# Portfolio Rebalancing and Wealth Inequality Among US Households During the Quantitative Easing Era

An Honors Thesis for the Department of Economics
Eleanor Jenke

Advised by Dr. Yannis Ioannides
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**Abstract**

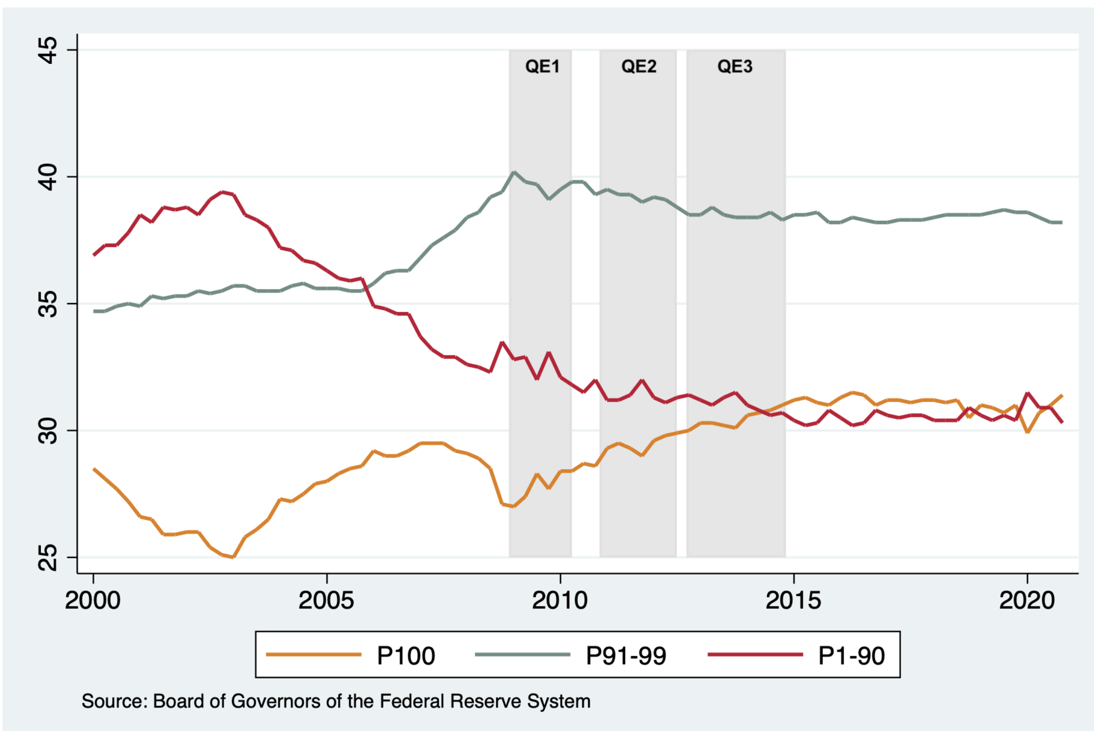
The Global Financial Crisis of 2008 was succeeded by strong risky asset price inflation during the Quantitative Easing (QE) era from 2009 to 2014, with capital gains accumulating to households who owned more risky financial assets. A wide body of literature documents limited asset market participation among poorer households, implying a redistribution of wealth toward the wealthy during QE, but few studies examine how this behavior changed after the financial crisis. In this paper, I ask whether households' portfolio allocation toward risky financial assets changed after the financial crisis and I consider the implications for household wealth inequality. I use a Heckman selection model to account for non-random selection into risky asset ownership and to model the effects on risky asset ownership and portfolio shares separately. I find that the bottom 90 percent of the wealth distribution experienced a sustained decline in risky financial asset ownership after 2007, while wealthy households saw only short-term fluctuations in ownership. This result was driven by a sell-off of stocks held indirectly in managed accounts, most of which are retirement accounts. My findings suggest that poorer households rebalanced their portfolios away from risky assets during the financial crisis, but did not readjust to take advantage of capital gains during the economic recovery and QE.

# Contents

# 1 Introduction

Amidst concurrent trends of globalization, technological change, and slow recovery from the Global Financial Crisis, widening wealth inequality in the United States has become a key focal point among economists. The proportion of net worth held by the top 10 percent of the wealth distribution rose from 63.2 to 69.6 percent between 2000 and 2020, according to Federal Reserve estimates.[1] This shift toward a more unequal wealth distribution accelerated in the aftermath of the Great Recession.

Figure 1: Distribution of Net Worth in the United States, 2000-2020




Given its instrumental role in shaping the post-recession economy, the Federal Reserve's Quantitative Easing (QE) program is a common culprit for the rise in wealth inequality. Under QE, the Federal Reserve implemented large-scale asset purchases (LSAPs) to stimulate the economy as the Federal Funds Rate approached its zero lower bound in late 2008. The three rounds of QE included purchases of federal agency debt, agency mortgage-backed securities (MBS), and long-term US Treasury securities, ~~inflat~~ rais ing the Federal Reserve's balance sheet from \$900 billion in 2008 to over \$4.5 trillion by the end of 2014.[2]

The financial market impact of QE is still debated, but empirical findings indicate that QE lowered long-term ~~rates and~~ [illegible] had spillover effects on the prices of other financial

[1] Federal Reserve Board, "Distributional Financial Accounts."
[2] Federal Reserve Board, "Recent Balance Sheet Trends."

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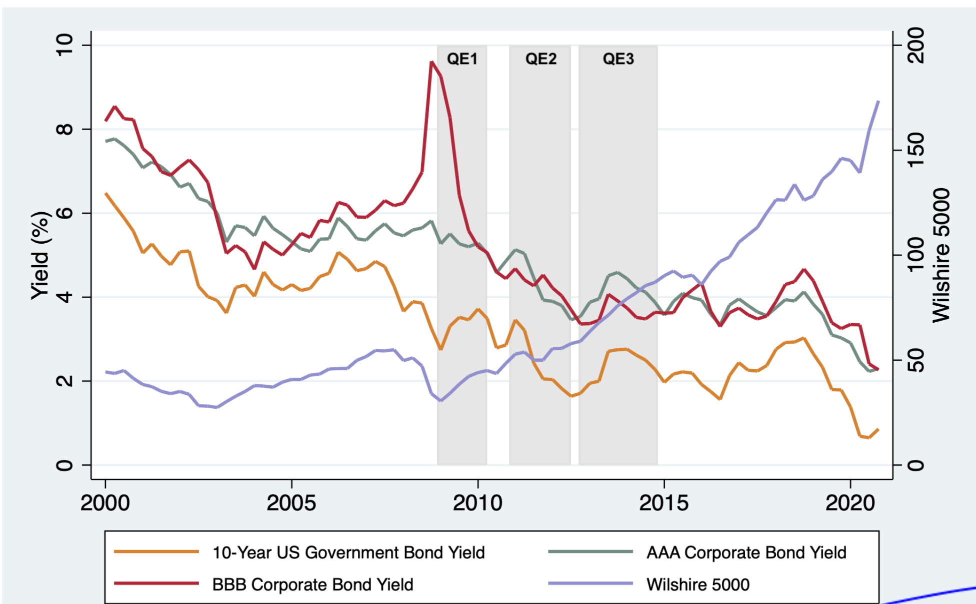
assets. One mechanism through which QE lowered long-term rates was the portfolio balance channel, discussed in Bernanke and Reinhart (2004): investors who sell long-term assets to the Fed may purchase assets with similar duration and credit risk because they view money as an imperfect substitute for financial assets, which raises the prices and reduces the yields of these assets. Using an event study methodology, Gagnon et al (2011) find evidence of this effect. Krishnamurthy and Vissing-Jorgensen (2011) also find evidence of the signaling channel, by which investors interpret QE announcements as the Federal Reserve committing to a lower federal funds rate going forward and thus bid up the prices of long-term assets. With lower long-term yields, investors seek higher returns by investing in riskier asset classes, such as corporate bonds and stocks.

Figure 2: Risky Asset Prices, 2000-2020




Sources: Federal Reserve Bank of St. Louis, Moody's, Wilshire Associates

The implications of these financial market effects for the household wealth distribution varies based on households' portfolio allocations. Those who owned risky, high-performing financial assets in the post-recession period will have had a greater opportunity for wealth appreciation than those who invested primarily in safe assets or held their wealth in nonfinancial assets. The Wilshire 5000 Total Market Index, which tracks the market-capitalization-weighted value of all US stocks, saw a 171 percent return between the start of QE1 and the end of QE3. To test whether the financial market impact of QE contributed to wealth inequality, it is insightful to study how households across the wealth distribution allocate their financial portfolios across risky versus safe assets, and whether these allocations changed during the QE era.

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I investigate this question using data spanning 2007 to 2019 from the Survey of Consumer

Finances (SCF), a triennial cross-sectional survey containing detailed information on the balance sheets of US households. Specifically, I implement a Heckman selection model to test whether US households increased their risky share of financial assets after 2007, and whether this effect was heterogeneous across the wealth distribution. In the data, I observe that wealthy households have more diversified portfolios, higher portfolio shares of financial assets, and higher shares of financial assets that are risky. Less wealthy households have poorly diversified portfolios concentrated in non-financial assets and cash. Based on these observations, I hypothesize that wealthy households tend to be skilled investors and that they were more likely to rebalance their portfolios toward risky financial assets during the QE era to capitalize on relative price gains.

I find that households in the bottom 90 percent of the wealth distribution faced a sustained decline in the ownership of risky financial assets. This effect was larger for indirectly held stocks in managed accounts than for directly held stocks in brokerage accounts. Ownership among households in the top decile was lower in 2013 and 2019 compared to 2007, by a smaller magnitude than the bottom 90 percent, but not in 2010 or 2016. Only the bottom quintile experienced a sustained decline in the risky share of financial assets. These results suggest that a large segment of the wealth distribution traded out of risky financial assets in response to the large negative shock of the financial crisis, but did not rebalance again to take advantage of capital gains during QE and the economic recovery. Meanwhile, households in the top decile appear to have ~~updated~~ reevaluated their portfolio allocations frequently as market conditions changed. These findings hold even after I allow for heterogeneous time effects across demographic groups.

It is critical to differentiate between capital gains and portfolio rebalancing when examining changes in the portfolio share of an asset class. An increase in the share results from either a rise in the relative value of the asset class compared to others, or from an increase in the quantity held of the asset class. In this paper, I focus on heterogeneous portfolio rebalancing across the wealth distribution after the financial crisis and the resulting implications for wealth inequality. Because the SCF is not a panel and does not differentiate between the value versus quantity of asset holdings, I cannot precisely separate capital gains from changes in portfolio allocation. However, I observe that the change in average stockholdings varies widely across the distribution and it moves in the opposite direction of stock prices. This would not be the case if only capital gains were in effect.

Some researchers test the impact of LSAPs on wealth inequality through simulations that multiply households' initial balance sheet holdings by respective asset price indicators (Ampudia et al, 2018; Casiraghi et al, 2018; Domanski et al, 2016; Lenza and Slacalek, 2018). This literature has primarily focused on Euro area countries, and most studies find that wealth inequality either did not change or slightly decreased. However, Domanski et al (2016) include US data and find that wealth inequality may have increased since the Great Recession due to high equity returns at the top of the distribution. This approach requires a strong assumption that households do not trade in or out of asset classes. Empirical evidence indicates that the majority of US households rarely alter their portfolio allocation, making this assumption seem reasonable (Ameriks and Zeldes, 2004; Agnew et al, 2003). However, research also suggests that portfolio rebalancing is positively correlated with wealth and education, so this assumption becomes less reliable when one is interested in measuring distributional effects (Bilias et al, 2010).

Further, households that rarely rebalance under normal economic conditions might rebalance after an economic shock like the financial crisis. Malmendier and Nagel (2011) find that individuals who have been exposed to lower stock market returns throughout their lives are more pessimistic about future stock returns and less likely to participate in the stock market, and those who do participate tend to invest a lower share of their assets in stocks. This research suggests that large macroeconomic shocks have long-lasting impacts on households' risk tolerance and portfolio strategies: after initially adjusting their portfolios to a shock, households return to a state of inertia.

I argue that heterogeneity in rebalancing is important to consider when implementing unconventional monetary policies such as LSAPs that inflate financial asset prices. In his op-ed titled "Aiding the Economy: What the Fed Did and Why," Bernanke states:

> Easier financial conditions will promote economic growth. For example, lower mortgage rates will make housing more affordable and allow more homeowners to refinance. Lower corporate bond rates will encourage investment. And higher stock prices will boost consumer wealth and help increase confidence, which can also spur spending. Increased spending will lead to higher incomes and profits that, in a virtuous circle, will further support economic expansion [Bernanke (2010)].

The idea that higher asset prices increase consumers' wealth, confidence, and spending, often called the wealth effect, is central to the stimulative effect of QE. Yet in practice, the wealth effect may be subdued as stock wealth is concentrated among the rich, and richer households have a lower marginal propensity to consume out of wealth (Carroll, 2017). By the Federal Reserve Act of 1913, the Federal Reserve's mandate is to promote maximum employment and ~~stable inflation~~ price stability.[3] Bernanke (2005) argues that inequality should be addressed through fiscal policies and other policies. However, the distributional consequencies of monetary policy are critical for the Federal Reserve to understand and account for if they limit policy

[3]Federal Reserve Act of 1913, Pub. L. No. 63-43, 38 Stat. 251.

transmission.

This paper is structured as follows. Section 2 discusses the Survey of Consumer Finances, and Section 3 includes an overview of household characteristics and portfolio allocations across the wealth distribution. Section 4 presents my methodology. I discuss the issue of sample selection in portfolio choice models and my motivation for using the Heckman model. Section 5 presents my empirical findings, and Section 6 includes additional robustness checks. Finally, I discuss my results and their implications for wealth inequality in the United States.

Federal Reserve Board (2020)

# 2 Data

## 2.1 The Survey of Consumer Finances

For this paper I use data from the Survey of Consumer Finances (SCF), a triennial cross-sectional survey sponsored by the Federal Reserve Board to study the wealth, income, and demographics of US households. The unit of observation in the SCF is the "primary economic unit" (PEU), which consists of an economically independent household head, his or her spouse or partner, and any financial dependents living in the same household. For ease, I use the word "household" throughout this paper to indicate the PEU. To capture household finances before and after the Great Recession, I use the 2007, 2010, 2013, 2016, and 2019 surveys. The data are collected between May and December of each survey year.

The SCF is the best available dataset for my research question because it enables me to observe how portfolio composition changed across the wealth distribution and across demographic groups after the recession. It is widely used by economists to study US household wealth as it contains detailed questions on households' asset holdings, their liabilities, and their sources of income. It also contains demographic information including the gender, age, race, education level, and employment history of both the household head and his or her spouse or partner.

The main drawback of the SCF is that it is not a panel, so I cannot track households' portfolios over time. However, I can track the average portfolio holdings of households with similar characteristics. The Panel Study of Income Dynamics (PSID) is an alternate dataset which includes panel data on US portfolio composition, but its questions on asset holdings are less granular and thus are subject to response bias. Pfeffer et al (2016) find that estimates of net worth are 11 percent higher in the SCF than in the PSID after adjusting for differences in sample construction. Most of this disparity arises from wealthy households, so the PSID is an unreliable source for understanding wealth at the top of the distribution. For these reasons, I use the SCF to obtain a more detailed, and likely accurate, depiction of the wealth distribution in the United States.

The structure of the SCF is key to consider when completing analysis. One valuable feature of the survey is that it over-samples wealthy households, which is critical as wealth is highly concentrated in the top percentiles of the distribution. The survey is composed of two samples: (1) a multi-stage area-probability sample that is designed to be representative of the demographic characteristics of the US population, and (2) a list sample drawn from IRS tax records that over-samples the wealthy. The list sample comprises between 20 and 25 percent of approximately 6,000 observations in each of the 2010-19 surveys, and it comprises 34 percent of about 4,500 observations in the 2007 sample. The Federal Reserve Board did not disclose a reason for the change in sample size after 2007. Households selected for the area-probability sample have a higher response rate than those selected for the list sample: in 2019, about 60 percent of the former group completed the survey, compared to about one-third of the latter group (Federal Reserve Bulletin, September 2020). To ensure that sample statistics are representative of the US population, each household is assigned a probability weight that indicates the number of US households it represents. The sum of the weight variable across all respondents approximately equals the number of households in the US Census.

Although the SCF is confidential, it suffers from non-response. Drawing upon data from the 1995 SCF, Kennickell (1998) presents reporting rates for various assets and liabilities. Nonresponse rates are in the teens for a number of financial assets – 14.1 percent for stocks and 13.5 percent for trusts and annuities – and the majority of these are refusals to respond. Some respondents refrain from answering detailed questions about their finances, such as how much money they have directly invested in stocks. To deal with this issue, the Federal Reserve Board employs multiple imputation to produce five estimates for all missing values. Multiple imputation is preferred over a single imputed value because it estimates the range of possible values for each missing data point. The SCF thus contains five observations for each household, forming five complete datasets called "implicates."

