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Three Essays on Financial Economics

Li Sun

Dissertation submitted to the
College of Business and Economics
at West Virginia University
in partial fulfillment of the requirements
for the degree of

Doctor of Philosophy
in
Economics

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ABSTRACT

Three Essays on Financial Economics

Li Sun

This dissertation analyzes households' asset allocation decisions and studies how the financial crisis affects income distribution using panel datasets from household surveys. The first essay focuses on how the precautionary saving motive can affect households' asset allocation decisions. It develops a life-cycle model that explicitly accounts for the effects of potential future expenditure shocks; the implications of this model better match the empirically observed investment behaviors of households. A precautionary index is constructed to measure the adequacy of households' precautionary saving, and it is found that this factor has significant explanatory power regarding households' stock market participation and risky asset allocation decisions. In the second essay, a life-cycle model is developed to investigate how health risk and rare event risk will affect retirees' optimal asset allocation decisions. Health Risk is modeled as a stochastic medical expenditure, calibrated using data from the Health and Retirement Survey. The rare event risk is modeled as a financial crisis risk where the stock market has a small but positive probability of crashing. Compared with models that do not take into account health risk or financial market risk, the optimal policy rules and the simulation results obtained from this model better explain retirees' equity holding behaviors as observed in the empirical data. In the third essay, a non-parametric decomposition methodology is applied to analyze the change of income distribution before and after the 2008 financial crisis in the United States. I decompose the Lorenz curve and its associated concentration curve by subgroups defined on the basis of race, gender, and retirement status using the 2007-2009 Survey of Consumer Finance (SCF) panel dataset. It is found that the income distribution shifted following the crisis. For households in the bottom to the 9th decile of the income distribution, income share increased, and the increases were more pronounced when measured by the concentration curve.

To my mother

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TABLE OF CONTENTS

NOTICE OF COPYRIGHT.....	i
ABSTRACT.....	ii
ACKNOWLEDGEMENTS	iv
LIST OF TABLES	viii
LIST OF FIGURES	x

CHAPTER 1

Introduction.....	1

CHAPTER 2:

Precautionary Saving and Asset Allocation	8
2.1 Introduction	9
2.2 Literature Review.....	13
2.2.1 Precautionary saving behavior	13
2.2.2 Background risk and portfolio choice	14
2.2.3 Limited participation in the stock market	15
2.3 Evidence on Households' Investment Behaviors.....	16
2.3.1 General overview of the Survey of Consumer Finance (SCF)	17
2.3.2 Normalized wealth and investment behavior	18
2.3.3 The saving motive and investment behavior	20
2.4 A Life Cycle Model Including Contingent Consumption	21
2.4.1 Preferences	21
2.4.2 The labor income process	22
2.4.3 The financial market.....	23
2.4.4 Households' optimization problem.....	23
2.4.5 Parameters and model calibration	24
2.4.6 The model solution: optimal portfolio policy.....	25

2.5	The Precautionary Index: Hypothesis Testing and Estimation	27
2.5.1	Construction of the precautionary saving index	27
2.5.2	Market participation hypothesis and regression results	29
2.5.3	Portfolio shares in risky assets	31
2.6	Discussion	33
2.6.1	Retirement accounts vs. non-retirement accounts	33
2.6.2	Non-retired households vs. retired households	35
2.6.3	Business owners vs. non-business owners	36
2.6.4	Control for risk preference.....	37
2.6.5	The effect of low normalized wealth.....	38
2.6.6	The impact of pension plans.....	39
2.7	Conclusion.....	40

CHAPTER 3:

	Tail Risk, Health Risk, and Portfolio Choices for Retirees	68
3.1	Introduction	69
3.2	The Model	73
3.2.1	The preference	73
3.2.2	Modeling health shock	74
3.2.3	The financial market	75
3.2.4	Retirees' optimization problem.....	75
3.3	Parameters and Model Calibration	78
3.3.1	Health expenditure calibration	79
3.3.2	Problem with health ratio calibration	82
3.4	Optimal Policy Rules	83
3.4.1	Policy rules without health risk.....	83
3.4.2	Policy rules with health shock	85
3.5	Extension: Heterogeneous Health Risk	87
3.6	Simulation Results	88
3.7	Conclusion.....	89

CHAPTER 4:

Impacts of Financial Crisis on Income Inequality: A Decomposed Approach 114

4.1	Introduction	115
4.2	Literature Review.....	118
4.2.1	Inequality before and after the crisis.....	118
4.2.2	Decomposing the inequality measure	119
4.2.3	Use of household survey data	120
4.3	Methodology	121
4.3.1	Decomposing the ordinates.....	121
4.3.2	Additive decomposition.....	123
4.4	Data.....	123
4.4.1	Income definition.....	125
4.5	Decomposition Results	126
4.5.1	Overall decomposition results	126
4.5.2	Decomposition by race	128
4.5.3	Decomposition by gender	131
4.5.4	Decomposition by retirement status	133
4.6	Discussion	135
4.6.1	Crisis effects in the longer run.	135
4.6.2	Comparison with the 1987 stock market crash	137
4.7	Conclusion.....	138

REFERENCES.....	166

LIST OF TABLES

Table 2-1: Descriptive statistics for key variables in the SCF.....	42
Table 2-2: Distribution of household normalized wealth level and risky asset share	43
Table 2-3: Normalized wealth regression (Logit model).....	44
Table 2-4: Average Marginal Effect for the normalized wealth regression.....	45
Table 2-5: Normalized wealth regression (risky share regression)	46
Table 2-6: Risky asset share regression for different levels of normalized wealth	47
Table 2-7: Saving motives in the SCF	48
Table 2-8: Saving motive regression (Logit model)	49
Table 2-9: Average marginal effect for the saving motive regression.....	50
Table 2-10: Saving motive regression (linear probability model)	51
Table 2-11: Model parameter values	52
Table 2-12: Summary statistics for the emergency fund	53
Table 2-13: Stock market participation regression (Logit model).....	54
Table 2-14: Average marginal effect for the stock market participation regression	55
Table 2-15: Precautionary ratio regression (linear probability model).....	56
Table 2-16: Risky Asset share regression (retirement account vs. non-retirement account).....	57
Table 2-17: Stock market participation regression (control for different status).....	58
Table 2-18: Average marginal effect for Stock market participation regressions	59
Table 2-19: Risky asset share regressions (control for different status)	60
Table 2-20: Stock market participation regression (control for normalized wealth)	61
Table 2-21: Average marginal effect for the stock market participation regression	62
Table 2-22: Risky asset share regression (control for normalized wealth)	63
Table 3-1: Benchmark parameter values	91
Table 3-2: Summary statistics for variables of interest in the HRS.....	92
Table 3-3: Summary statistics for health expenditure	93
Table 3-4: Social Security and pension income.....	94
Table 3-5: Summary statistics for medical expense ratio	95

Table 3-6: Mean portfolio share in stock	96
Table 3-7: Portfolio share for different cohorts by age.....	97
Table 4-1: Summary statistics for key variables in the SCF 2007 & 2009.....	140
Table 4-2: Summary statistics for the income variable by group.....	141
Table 4-3: Decile composition by subgroups (2007)	142
Table 4-4: Group composition by 2007 decile.....	143
Table 4-5: Group composition by 2009 decile.....	144
Table 4-6: Lorenz ordinates decomposition for the overall sample (2007 vs. 2009).....	145
Table 4-7: Lorenz ordinates and subsample decomposition by race (2007)	146
Table 4-8: Lorenz ordinates and subsample decomposition by race (2009)	147
Table 4-9: Concentration ordinates and subsample decomposition by race (2009)	148
Table 4-10: Lorenz ordinates and subsample decomposition by gender (2007)	149
Table 4-11: Lorenz ordinates and subsample decomposition by gender (2009)	150
Table 4-12: Concentration ordinates and subsample decomposition by gender (2009)	151
Table 4-13: Lorenz ordinates and subsample decomposition by retirement status (2007).....	152
Table 4-14: Lorenz ordinates and subsample decomposition by retirement status (2009).....	153
Table 4-15: Concentration ordinates and subsample decomposition by retirement status (2009)	154
Table 4-16: Lorenz ordinates decomposition for the overall sample (2006 vs. 2012).....	155
Table 4-17: Lorenz ordinates and subsample decomposition by race (2006)	156
Table 4-18: Lorenz ordinates and subsample decomposition by race (2012)	157
Table 4-19: Concentration ordinates and subsample decomposition by race (2012)	158
Table 4-20: Lorenz ordinates and subsample decomposition by race (1986)	159
Table 4-21: Lorenz ordinates and subsample decomposition by race (1988).....	160
Table 4-22: Concentration ordinates and subsample decomposition by race (1988).....	161
Table 4-23: Chi-Squared test results by race (2007 vs. 2009).....	162
Table 4-24: Chi-Squared test results by gender (2007 vs. 2009).....	162
Table 4-25: Chi-Squared test results by retirement status (2007 vs. 2009)	163

LIST OF FIGURES

Figure 2-1: Labor income process: age profile	64
Figure 2-2: Policy rules for portfolio choice (without contingent consumption)	65
Figure 2-3: Policy rules for portfolio choice (with contingent consumption)	66
Figure 2-4: Optimal policy rule for normalized wealth level below 5	67
Figure 3-1: Medical expense ratio	98
Figure 3-2: Medical expense by age group	99
Figure 3-3: Medical expense ratio by health status	100
Figure 3-4: Policy rules for two cases	101
Figure 3-5: Policy function with health risk and financial crisis	102
Figure 3-6: The portfolio rule for the good health group	103
Figure 3-7: The portfolio rule for the poor health group	104
Figure 3-8: Policy functions for retirees at different ages (without health risk but with financial crisis risk)	105
Figure 3-9: Policy functions for retirees at different age (with health risk but without financial crisis risk)	106
Figure 3-10: Policy functions for retirees at different ages (with health risk and financial crisis risk)	108
Figure 3-11: The portfolio rule at age 65 by health status	108
Figure 3-12: The portfolio rule at age 75 by health status	109
Figure 3-13: The portfolio rule at age 85 by health status	110
Figure 3-14: Initial wealth distribution for retirees	110
Figure 3-15: Simulation results: Without health risk	112
Figure 3-16: Simulation results: With health risk	113
Figure 4-1 : Decomposed Lorenz ordinates by race (2007)	164
Figure 4-2: Decomposition histogram (by race)	165

Chapter 1

Introduction

Chapter 1

Introduction

In the past several decades, the life cycle model, which applies stochastic optimal control methodology, has been used to study households' inter-temporal saving and consumption decisions. It also helps us understand how households allocate their wealth into risky and riskless assets, i.e., the asset allocation problem. In the seminal work developed by Merton (1971, 1973), it is found that, in the absence of the labor income or if labor income is perfectly tradable, investors' optimal allocation of wealth to risky assets should depend only on investors' risk preference and the mean and volatility of stock market returns. Subsequent research has extended the model to account for a more realistic characterization of households' budget constraints, where labor income is added to the model, and background risk is emphasized as an important factor which can affect households' investment decisions (Cocco et al., 2005; Gomes and Michaelides, 2005; Wachter and Yogo, 2010).

Another strand of literature focuses on the precautionary saving motives of households. Carroll (1992, 1994, and 1997) finds that current consumption is strongly related to future income uncertainty, which is contrary to the permanent income hypothesis that households' current consumption will depend on lifetime income. Analysis of the Survey of Consumer Finance indicates that precautionary saving is a strong motive for households to accumulate wealth and therefore can reduce current consumption. Precautionary saving can be seen as households' hedge against uncertainty in labor income and other types of background risks, such as unexpected health expenditure. While most previous literature has focused on uncertainty in labor income, few studies have analyzed how emergency expenditure shock can affect households' saving and

portfolio choices. Future emergency expenditure shocks can be seen as a form of contingent consumption which can affect households' future consumption level if not properly hedged. Emergency expenditure can be seen as similar to spending on necessity goods, consumption of which households have little flexibility to reduce once they occur, such as unexpected medical expense. Compared to other types of consumption, spending related to medical expense is less discretionary and can crowd out households' other consumption.

In the first essay of the dissertation, I develop a simple life cycle model to account for the impact of the future emergency expenditure shock and analyze how households' saving and investment behavior will be affected by this expenditure shock. Instead of focusing on households' inter-temporal budget constraints, I argue that future expenditure shock can be modeled as a form of contingent consumption that can affect households' utility function. Households will not know when emergency expenditure shock will occur, but they can have prior knowledge of the distribution of the size of these shocks; therefore, they can estimate the expected value of this amount. Due to the uncertainty in its timing, households need to hedge this expenditure shock every period; thus, households' utility function will depend on both their current consumption and the expected value of this expenditure shock.

In spirit, this model shares features with the "habit formation" models, in which the agent's utility function depends on the difference between consumption and a "habit" (Constantinides, 1990; Campbell and Cochrane, 1999; Polkovnichenko, 2007). However, the crucial difference between my model and the habit formation model lies in the characterization of "habit." In much of the habit formation literature, habit is a representation of past aggregate consumption, while in

my model, habit is defined as the value of expected emergency expenditure, which can reduce the effective consumption level of households once it occurs.

The policy function derived from the model implies that the optimal risky asset share starts very low when normalized wealth is low and increases as normalized wealth increases. Compared to models that do not account for the expenditure shock (Cocco, 2005), this model can better explain the empirical observation that households with higher normalized wealth have a higher share invested in risky assets.

As precautionary saving can be a major reason for households to accumulate wealth so they can have enough resources to meet future emergency expenditure shock, the sufficiency of this saving can affect households' investment risk taking. Using a reported variable of desired level of emergency funds and the actual households' asset data from the Survey of Consumer Finance, I construct a precautionary index to measure the adequacy of households' precautionary saving. The index is defined as the ratio of households' total available resources to the desirable amount of funds, and a higher value of this index indicates that the household will have greater ability to meet its emergency needs and therefore can increase the household's risk tolerance.

Using regression analysis, I further analyze how the index affects households' stock market participation and portfolio choice decisions. The regression results show that the precautionary index has a positive and statistically significant effect on the probability of households' decisions to participate in the stock market. The share invested in risky assets is also higher when the precautionary index is higher. Specifically, a one percent increase in the precautionary index will increase the predicted probability of holding equity by 0.0377 percentage points and will increase the risky asset share by 0.023 percentage points. In addition, the precautionary index's impact on

the risky asset share is larger for investments held in households' retirement accounts than for directly held stocks.

In further research, it will be useful to see how other major future expenditure, such as that for housing purchase and medical expenses, can be incorporated into households' inter-temporal optimization models. Together with the emergency expenditure discussed in this essay, they can be seen as special types of contingent consumption households need to consider when they make saving and asset allocation decisions. Modeling these future spending needs as contingent consumption that would reduce the effective level of current consumption provides insights into households' asset allocation decisions.

In the second essay of this dissertation, I use the life-cycle model to analyze retirees' saving and asset allocation decisions. Previous literature has often modeled the labor income of retirees as a certain percentage of their last working year's wages, which is a fixed amount and will not be subjected to permanent income shock (Cocco, 2005). This implies that retirees' income is less risky and that they should have a *higher* percentage of their wealth invested in risky assets. However, empirical evidence has shown that the risky asset share actually decreases after retirement, which cannot be explained by the previous characterization of the labor income process in the retirement phase. On the other hand, a large body of literature has documented that health risk can play an important role in determining investors' risk taking behaviors (Yogo, 2009; De Nardi et al., 2010; Hugonnier et al., 2012; Scholz and Seshadri, 2013). The health risk factor can be particularly relevant for retirees because health risk increases as people age.

I develop a life cycle model where the health risk is modeled as stochastic expenditure which can effectively reduce retirees' income. I calibrate the health expenditure ratio using data

from the Health and Retirement Survey (HRS), which provides the most comprehensive panel data on U.S. retirees' health condition, out-of-pocket health expenditure, income, and asset holding. In addition, I take into account the possibility of a financial crisis, the effect of which may be different between retirees and non-retirees, whose investment horizon is longer and who can have more time to recoup from the large loss caused by the financial crisis. This is an extension of the notion in the rare event or the tail risk literature, which tries to address the risk premium in asset pricing by considering the occurrence of rare events that could happen in the financial market and whose detrimental effect on wealth can raise the risk premium of stocks (Liu, 2005; Todorov, 2011; Gabaix, 2012; Wachter, 2013).

By incorporating these two important factors in the life cycle model, I derive the retirees' optimal consumption and portfolio choice functions. The optimal policy rules imply that for all age groups (except in the year before death), the portfolio share in stocks gradually increases as normalized wealth approaches 4.5 and slowly declines until leveling out when normalized wealth is higher than 15. This model can explain the investment decisions when normalized wealth is in the range of 1 to 6, where that of 75% of retirees falls. Based on the optimal policy functions and initial wealth distribution, calibrated from the HRS, I conduct a simulation analysis for 5000 retirees and calculate the mean, 5th, and 95th percentiles of the cross-sectional distribution of the risk asset share, and the results are very close to the actual holding level found in the HRS. In addition, I extend the model by incorporating heterogeneous health risk and find that the model implies that households with a higher mean health expenditure ratio would hold fewer risky assets, which is consistent with findings in the empirical literature (Rosen 2004, Edwards; 2008).

In the third essay of this dissertation, I characterize the income distribution of the U.S. population using the Lorenz curve, which calculates the income share for households in each decile. Compared to a single index measurement, such as the Gini coefficient, the Lorenz curve offers a more complete description of income inequality. I then apply a decomposition methodology proposed in Bishop et al. (2004) to study the impact of the 2008 financial crisis on the change in income distribution of U.S. households. By analyzing the Lorenz curve and its associated concentration curve with panel data, this decomposition methodology can track the conditional change in income inequality before and after the financial crisis. Furthermore, this methodology allows us to decompose the Lorenz and the concentration ordinates by population subgroups, based on demographic characteristics, and examine how different groups contribute to the ordinates before and after the crisis.

The analysis results indicate that in the short run, overall income distribution shifted as a result of the financial crisis. The income share of households in the top decile declines, and it increases for households in the bottom nine deciles. This change is reflected in the cross year Lorenz ordinates but is more evident in the concentration ordinates, where households in each decile do not change. Households in the top 10% of the income distribution earned 47% of the total earnings in 2007, and received only 37.7% of total income in 2009, if we preserve the ranking of each household. In addition, the decomposed concentration ordinates for subgroups, characterized by race, gender, and retirement status, followed a pattern similar to that found for the overall sample.

Chapter 2

Precautionary Saving and Asset Allocation

Chapter 2

Precautionary Saving and Asset Allocation

2.1 Introduction

Life cycle models have been widely used in studying households' consumption and portfolio choice decisions. With power utility preference, most life cycle models imply that at low normalized wealth levels, households should invest all their wealth in risky assets. This implication fails to explain the phenomena of low stock market participation and the low share of the portfolio invested in risky assets (Cocco et al., 2005). Even after accounting for housing consumption (Cocco, 2005; Yao, 2005), the life cycle model's prediction for optimal risky asset holdings is still too high compared to the empirical data. This paper presents a simple model that incorporates households' unexpected future expenditure, or contingent consumption, into the power utility. The optimal portfolio rule derived from this model explains the low portfolio share of risky asset holdings when normalized wealth is low. It also explains why the investment share in risky assets increases along with normalized wealth when wealth level is relatively low.

This model is closely related to the habit model, according to which the household's utility depends not only on current consumption but also on a "habit" level of consumption. The habit model generates a more realistic optimal portfolio rule than the non-habit model (Polkovnichenko, 2007). However, in the habit formation model, the "habit" is usually related to past consumption levels or a minimum sustainable level of consumption. In my model, the "habit" is not internally

formed, nor is it related to the past consumption level; rather, it represents the level of unexpected future expenditure that can be seen as a form of contingent consumption that a household has to spend when it occurs. With the anticipation of this type of emergency expenditure, households will hold fewer risky assets and engage more in precautionary saving behavior. After solving the model that explicitly accounts for this emergency expenditure, I further study how precautionary saving and the household's ability to meet its emergency needs can affect its investment risk-taking behavior.

Previous studies on consumer behaviors have found that the precautionary saving motive plays an important role in households' wealth accumulation. Uncertainty about future income and expenditure causes households to engage in buffer-stock saving behavior by reducing their current consumption. Precautionary saving can be seen as a hedge against households' background risks, which include but are not limited to labor income risk, unexpected health expenditure risk, longevity risk, and business risk. Studies on portfolio choices have documented that households with higher uninsured background risks will reduce their financial risk taking. Since precautionary saving can be used to insure against households' background risks, households are more likely to hold risky assets if their precautionary savings are sufficient to cover background risks. By contrast, if households' precautionary savings are not sufficient to protect them from uninsured background risks, they will hold more safe assets and reduce risk-taking behaviors. Therefore, the adequacy of precautionary saving is an important determinant of household financial risk-taking behavior. This paper contributes to the existing literature by quantitatively measuring the adequacy of households' precautionary saving and examining its impact on risky asset investment decisions.

Using a variable of reported desired level of emergency funds and the actual households' asset holding data from the Survey of Consumer Finance, I compute a precautionary index that

captures the adequacy of households' precautionary saving and examine its effect on the households' stock market participation and asset allocation decisions. As documented in previous studies (Calvet and Sodini, 2014; Wachter and Yogo, 2010; Haliassos and Jappelli, 2003; Berkowitz and Qiu, 2006), wealthy households are more likely to participate in the stock market and to hold more risky assets than non-wealthy households. The elasticity of the share of risky assets with respect to financial wealth is large and significant. However, other studies (Cocco et al. 2005) find that non-participation exists even among wealthy households. Higher wealth alone cannot fully account for households' ability to manage background risks. The amounts desired in emergency funds reflect how much households need in case of an emergency, which can be interpreted as the amount of funds required for reducing background risk. The ratio of a household's actual assets to the amount of emergency funds desired, which combines information relating to both budgets and needs, can be a more effective measurement of households' ability to manage background risk and can better predict their risk-taking behaviors.

