset share is 9.2pp and 4.2pp higher when both spouses and one spouse is working relative to neither working. This implies that the risky asset share of both working spouses is 5pp larger than when one is working. All of the differences are statistically significant at the standard levels of significance. Moreover, these estimates become a bit smaller when we include lagged risky asset share as an additional control, but all of the differences continue to be sizeable and highly significant. Households where both members are working display a higher share of risky investments than

[8]Our estimates change very little if we define the hours measure using 100 or zero hours.

both and none working even while considering the hours cutoff measure. The key takeaway from this exercise is that risky asset shares vary with the number of working households within married families, thus, indicating that within-household insurance can explain heterogeneity in risky portfolios among married and non-married households.

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 et al. (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

$$\psi' = (R' - 1)s' + R_f f' \tag{4}$$

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

$$y_{g,j} = \max\{\exp(\alpha_{1,g} + \alpha_{2,g} j + \alpha_{3,g} j^2 + z_{g,j} + \varepsilon_{g,j}), \underline{y}\} \tag{5}$$

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

$$z' = z + \eta' \tag{6}$$

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.[9] Further, we assume that there exists a gender income gap that arises through the time 0 permanent income level such that $\exp(z_{m,0}) < \exp(z_{m,0})$. 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

$$V_g(j, z, \varepsilon, s, \psi) = \max_{c, s', f'} \left\{ c^\gamma + \beta \mathbb{E}_{z', \varepsilon', R'} \left[V_g\left(j+1, z', \varepsilon', s', \psi'\right)^\alpha \right]^{\frac{\gamma}{\alpha}} \right\}^{\frac{1}{\gamma}} \tag{7}$$

subject to

$$c + d + f' \leq y_{g,j}(z, \varepsilon)^{1-\tau}(1 - h(j)) + \psi - \mathbb{1}_{s \neq s'} \phi \tag{8}$$

$$\psi' = (R' - 1)s' + R_f f' \tag{9}$$

$$s' = s + d; \quad c, s', f' \geq 0; \tag{10}$$

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 (5), 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.

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

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

$$V_g(j, z_J, 0, s, \psi) = \max_{c,s',f'} \{c^\gamma + \beta \mathbb{1}_{j<J+J_R} \mathbb{E}_{R'} \left[V_g\left(j+1, z_J, 0, s', \psi'\right)^\alpha\right]^{\frac{\gamma}{\alpha}} + \beta \mathbb{1}_{j=J+J_R} \mathbb{E}_{R'} \left[B(\psi' + s')^\alpha\right]^{\frac{\gamma}{\alpha}} \Big\}^{\frac{1}{\gamma}} \tag{11}$$

subject to

$$c + d + f' \leq b(z_J)^{1-\tau}(1 - h(j)) + \psi - \mathbb{1}_{s \neq s'} \phi \tag{12}$$

$$\psi' = (R' - 1)s' + R_f f' \tag{13}$$

$$B(x) = L\left(\Phi + x\right) \tag{14}$$

$$s' = s + d; \qquad c, s', f' \geq 0 \tag{15}$$

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

$$V(j, z_m, z_f, \varepsilon_m, \varepsilon_f, s, \psi) = \max_{c,s',f'} \left\{ \left(\frac{c}{1+\chi} \right)^{\gamma} + \beta \mathbb{E}_{z'_m, \varepsilon'_m, z'_f, \varepsilon'_f, R'} \left[V\left(j+1, z'_m, z'_f, \varepsilon'_m, \varepsilon'_f, s', \psi'\right)^{\alpha} \right]^{\frac{\gamma}{\alpha}} \right\}^{\frac{1}{\gamma}} \tag{16}$$

subject to

$$c + d + f' \leq \{y_m(z_m, \varepsilon_m) + y_f(z_f, \varepsilon_f)\}^{1-\tau} (1 - h(j)) + \psi - \mathbb{1}_{s \neq s'} \phi \tag{17}$$

$$\psi' = (R' - 1)s' + R_f f' \tag{18}$$

$$s' = s + d; \quad c, s', f' \geq 0; \tag{19}$$

where χ denotes the consumption equivalence scale.

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

$$\begin{aligned} V(j, z_{m,J}, z_{f,J}, 0, 0, s, \psi) = \max_{c,s',f'} \Bigg\{ \left(\frac{c}{1+\chi} \right)^{\gamma} & + \beta \mathbb{1}_{j < J+J_R} \mathbb{E}_{R'} \left[V\left(j+1, z_{m,J}, z_{f,J}, 0, 0, s', \psi'\right)^{\alpha} \right]^{\frac{\gamma}{\alpha}} \\ & + \beta \mathbb{1}_{j = J+J_R} \mathbb{E}_{R'} \left[B(\psi' + s')^{\alpha} \right]^{\frac{\gamma}{\alpha}} \Bigg\}^{\frac{1}{\gamma}} \end{aligned} \tag{20}$$

subject to

$$c + d + f' \leq \{b(z_{m,J}) + b(z_{f,J})\}^{1-\tau} (1 - h(j)) + \psi - \mathbb{1}_{s \neq s'} \phi \tag{21}$$

$$\psi' = (R' - 1)s' + R_f f' \tag{22}$$

$$B(x) = L\left(\Phi + x\right) \tag{23}$$

$$s' = s + d; \quad c, s', f' \geq 0; \tag{24}$$

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:

$$\varepsilon_{i,g,t} \sim \text{iid } N\left(0, \sigma^2_{\varepsilon,g}\right), \; \eta_{i,g,t} \sim \text{iid } N\left(0, \sigma^2_{\eta,g}\right) \tag{25}$$