To account for multiple imputation in regression analysis, I use the repeated-imputation inference (RII) technique described in Rubin (1987). This method involves running the regression model for each implicate, then using these results to calculate coefficients and standard errors that account for within-implicate and between-implicate variation. Whether or not to include population weights in multivariate analysis is controversial among economists. Lindamood et al (2007) find that weighted RII regressions were more likely to report higher significance levels than unweighted analysis. Despite potential drawbacks, I use population weights in my analysis to account for the oversampling of wealthy households.

# 3 Summary Statistics Across the Distributions

## 3.1 Portfolio Characteristics

Before proceeding with my analysis, I present an overview of portfolio allocation across the wealth distribution. I label the wealth groups as follows: P1-20 denotes the 1st through 20th percentiles of the distribution, P21-40 denotes the 21st through 40th percentiles, and so on. I divide the last quintile into deciles, named P81-90 and P91-100, as wealth is highly concentrated at the top of the distribution so the portfolio characteristics of these two groups vary. These tables report probability-weighted averages across all five implicates and all five survey years, unless otherwise specified. I exclude households with zero assets, which amounts to about 12 percent of households in the bottom quintile. over ?

Table 1 presents portfolio allocation toward each asset class across the distribution at both the extensive and intensive margins. The extensive margin is measured by the percent of households in each wealth group that own the asset class, ~~and~~ the intensive margin is measured as the average portfolio share among households that own the asset class. At the bottom of the table, I include these figures for the broader categories of financial and non-financial assets. A description of these asset classes is provided in Table 6 in the Appendix.

One key takeaway is that wealthy households have higher ownership rates and portfolio shares of financial assets, while less wealthy households hold the majority of their wealth in non-financial assets. Among all wealth groups, the top decile has the largest average portfolio share of financial assets at 49.6 percent, while the middle quintile has the largest average portfolio share of non-financial assets at 78.5 percent. Data at the asset class level provide more insight into this disparity. Wealthy households' emphasis on financial assets is driven by notably higher ownership rates and portfolio shares of stocks and bonds. In contrast, poorer households display high rates of non-ownership for these asset classes. Across all survey years, 88.1 and 92.9 percent of households in the top decile held stocks and bonds, respectively. These rates were 38.9 and 53.8 percent for the middle quintile, and 25.4 and 16.9 percent for the bottom quintile.

In comparison, the portfolios of less wealthy households are Poss ~~[illegible]~~ diversified and concentrated in non-financial assets. The middle class holds the majority of its wealth in residential real estate: for the third and fourth quintiles, average portfolio shares in residential real estate neared 60 percent. The first and second quintiles have lower shares in residential real estate due to significantly lower rates of homeownership. However, consumer durables comprise over 40 percent of total assets for these wealth groups. The bottom two quintiles also hold a large share of their financial assets in cash and cash equivalents, which yield lower returns than riskier financial assets like stocks and bonds. Both the lack of diversification

Table 1: Asset Class Ownership and Average Portfolio Shares Across the Wealth Distribution

| | **P1-20** | **P21-40** | **P41-60** | **P61-80** | **P81-90** | **P91-100** | **Total** |
|---|---|---|---|---|---|---|---|
| | % households that own assets / % total assets | | | | | | |
| **Cash and equivalents** | | | | | | | |
| Ownership | 76.3 | 89.9 | 96.1 | 98.7 | 99.8 | 99.9 | 92.1 |
| Share | 27.9 | 11.5 | 6.9 | 7.5 | 7.9 | 6.9 | 11.9 |
| **Bonds** | | | | | | | |
| Ownership | 25.4 | 34.8 | 53.8 | 70.0 | 84.7 | 92.9 | 55.3 |
| Share | 4.3 | 6.4 | 8.2 | 12.4 | 17.1 | 19.1 | 10.0 |
| **Stocks** | | | | | | | |
| Ownership | 16.9 | 23.0 | 38.9 | 57.2 | 75.0 | 88.1 | 44.2 |
| Share | 1.8 | 2.7 | 3.9 | 7.1 | 12.9 | 21.2 | 6.6 |
| **Life insurance** | | | | | | | |
| Ownership | 8.2 | 13.2 | 19.7 | 26.5 | 30.2 | 36.5 | 20.5 |
| Share | 2.3 | 2.2 | 1.6 | 1.5 | 1.3 | 1.1 | 1.7 |
| **Other financial assets** | | | | | | | |
| Ownership | 7.4 | 7.8 | 8.5 | 9.7 | 12.1 | 20.3 | 10.0 |
| Share | 2.1 | 1.2 | 0.8 | 0.7 | 0.8 | 1.3 | 1.1 |
| **Residential real estate** | | | | | | | |
| Ownership | 19.4 | 40.7 | 85.1 | 93.1 | 95.4 | 96.7 | 68.0 |
| Share | 14.5 | 30.4 | 61.8 | 56.5 | 44.4 | 28.1 | 40.5 |
| **Commercial real estate** | | | | | | | |
| Ownership | 2.9 | 3.5 | 8.8 | 16.1 | 27.9 | 43.0 | 13.6 |
| Share | 1.2 | 1.4 | 2.5 | 4.0 | 6.0 | 6.9 | 3.2 |
| **Consumer durables** | | | | | | | |
| Ownership | 70.6 | 90.7 | 92.5 | 93.5 | 94.9 | 94.9 | 88.8 |
| Share | 44.6 | 43.2 | 12.3 | 7.3 | 4.6 | 2.7 | 21.7 |
| **Private business** | | | | | | | |
| Ownership | 2.9 | 3.5 | 8.0 | 13.2 | 18.9 | 40.4 | 11.7 |
| Share | 0.7 | 0.9 | 1.8 | 3.0 | 4.9 | 12.7 | 3.1 |
| **Financial assets** | | | | | | | |
| Ownership | 90.2 | 92.7 | 97.3 | 99.4 | 99.8 | 100.00 | 96.0 |
| Share | 38.5 | 24.1 | 21.5 | 29.2 | 40.1 | 49.6 | 31.5 |
| **Non-financial assets** | | | | | | | |
| Ownership | 72.4 | 95.2 | 98.6 | 99.6 | 99.4 | 99.6 | 93.5 |
| Share | 61.0 | 75.9 | 78.5 | 70.8 | 59.9 | 50.4 | 68.4 |

and the limited financial market participation among less wealthy households contradict traditional investment advice. Meanwhile, the average household in the top decile does not hold more than 30 percent of total assets in any one asset class.

I also find that households across the wealth distribution widely differ in the risk profile of their financial assets. Following Bertaut and Starr-McCluer (2000), I classify financial assets into the following categories: (1) safe financial assets, which include cash, cash equivalents, and savings bonds; (2) fairly safe financial assets, which include safer bonds (US government

Figure 3: Risk Profile of Financial Assets by Wealth Group

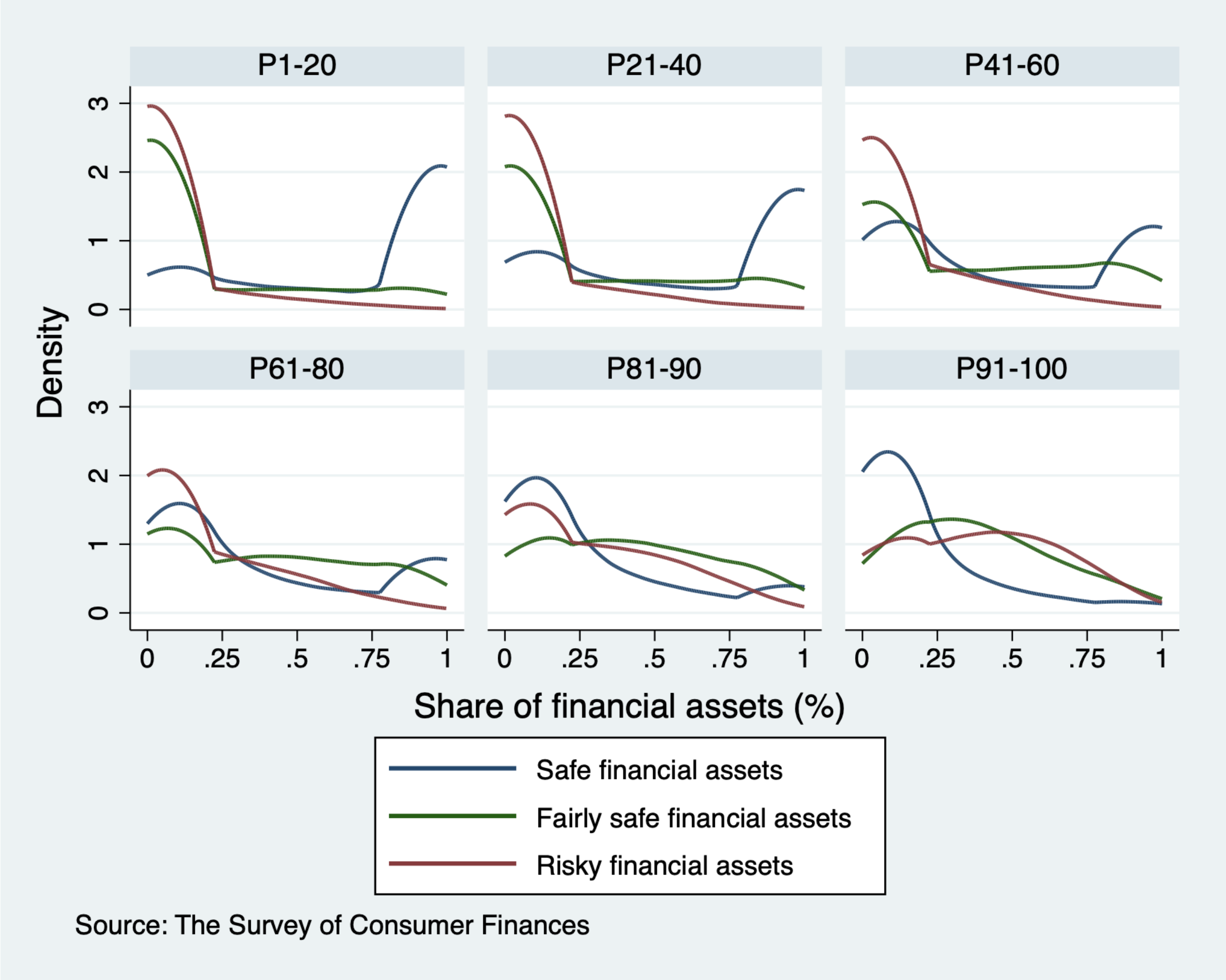


Figure 4: Average Direct and Indirect Stock Wealth by Wealth Group in 2007

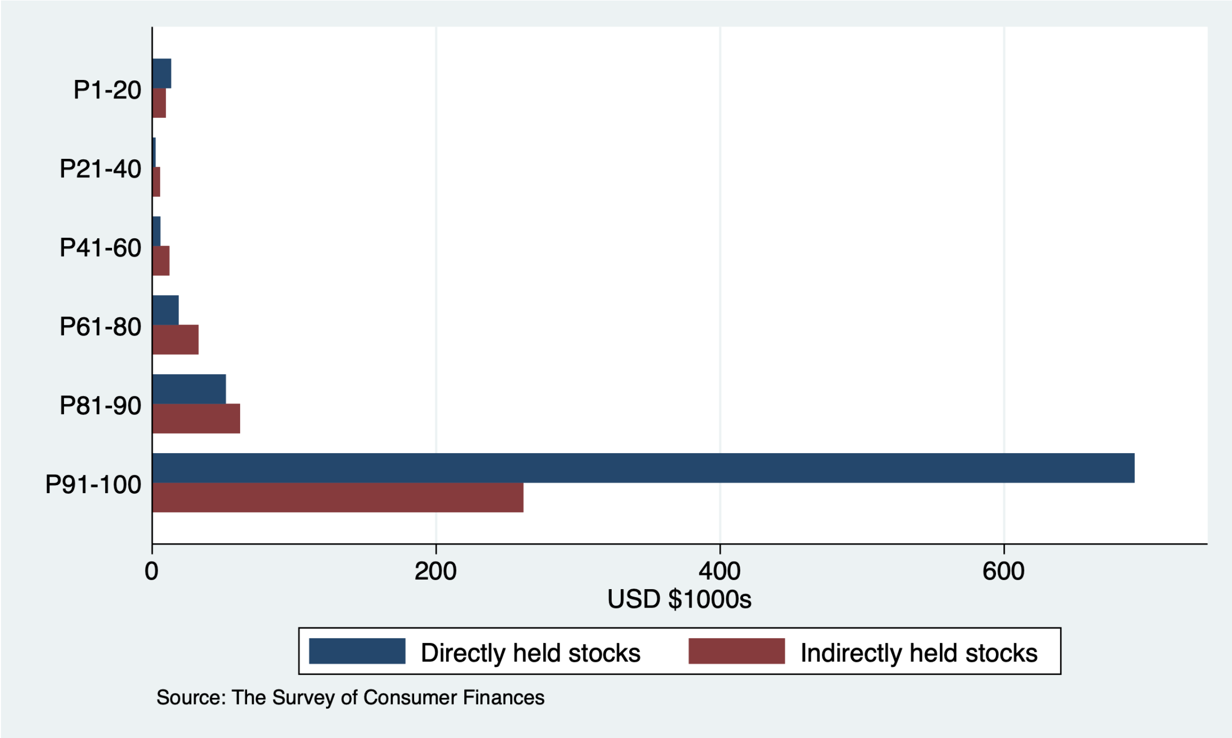



Figure 5: Share of Aggregate Stock Wealth in Retirement Accounts by Wealth Group in 2007

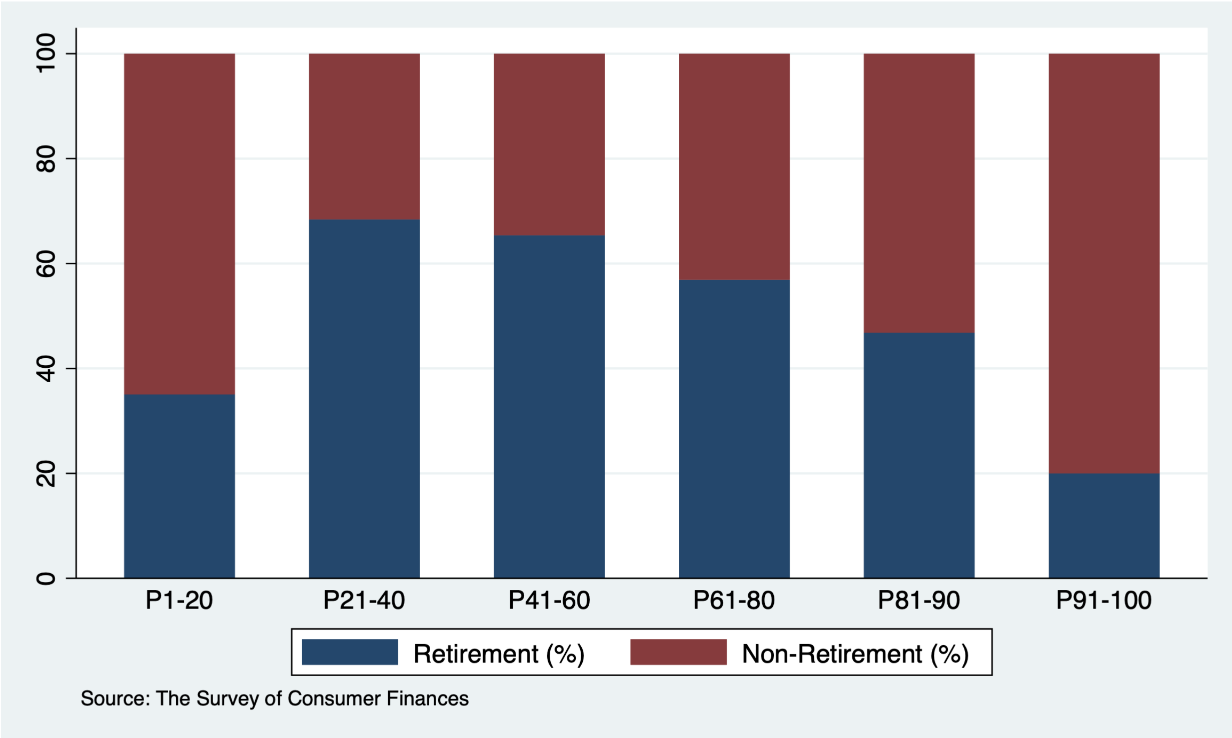
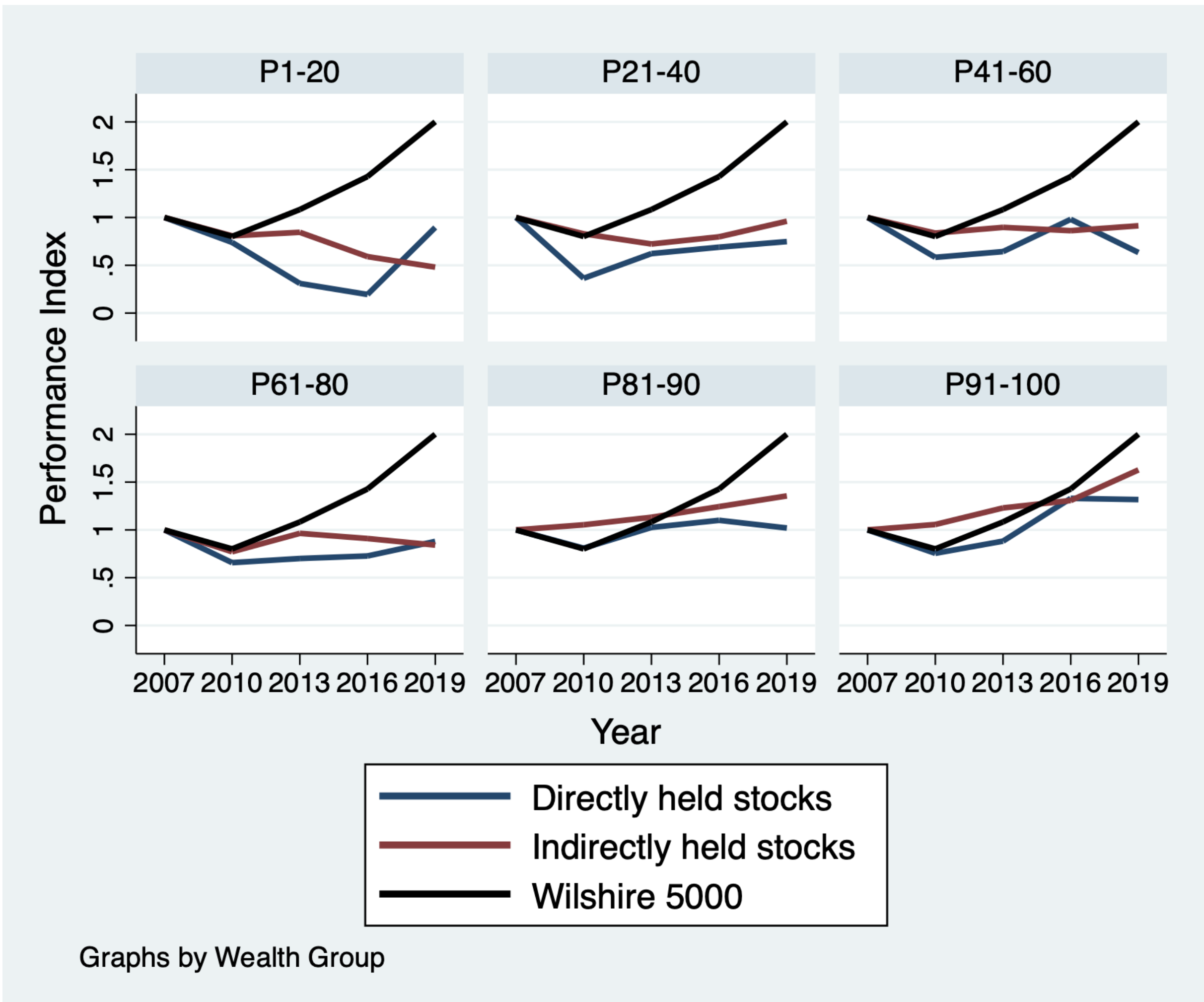