Households with higher background risks desire a higher amount of precautionary savings than households with lower background risks. For two households with similar levels of assets, the household which desires a higher amount of precautionary savings has a lower precautionary index. Its assets might not be sufficient to cover its emergency needs as compared to those of the household which desires a lower level of precautionary saving. A higher precautionary index value indicates that the households' available assets are high compared to their emergency needs, which can increase their abilities to manage background risk and can affect their risk-taking behavior.

To test this empirically, I use a logit model to estimate the precautionary index's impact on households' stock market participation decisions, and I use a linear probability model to estimate the risky asset share equation. The analysis yields the following findings. First, the effects of the

precautionary index on the probability of participating in the stock market and on the share of risky assets held among the financial assets are both positive and statistically significant. A one percent increase in the precautionary index, which can be due to a decrease in the desired amount of emergency funds, will increase the predicted probability of holding equity by 0.0377 percentage points and will increase the risky asset share by 0.023 percentage points. These results are consistent with the previous results found in the limited participation and background risk literature (Haliassos and Jappelli, 2003; Calvet and Sodini, 2014; Guiso et al., 1996; Palia et al., 2014).

Second, many households hold equity both in their retirement accounts, such as 401(k), IRA, and Keogh Accounts, and outside these accounts, and I find the effect of the precautionary index on risky asset share in these two types of accounts is different in magnitude. Retirement accounts typically have a longer investment horizon and stricter withdrawal policies, so households are less likely to withdraw funds from these accounts when emergency funds are needed. The precautionary index's impact on risky asset share should be smaller for directly held stocks. The estimation results confirm this prediction. The last major finding of this paper is that the impact of the precautionary index is greater on the risky asset share for households who are retired or risk-averse and less for households which have actively managed businesses.

This Chapter will proceed as follows: Section 2.2 introduces the relevant literature. Section 2.3 provides empirical evidence for the relationship between households' investment behaviors and their wealth level. Section 2.4 presents a life cycle model that explicitly accounts for the emergency consumption by households. Section 2.5 develops hypothesis tests and provides estimation results regarding the precautionary index. Section 2.6 discusses the effects of the precautionary index in different subsamples. Section 2.7 concludes this Chapter.

2.2 Literature Review

2.2.1 Precautionary saving behavior

The life cycle/permanent income hypothesis, first proposed by Friedman (1957) and Modigliani and Brumberg (1954), suggests that a household's current consumption should be affected not by current income but by expected lifetime income. The model implies that households save primarily for retirement in order to smooth consumption when their income after retirement drops. However, research on consumption behavior shows that the predictions from the permanent income hypothesis are not consistent with observed consumption behavior. Carroll (1992, 1994, and 1997) find current consumption is unrelated to predictable changes in income, but is strongly related to future unemployment expectation, and more generally, to future income uncertainty. Households reduce consumption and hold more assets to protect themselves from unpredictable future fluctuations in income. Deaton (1991) also shows that in the presence of borrowing constraints, the precautionary demand for saving provides a motive for a household to hold assets.

Subsequent empirical research has tried to quantify household risk and measure its impact on households' precautionary wealth accumulation. Carroll and Samwick (1998) find that about 40 percent of wealth accumulated can be attributed to a precautionary saving motive induced by income uncertainty. Lusardi (1998) finds that saving and wealth accumulation are associated with variance of income. Guariglia (2001) finds that labor income risk has a statistically significant effect on households' saving decisions. Cagetti (2003) finds that wealth accumulation is driven mostly by precautionary motives at the beginning of the life cycle, whereas savings for retirement purposes become significant only closer to retirement.

Though empirical evidence shows some support for precautionary wealth accumulation, the analysis has its drawbacks. As pointed out by Hurst et al. (2005), households with high income uncertainty, such as business owners, will hold a large amount of wealth for non- precautionary reasons. Simply regressing wealth on risky labor income will lead to an overestimation of the importance of the precautionary motive in the wealth accumulation process. The availability of a direct measure of precautionary wealth in household surveys provides a better estimation of the precautionary motive in wealth accumulation; however, the results are mixed. Jappelli (2008) uses a precautionary wealth variable from Italian household survey data to test the precautionary saving/buffer stock model and finds no support for buffer stock behavior. For U.S. households, Kennickell and Lusardi (2004) use the desirable amount of emergency funds reported in the Survey of Consumer Finance as a proxy for precautionary saving and find that precautionary wealth exists but that it is not as large as previously estimated. They find that precautionary wealth accounts for only 8% of the total wealth holdings. They also find that precautionary saving is more important to older households and business owners.

2.2.2 Background risk and portfolio choice

In a perfect market environment, if income or background risk is perfectly insurable, investment behavior should not be affected by background risks. However, imperfection in the financial market and uninsured background risk induce risk-averse households to reduce their risky asset holdings when background risk exists. One of the biggest motives behind precautionary saving is to insure against unexpected income risk, which is an important background risk households face. Previous research has examined how labor income risk can affect portfolio choice. With Italian household data, Guiso et al. (1996) find uninsured labor income risk, as measured by

the subjective expected labor income variance over the next 12 months, has a small but statistically significant negative effect on the share of risky assets held by households. Hochguertel (2003) finds subjective income uncertainty has an effect on risky asset holding; however, the effect is economically small and not as important as the level of financial asset holdings, age, education, and tax incentive.

In addition to the labor income risk, background risks can include health and longevity risk as well as unexpected change in housing expenditure or business risk, and studies find that the presence of these background risks can also affect households' asset allocation decisions. Fratantoni (1998) finds households with higher housing expenditure relative to labor income hold a lower share of risky assets among their financial wealth. Heaton (2000) finds that risky human capital is an important determinant of stock market participation and asset allocation decisions at different stages of an investor's life. Palia et al. (2014) find households' background risks, as measured by volatilities of labor income and its correlation with stock returns, housing risk, and business income, are statistically significant and economically important for households' stock market participation decisions and stock holdings.

2.2.3 Limited participation in the stock market

Merton (1971) and Samuelson (1969) indicate that the optimal holding of risky assets should depend only on an individual's risk aversion, risk premium, and stock volatility in a perfect market. However, it is a well-documented fact that a large number of households do not hold stocks at all. Many studies have attempted to explain these non-participation phenomena. The major thesis of the limited participation literature is that households face higher costs of participating in the stock market. Haliassos (1995) show that liquidity, information cost, and risk embedded human

capital are the major determinants of the decision not to participate. Zhan (2015) finds credit constraints, occupation-linked income risk, and entrepreneurial risks, but not housing, are major factors reducing stock market participation in the Euro area.

Information cost can also affect the decision to participate in the stock market. Households with lower education and cognitive skills have higher costs in obtaining information necessary for stock market investment. Rooij et al. (2011) find that those with low financial literacy are much less likely to invest in stocks. Christelis et al. (2010) find that the propensity to invest in stocks is strongly correlated with cognitive abilities. Brown et al. (2008) find that social interaction matters in stock market participation decisions. In particular, the community stock participation rate has a causal effect on an individual household's decision to own stocks.

Studies also show personality traits and one's psychological profile can affect one's propensity to own stock. Guiso and Zingales (2008) find that lack of trust is an important factor in explaining limited stock market participation. Less trusting individuals are less likely to buy stocks as they feel a greater risk of being cheated. Dimmock and Kouwenberg (2010) find that higher loss aversion lowers stock market participation, along with the share of risky assets owned. Gyllenram and Hanes (2014) find that individuals who can better cope with stressful situations are more likely to own stocks. This effect is even more pronounced among the wealthiest households.

2.3 Evidence on Households' Investment Behaviors

The traditional life cycle models imply that the portfolio share in risky assets should decrease when normalized wealth level rises (Cocco et.al.,2005); households with lower normalized wealth levels should invest more in stocks. However, empirical data show that stock holding rises with wealth. In this section, I present findings that show both stock participation and

portfolio shares invested in risky assets are significantly lower when normalized wealth is below certain cutoff points. All household data are obtained from the Survey of Consumer Finance.

2.3.1 General overview of the Survey of Consumer Finance (SCF)

The SCF is triennial cross-sectional survey data published by the Federal Reserve. The survey provides detailed information on household finance, including households' asset holdings, credit and debts, income, and wealth, as well as a set of characteristic and preference questions. The SCF contains two important subsamples. The first sample uses a random statistical area probability model to choose households across the country, and it represents the characteristics of the general population in the United States when weighted. The second subsample focuses on the wealthy households; in this subsample, the SCF uses households' IRS filing information to select households in the top decile of the wealth distribution. The dual-frame sample design provides a comprehensive picture of U.S. households' balance sheets, as well as those of households in the top wealth distribution, whose financial situation may be different from that of the general public.

Since the SCF collects sensitive financial data which some households are reluctant to provide and information is consequently missing for some questions, the Federal Reserve developed a set of imputation techniques to correct for the missing data by imputing the missing values five times. Following Calati et al. (2008) and Lee and Carlin (2010), I use the average of all five imputations as an observation value. The survey unit in the SCF is the household, and all financial data are collected on a household basis. The survey respondent is determined to be the person "most knowledgeable about family finances" and is usually the head of the household.

[Insert Table 2-1 here]

Table 2-1 presents a summary of the statistics for key variables in the SCF. All variables are weighted using the weight provided by the Federal Reserve. Liquid assets include assets in checking accounts, saving accounts, and money market funds. Financial assets include all liquid assets, CDs, stocks, assets in retirement accounts, saving bonds, cash values of whole life insurance policies, and other managed accounts (trusts, annuities, and managed investment accounts in which HH has an equity interest). Equity includes directly held stocks, stock mutual funds, and stocks in combination mutual funds. Distributions of the financial variables are skewed to the right; mean values of income, equity, assets, and net worth are substantially higher than the median values. Table 2-1 also provides summary statistics for a subjective measure of households' risk-taking attitudes regarding investment.

2.3.2 Normalized wealth and investment behavior

As shown in Wachter and Yogo (2010), the portfolio share of risky assets rises as net worth increases for middle-age households. They use the log of wealth as a measure of the wealth effect, which is not directly related to the normalized wealth concept typically used in the life-cycle model. In this section, I provide further evidence showing that a lower level of normalized wealth not only reduces a household's risky asset share but also decreases the probability of a household's participation in the stock market. I calculate the normalized wealth level by dividing the household's total financial wealth by the household's income. Ideally, I should use the household's permanent income as the denominator to calculate the normalized wealth, yet permanent income

is not an observable variable, so I use the household's actual income¹ as a proxy. I create two dummy variables to indicate that the household's normalized wealth is below 1 and 2, respectively.

[Insert Table 2-3 to Table 2-6 here]

As shown in the second and third column of Table 2-3, the coefficients on the normalized wealth dummy variables are significantly negative. After controlling for other demographic, income, and wealth variables, a household's probability of holding any stock will be reduced by 17.23 percentage points and 9.53 percentage points if the household's normalized wealth is below 1 and 2, respectively. Table 2-5 shows the effect of normalized wealth on portfolio share. A household's portfolio share in risky assets will be reduced by 14.17 percentage points if the household's normalized wealth is below 1 and will be reduced by 9.01 percentage points if the normalized wealth is below 2.

Table 2-6 shows the normalized wealth regression results for subsamples of different normalized wealth levels. Model I restricts the sample to households whose normalized wealth is under 2 and for whom the coefficient on the normalized wealth variable is large and highly significant, indicating that when normalized wealth is low, risky asset share increases as normalized wealth rises. Model II restricts the sample to households whose normalized wealth is above 5 and for whom the coefficient on the normalized wealth variable is no longer significant. When normalized wealth is sufficiently high, the risky asset share does not rise when normalized wealth increases.

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¹ The SCF asks if the household income is normal or typical of that year. A normal income is a better proxy for the permanent income.

2.3.3 The saving motive and investment behavior

The traditional life-cycle model indicates that households save to smooth consumption over time, and they save during their working life and dis-save during their retirement stage, which implies that households should save primarily for retirement. However, as Carroll (1994, 1996, and 1997) and subsequent precautionary saving literature have found, households also engage in precautionary saving behavior. Different saving motives can influence households' investment behavior; this section provides evidence showing that households with different saving motives can have different investment behaviors.

[Insert Table 2-7 here]

The SCF surveys households' primary saving motives; Table 2-7 provides a description of households' major saving motives and the distribution of these motives. In the SCF sample, 35.5% of the households report the primary reason for their saving is retirement, and 31.5% of the households save primarily for an emergency; i.e., they are precautionary savers.

[Insert Table 2-8 to Table 2-10 here]

The regression results show that households which save primarily for retirement have a 7.67% higher probability of participating in the stock market, and the part of their portfolio invested in risky assets is 6.13 percent higher than that of other households. On the other hand, precautionary savers, whose primary goal is saving for emergency needs, have a lower probability of participating in the stock market, and the part of their portfolio invested in risky assets is 2.78 percentage points lower than that of other households. These results suggest that the impact of precautionary saving on risky asset investment can be fundamentally different from that of long term saving behavior (i.e., saving for retirement), households perceive emergency needs as

contingent expenditures that need to be made once they occur, and the existence of these emergency needs can change a household's investment behavior.

In the next section, I present a life cycle model that explicitly accounts for households' emergency needs and derive its implications for optimal portfolio choice. This model can better explain the empirical pattern observed in the data: stock market participation and risky asset share both rise with normalized wealth when the normalized wealth level is low.

2.4 A Life Cycle Model Including Contingent Consumption

2.4.1 Preferences

I model emergency needs as expenditure shock that can occur in each period and households' utility function depends both on current consumption and on this contingent expenditure shock. The model is similar to the habit model, where a household's utility depends on the difference between current consumption and a "habit," which can be seen as a general level of aggregate consumption or a subsistence level of consumption. In my model, households take their emergency needs into consideration, and they see emergency needs as a contingent expenditure, which can reduce consumption significantly if it occurs. This variable measures how much households need to spend if an emergency situation emerges; however, it does not affect a household's intertemporal budget constraints because households do not pay insurance premiums to reduce emergency risk in this model. The amount of the emergency fund is exogenous in this model, much like in the habit model, in which "habit formation is external." Emergency spending can also be seen as a type of expenditure shock which effectively reduces a household's

consumption once it occurs. Taking this shock into consideration, household i 's preference is characterized by a power utility function:

$$U_i^i = E_1 \sum_{t=1}^T \beta^{t-1} \left(\prod_{j=1}^{t-1} p_{j-1} \right) \frac{(C_{it} - E_{it})^{1-\gamma}}{1-\gamma} \quad (2-1)$$

where the household is assumed to live a maximum T period. In each period, there is a possibility that the household will die. Let p_t denote the probability that the household is alive at date $t + 1$, conditional on it being alive at date t . The household maximizes expected life utility with a constant relative risk aversion γ and time preference parameter β . Values for these parameters will be discussed in Section 2.4.5.

2.4.2 The labor income process

Following previous literature (Carroll, 1997; Winter et al., 2012; Cocco et al., 2005), the labor income process can be modeled as comprising a deterministic component and two stochastic components, which can be specified as:

$$y_{it} = f(t, Z_{it}) + u_t + e_{it} \quad (2-2)$$

where y_{it} is the log of labor income, $f(t, Z_{it})$ is a deterministic function, Z_{it} represents a vector of variables capturing information regarding individual characteristics, including demographics, education, and the number of years working. u_t captures the permanent income shock, which is modeled as an AR(1) process, and the variance of the permanent income shock is σ_u^2 ; e_{it} is the transitory shock, which is i.i.d and is distributed as $N(0, \sigma_e^2)$.

2.4.3 The financial market

In each period, investors can invest in two assets in the financial market: a riskless and a risky asset. The riskless asset has a return r_f for each period, and the risky asset is characterized by a mean risk premium of μ and an innovation component η_{t+1} :

$$\tilde{r}_t = r_f + \mu + \eta_{t+1} \quad (2-3)$$

where η_{t+1} is assumed to be independent and identically distributed (i.i.d) as $N(0, \sigma_\eta^2)$.

2.4.4 Households' optimization problem

After the household has made the consumption decision and the asset allocation decision, its financial wealth at the beginning of next period, $t+1$, will be:

$$W_{i,t+1} = r_{i,t+1}^p (W_{it} + Y_{it} - C_{it}) \quad (2-4)$$

The return of the portfolio from time t to time $t + 1$ is given by:

$$\tilde{r}_{i,t+1}^p = \alpha_{it} \tilde{r}_{t+1} + (1 - \alpha_{it}) r_f \quad (2-5)$$

where α_{it} is the portfolio share invested in the risky assets and $1 - \alpha_{it}$ is the portfolio share invested in the risk-free assets. Assuming that the household faces borrowing constraints and cannot short sell the risk-free asset, α is restrained to be in the interval $[0, 1]$. The household's optimization problem is to maximize the objective function (2-1) subject to the constraints (2-2) through (2-5). The state variables are $\{t, X_t, Y\}$, and the control (choice) variables are $\{C_t, \alpha_t\}$. For each period, the optimal rules of consumption and portfolio share are functions of the state variables t, X_t , and Y . The Bellman equation for a household's optimization problem is given by:

$$V_{it}(X_{it}) = \max_{C_{it} \geq 0, 0 \leq \alpha_{it} \leq 1} [U(C_{it}) + \beta p_t E_t V_{i,t+1}(X_{i,t+1})], \quad t \leq T \quad (2-6)$$

where $V_{it}(X_{it})$ is the value function, denoting the maximized utility. Given X_{it} , the next period total resource is:

$$X_{i,t+1} = W_{i,t+1} + Y_{i,t+1} \quad (2-7)$$

Substituting (2-4) and (2-5) into (2-7), $X_{i,t+1}$ can be expressed as:

$$X_{i,t+1} = (X_{it} - C_{it})(\alpha_{it}r_{t+1} + (1 - \alpha_{it})r_f) + Y_i \quad (2-8)$$

2.4.5 Parameters and model calibration

Table 2-11 presents the parameter values of the model. Households retire at age 65 and have a maximum lifespan of 100 years. As shown in Cocco (2005), the deterministic part of the labor income process can be fitted to a third-degree polynomial, and the coefficients are estimated for different educational levels. I use their estimation coefficients for high school graduates as a benchmark case here. During their working life, the deterministic part of their labor income $f(t)$ is additively separable in t and Z_{it} , and can be specified as:

$$f(t) = -2.1700 + 0.1682t - 0.00323 \times Age^2 + 0.00002 \times Age^3 \quad (2-9)$$

After retirement, the deterministic part of the labor income is replaced by a constant value, which is the household's last working year's income multiplied by a replacement ratio: 0.682. Figure 2-1 presents the graph of the age profile of the deterministic part of the labor income for both high school graduates and college graduates.

[Insert Figure 2-1 here]

The variance of the permanent and temporal labor income shock are also obtained from Cocco (2005). The mean value of the contingent consumption (emergency funds) to the permanent

income ratio is estimated from the Survey of Consumer Finance. The mean value for the whole sample is 0.48. Financial market parameters follow the standard benchmark values used in the literature.

2.4.6 The model solution: optimal portfolio policy

Using the parameter value discussed in Section 2.4.5, I solve the model numerically to obtain the optimal portfolio policy. This section presents these optimal rules under two different scenarios.

2.4.6.1 Policy rules without considering emergency spending

As discussed in the previous section, if we do not consider the effect of contingent consumption (i.e., $E = 0$), the household's utility function will be $U_t^i = \frac{c_{it}^{1-\gamma}}{1-\gamma}$. The optimal share invested in risky assets should be very high when the normalized wealth is low, as the present value of the riskless human capital is large compared to the wealth; therefore, the household should invest more in risky assets. This is the result implied by the life cycle model in Cocco *et al.* (2005). Figure 2-2 presents this case:

[Insert Figure 2-2 here]

Figure 2-2 shows that households should invest all their cash-at-hand in the risky assets when the normalized cash-at-hand is below 5, and this holds across all age groups. As normalized wealth increases, the optimal share invested in risky assets decreases. When the normalized wealth is high, the present value of the future human capital is smaller relative to the normalized wealth, and households should tilt their investment towards more riskless assets and reduce their risk exposure. This optimal portfolio policy, however, cannot explain some important empirical facts about households' behavior. In the SCF, the mean normalized wealth is 1.78, and the mean risky

asset share is 0.25. The median normalized wealth is only 0.55, and the median risky asset share is 0.10. 75% of households have a normalized wealth ratio below 2. The benchmark life cycle model fails to explain households' optimal behavior when normalized wealth is low, which is the case for most American households. In the next section, I present the optimal portfolio rule when the effect of contingent expenditure is considered.

2.4.6.2 *Policy rules considering emergency spending*

As discussed in Section 2.4.1, the presence of emergency spending can change a household's risk taking behavior. In this case, household utility depends on consumption as well as contingent consumption. Household utility is given by: $U = \frac{(C-E)_{it}^{1-\gamma}}{1-\gamma}$.

[Insert Figure 2-3 and Figure 2-4 here]

Figure 2-3 presents the optimal portfolio rule when contingent consumption has been accounted for. This result is qualitatively similar to the one obtained from the “habit” model (Polkovnichenko, 2007). The optimal policy rules differ substantially from those in the benchmark case. The optimal risky asset share starts very low when normalized wealth is low and increases as normalized wealth increases. Since most households have a normalized wealth ratio below 2, it is useful to further examine the optimal portfolio share when normalized wealth level is low. Figure 2-4 shows a more detailed portrait for households at different ages when normalized wealth is below 5. This model better captures the dynamics of stock investment, especially when normalized financial wealth is below 1.8, where that of half of the American households falls. The model implies that the mean optimal portfolio share is about 0.1, closer to the actual mean portfolio share of 0.17 found in the SCF, when normalized wealth is below 1. In the next section, I construct a precautionary index

that measures households' ability to meet expenditure shock and quantify the effect of this index on households' risk-taking behaviors.

2.5 The Precautionary Index: Hypothesis Testing and Estimation

2.5.1 Construction of the precautionary saving index

From 1995 onwards, the SCF has asked a question about how much households will need in precautionary savings for emergencies. The question is stated as follows:

"About how much do you think you and your family need to have in savings for unanticipated emergencies and other unexpected things that may come up?"

