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

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September 15, 2022

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Abstract

This paper examines the source of gender and marital status differences in portfolio choices across US 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 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 (i) women face a higher individual income risk relative to men, and (ii) two-earner married households hold a higher fraction in risky assets than single-earner married households, indicating a role for spousal insurance. To quantitatively investigate the importance of these channels, we develop a two-asset incomplete market life-cycle model with heterogeneous agents. Preliminary results show that both the gender wage gap and the higher income risk faced by women play an important role towards explaining the differences in risky investment across households.

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1 Introduction

It is well documented that men and women exhibit differences in terms of their financial decisions (Huang & Kisgen, 2013; Hardies, Breesch, & Branson, 2013; Neelakantan, 2010; Sunden & Surette, 1998). Further, large wealth differences exist between married, single male and single female households (Schmidt & Sevak, 2006; Borella, De Nardi, & Yang, 2018). This paper explores the asymmetry in risky portfolio decisions over gender as well as marital status. We find empirical evidence that single households[1] invest a lower fraction of their wealth in risky assets, as compared to married households. Further, among single households, women undertake less risky investments relative to men. We investigate whether these differences in portfolio choices can be explained by the differential income risk that men and women face over their lifetime as opposed to differences in risk preferences. Further, we assess the role of spousal insurance in impacting risk-taking behavior for married households relative to single households.

Portfolio choices directly impact wealth. Since risky investments are usually associated with higher returns on average, difference in risk-taking behavior can translate into persistent wealth gaps across households. Schmidt and Sevak (2006) find evidence that at all points of the wealth distribution, the net worth of married households is significantly higher than single households [2], and among single households, the net worth was higher for men relative to women. Similarly Borella et al. (2018) find evidence that the gap in average assets held by single female, single male, and married households increases over the life-cycle.

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. Wealth is an important indicator of household well-being. As discussed by Wolff (1998), wealth provides direct financial income, and can be converted to cash or liquidity to fulfill consumption needs even in the absence of income. Further, family wealth directly impacts access to education (F. T. Pfeffer, 2018), which subsequently leads to persistent gaps in lifetime earnings, and further wealth accumulation (Bartscher, Kuhn, & Schularick, 2020). Bartscher, Kuhn, Schularick, and Wachtel (2021) and Benhabib, Bisin, and Zhu (2011) discuss the role of wealth in the transmission of fiscal and monetary policy. This motivates us to investigate the extent and sources of risky portfolio holdings along the gender

[1] Our definition of single includes household heads who have never been married, are divorced, separated or are widowed.

[2] In 2001, the average net worth of married households on average was $\$262,929$, single male households was $\$119,861$ and that for female households was $\$112,547$.

and marital status dimension.

In this paper, we use the Panel Study of Income Dynamics (PSID) and the Survey of Consumer Finances (SCF) to study the investment decisions made by single male, single female, and married households. We use two alternative definitions of risky assets, as elaborated further in Section 2.2. In the first, we restrict our attention to financial wealth, wherein risky assets include only stocks. In the second, we look at total wealth (except housing), and risky assets include stocks, business net worth, net worth of real estate excluding primary residence and Individual Retirement Accounts (IRAs).

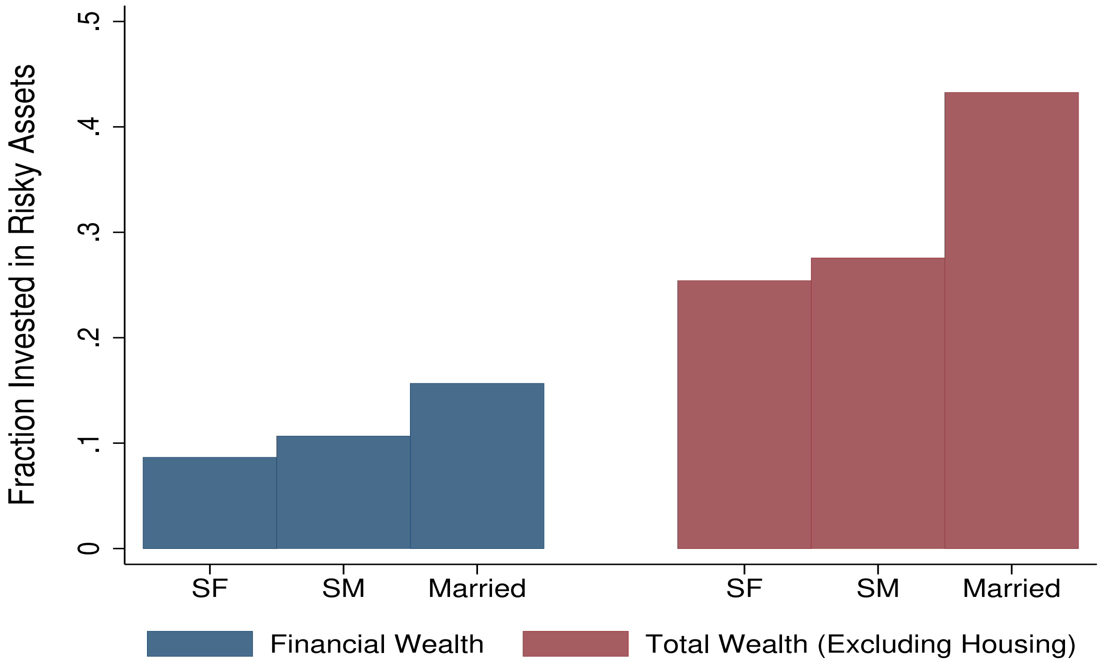


Figure 1: Risky Asset Share in PSID

Figure 1 shows the average risky share in wealth for married, single male and single female households using the two definitions in the PSID. The blue and red bars correspond to the risky asset share definition using financial assets and total wealth excluding housing respectively. “SF” and “SM” denotes single female-headed and male-headed household respectively. The figure highlights that married households hold a riskier portfolio than single males who in turn hold more than single females. Single males invest 38% and 4% more than single females in the risky asset share in financial wealth and net wealth respectively. Married households hold 72% and 34% (25% and 29%) higher fraction in risky asset share than single female-headed (single male-headed) households for the two definitions respectively.