Figure 6: Growth of Average Stock Wealth Against the Wilshire 5000, 2007-2019



and tax-exempt) and cash life insurance; and (3) risky financial assets, which include stocks and riskier bonds (corporate, foreign, and mortgage-backed). I omit “other financial assets” from these categories (but keep them in total financial assets) as this asset class entails miscellaneous financial assets of varying risk levels. The SCF does not ask respondents what type of bonds are held in their managed accounts, so I categorize these indirectly held bonds under fairly safe financial assets. Thus, my measure of risky financial assets only includes direct holdings of risky bonds and bond mutual funds.

Figure 3 presents kernel density plots for the risk profile of financial assets for each wealth group. I include only households who own financial assets in this figure, which amounts to about 96 percent households who own assets. For the majority of households in the bottom 80 percent of the wealth distribution, over 75 percent of their financial assets are safe. In contrast, for most households in the top quintile, less than 25 percent of financial assets are safe. Remaining financial assets among the top quintile are evenly split among the risky and fairly safe categories, further illustrating wealthy households' portfolio diversification.

The findings of low portfolio diversification and low risky asset ownership among less wealthy households are well-studied in the literature. Mankiw and Zeldes (1991) first documented this low rate of stockownership, and Haliassos and Bertaut (1995) found that significant risk aversion among low income households and inertia in stockownership are key explanations for this phenomenon. More recent studies find that asset market participation costs deter many households from investing in stocks and bonds (Vissing-Jorgenson, 2002; Haliassos and Michaelides, 2003; Campbell, 2006). These costs involve both money and time, and they include the costs associated with financial education, setting up an investment account, finding a financial advisor, and filing taxes. Although the percent of households that own stocks remains below 50 percent, it has risen significantly from the 25 percent rate reported in Mankiw and Zeldes (1991). This rise is largely attributed to the expansion of defined-contribution (DC) pension plans (Campbell, 2006; Badarinza et al, 2016; Curcuru et al, 2009).

Households also differ in whether they hold financial securities directly through a brokerage account or indirectly through a managed account. Figure 4 presents the average holdings of directly held and indirectly held stocks among stockowners across the wealth distribution in 2007. Middle class households from the 21st through 90th percentiles of the distribution hold the majority of their stock wealth indirectly in managed accounts. As Figure 5 indicates, most of these indirectly held stocks are in retirement accounts such as 401(k)s or IRAs. This data also shows that stockholders at the top of the distribution have significantly higher stock wealth. The stock wealth of the average stockowning household in the top decile was over eight times that of the average stockowning household in the second-highest decile, and over forty times that of the average stockowning household in the bottom quintile. These trends hold throughout the period from 2007 to 2019.

Although SCF data does not allow me to explicitly differentiate between capital gains versus stock trading, I gain insight from the relative growth of average stockholdings against a stock market index. In Figure 6, I plot the real growth of average direct and indirect stockholdings for each wealth group against the Wilshire 5000. Average stockholdings for each wealth group grew at a slower rate than the stock market index. However, underperformance was larger for lower segments of the wealth distribution. Additionally, the top quintile saw positive relative growth for average indirect stockholdings in 2010 and in 2013.

This result suggests that portfolio rebalancing was heterogeneous across the distribution. Variation in stockholdings over time arise from either capital gains or losses, which occur as stock prices rise or fall, or from active rebalancing, which entails purchases or sales of stocks. Capital gains might vary if some households are more skilled at selecting high-performing securities than others. This explanation is plausible for directly held stock wealth, particularly among households that invest in individual equities rather than mutual funds, but less so for indirectly held stock wealth. Managed accounts are typically run by institutional investors which benchmark their portfolios to a broad market index such as the S&P 500. Presumably, the performance of these managed accounts do not vary significantly across the distribution.

## 3.2 Household Characteristics

Variation in portfolio allocation across the wealth distribution is largely influenced by demographics and other household characteristics. In Table 2, I present data on the age, race, education, marital status, risk tolerance, labor market status, and retirement plan participation of households in each wealth group. These variables all vary notably across the distribution, and in my analysis, I include them as control variables. In the following paragraphs, I detail the key differences and discuss empirical findings from previous literature on demographics and portfolio choice.

Unsurprisingly, younger households are concentrated at the bottom end of the distribution. I find that 41.3 percent of households in the bottom quintile are under 35, while this figure is only 1.6 percent for the top decile. Households over 75 are primarily in the top 40 percent, and those aged 35 to 54 are spread fairly evenly across the distribution. Intuitively, older households should be wealthier as they have had more time to accumulate savings. There is extensive literature covering the relationship between age and portfolio allocation. The traditional life-cycle model predicts a negative relationship between age and allocation

Table 2: Household Characteristics by Wealth Group

| | Wealth Group | | | | | | |
|---|---|---|---|---|---|---|---|
| | **P1-20** | **P21-40** | **P41-60** | **P61-80** | **P81-90** | **P91-100** | **Total** |
| | | | % households | | | | |
| **Age** | | | | | | | |
| Age 18-34 | 41.3 | 34.2 | 18.4 | 8.1 | 3.4 | 1.6 | 20.9 |
| Age 35-54 | 35.2 | 38.6 | 40.3 | 37.9 | 35.9 | 30.3 | 37.0 |
| Age 55-64 | 12.2 | 13.4 | 17.3 | 20.6 | 24.9 | 30.8 | 18.3 |
| Age 65-74 | 6.3 | 8.4 | 12.5 | 16.3 | 20.2 | 22.3 | 12.9 |
| Age 75+ | 5.0 | 5.5 | 11.6 | 17.2 | 15.6 | 14.9 | 10.9 |
| **Race** | | | | | | | |
| White | 52.7 | 58.9 | 71.6 | 80.0 | 85.4 | 89.2 | 70.1 |
| Black | 27.2 | 19.3 | 13.6 | 8.9 | 5.0 | 2.3 | 14.6 |
| Hispanic | 16.1 | 16.8 | 10.6 | 6.5 | 4.3 | 2.0 | 10.6 |
| Other race | 4.0 | 5.0 | 4.2 | 4.5 | 5.4 | 6.5 | 4.7 |
| **Education level** | | | | | | | |
| No high school | 20.0 | 18.8 | 13.6 | 8.8 | 4.0 | 1.9 | 12.8 |
| High school | 58.2 | 63.3 | 59.5 | 54.7 | 42.9 | 23.8 | 53.8 |
| College | 21.7 | 17.9 | 27.0 | 36.5 | 53.1 | 74.4 | 33.3 |
| **Marital status** | | | | | | | |
| Married | 24.1 | 36.1 | 49.8 | 59.4 | 68.4 | 77.1 | 48.4 |
| Unmarried male | 33.4 | 33.1 | 23.8 | 18.1 | 14.6 | 12.2 | 24.4 |
| Unmarried female | 42.4 | 30.8 | 26.3 | 22.6 | 17.0 | 10.7 | 27.2 |
| **Risk tolerance** | | | | | | | |
| Risk-averse | 55.4 | 54.3 | 49.1 | 38.4 | 24.9 | 11.9 | 43.1 |
| Risk-neutral | 28.7 | 30.6 | 33.5 | 41.7 | 50.2 | 54.9 | 37.4 |
| Risk-loving | 16.0 | 15.1 | 17.5 | 20.0 | 24.9 | 33.1 | 19.5 |
| **Labor market status** | | | | | | | |
| Retired | 8.8 | 11.3 | 21.3 | 30.5 | 34.6 | 32.5 | 21.1 |
| Self-employed | 5.5 | 6.2 | 7.8 | 10.7 | 14.5 | 30.2 | 10.5 |
| Unemployed in past year | 25.4 | 17.3 | 10.2 | 6.5 | 4.8 | 2.7 | 12.6 |
| **Retirement plan** | | | | | | | |
| DC pension | 13.1 | 20.2 | 28.5 | 31.3 | 32.9 | 35.3 | 25.4 |
| DB pension | 7.6 | 9.4 | 14.1 | 14.9 | 15.8 | 11.2 | 11.9 |
| Employer-based IRA | 1.7 | 2.9 | 6.7 | 13.8 | 23.5 | 33.4 | 10.7 |

toward risky assets, as younger households have longer investment horizons and must save for retirement. However, Ameriks and Zeldes (2004) find that equity shares do not decrease as households age and discuss the difficulty of empirically separating age effects from cohort effects.[4] Some research suggests that young households invest a suboptimal amount in risky financial assets due to career uncertainty, as the risk of losing labor income incentivizes them to hold a buffer of safe assets (Bertaut and Haliassos, 1997; Gomes and Michaelides, 2005).

[4]Cohort effects account for differences across generations, assuming that individuals born in the same generation have shared experiences that shape their behavior similarly.

In addition, the data show a large racial wealth gap. Almost one half of households in the bottom quintile are non-white, while only one-tenth of households in the top decile are non-white. Among minority races, the proportion of households that are black or hispanic drops off in higher wealth groups, while the proportion in other racial categories stays fairly constant. Chiteji and Stafford (1998) observe that white households have historically been more likely to own stocks and bonds, and they find evidence that low equity ownership among African American households can be explained by the influence of parents' investing behavior on their children.

The racial wealth gap likely relates to educational disparities and network effects. About three quarters of households in the top decile have college degrees, while this figure is less than one quarter for the bottom decile. Education provides an opportunity to build financial literacy, and research suggests that financially literate households participate more in financial markets and to invest more efficiently (Calvet et al, 2007; van Rooij et al, 2011). Additionally, a number of studies show the presence of peer effects in investing. Brown et al (2008) find that an individual's decision to own stocks correlates with the rate of ownership in one's community. Kaustia and Knüpfer (2012) find that individuals are more likely to invest in stocks when others in the same zip code have experienced positive recent stock returns.

Wealthier households are also more likely to be married and tolerant of risk. In the bottom 60 percent of the distribution, the majority of households are unmarried, with a concentration of unmarried females in the bottom quintile. Existing research suggests that women are more averse to financial risk than men. Using data from the 1989 SCF, Jianakoplos and Bernasek (1998) find that the effect of wealth on the share of wealth in risky assets is lower for single women than for single men. Correspondingly, the poorer households exhibit much higher risk aversion: about half of households in the bottom 60 percent of the distribution identify as risk averse.

Finally, the data show that wealthier households are more likely to be retired and self-employed, and less likely to have been recently unemployed. They are also more likely to have retirement accounts, particularly DC plans and IRAs. The finding of lower unemployment indicates that wealthy households face lower labor income uncertainty, which may explain the higher risk tolerance observed at the top end of the distribution.

# 4 Methodology

In this paper, my goal is to estimate how households' portfolio allocation toward risky assets changed after the financial crisis and during the QE era. My dependent variable of interest is the share of households' financial assets that are risky, denoted $share_i$, where risky financial assets include both stocks and directly held risky bonds. Equation 1 shows the baseline model. This model does not yet account for heterogeneity in rebalancing across the distribution, so it captures aggregate trends.

$$share_{it} = \beta_0 + \beta_1 year_t + \beta_2 group_{it} + \beta_3 X_{it} + \epsilon_{it}. \tag{1}$$

In this model, households are indexed by $i$ and survey years by $t$. Since I use pooled cross-sectional data, no household shows up more than once. $year_t$ represents survey year effects, with 2007 omitted. Thus, $\beta_1$ is interpreted as a percentage point change in the share of risky financial assets in some survey year compared to 2007, on average and holding all else constant. $group_{it}$ are dummy variables that indicate which wealth group a household is in, with the bottom quintile omitted. The term $X_{it}$ includes a number of household characteristics that influence portfolio choice. These variables can be grouped into four categories, presented below. Table 2 shows a summary of these characteristics by quintile throughout the period.

i **Household financial characteristics:** To control for household finances, I include the logs of total household debt and total household income. I also account for the portfolio constraint imposed by housing by including residential real estate as a percent of the household's total assets.

ii **Demographics:** The demographic characteristics I include are age, race, marital status, and education level. For age I include dummy variables for whether the household head is 18 to 34, 35 to 54, 65 to 74, or over 75, with 55 to 64 omitted. The marital status of each household is either married, unmarried and male, or unmarried and female. The race variables indicaate whether a household is primarily white, black, Hispanic, or another race. Education is captured by dummy variables for whether the household head has a high school degree, a college degree, or neither.

iii **Labor market characteristics:** I account for whether the household head is retired, is self-employed, or was recently unemployed within the 12 months prior to the survey date. I also include the share of total income derived from labor income as a measure of households' exposure to labor market fluctuations.

iv **Risk tolerance:** The SCF asks respondents whether they are willing to take substantial, above average, average, or below average financial risks, expecting to earn proportional returns. I combine the first two options and code them as risk loving, and I code the latter two as risk neutral and risk averse, respectively

I cannot use OLS regression to estimate this model because the observed risky share, $share_i$, may be considered censored data. Suppose each household has a latent optimal risky share of financial assets, denoted $share_i^*$. We only observe this optimal share if the household owns risky financial assets, which occurs only if the optimal share exceeds the zero threshold. If a household's optimal share is below this threshold, its observed share is zero. The risky share can be estimated using a censored regression model such as Tobit.

$$share_i^* = x_i\beta + \epsilon_i \tag{2}$$

$$share_i = \begin{cases} 0 & \text{if } share_i^* < 0 \\ share_i^* & \text{if } share_i^* \geq 0. \end{cases} \tag{3}$$

However, those who own risky financial assets might differ from those who do not in unobserved ways. In this case, the Tobit model suffers from sample selection bias, as we do not know the optimal share for households that decide not to hold risky financial assets. The Heckman selection model accounts for this issue by modeling the ownership decision and the portfolio share separately (Heckman, 1979). Let $owns_i$ be a binary variable indicating whether a household owns risky financial assets and let $share_i$ be the observed share as defined above. The model consists of a selection equation (Eqn. 4) and an outcome equation (Eqn. 5). The selection equation estimates the probability of owning risky financial assets. The outcome equation estimates the share of financial assets that are risky, conditional on ownership, and it accounts for each households' propensity to own risky financial assets based on the selection equation.