Kennickell and Lusardi (2004) provides a comprehensive review for this variable. They argue that this variable captures the amount of precautionary wealth households wish to have.

[Insert Table 2-12 here]

Table 2-12 provides summary statistics of the desirable precautionary wealth for the whole sample and for subsamples. The mean value of the precautionary wealth is \$25,511, and the median value is \$5,762. Panel A shows the precautionary wealth by different net worth levels. Households with higher net worth demand a higher level of precautionary wealth in case of emergency as expenditure can be proportional to the household's wealth level. The median desirable precautionary wealth for households with above median wealth is \$11,330, three times higher than that for households whose wealth is below the median. Panel B shows that retired households have a higher need for precautionary wealth than non-retired households. The median value for retired households is \$10,000, whereas the median value for non-retired households is \$5,665.

To measure households' ability to meet their emergency needs, I construct an index incorporating information from both the desirable level of emergency funds and households' available assets. Following Kennichell (2004), I calculate the household's available liquidity as a weighted sum of its total assets minus six months' debt payments. The weight of each class of assets is assigned to reflect the liquidity nature of the assets. Liquid assets, which include cash, checking accounts, saving accounts, and money market mutual funds, have a weight of 1; stock in non-retirement accounts has a weight of 0.8. Assets in retirement accounts have a weight of 0.3, and non-financial assets have a weight of 0.5. In practice, households can also borrow against their home equity or engage in other types of loans to manage their liquidity. However, I do not explicitly include these considerations in the available resources calculation.²

I compute the precautionary index by dividing the total available resources by the desirable amount of emergency funds. This index measures the extent to which households are able to cover the need for emergency funds using their available assets. A higher precautionary index indicates that a household's assets are abundant relative to the amount needed in an emergency situation, which can make the household more risk tolerant. A ratio equal to one indicates that a household needs to use all its liquidity resources to cover the expected emergency spending. A ratio above one indicates that the household's own assets are inadequate to cover the emergency needs. The inability to meet its precautionary needs can reduce a household's risk-taking capacity.

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² The value of the housing asset partially reflects the amount of home equity loan that households can borrow when facing emergency situations.

2.5.2 Market participation hypothesis and regression results

In this section, I estimate how the precautionary index can affect households' stock market participation decisions using a logit model. The hypothesis is that a low precautionary index would reduce a household's probability of holding risky assets. As discussed in the previous section, holding other things constant, a low precautionary index indicates that a household's available assets are low compared to the desirable level of emergency funds. In this case, a household faces a relatively high risk of not being able to finance its needs using its assets when an emergency occurs. This can also be an indication of higher background risk, which can prevent households from holding equity in the stock market. The estimation equation can be stated as:

$$\text{logit}(E[\text{hequity}_i | x_{1,i}, \dots, x_{m,i}]) = \alpha_0 + \alpha_1 \text{precaution}_{i,t} + \sum_{j=1}^n \beta_j \text{controls}_{i,t}^j \quad (2-10)$$

hequity is a dummy variable, which is equal to 1 if a household owns any equity and 0 otherwise. *precaution* is the precautionary saving index described in Section 2.5.1. *controls* is a set of control variables, including age, gender, education, race, marital status, number of children, employment status, income, and wealth. In the logistic regression, the dependent variable is the log of the odds ratio, which can be stated as follows:

$$\log \frac{\hat{p}_i}{1 - \hat{p}_i} = \alpha_0 + \alpha_1 \text{precaution}_{i,t} + \sum_{j=1}^n \beta_j \text{controls}_{i,t}^j \quad (2-11)$$

The odds ratio is the probability of holding equity, $\tilde{p}_i$, divided by the probability of not holding any equity $1 - \tilde{p}_i$. In the logistic regression, the log of the odds ratio is a linear function of the explanatory variables.

[Insert Table 2-13 here]

Table 2-13 presents the estimation results of equation (2-11). The precautionary index has a significantly positive effect on a household's stock market participation decisions. However, the precise quantitative impact of this index cannot be obtained directly from the estimated coefficient as the estimated coefficient in the logistic results measures how a one-unit change in the explanatory variables results in a change in the log of the odds ratio, not the probability of holding equity. To interpret the results meaningfully, we need to estimate the marginal effect of the precautionary index on the probability of holding equity. The marginal effect is calculated for each observation, measuring how the change in the precautionary index will change the probability of holding equity:

$$\text{Marginal Effect of } x_p = \lim_{\Delta \rightarrow 0} \frac{\Pr(Y = 1 | X, x_p + \Delta) - \Pr(Y = 1 | X, x_p)}{\Delta} \quad (2-12)$$

where X is a vector of the control variables, evaluated at their original value for each observation. The marginal effect of x_p is calculated by computing the difference between the predicted probability before and after a small change in x_p , and its value also depends on the value of the control variables. As the control variables are different for each observation, the marginal effect of x_p is different for each observation, and I take the average of the marginal effects across all observations.

[Insert Table 2-14 here]

Table 2-14 reports the average marginal effect of the explanatory variables on stock market participation decisions. For the categorical variables, the marginal effect is taken to be the change in the predicted probability when the categorical variable changes from 0 to 1. For example, the average marginal effect for *Race* is 0.0794, indicating that for a white household (*Race*=1), the probability of holding equity will be 7.94 percentage points higher than it will for a non-white

household on average. For continuous variables, the interpretation of the coefficient is the effect of a small change in the explanatory variable on the change of predicted probability of holding equity. Since the log value of the precautionary index is used in estimating equation (2-11), the marginal effect can be used to assess the impact of a one percent change in the precautionary ratio on the change of the predicted probability of holding equity.

The results show that a one percent increase in the precautionary ratio will increase the predicted probability of holding equity by 0.0377 percentage points. A change in the precautionary index can be caused by a change in the desirable amount of emergency funds and/or a change in the available assets. The change in the precautionary index is not bounded by 100%, and its effect on the probability of holding equity can be quite substantial. Take a hypothetical scenario: for example, consider two households which have the same assets of \$50,000 but one of which has a desirable amount of precautionary wealth of \$10,000 and the other has a desirable amount of precautionary wealth of \$20,000. The first household's precautionary index is twice that of the second. Taking the average marginal effect as an approximation, the lower precautionary index of the second household will decrease the probability of holding equity by 3.77 percentage points compared to the first household.

2.5.3 Portfolio shares in risky assets

In this section, I estimate how the precautionary index affects the portfolio share invested in risky assets. The estimation equation can be stated as:

$$share_{i,t} = \alpha_0 + \alpha_1 precaution_{i,t} + \sum_{j=1}^n \beta_j controls_{i,t}^j + \varepsilon_{i,t} \quad (2-13)$$

where *share* measures the ratio of a household's equity to its financial assets. For a robustness check, I also examine different measures of the portfolio share. I use a linear probability model to estimate equation (2-13).

[Insert Table 2-15 here]

Table 2-15 presents the regression results of the impact of the precautionary index on share of the portfolio in risky assets. For the linear probability model, we can directly interpret the effect from the estimated coefficient of the regression results. The estimated coefficient of the precautionary index is positive and statistically significant. Taking the previously discussed hypothetical scenario, consider two households which have the same assets of \$50,000 but one of which has a desirable amount of precautionary wealth of \$10,000 and the other has a desirable amount of precautionary wealth of \$20,000. The first household's precautionary index is twice that of the second. Based on the estimation results shown in Table 2-15, the second household's risky asset share would be 2.27 percentage points lower than that of the first.

Other variables, race, gender, education, marital status, unemployment status, income, and wealth, are also statistically significant and have the expected signs. Age has a non-linear effect on risky asset holdings as households typically hold a higher percentage of equity during their middle age than during either their young age or their old age. The number of children does not appear to have a significant impact on the portfolio share of risky assets.

Using only the desirable amount of precautionary wealth, Telyukova (2013) finds there is a positive relationship between desirable precautionary wealth and investment share in risky assets. He argues that a causality relationship exists between holding risky assets and the amount of desirable precautionary wealth. The risk entailed by holding stock enables households to hold more precautionary wealth as the risk in the overall household portfolio increases. By contrast,

households which hold only safe assets will significantly reduce the desirable level of precautionary wealth. In other words, the stronger demand for precautionary wealth reflects a higher level of risk incurred from investing in stocks. In his analysis, the desirable amount of precautionary wealth is endogenously determined by an exogenous level of risky asset holdings. However, the precautionary index, which is the ratio of total weighted assets to the desirable amount of emergency funds, can serve as a proxy for measuring the risk-bearing ability of the household, and the risk can include income risk as well as other background risks. The higher the value of the precautionary index, the better households can handle emergency risk, which can induce them to hold more equities. In other words, the share invested in risky assets is endogenously chosen to be commensurate with their ability to handle risk.

2.6 Discussion

2.6.1 Retirement accounts vs. non-retirement accounts

As argued in Carroll (1997, 1998), precautionary saving is an important reason for households to save, while saving for retirement does not seem to be a priority, especially for young households. In the 1983 SCF, only 15% of the respondents said they were saving for retirement. However, as defined contribution plans become the major source of retirement funds and with the gradual phase-out of defined benefit plans, households have to save for their own retirement income by investing in bonds and stocks. In recent waves of the SCF, the percentage of households' saving for retirement has increased: as shown in Table 2-7, 35% of all respondents indicate that they are saving mainly for retirement. Despite the increase in retirement saving, saving for precautionary purposes is also prevalent: 32% of all respondents in the SCF said they were saving

mainly for emergency and precautionary purposes. If households have equity invested both in their retirement accounts and outside their retirement accounts (in non-retirement accounts), the effect of the precautionary index on investments in these two types of accounts may be different. The hypothesis is that the precautionary ratio would have a smaller effect on investment behavior with regard to the retirement accounts as the investment horizon for retirement saving is usually longer than it is for precautionary saving. Emergency needs often occur in the short run and demand more liquidity. The SCF provides detailed financial information on households' retirement accounts and non-retirement accounts, and I estimate equations (2-11) and (2-13) for both retirement accounts and non-retirement accounts. For non-retirement accounts, equation (2-11) can be estimated as

$$\text{logit}(E[hdeq_i | x_{1,i}, \dots, x_{m,i}]) = \alpha_0 + \alpha_1 \text{precaution}_{i,t} + \sum_{j=1}^n \beta_j \text{controls}_{i,t}^j \quad (2-14)$$

for the market participation decision, where *hdeq* is a dummy variable indicating whether households hold any equity directly (i.e., outside their retirement accounts). For retirement accounts, the equation is:

$$\text{logit}(E[hreteq_i | x_{1,i}, \dots, x_{m,i}]) = \alpha_0 + \alpha_1 \text{precaution}_{i,t} + \sum_{j=1}^n \beta_j \text{controls}_{i,t}^j \quad (2-15)$$

where *hequity* is a dummy variable indicating whether households hold any equity in their retirement accounts, such as 401(k) plans, IRAs, Keogh accounts, etc. The logistic results (not shown here) indicate that the effects of the precautionary index on households' participation decisions do not differ much between retirement accounts and non-retirement accounts. However, the risky asset shares invested in these two types of accounts differ, so I will estimate (2-16) for these two types of accounts separately:

$$share_{i,t} = \alpha_0 + \alpha_1 precaution_{i,t} + \sum_{j=1}^n \beta_j controls_{i,t}^j + \varepsilon_{i,t} \quad (2-16)$$

For retirement accounts, the *share* is calculated by dividing the equity held in the retirement account by the total retirement assets. For the non-retirement accounts, the *share* is calculated by dividing directly held equity by total financial assets excluding retirement assets.

[Insert Table 2-16 here]

Table 2-16 presents the estimation results using the linear probability model. Model I is for overall risky asset share. Model II and Model III show the results for non-retirement accounts and retirement accounts, respectively. A one-percent increase in the precautionary index will increase risky asset share in non-retirement accounts by 0.0176 percentage points and will increase the risky asset share in retirement accounts by 0.0109 percentage points. An increase in the precautionary index increases the risky asset share in both types of accounts; however, the impact is smaller for equity held in retirement accounts, and this is consistent with the hypothesis that the precautionary index should have a lower impact on long horizon investment behavior.

2.6.2 Non-retired households vs. retired households

As documented in Kennickell and Lusardi (2004), the desirable level of precautionary saving is important for two groups: older people and business owners. As shown in Table 2-12, the mean and the median desirable amounts of emergency funds are substantially higher for retired households. In this section, I investigate whether the precautionary index has different effects for households with different retirement status. The next section will look at the behavior of the business owners.

[Insert Table 2-17 here]

Model I in Table 2-17 presents the results for the market participation decision regression with two additional variables: a dummy variable indicating the household head's retirement status and an interaction term between the retirement dummy and the precautionary ratio. Being retired lowers the probability of participating in the stock market, holding other variables constant. However, the coefficient of the interaction term is positive and significant, indicating that the effect of the precautionary index is larger for retired households. Similar results also hold for the risky asset share regression. The precautionary ratio has a larger impact on retired households' risky asset share. For non-retired households, a one-percent increase in the precautionary index will increase the risky asset share by 0.0213 percentage points, but for retired households, it will increase the risky asset share by an *additional* 0.0074 percentage points. For retired households, having more available resources can have an even more significant effect on their investment risk-taking behavior. Further, not having enough resources to meet emergency needs can discourage retired households, more than non-retired households, from investing in risky assets.

2.6.3 Business owners vs. non-business owners

Also as pointed out in Kennickell and Lusardi (2004), business owners have a significantly higher desired level of precautionary saving. Heaton (2001) and Yilmazer and Scharff (2014) show that business owners are less likely to hold risky equity investment. In this subsection, I construct a dummy variable indicating a household's business ownership status and add an interaction term between the business ownership dummy variable and the precautionary index in the regression analysis. Following the SCF documentation and Kennickell and Lusardi (2004), business owners are households that own a business in which they have an active management interest. In the 1995-

2010 SCF sample, 30.2%, or 7,762 households, are identified as business owners. Households owning businesses have substantially higher median income, equity holding, and assets than non-business owners. The median (weighted) equity holding for business owners is \$20,000, whereas for non-business households, the median is \$919. As business owners have higher net worth and can face higher background risk, the desirable level of precautionary wealth is also higher. For business owners, the median value is \$12,254, but for non-business owners, the median value is \$5,753.

Model II of Table 2-19 presents the estimation results by explicitly controlling for business ownership. We see that having a business increases the probability of participating in the stock market and investing in risky assets; however, having a business *reduces* the effects of the precautionary index on risk-taking behavior. The coefficient for the interaction term is negative and significant. For households having a business, a higher precautionary index still increases the risky asset share. However, the increase is 0.016 percentage points *smaller* as compared to households that do not have a business. As shown by the analysis regarding retirement status, having insufficient funds to meet emergency needs can be a major reason for retirees to be less likely to participate in the stock market, or to hold a lower share in risky assets if they do participate. For business owners, having sufficient funds to meet emergency needs is less important in determining their investment risk-taking behavior. There can be factors that affect business owners other than precautionary motives.

2.6.4 Control for risk preference

As Kimball (1990) points out, the precautionary saving motive is closely related to the Arrow-Pratt theory of risk aversion. It may be the case that households that are more risk averse

wish to hold more emergency funds than others when facing similar emergency situations. We cannot rule out the possibility that a higher precautionary index is the result of a more risk-averse preference. To address whether the precautionary index contains more information than just risk preference, I add a household risk taking preference variable as an additional control variable in the regression analysis, and it does not greatly change the previous results, which suggests that the precautionary ratio itself, independent of risk preference, is important in determining households' risk taking decisions. Moreover, in Model III of Table 2-19, an interaction term between the risk averse dummy variable and the precautionary index is added to the regression analysis, and it has a positive and marginally significant effect. For households who are relatively more risk averse, a 1% increase in the precautionary index will increase their risky asset share by an *additional* 0.0037 percentage points as compared to households that are less risk averse.

2.6.5 The effect of low normalized wealth

[Insert Table 2-20 to Table 2-22 here]

As the empirical evidence in Section 2.3.2 and the optimal policy rule derived in Section 2.4.6 show, households having a low normalized wealth level are less likely to participate in the stock market, and their risky asset share is lower when they do participate. Households' ability to meet emergency consumption spending needs can be lower when their normalized wealth level is low, which reduces their investment risk-taking behavior. Other things being equal, a higher precautionary index can be particularly valuable for households whose normalized wealth level is low. In this section, I examine whether the precautionary index has a larger impact for households whose normalized wealth is relatively low. The mean normalized wealth ratio from the SCF is 1.8. I construct a dummy variable that is equal to 1 if the household's normalized wealth is below 2

and equal to 0 otherwise. I also add an interaction term between the normalized wealth dummy variable and the precautionary ratio. Table 2-20 presents the results for the logit model. Table 2-22 presents the results for the risky asset share model.

Households whose normalized wealth is below 2 are 26.5% less likely to participate in the stock market, and the risky asset share of their portfolios is 16.8 percentage points lower than that of households whose normalized wealth is above 2. However, the coefficients of the interaction term are positive and significant, indicating that for relatively low normalized wealth households, having a higher precautionary index can be more important in their investment behavior as compared to high wealth households. For low normalized wealth households, a one percent increase in the precautionary ratio increases the probability of stock market participation by an *additional* 0.01 percentage point and increases the risky asset share of their portfolios by an *additional* 0.009 percentage point.

2.6.6 The impact of pension plans

Households' saving and investment behavior can be affected if they have pension plans. Among the 25,647 households in the SCF 1995-2010 sample, 15,050 households had some pension plan, and 10,419 households reported no pension plan for either household head or spouse. It is interesting to observe whether the precautionary index has different effects for those who have a pension plan and those who do not have one. In addition, the type of the pension plan also differs among households. Generally, households have a defined contribution pension plan, a defined benefit pension plan, or both. Households with a defined contribution plan have to take more responsibility for their own retirement savings, and the composition of the retirement account is

entirely determined by the household's choice. It is of interest to observe whether the precautionary index has a different impact for households with different types of pension plans.

To investigate these two issues, I conduct two sets of tests. First, I divide the whole sample into two subsamples: those who have a pension plan and those who do not. The regression results show there are no significant differences in their stock market participation decisions or in the risky asset share of their portfolios. In the second set of the test, I obtain a subsample which consists of 6,379 households with only a defined contribution plan and no defined benefit plan. I also obtain another subsample of 4,988 households that have only a defined benefit pension plan and no defined contribution plan. Among households that have defined benefit plans, half (2,453) still hold some additional retirement account, such as an IRA, Keogh, or thrift type account. I find no significant difference in the estimated effects of the precautionary index for households that have defined contribution plans versus those with defined benefit plans. The precautionary index reduces the risky asset share in both their non-retirement accounts and their retirement accounts, and the magnitude of reduction is similar for households regardless of their pension account type.

2.7 Conclusion

This paper incorporates desired emergency saving for future expenditure shock into the power utility function and derives the optimal portfolio choice given this type of preference. Unexpected future expenditure or emergency needs can have a significant impact on a household's risk taking behavior. Implications from the model better match the investment behavior observed in the empirical data. When the normalized wealth level is low, households' stock market participation probability and risky asset share of their portfolios both increase as normalized wealth increases. Traditional "habit" models produce qualitatively similar results. However, the "habit"

models do not take emergency expenditure into consideration. The precautionary saving motive from these models arises purely from income shocks, not from expenditure shocks, which can be another major source of households' background risk. This paper explicitly models this risk into households' preferences.

After incorporating emergency expenditure into the habit model, this paper further constructs an index to measure how well households can manage emergency needs using their available assets. Better ability to meet unexpected expenditure or emergency needs can increase a household's risk holding capacity and induce them to hold more risky investments. This research potentially expands on analyses found in the current literature to analyze asset allocation decisions in a more "liability induced" environment, where households need to take a certain type of future expenditure into consideration.

Table 2-1: Descriptive statistics for key variables in the SCF

This table provides summary statistics for key variables in the SCF from 1995 to 2010. Liquid assets include assets in checking accounts, saving accounts, and money market funds. Financial assets include all liquid assets, CDs, Stocks, assets in retirement accounts, saving bonds, cash values of whole life insurance accounts, and other managed accounts. Equity includes directly held stocks, stock mutual funds, and stocks in combination mutual funds. All dollar amounts are in 2010 dollar value. All values are weighted using the weight provided by the SCF.

Variable	Definition	Mean	Median	Std. Dev.	N
Age	In Years	49.4	47	17.24	28464
Education	Number of years	13.2	13	2.86	28464
Gender	=1 if male; =0 female	0.72	1	0.44	28464
Married	=1 if married	0.59	1	0.49	28464
Children	Number of Children	0.82	0	1.15	28464
Race	=1 if white; =0 others	0.73	1	0.44	28464
Unemployed	=1 if unemployed in past 12 months	0.11	0	0.33	28464
Health Status	Ordered Categorical Variable (1-4) 1=Excellent; 2=Good; 3=Fair 4=Poor	2.03	2	0.78	28464
Risk Aversion Index	Ordered Categorical Variable (1-4) 1=Least Risk Averse 4=Most Risk Averse	3.19	3	0.85	28464
Income	Total Household Income	78,106	47,169	292,236	28464
Liquid Asset	Total Liquid Assets	25,175	3,221	234,633	28464
Equity	Total Equity Holdings	105,607	325	947,510	28464
Financial Asset	Total Financial Assets	206,382	22,497	1,360,228	28464
Total Asset	All Household Assets	546,386	173,714	2,821,554	28464
Net Worth	Total Household Wealth	466,671	98,511	2,763,062	28464

Table 2-2: Distribution of household normalized wealth level and risky asset share

This table presents the distribution of households' normalized wealth level and the risky asset share. Normalized wealth is defined as the ratio of the total financial wealth to the household's income. Risky asset share is defined as the ratio of households' total equity to total financial assets. All data are obtained from the SCF 1995-2010 waves and in 2010 dollars. Values are weighted using the weight provided by the SCF.