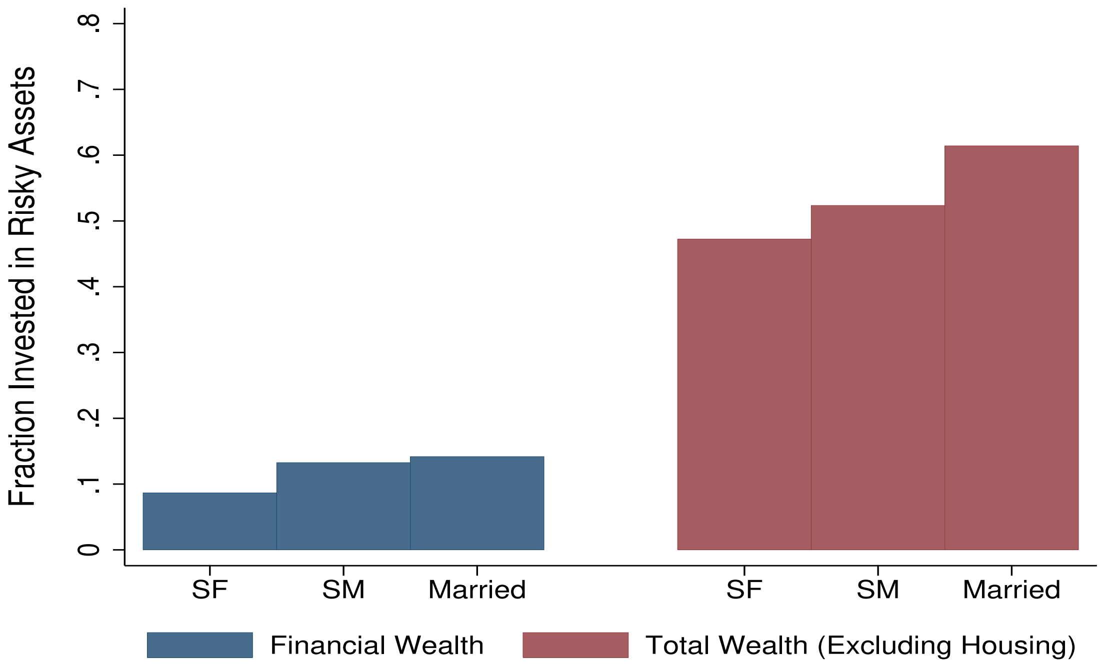


Figure 2: Risky Asset Share in SCF

Figure 2 shows the mean fraction of wealth invested in risky assets by married, single male and single female households using the two definitions in the SCF. We again find the same ranking across gender and marital status dimensions for risky asset shares in the SCF too.

The above figures display the mean risky asset share for the various demographic groups without controlling for any observable characteristics. We use a linear regression model to validate whether the relative ordering across the marital status and gender dimension is maintained even after controlling for observable characteristics such as, income, wealth, family size, age, education, etc. We find that married households hold 32% and 24% higher risky portfolio in total wealth without housing than single men and women respectively in the PSID. We find similar numerical results in the SCF, and considering risky investments in financial wealth instead of net wealth. We also find our results to be robust to controlling for unobservable household characteristics using previous period risky asset share in the PSID, and accounting for self-reported measures of financial knowledge and risky appetite in the SCF. We also find the same ranking across households while considering two-sided censored Tobit regressions rather than an OLS regression specification. Bertocchi, Brunetti, and Torricelli (2011) look at Italian data and find 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. They arrive at this result by performing two separate regressions so, cannot compare across the groups. But to the best of our knowledge, ours is the first paper to document a joint ranking over married, single men and single women in risky share after controlling for observable and unobservable traits.[3] Moreover, we show that this ranking holds for multiple measures of the risky asset share.

While portfolio choice differences by gender has received considerable attention in the literature, most of it has been attributed to the fact that women are more risk averse as compared to men, as a result of which they are less likely to undergo risky investments (Addoum, Kung, & Gonzalo, 2016; Neelakantan & Chang, 2010; Jianakoplos & Bernasek, 1998). But, spousal insurance has been shown to play an important role in household consumption smoothing (Bardóczy, 2020; Blundell, Pistaferri, & Saporta-Eksten, 2016). Two-earner households are better equipped to self-insure against background risk than a single-earner household. We provide evidence in the data that households with both spouses working hold a higher risky share compared to when at most a single spouse is working. Further, as highlighted by Catherine (2016) and (Lynch & Tan, 2011), individual income risk can be an important determinant of household portfolio allocation. Angerer and Lam (2009) find that as the variance of permanent income increases then equity investment falls. We document from the data that the variance in permanent income is higher for women as compared to men and this difference is statistically significant. This might be an explanation for the gender asymmetry that we observe in investment behavior.

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). In this model, individuals are risk averse and differ with respect to gender, age, marital status, permanent income, transitory shock to income, and wealth levels, and endogenously determine their consumption, investment in the risky asset, and investment in the safe asset over their lifetime. For married households, we use a unitary framework, where agents make joint decisions. We use the panel structure of the PSID to estimate the income process separately for men and women and incorporate that in our quantitative analysis. Preliminary results from the model suggest that even though we assume that men and women do not differ with respect to their preference for risk, a higher risk in the permanent income for women translates into a lower investment in risky assets for single female households relative to single male households

[3] For detailed surveys on the empirical household finance literature, readers are referred to Gomes, Haliassos, and Ramadorai (2021) and Guiso and Sodini (2013).

at almost every point over the life-cycle.

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 and Section 5 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 (F. 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 1 even after controlling for household characteristics, we consider the following linear model:

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

[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 (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.

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 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, Peng, and Zhang (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

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

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.

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

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
	(0.008)	(0.008)	(0.008)	(0.016)
Married	0.121***	0.118***	0.092***	0.090***
	(0.008)	(0.008)	(0.008)	(0.015)
Income squared		−0.000**		
		(0.000)		
Wealth squared		−0.000***		
		(0.000)		
Above Average Risk			0.027**	0.052**
			(0.012)	(0.023)
Average Risk			−0.045***	0.006
			(0.012)	(0.022)
No Risk			−0.204***	−0.140***
			(0.012)	(0.022)
Moderate Knowledge				0.012
				(0.011)
Limited Knowledge				−0.042***
				(0.012)
No Knowledge				−0.128***
				(0.024)
Constant	0.145***	0.150***	0.285***	0.247***
	(0.014)	(0.014)	(0.018)	(0.037)
Observations	27483	27483	27483	6817
Single Male=Married	0	0	0	0

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

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***
	(0.006)	(0.006)	(0.006)	(0.010)
Married	0.053***	0.050***	0.037***	0.038***
	(0.005)	(0.005)	(0.005)	(0.010)
Constant	0.003	0.009	0.096***	0.110***
	(0.010)	(0.010)	(0.013)	(0.023)
Observations	27382	27382	27382	6787
Single Male=Married	.004	.01	.002	.76

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

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 13 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

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

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 (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 14 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

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

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 spouse, 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 a hours based measure of employment status. Lagged risky portfolio fraction is included in the regression specification in the second and fourth column 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 spouse 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 higher risky investments than both and

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

none working even while considering the hours cutoff measure. The key take-away 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 highlight the various forces at play in risky portfolio choices. Time is discrete. The economy is populated with individuals of two genders, males and females, who work for the first J periods of their life, retire and live for another J_R periods after which they die. Further, there are three types of households: (a) single female-headed, (b) single male-headed, and (c) married, which comprise of one male and one female. We assume that there are no marriage or divorce shocks in this environment.

Agents are assumed to be risk averse and derive utility only from consumption, c. Each period, households decide how much to consume, and how much to save, $a' \geq 0$. 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 $(1 - p_{\text{tail}}$ probability, each individual draws a realisation of R from a distribution with 3 values with equal probability such that $\mathbb{E}(R) > R_f$, but all individuals experience a stock market crash with p_{tail} probability following Fagereng et al. (2017). Moreover, adjustment of the risky asset requires the household to incur a variable cost, ϕ. 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.