CONSISTENT?

$$owns_{it} = x_{it}\alpha + v_{it};\ owns_{it} \in 0, 1. \tag{4}$$

$$share_i = w_i\gamma + z_i. \tag{5}$$

The selection equation is estimated with Probit and the outcome equation with OLS regression. I use maximum likelihood estimation to derive these estimates.[5] The Heckman model reports two important additional figures: (1) rho, defined as the correlation of the error terms in the selection and outcome equations, $\rho = Corr(v, z)$; and (2) sigma, defined as the standard error of the residual in the outcome equation. Researchers typically interpret the significance of rho as the presence of sample selection bias.

In the Heckman model, there must be at least one regressor in the selection equation

[5] I omit the fifth implicate dataset from this analysis because the Heckman model fails to converge with this implicate. However, this omission does not make a substantive difference as the estimated coefficients are similar across implicates. In subsequent analysis where I run separate models for ownership and portfolio shares, I use all five implicates.

SAME AS rho NO?

that is not in the outcome equation. This regressor must be an exogenous variable that influences a household's decision to own risky financial assets but not its optimal share. I incorporate three additional variables in the selection equation for this purpose. These variables indicate whether the household has one of the following employer-sponsored plans: a defined-contribution (DC) pension plan, a defined-benefit (DB) pension plan, or an IRA or Keogh plan. I expect that a DC plan, IRA, or Keoghs positively impacts risky asset ownership as these retirement plans entail creating managed accounts that invest in stocks and bonds. I anticipate that DB plans negatively impact ownership as they guarantee a future stream of income from the employer's investment fund, disincentivizing participants from investing on their own. I make two critical assumptions here: (1) all households are equally likely to participate or not participate in these retirement plans, and (2) households do not select their jobs based on the availability of these plans.

Before implementing the model I drop all observations with no financial assets, as the behavior of households who own no financial assets might differ from that of households who own financial assets but no risky financial assets. This amounts to over 4 percent of households accounting for probability weights, as shown in Table 1. Among the remaining observations, about 46 percent own risky financial assets.

# 5 Results

## 5.1 Sample Selection

Table 3 presents the Tobit and Heckman selection models without the wealth group interaction. The outcome and selection equations are shown in the second and third columns, respectively. Because the selection equation is estimated using Probit, the magnitudes of its coefficients are not interpretable, so I report the marginal effects at the means of the independent variables in the fourth column. These marginal effects may be interpreted as the percentage point change in the probability of owning risky financial assets due to a unit change in the explanatory variable, on average and holding all else constant.

The Heckman coefficients indicate whether changes in ownership or in portfolio shares of risky financial assets underlie the Tobit coefficients. As discussed earlier, the significance of rho and sigma indicate whether sample selection into risky asset ownership is endogenous. I find that both rho and sigma are significant at the one percent level, so I conclude that the Tobit model suffers from sample selection bias. Thus, it is necessary to model the ownership and portfolio share of risky financial assets separately. In the following paragraphs I discuss the main findings from the Heckman model.

Table 3: Tobit and Heckman Models for Risky Share of Financial Assets with Homogeneous Time Effects

| | (1) | | (2) | | | | (3) | |
|---|---|---|---|---|---|---|---|---|
| | Tobit | | Heckman | | | | Heckman (mfx) | |
| | Share | | Share | | Ownership | | Ownership | |
| | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Year=2010 | -0.026*** | 0.010 | -0.020** | 0.008 | -0.333*** | 0.036 | -0.129*** | 0.014 |
| Year=2013 | -0.030*** | 0.010 | -0.011 | 0.008 | -0.366*** | 0.038 | -0.142*** | 0.014 |
| Year=2016 | -0.032*** | 0.010 | -0.021** | 0.008 | -0.357*** | 0.037 | -0.139*** | 0.014 |
| Year=2019 | -0.034*** | 0.010 | -0.021** | 0.009 | -0.357*** | 0.039 | -0.139*** | 0.014 |
| P21-40 | 0.104*** | 0.013 | 0.024* | 0.013 | 0.253*** | 0.038 | 0.101*** | 0.015 |
| P41-60 | 0.238*** | 0.014 | 0.041*** | 0.012 | 0.626*** | 0.043 | 0.245*** | 0.015 |
| P61-80 | 0.338*** | 0.014 | 0.068*** | 0.013 | 0.959*** | 0.046 | 0.364*** | 0.015 |
| P81-90 | 0.417*** | 0.015 | 0.110*** | 0.014 | 1.249*** | 0.051 | 0.439*** | 0.013 |
| P91-100 | 0.467*** | 0.016 | 0.173*** | 0.015 | 1.463*** | 0.060 | 0.489*** | 0.013 |
| Log debts | 0.007*** | 0.001 | 0.001 | 0.001 | 0.017*** | 0.003 | 0.007*** | 0.001 |
| Log income | 0.062*** | 0.005 | 0.005 | 0.004 | 0.210*** | 0.020 | 0.083*** | 0.008 |
| Housing assets share | -0.002*** | 0.000 | -0.000*** | 0.000 | -0.005*** | 0.000 | -0.002*** | 0.000 |
| Age 18-34 | 0.006 | 0.011 | -0.022** | 0.010 | 0.037 | 0.042 | 0.015 | 0.016 |
| Age 35-54 | 0.009 | 0.009 | 0.007 | 0.007 | -0.003 | 0.035 | -0.001 | 0.013 |
| Age 65-74 | 0.013 | 0.012 | -0.006 | 0.010 | 0.082* | 0.048 | 0.033* | 0.018 |
| Age 75+ | 0.064*** | 0.016 | 0.023 | 0.015 | 0.241*** | 0.061 | 0.096*** | 0.021 |
| Black | -0.086*** | 0.010 | -0.034*** | 0.009 | -0.261*** | 0.034 | -0.102*** | 0.013 |
| Hispanic | -0.144*** | 0.012 | -0.038*** | 0.011 | -0.432*** | 0.041 | -0.164*** | 0.014 |
| Other race | -0.058*** | 0.014 | -0.032*** | 0.011 | -0.120** | 0.053 | -0.047** | 0.020 |
| Married | 0.011 | 0.008 | -0.018** | 0.008 | 0.027 | 0.030 | 0.011 | 0.012 |
| Unmarried female | 0.036*** | 0.010 | -0.005 | 0.009 | 0.124*** | 0.032 | 0.049*** | 0.013 |
| No high school | -0.094*** | 0.014 | 0.012 | 0.016 | -0.258*** | 0.043 | -0.100*** | 0.016 |
| College degree | 0.077*** | 0.007 | 0.033*** | 0.006 | 0.284*** | 0.026 | 0.113*** | 0.010 |
| Self-employed | -0.107*** | 0.011 | -0.055*** | 0.008 | -0.214*** | 0.040 | -0.084*** | 0.015 |
| Recently unemployed | -0.045*** | 0.011 | 0.001 | 0.011 | -0.047 | 0.037 | -0.019 | 0.014 |
| Retired | 0.026** | 0.013 | -0.002 | 0.010 | 0.143*** | 0.048 | 0.057*** | 0.018 |
| Labor income share | 0.098*** | 0.012 | -0.016* | 0.009 | 0.197*** | 0.040 | 0.078*** | 0.015 |
| Risk averse | -0.151*** | 0.008 | -0.053*** | 0.008 | -0.410*** | 0.027 | -0.161*** | 0.010 |
| Risk loving | 0.031*** | 0.007 | 0.039*** | 0.006 | 0.043 | 0.031 | 0.017 | 0.012 |
| DC pension | | | | | 1.052*** | 0.031 | 0.398*** | 0.010 |
| DB pension | | | | | -0.052 | 0.036 | -0.021 | 0.014 |
| IRA/Keogh from job | | | | | 0.731*** | 0.042 | 0.281*** | 0.015 |
| Rho | | | 0.248*** | | | | | |
| Sigma | | | 0.239*** | | | | | |
| Mean of Share | 0.158 | | 0.158 | | | | | |
| Number Selected | | | 15138 | | | | | |
| Observations | 27274 | | 27274 | | | | | |

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

Both models indicate that US households experienced a sustained aggregate decline in risky financial asset ownership and portfolio shares after the Great Recession. Based on estimates in the selection equation, compared to 2007, households were over 12 percentage points less likely to own risky financial assets in the four subsequent survey years. These time effects are significant at the one percent level and have similar magnitudes, indicating a prolonged drop in ownership. The outcome equation predicts that in 2010, 2016, and 2019, the risky share of financial assets among US households was almost 2 percentage points lower than in 2007, on average and holding all else constant. These estimates are significant at the five percent level. The effect on portfolio shares is still negative, but not significant, in 2013.

As expected, wealthier households display significantly higher risky financial asset ownership and portfolio shares. The estimated coefficients on each wealth group are all positive and their magnitudes are larger and more significant for groups higher up the distribution. The middle quintile and top decile are more likely to own risky financial assets than the bottom quintile by 24.5 and 48.9 percentage points, respectively, and their risky shares of financial assets are estimated to be 4.1 and 17.3 percentage points higher. Both a one percent increase in debt and a one percent increase in income correspond with a higher probabilities of ownership and portfolio shares, but only the effects on ownership are significant. A percentage point increase in the housing share of assets corresponds with lower risky financial asset ownership and portfolio shares. These effects have small magnitudes and are significant at the one percent level. This finding is consistent with the theory that illiquidity risk from homeownership incentivizes homeowners to reduce their exposure to financial market risk (Flavin and Yamashita 2002, Cocco 2005).

Contrasting the lifecycle model of portfolio choice, I find that older households are more likely than young households to own risky financial assets and that their risky portfolio shares are higher. Households aged 65 to 74 and those over 75 are 3.3 and 9.6 percentage points more likely to own risky financial assets than those aged 55 to 64, respectively, on average and holding all else constant. I find no significant effects on ownership for the other age groups. In the outcome equation, risky shares of financial assets are 2.3 percentage points higher for households over 75 and 2.2 percentage points lower for households aged 18 to 34.

agree with

The effects of other demographic factors ~~are~~ intuit~~ive~~ion. College-educated households are 11.3 percentage points more likely to own risky financial assets and they have 3.3 percentage point higher portfolio shares than high school graduates, ceteris paribus. Meanwhile, households without high school diplomas have significantly lower probabilities of ownership. Non-white households invest less in risky financial assets: compared to white households, their probabilities of ownership are over 10 percentage points lower and their portfolio shares are over 3 percentage points lower, on average. Risk averse households are over 16 percentage points less likely to own risky financial assets, and households with higher risk tolerance have significantly higher risky shares of financial assets. I do find that unmarried females are significantly more likely to own risky financial assets than unmarried males, which contradicts existing studies on gender and portfolio allocation. However, this result might arise because I have controlled for other factors, such as risk tolerance, that explain variation in behavior between men and women.

I find that retirement plans are a key determinant of risky financial asset ownership. Households with either DC plans or employer-offered IRAs or Keoghs are significantly more likely to own stocks and risky bonds. These effects have large magnitudes: households with DC plans are 39.8 percentage points more likely to own these risky assets, and those with employer-offered IRAs or Keoghs are 28.1 percentage points more likely. Participation in a DB plan negatively impacts the probability of ownership, although this effect is not significant. This result is intuitive as DB plans guarantee future income for participants, disincentivizing households from seeking income through stocks and risky bonds.

Finally, I find that households' labor market status impacts their financial asset portfolios. Retired households are 5.7 percentage points more likely to own risky financial assets than non-retired households, although their risky shares are negligibly smaller. Self-employed households have significantly lower probabilities of ownership and portfolio shares. This finding might result from the fact that self-employed individuals are already exposed to risk from equity in their own private businesses, leading them to allocate the remainder of their portfolio toward safe assets (Campbell, 2006).

## 5.2 Heterogeneity in Time Effects Across the Distribution

To test for heterogeneity in portfolio rebalancing, I allow time effects to vary across the distribution in the Heckman selection model by including an interaction term between wealth group and survey year. This model is shown in Equations 6 and 7

$$owns_i = \alpha + \alpha_1 year_t + \alpha_2 group_{it} + \alpha_3 year_t \times group_{it} + \alpha_4 X_{it} + v_{it}, \tag{6}$$

$$share_i = \gamma_0 + \gamma_1 year_t + \gamma_2 group_{it} + \gamma_3 year_t \times group_{it} + \gamma_4 X_{it} + z_{it}. \tag{7}$$

Figure 7 displays the interaction coefficients with 95 percent confidence interval bands. This plot highlights the variation in time effects across the distribution. In Table 4, I add the survey year coefficient to each interaction coefficient and take the joint significance. This table indicates whether time effects were significant for each wealth group. For full regression results, refer to Table 7 in the Appendix.

Figure 7: Heckman Model Interaction for Risky Financial Assets

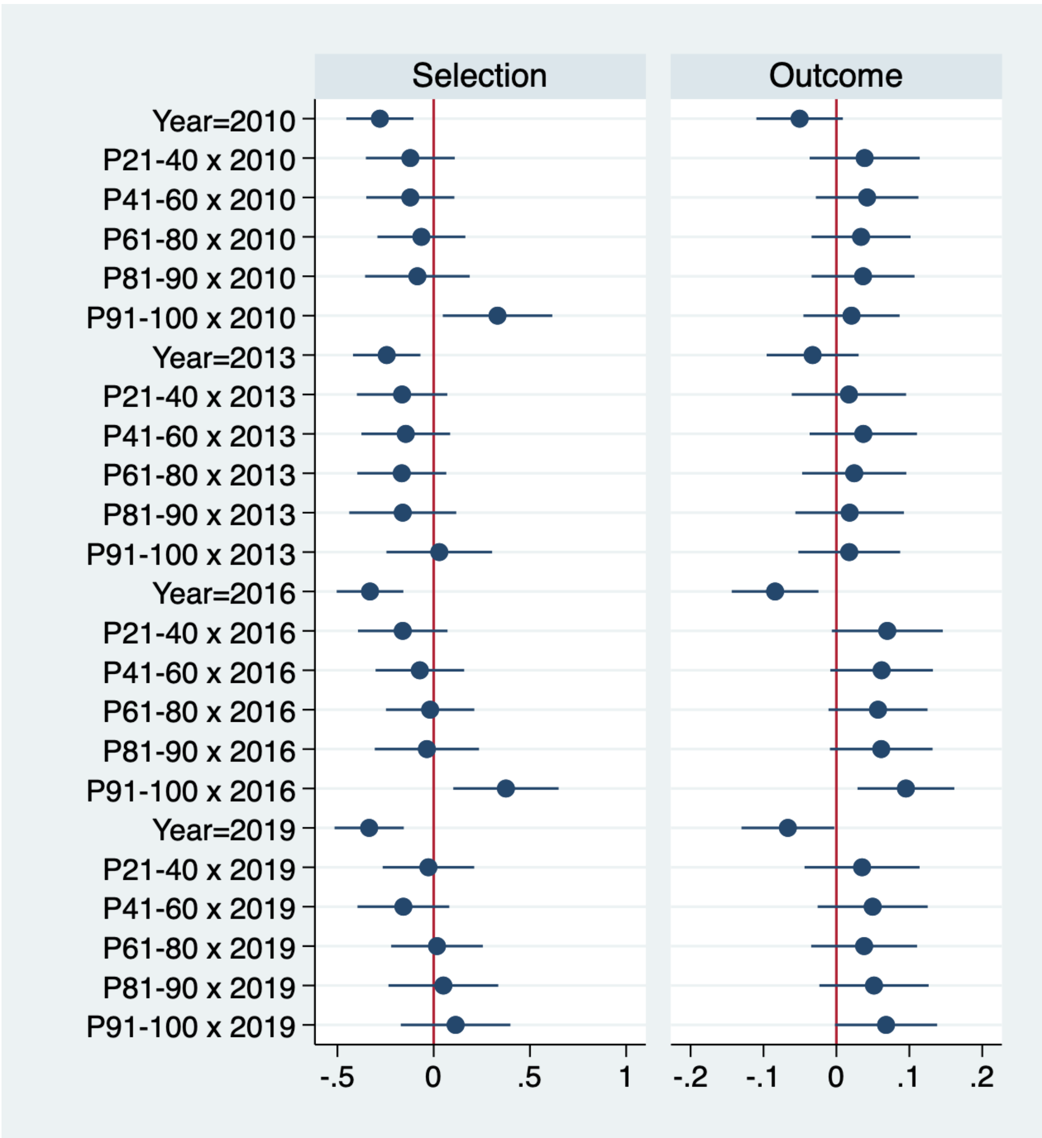


Table 4: Joint Significance of Survey Year and Wealth Group Interaction

| | Selection (mfx): Ownership | | | | Outcome: Share | | | |
|---|---|---|---|---|---|---|---|---|
| | **2010** | **2013** | **2016** | **2019** | **2010** | **2013** | **2016** | **2019** |
| **P1-20** | -0.109*** | -0.096*** | -0.129*** | -0.130*** | -0.050* | -0.033 | -0.084*** | -0.067** |
| **P21-40** | -0.157*** | -0.160*** | -0.192*** | -0.141*** | -0.012 | -0.015 | -0.014 | -0.031 |
| **P41-60** | -0.157*** | -0.153*** | -0.157*** | -0.192*** | -0.008 | 0.004 | -0.022 | -0.017 |
| **P61-80** | -0.134*** | -0.160*** | -0.136*** | -0.123*** | -0.017 | -0.008 | -0.027 | -0.029 |
| **P81-90** | -0.142*** | -0.159*** | -0.143* | -0.110** | -0.014 | -0.014 | -0.023 | -0.015 |
| **P91-100** | 0.023 | -0.084** | 0.019 | -0.085** | -0.030* | -0.015 | 0.011 | 0.002 |

I find that households in the bottom 90 percent of the wealth distribution were significantly less likely to own risky financial assets in each post-recession survey year compared to 2007. Those in the base group, the bottom quintile, were over 10 percentage points less likely to own stocks and risky bonds throughout the period. The interaction terms were negative but not significant for the 21st through 90th percentiles, indicating that households in the middle of the distribution experienced a relatively larger negative effect on risky financial asset ownership. By contrast, households in the top decile were only 8 percentage points less likely to own risky financial assets in 2013 and 2019, and in 2010 and 2016, they were about 2 percentage points more likely.