	Mean	P25	Median	P75	P90
Normalized Wealth Level	1.78	0.10	0.55	1.90	4.83
Risky Asset Share					
All sample	0.25	0	0.10	0.48	0.77
For Normalized Wealth >5	0.43	0.14	0.43	0.69	0.90
For Normalized Wealth <5	0.21	0	0	0.38	0.70

Table 2-3: Normalized wealth regression (Logit model)

This table presents the regression results for the normalized wealth regression. The dependent variable is a dummy variable, equal to 1 if household holds any equity, and zero otherwise. Normalized wealth is defined as the ratio of the total financial wealth to the household's income. NormD1 is a dummy variable indicating that the household's normalized wealth is below 1 and NormD2 is a dummy variable indicating that the household's normalized wealth is below 2. The standard error is in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II	Model III
Intercept	-11.77*** (0.266)	-10.045*** (0.2727)	-11.041*** (0.2755)
Normalized Wealth	0.2744*** (0.0133)	0.1313*** (0.0100)	0.1797*** (0.0133)
NormD1		-1.2914*** (0.0532)	
NormD2			-0.6911*** (0.0711)
Gender	-0.1688*** (0.0592)	-0.1443** (0.0601)	-0.1639*** (0.593)
Age	0.0412*** (0.0066)	0.0354*** (0.0066)	0.0414*** (0.0066)
Age ²	-0.0007*** (0.0001)	-0.0006*** (0.0001)	-0.0007*** (0.0001)
Education	0.1332*** (0.0077)	0.1277*** (0.0078)	0.1333*** (0.0077)
Race	0.364*** (0.0421)	0.3449*** (0.0430)	0.3597*** (0.0421)
Married	0.177*** (0.0542)	0.2006*** (0.0550)	0.1802*** (0.0542)
Kids	-0.0695*** (0.0168)	-0.0527*** (0.0171)	-0.0682*** (0.0168)
Unemployed	-0.063 (0.0578)	-0.0388 (0.0589)	-0.0667*** (0.0579)
Log(Income)	0.6789*** (0.0283)	0.724*** (0.0283)	0.6877*** (0.0283)
Log(Net Worth)	0.1827*** (0.0139)	0.1021*** (0.0140)	0.1708*** (0.0138)
N	20137	20137	20137

Table 2-4: Average Marginal Effect for the normalized wealth regression

This table calculates the average marginal effect from the results of the logistic regressions in Table 2-3. Normalized wealth is defined as the ratio of the total financial wealth to the household's income. NormD1 is a dummy variable indicating that the household's normalized wealth is below 1, and NormD2 is a dummy variable indicating that the household's normalized wealth is below 2.

Variables	Model I	Model II	Model III
Normalized Wealth	0.0381	0.0175	0.0248
NormD1		-0.1723	
NormD2			-0.0953
Gender	-0.0234	-0.0193	-0.0226
Age	0.0057	0.0047	0.0057
Age ²	-0.0001	-0.0001	-0.0001
Education	0.0185	0.0170	0.0184
Race	0.0505	0.0460	0.0496
Married	0.0246	0.0268	0.0249
Kids	-0.0096	-0.0070	-0.0094
Unemployed	-0.0087	-0.0052	-0.0092
Log(Income)	0.0942	0.0966	0.0949
Log(Net Worth)	0.0253	0.0136	0.0236
N	20137	20137	20137

Table 2-5: Normalized wealth regression (risky share regression)

This table presents the results of the linear probability model for the normalized wealth regression. The dependent variable is the portfolio share invested in equity. Normalized wealth is defined as the ratio of the total financial wealth to the household's income. NormD1 is a dummy variable indicating that the household's normalized wealth is below 1 and NormD2 is a dummy variable indicating that the household's normalized wealth is below 2. The standard error is in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II	Model III
Intercept	-0.6659*** (0.022)	-0.4373*** (0.0229)	-0.5347*** (0.0232)
Normalized Wealth	0.0106*** (0.0005)	0.0061*** (0.0005)	0.0059*** (0.0006)
NormD1		-0.1417*** (0.0048)	
NormD2			-0.0901*** (0.0054)
Gender	0.0155** (0.0066)	0.0177*** (0.0065)	0.0163** (0.0066)
Age	0.0061*** (0.0007)	0.0049*** (0.0007)	0.0058*** (0.0007)
Age ²	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)
Education	0.0191*** (0.0008)	0.0164*** (0.0008)	0.0181*** (0.0008)
Race	0.0574*** (0.0048)	0.0501*** (0.0048)	0.0547*** (0.0048)
Married	0.0068 (0.0058)	0.0065 (0.0057)	0.0069 (0.0058)
Kids	-0.0017 (0.0018)***	-0.0005 (0.0017)	-0.0012 (0.0017)
Unemployed	-0.0334 (0.0067)	-0.0283*** (0.0066)	-0.0331*** (0.0067)
Log(Income)	0.027*** (0.0021)	0.0355*** (0.0021)	0.0301*** (0.0021)
Log(Net Worth)	0.0181*** (0.0014)	0.0051*** (0.0014)	0.0129*** (0.0014)
R ²	0.2472	0.2734	0.2558
N	23702	23702	23702

Table 2-6: Risky asset share regression for different levels of normalized wealth

This table presents the results of the linear probability model for the normalized wealth regression. The dependent variable is the portfolio share invested in equity. Normalized wealth is defined as the ratio of the total financial wealth to the household's income. Model I is estimated based on the subsample where the household's normalized wealth is below 2, and Model II is estimated based on the subsample where household's normalized wealth is above 5. The standard error is in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II
Intercept	0.1087*** (0.0361)	0.0636 (0.0084)
Normalized Wealth	0.0634*** (0.0057)	-0.00002 (0.00003)
Gender	0.0435** (0.0112)	0.0289* (0.0177)
Age	0.0067*** (0.0007)	0.0040 (0.0025)
Age ²	-0.0001*** (0.0000)	-0.0001 (0.0000)
Education	0.0009*** (0.0013)	0.0188*** (0.0023)
Race	0.0369*** (0.0075)	0.0733*** (0.0191)
Married	-0.0344 (0.0058)	-0.0090 (0.0144)
Kids	0.0022 (0.0018)***	0.0052 (0.0054)
R ²	0.0362	0.0264
N	8696	4115

Table 2-7: Saving motives in the SCF

This table presents the distribution of different saving motives reported in the SCF 1995-2010 waves.

Saving Motives	Percentages in all samples
For emergence, precautionary	31.5%
For retirement	35.5%
For education	10.0%
For buying a house	3.3%
For future expenditure on house improvement, vehicle, durable goods, vacations	8.1%
Other saving motive	8.6%
Don't/can't save	3.1%

Table 2-8: Saving motive regression (Logit model)

This table presents the regression results for the saving motive regression. The dependent variable is a dummy variable, equal to 1 if the household holds any equity, and zero otherwise. Save1 is equal to 1 if the household is saving for precautionary purpose; Save2 is equal to 1 if the household is saving for retirement purposes; Save3 is equal to 1 if the household is saving for purchasing housing/durable goods and vacation purposes; Save4 is equal to 1 if the household is saving for other purposes. The standard error is in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II	Model III	Model IV
Save1	-0.2008*** (0.0363)			
Save2		0.5409*** (0.0383)		
Save3			-0.1343*** (0.0516)	
Save4				-0.0501 (0.0603)
Gender	-0.1935*** (0.0572)	-0.1861*** (0.0575)	-0.1880** (0.0572)	-0.1899 (0.0572)
Age	0.0051*** (0.0063)	-0.0112* (0.0064)	0.0051* (0.0063)	0.0062 (0.0063)
Age ²	-0.0002*** (0.0001)	-0.0001 (0.0001)	-0.0002 (0.0001)	-0.0003 (0.0001)
Education	0.1537*** (0.0074)	0.1534*** (0.0074)	0.1539*** (0.0074)	0.1542 (0.0074)
Race	0.3890*** (0.0418)	0.3618*** (0.0421)	0.4008*** (0.0418)	0.3996 (0.0418)
Married	0.1190*** (0.0525)	0.1051** (0.0528)	0.124* (0.0525)	0.1242 (0.0525)
Kids	-0.0822*** (0.0168)	-0.0547*** (0.0169)	-0.0827** (0.0168)	-0.0772 (0.0172)
Unemployed	-0.0678 (0.0597)	-0.065 (0.0583)	-0.068 (0.0578)	-0.0677 (0.0578)
Log(Income)	0.5377*** (0.0265)	0.5178*** (0.0264)	0.5408*** (0.265)	0.5425 (0.0265)
Log(Net Worth)	0.3772*** (0.0128)	0.3711*** (0.0128)	0.3737*** (0.0128)	0.3765 (0.0127)
N	24131	24131	24131	24131

Table 2-9: Average marginal effect for the saving motive regression

This table calculates the average marginal effect from the results of the logistic regressions in Table 2-8. Save1 is equal to 1 if the household is saving for precautionary purposes; Save2 is equal to 1 if the household is saving for retirement purposes; Save3 is equal to 1 if the household is saving for housing/durable goods and vacation purposes; Save4 is equal to 1 if the household is saving for other purposes.

Variables	Model I	Model II	Model III	Model IV
Save1	-0.0288			
Save2		0.0767		
Save3			-0.0193	
Save4				-0.0072
Gender	-0.0277	-0.0263	-0.027	-0.0272
Age	0.0007	-0.0016	0.0007	0.0009
Age ²	0.0000	0.0000	0.0000	0.0000
Education	0.0220	0.0217	0.0221	0.0221
Race	0.0557	0.0512	0.0575	0.0573
Married	0.0170	0.0149	0.0178	0.0178
Kids	-0.0118	-0.0077	-0.0119	-0.0111
Unemployed	-0.0097	-0.0092	-0.0097	-0.0097
Log(Income)	0.0770	0.0733	0.0776	0.0778
Log(Net Worth)	0.0540	0.0526	0.0536	0.0540
N	24131	24131	24131	24131

Table 2-10: Saving motive regression (linear probability model)

This table presents the regression results for the saving motive regression. The dependent variable is the portfolio share invested in equity. Save1 is equal to 1 if the household is saving for precautionary purposes; Save2 is equal to 1 if the household is saving for retirement purposes; Save3 is equal to 1 if the household is saving for housing/durable goods and vacation purposes; Save4 is equal to 1 if the household is saving for other purposes. The standard error is in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II	Model III	Model IV
Intercept	-0.6727*** (0.0221)	-0.6451*** (0.022)	-0.6744*** (0.0222)	-0.6903*** (0.0220)
Save1	-0.0278*** (0.0040)			
Save2		0.0613*** (0.0040)		
Save3			-0.0256*** (0.0061)	
Save4				0.0017 (0.0064)
Gender	0.0130** (0.0066)	0.0131** (0.0066)	0.0138** (0.0066)	0.0136** (0.0066)
Age	0.0040*** (0.0007)	0.0019** (0.0007)	0.004*** (0.0007)	0.0042*** (0.0007)
Age ²	-0.0001*** (0.0000)	0.0000*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)
Education	0.0209*** (0.0008)	0.0204*** (0.0008)	0.021*** (0.0008)	0.0211*** (0.0008)
Race	0.0554*** (0.0049)	0.0515*** (0.0049)	0.0570*** (0.0049)	0.0570*** (0.0049)
Married	0.0019 (0.0058)	-0.0017 (0.0058)	0.0029 (0.0059)	0.0031 (0.0059)
Kids	-0.0037** (0.0018)	-0.0006 (0.0018)	-0.0038** (0.0018)	-0.0036** (0.0018)
Unemployed	-0.0293*** (0.0068)	-0.0276*** (0.0068)	-0.0294*** (0.0068)	-0.0296*** (0.0068)
Log(Income)	0.0194*** (0.0021)	0.0202*** (0.0021)	0.0194*** (0.0021)	0.0194*** (0.0021)
Log(Net Worth)	0.0306*** (0.0013)	0.0299*** (0.0013)	0.0300*** (0.0013)	0.0304*** (0.0013)
R ²	0.2372	0.2429	0.2358	0.2429
N	24131	24131	24131	24131

Table 2-11: Model parameter values

This table presents the benchmark parameter values for the model calibration. Preference parameters, labor income parameters, and financial market parameters are obtained from Cocco et al. (2005). The emergency fund/permanent income ratio is calibrated from data from the Survey of Consumer Finance.

Description	Parameter Value
Preference Parameters:	
Retirement age (K)	65
Life span (T)	100
Discount factor (δ)	0.96
Risk aversion (γ)	7
Labor Income Parameters:	
Variance of Permanent Labor Income Shock	0.074
Variance of Transitory Labor Income Shock	0.011
Replacement rate	0.682
Emergency fund / Permanent Income ratio	0.48
Financial Market Parameters:	
Riskless rate (r_f)	0.02
Mean of stock return (μ)	0.06
Standard Deviation of stock return (σ_η)	0.157

Table 2-12: Summary statistics for the emergency fund

This table presents the summary statistics for the desirable amount of emergency funds for the overall sample, and for subsamples based on wealth status, health status, and retirement status. All samples are weighted using the weight provided by the SCF.

Sample	Mean	Median	St Dev	N
Overall Sample:	25,511	5,762	196,974	28,464
<u>Panel A: By Wealth Status:</u>				
Above Median	38,194	11,330	67,662	16,822
Below Median	9,635	3,000	141,702	11,058
<u>Panel B: By Retirement Status:</u>				
Non-Retired	21,839	5,665	162,536	4,935
Retired	40,600	10,000	298,971	28,464

Table 2-13: Stock market participation regression (Logit model)

This table presents the logistic regression results for stock market participation. The dependent variable is a dummy variable, equal to 1 if the household holds any equity and 0, otherwise. PRatio1 is log of (weighted available resource/desirable amount of emergency funds), PRatio2 is log of (income/ desirable amount of emergency funds), and PRatio3 is log of ((financial asset-retirement asset)/ desirable amount of emergency funds). Standard error is in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II	Model III
Intercept	-13.2541*** (0.2457)	-7.1634*** (0.1681)	-12.5954*** (0.2479)
PRatio1	0.2532*** (0.0108)		
PRatio2		0.0342*** (0.0114)	
PRatio3			0.2803*** (0.0088)
Gender	-0.0529 (0.0541)	0.2395*** (0.0495)	-0.0384 (0.0543)
Age	0.0336** (0.0059)	0.0990*** (0.0054)	0.0599*** (0.0059)
Age ²	-0.0003*** (0.0001)	-0.0009*** (0.0001)	-0.0006*** (0.0001)
Education	0.1808*** (0.0071)	0.2915*** (0.0066)	0.1637*** (0.0072)
Race	0.4564*** (0.0397)	0.686*** (0.0368)	0.4366*** (0.0398)
Married	0.0873* (0.0501)	0.6036*** (0.0453)	0.1653*** (0.0503)
Kids	-0.092** (0.0159)	-0.0248* (0.0148)	-0.0479*** (0.0161)
Unemployed	-0.1183*** (0.054)	-0.5411*** (0.0508)	-0.1165** (0.0545)
Income		0.0059*** (0.0007)	
Log(Income)	0.8799** (0.0234)		0.8246*** (0.0235)
Net Worth	-0.0001 (0.0000)	0.0002*** (0.0000)	-0.0001 (0.0000)
N	25465	25465	25465

Table 2-14: Average marginal effect for the stock market participation regression

This table calculates the average marginal effect from the results of the logistic regressions in Table 2-13. PRatio1 is log of (weighted available resource/desirable amount of emergency funds), PRatio2 is log of (income/ desirable amount of emergency funds), and PRatio3 is log of ((financial asset-retirement asset)/ desirable amount of emergency funds).

Variables	Model I	Model II	Model III
PRatio1	0.0377		
PRatio2		0.0058	
PRatio3			0.0406
Gender	-0.0079	0.0407	-0.0056
Age	0.0050	0.0168	0.0087
Age ²	-0.0001	-0.0002	-0.0001
Education	0.0269	0.0495	0.0237
Race	0.0679	0.1165	0.0632
Married	0.013	0.1026	0.0239
Kids	-0.0137	-0.0042	-0.0069
Unemployed	-0.0176	-0.0919	-0.0169
Income		0.0010	
Log(Income)	0.1308		0.1193
Net Worth	0.00001	0.00001	0.00001
N	25465	25465	25465

Table 2-15: Precautionary ratio regression (linear probability model)

This table presents the results for the linear probability model of the precautionary ratio regression. The dependent variable is the risky asset share in financial assets. PRatio1 is log of (weighted available resource/desirable amount of emergency funds), PRatio2 is log of (income/ desirable amount of emergency funds), and PRatio3 is log of ((financial asset-retirement asset)/ desirable amount of emergency funds). The standard error is in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II	Model III
Intercept	-0.8833*** (0.0207)	-0.6728*** (0.0193)	-0.8333*** (0.0212)
PRatio1	0.0227*** (0.0011)		
PRatio2		0.0083*** (0.0013)	
PRatio3			0.0192*** (0.0009)
Gender	0.0227*** (0.0063)	0.0538*** (0.0065)	0.0245*** (0.0063)
Age	0.0063*** (0.0007)	0.0128*** (0.0007)	0.0081*** (0.0007)
Age ²	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)
Education	0.0222*** (0.0008)	0.0352*** (0.0007)	0.0208*** (0.0008)
Race	0.0596*** (0.0047)	0.0883*** (0.0048)	0.0594*** (0.0047)
Married	-0.0037 (0.0057)	0.0393*** (0.0058)	0.0023 (0.0056)
Kids	-0.0041** (0.0017)	0.0018 (0.0018)	-0.0014 (0.0017)
Unemployed	-0.0288*** (0.0063)	-0.0638*** (0.0065)	-0.0293*** (0.0063)
Income	0.0547*** (0.0017)	0.00001 (0.0000)	
Log(Income)			0.0516*** (0.0018)
Net Worth	-0.00001 (0.0000)	0.00001*** (0.0000)	-0.00005*** (0.0000)
Adj R ²	25465	25465	25465
N	0.2379	0.1847	0.2394

Table 2-16: Risky Asset share regression (retirement account vs. non-retirement account)

This table presents the results for the linear probability model of the risky asset share regression. In Model I, the dependent variable is the ratio of total risky assets to all financial assets. In Model II, the dependent variable is the ratio of total direct held equity to all non-retirement financial assets. In Model III, the dependent variable is the share of risky assets in a retirement account. PRatio is log of (weighted available resource/desirable amount of emergency funds). The standard error is in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II	Model III
Intercept	-0.3532*** (0.0310)	-0.7817*** (0.0309)	-0.0135 (0.0386)
PRatio	0.0147*** (0.0016)	0.0176*** (0.0016)	0.0109*** (0.0021)
Gender	0.0481*** (0.0092)	0.0376*** (0.0092)	0.0517*** (0.0115)
Age	0.0051*** (0.0011)	-0.0013*** (0.0011)	-0.0001 (0.9641)
Age ²	-0.0001*** (0.0000)	0.00001*** (0.0000)	0.00001*** (0.0000)
Education	0.0188*** (0.0011)	0.0212*** (0.0011)	0.0161*** (0.0014)
Race	0.0516*** (0.0066)	0.0542*** (0.0066)	0.0466*** (0.0082)
Married	-0.0352*** (0.0077)	-0.0206*** (0.0077)	-0.0294*** (0.0096)
Kids	0.0002 (0.0022)	-0.006*** (0.0022)	-0.0027 (0.0027)
Unemployed	-0.0104 (0.0096)	0.0047 (0.0096)	-0.0156 (0.012)
Log(Income)	0.0264*** (0.0022)	0.0496*** (0.0022)	0.0298*** (0.0027)
Net Worth	-0.00001** (0.0000)	-0.00001*** (0.0000)	-0.00001* (0.0000)
Adj R ²	0.0798	0.1532	0.0583
N	16058	16058	16058

Table 2-17: Stock market participation regression (control for different status)

This table presents the results for the stock market participation regression of different groups. The dependent variable is a dummy variable, equal to 1 if the household holds any equity and 0, otherwise. Model I controls for retirement status; Model II controls for business ownership status; Model III controls for investment risk preferences. The standard error is in parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II	Model III
Intercept	-13.3294 (0.2495)	-6.8721*** (0.1700)	-12.2270*** (0.2523)
PRatio	0.2417*** (0.0119)	0.3680*** (0.0117)	0.2254*** (0.0244)
Retired	-0.0646 (0.0983)		
PRatio*Retired	0.0622** (0.0276)		
HBUS		0.5917*** (0.0900)	
PRatio*HBUS		-0.1845*** (0.0265)	
Riska			-0.7476*** (0.0789)
PRatio*Riska			0.0280 (0.0265)
Controls	Yes	Yes	Yes
N	25670	25859	25859

Table 2-18: Average marginal effect for Stock market participation regressions

This table calculates the average marginal effect from the results of the logistic regressions in Table 2-17. Model I controls for retirement status; Model II controls for business ownership status; Model III controls for investment risk preferences.