3.2 Single Households

For single households, individual earnings, y, for each working period ($j \leq J$), comprise of two components: (a) their permanent income, z, and (b) a transitory shock, ε, and is denoted by

$$y_{g,j} = \max\{\exp(z + \varepsilon), \underline{y}\} \tag{5}$$

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 which arises through the time 0 permanent income level such that $\exp(z_{m,0}) = 1$ and $\exp(z_{f,0}) = 0.7$.[10] Retired households receive pension earnings, $b(z_J)$, which are a function of their permanent income level in the last working period. 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

$$V(j, z, \varepsilon, s.\psi) = \max_{c,f',d} u(c) + \beta \mathbb{E}_{z',\varepsilon',R'} \left[V\left(j+1, z', \varepsilon', s', \psi'\right) \right] \tag{7}$$

subject to

$$c + d + f' \leq y_{g,j}^{1-\tau} + \psi - \phi \mathbb{1}_{d \neq 0} \tag{8}$$

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

$$d = s' - s \tag{9}$$

$$c, f', s' \geq 0 \tag{10}$$

where $u(c)$ is the period utility function, β is the discount factor, and $y_{g,j}$ is given by equation (5), as described above. d captures the withdrawl 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).

[10] The ratio of median female earnings to median male earnings has been around 70% in the US over the past four decades.

For retired households ($J < j \leq J + J_R$), the problem is given by

$$V(j, z_J, 0, s, \psi) = \max_{c,f',d} u(c) + \mathbb{1}_{j \neq J+J_R} \beta \mathbb{E}_{R'} \left[V\left(j+1, z_J, 0, s', \psi'\right) \right] \tag{11}$$

subject to

$$c + d + f' \leq \{b(z_J)\}^{1-\tau} + \psi - \phi \mathbb{1}_{d \neq 0} \tag{12}$$

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

$$d = s' - s \tag{14}$$

$$c, s, f \geq 0 \tag{15}$$

as we assume that they do not receive any transitory or permanent shocks to their income.

3.3 Married Households

For married households, family earnings, y, 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 denoted by

$$y = \max\{\exp(z_m + \varepsilon_m) + exp(z_f + \varepsilon_f), \underline{y}\} \tag{16}$$

where $\begin{bmatrix} \varepsilon_m \\ \varepsilon_f \end{bmatrix} \sim F_j^M(\varepsilon_m, \varepsilon_f)$. As in the case for single households, $\underline{y}$ denotes some minimum level of family earnings, and can be perceived as benefits to unemployed members. The permanent income process for each member is given by

$$z'_g = z_g + \eta'_g \tag{17}$$

where η_g represents shock to the permanent income process of gender g and $\begin{bmatrix} \eta'_m \\ \eta'_f \end{bmatrix} \sim G_j^M(\eta'_m, \eta'_f)$. Further we assume that $\exp(z_{m,0}) = 1$ and $\exp(z_{f,0}) = 0.7$ due to the gender income gap. The individual transitory and permanent income shocks are uncorrelated to each other and exhibit no serial correlation. We allow for the individual-specific income shocks of the spouses to be correlated. We specify this structure in more detail in Section 4.2. 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. Their earnings net of taxes is given by $y^{1-\tau}$.

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

$$V_M(j, z_m, z_f, \varepsilon_m, \varepsilon_f, s, \psi) = \max_{c, f', d} u\left(\frac{c}{1+\chi}\right) + \beta \mathbb{E}_{z'_m, z'_f, \varepsilon'_m, \varepsilon'_f, R'}\left[V_M\left(j+1, z'_m, z'_f, \varepsilon'_m, \varepsilon'_f, s', \psi'\right)\right] \tag{18}$$

subject to

$$c + d + f' \leq y^{1-\tau} + \psi - \phi \mathbb{1}_{d \neq 0} \tag{19}$$

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

$$d = s' - s \tag{21}$$

$$c, s', f' \geq 0 \tag{22}$$

where χ denotes the consumption equivalence scale and y is described by equation (16).

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

$$V_M(j, z_{m,J}, z_{f,J}, 0, 0, s, \psi) = \max_{c, f', d} u\left(\frac{c}{1+\chi}\right) + \mathbb{1}_{j \neq J+J_R} \beta \mathbb{E}_{R'}\left[V_M\left(j+1, z_{m,J}, z_{f,J}, 0, 0, s', \psi'\right)\right] \tag{23}$$

subject to

$$c + d + f' \leq \{b(z_{m,J}) + b(z_{f,J})\}^{1-\tau} + \psi - \phi \mathbb{1}_{d \neq 0} \tag{24}$$

$$\psi' = (R' - 1)s' + R_f f' \tag{25}$$

$$d = s' - s \tag{26}$$

$$c, s', f' \geq 0 \tag{27}$$

4 Quantitative Analysis

4.1 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 10 lists the parameter values used.

This is an annual model and therefore the discount factor β takes a value of 0.96, same as Aiyagari (1994). 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, $J_R = 14$. Households receive utility from leaving bequests after they die which is given by:

$$B(\psi' + s') = \left[L(\phi + \psi' + s')^{\alpha}\right]^{\frac{\gamma}{\alpha}} \tag{28}$$

The parameter L measures the strength of the bequest motive and ϕ reflects the luxuriousness of the bequest motive. The values for L and ϕ are set to 0.031 and 1.834 as per Cooper and Zhu (2016).

We assume a Epstein-Zin per period utility function where

$$U_t = \left\{c^{\gamma} + \beta \mathbb{E}\left[U_{t+1}\right]^{\frac{\gamma}{\alpha}}\right\}^{\frac{1}{\gamma}}$$

where, γ affects the elasticity of intertemporal substitution and α controls the degree of risk aversion. 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.

Table 10: Parameter Choices

Name	Source	Value
β	Aiyagari (1994)	0.96
α	Campanale et al. (2015)	-4
γ	Campanale et al. (2015)	-3
χ	OECD (n.d.)	0.7
R_f	Krueger and Wu (2021)	1.02
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
ϕ		0.1

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 individual return on risky assets is assumed to take one out of three possible values, 27.03%, 13%, and −15.25%, with equal probability. This yields a mean return of 8.26%. These values are taken from Neelakantan and Chang (2010) who estimate the returns using Standard & Poor's 500. The fixed cost of adjusting risky assets is 0.1.

4.2 Estimation of the Income process

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

$$\varepsilon_{i,g,t} \sim \text{iid } N\left(0, \sigma^2_{\varepsilon,g}\right), \ \eta_{i,g,t} \sim \text{iid } N\left(0, \sigma^2_{\eta,g}\right) \tag{29}$$

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. 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:

$$\begin{bmatrix} \varepsilon_{i,m,t} \\ \varepsilon_{i,f,t} \end{bmatrix} \sim \text{iid } N \left(0, \begin{bmatrix} \sigma^2_{\varepsilon,m} & \sigma_{\varepsilon,mf} \\ \sigma_{\varepsilon,mf} & \sigma^2_{\varepsilon,f} \end{bmatrix} \right) \tag{30}$$

$$\begin{bmatrix} \eta_{i,m,t} \\ \eta_{i,f,t} \end{bmatrix} \sim \text{iid } N \left(0, \begin{bmatrix} \sigma^2_{\eta,m} & \sigma_{\eta,mf} \\ \sigma_{\eta,mf} & \sigma^2_{\eta,f} \end{bmatrix} \right) \tag{31}$$

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.