Notably, time effects on ownership varied across the four years for the top decile while they stayed at a similar magnitude for each of the other wealth groups. This result suggests that households at the top of the distribution update their portfolio allocation frequently in response to market conditions, while less wealthy households rebalance their portfolios infrequently, only in response to large shocks. This inequality in rebalancing holds implications for wealth inequality. By selling off risky financial assets during the financial crisis and not repurchasing them in subsequent years, the bottom 90 percent of households lost the opportunity for capital gains during economic recovery and QE. Meanwhile, the wealthiest households benefitted from these capital gains as they either retained or quickly repurchased stocks and risky bonds.

In the outcome equation, only the bottom quintile saw a significant decline in the risky share of financial assets throughout the post-recession period. The magnitude of these negative effects increased in 2016 and in 2019. The wealth interaction terms were positive in each year, and significant for most wealth groups in 2016, amounting to zero or slightly negative time effects on risky shares for the top 90 percent of the distribution. The disparity in time effects was strongest in 2016, as the bottom quintile saw a 8 percentage point decline in the risky share of financial assets relative to 2007 while the top decile saw a 1 percentage point increase, this latter effect was not statistically significant.

## 5.3 Directly Versus Indirectly Held Stocks

Table 5: Joint Significance of Survey Year and Wealth Group Interaction

| | Directly Held Stocks | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Probit (mfx): Ownership | | | | OLS: Share | | | |
| | 2010 | 2013 | 2016 | 2019 | 2010 | 2013 | 2016 | 2019 |
| **P1-20** | -0.067* | -0.112*** | -0.129*** | -0.065* | -0.047 | 0.053 | -0.021 | -0.021 |
| **P21-40** | -0.082** | -0.067** | -0.081*** | -0.004 | 0.014 | 0.008 | 0.057 | -0.028 |
| **P41-60** | -0.070** | -0.096*** | -0.032* | -0.098*** | -0.059 | 0.029 | -0.044 | -0.000 |
| **P61-80** | -0.074*** | -0.085*** | -0.089*** | -0.079*** | 0.005 | 0.004 | 0.008 | 0.002 |
| **P81-90** | -0.075*** | -0.077*** | -0.068*** | -0.096*** | -0.022 | -0.013 | -0.023 | -0.018 |
| **P91-100** | 0.042 | -0.041** | 0.014 | -0.073*** | -0.057*** | 0.020 | 0.008 | -0.006 |

| | Indirectly Held Stocks | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Probit (mfx): Ownership | | | | OLS: Share | | | |
| | 2010 | 2013 | 2016 | 2019 | 2010 | 2013 | 2016 | 2019 |
| **P1-20** | -0.112*** | -0.090** | -0.104*** | -0.171*** | -0.044 | -0.042 | -0.071** | -0.050 |
| **P21-40** | -0.147*** | -0.173*** | -0.192*** | -0.165*** | -0.007 | -0.009 | -0.019 | -0.028 |
| **P41-60** | -0.127*** | -0.132*** | -0.132*** | -0.159*** | 0.007 | 0.014 | -0.022 | -0.012 |
| **P61-80** | -0.108*** | -0.125*** | -0.101*** | -0.091*** | -0.019 | 0.000 | -0.019 | -0.028 |
| **P81-90** | -0.064* | -0.078* | -0.025 | -0.017 | -0.011 | -0.017 | -0.035* | -0.010 |
| **P91-100** | -0.068* | -0.069* | 0.004 | -0.051 | 0.013 | 0.018 | 0.002 | 0.031** |

To understand the above results further, I analyze the two main components of risky financial assets separately: directly held stocks and indirectly held stocks. I exclude analysis of directly held higher-risk bonds because only 2 percent of households with financial assets own this asset class, over 90 percent of which are in the top decile of the wealth distribution, so there is insufficient data for the model. By contrast, over 32 percent and 44 percent directly and indirectly own stocks, respectively. Additionally, because maximum likelihood estimation of the Heckman model fails to converge for these narrower asset classes, I instead run a Probit model for asset class ownership and a separate OLS regression for the asset class's share of financial assets. I use the same regressors as in the selection and outcome equations, respectively. I run the model conditional on ownership, so the results reflect only the behavior of households that own each asset class.

The regression results are in Tables 8 and 9 in the Appendix, and the joint significance of the year and interaction coefficients is in Table 5. The differentiation between directly and indirectly held stocks provides insight into whether the time effects on households' direct stock trading differ from the time effects on stock trading in households' managed investment accounts. The former entails buying or selling shares, while the latter may entail either the portfolio manager or the household updating the account's portfolio allocation, say from a 70/30 stock to bond ratio to a 60/40 ratio.

I find that households in the bottom 90 percent of the wealth distribution experienced negative time effects on the probability of directly owning stocks in all survey years after 2007. Nearly all of these effects are significant, and they primarily range from a 6 to 10 percentage point drop in the probabiliity of directly owning stocks (a few marginal effects fall outside this range). The top decile saw significant negative time effects in 2013 and 2019, but the decline in ownership was of a smaller magnitude than that of the other wealth groups. Meanwhile, the top decile saw a slight increase in the probability of ownership in 2010 and 2016, although these effects are insignificant.

The drop in the rate of ownership of indirectly held stocks after 2007 was larger and more significant among the bottom 80 percent of households. The marginal effects indicate that the probability of ownership fell by 9 to 18 percentage points for these households, and almost all are significant at the 1 percent level. The top quintile saw smaller negative time effects in 2010 and 2013, significant only at the 10 percent level, and no significant effects in 2016 or 2019. In 2016, the probability of ownership slightly increased for the top decile.

Conditional on ownership, households' allocation of financial assets toward directly and indirectly held stocks did not significantly change. For the most part, time effects on portfolio shares are insignificant and they fluctuate for each wealth group across years. However, there are a few key insights. Notably, the average portfolio share of directly held stocks among households in the top decile significantly fell by 5.7 percentage points in 2010, but rebounded in subsequent years. This effect is not observed among the other wealth groups. A possible explanation is that households in the top decile who experienced large capital losses did not sell their risky financial assets, pulling down the top decile's average risky asset share. Meanwhile, the bottom quintile's decrease in allocation toward risky financial assets appears to be driven by lower portfolio shares of indirectly held stocks. I cannot empirically detect whether this effect is a result of capital losses or rebalancing. However, this result is observed for indirectly held stocks in managed accounts, which are usually benchmarked against a broad market index. Assuming that managed accounts perform similarly on average for households across the distribution, I conclude that stockowners in the bottom quintile actively decreased their portfolio share of indirectly held stocks.

Evidently, the results observed in the Heckman model are driven by declines in the ownership rates of both directly and indirectly held stocks. The divestment from directly held stocks was more widespread, with a sustained decline in ownership among households in the top quintile, while the divestment from indirectly held stocks only held for the bottom 80 percent of the distribution in the long term. Additionally, the fall in ownership had a larger magnitude for indirectly held stocks than directly held stocks. This result is particularly consequential for wealth inequality because the majority of stock wealth for the middle class is held indirectly, mainly in retirement accounts (see Figure 5). My evidence suggests that the financial crisis sparked a disproportionate sell-off of stocks among lower and middle class households that prevented them from capitalizing on the boom in asset prices during the QE era. Because this sell-off took place during the crisis when asset prices dropped, the lower and middle classes locked in losses. Wealthy households faced an initial decline in the portfolio share of risky financial assets as asset prices fell, but the value of these assets recovered in subsequent years.

# 6 Robustness Checks

## 6.1 Heterogeneity in Time Effects Across Household Characteristics

So far, my model only allows time effects to vary across the wealth distribution. Within each wealth group, it assumes that time effects are the same for households with different characteristics. However, it may be the case that households of different races, education levels, or some other characteristic rebalanced differently. In Table 2 I showed that wealthier households are older and more likely to be white, college-educated, risk-loving, and stably employed. Thus, heterogeneous rebalancing across demographic groups may underlie the observed time effects across the wealth distribution, causing my model to suffer from omitted variable bias.

A handful of studies examine how the wealth inequality across demographic groups evolved in the post-recession period. Glover et al (2020) construct an overlapping generations model that predicts how US households of different age groups altered their portfolios after the financial crisis. The authors predict that as risky asset prices fall due to the recessionary shock, younger households will buy risky assets at low prices, allowing them to accumulate wealth in the future, while older households are forced to sell risky assets at low prices to fuel consumption. This effect would amount to a redistribution of wealth from older to younger households, and thus from the top to the bottom of the wealth distribution. However, if this model holds, then the rise in risky asset prices due to QE would mitigate or reverse this effect.

I test this hypothesis by running a Probit model for risky financial asset ownership and an OLS model for the risky share of financial assets with an interaction between age group and survey year, in addition to the wealth group interaction. The age interaction coefficients are shown in Figure 8, and in Figure 9 I show how time effects across the wealth distribution change after accounting for age. In the Appendix, I repeat this analysis for interactions with education level, race, risk tolerance, and whether a household was recently unemployed.

Figure 8: Age x Year Interaction in the Model for Risky Financial Asset Ownership

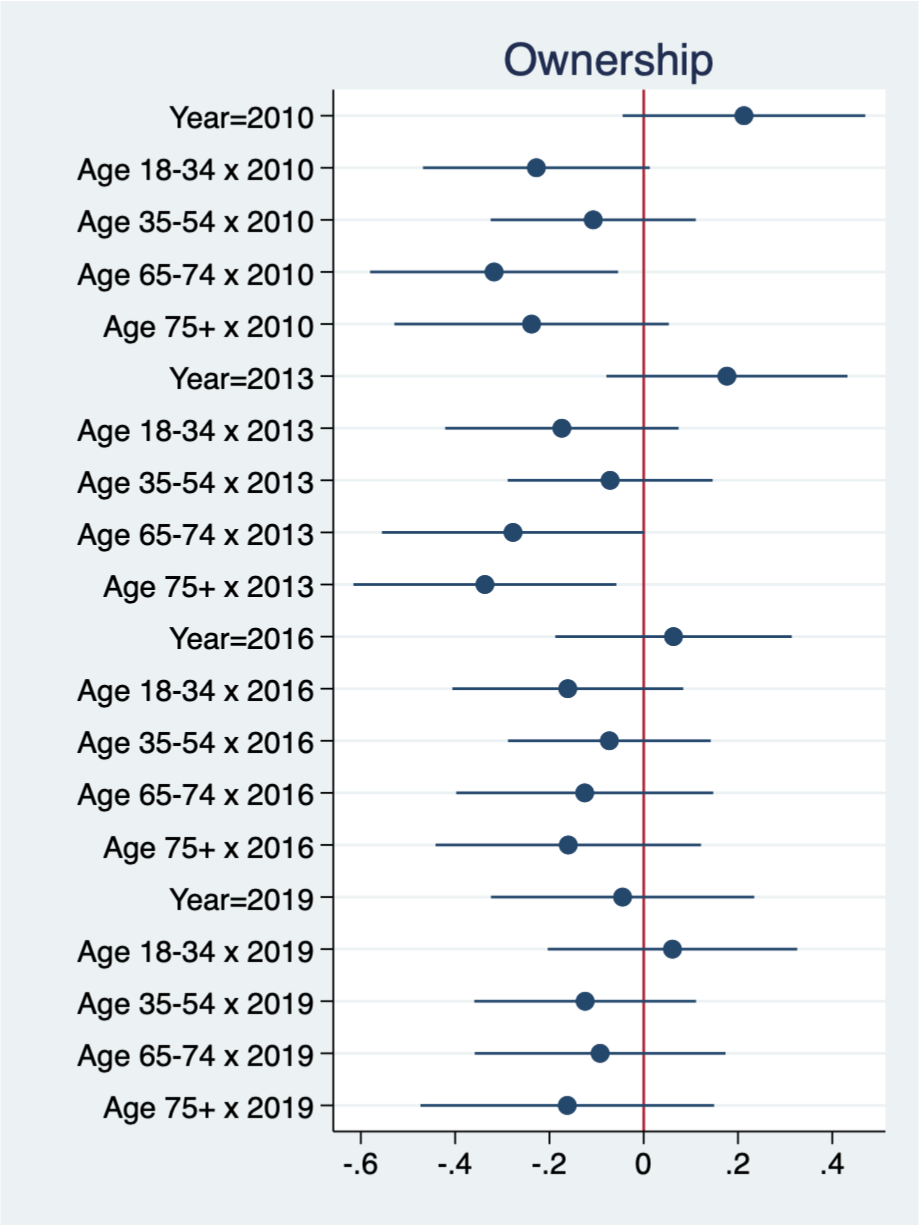
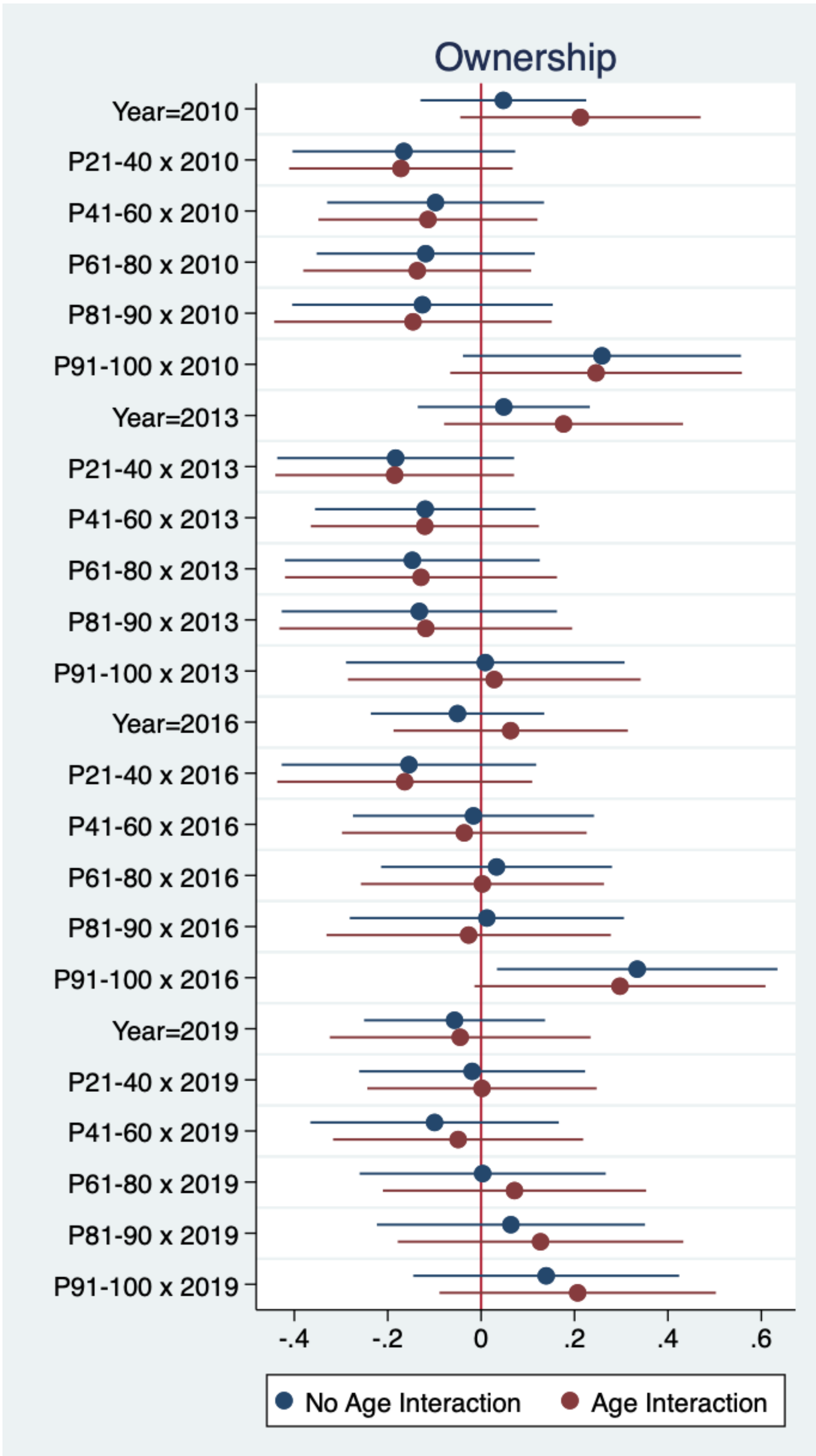


Figure 9: Wealth Group x Year Interaction After Incorporating Age



The age interaction coefficients suggest that there was a redistribution of risky financial assets from older households to middle-aged households. The base group of 55 to 64 year olds had positive but insignificant time effects, and their magnitudes were largest in 2010 and in 2013. All other age groups had lower time effects on the probability of ownership. The magnitudes of the negative interaction terms are largest among households aged 65 to 74 and over 75 in 2010 and in 2013, indicating that these age groups experienced the largest drop in risky financial asset ownership after the financial crisis. As the economy recovered in 2016 and in 2019, the variation in time effects across age groups was smaller. These results partially align with those in Glover et al (2020): older households sold off risky financial assets, locking in losses, but I find no evidence that younger households purchased risky assets at low prices.