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[10]. 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:

$$\begin{bmatrix} \varepsilon_{i,m,t} \\ \varepsilon_{i,f,t} \end{bmatrix} \sim \text{iid } N \left(0, \begin{bmatrix} \sigma^2_{\varepsilon,m} & \sigma_{\varepsilon,mf} \\ \sigma_{\varepsilon,mf} & \sigma^2_{\varepsilon,f} \end{bmatrix} \right) \tag{26}$$

$$\begin{bmatrix} \eta_{i,m,t} \\ \eta_{i,f,t} \end{bmatrix} \sim \text{iid } N \left(0, \begin{bmatrix} \sigma^2_{\eta,m} & \sigma_{\eta,mf} \\ \sigma_{\eta,mf} & \sigma^2_{\eta,f} \end{bmatrix} \right) \tag{27}$$

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 correlation 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 5 and 6 can be written as:

$$\ln y_{i,g,t} = \alpha^0_g + \alpha^1_g * t + \alpha^2_g * t^2 + \varepsilon_{i,g,t} + z_{i,g,t} \tag{28}$$

$$\Delta \ln y_{i,g,t} = \chi_g + \varepsilon_{i,g,t} + \varepsilon_{i,g,t-1} + \eta_{i,g,t} \tag{29}$$

where $\chi_g = \alpha^1 + \alpha^2_g * (2t + 1)$. 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 30. On the other hand, permanent income shock only shows

[10] 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.

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.

$$\text{Cov}\left(\Delta \ln y_{i,g,t}, \Delta \ln y_{i,g,t+1}\right) = -\sigma^2_{\varepsilon,g} \tag{30}$$

$$\text{Cov}\left(\Delta \ln y_{i,g,t}, \Delta \ln y_{i,g,t} + \Delta \ln y_{i,g,t-1} + \Delta \ln y_{i,g,t+1}\right) = \sigma^2_{\eta,g} \tag{31}$$

The identification of the covariance parameters for husband and wife depend on the cross income growth and follows a similar intuition as above. Equation 32 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 33). In this case, clearly there exist overidentifying equations.

$$\text{Cov}\left(\Delta \ln y_{i,m,t}, \Delta \ln y_{i,f,t+1}\right) = -\sigma_{\varepsilon,mf} \tag{32}$$

$$\text{Cov}\left(\Delta \ln y_{i,m,t}, \Delta \ln y_{i,f,t} + \Delta \ln y_{i,f,t-1} + \Delta \ln y_{i,f,t+1}\right) = \sigma_{\eta,mf} \tag{33}$$

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^0, α^1, and α^2 as described above in the income process equation. Table 10 displays the estimated coefficients. We normalize the constant (α^0) 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^1, α^2) 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.

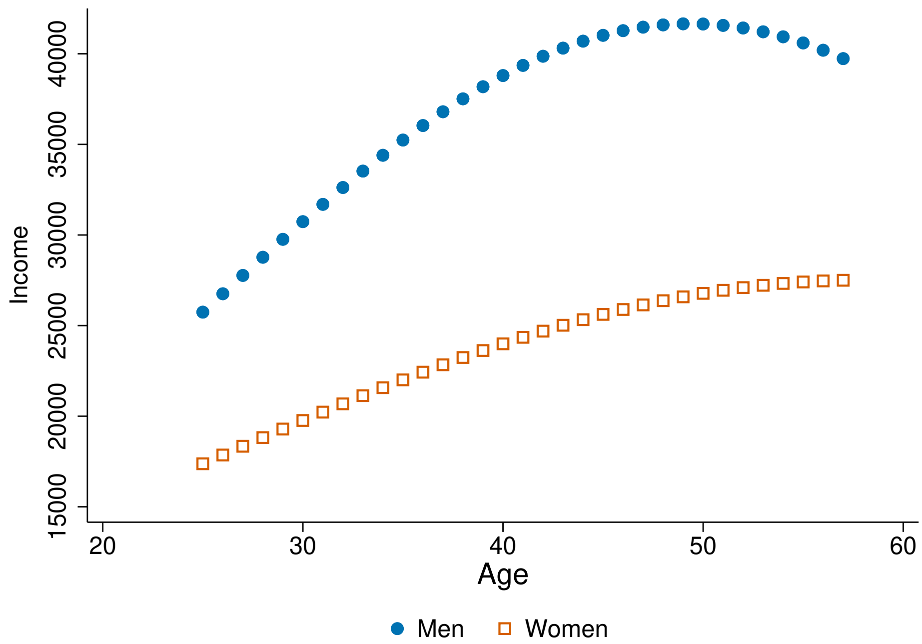


Figure 2: Income profiles by gender

The income risk parameters are presented in Table 10. The variance of permanent shock for men and women are 0.026 and 0.047 respectively. Permanent income variance for women is 81% higher than men and this gap is statistically significant. On the other hand, the transitory shock variance is 0.032 and 0.028 for males and females respectively. This difference is not statistically significant. Blundell et al. (2016) find that women have a higher permanent wage shock than men but the difference is much smaller. The deviation in results can be attributed to two reason: (1) they focus on wage rather than income, and (2) they only consider married households in their estimation unlike ours where single male- and female-headed households are also included. 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 10: Income Process Parameters

	Male	Female	P-value
Constant (α^0)	0	-0.38098	
Age (α^1)	0.041	0.029	
Age Squared (α^2)	-0.00081	-0.00042	
Variance Permanent	0.026***	0.047***	0
	(21.61)	(24.90)	
Variance Temporary	0.032***	0.028***	0.203
	(14.69)	(10.55)	
Covariance Permanent	0		
	(0.37)		
Covariance Temporary	0.002		
	(1.35)		