We use PSID from 1997 to 2019 to estimate the variances and covariances of the income process. 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:

$$\ln y_{i,g,t} = \varepsilon_{i,g,t} + z_{i,g,t} \tag{32}$$

$$\Delta \ln y_{i,g,t} = \varepsilon_{i,g,t} + \varepsilon_{i,g,t-1} + \eta_{i,g,t} \tag{33}$$

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 34. 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.

$$\text{Cov}\left(\Delta \ln y_{i,g,t}, \Delta \ln y_{i,g,t+1}\right) = -\sigma^2_{\varepsilon,g} \tag{34}$$

$$\text{Cov}\left(\Delta \ln y_{i,g,t}, \Delta \ln y_{i,g,t} + \Delta \ln y_{i,g,t-1} + \Delta \ln y_{i,g,t+1}\right) = \sigma^2_{\eta,g} \tag{35}$$

The identification of the covariance parameters for husband and wife depend on the cross income growth and follows a similar intuition as above. Equation 36 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 37). In this case, clearly there exist overidentifying equations.

$$\text{Cov}\left(\Delta \text{ln} y_{i,m,t}, \Delta \text{ln} y_{i,f,t+1}\right) = -\sigma_{\varepsilon,mf} \tag{36}$$

$$\text{Cov}\left(\Delta \text{ln} y_{i,m,t}, \Delta \text{ln} y_{i,f,t} + \Delta \text{ln} y_{i,f,t-1} + \Delta \text{ln} y_{i,f,t+1}\right) = \sigma_{\eta,mf} \tag{37}$$

We implement a multi-step estimation strategy. First, we regress 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.

The income risk parameters are presented in Table 11. 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 11: Income Process Parameters

	Male	Female	P-value
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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 Results

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 5 values, whereas both shocks to permanent income, η, and transitory income, ε, take 3 values. 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 backwards 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. Figure 3 shows the simulated income profiles of single females, single males and couples. The gender wage gap faced by females can be seen through the difference in the income profiles of single men and women. The significant gap between the household income across marital status also stands out while looking at Figure 3.

Figure 4 illustrates the average fraction of their wealth invested in risky assets by single male and single female households over their lifetime. The fraction invested in risky assets rises during early working life as households are able to buy more risky assets as they accumulate more wealth and earn more income. Higher wealth and income helps to pay the fixed cost. During the middle life, portfolio reallocation motive kicks in as households have acquired plenty of risky assets so in relative terms they purchase less risky assets than safe asses.

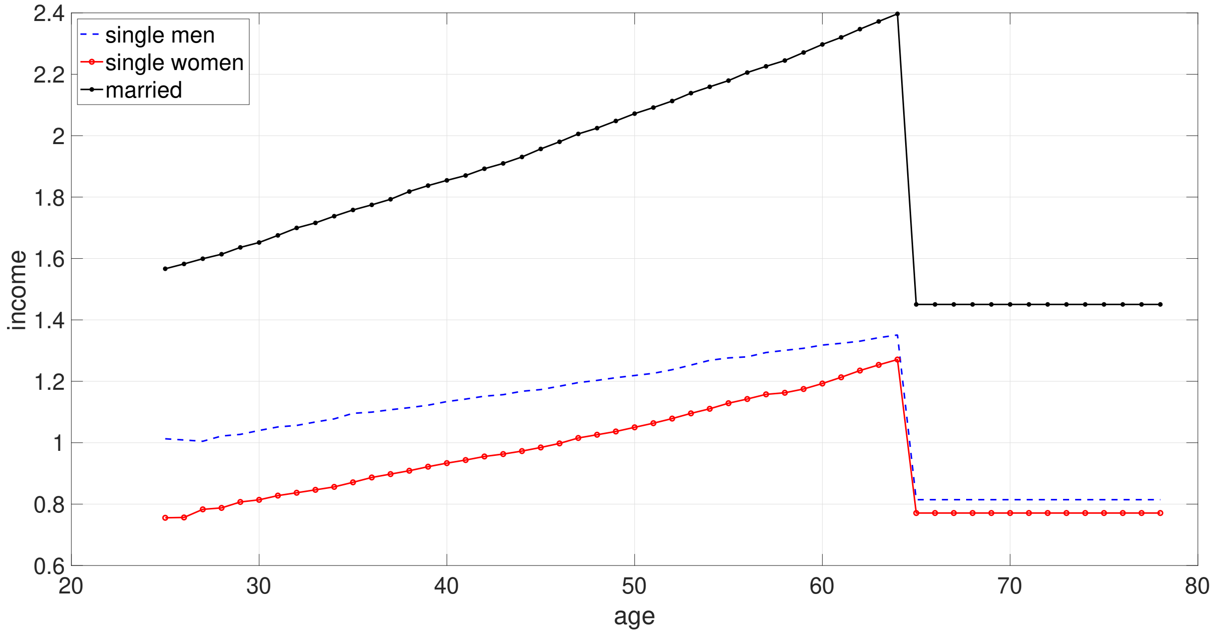


Figure 3: Differences in income profile across gender and marital status

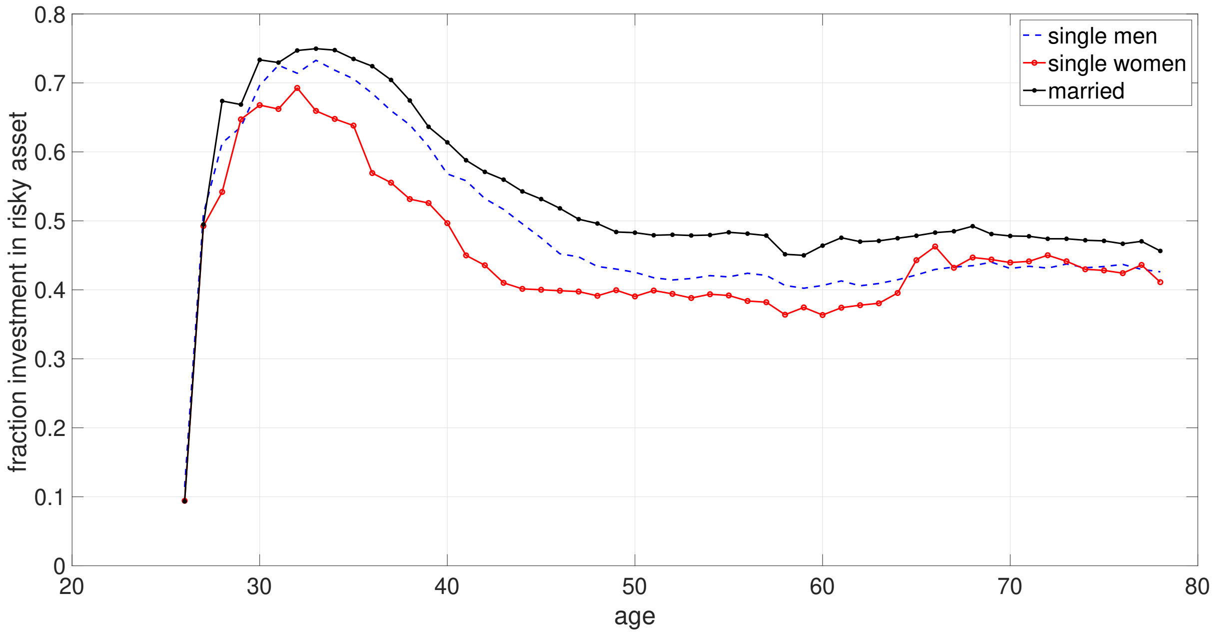


Figure 4: Risky asset share profile of single men, women and couples

As is observed in Figure 4, at almost every working age, single female households invest a lower fraction of their wealth in risky assets, which is consistent with the empirical results. Averaging over all ages, our model predicts that single men would invest 51% of their wealth in risky assets, whereas single women would only invest 46%. The empirical results also showed that single men hold around 3-5 pp more in risky assets and so, our model can quantitatively produce similar results. Apart from the initial couple of working age, married households invest more in risky assets than singles. The average fraction of risky asset share over the working life is 55.4% which is 4.4 pp and 9.4 pp higher for than single male and female respectively. These differences can have significant on lifetime wealth accumulation and consumption profile.