However, I find no evidence of omitted variable bias. After allowing for heterogeneous time effects across age and each of the other household characteristics, the wealth interaction coefficients maintain a similar magnitude and significance level. Thus, there must be some unobserved factors correlated with wealth that drive heterogeneous portfolio rebalancing across the distribution.

## 6.2 Households' Confidence and Financial Literacy

Based on existing literature, I consider three plausible explanations for the significant variation in portfolio rebalancing. First, wealthy households might be more confident in their investing abilities, making them less likely to withdraw from the market during financial crises. Second, wealthy households might have greater financial literacy, making them more aware of the risks of selling when prices are low. Third, because a larger proportion of wealthy households own risky financial assets, wealthy households might benefit more from peer network effects and make smarter investing decisions.

In 2016, the SCF introduced questions that assess households' confidence in their investing abilities and their financial literacy, providing data on the first two of the three explanations offered above. I find that both of these variables are correlated with wealth. I cannot empirically test whether they drive my results because the data is not available throughout my sample period. However, several studies show that these characteristics influence asset market participation. Cupák et al (2020) analyze the 2016 SCF data and find that households with greater confidence and financial literacy invest more in risky financial assets, both on the extensive and intensive margins. Additionally, using panel data on German households, Bucher-Koenen and Ziegelmeyer (2013) find that financially illiterate households were more likely to sell risky financial assets after the Global Financial Crisis.

Figure 10: Self-Assessed Financial Knowledge by Wealth Group, 2016-2019

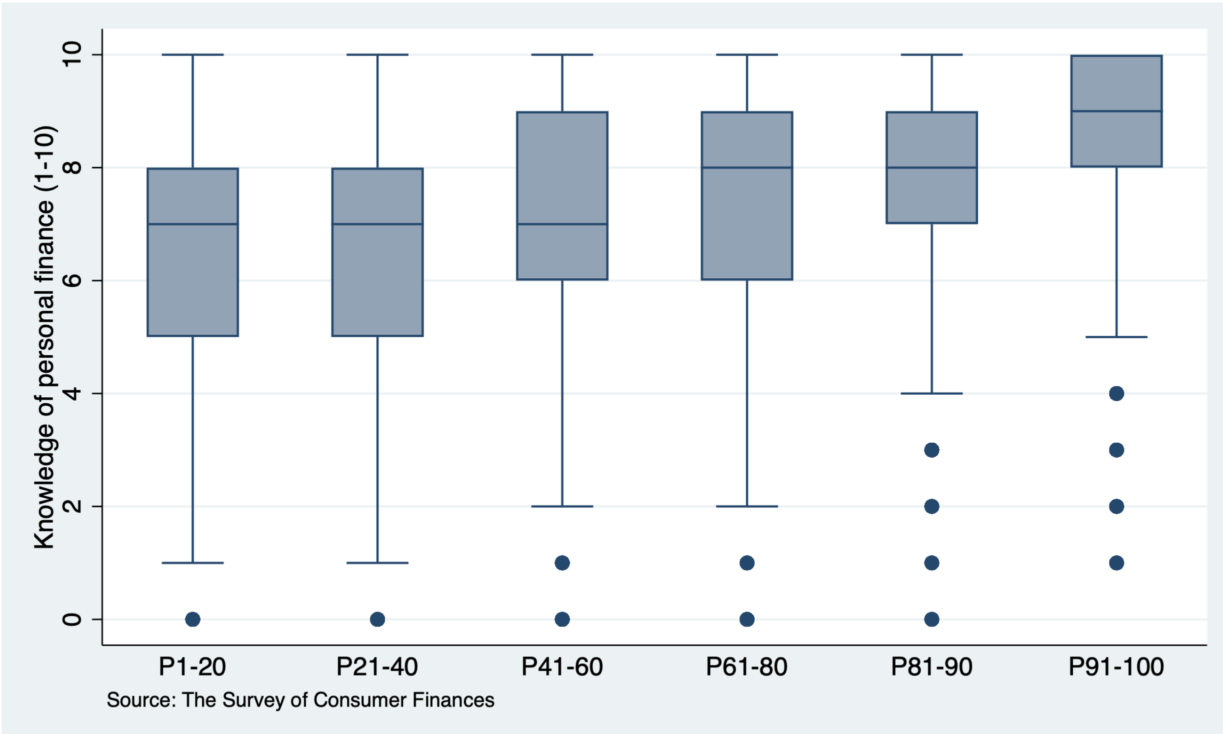
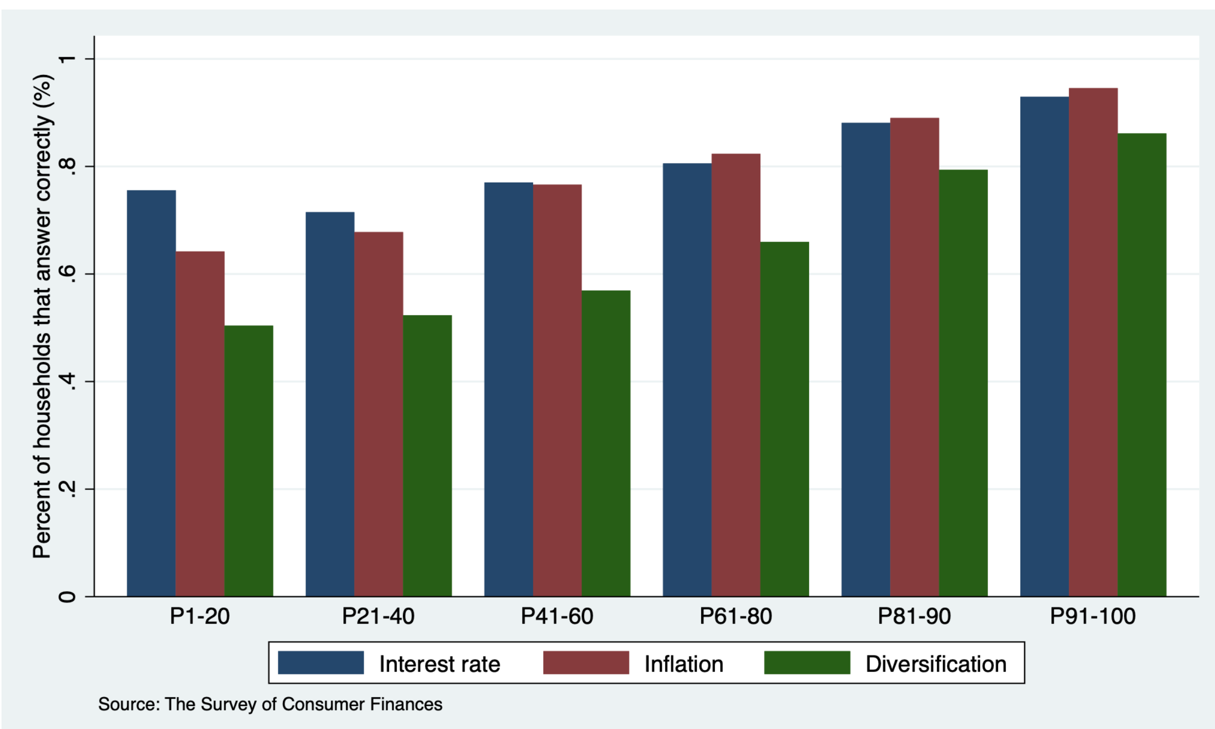



Figure 11: Accuracy in Answering Personal Finance Questions by Wealth Group, 2016-2019



To measure confidence, the SCF asks: "On a scale from zero to ten, where zero is not at all knowledgeable about personal finance and ten is very knowledgeable about personal finance, what number would you (and your husband/wife/partner) be on the scale?" Meanwhile, the SCF assesses a household's financial literacy by asking true or false questions about three concepts central to finance: interest rates, inflation, and diversification. These questions were designed by Lusardi and Mitchell (2014), who found that a correct answer to an additional question corresponded with a 3 to 4 percentage point higher chance of planning for retirement among respondents in a number of countries.

1. "Suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow: more than \$102, exactly \$102, or less than \$102?"

2. "Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy more than today, exactly the same as today, or less than today with the money in this account?"

3. "Do you think that the following statement is true or false: buying a single company's stock usually provides a safer return than a stock mutual fund?"

Figure 10 shows that on average, households higher up the wealth distribution are more assured in their knowledge of personal finance. Figure 11 indicates that wealthy households are more likely to answer the true or false questions correctly so they are more financially literate, on average. These results suggest that policies aimed at increasing financial literacy might be effective in reducing risky asset sales among poor households during financial crises.

# 7 Discussion

While the higher rate of financial market participation among wealthy households is well-studied, we still lack a comprehensive understanding of household portfolio rebalancing in response to economic shocks and how this behavior corresponds with wealth. This paper studies how US households across the wealth distribution reallocated their portfolios after the Global Financial Crisis and considers the implications for wealth inequality.

The main finding is that households in the bottom 90 percent of the distribution experienced a sustained decline in the ownership rate of risky financial assets after the financial crisis. This negative effect was stronger and more significantly for stocks indirectly held in managed accounts than for stocks directly held in brokerage accounts. This divestment occurred between 2007 and 2010, while the stock market did not recover to its pre-crisis level until 2012. Thus, lower and middle class households locked in losses and lost an opportunity for wealth appreciation during economic recovery. No observed characteristics in the data account for the variation in time effects across wealth groups. However, newer SCF data and existing literature suggest that greater financial literacy, confidence in one's investing capabilities, and network effects among wealthy households might explain my results.

Considering the implications for wealth inequality, the capital gains during the QE period accumulated disproportionately to wealthy households. This disparity would have occurred even if portfolio allocation stayed constant: consistent with existing literature, I observe that wealthy households hold more risky financial assets on both the extensive and intensive margins. However, heterogeneous rebalancing across the wealth distribution amplified the disparity as poorer households, who already had less risky asset allocations, were more likely to sell their risky financial asset holdings.

My results hold important implications for both fiscal and monetary policy. Fiscal policies targeted to improve financial literacy, particularly among poorer households, might encourage ~~stronger~~ better portfolio decision-making. Such policies would be particularly beneficial during economic downturns, when poor households might become discouraged from investing and withdraw from the market, making permanent any capital losses. Regarding monetary policy, while it is not the Federal Reserve's responsibility to address distributional concerns, unconventional policies aimed at raising asset prices might be less effective at stimulating the economy if low and middle class households experience disproportionately lower capital gains. The Federal Reserve should account for inequality when assessing the transmission of monetary stimulus.

Finally, the limitations of this paper open avenues for future research. Although I measured changes in portfolio allocation over time, I did not identify what caused these changes. Panel data such as the Panel Study of Income Dynamics could be used to estimate whether the stock market crash, monetary policy announcements, loss of employment, or other events caused portfolio rebalancing. Future studies could also investigate why the drop in risky asset ownership persisted despite economic recovery. Based on existing literature, inertia in stockownership and newfound pessimism toward investing are two possible explanations for this result. Finally, one could incorporate additional channels affecting wealth inequality such as changes in income and employment to obtain a more comprehensive view of wealth redistribution after the Global Financial Crisis.

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# 8 Appendix

## 8.1 Components of Net Worth

Table 6: Components of Net Worth

| Category | Item | Description |
|---|---|---|
| Financial assets | Cash | Physical cash, checking accounts, savings accounts, money market accounts, certificates of deposit, and call accounts |
| | Bonds | Holdings of US government bonds, corporate bonds, foreign bonds, mortgage-backed bonds, and other bonds, as well as bond mutual funds. May be held directly or indirectly through retirement accounts, trusts, or other managed accounts.[1] |
| | Stocks | Holdings of corporate equities or equity mutual funds. May he held directly or indirectly through retirement accounts, trusts, or other managed accounts. |
| | Life insurance | Value of life insurance policies that build up a cash value. |
| | Other financial assets | Loans to others and other miscellaneous financial assets. |
| Non-financial assets | Residential real estate | Value of the household's primary residence and vacation homes. |
| | Commercial real estate | Value of residential and commercial properties owned for renting out to others. |
| | Consumer durables | Vehicles, furniture, art objects, jewelry, and other physical assets. |
| | Private business | Actively or non-actively managed businesses that are not publicly traded. |
| Liabilities | Mortgage debt | Mortgage loans on the household's primary residence, mortgage loans on other real estate, and home equity lines of credit. |
| | Non-mortgage debt | Consumer loans, non-home equity lines of credit, and other loans and advances. |

[1] For most managed accounts, the SCF asks the respondent what percent of the account's assets are invested in stocks. I assume that the remaining assets are invested in bonds. If the percent in stocks is not specified, which only occurs for combination mutual funds, charitable trusts, and foundations, I assume a 60-40 split between stocks and bonds.

## 8.2 Additional Tables and Figures

Table 7: Heckman Selection Model for Risky Financial Assets
with Heterogeneous Time Effects

| | (1) | | | | (2) | |
|---|---|---|---|---|---|---|
| | Heckman | | | | Heckman (mfx) | |
| | Share | | Ownership | | Ownership | |
| | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| P21-40 | -0.009 | 0.031 | 0.344*** | 0.094 | 0.137*** | 0.036 |
| P41-60 | 0.001 | 0.030 | 0.725*** | 0.095 | 0.282*** | 0.034 |
| P61-80 | 0.036 | 0.030 | 1.006*** | 0.098 | 0.379*** | 0.031 |
| P81-90 | 0.075** | 0.031 | 1.297*** | 0.112 | 0.451*** | 0.028 |
| P91-100 | 0.131*** | 0.030 | 1.307*** | 0.116 | 0.453*** | 0.027 |
| Year=2010 | -0.050 | 0.031 | -0.279*** | 0.089 | -0.109*** | 0.034 |
| P21-40 x 2010 | 0.039 | 0.039 | -0.121 | 0.118 | -0.048 | 0.046 |
| P41-60 x 2010 | 0.042 | 0.037 | -0.122 | 0.118 | -0.048 | 0.045 |
| P61-80 x 2010 | 0.034 | 0.035 | -0.064 | 0.117 | -0.025 | 0.046 |
| P81-90 x 2010 | 0.037 | 0.038 | -0.085 | 0.139 | -0.033 | 0.054 |
| P91-100 x 2010 | 0.021 | 0.034 | 0.332** | 0.148 | 0.132** | 0.057 |
| Year=2013 | -0.033 | 0.032 | -0.244*** | 0.091 | -0.096*** | 0.034 |
| P21-40 x 2013 | 0.017 | 0.040 | -0.164 | 0.123 | -0.064 | 0.046 |
| P41-60 x 2013 | 0.037 | 0.038 | -0.145 | 0.118 | -0.057 | 0.046 |
| P61-80 x 2013 | 0.024 | 0.037 | -0.166 | 0.122 | -0.065 | 0.045 |
| P81-90 x 2013 | 0.018 | 0.038 | -0.161 | 0.144 | -0.063 | 0.055 |
| P91-100 x 2013 | 0.018 | 0.036 | 0.029 | 0.145 | 0.012 | 0.056 |
| Year=2016 | -0.084*** | 0.031 | -0.331*** | 0.091 | -0.129*** | 0.033 |
| P21-40 x 2016 | 0.070* | 0.039 | -0.161 | 0.123 | -0.063 | 0.046 |
| P41-60 x 2016 | 0.062* | 0.037 | -0.072 | 0.123 | -0.028 | 0.046 |
| P61-80 x 2016 | 0.057 | 0.035 | -0.018 | 0.119 | -0.007 | 0.046 |
| P81-90 x 2016 | 0.061* | 0.037 | -0.035 | 0.145 | -0.014 | 0.055 |
| P91-100 x 2016 | 0.095*** | 0.035 | 0.375*** | 0.145 | 0.148*** | 0.054 |
| Year=2019 | -0.067** | 0.033 | -0.335*** | 0.094 | -0.130*** | 0.035 |
| P21-40 x 2019 | 0.035 | 0.041 | -0.027 | 0.123 | -0.011 | 0.048 |
| P41-60 x 2019 | 0.050 | 0.039 | -0.157 | 0.130 | -0.062 | 0.047 |
| P61-80 x 2019 | 0.038 | 0.038 | 0.017 | 0.123 | 0.007 | 0.048 |
| P81-90 x 2019 | 0.052 | 0.039 | 0.050 | 0.146 | 0.020 | 0.058 |
| P91-100 x 2019 | 0.068* | 0.036 | 0.114 | 0.147 | 0.045 | 0.058 |
| Mean of Share | 0.158 | | | | | |
| Rho | 0.244*** | | | | | |
| Sigma | 0.239*** | | | | | |
| Observations | 27274 | | | | | |