Variables	Model I	Model II	Model III
PRatio	0.0360	0.0588	0.0331
Retired	-0.0095		
PRatio*Retired	0.0093		
HBUS		0.0945	
PRatio*HBUS		-0.0295	
Riska			-0.1098
PRatio*Riska			0.0041
N	25670	25859	25859

Table 2-19: Risky asset share regressions (control for different status)

This table presents the results for the linear probability regression of the risky asset share model. Model I controls for retirement status; Model II controls for business ownership status; Model III controls for investment risk preferences. The standard error is in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II	Model III
Intercept	-0.8846*** (0.0210)	-0.9390*** (0.0220)	-0.6869*** (0.0220)
PRatio	0.0213*** (0.0012)	0.02708*** (0.0013)	0.0186*** (0.0021)
Retired	-0.0178* (0.0101)		
PRatio*Retired	0.0074*** (0.0026)		
HBUS		0.02155*** (0.0094)	
PRatio*HBUS		-0.0160*** (0.0025)	
Riska			-0.1302*** (0.0081)
PRatio*Riska			0.0037* (0.0023)
Controls	Yes	Yes	Yes
R ²	0.2381	0.2405	0.2613
N	25465	25465	25465

Table 2-20: Stock market participation regression (control for normalized wealth)

This table presents the logistic regression results for stock market participation, controlling for normalized wealth. The dependent variable is a dummy variable, equal to 1 if the household holds any equity and 0, otherwise. PRatio is log (weighted available resource/desirable amount of emergency funds). Normd is a dummy variable indicating whether a household's normalized wealth is below 2 or not. Normd*PRatio is the interaction term between PRatio and Normd. The standard error is in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II
Intercept	-13.2541*** (0.2457)	-10.5081*** (0.2702)
PRatio	0.2532*** (0.0108)	0.1286*** (0.0282)
Normd		-1.8921*** (0.1061)
Normd*PRatio		0.0731** (0.0304)
Gender	-0.0529 (0.0541)	-0.0695 (0.0558)
Age	0.0336** (0.0059)	0.0429*** (0.0061)
Age ²	-0.0003*** (0.0001)	-0.0006*** (0.0001)
Education	0.1808*** (0.0071)	0.1539*** (0.0074)
Race	0.4564*** (0.0397)	0.3607*** (0.0404)
Married	0.0873* (0.0501)	0.1253** (0.0516)
Kids	-0.092** (0.0159)	-0.0758*** (0.0161)
Unemployed	-0.1183*** (0.054)	-0.0970* (0.0545)
Log(Income)	0.8799** (0.0234)	0.8351*** (0.0239)
Net Worth	-0.0001 (0.0000)	-0.0001 (0.0000)
N	25465	25465

Table 2-21: Average marginal effect for the stock market participation regression

This table calculates the average marginal effect from the logistic regression in Table 2-20. PRatio1 is log (weighted available resource/desirable amount of emergency funds). Normd is a dummy variable indicating whether a household's normalized wealth is below 2 or not. Normd*PRatio is the interaction term between PRatio and Normd.

Variables	Model II	Model I
PRatio1	0.0180	0.0377
Normd	-0.2652	
PRatio*Normd	0.0102	
Gender	-0.0097	-0.0079
Age	0.006	0.005
Age ²	-0.0001	-0.0001
Education	0.0216	0.0269
Race	0.0506	0.0679
Married	0.0176	0.013
Kids	-0.0106	-0.0137
Unemployed	-0.0136	-0.0176
Log(Income)	0.1171	0.1308
Net Worth	0.0001	0.00001
N	25465	25465

Table 2-22: Risky asset share regression (control for normalized wealth)

This table presents the results for the linear probability regression of the risky asset share estimation. PRatio is log (weighted available resource/desirable amount of emergency funds). Normd is a dummy variable indicating whether a household's normalized wealth is below 2 or not. Normd*PRatio is the interaction term between PRatio and Normd. The standard error is in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels of confidence, respectively.

Variables	Model I	Model II
Intercept	-0.8833*** (0.0207)	-0.5607*** (0.0237)
PRatio1	0.0227*** (0.0011)	0.0100*** (0.0021)
Normd		-0.1658*** (0.0090)
PRatio*Normd		0.0090*** (0.0024)
Gender	0.0227*** (0.0063)	0.0205*** (0.0062)
Age	0.0063*** (0.0007)	0.0055*** (0.0007)
Age ²	-0.0001*** (0.0000)	-0.0001*** (0.0000)
Education	0.0222*** (0.0008)	0.0181*** (0.0008)
Race	0.0596*** (0.0047)	0.0488*** (0.0046)
Married	-0.0037 (0.0057)	-0.003 (0.0056)
Kids	-0.0041** (0.0017)	-0.0023 (0.0017)
Unemployed	-0.0288*** (0.0063)	-0.0274*** (0.0062)
Log(Income)	0.0547*** (0.0017)	0.0481*** (0.0017)
Net Worth	-0.00001 (0.0000)	-0.00001*** (0.0000)
Adj R ²	0.2379	0.2662
N	25465	25465

Figure 2-1: Labor income process: age profile

This figure plots fitted third-order polynomials of the labor income process for both high school graduates and college graduates.

Figure 2-2: Policy rules for portfolio choice (without contingent consumption)

This figure plots the optimal portfolio share invested in stocks at different normalized wealth levels and for different stages of the life cycle when no contingent consumption is considered.

Figure 2-3: Policy rules for portfolio choice (with contingent consumption)

This figure plots the optimal portfolio share invested in stocks at different normalized wealth levels and for different stages of the life cycle when contingent consumption is considered.

Figure 2-4: Optimal policy rule for normalized wealth level below 5

This figure plots the optimal portfolio share invested in stocks at different normalized levels (below 5) and for different stages of the life cycle when contingent consumption is considered.

Chapter 3

Tail Risk, Health Risk, and Portfolio Choice for Retirees

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Tail Risk, Health Risk, and Portfolio Choice for Retirees

3.1 Introduction

The theory of asset allocation predicts that investment in risky assets depends on investors' risk preference, along with the mean and the volatility of stock market returns (Merton, 1971). Empirical evidence, however, shows that individual investment behavior is affected by factors that are not emphasized in classical portfolio choice theory. One factor that has important implications for asset allocation decisions is investors' human capital. In an incomplete financial market, individuals cannot fully hedge their labor risk. Fluctuations in labor income, therefore, is a major risk associated with human capital. Subsequent research on the life cycle model has incorporated human capital risk into the analysis and derived the optimal behavior that better matches the empirical data.

For retirees, the risk of human capital can be different. Major income sources for retirees are from Social Security and pension benefits, which normally are not subject to business cycles or periods of unemployment; therefore, their income is less risky compared to working individuals' income. However, increased health risk among retirees can be seen as another type of shock to their human capital. Health shock can significantly affect their budget constraints, consumption behaviors, and financial decisions. In addition to health risks, another important risk of investing in the stock market for retirees is the risk of financial crisis. A financial crisis is characterized by a disastrous outcome in the stock market, which has a small probability of occurrence. Since

retirees' investment horizon is shorter, and their ability to recover from a loss is lower than that of working individuals, a financial disaster's detrimental effect on wealth can be large enough to reduce their equity holdings. This paper contributes to the literature by analyzing retirees' consumption and financial decisions when they are faced with these two important risks, using a structural life-cycle model.

This study is related to three strands of research: work on the application of the life cycle model to the study of households' optimal behavior, work on health and portfolio choice, and work on the tail risk associated with rare events in financial markets. By unifying these three strands in the literature, I attempt to study retirees' consumption decisions and portfolio choices when they are faced with realistic health risk and rare event risk in the financial markets.

The literature on the life cycle of consumption starts with Friedman's life cycle and the permanent income hypothesis, which state that individuals' current consumption should be determined by their expected lifetime income, not just by their current income. The life cycle model has since become the basis for studying dynamic household behavior (Cocco and Maenhout, 2005; Gomes and Michaelides, 2005; Wachter and Yogo, 2010). The life cycle model has also been used to study retirement behavior. Blau (2008) studies a life cycle model where households, uncertain about the time of retirement, experience a sharp decline in consumption at the time of retirement. Huang et al. (2012) solve for retirees' optimal consumption rate in a life cycle model where the mortality rate is stochastic and learnable from health status. Kremer et al. (2013) derive retirees' optimal consumption and portfolio choices using a logistic model of mortality. Ding (2014) develops a life-cycle model incorporating a bequest motive, housing decisions, and public pensions for retirees. The model is calibrated to ABS data from the Household Expenditure Survey

and the Survey of Income and Housing. Their model can reasonably explain the financial behavior of surveyed households and the concentration of wealth in housing for retirees in Australia.

This paper is also related to the study of health and portfolio choice. Health risk is one of the important background risks that affect households' financial decisions. Rosen (2004) finds that households in poor health are less likely to hold risky financial assets after controlling for their attitudes toward risk, planning horizon, and health insurance availability. Edwards (2008) finds that adverse health shocks to retirees in the future may explain twenty percent of the age-related decline in financial risk-taking after retirement. De Nardi et al. (2010) argue that the most important reason that the elderly save is longevity risk and rising out-of-pocket medical expense with age. Coile and Milligan (2009) find that households decrease their ownership of housing, vehicles, financial assets, and businesses as they age and increase their share in safe assets in the presence of a health shock. They also find that the effect of health shocks on safe asset holding strengthens with time after the shock. Finkelstein et al. (2013) find that the marginal utility of consumption declines as health deteriorates.

In addition to the reduced form estimation, some studies use a structural model to explain how health affects households' financial decisions. Yogo (2009) develops a life-cycle model where retirees choose health expenditures endogenously in response to the stochastic depreciation of health. The model is calibrated to explain the joint dynamics of health expenditure, health, and asset allocation for retirees in the Health and Retirement Study. Hugonnier et al. (2012) develop a dynamic model where households make consumption, portfolio, health investment, and health insurance decisions jointly. Scholz and Seshadri (2013) develop a life cycle model to study consumption and health investment choices where health affects both longevity and the utility

function. The model's result matches the distribution of medical expenses across households in the data.

Third, this paper is related to the literature on tail risk and rare events in financial markets. Liu et al. (2005) find that uncertainty aversion to rare events plays an important role in option premium. Bollerslev and Todorov (2011) find that compensation for rare events accounts for a large fraction of the equity and variance risk premium in the S&P 500 market index. Gabaix (2012) finds that the possibility of rare, large disasters affects risk premium, and suggests that fear of disaster can be viewed as a tractable way to model time-varying risk-aversion or investor sentiment. Wachter (2013) finds that a small possibility of a large decline in consumption can substantially increase equity premium. Time-variation in the probability of this outcome drives high stock market volatility and excess return predictability.

While many rare event studies focus on their effects on asset pricing, fewer look at how they directly affect investors' decisions in a life-cycle model context. One study that has incorporated the disaster factor into the life-cycle model is reported in Kolusheva (2011), where she develops a life-cycle model with possible rare disasters in the stock market and the labor market to analyze investors' consumption and asset allocation decisions. In her paper, rare disasters are calibrated to match the joint empirical distribution of stock market crashes and macroeconomic contractions. She finds that a small probability of disaster is sufficient to deter median investors from investing in stocks during their working life.

The model in this paper differs from that in Kolusheva (2011) in two important aspects: First, the length of the investment horizon; and second, the nature of human capital shock. Her paper emphasizes the whole life cycle, from early working life until death, whereas mine focuses on retirees' behavior. In her model, the shock to permanent income comes from the risk of

macroeconomic contraction, which affects an investor only during his working life. The insulation from labor market risk after retirement implies that retirees will hold more risky assets than before retirement, an implication which does not hold empirically. This paper addresses this issue by considering health risk as a shock to retirees' human capital; the shock is idiosyncratic and does not correlate with general stock market crisis.

This paper will proceed as follows: Section 3.2 sets up the model. Section 3.3 describes parameter values and calibrates the model using data from the Health and Retirement Survey (HRS). Section 3.4 describes the model and presents the results of optimal behavior under different scenarios. Section 3.5 extends the model to incorporate heterogeneous health risk. Section 3.6 presents the simulation results and compares the results with the empirical distribution of risky asset holdings in the Health and Retirement Survey, and Section 3.7 concludes.

3.2 The Model

3.2.1 The preference

Retiree i 's preference is characterized by a time-separable power utility function:

$$U_1^i = E_1 \sum_{t=1}^T \beta^{t-1} \left(\prod_{j=1}^{t-1} p_{j-1} \right) \frac{C_{it}^{1-\gamma}}{1-\gamma} \quad (3-1)$$

The retiree is assumed to live a maximum of T periods. In each period, there is a possibility that the retiree will die. Let p_t denote the probability that the retiree is alive at date $t+1$, conditional on being alive at date t . The retiree maximizes expected life utility with a constant relative risk aversion γ and time preference parameter β . Values for these parameters will be discussed in Section 3.3.

3.2.2 Modeling health shock

Each period, retirees will receive pension and Social Security benefits as labor income. The riskiness of labor income plays an important role in an investor's investment behavior and needs to be taken into consideration when solving the life-cycle model. Previous literature (e.g. Carroll, 1997; Winter et al. 2012) show that the risky labor income process can be modeled as having a deterministic component and stochastic components. In my model, labor income is assumed to be at a fixed level, as income from social security and pension is normally not subjected to labor market fluctuation³. For retirees, however, health risk can be a major shock to their income stream. I model the magnitude of a health shock to be proportional to their income, and the income after health shock is specified as:

$$Y_{i,t} = Y_i - Y_i \times h_{i,t} \quad (3-2)$$

where $h_{i,t} \in [0,1]$. When $h_{i,t} = 0$, there will be no health shock for the period; health expenditure will be zero, and the retiree's disposable income will be equal to his social security/pension income. When $h_{i,t} > 0$, there will be a health shock for the period, and the retiree's disposable income will be reduced. $h_{i,t}$ is bounded above by 1, so the maximum health expenditure will not exceed current income; i.e., $Y_{i,t}$ has a lower bound of zero. For each period, the health expenditure ratio, $h_{i,t}$, can be different, and the retiree knows the realization of $h_{i,t}$ only when he enters that period. However, the retiree has prior knowledge of the distribution of $h_{i,t}$ and optimizes his

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³ In the life-cycle model developed by Cocco et al. (2005), retirement income is modeled as a constant fraction of permanent labor income in the last working year before retirement.

behavior based on his expectation of $h_{i,t}$. The distribution of $h_{i,t}$ is estimated using data from the Health and Retirement Survey and will be discussed in more detail in Section 3.3.

3.2.3 The financial market

Each period, investors can invest in two assets in the financial market: a riskless and a risky asset. The riskless asset has a return r_f for each period. For the risky asset, there are two states: a non-crisis state characterized by a mean risk premium of μ and an innovation component η_{t+1} :

$$\tilde{r}_t^{noncrash} = r_f + \mu + \eta_{t+1} \quad (3-3)$$

where η_{t+1} is assumed to be independent and identically distributed (i.i.d) as $N(0, \sigma_\eta^2)$. There is also a non-zero probability π^{crash} that the stock market will crash, and stock return will be $\tilde{r}^{crash}$ if the market crashes. Combining these two states, we can express the risky asset return as:

$$\tilde{r}_t = \begin{cases} \tilde{r}^{noncrash} , & \text{with probability } 1 - \pi^{crash} \\ \tilde{r}^{crash} , & \text{with probability } \pi^{crash} \end{cases} \quad (3-4)$$

The parametrizations of r_f , μ , σ_η^2 , π^{crash} , and $\tilde{r}^{crash}$ will be discussed in Section 3.3.

3.2.4 Retirees' optimization problem

For simplicity, this model assumes that the health risk is exogenous and that the retiree does not choose the amount of health care; rather, he takes it as a shock which reduces his disposable income, and he makes his optimal consumption and asset allocation decisions accordingly. The timing of the events is as follows: at the beginning of each period t , the retiree starts with financial wealth W_t , receives a pension income Y_i , And observes the health shock $h_{i,t}$ to his income. The uncertainty associated with disposable income dissipates once the retiree enters

period t . Following Deaton (1991) and Cocco et al. (2005), I denote the total available resources as cash-at-hand $X_{i,t}$, where $X_{i,t} = W_{i,t} + Y_{i,t}$. $X_{i,t}$ is the total amount of available resources for the retiree during the period t , and his problem is to decide how much to consume in this period C_t . The resources not consumed will be saved and used to generate the next period's financial wealth, $W_{i,t+1}$. The financial market offers two available assets for saving: one risk-free asset and one risky asset. The retiree needs to make an allocation decision (i.e., the portfolio share that will be invested in risky assets, $\alpha_{i,t}$). After the consumption decision and the asset allocation decision have been made, his financial wealth at the beginning of the next period $t+1$, will be:

$$W_{i,t+1} = r_{i,t+1}^p (W_{i,t} + Y_{i,t} - C_{i,t}) \quad (3-5)$$

The return of the portfolio from time t to time $t+1$ is given by:

$$\tilde{r}_{i,t+1}^p = \alpha_{i,t} \tilde{r}_{i,t+1} + (1 - \alpha_{i,t}) r_f. \quad (3-6)$$

where $\alpha_{i,t}$ is the portfolio share invested in risky assets and $(1 - \alpha_{i,t})$ is the portfolio share invested in the risk-free asset. Assuming the retiree faces borrowing constraints and cannot short-sell the risk-free asset, α is restrained to 1. The retiree's optimization problem is to maximize the objective function (3-1) subject to constraints (3-2) through (3-6). The state variables are $\{t, X_t, Y\}$, and the control (choice) variables are $\{C_t, \alpha_t\}$. For each period, the optimal rules of consumption and portfolio share are functions of the state variables t, X_t , and Y .

The Bellman equation for a retiree's optimization problem is given by:

$$V_{it}(X_{it}) = \max_{C_{it} \geq 0, 0 \leq \alpha_{it} \leq 1} [U(C_{it}) + \beta p_t E_t V_{i,t+1}(X_{i,t+1})], \quad t \leq T \quad (3-7)$$

where $V_{it}(X_{it})$ is the value function, denoting the maximized utility given X_{it} , and the next period total resource $X_{i,t+1}$ is:

$$X_{i,t+1} = W_{i,t+1} + Y_{i,t+1} \times (1 - h_{i,t+1}) \quad (3-8)$$

Substituting (3-5) and (3-6) into (3-8), $X_{i,t+1}$ can be expressed as:

$$X_{i,t+1} = (X_{it} - C_{it})(\alpha_{it} r_{t+1} + (1 - \alpha_{it}) r_f) + Y_i \times (1 - h_{i,t+1}) \quad (3-9)$$

where $X_{i,t+1}$ depends on the amount of saving this period, the return on the savings (which in term depends on the portfolio choice α_{it}), and the next period's health shock.

Since this model does not have a closed form analytical solution, I use a numerical method to find the value function and the associated optimal policy rules. Unlike an infinite period dynamic programming problem, this model has finite periods as the retiree can live only a maximum of T years. Specifically, the retiree retires at 65 and is expected to live 30 years after retirement. A finite period setting allows us to solve the model recursively from the last period. The procedure is as follows: set the retiree's last period value function V_T equal to zero as he dies at time T , and assume there is no bequest motive. Given this condition, substitute $V_T=0$ into the Bellman equation (3-7), and the optimal value for V_{T-1} , which is the utility function evaluated at total cash-at-hand, at $T-1$. Having found V_{T-1} , we can solve for V_{T-2} , and so on. The process continues until $V_1(x)$, which is the value function at the beginning of the period, is found. The value functions of a finite horizon discrete Markov decision model are always well defined. By finding the value functions for each period, we can also obtain the optimal consumption and portfolio choice for each period, which generate the value function.

As demonstrated in previous literature (Carrol, 1997; Cocco et al., 2005; Kolusheva, 2011), it is possible to reduce the state variable space by normalizing wealth with respect to permanent income, which is a constant pension level Y in this case. Results in Section 3.4 will be expressed in terms of the normalized version of the cash-at-hand variable and the consumption variable.

3.3 Parameters and Model Calibration

[Insert Table 3-1 here]

To solve the model, we need to choose appropriate parameter values for retirees' preference and financial market parameters. For retirees' risk preference and standard financial market parameters, I use the standard values obtained from Cocco et al. (2005) and Kolusheva (2011). Table 3-1 provides a summary of the values of the benchmark parameters. The coefficient of relative risk aversion is set to 7, and the risk-free rate, mean of stock market return, and standard deviation of stock market return are set to 0.02, 0.06 and 0.15, respectively. The retiree dies with a probability of one at age 95. Prior to this age, the conditional survival probability value, p_j , is obtained from the mortality tables of the National Center for Health Statistics.

The parameter values for π^{crash} and $\tilde{r}^{crash}$ are obtained from Barro and Ursua (2009) and Kolusheva (2011), where market crashes are defined as peak-to-trough cumulative real returns of -25% or worse. Kolusheva (2011) finds that the unconditional probability of a stock market crash is 10.11%, and the probability of a stock market crash and no economic contraction is 7.47%. Ideally, the model used in this paper should also be calibrated using the empirical distribution of historical stock market crashes. To simplify the analysis, however, I set the stock return of a market crash, $\tilde{r}^{crash}$, to be -20%, close to the upper bound of the market crash return documented in Barro

and Urusa (2009). I set the probability of a crash to be 8%, close to the value found in Kolusheva (2011). With this parameterization, the market crash can happen with a probability of 8%, and the return will be -20% when it happens. Similar optimal policy rules can be drawn when the crash return is set to -25% and the crash probability is 10%. The only parameter that needs to be estimated is the magnitude and distributional properties of the health expenditure shock.

3.3.1 Health expenditure calibration

In this section, I use the data from the Health and Retirement Survey (HRS) to characterize the empirical distribution of the health expenditure ratio. The Health and Retirement Survey is a biannual study conducted by the Institute for Social Research at the University of Michigan and funded by the National Institute on Aging. This survey provides a comprehensive set of variables including the demographics, health, income, wealth, and pensions of American elderly. The survey starts in 1992 and interviews 22,000 Americans aged 50 or older. RAND provides an easy-to-use version of the HRS, which combines all the waves from 1992 to 2010 and calculates imputations for income, assets, and medical expenditures from the original survey data. Based on when the respondent was born, the HRS further divides the respondents into different cohorts. The largest cohort is the HRS cohort, who were born between 1931 and 1941. Other cohorts include the AHEAD, who were born before 1924; Children of Depression (CODA), born between 1924 and 1930; War Babies (WBs), born from 1942 to 1947; and Early Baby Boomers (EBBs), born between 1948 and 1953. In this study, I use data from all of the cohorts.