Figure 5 shows the wealth accumulation over the working life for the three groups. Households accumulate wealth over their lifecycle. There is a sharp drop in wealth due to the stock market crash at age 57. The differences in fraction risky matter as we significant differences in average wealth across the three groups. Married households accumulate 20% more wealth at the time of wealth compared to single men who in turn accumulate around 25% more wealth than single women at the time of death.

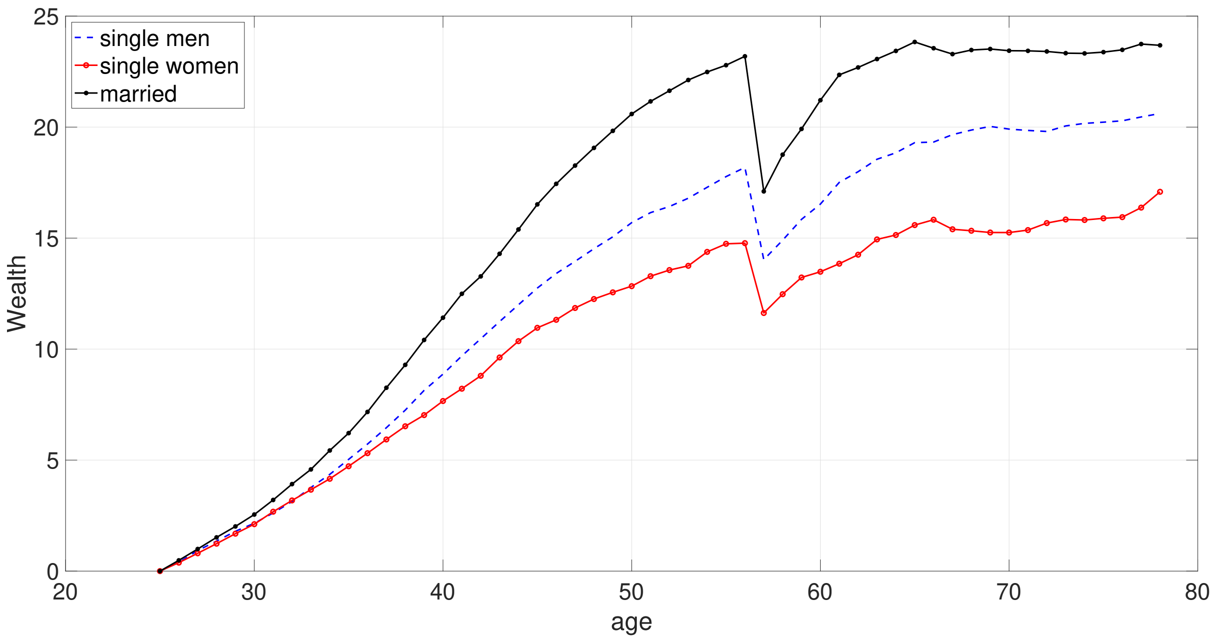


Figure 5: Wealth profile of single men, women and couples

Figure 6 shows the consumption profile over the lifecycle for singles by gender and couples. A common pattern across all groups is the gradual increase in consumption as households get older, the steep fall in consumption at age 57 due to the stock market crash and then the gradual recovery and during the later stages of working life and eventually flat consumption profile during the retirement stage.

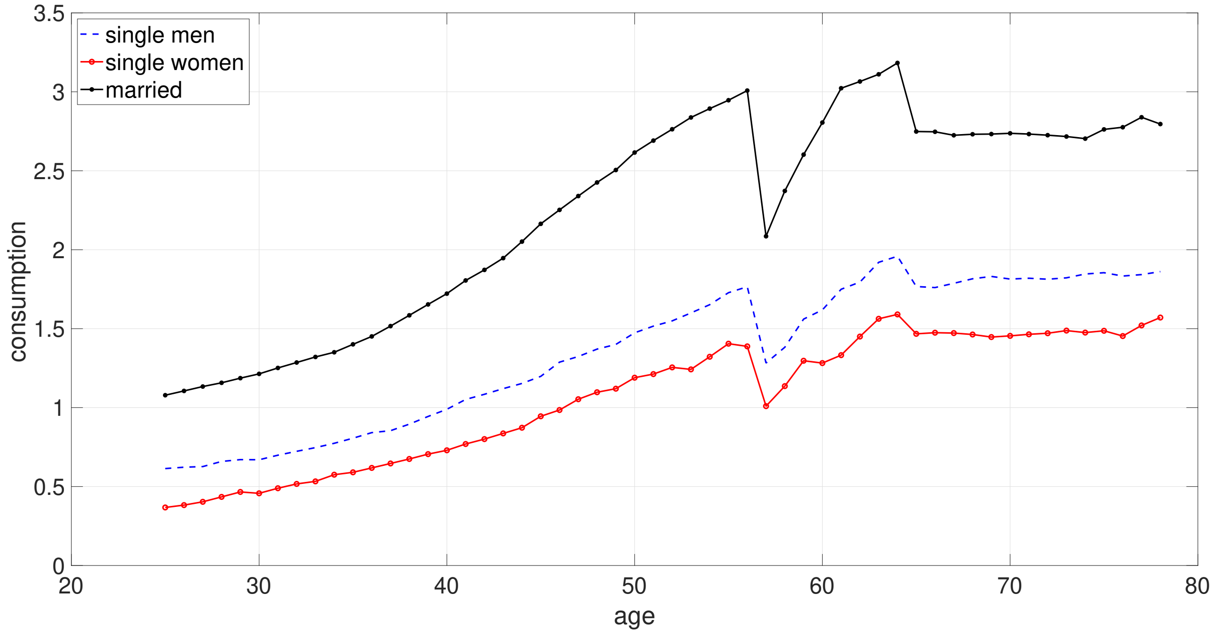


Figure 6: Consumption profile of single men, women and couples

4.4 Role of Gender Wage gap

We can quantitatively attain estimates between portfolio share across gaps which are in similar magnitude to the empirical facts assuming that all households have the same risk preferences (Neelakantan & Chang, 2010). There are two forces that we would like to disentangle to understand its impact on risky asset share and subsequently on wealth accumulation– (1) gender wage gap, (2) women higher permanent income variance.