Table 8: Probit and OLS Models for Ownership and Portfolio Share of Directly Held Stocks

| | (1) Share | | (2) Ownership | | (3) Ownership (mfx) | |
|---|---|---|---|---|---|---|
| | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| P21-40 | -0.001 | 0.066 | 0.137 | 0.124 | 0.044 | 0.041 |
| P41-60 | 0.008 | 0.055 | 0.545*** | 0.121 | 0.190*** | 0.045 |
| P61-80 | -0.024 | 0.052 | 0.896*** | 0.112 | 0.322*** | 0.042 |
| P81-90 | 0.011 | 0.053 | 1.198*** | 0.121 | 0.441*** | 0.044 |
| P91-100 | 0.039 | 0.052 | 1.473*** | 0.116 | 0.510*** | 0.038 |
| Year=2010 | -0.048 | 0.060 | -0.225* | 0.122 | -0.067* | 0.035 |
| P21-40 x 2010 | 0.062 | 0.086 | -0.049 | 0.168 | -0.015 | 0.051 |
| P41-60 x 2010 | -0.012 | 0.073 | -0.009 | 0.163 | -0.003 | 0.051 |
| P61-80 x 2010 | 0.053 | 0.067 | -0.023 | 0.144 | -0.007 | 0.044 |
| P81-90 x 2010 | 0.026 | 0.066 | -0.026 | 0.156 | -0.008 | 0.048 |
| P91-100 x 2010 | -0.009 | 0.063 | 0.269* | 0.146 | 0.091* | 0.053 |
| Year=2013 | 0.053 | 0.068 | -0.392*** | 0.130 | -0.112*** | 0.034 |
| P21-40 x 2013 | -0.045 | 0.088 | 0.139 | 0.173 | 0.045 | 0.059 |
| P41-60 x 2013 | -0.024 | 0.081 | 0.050 | 0.159 | 0.016 | 0.051 |
| P61-80 x 2013 | -0.050 | 0.074 | 0.083 | 0.157 | 0.027 | 0.052 |
| P81-90 x 2013 | -0.066 | 0.074 | 0.107 | 0.160 | 0.035 | 0.054 |
| P91-100 x 2013 | -0.073 | 0.071 | 0.213 | 0.156 | 0.071 | 0.055 |
| Year=2016 | -0.021 | 0.069 | -0.457*** | 0.126 | -0.129*** | 0.032 |
| P21-40 x 2016 | 0.078 | 0.094 | 0.148 | 0.169 | 0.048 | 0.058 |
| P41-60 x 2016 | -0.023 | 0.083 | 0.285* | 0.163 | 0.097 | 0.059 |
| P61-80 x 2016 | 0.029 | 0.073 | 0.124 | 0.148 | 0.040 | 0.050 |
| P81-90 x 2016 | -0.002 | 0.076 | 0.184 | 0.156 | 0.061 | 0.054 |
| P91-100 x 2016 | 0.029 | 0.075 | 0.412*** | 0.151 | 0.143** | 0.057 |
| Year=2019 | -0.021 | 0.061 | -0.216* | 0.122 | -0.064* | 0.035 |
| P21-40 x 2019 | -0.007 | 0.081 | 0.182 | 0.168 | 0.060 | 0.058 |
| P41-60 x 2019 | 0.020 | 0.076 | -0.111 | 0.164 | -0.033 | 0.048 |
| P61-80 x 2019 | 0.023 | 0.067 | -0.046 | 0.143 | -0.014 | 0.044 |
| P81-90 x 2019 | 0.003 | 0.067 | -0.103 | 0.155 | -0.031 | 0.045 |
| P91-100 x 2019 | 0.015 | 0.065 | -0.028 | 0.146 | -0.009 | 0.045 |
| Mean | 0.343 | | 0.325 | | | |
| (Pseudo) R-squared | .259 | | .271 | | | |
| Observations | 27274 | | 27274 | | | |

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

Table 9: Probit and OLS Models for Ownership and Portfolio Share of Indirectly Held Stocks

| | (1) Share | | (2) Ownership | | (3) Ownership (mfx) | |
|---|---|---|---|---|---|---|
| | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| P21-40 | -0.024 | 0.036 | 0.316*** | 0.117 | 0.125*** | 0.046 |
| P41-60 | -0.043 | 0.031 | 0.542*** | 0.112 | 0.214*** | 0.043 |
| P61-80 | -0.025 | 0.032 | 0.725*** | 0.114 | 0.282*** | 0.041 |
| P81-90 | -0.021 | 0.035 | 0.798*** | 0.117 | 0.307*** | 0.040 |
| P91-100 | -0.062** | 0.030 | 0.815*** | 0.117 | 0.316*** | 0.043 |
| Year=2010 | -0.044 | 0.036 | -0.288*** | 0.095 | -0.111*** | 0.036 |
| P21-40 x 2010 | 0.037 | 0.042 | -0.092 | 0.136 | -0.036 | 0.052 |
| P41-60 x 2010 | 0.051 | 0.046 | -0.040 | 0.124 | -0.016 | 0.048 |
| P61-80 x 2010 | 0.025 | 0.037 | 0.009 | 0.121 | 0.004 | 0.047 |
| P81-90 x 2010 | 0.033 | 0.047 | 0.120 | 0.142 | 0.047 | 0.056 |
| P91-100 x 2010 | 0.057 | 0.039 | 0.109 | 0.139 | 0.043 | 0.055 |
| Year=2013 | -0.042 | 0.033 | -0.231** | 0.102 | -0.090** | 0.038 |
| P21-40 x 2013 | 0.033 | 0.045 | -0.217 | 0.137 | -0.083 | 0.051 |
| P41-60 x 2013 | 0.056 | 0.040 | -0.107 | 0.130 | -0.042 | 0.050 |
| P61-80 x 2013 | 0.042 | 0.038 | -0.091 | 0.139 | -0.035 | 0.054 |
| P81-90 x 2013 | 0.026 | 0.039 | 0.031 | 0.155 | 0.012 | 0.061 |
| P91-100 x 2013 | 0.060* | 0.035 | 0.053 | 0.138 | 0.021 | 0.055 |
| Year=2016 | -0.071** | 0.034 | -0.269*** | 0.104 | -0.104*** | 0.039 |
| P21-40 x 2016 | 0.052 | 0.051 | -0.229 | 0.161 | -0.088 | 0.060 |
| P41-60 x 2016 | 0.048 | 0.041 | -0.072 | 0.148 | -0.028 | 0.057 |
| P61-80 x 2016 | 0.051 | 0.038 | 0.008 | 0.130 | 0.003 | 0.051 |
| P81-90 x 2016 | 0.036 | 0.041 | 0.200 | 0.149 | 0.079 | 0.059 |
| P91-100 x 2016 | 0.073** | 0.036 | 0.271* | 0.147 | 0.108* | 0.058 |
| Year=2019 | -0.050 | 0.036 | -0.451*** | 0.112 | -0.170*** | 0.040 |
| P21-40 x 2019 | 0.022 | 0.044 | 0.014 | 0.144 | 0.005 | 0.057 |
| P41-60 x 2019 | 0.037 | 0.041 | 0.029 | 0.156 | 0.012 | 0.062 |
| P61-80 x 2019 | 0.021 | 0.041 | 0.201 | 0.145 | 0.080 | 0.058 |
| P81-90 x 2019 | 0.039 | 0.045 | 0.388** | 0.161 | 0.154** | 0.063 |
| P91-100 x 2019 | 0.081** | 0.037 | 0.302** | 0.143 | 0.120** | 0.057 |
| Mean | 0.226 | | 0.446 | | | |
| (Pseudo) R-squared | 0.195 | | 0.326 | | | |
| Observations | 27274 | | 27274 | | | |

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

Figure 12: Education x Year Interaction in the Model for Risky Financial Asset Ownership

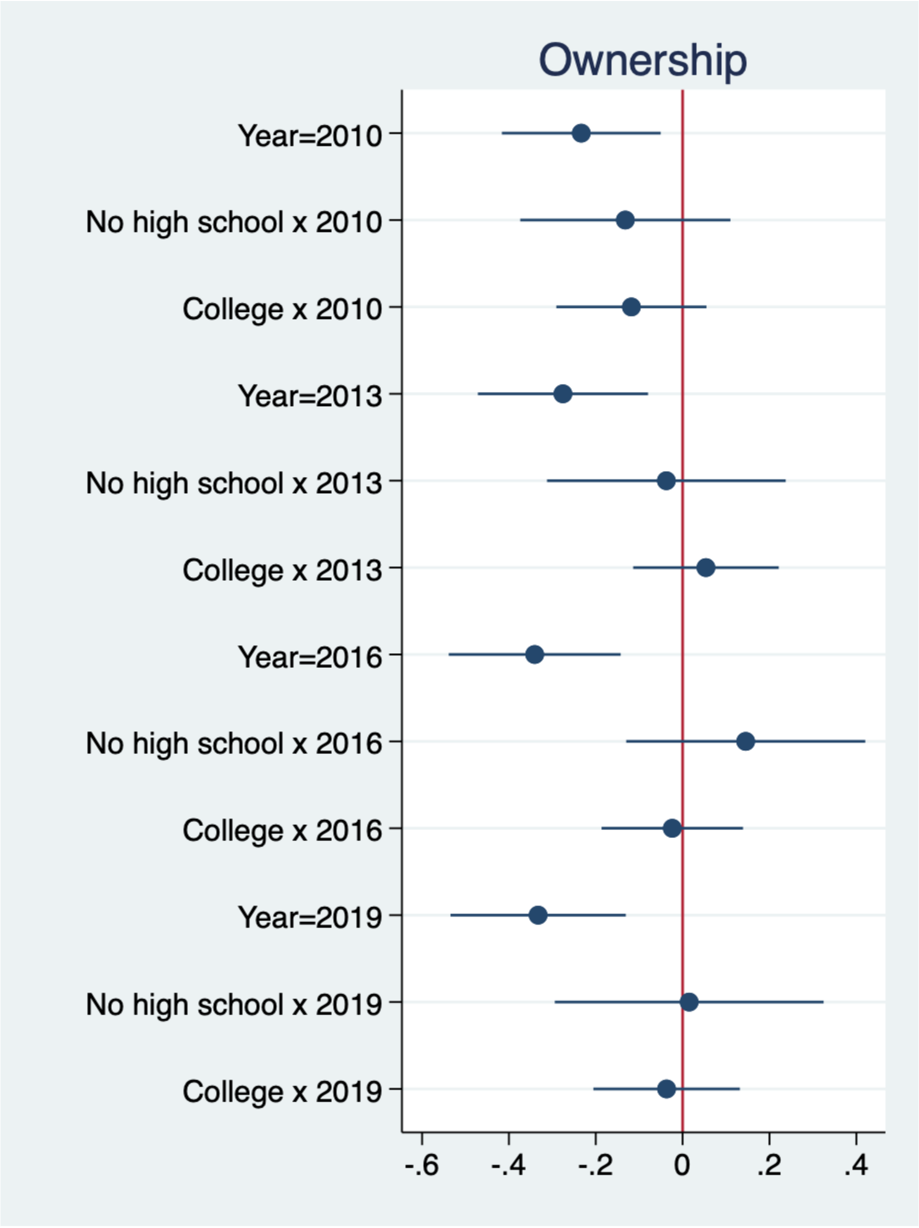

Figure 13: Wealth Group x Year Interaction After Incorporating Education Level

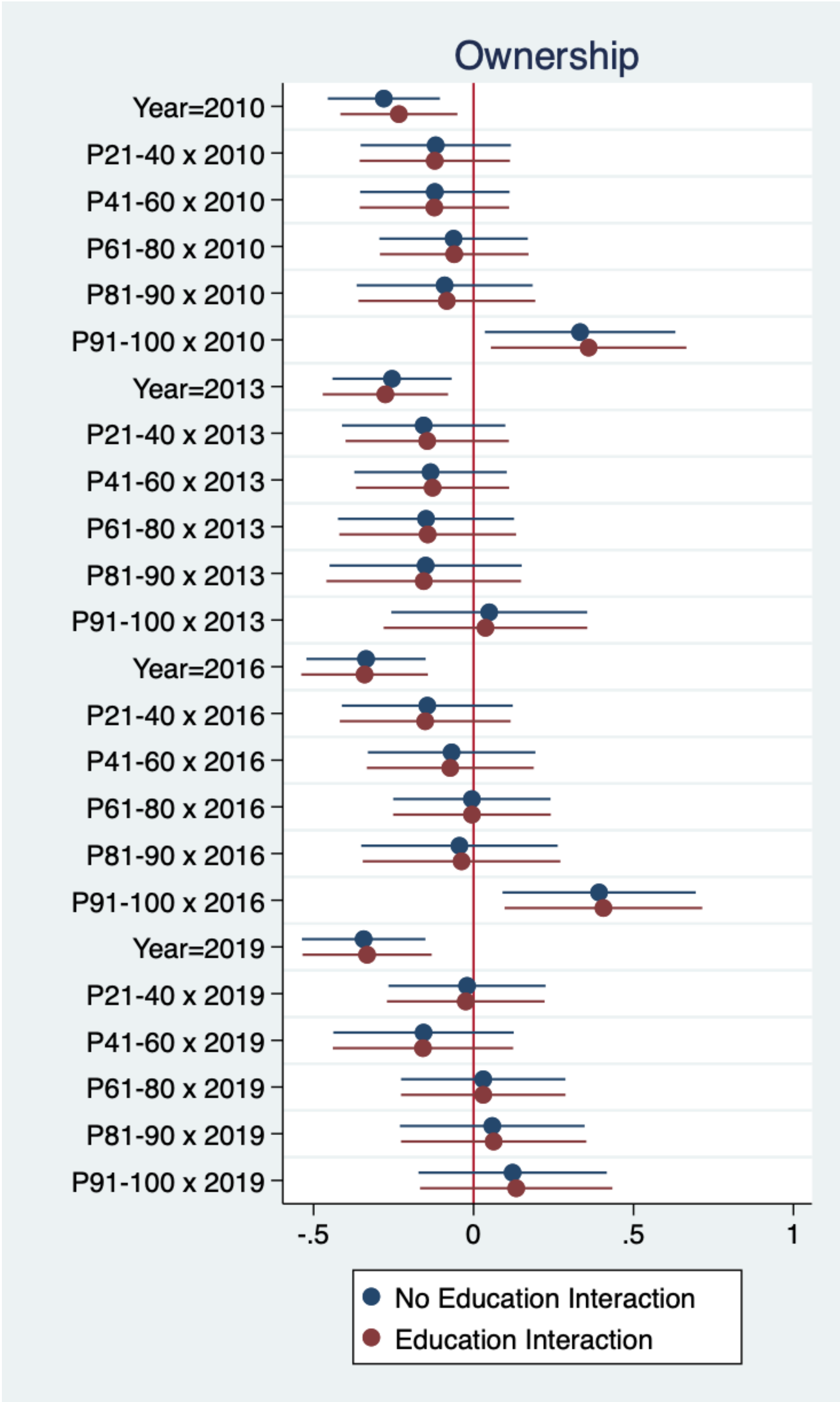

Figure 14: Race x Year Interaction in the Model for
Risky Financial Asset Ownership