[Insert Table 3-2 and Table 3-3 here]

Since the model intends to explain the saving and investment decisions of retirees, I restrict the sample to retired households only. For married couples, retirement status means that both

husband and wife are retired. Table 3-2 provides summary statistics for some key variables for retirees. Health expense E , which includes all private insurance premiums and all out-of-pocket medical expenses, has a mean value of \$2,707, and its standard deviation is \$8,350, implying that a large variation in health expense exists among retirees. Table 3-3 provides more detailed summary statistics for the medical expenses for different cohorts across years. For Social Security and pension income, the mean value is \$24,314. Financial net worth, which is the sum of the dollar amounts in checking accounts, saving accounts, CDs, money market accounts, bonds, stocks, and mutual funds, has a mean value of \$129,970. Total net worth is the difference between total assets and total liability and has a mean value of \$370,754. Since this study focuses on the portfolio choice problem, financial wealth is a more relevant wealth measure as the allocation is made from financial wealth, not total household wealth, which includes non-liquid assets.

[Insert Table 3-4 here]

As discussed in Section 3.2, I use Social Security and pension income P as a proxy for permanent income after retirement. Table 3-4 provides a more detailed description of this variable for different cohorts across years. The numbers show that income is relatively stable across years after adjusting for inflation, which is consistent with the assumption that permanent income does not grow or decline significantly for retirees. Therefore, permanent income can be used to normalize wealth, and normalized cash-at-hand is the key state variable for this model. The health expense ratio is calculated as the ratio of annual health expenditure E to permanent income P . As discussed above, retirees have a relatively constant stream of Social Security/pension income each year. Health shocks, however, are more stochastic, and health expenditures are often unavoidable. This expense can be seen as a reduction in the retiree's income, which is similar to a negative

transitory shock to the usual labor income process. To determine the distribution of this shock's magnitude, I calculate the ratio for each household annually.

[Insert Table 3-5 here]

Table 3-5 provides summary statistics for the medical expense ratio. The mean annual health expenditure to permanent income ratio is 17.7% for the overall sample, with a median of 5.4% and a standard deviation of 89.3%. As health expenditures are closely related to health status, I further classify the whole sample into two subsamples by respondents' health status. HRS has a self-reported health status variable, ranking from 1 to 5, with 1 as excellent health and 5 as poor health. If a retiree said his health is excellent, very good, or good, the health status is set to be good, and if a retiree said his health is fair or poor, the health status is set to be poor. I then calculated the health expenditure ratio for these two groups separately. As shown in Table 3-5, the good health group has a mean health expenditure ratio of 13.2%, whereas the poor health group's ratio is 23.8%, substantially higher than that of the good health group.

In addition to health status, another factor that can significantly affect the medical expense ratio is age. Older people, especially those who are at the end of their life-span, can have large medical expenses which are not covered by Medicare or private health insurance. An example is long-term care expenses, which are not typically covered in standard insurance programs. To assess the age effect, I divide the whole sample into two groups: those between 65 and 85 years old and those who are older than 85. The younger group has an average 15.8% medical expense ratio, while the older group has an average ratio of 31.2%. If we further divide the age group into different health categories, substantial heterogeneity exists among different groups. The healthy younger retirees have an average ratio of 11.8%, whereas for the older group with poor health, the average health expenditure to income ratio climbs to 40%.

[Insert Figure 3-1 here]

Figure 3-1 shows the empirical frequency distribution of the medical expense ratio for the overall sample, and I fit it to a lognormal distribution with mean equal to -2.8 and a standard deviation of 1.4. The parameters of the fitted distribution will be used as inputs for the model calibration to characterize the shocks to the retirees' income. The results in the next section are based on the assumption that all retirees face the same health shock distribution. In an extension section of this study, I calibrate the health expenditure ratio and solve the model for the good health and poor health groups separately, and the results are presented in Section 3.5.

3.3.2 Problem with health ratio calibration

Among the several known distributions, log-normal distribution best fits the health expenditure ratio. However, the Kolmogorov–Smirnov test still rejects the hypothesis that the health expenditure ratio comes from a log-normal distribution. One reason is that the parameters specified in the KS test are estimated from the actual data, which violates the assumption that the parameters should be pre-specified and should not come from the data. In a robust check, I apply the Monte-Carlo simulation to find the expected value of the value function. In the simulation, I do not calibrate the health expenditure ratio to any parametric distribution. Instead, I randomly draw 500 samples from the empirical distribution of the health expenditure ratio and incorporate them in the numerical analysis. This method does not rely on any parameterization assumption, but can reasonably capture the distributional property of health shock. The simulation analysis generates results similar to those obtained when the health expenditure ratio is calibrated to the log-normal distribution.

3.4 Optimal Policy Rules

Using the parameter value discussed in Section 3.3, I solve the model numerically to obtain the optimal consumption and portfolio choice rules. This section presents the optimal rules under different scenarios. As a benchmark analysis, Section 3.4.1 discusses retirees' optimal policy rules when there is no health risk. In this case, retirees do not have any health shock to their Social Security/pension income, but they are still subject to financial crisis risk. Section 3.4.2 adds health risk to retirees' income, which is the main feature of this model. Section 3.4.2.1 presents a case where I only consider the health risk but do not account for the financial crisis risk. Finally, Section 3.4.2.2 discusses the results of the full model where both health risk and financial crisis risk are considered.

3.4.1 Policy rules without health risk

[Insert Figure 3-4 here]

Figure 3-4 (a) shows the results of the portfolio choice when there is no health shock to the income. In this case, the optimal share invested in risky assets decreases as normalized wealth rises. Retirees with higher (normalized) wealth level have a lower share of their financial wealth invested in risky assets. This result is consistent with the implications of the study by Cocco et al. (2005). The reason for the result is that if labor income does not have any risk after retirement, it is equivalent to risk-free assets. Therefore, retirees' total wealth can be seen as a combination of financial wealth and human capital wealth (the discounted value of all future Social Security and pension income). For retirees with lower normalized financial wealth, the proportion of risk-free human capital out of total wealth is higher than it is for retirees with a large amount of financial wealth. It is the *relative* weight of risk-free assets as a portion of one's total wealth that determines

how much risky assets one should hold. Retirees with lower normalized financial wealth have a higher proportion of risk-free assets (discounted future Social Security/pension income) in their wealth holding; therefore, they will invest more aggressively in stocks. The optimal share invested in stocks also decreases with age, except for the case when the normalized wealth is smaller than 4. As the retiree ages, he will reduce his optimal risky asset holdings.

[Insert Figure 3-8 here]

To provide a better illustration of the optimal portfolio choice, Figure 3-8 (a) presents the two-dimensional graph for retirees' behavior for each level of normalized wealth at different ages. For retirees who are older than 65, the share invested in stocks monotonically decreases as normalized wealth increases, and with a given level of normalized wealth, older retirees will have a lower share invested in risky assets.

Financial crisis risk makes investing in stocks riskier. Compared with the case without any financial crisis (results not shown here)⁴, the difference is that at each level of normalized wealth, the optimal share invested in stocks is lower if we consider a financial crisis. The lower level of stock investment is consistent with the empirical observations found in the HRS. However, the result predicted by this case implies that as normalized wealth decreases, optimal share in stocks should increase, which is not consistent with the fact that wealthy investors generally have a higher portfolio share in stocks than do poor investors (Wachter, 2010). In the HRS, the 75 percentile value of the normalized financial wealth is 5.87; a more accurate model should be able to generate the optimal policy rule for the majority of retirees (i.e., those who have a normalized wealth ratio below 6). The baseline model's failure can be attributed to its failure to take health risk into account.

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⁴ Results available upon request.

Though retirees receive a fixed amount of income after retirement, due to health risks and the nature of health expenditures, the effective income of the retiree is not without risk. In the next section, I incorporate health shocks into the model and analyze how health shock affects retirees' optimal behavior.

3.4.2 Policy rules with health shock

In this section, health shocks are added to retirees' income. The average value of their health expenditure is 17% of their income. The health shock is assumed to be i.i.d for each period. First, I examine the case when there is no financial crisis.

3.4.2.1 Without Financial Crisis

[Insert Figure 3-4, Figure 3-9 and Table 3-6 here]

Figure 3-4 (b) shows the portfolio rule when income is subjected to a health shock but there is no financial crisis. The results show that the portfolio share is lower when normalized wealth is low and gradually increases as normalized wealth increases and then decreases when normalized wealth increases further; the implication of this model can partly explain the phenomenon that the portfolio share increases with wealth as shown in Table 3-6.

Figure 3-9 presents a 2-dimensional graph for retirees at each normalized wealth level at different ages. The pattern is not very clear when the normalized wealth is below 1. However, when the normalized wealth is above 1, the portfolio share increases with normalized wealth for all age groups (except for the 94-year-old case) and gradually declines after normalized wealth reaches 4.5. This result is more aligned with the actual observations. However, one drawback of this model is that the optimal portfolio share is much higher than that shown by the actual observations, especially for people who have recently retired, for whom it increases from 20% to

90% when normalized wealth reaches 4 and stays above 50% when normalized wealth level further increases. And for those who are 75 years old, the optimal share also increases to a significantly high level of 75% when normalized wealth is around 5, which is not consistent with what we observe in the real data. The substantially high level of risky asset share can be attributed to the fact that financial crisis risk is not accounted for.

3.4.2.2 *With financial crisis*

[Insert Figure 3-5 and Figure 3-10 here]

This section presents the results of the full model where both health risk and financial crisis risk are considered. From Figure 3-5(a) we see that the optimal portfolio share drops slightly when normalized wealth is low and gradually increases as normalized wealth increases. Figure 3-10 (a) shows a more detailed portrait for retirees at each normalized wealth level at different ages. We can see that for all age groups (except at 94 years old), the portfolio share in stocks gradually increases as normalized wealth approaches 4.5 and then declines slowly until leveling out when normalized wealth is higher than 15. When these results are compared with the empirical data, it is clear that this model better captures the dynamics of stock investment, especially when normalized wealth is in the range of 1 to 6, where the normalized wealth of 75% of retirees falls. The magnitude of the risky asset share is also captured reasonably well. For example, for the 65 age group, the portfolio share increases from 20% to around 45% and remains at 30% as normalized wealth further increases. For the 75 age group, the portfolio share increases to 35% when the normalized wealth level is 3 and stays at a relatively constant level of 20% when the normalized wealth level is higher than 9.

Despite the better prediction generated by this model for the majority of retirees, it fails to explain the behavior of retirees whose normalized wealth is very high (i.e., those in the highest decile of the normalized wealth distribution) as shown in Table 3-6, where the mean risky asset holding increases with the mean normalized wealth ratio. In addition, the optimal behavior predicted by this model underestimates the risky asset share observed in the HRS, which is about 50% for those whose normalized wealth level is above 30. One possible explanation is that in this model, every retiree is assumed to face the same financial crisis risk. However, it is possible that very wealthy retirees (as measured by high normalized financial wealth ratio) may be more risk tolerant and have better risk management skills, and more knowledge about financial market that would enable them to mitigate the detrimental effects of the financial crisis, so their behavior shows a closer resemblance to that predicted by the no financial crisis scenario as shown in Figure 3-9 (a).

3.5 Extension: Heterogeneous Health Risk

In the previous discussion, I assume all retirees have the same health shock risk. However, as shown in Section 3.3, the health expenditure ratio can differ substantially between the good health group and the poor health group. This section examines how different health status affects retirees' optimal portfolio choice. Figure 3-3 presents the empirical distribution as well as the fitted distribution of the health expenditure ratio for the good health group versus the poor health group. Each group is fitted to a lognormal distribution; for the good health group, $\mu = -3.0$ best captures the features of the data, while for the poor health group, $\mu = -2.5$ fits better. Using these parametric values, I solve the model for the good health group and the poor health group separately.

[Insert Figure 3-11 to Figure 3-13 here]

Figure 3-11 to Figure 3-13 compare the portfolio choices for the good health and poor health groups at different ages. We see that the good health group consistently holds more stocks than the poor health group, with or without a financial crisis. The result is consistent with the empirical observation from the HRS and also with the results found in previous studies (Rosen, 2004; Edwards, 2008) that investors' poor health reduces their risky asset holdings.

3.6 Simulation Results

[Insert Figure 3-14 to Figure 3-16 here]

To assess the distributional properties of consumption and the risky asset share, I simulate the consumption and investment profiles of 5,000 retirees using the policy function obtained in Section 3.4. The retirees' initial normalized wealth is drawn from the empirical distribution of the normalized wealth calculated from the HRS. Figure 3-14 presents the histogram of this empirical distribution. The frequency distribution of normalized wealth shows that the majority of retirees in the HRS have a normalized financial wealth ratio below 10.

I first simulate the case discussed in Section 3.4.1 where there is no health shock to retirees' income. Figure 3-15 presents the mean and the 5th and 95th percentiles of the cross-sectional distribution of risky asset share. Figure 3-16 displays the results when financial crisis risk is present. The mean of the simulated risky asset share is close to 100% until the end of life. The simulation results do not match the empirical mean risky share shown in Table 3-7, where the mean risky share is about 25% after retirement. This result is also higher than the results in Kolusheva (2011); where her model implies that the mean risky asset share is about 50% after retirement with disastrous stock market risk. Despite being lower than the results shown here, Kolusheva's results

are still too high to match the empirical distribution of the risky asset share. Failure to consider health risk can be a major factor leading to the prediction of this unrealistically high portfolio share.

I then simulate the case where there is health shock to the retirees' income. Figure 3-16 presents the mean and the 5th and 95th percentiles of the cross-sectional distribution of the simulated risky asset share. Part (a) of Figure 3-16 presents the results when there is no financial crisis risk, and Part (b) shows the results when the financial crisis risk is considered. After the addition of health risk, the model better explains the actual risky asset holding behavior of retirees. From the simulation results, we can see that the mean risky share decreases after the age of 75. However, if we consider only health risk but not the financial crisis risk, the mean risky asset share is 60% for retirees in their 70s, which is still too high when compared with the empirical findings. After both risks are added to the simulation, the mean optimal risky share decreases to 30% for retirees at 75 years old, and it decreases further when retirees get older, results which are very close to the actual holding level found in the Health and Retirement Survey. Though retirees start with different levels of normalized wealth and there is more variation in investing risky assets when retirees first retire, the heterogeneity in the risky asset share decreases as retirees approach very old age. We can see the 5th percentile, the mean, and the 95th percentile gradually converge as retirees approach very old age.

3.7 Conclusion

Most life cycle literature assumes retirees' income is not subject to the income shocks that occur during the working life. The lack of income shocks during the retirement stage predicts that households will hold a slightly higher share in risky assets after retirement (Cocco *et al.*, 2005). However, empirical studies have found that investment in stocks normally drops after retirement.

This paper extends the life cycle model by incorporating health risk and financial crisis risk into the analysis of retirees' optimization problem. By modeling health risk as a stochastic shock to retirees' income and adding financial crisis to the retirees' optimization problem, this model generates policy functions that can better explain the observed investment behaviors of retirees.

For relatively young retirees with normalized wealth levels between 1.5 and 4.5, the optimal share invested in the risky assets increases as normalized wealth rises, and declines as normalized wealth increases beyond 4.5. For older retirees, i.e., those who are over 85 years old, the optimal share in risky assets remains rather flat and does not rise or decline when the normalized wealth level is higher than 3. In addition, the optimal policy rules derived from the model imply that retirees with good health status should hold a higher level of risky assets compared to retirees whose health status is poor. This result is consistent with the findings of several empirical studies (Rosen, 2004; Edwards, 2008) that poor health can reduce a household's investment in risky assets.

Table 3-1: Benchmark parameter values

This table presents the benchmark parameters for the model. Preference parameters and financial market parameters are obtained from Cocco et al. (2005), and health expenditure parameters are calibrated to the data from the Health and Retirement Survey.

Description	Parameter Value
Preference Parameters:	
Retirement age (K)	65
Discount factor (δ)	0.96
Risk aversion (γ)	7
Health Expenditure Parameters:	
Mean of $\log(\frac{Health\ Expenditure}{Income})$ (μ_h)	-2.5
Standard Deviation of $\log(\frac{Health\ Expenditure}{Income})$ (σ_h)	1.2
Financial Market Parameters:	
Riskless rate (r_f)	0.02
Mean of stock return (μ)	0.06
Standard Deviation of Stock return (σ_η)	0.157
Crash Probability (π^{crash})	0.08
Return when market crashes (r^{crash})	-0.20

Table 3-2: Summary statistics for variables of interest in the HRS

This table presents summary statistics for key variables of the Health and Retirement Survey from 1992 to 2010. Values are in 2010 dollars, adjusted using CPI data from the Federal Reserve of Minneapolis.

Variable	Mean	Median	Standard Deviation	N
Age	73.11	73.00	9.36	59043
Education	12.08	12.00	3.21	59017
Health Expenditure	3046.08	1265.59	9213.04	59044
Pension/Social Security Income	26803.64	19987.63	255303.71	59044
Total Income	42062.61	27492.00	263385.69	59044
Stock	75903.71	0	439745.68	59044
Financial Net Worth	210203.11	34116.45	710615.72	59044
Net Home Equity	127011.97	80843.50	267053.19	59044
Net Worth (Excluding Primary Residence)	293861.83	62967.56	878640.35	59044
Total Net Worth	293861.83	62967.56	878640.35	59044

Table 3-3: Summary statistics for health expenditure

This table presents summary statistics for annual health expenditure for different cohorts of the Health and Retirement Survey from 1992 to 2010. AHEAD were born 1923 or earlier; CODA (Children of Depression) were born from 1924 from 1930; HRS were born 1931-1941; WBs (War Babies) were born from 1942 to 1947; EBBs (Early Boomers) were born from 1948 to 1953; MBB (Mid Boomers) were born from 1954 to 1959. All dollar amounts are in 2010 dollars using CPI data from the Federal Reserve of Minneapolis.

	1992	1996	2000	2006	2012
COHORT					
AHEAD					
Mean	2251	2776	2731	4040	4151
Median	1220	1043	1146	1298	1046
Std Dev	3119	6156	5985	9585	9631
N	21	1638	2212	1737	889
HRS					
Mean	2069	2661	2256	2782	2674
Median	945	1210	1228	1558	1352
Std Dev	4466	4955	3971	17,609	5571
N	514	1253	1963	3608	4396
CODA					
Mean	-	-	2049	3586	3038
Median	-	-	1140	1558	1226
Std Dev	-	-	3364	9129	7100
N	-	-	961	1048	857
War Babies					
Mean	-	-	1465	3225	2879
Median	-	-	430	1525	1562
Std Dev	-	-	1892	4867	5077
N	-	-	53	227	683
Early Baby Boomers					
Mean	-	-	-	2781	2081
Median	-	-	-	773	956
Std Dev	-	-	-	7058	3048
N	-	-	-	45	348
Mid Baby Boomers					
Mean	-	-	-	-	1501
Median	-	-	-	-	401
Std Dev	-	-	-	-	2987
N	-	-	-	-	93

Table 3-4: Social Security and pension income

This table presents summary statistics for Social Security & Pension income for different cohorts of the Health and Retirement Survey from 1992 to 2010. AHEAD were born 1923 or earlier; CODA (Children of Depression) were born from 1924 from 1930; HRS were born 1931-1941; WBs (War Babies) were born from 1942 to 1947; EBBs (Early Boomers) were born from 1948 to 1953; MBBs (Mid Boomers) were born from 1954 to 1959. All dollar amounts are in 2010 dollars using CPI data from the Federal Reserve of Minneapolis.

COHORT	1992	1996	2000	2006	2012
AHEAD					
Mean	22304	25711	24819	22863	20922
Median	21443	21807	20309	18302	15750
Std Dev	7921	19000	23475	17317	26580
N	21	1638	2212	1737	889
HRS					
Mean	24501	28704	30067	31186	24016
Median	18656	23367	24295	24716	20401
Std Dev	19716	28512	23338	35205	18410
N	514	1253	1963	3608	4396
CODA					
Mean	-	-	29066	29187	25220
Median	-	-	23553	22826	20270
Std Dev	-	-	21580	23850	20227
N	-	-	961	1048	857
War Babies					
Mean	-	-	24390	26291	24937
Median	-	-	17597	18173	20924
Std Dev	-	-	18641	27233	18374
N	-	-	53	227	683
Early Baby Boomers					
Mean	-	-	-	21430	20718
Median	-	-	-	14927	13840
Std Dev	-	-	-	16709	20040
N	-	-	-	45	180
Mid Baby Boomers					
Mean	-	-	-	-	13093
Median	-	-	-	-	8322
Std Dev	-	-	-	-	12743
N	-	-	-	-	93

Table 3-5: Summary statistics for medical expense ratio

This table presents the summary statistics for the medical expense ratio for the overall sample and for subsamples based on health status and age from the Health and Retirement Survey.

Sample	Mean	Median	St Dev	N
Overall Sample:	0.175	0.055	0.577	54342
By Health Status:				
Excellent/Good	0.135	0.044	0.505	23109
Fair/Poor	0.230	0.076	0.658	31233
Subsample A: 65<=Age<=85				
	0.163	0.054	0.543	48407
By Health Status:				
Excellent/Good:	0.125	0.043	0.472	27995
Fair/Poor:	0.215	0.075	0.624	20412
Subsample B: Age>85				
	0.274	0.065	0.794	5935
By Health Status:				
Excellent/Good:	0.217	0.053	0.722	3238
Fair/Poor:	0.343	0.084	0.867	2697

Table 3-6: Mean portfolio share in stock

This table divides the retirees into 10 decile groups based on the normalized wealth level. Panel A presents the mean portfolio share for different normalized wealth deciles of the overall sample; Panel B presents the mean portfolio share for different normalized wealth deciles by age; Panel C presents the mean portfolio share for different wealth deciles by health status.