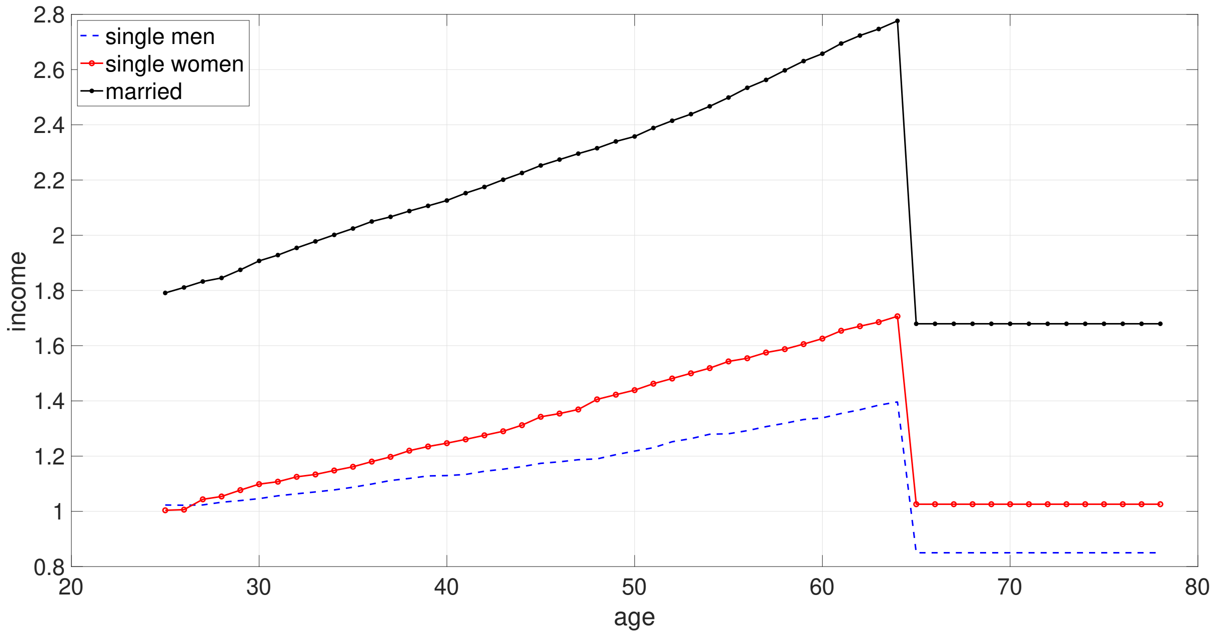
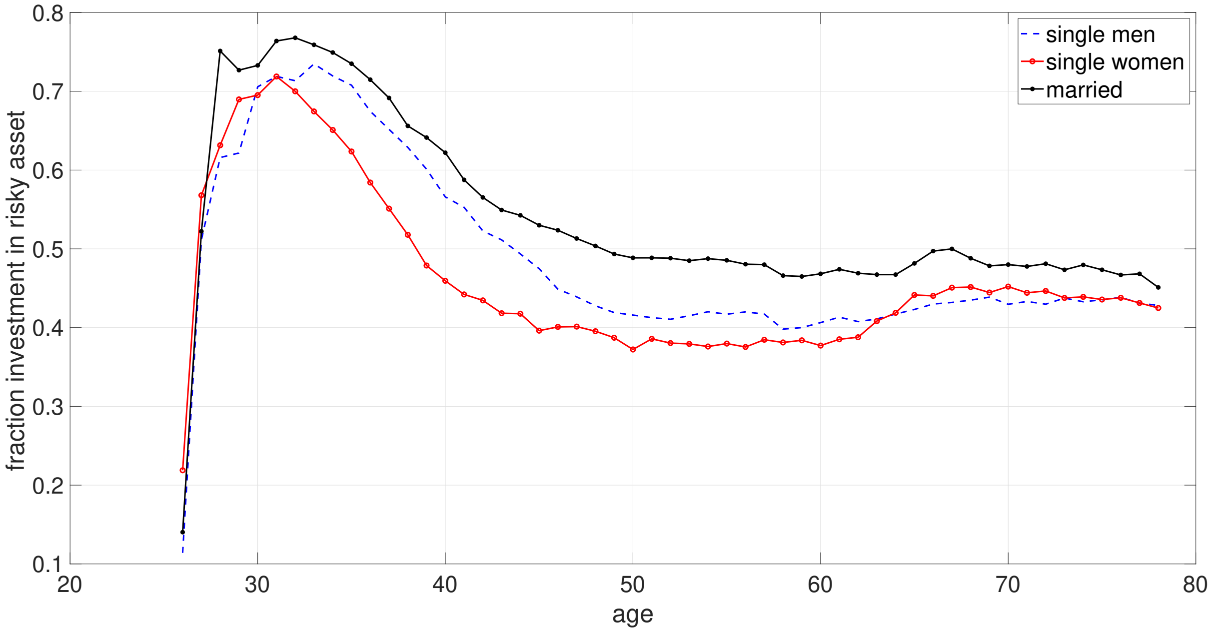
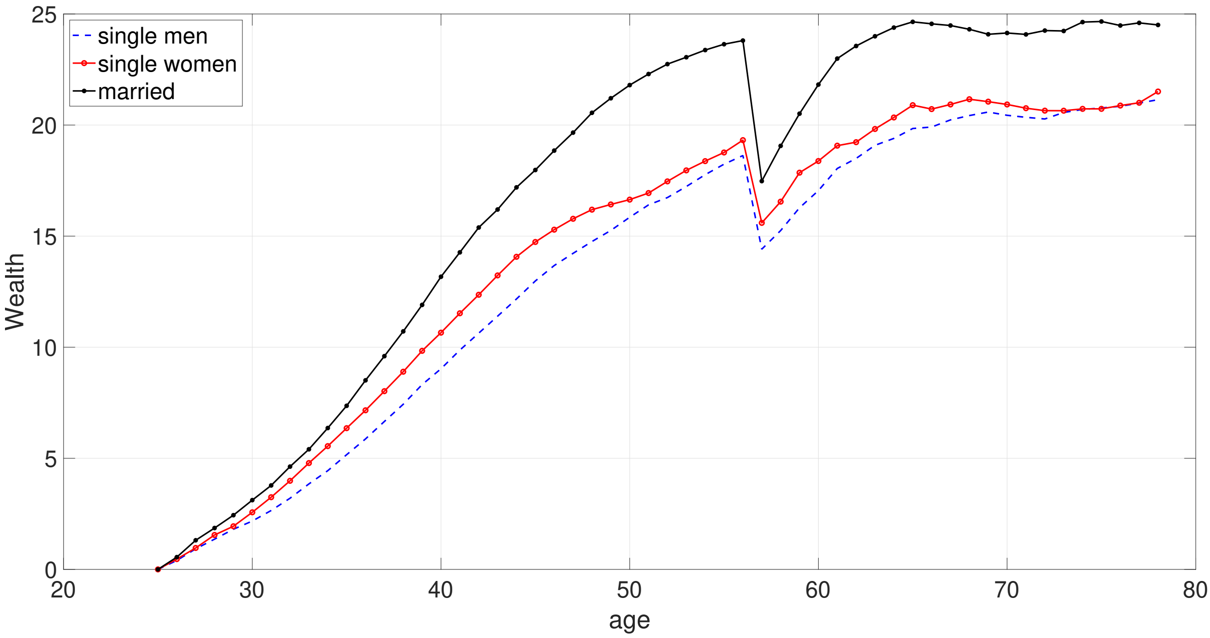


Figure 7: Income profile across gender and marital status without gender wage gap

Figure 7 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 more in average than men as they experience larger positive shocks whereas really large negative shocks are insured equally due to minimum income support.