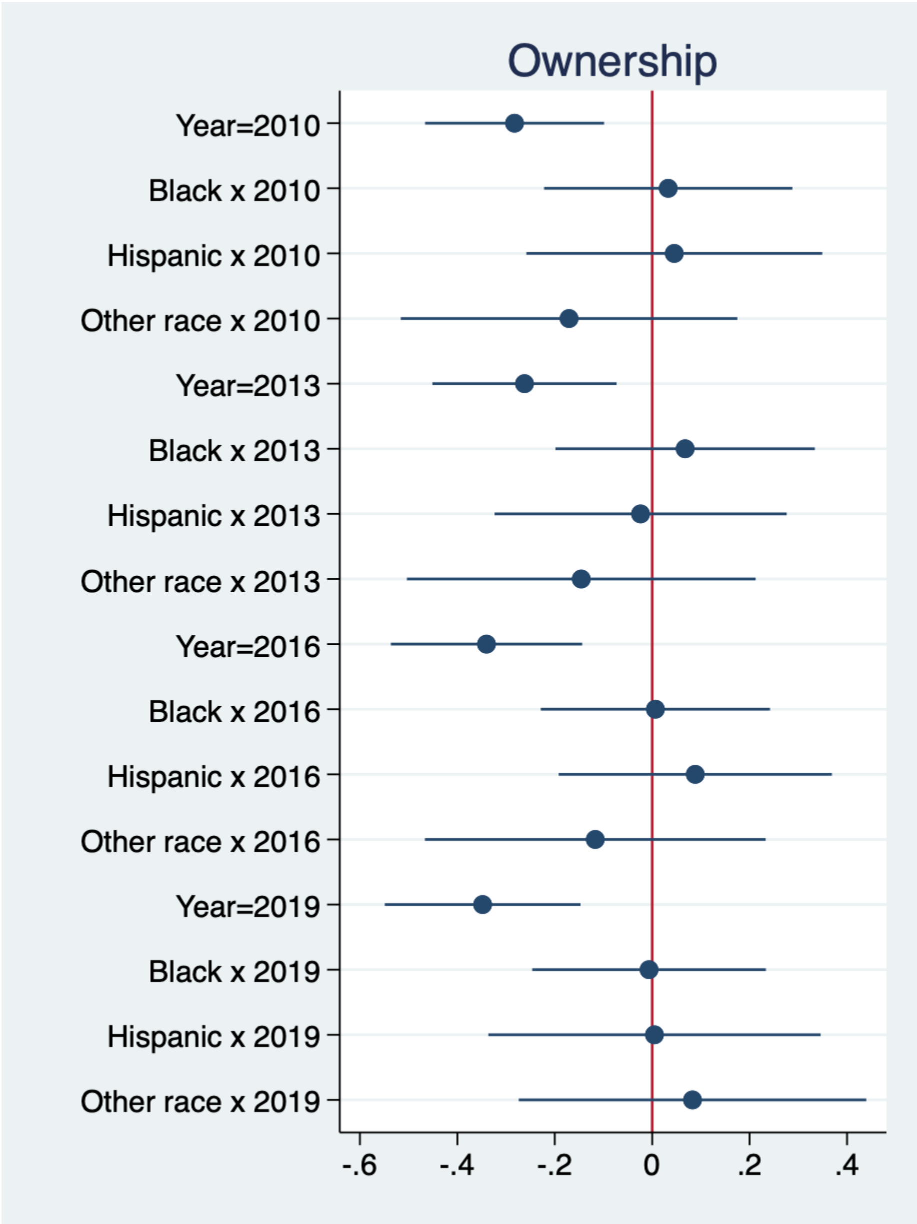

Figure 15: Wealth Group x Year Interaction After Incorporating Race

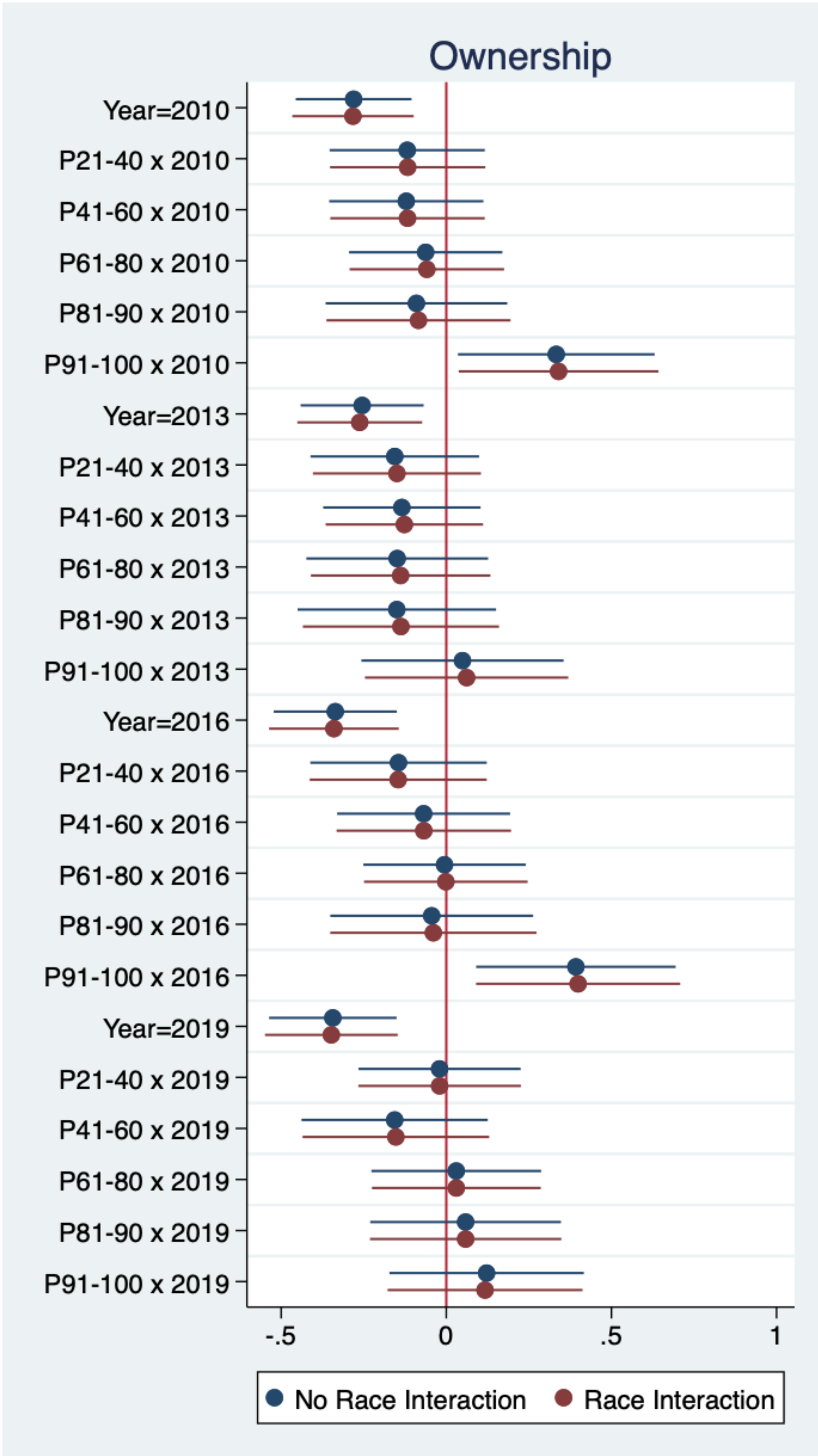

Figure 16: Risk x Year Interaction in the Model for
Risky Financial Asset Ownership

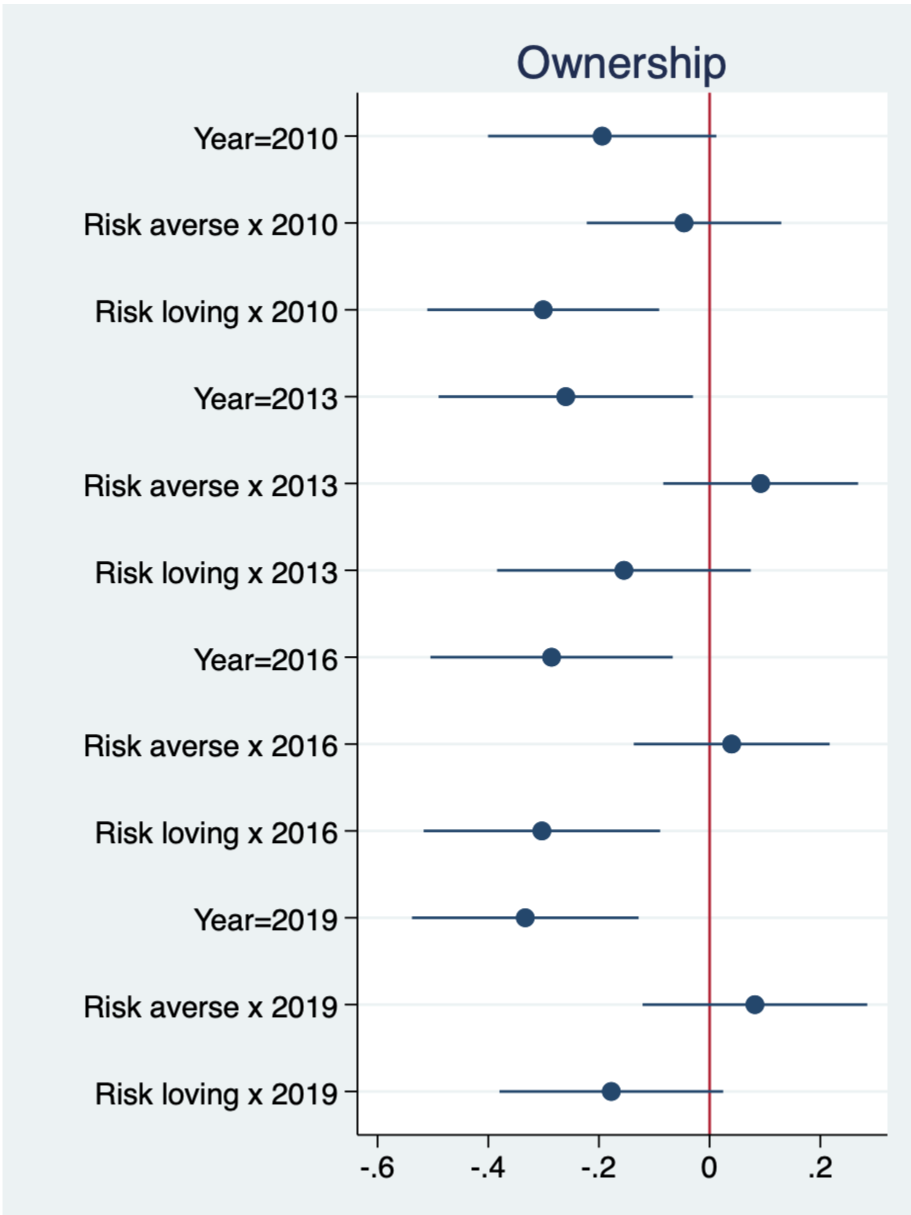

Figure 17: Wealth Group x Year Interaction After Incorporating Risk Tolerance

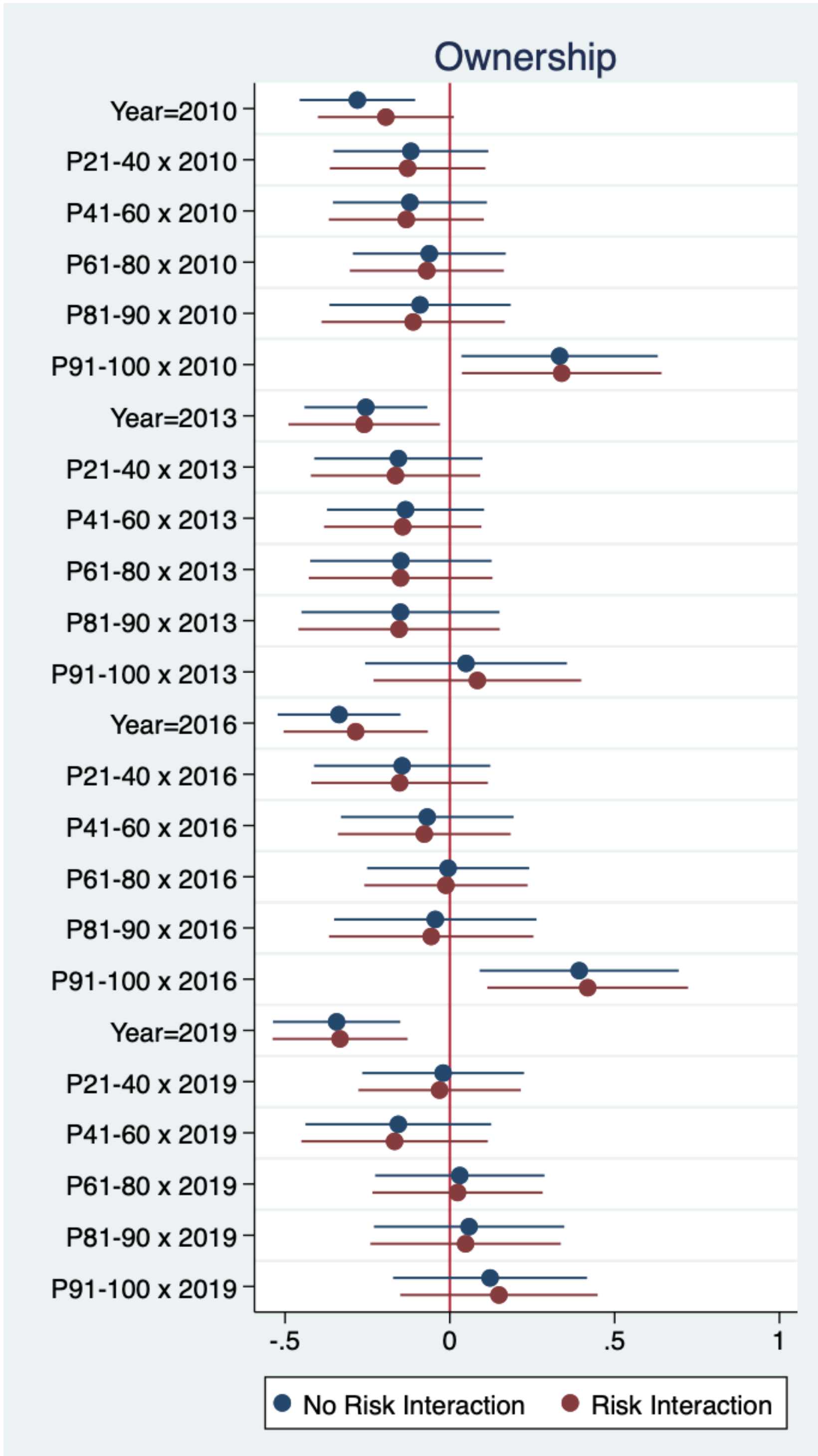

Figure 18: Unemployment x Year Interaction in the Model for Risky Financial Asset Ownership

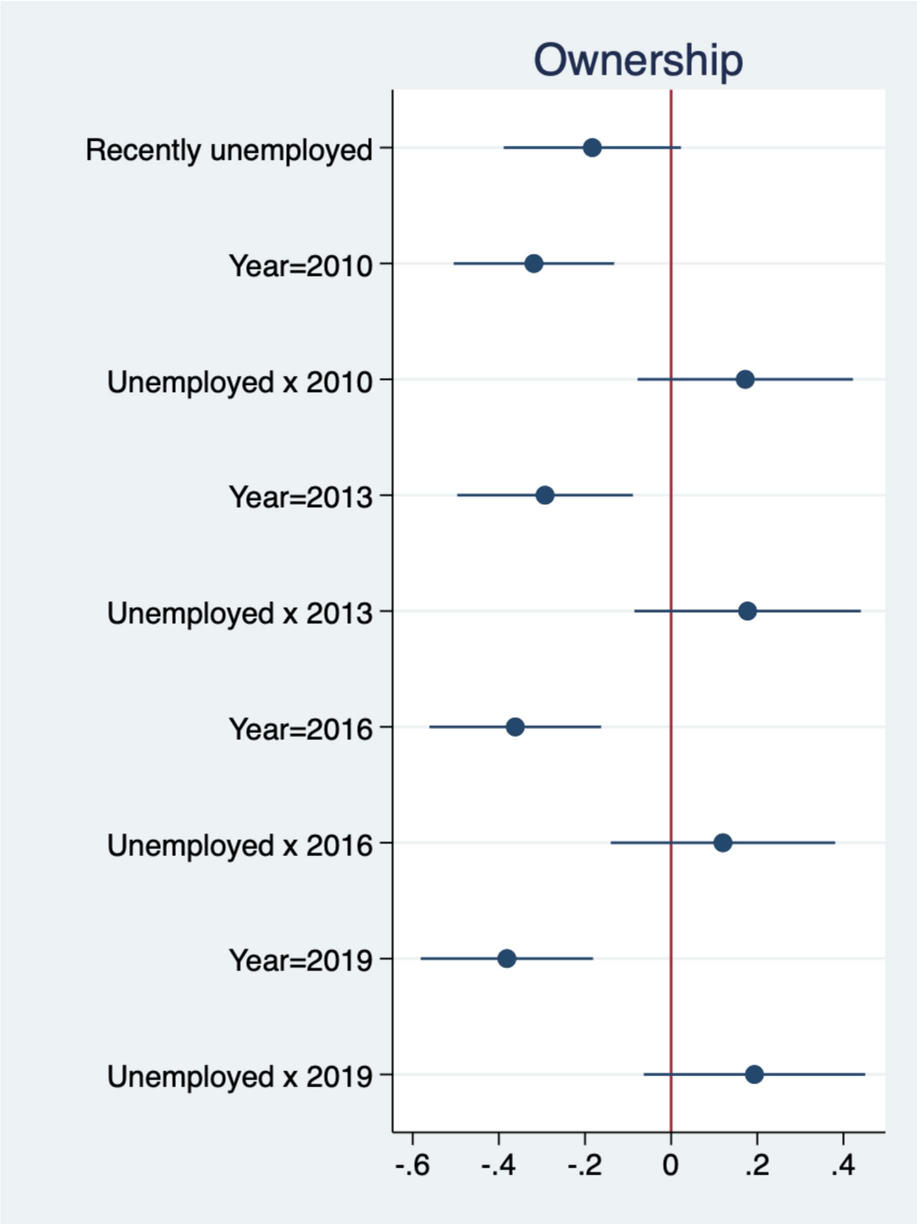

Figure 19: Wealth Group x Year Interaction After Incorporating Recent Unemployment