T-statistics in parentheses
The third colum shows the test of equality between the variances of males and females
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 11 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 $\chi = 0.7$ 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:

$$B(\psi' + s') = \left[L(\Phi + \psi' + s')\right] \tag{34}$$

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

Table 11: 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

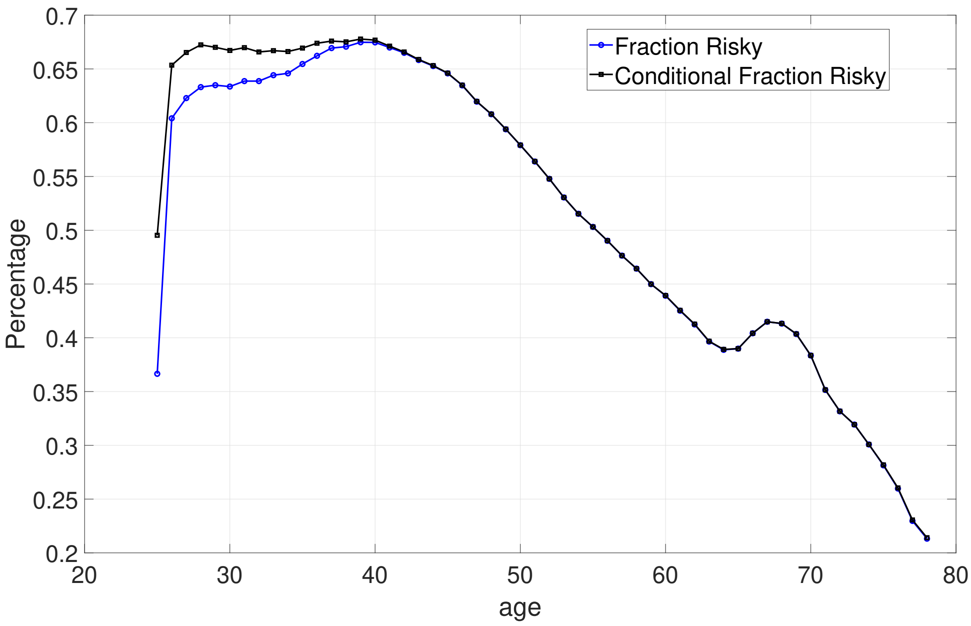
5.1 Aggregates

Table 12 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 12: 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.



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

5.2 Differences across gender and marital status

Table 13 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 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 13: 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.

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.

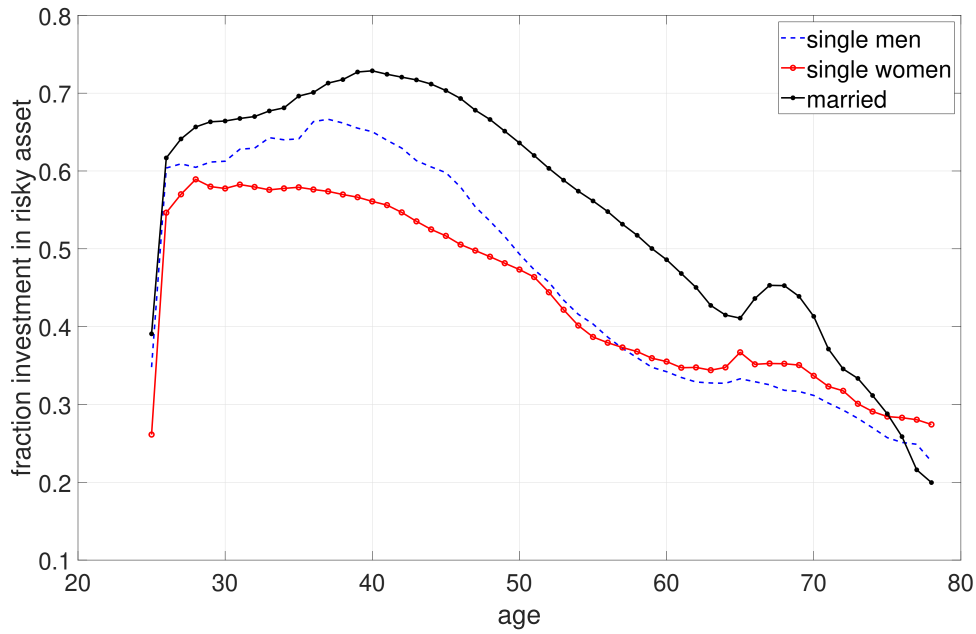


Figure 4: Risky asset share profile of single men, women, and couples

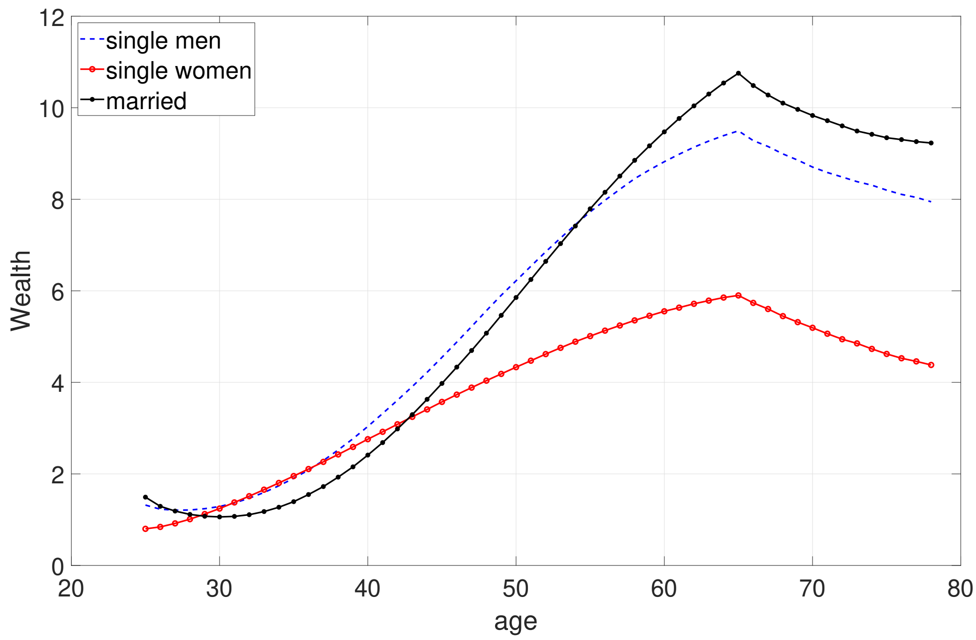


Figure 5: Wealth profile of single men, women, and couples

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.