Decile	1	2	3	4	5	6	7	8	9	10
Mean WRatio	0.030	0.132	0.351	0.736	1.372	2.371	3.897	6.386	11.574	31.391

Panel A: Mean Stock Holding Ratio

All Sample:	0.021	0.035	0.066	0.114	0.166	0.220	0.272	0.345	0.399	0.496

Panel B: By Age Group:

60<=Age<70	0.033	0.047	0.069	0.152	0.184	0.276	0.290	0.380	0.422	0.498
70<=Age<80	0.014	0.033	0.067	0.115	0.181	0.214	0.275	0.351	0.421	0.506
80<=Age<90	0.022	0.035	0.063	0.092	0.124	0.192	0.254	0.323	0.365	0.488
Age>=90	0.021	0.009	0.052	0.062	0.103	0.144	0.257	0.271	0.340	0.453

Panel C: By Health Status:

Excellent/Good	0.018	0.040	0.071	0.121	0.188	0.237	0.286	0.361	0.412	0.508
Fair/Poor	0.023	0.030	0.058	0.105	0.131	0.191	0.244	0.314	0.356	0.468

Table 3-7: Portfolio share for different cohorts by age

This table presents the mean portfolio share for different age by cohorts. The HRS cohort members were born between 1931 and 1941. The Children of Depression (CODA), were born between 1924 and 1930; The AHEAD cohort members were born before 1924.

Age:	66	68	70	72	74	76	78	80	82	84	86	88	90	92	94
Cohort:															
HRS:	0.240	0.235	0.211	0.202	0.178	0.169	0.176	-	-	-	-	-	-	-	-
CODA:	-	-	0.216	0.215	0.205	0.225	0.204	0.199	0.204	-	-	-	-	-	-
AHEAD1:	-	-	0.217	0.243	0.251	0.252	0.260	0.209	0.222	0.191	-	-	-	-	-
AHEAD2:	-	-	-	-	0.222	0.249	0.246	0.218	0.225	0.229	0.214	0.192	-	-	-
AHEAD3:	-	-	-	-	-	-	-	0.189	0.235	0.232	0.233	0.252	0.202	0.193	0.199

Figure 3-1: Medical expense ratio

This figure displays the histogram of the empirical medical expense ratio and the fitted lognormal distribution.

Figure 3-2: Medical expense by age group

This figure displays the histogram of the medical expense ratio and the fitted lognormal distribution for the younger age group and older age group, respectively.

(a) Age Group 1: $65 \leq \text{Age} \leq 85$

(b) Age Group 2: $\text{Age} \geq 85$

Figure 3-3: Medical expense ratio by health status

This figure displays the histogram of the medical expense ratio and the fitted lognormal distribution for the excellent/good health group and the fair/poor health group, respectively.

(a) Excellent/Good Health

(b) Poor/Fair Health

Figure 3-4: The portfolio rule for two cases

The surface plot in panel (a) displays the policy functions for the portfolio share invested in stocks at different normalized wealth levels and ages when there is financial crisis risk but no health risk. The surface plot in panel (b) displays the policy functions for the portfolio share invested in stocks at different normalized wealth level and age when there is health risk but no financial crisis risk.

(a) Without health risk but with financial crisis risk

(b) With health risk but without financial crisis risk

Figure 3-5: Policy function with health risk and financial crisis

The surface plots display the policy functions for the portfolio share invested in stocks and the consumption rule at different normalized wealth levels and ages when there are both health risk and financial crisis risk.

(a) The portfolio rule under both health risk and financial crisis risk

(b) The consumption rule under both health risk and financial crisis risk

Figure 3-6: The portfolio rule for the good health group

The surface plots display the policy functions for the portfolio share invested in stocks at different ages for the good health group (a) without considering financial crisis, and (b) considering financial crisis, respectively.

(a) Portfolio Rule for good health group (without financial crisis risk)

(b) The portfolio rule for the good health group (with financial crisis risk)

Figure 3-7: The portfolio rule for the poor health group

The surface plots display the policy functions for the portfolio share invested in stocks at different ages for the poor health group (a) without considering financial crisis, and (b) considering financial crisis, respectively.

(a) The portfolio rule for the poor health group (without financial crisis risk)

(b) The portfolio rule for the poor health group (with financial crisis risk)

Figure 3-8: Policy functions for retirees at different ages (without health risk but with financial crisis risk)

This graph plots the policy functions for the portfolio share invested in stocks (a) and the saving rule (b) at different ages when there is financial crisis risk but no health risk.

(a) The portfolio rule for retirees at different ages (perfect income, no health risk)

(b) The saving rule for retirees at different ages (perfect income, no health risk)

Figure 3-9: Policy functions for retirees at different age (with health risk but without financial crisis risk)

This graph plots the policy functions for the portfolio share invested in stocks (a) and the saving rule (b) at different ages when there is health risk but no financial crisis risk.

(a) The portfolio rule for retirees at different ages (with health shocks)

(b) The saving rule for retirees at different ages (with health shocks)

Figure 3-10: Policy functions for retirees at different ages (with health risk and financial crisis risk)

This graph plots the policy functions for the portfolio share invested in stocks (a) and the saving rule (b) at different ages when there are both health risk and financial crisis risk.

(a) The portfolio rule for retirees at different ages (with health and financial crisis risk)

(b) The saving rule for retirees at different ages (with health and financial crisis risk)

Figure 3-11: The portfolio rule at age 65 by health status

This graph plots the policy functions for the portfolio share invested in stocks for the good health group vs. the poor health group at age of 65; part (a) plots the no financial crisis case and part (b) plots the financial crisis case.

(a) The portfolio rule for good health vs. poor health at 65 (without financial crisis risk)

(b) The portfolio rule for good health vs. poor health at 65 (with financial crisis risk)

Figure 3-12: The portfolio rule at age 75 by health status

This graph plots the policy functions for the portfolio share invested in stocks for the good health group vs. the poor health group at age of 75; part (a) plots the no financial crisis case and part (b) plots the financial crisis case.

(a) The portfolio rule for good health vs. poor health at 75 (without financial crisis risk)

(b) The portfolio rule for good health vs. poor health at 75 (with financial crisis risk)

Figure 3-13: The portfolio rule at age 85 by health status

This graph plots the policy functions for the portfolio share invested in stocks for the good health group vs. the poor health group at age of 85; part (a) plots the no financial crisis case and part (b) plots the financial crisis case.

(a) The portfolio rule for good health vs. poor health at 85 (without financial crisis risk)

(b) The portfolio rule for good health vs. poor health at 85 (with financial crisis risk)

Figure 3-14: Initial wealth distribution for retirees

This figure presents the empirical distribution of the normalized wealth ratio obtained from the Health and Retirement Survey. The normalized wealth ratio is calculated by dividing total household financial wealth by pension/Social Security income.

Figure 3-15: Simulation results: Without health risk

This figure plots the mean, 5th, and 95th percentile of the cross-sectional distribution of the simulated portfolio share in risky assets when there is financial crisis risk but no health risk.

Figure 3-16: Simulation results: With health risk

This figure plots the mean, 5th, and 95th percentile of the cross-sectional distribution of the simulated portfolio share in risky assets when there is health risk and (a) no financial crisis risk and (b) financial crisis risk.

(a) Simulated portfolio share (with health risk but no financial crisis risk)

(b) Simulated portfolio share (with both health risk and financial crisis risk)

Chapter 4

Impacts of Financial Crisis on Income Inequality: A Decomposed Approach

Chapter 4

Impacts of Financial Crisis on Income Inequality: A Decomposed Approach

4.1 Introduction

Income inequality has been rising steadily over the last 40 years in the United States. Among the papers written on the subject, many focus on the long run trends in income distribution, which are more closely related to economic development and productivity change. However, shocks to the economy, especially those like the 2008 financial crisis, have a major impact on the production and allocation of economic resources, and can potentially cause a substantial change to the income distribution of households. This paper provides a quantitative measure of how income distribution changed following the crisis. To gain a more complete picture of the change in the income distribution, I analyze the Lorenz curve and its associated concentration curve instead of choosing a single inequality measure, such as the Gini coefficient. The use of the Lorenz curve provides us with a means to decompose the overall population income distribution by subgroups and allows us to capture how different subgroups, defined by race, gender, or other household characteristics, contributed to overall income inequality before and after the financial crisis.

This study is closely related to three strands of research: work on how major economic shocks, particularly financial crisis, affect income distribution in the economy; work on top income share change in the United States; and work on the application of non-parametric approaches to decompose income inequality by subgroups. Two approaches have been used in empirical studies

to assess the impacts of economic crises on income level and income distribution. One approach uses economic models to calibrate household behaviors to the real economy and uses microsimulation analysis to measure the impact of the shocks (Robilliard *et al.*, 2001; Habib *et al.*, 2010). This approach is often used when real time economic data are not available during the crisis, but immediate analysis is needed to make important policy assessments. The other approach utilizes available income data to conduct a descriptive study of the impact of the crisis. The results obtained using this approach have been inconclusive; some studies have found that financial crisis has a lasting effect on income distribution (Cerra and Saxena, 2008), while other studies have found that the effect of crisis on income distribution is temporary and that income distribution reverts back to its previous state in the longer term (Faik, 2012; Morelli, 2014).

In addition to the study of changes in overall income distribution, examination of the change in top income shares also plays an important role in income inequality analysis. Top income shares indicate how much total income is earned by people in the top tail of the income distribution, such as the top 1%, the top 5%, and the top 10% of the income distribution. In the United States, households in the top 10% of the income distribution earned 47% of the total earnings in 2007. Financial crisis can have a large impact on the income of the top earners as many wealthy households hold a substantial amount of stocks. A large drop in capital income caused by the financial crisis can severely reduce their income. By analyzing the ordinates of the Lorenz curve and its associated concentration curve, I am able to assess the top earners' income share before and after the crisis and to examine how the crisis changed their income share.

Furthermore, in analyzing how the financial crisis affects income distribution by subgroups, I adopt the decomposition methodology proposed in Bishop *et al.* (1993, 2004). As compared to

other decomposition studies (Shorrocks, 1984; Deutsch and Silber 1999), the application of Bishop *et al.*'s (2004) methodology allowed me to track the subgroup changes for the whole income distribution, instead of just the change in a single index. The SCF 2007-2009 panel dataset provides detailed household income data as well as demographic variables, which are ideal for constructing a decomposed Lorenz curve and its associated concentration curve.

The analysis yielded three key findings. First, I find that the overall income distributions shifted from 2007 to 2009. Income shares for the bottom to 9th decile increased, and top earners, defined as households in the top 10% of the income distribution, had a lower income share after the crisis. Comparing Lorenz curves in 2007 and 2009, I find that the top 10% of households in the income distribution earned 47.2% in 2007, and their income share decreased to 42.3% in 2009. In particular, the decreases in the income share for the top earners was more pronounced in the concentration ordinates, which measure the income share changes for households ranked based on their pre-crisis income level. Households which were in the top 10% of the income distribution in 2007 received only 37.7% of total income in 2009, a 5 percentage point reduction compared to the results implied by the 2009 Lorenz curve.

Second, I find that the decomposed concentration ordinates for subgroups, characterized by race, gender, and retirement status, followed a pattern similar to that found for the overall sample. The decomposed concentration ordinates for each of the subgroups rose from the bottom to the 9th decile and decreased substantially for the top decile group. However, the decomposed ordinates of the 2009 Lorenz curve showed a less uniform pattern: not all subgroups' decomposed Lorenz ordinates increased. Non-white groups' Lorenz ordinates fell from the 7th decile to the 9th

decile and rose for the top decile group in 2009. Female groups' Lorenz ordinates decreased in all deciles, except for the 9th and the top decile.

Third, the additive decomposition based on race and retirement status did not change much from the 2007 Lorenz curve to the 2009 Lorenz curve. With regard to subgroups based on gender, males' contribution share increased in the bottom 6 deciles, whereas female groups' contribution share decreased in those deciles.

The results are consistent with previous findings (Faik, 2012; Morelli, 2014) that overall income inequality dropped immediately after the crisis. In an extension study, I use the Panel Study of Income Dynamics (PSID) as a supplementary dataset to analyze longer-term effects of the financial crisis. For a comparison study, I also use the PSID to assess the impacts of the 1987 stock market crash on the income distribution to see how it differed from the 2008 financial crisis in terms of its impacts on household income distribution.

The rest of this Chapter is organized as follows. Section 4.2 presents the relevant literature review. Section 4.3 describes the decomposition methodology of the Lorenz and concentration curves. Section 4.4 describes the data used for constructing the inequality measure and defines the income variable for my analysis. Section 4.5 analyzes the decomposition results based on race, gender, and retirement status. Section 4.6 extends the study using the PSID. Section 4.7 concludes.

4.2 Literature Review

4.2.1 Inequality before and after the crisis

Literature on the effects of financial crises on income distribution falls mainly into two broad categories: the first one focuses on financial crises in the developing countries and their

impact on income distribution and poverty. These crises are often associated with rapid depreciation of the local currency, and have a detrimental effect on the local economy, such as happened in the 1997 Asian Financial Crisis. For example, Baldacci *et al.* (2002) focus on the effects of currency crashes, and they examine income changes in Mexico after the Peso's crash in December 1994. They find that income inequality increases as the result of a more-than-proportional fall in the income share of the lowest income quintile of the population. Robilliard *et al.* (2001) and Habib *et al.* (2010) use a microsimulation approach to examine the distributional effects of financial crises. They find that income shocks are relatively large in the middle parts of the income distribution. But such shocks will not automatically lead to higher inequality, as measured by the Gini coefficient. Overall inequality worsens when the losses are disproportionately high among the poor. Only in Mexico, where a larger shock is projected at the lower end of the distribution, was there an increase in the aggregate inequality.

The second category of the literature focuses on income inequality in the U.S. and other OECD countries before and after the 2008-2009 financial crisis. Several studies have provided descriptive analysis, and their results are mixed. De Beer (2012) finds that there is no uniform pattern in the impact of the crisis on earnings and income distribution among the EU countries. Faik (2012) uses data from the German Social-Economic Panel (SOEP) to study inequality and poverty before and during the economic crisis, and he finds that inequality dropped at the peak of the crisis but increased afterwards.

4.2.2 Decomposing the inequality measure

Studies on income inequality usually use a single inequality measure, such as the Gini coefficient, to provide summary statistics for the overall income distribution. Despite its simplicity,

this measurement, because of its aggregate nature, fails to account for the sources of the inequality. To better understand how different subgroups contribute to the total income inequality, several studies have attempted to decompose the inequality measure. Deutsch and Silber (1999) analyze total inequality in the population as a consequence of the income difference between population subgroups, classified by characteristics such as age, gender, race, and education level. They focus on decomposing a single inequality index, and they consider the issue of inequality decomposition by population subgroups as an index number problem. Shorrocks (1984) uses income inequality measures from population subgroups to determine the aggregate inequality index. Bishop *et al.* (2011) look at the interdistributional inequality among population subgroups. My study differs from those in the previous literature in two major aspects. Previous studies have focused on decomposing a single inequality index, such as the Gini coefficient. My study, however, decomposes the whole Lorenz curve, and hence does not suffer from the index selection problem (Bishop *et al.* 2003). In addition, I use panel data from the Survey of Consumer Finance to construct a concentration curve, in which after-crisis earnings are arranged by the households' positions in the pre-crisis income distributions. The concentration curve is a more accurate measure of the *conditional* change in the household income distribution.

4.2.3 Use of household survey data

Household survey data, which often include detailed household financial information, can be useful in studying income distribution changes. Milanovic (2002) uses household surveys to conduct a cross-country analysis focusing on the Gini coefficient. Zietz and Zhao (2009) use the Panel Study of Income Dynamics (PSID) to study the effects of a stock price change on U.S. income inequality. Their study focuses on the short run effects, but instead of looking at a crisis,

they examine how stock market appreciation affects U.S. income inequality. Using a regression-based method to calculate the Gini coefficient, they find that the stock market appreciation raised the Gini coefficient by about 2% in the 1980s and by 3% in the 1990s.

4.3 Methodology

4.3.1 Decomposing the ordinates

Following the decomposition methodology in Bishop et al. (2003), let (x, y) be a vector of continuous income variables, where x, y are jointly distributed with a probability density function $f(x, y)$; x and y represent the earnings of the same household in the pre-crisis year and the after-crisis year, respectively. Using an indicator variable approach, each household is assigned a decile group using the binary indicator variable, $I_\tau^x = 1$ if $x \leq \tau$ and $I_\tau^x = 0$ otherwise. The overall Lorenz ordinate and the concentration ordinate can be expressed as:

$$L(\tau; x) = \frac{\int_0^x xf(x)dx}{\mu_x} = \frac{\int_0^\infty xI_\tau^x dF(x)}{\mu_x} = \frac{E(x \cdot I_\tau^x)}{E(x)} \quad (4-1)$$

$$C(\tau; y) = \frac{\int_0^\tau \int_0^\infty yf(x, y) dy dx}{\mu_y} = \frac{\int_0^\infty \int_0^\infty yI_\tau^x f(x, y) dy dx}{\mu_y} = \frac{E(y \cdot I_\tau^x)}{E(y)} \quad (4-2)$$

where μ_x is the mean of x and μ_y is the mean of y , $L(\tau, x)$ represents the proportion of total 2007 income received by households whose income level is less than or equal to τ , $C(\tau, y)$ represents the proportion of total 2009 income received by households whose 2007 income is less than or equal to τ , and τ is the inverse CDF of the base year income: $\tau = F^{-1}(p)$.

To decompose the overall Lorenz ordinates and concentration ordinates by subgroups, I create K mutually exclusive population groups: $\Phi_k, k = 1, 2, \dots, K$ and define an indicator variable G_k^x such that $G_k^x = 1$ if the household belongs to group k and $G_k^x = 0$, otherwise. I use 2007 pre-crisis data to create the groups, and the group identification remains the same for constructing the decomposed 2009 concentration curve. Following Bishop et al. (2003), the decomposed Lorenz curve and concentration curve for group k can be expressed as:

$$L(\tau, x^{(k)}) = \frac{E(x \cdot G_k^x \cdot I_\tau^x)}{E(x \cdot G_k^x)} \quad (4-3)$$

$$C(\tau, y^{(k)}) = \frac{E(y \cdot G_k^y \cdot I_\tau^x)}{E(y \cdot G_k^y)} \quad (4-4)$$

where $k=1, 2, \dots, K$. By the law of large numbers, (4-3) and (4-4) can be empirically estimated as the ratio of two sample means:

$$\hat{L}^{(k)} = \hat{L}(\tau_i, x^{(k)}) = \frac{N^{-1} \sum_{j=1}^N x_j \cdot G_k^{x_j} \cdot I_{\tau_i}^{x_j}}{N^{-1} \sum_{j=1}^N x_j \cdot G_k^{x_j}} \quad (4-5)$$

$$\hat{C}_{i,t}^k = \hat{C}(\tau_i, y^k) = \frac{N^{-1} \sum_{j=1}^N y_j \cdot G_k^{y_j} \cdot I_{\tau_i}^{x_j}}{N^{-1} \sum_{j=1}^N y_j \cdot G_k^{y_j}} \quad (4-6)$$

4.3.2 Additive decomposition

For a particular decile, Group k 's contribution to the overall Lorenz ordinate in that decile can be expressed as:

$$\begin{aligned} p_{\tau}^k &= \frac{E(x \cdot G_k^x \cdot I_{\tau}^x)}{E(x \cdot I_{\tau}^x)} \\ &= \frac{E(x \cdot G_k^x \cdot I_{\tau}^x)}{E(x \cdot I_{\tau}^x)} \times \frac{E(x)}{E(x \cdot G_k^x)} \times \frac{E(x \cdot G_k^x)}{E(x)} \\ &= \frac{L(\tau, x^{(k)})}{L(\tau, x)} \times p^{(k)} \end{aligned} \quad (4-7)$$

From (4-7), the additive decomposition can be calculated as the ratio of the decomposed Lorenz ordinates to the overall Lorenz ordinates, multiplied by the income of group k , p^k .

4.4 Data

In the main analysis, I use the Survey of Consumer Finance (SCF) published by the Federal Reserve. This triennial survey includes household demographics, income, and balance sheet information. I use the 2007 sample data, which were collected before the onset of the 2008 financial crisis. In 2009, The Federal Reserve decided to do a panel⁵ study following the crisis and re-interviewed the same households surveyed in 2007 with similar questions⁶ to assess how their financial situations had changed after the crisis. The 2007 and 2009 waves of the SCF panel dataset included 3,862 families, and five observations were deleted from the public available dataset to

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⁵ Federal Reserve samples a different set of households every three years. The 2009 panel is a rare exception. The only previous panel was done for the 1983-1989 wave.

⁶ The 2009 survey added a set of attitudinal questions regarding the 2008 financial crisis and its consequences.

protect the privacy of the households. Because the SCF asks about sensitive financial data, some households are reluctant or unable to provide accurate answers. The Federal Reserve has developed a set of imputation techniques to correct for the missing data problem⁷. Each missing record is imputed 5 times, and there are a total 19,285 records in the public dataset. Following Calati *et al.* (2008) and Lee and Carlin (2010), I use the average of the five imputations as the observed value for a household.

The SCF adopts a dual-frame design in the data collection process. One subsample uses a multi-stage area-probability model to choose the households across the country, and it represents the characteristics of the general population in the United States. In addition to this sample, the SCF also samples households with high net worth, selected from the IRS tax return filings. Compared to other panel studies, the dual-frame design of the SCF provides more complete information on the households in the top decile of the income distribution, whose income can change substantially during a financial crisis. Neither subsample has an equal-probability design; therefore, weight is assigned to each observation, and this needs to be taken into consideration when an inference is made about the population.

[Insert Table 4-1 here]

Table 4-1 provides summary statistics for some key variables in the SCF 2007-2009 panel dataset. The mean income dropped significantly, from \$89,036 in 2007 to \$80,816 in 2009. Median income also dropped slightly, from \$49,841 to \$49,810. For assets and net worth, both mean and median value dropped significantly after the crisis.

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⁷ The imputation procedure is described in “Multiple Imputation in the Survey of Consumer Finances,” Arthur B. Kennickell, September 1998, <http://www.federalreserve.gov/pubs/oss/oss2/method.html>.