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



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

Figure 8a shows that married households acquire 56.3% of their wealth in risky assets, single males hold 51% and single females hold 47%. Thus, the portfolio gap reduces between single men and women from 5pp in baseline model to 4pp in model without gender wage gap. But, the portfolio gap increases comparing couples and single men. The reason is that as cash-in-hand rises then individuals acquire enough liquidity allowing single females to hold more wealth in risky assets than single men in early working life. The higher fraction risky share and higher income allows women to build more wealth than men as shown in Figure 8*b*. The higher wealth generates stronger portfolio diversification in middle aged households among those with higher wealth and so, single females hold lesser equity share than males in the counteractual compared to the baseline simulation. The net effect is that overall there is a fall in the risky share asset difference between single males and females.

4.5 Role of Income Risk

Figure 9 shows the income profiles when men and women experience the same variance in permanent income. This implies that on average, the gender wage gap persists over life.

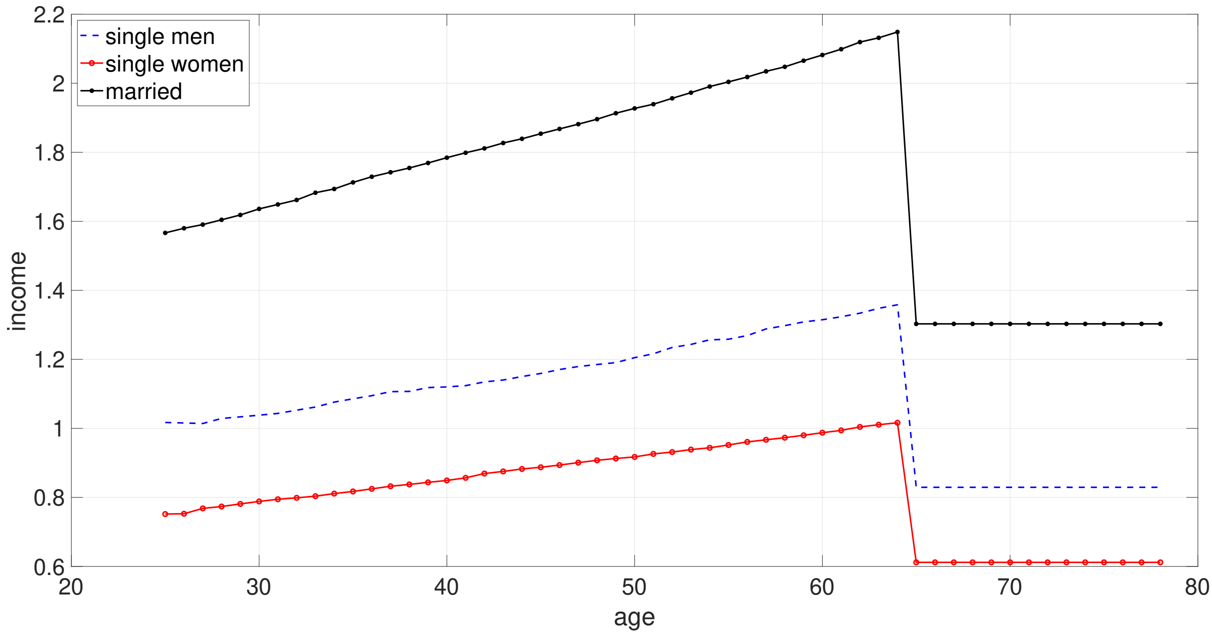
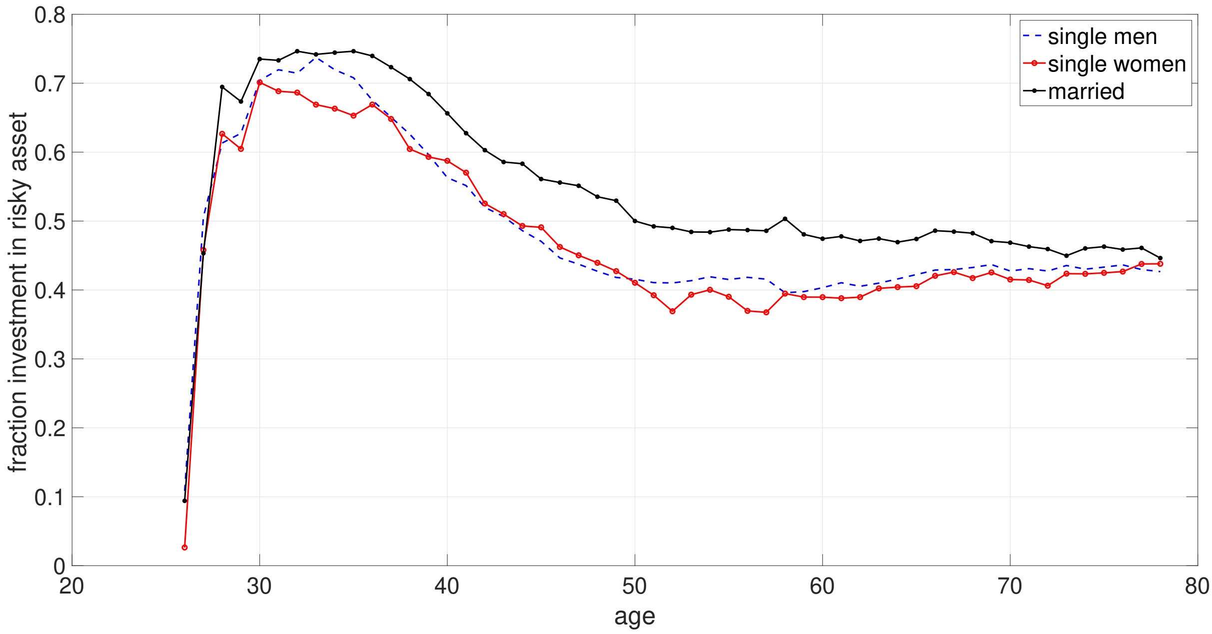
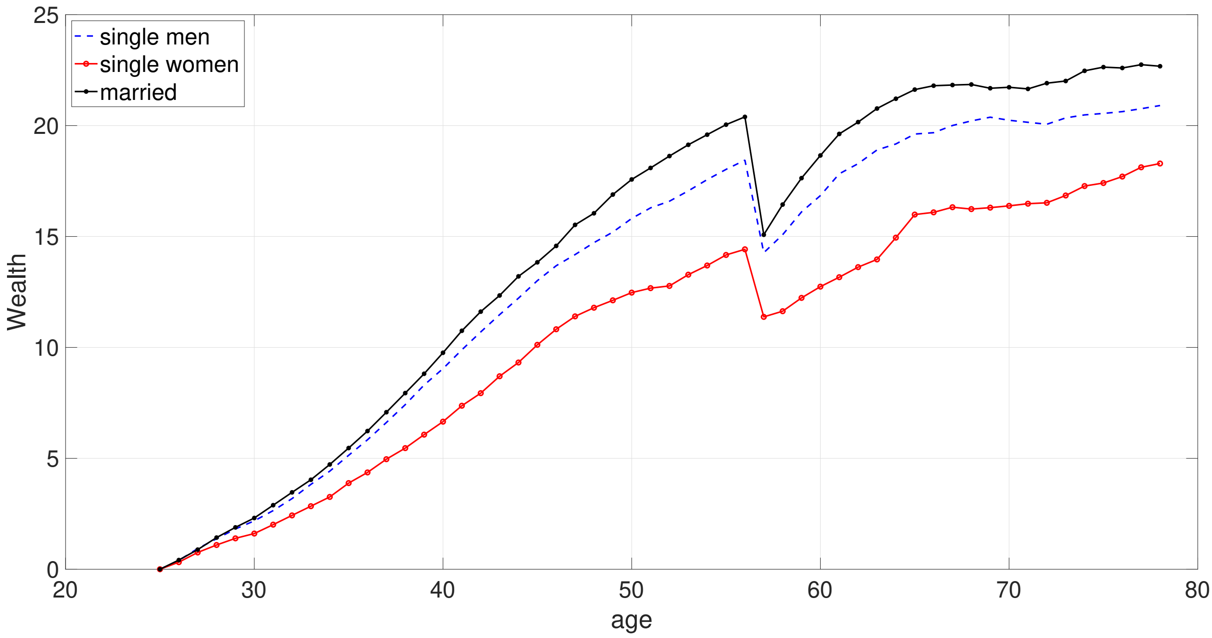