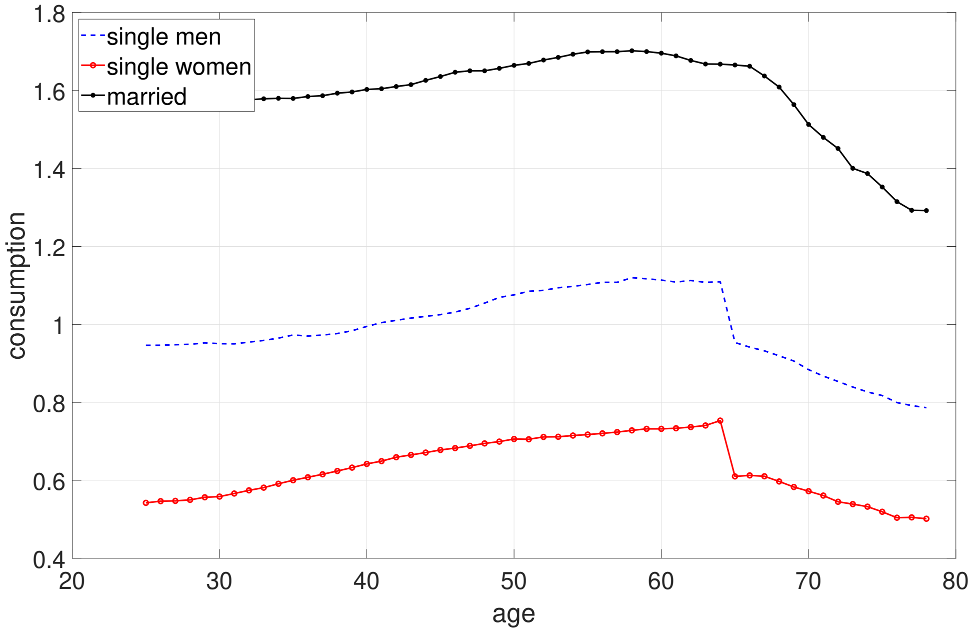
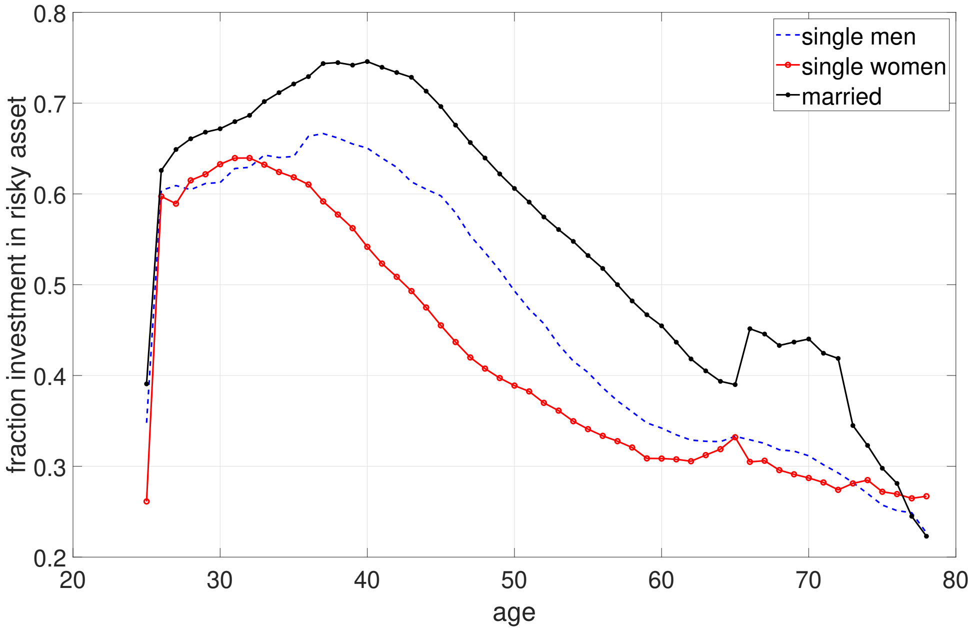