Figure 9: Differences in income profile across gender and marital status without asymmetric income risk

Figure 10*a* shows the risky asset share across groups without asymmetric income risk. The portfolio gap between singles reduces to 2.5pp as single men and women hold 50.5% and 49% risky asset shares. Precautionary savings induces risk averse individuals to hold more safe assets. As income risk faced by women falls, they hold less safe assets than before and accumulate less wealth than before as seen in Figure 10*b*. Thus, more portfolio is allocated to risky assets than before by females. Similarly, married households hold more risky asset share (57%) and the gap between married and single males rises to 6.5% in the counterfactual with equalized variances compared to 4.5% in baseline model. The similar logic holds that lower background risk leads to a higher investment in the risky asset.



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



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

4.6 Other Mechanisms

We also investigate other differences in preferences across groups or role of disaster risk in explaining the mechanisms behind the model results. Table 12 shows portfolio share across different counterfactual experiments. Columns (1) and (2) show the risky asset share when wage gap and variance differences are removed. Column (3) shows the portfolio risky share when $\chi = 1$. The equity shares are almost unchanged from the benchmark mode. The higher equivalence share implies that households save less than before but the fall in savings is not large and so, leads to very similar portfolio shares as before.

Column (4) shows the risky asset share investment when disaster risk is removed $p_{\text{tail}} = 0$. The first thing to notice is that all groups hold more equity share as the probability of a large negative returns does not exist anymore. Second, the portfolio gap between single males and females reduces as single females accumulate more risky asset as background risk has fallen and so they undertake less precautionary savings. Similary, the portfolio gap between married and single men falls by the same logic. Though, one thing to note is that the model with disaster risk produces risky asset shares more in line with the data as seen in the Figure 2 that shows the risky asset share across gender and marital groups. Column (5) shows the model where risk aversion is 3 compared to the benchmark model which had a risk aversion degree of 5. As individuals are less risk averse, they unsurprisingly accumulate more risky assets than the benchmark model leading to much higher equity shares. Moreover, the portfolio gap reduces between single males and females as single women worry less about background risk.

Table 12: Risky Asset Share across various parameter values

Household type	Benchmark	(1)	(2)	(3)	(4)	(5)
Single Female	0.458	0.468	0.490	0.455	0.584	0.603
Single Male	0.510	0.507	0.505	0.508	0.620	0.623
Married	0.554	0.563	0.571	0.554	0.645	0.657

(1): No wage gap; (2): No variance gap; (3): No economies of scale; (4): No disaster risk; (5): Lower risk aversion

5 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 investment 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 markets 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 alongwith 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. Gender wage gap has an important role to play only in early working life when individuals have not built up sufficient wealth to pay for adjusting their risky asset holding.

Acknowledgements

We thank Aaradhya Gupta and Roopal Jain for outstanding research assistance. Pubali Chakraborty acknowledges financial assistance provided by the Department of Economics, Ashoka University.

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*.

Aiyagari, S. R. (1994). Uninsured idiosyncratic risk and aggregate saving. *The Quarterly Journal of Economics*, *109*(3), 659–684.

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

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*.

Bartscher, A. K., Kuhn, M., Schularick, M., & Wachtel, P. (2021). Monetary policy and racial inequality. *CEPR Discussion Paper No. DP15734*.

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.

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. (2016). Countercyclical income risk and portfolio choices over the life-cycle. *Working Paper*.

Chang, M. (2020). A house without a ring: The role of changing marital transitions in housing decisions. *Working Paper*.

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.

Gomes, F., Haliassos, M., & Ramadorai, T. (2021). Household Finance. *Journal of Economic Literature*, *59*(3), 919–1000.

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

Guiso, L., & Sodini, P. (2013). Household Finance: An Emerging Field. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), *Handbook of the economics of finance* (Vol. 2B, pp. 1397–1532). Elsevier. Retrieved from http://dx.doi.org/10.1016/B978-0-44-459406-8.00021-4 doi: 10.1016/B978-0-44-459406-8.00021-4

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.

Jianakoplos, N. A., & Bernasek, A. (1998). Are women more risk averse? *Economic inquiry*, *36*(4), 620–630.

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.

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.

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.

Pfeffer, F. T. (2018). Growing wealth gaps in education. *Demography*, *55*(3), 1033–1068.

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.

Wachter, J. A., & Yogo, M. (2010). Why do household portfolio shares rise in wealth? *The Review of Financial Studies*, *23*(11), 3929–3965.

Wolff, E. N. (1998). Recent trends in the size distribution of household wealth. *Journal of Economic Perspectives*, *12*(3), 131–150.

Appendix

A Empirical Evidence

Table 13: Regression to invest in Risky Asset or not in SCF

	(1)	(2)	(3)	(4)
Single Male	0.057***	0.055***	0.026***	0.048***
	(0.009)	(0.009)	(0.008)	(0.016)
Married	0.124***	0.119***	0.094***	0.086***
	(0.008)	(0.008)	(0.008)	(0.015)
Constant	0.012	0.020	0.162***	0.181***
	(0.015)	(0.015)	(0.018)	(0.036)
Observations	28846	28846	28846	7103
Single Male=Married	0	0	0	.025

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 14: 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***
	(0.008)	(0.007)	(0.006)
Married	0.122***	0.098***	0.076***
	(0.008)	(0.006)	(0.006)
Constant	0.145***	0.379***	0.048***
	(0.014)	(0.012)	(0.011)
Observations	27186	27186	27186
Single Male=Married	0	0	0

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