Figure 6: Consumption profile of single men, women, and couples

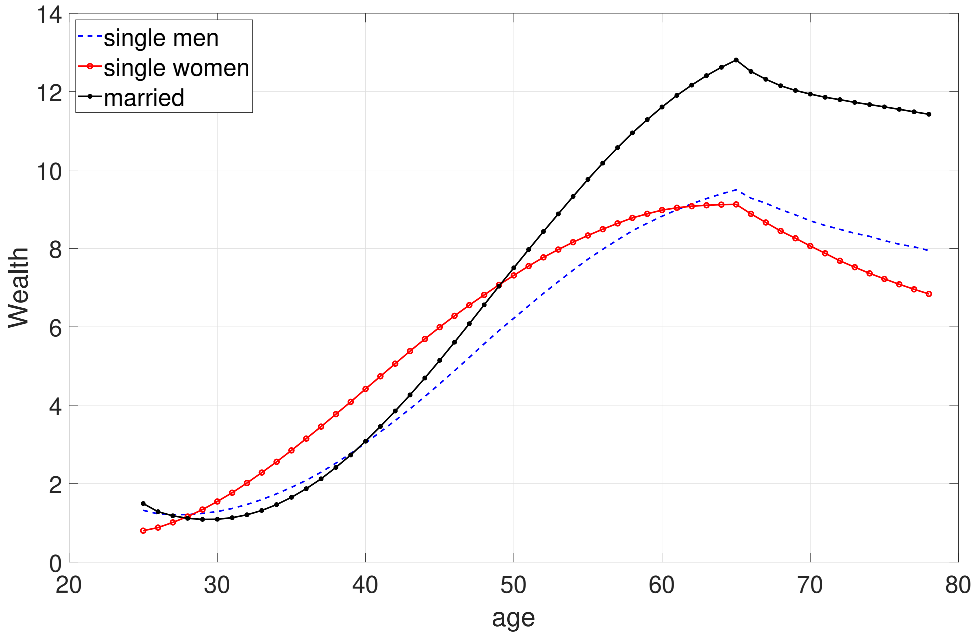
So far, we have shown that quantitatively the differences in risky portfolio shares across households are similar in magnitude to our empirical estimates, even though the risk preferences across households have been assumed to be the same, unlike (Neelakantan & Chang, 2010). Our next step involves quantifying 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 14 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

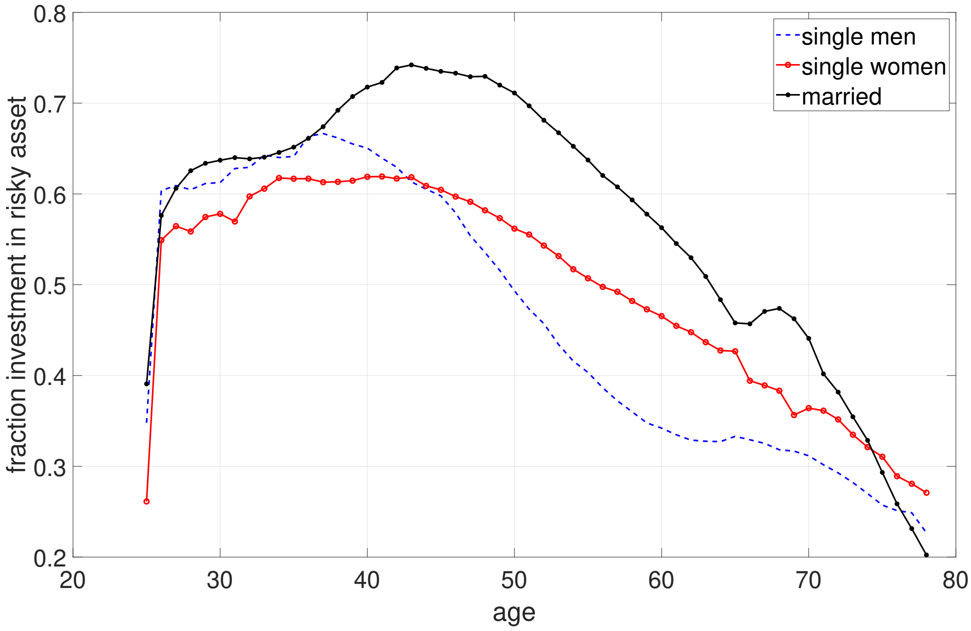
Figure 14 in the Appendix shows the income profiles when men and women experience the same variance in permanent income [11]; however, the gender wage gap remains. Figures 8a and 8b illustrate the risky portfolio shares and wealth accumulation across households in this environment, respectively.

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 **??**, 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.

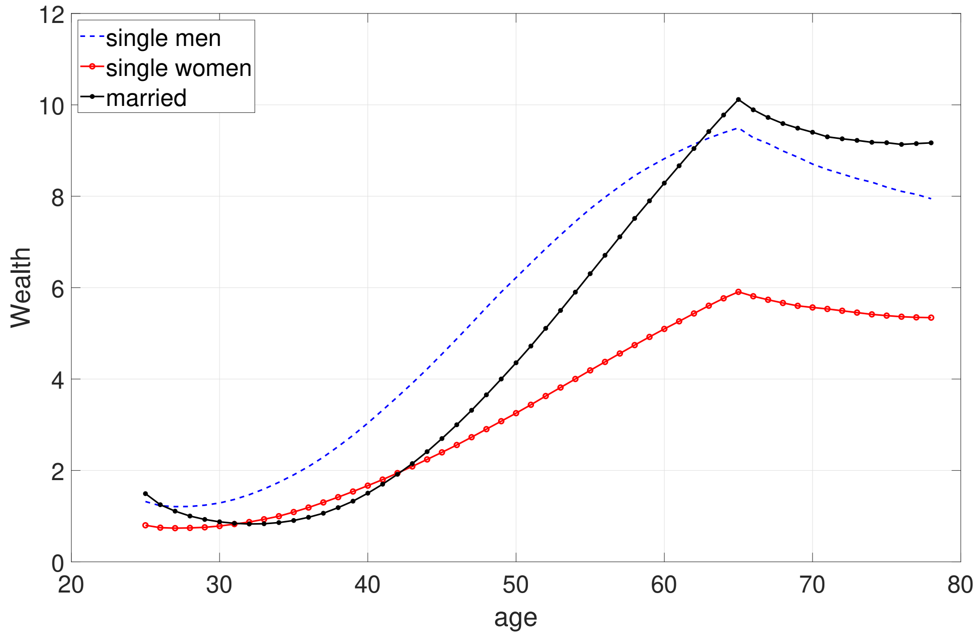
5.5 Other Mechanisms

Table 14 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

[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

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

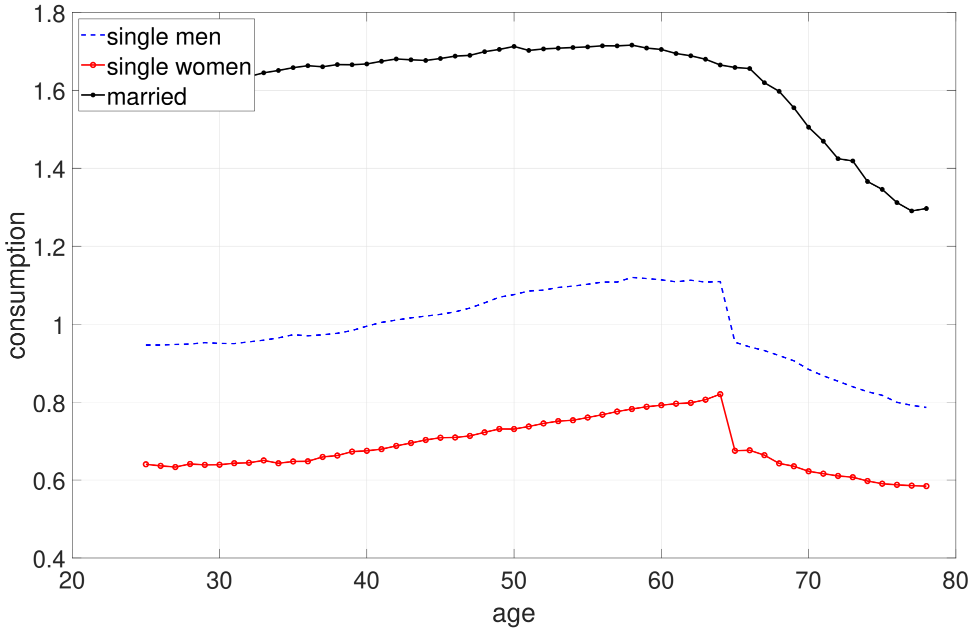


Figure 9: Consumption across gender and marital status without asymmetric income risk

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 14: 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 9 before.

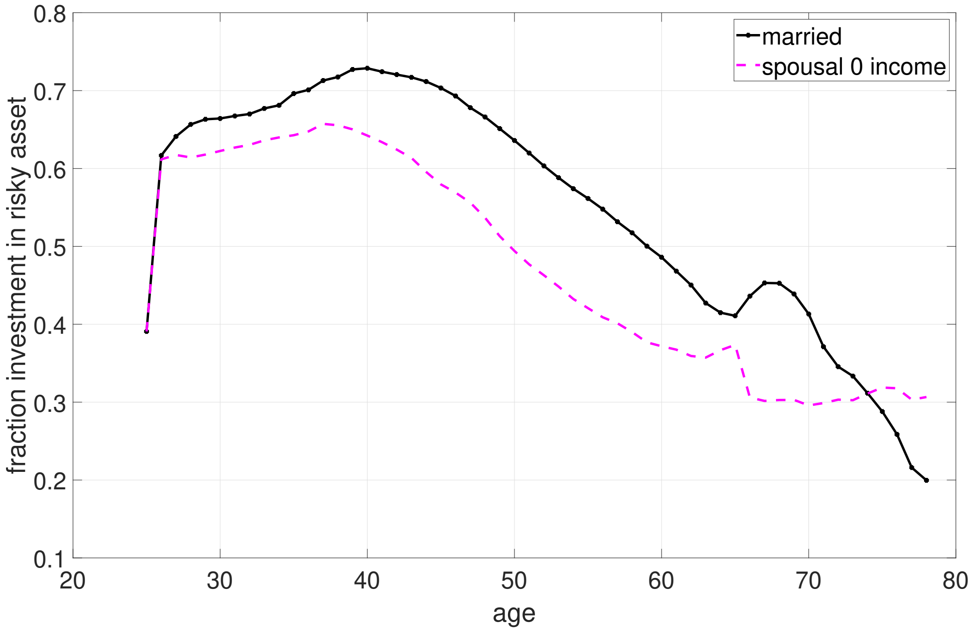


Figure 10: Risky asset share for single-earner versus dual-earner couples

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 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.

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Appendix

A Empirical Evidence

Table 15: Descriptive Statistics: PSID and SCF

	PSID	SCF
Single Women	.207	.203
Single Men	.198	.134
Married	.595	.663
Never Married Women	.0774	.0775
Separated Women	.129	.125
Never Married Men	.106	.069
Separated Men	.0917	.0651
High School dropout	.0954	.0796
High School Graduate	.256	.217
Attended College at least	.649	.703
White	.865	.727
Black	.0957	.126
Other races	.0396	.147
Homeowner	.661	.703
Income	83418	96847
Wealth	285943	370602
Wealth excluding Housing	155029	379640
Participation in risky asset without housing	.521	.752
Share in risky asset without housing	.386	.57
Conditional Share in risky asset without housing	.741	.758
Observations	46421	27489

Table 16: Regression to invest in Risky Asset or not in SCF

	(1)	(2)	(3)	(4)
Single Male	0.057***	0.055***	0.026***	0.048***
	(0.010)	(0.010)	(0.009)	(0.017)
Married	0.124***	0.119***	0.094***	0.086***
	(0.008)	(0.008)	(0.008)	(0.014)
Constant	0.012	0.020	0.162***	0.181***
	(0.016)	(0.016)	(0.022)	(0.038)
Observations	28846	28846	28846	7103
Single Male=Married	0	0	0	.045

Robust Standard errors in parentheses
Includes age-bins, income, wealth, family size, number of children, self-employment dummy and year, state, race, education and child present fixed effects as controls in all columns
Compared to Column (1), Column (2) additionally includes income and wealth squared, Column (3) includes risky behaviour categorical dummies and Column (4) includes dummies for financial knowledge
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Regression for investing in Risky Assets with Alternative Definitions in SCF

	(1) Without Housing	(2) With Housing	(3) IRA Safe
Single Male	0.050***	0.029***	0.051***
	(0.010)	(0.009)	(0.007)
Married	0.122***	0.098***	0.076***
	(0.009)	(0.008)	(0.006)
Constant	0.145***	0.379***	0.048***
	(0.018)	(0.017)	(0.013)
Observations	27186	27186	27186
Single Male=Married	0	0	.003

Robust Standard errors in parentheses
Includes age-bins, income, wealth, family size, number of children, self-employment dummy and year, state, race, education and child present fixed effects as controls in all columns
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

B Additional Figures

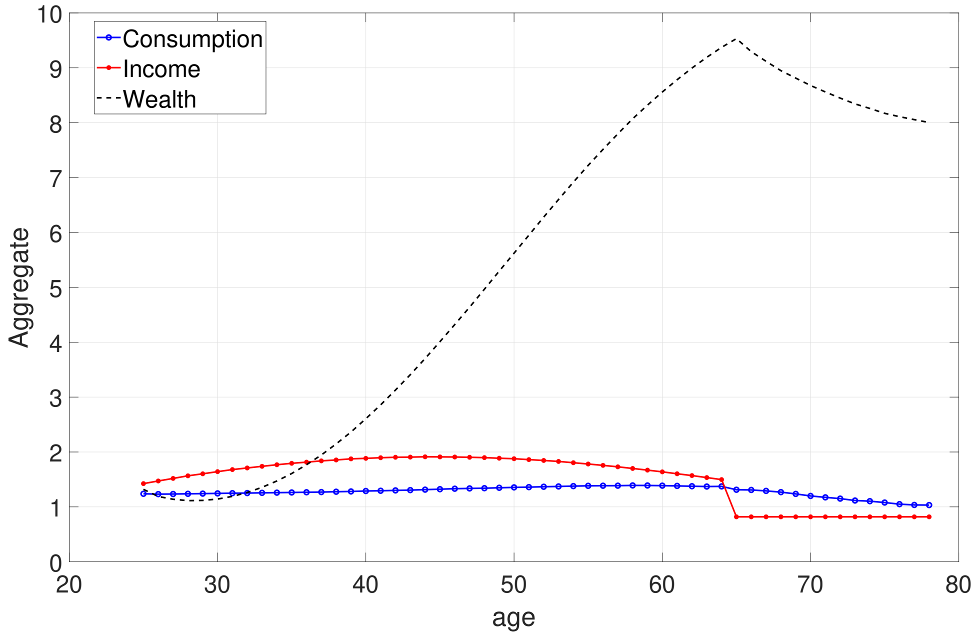

Figure 11: Lifecycle profile of aggregates

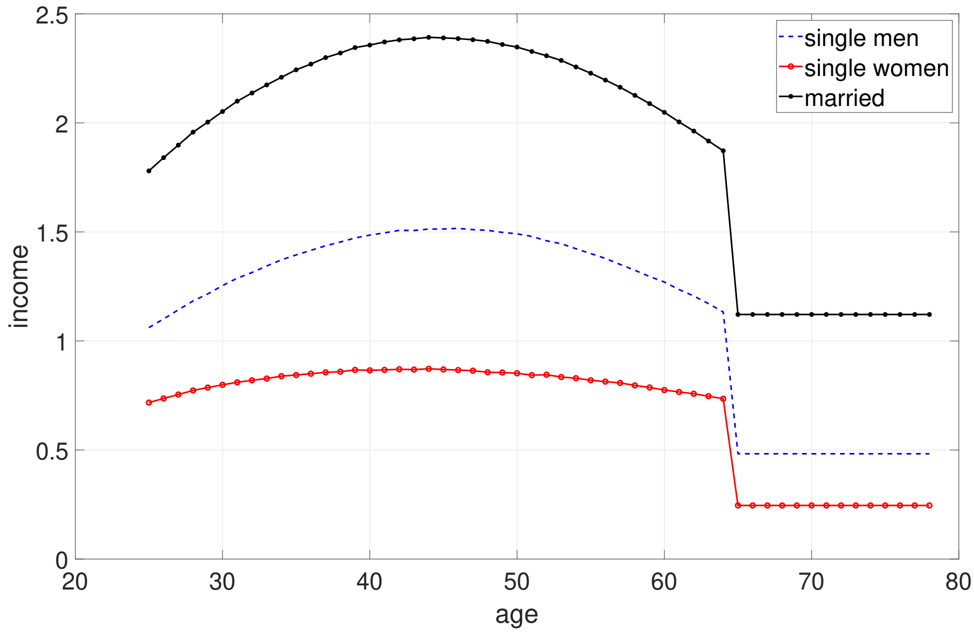

Figure 12: Differences in income profile across gender and marital status

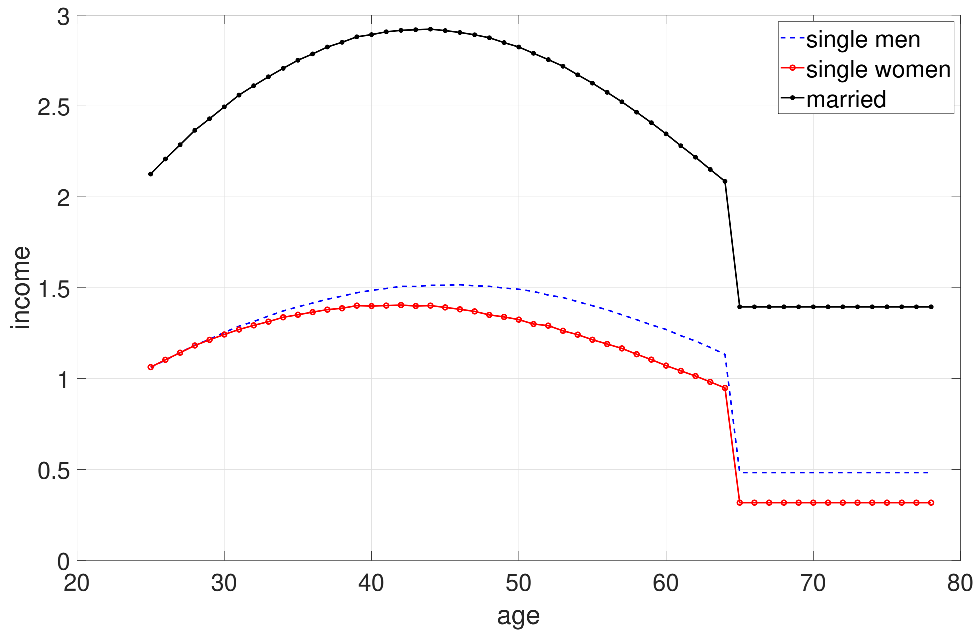

Figure 13: Income profile across gender and marital status with no gender wage gap

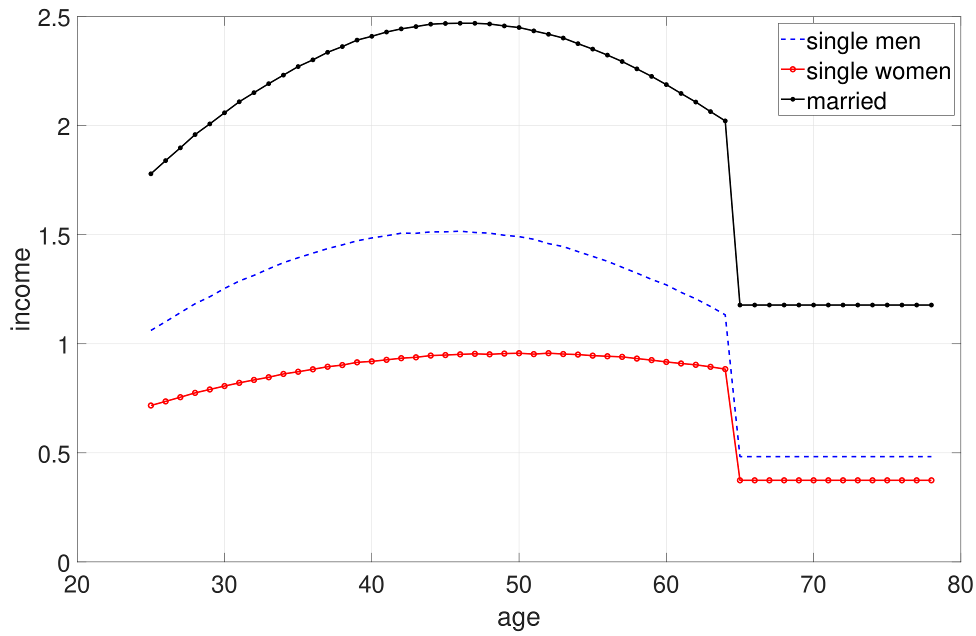

Figure 14: Income profile across gender and marital status with same income risk

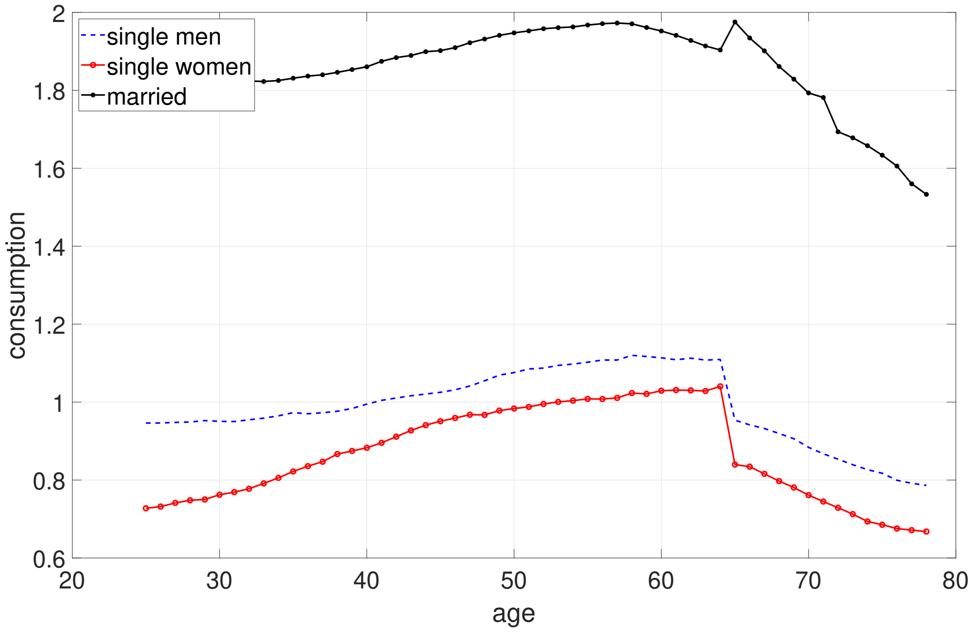

Figure 15: Consumption profile across gender and marital status with no gender wage gap