4.4.1 Income definition

Since the focus of this paper is on the effects of the financial crisis on the overall and subgroup income distributions, the definition of the income variable is important to the analysis. Following Piketty and Saez (2003, 2014), I use pre-tax gross income for the calculation, and this includes wage and salary income, business income, interest and dividend income, capital gain/loss income⁸, pension, social security, and income from transfer payments. To examine how changes occur in different demographic subgroups, I divide the whole sample into mutually exclusively population subsamples based on households' characteristics. The variables used in the subgroup analysis are race, gender, and retirement status.

[Insert Table 4-2 here]

Table 4-2 presents summary statistics for the income variable based on each group classification. As the SCF uses the household as the unit of observation, race, gender, and retirement status are based on the information about the household head. In the SCF, if a household does not include a couple, the head is taken to be the single core individual in that household. If a household has a central couple, the head is taken to be either the male in a mixed-sex couple or the older individual in a same-sex couple. The first two panels display income information based on race and gender. Panel A displays the results by race; I divide the whole sample into two racial categories: white and non-white. Both groups' median income dropped after the crisis, but that of the white group dropped more, from \$103,552 to \$91,750. For the non-white group, median household income dropped from \$58,211 to \$57,490. Panel B presents the results based on gender;

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⁸ This is annual income from net gains or losses from mutual funds or from the sale of stocks, bonds, or real estate, before deductions for taxes.

773 observations in the SCF 2007-2009 panel dataset are for female households. For the whole population, the percentage of female households is 27.4%, and they contribute 11.3% to the total income. Households with a female head have a significantly lower level of median income compared to households with a male head. However, the median income for a household with a female head did not drop after the crisis; on the contrary, it increased from \$36,905 in 2007 to \$38,987 in 2009.

Panel C presents the income information based on the household head's retirement status. Retirement often marks a significant change in income source and level, and it is interesting to examine how the crisis affected retired households versus non-retired households. In the sample, 677 observations had a retired household head; for the overall population, 18.8% of the households had a retired household head, and retired households earned 15% of the total income. The median income for both retired and non-retired households dropped after the crisis, and the degree of the drop was similar in both groups.

4.5 Decomposition Results

4.5.1 Overall decomposition results

[Insert Table 4-6 here]

Table 4-6 provides the Lorenz ordinates for the overall sample. The first row in each panel presents the order statistics, which are the upper cutoff income levels of the overall sample for 2007 and 2009, respectively. Each observation is weighted when the order statistics are calculated. For 2007, the order statistic for the bottom decile is 13,632, indicating that the bottom 10% of the total population had income less than \$13,632. Comparing the order statistics before and after the

financial crisis, I find that the order statistics generally decreased, with the exception of the bottom decile, where the order statistic increased from \$13,632 to \$13,947.

The second row of each panel calculates the ordinates for the overall Lorenz curve at each decile level for 2007 and 2009, respectively. The standard error is given in parentheses. The Lorenz ordinate for the bottom decile is 0.0098 in 2007, indicating that the bottom 10% of the overall population received less than 1% of the total earnings in 2007. The Lorenz ordinate for the ninth decile is 0.5218, indicating that the bottom 90% of the overall population received 52.18% of the total income in 2007, and this implies that the top 10% of the population received 48% of the total income. The Lorenz ordinates uniformly drop after the crisis, and the decrease for the highest decile is the most significant. The bottom 90% of the population received 57.8% of the total income in 2009, a 5% increase from the 2007 level. Correspondingly, the top 10% of the population's income share dropped from 48% to 43% from 2007 to 2009. It is not surprising to see that their income share dropped substantially, as capital gain income was significantly reduced due to the financial crisis. The effect is even more pronounced among the top 1% of income earners, who may have a large proportion of their income come from capital gain. This finding is consistent with Piketty and Saez (2012), where it is found that the income growth for the bottom 99% of earners was -11.6% during the 2007 to 2009 period, while for the top 1% of earners, the real income growth was -36.3%. The loss in earnings for the top 1% of earners was much more severe than it was for the rest of the population. In the next section, I decompose the overall Lorenz curve by race and examine how each group contributed to the overall Lorenz ordinates and how their contribution changed after the financial crisis.

4.5.2 Decomposition by race

[Insert Table 4-7 to Table 4-9 here]

Table 4-7 to Table 4-9 present the ordinate decomposition by race. I divide the whole population into two subgroups, the white group and non-white group, and track the ordinate changes within these subgroups before and after the crisis. Table 4-7 shows the decomposed Lorenz ordinates for 2007. The decomposed ordinates of the bottom decile of the white group is 0.0077, which means that only 0.77% of the total white group's income was accrued to those in the bottom decile of the overall earning distribution. Similarly, the decomposed ordinates for the bottom decile of the non-white group is 0.023, which indicates that 2.3% of the non-white group's income was received by those in the bottom 10% of the population. It is not surprising to see that the top decile earners were mostly in the white group, and more than half of the total white group income was received by workers in the top decile, while only about 25% of the non-white group income was earned by those in the top decile.

Panel B in Table 4-7 shows the additive decomposition results by subgroup. The contribution of the white group to the bottom decile was 53.4%, and the non-white group contributed 46.6%. The white group's contribution share increased for each subsequent decile. For the 9th decile, the white group contributed 70.7% to the overall Lorenz ordinates in that decile, while the remaining 29% was contributed by the non-white group.

Table 4-8 presents the decomposed Lorenz ordinates and the additive decomposition for the 2009 data. Though the overall Lorenz ordinates increased after the crisis, the decomposed Lorenz ordinates for the two subgroups exhibited different patterns: the white group's decomposed Lorenz ordinates increased for each decile, while the non-white group's decomposed Lorenz

ordinates actually decreased for the 7th to the 9th deciles. For example, in 2007, 74.2% of the total non-white group's income accrued to the bottom 90% of workers, while in 2009, 72.2% of total non-white income was earned by the bottom 90% of workers. In other words, the non-white households in the top 10% of the income distribution received 2 percent more of the income after the crisis, which implies that a crisis can have different impacts on the within-group income distribution. Despite the different patterns of changes in the decomposed Lorenz ordinates for the white vs. the non-white group, no significant change was found in the additive decomposition for these two subgroups.

[Insert Table 4-9 here]

Table 4-9 Panel A presents the concentration ordinates for the subsample. Households who were in the bottom earning decile before the crisis received 0.98% of the total 2007 income, whereas the same group of households received 2.25% of the total 2009 income. The top 10% of households received 47.82% of 2007 income, but their income share dropped to 42.12% after the crisis. Both white and non-white decomposed concentration ordinates exhibited patterns similar to those of the overall ordinates. Measured by the income share of each decile, income inequality decreased in both groups. Panel B shows the additive decomposition result; the only significant change in the contribution share occurred in the bottom decile, where the white group's contribution increased from 53.4% to 60.4%. For other deciles, no significant change was found in terms of percentage contributions.

[Insert Table 4-23 here]

To test the significance of the differences in the decomposed Lorenz ordinates between the white and the non-white group, I conduct a chi-square test. The null hypothesis is that there will be no difference in the Lorenz ordinates between the two subgroups. It can be defined as:

$$H_0 : \gamma = \mathbf{0}$$

where $\gamma = (\hat{L}_1^{(white)} - \hat{L}_1^{(non-white)}, \dots, \hat{L}_9^{(white)} - \hat{L}_9^{(non-white)})$ is a 1×9 vector of sample estimates of the differences between the decomposed white group's Lorenz ordinates and the non-white group's Lorenz ordinates. Table 4-23 panel A and B provide the test results for the difference between the white and the non-white groups' Lorenz ordinates in 2007 and 2009, respectively. The chi-square test results are statistically significant, indicating that differences exist between the subgroups. The magnitude of the chi-square test statistics increased from 32,602 in 2007 to 50,321 in 2009, indicating that the white and the non-white groups become less alike after the crisis.

The chi-square test can also be used to test whether the subgroups' ordinates are different across years. The null hypothesis can be specified as:

$$H_0 : \psi = \mathbf{0}$$

where $\psi = (\hat{L}_1^{(white)} - \hat{C}_1^{(white)}, \dots, \hat{L}_9^{(white)} - \hat{C}_9^{(white)})$ is a 1×9 vector of sample estimates of the differences between the white group's decomposed Lorenz ordinates and its concentration ordinates before and after the crisis. Panel C of Table 4-23 provides the chi-square statistics, and we can see that for both the white and the non-white group, the difference between the concentration ordinates and the Lorenz ordinates is significant, indicating that the financial crisis had an effect on the *conditional* change in the income share.

4.5.3 Decomposition by gender

[Insert Table 4-10 to Table 4-12 here]

Table 4-10 shows the decomposed Lorenz ordinates for 2007. Female-headed households had a more equal distribution of income across deciles. For example, 48% of the female-headed households' income accrued to those below the median income level, while for the male-headed households, only 10.5% of the income was received by those below the median income level. Moreover, as shown in Table 4-4, only 1.45% of female-headed households are in the top 10% of the overall income distribution, while 13.25% of male-headed households are in the top 10% of the overall income distribution. The decomposed Lorenz ordinates in the top decile reflect a similar pattern: 52.5% of all male-headed households' earnings was earned by those in the top 10% decile, while only 11% of all female-headed households' earnings was earned by those in the top 10% decile.

Panel B of Table 4-10 presents the additive decomposition results by subgroup based on gender. The contribution of the male group to the overall sample ordinates for the bottom decile was 38.2%, and the female group contributed the remaining 61.8%. The male group's contribution share increased for each subsequent decile. For the 9th decile, the male group contributed 80.8% to the overall Lorenz ordinates, while the female group contributed only 11.3% to the Lorenz ordinates in the top decile. This is consistent with the findings in Table 4-3, where we can see that the female group accounts for a much smaller proportion in the top earning decile.

Table 4-11 presents the decomposed 2009 Lorenz curve, and Table 4-12 presents the decomposed 2009 concentration curve. For the male group, ordinates in each decile increased for both the Lorenz curve and concentration curve after the crisis, but the increases in the concentration

ordinates were more pronounced. For example, the decomposed Lorenz ordinates for the bottom decile was 0.0042 for the male group in 2007, and it increased to 0.0055 in 2009, whereas the increase in the decomposed concentration ordinates for the bottom decile of the male group was larger: 0.0132 in 2009. As discussed before, the concentration curve is a conditional Lorenz curve, and in it the decile cutoff point did not change from before to after the crisis. It was the same group of households in each decile, and only their income share changed. In 2007, only 0.42% of total male group income was earned by the male-headed households in the bottom decile of the population, this same group of male households earned 1.32% of the total male group income in 2009. The male group's income became more equally distributed, measured either by the 2009 Lorenz ordinates or the concentration ordinates, but the *conditional* ordinates showed even more equality.

The change in the female group is interesting: the decomposed Lorenz ordinates, in which all households have been re-ordered according to their 2009 income level, decreased in each decile except the 9th. For example, the decomposed Lorenz ordinates of the female group in the bottom decile are 0.0541 in 2007 and 0.0481 in 2009. If only these two numbers were compared, we would conclude that the female-headed households in the bottom decile of the income distribution had received a smaller proportion (4.81%) of the female group's income after the crisis. However, if we examine the decomposed ordinates of the concentration curve, which is 0.0842 for the female group in the bottom decile, we find that the female-headed households who were in the bottom decile of the 2007 income distribution received 8.42% of the entire female group's income in 2009. This different pattern indicates that some female-headed households migrated from the bottom decile of the income distribution in 2007 to a higher decile income group in 2009. It can also be

seen from Table 4-4 and Table 4-5 that based on the 2007 income ranking, 22.2% of all female-headed households were located in the bottom decile, whereas based on the 2009 income ranking, only 20.27% of female-headed households were located in the bottom decile in that year. The location of the female group's distribution shifted relative to the male group's distribution. Income inequality among the female-headed households decreased after the crisis.

[Insert Table 4-24 here]

Table 4-24 shows the chi-square test statistics for the difference in the decomposed Lorenz ordinates between the male- and female-headed households. The difference was significant for both 2007 and 2009; however, the test statistics indicated that the male- and female-headed households became more alike after the crisis, as the chi-square statistics dropped from 92,704 in 2007 to 17,414 in 2009. The chi-square statistics were also significant for the tests that compared the decomposed Lorenz and concentration curve ordinates within each gender group before and after the crisis. The results are similar to the ones obtained in the previous section, where the subgroups were created based on racial characteristics.

4.5.4 Decomposition by retirement status

[Insert Table 4-13 here]

In this section, I present the decomposition results based on the retirement status of the household head. Retirement can significantly change households' income level and composition, and it is useful to examine whether the financial crisis had different effects on households with different retirement statuses. Table 4-15 presents the decomposed 2007 Lorenz ordinates by retirement status. In 2007, retired households in the bottom 50% of the income distribution received 23.3% of their group's income, while non-retired households in the bottom 50% of the

2007 income distribution received 13.2% of their group's income. The retired households had a more equal income distribution. This is consistent with the finding from Panel C of Table 4-4, which shows that 67.5% of the retired households were in the bottom 50% of the income distribution, while only 46.1% of the non-retired households were in the bottom 50% of the income distribution, and this can partly explain why the retired households in the bottom 50% of the income distribution received a higher share of their group's income compared to the non-retired households.

It is interesting to note that the decomposed ordinates are very similar in the top decile of the income distribution for both groups. However, combining information from Table 4-4 and Table 4-13, we can see that 6.3% of retired households were in the top 10% income distribution and they received 47% of their group's income, whereas 10.7% of the non-retired households were in the top 10% income distribution, and they also received about 47% of their group's income in 2007. Both groups had the same decomposed Lorenz ordinates for the top decile, but the retired group had a smaller percentage of households in the top decile, which implies that the income was more skewed to the right within the retirement group.

Panel B of Table 4-13 presents the additive decomposition results by subgroup. The contribution of the retired group to the overall sample ordinates in the bottom decile was 30.9%, and the non-retired group contributed 69.1%. The retired group's contribution share decreased for each subsequent decile. In the 9th decile, the retired group contributed only 14.8% to the overall Lorenz ordinates, while the non-retired group contributed the remaining 85.2%.

[Insert Table 4-14 and Table 4-15 here]

Table 4-14 and Table 4-15 present the results for the decomposed Lorenz curve and the concentration curve in 2009. For both the retired group and the non-retired group, the decomposed Lorenz ordinates and the concentration ordinates increased in all 9 deciles. However, the decomposed concentration ordinates increased even more. In 2007, the retired households in the bottom decile of the income distribution received 1.83% of their group's income, whereas this same group of households received 3.65% of the total retirement income in 2009. But if we focus only on the change in the decomposed Lorenz ordinates, the change was smaller, i.e., from 0.0183 in 2007 to 0.0240 in 2009, which can be interpreted as a result of the fact that the retired households in the bottom decile of the 2009 income distribution received 2.4% of their group's income in 2009. Despite the difference in magnitude, both the decomposed 2009 Lorenz curve and concentration curve indicate that income inequality decreased for both subgroups after the crisis.

4.6 Discussion

4.6.1 Crisis effects in the longer run.

Though the SCF provides more complete information with which to study the income distribution of American households, especially for households in the top decile, where incomes were most affected by the negative impact of the financial crisis, the panel dataset has its drawbacks. It has observations for only two waves, which makes it impossible to study the longer term effect of financial crisis using the decomposition method. In this section, I supplement the analysis by using data from the Panel Study of Income Dynamics (PSID), a panel dataset of a nationally representative sample of 5,000 households since 1968. The PSID has collected social, economic, and income data from the originally interviewed families, as well as from families

started by the descendants of the original families, for over four decades. This longitudinal dataset allows researchers to track households' income change over a longer period of time. Nevertheless, one drawback of the PSID is that the households surveyed were a representative national sample in 1968 but might fail to consist of the most updated representative sample for the recent decade. And unlike the SCF, which provides more accurate measurement for high-income earners, the PSID does not cover enough wealthy households, and this makes it less than ideal for studying change in the top decile of the income distribution. Despite the limitations of the PSID, some useful inferences can still be made for studying the longer term effects of the financial crisis.

[Insert Table 4-16 to Table 4-19 here]

To study the longer term effects of the 2008 financial crisis, I use the PSID 2006 and 2012 waves, the latter being the most recent available one. In this analysis, I focus on decomposing the overall Lorenz curve and the concentration curve into the white and the non-white groups.⁹ In 2012, four years after the financial crisis, while the U.S. stock market rebounded to its previous level and continued to rise, the decomposed ordinates of the Lorenz curve for the white group reverted back to their pre-crisis level. However, the decomposed ordinates for the non-white group were still higher in 2012. In addition, for both groups, the decomposed concentration ordinates remained higher than the pre-crisis level. For example, measured by the PSID data, non-white households in the bottom 9 deciles of the income distribution received 78.7% of their groups' income in 2006. And these same sets of households received 85% of their group's income in 2012. Similar results hold for the white group. In 2006, white households in the bottom 9 deciles of the

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⁹ Decomposition based on other characteristics such as gender and retirement status can be done similarly; the results are not shown here.

income distribution received 63.7% of their group's income, and the same households received 68.7% of their group's income in 2012, a five percent increase from their 2006 level. These results imply that the longer term effects of the financial crisis do exist as measured by the concentration ordinates.

4.6.2 Comparison with the 1987 stock market crash

In addition to the usefulness of the PSID for studying the longer term effects of the 2008 financial crisis, the span of the PSID also provides us with a means to study the change in the income distribution in relation to previous stock market crashes, and to see if they had impacts on the income distribution similar to those found for the 2008 financial crisis. Historically, another dramatic decline in the stock market happened in October, 1987. To compare the impacts of these two financial crises, I conducted a similar decomposition analysis to examine the impact of the 1987 stock market crash on U.S. households' income distribution. For this analysis, I used two years of PSID data: those from the 1986 and 1988 waves.

[Insert Table 4-20 to Table 4-22 here]

Table 4-20 to Table 4-22 present the decomposition results. I find that the 1987 stock market crash had a similar immediate effect on income distribution, measured by the 1988 concentration ordinates. Both the white and the non-white groups' *conditional* income share in the bottom 9 deciles increased after the crisis. The results also hold for the decomposed 1988 Lorenz ordinates from the bottom to the 7th deciles for the white group, but the magnitude was smaller. Despite the lower stock market participation rate of the average household 20 years ago, the 1987 stock market crash still led to a change in the income distribution in the short run, especially for the non-white group, but the magnitude appears to be smaller.

4.7 Conclusion

Income inequality has risen substantially in the last 40 years in the U.S., and many studies have attempted to explain the cause of this trend. In addition to other events, economy-wide shocks can have a large impact on the distribution of income. The 2008 Financial Crisis, the largest economic recession since World War II, reduced many households' income level, and the reduction was not uniform for all households, which led to a change in the income distribution among U.S. households. This paper documents income distribution changes before and after the Financial Crisis. Using the Survey of Consumer Finance 2007-2009 panel dataset, I apply a non-parametric decomposition method to quantify the change in the income distribution, measured by the Lorenz curve and its associated concentration curve. Instead of focusing on a single inequality index, this approach analyzes the whole income distribution, and can thus better track income share changes of the households in each decile. Moreover, the decomposition approach allows me to examine how different subgroups, defined based on households' demographic characteristics, contribute to the overall income inequality.

The findings show that income inequality dropped immediately after the financial crisis, and most of the drop came from the decrease in the income share of the top income earners, defined as the households in the top 10% of the income distribution. The drop was more substantial in the associated concentration ordinates, a conditional measure of the Lorenz ordinates. Subgroup decomposition shows that non-white, female-headed, or retired households contributed relatively more to the lower deciles of the overall Lorenz and concentration ordinates, while white, male-headed, or non-retired households contributed more to the higher deciles of the overall Lorenz and the concentration ordinates. All decomposed concentration ordinates increased for each subgroup

in 2009, and the bottom nine deciles' ordinates remained larger 4 years after the financial crisis, while the decomposed Lorenz ordinates reverted back to their pre-crisis level during this longer time span. In addition, compared to the impact of the 1987 stock market crash on income distribution, the short run effect of the 2008 financial crisis was larger, measured by both the Lorenz ordinates and the concentration ordinates.

Table 4-1: Summary statistics for key variables in the SCF 2007 & 2009

This table provides summary statistics for the key variables of the SCF 2007-2009 panel data; all data are weighted using the weight provided by the SCF.

Variable	Mean	Median	Standard Deviation	N
Age	49.4	48.0	16.8	3857
Education	13.4	13.0	2.8	3857
Income				
2007	89,036	49,841		3857
2009	80,816	49,810		3857
Assets				
2007	698,251	226,796	3,501,309	3857
2009	583,014	197,900	2,858,847	3857
Debts				
2007	102,509	33,346	193,751	3857
2009	103,939	33,000	206,227	3857
Leverage Ratio				
2007	22	0.227	419	3847
2009	26	0.257	528	3847
Net Worth				
2007	595,742	128,000	3,446,799	3857
2009	479,074	96,900	2,801,402	3857

Table 4-2: Summary statistics for the income variable by group

This table provides summary statistics for the income variable based on race, gender, and retirement status.

Sample	Number of Observations	Weighed Percentage Of Observations	Percentage of Earnings Contributed		Median Equivalent Earnings	
			2007	2009	2007	2009
Panel A: By Race						
White	2,915	68.2%	79.2%	77.4%	103,552	91,750
Non-White	942	31.8%	20.8%	22.6%	58,211	57,490
Panel B: By Gender						
Male	3084	72.6%	88.7%	86.7%	108,795	96,617
Female	773	27.4%	11.3%	13.3%	36,905	38,987
Panel C: By Retirement Status						
Retired	677	18.8%	15%	14.3%	71,550	61,770
Non-Retired	3180	81.2%	85%	85.7%	93,183	85,253

Table 4-3: Decile composition by subgroups (2007)

This table presents the decile composition by race, gender, and retirement status.

Decile		1	2	3	4	5	6	7	8	9	10
Panel A: By Race											
White	Count	1219273	1278994	1446992	1461333	1541349	1733279	1381665	1714052	1753806	1904269
	%	53%	57%	64%	66%	66%	72%	66%	75%	77%	85%
Non-White	Count	1061083	965562.5	813174.6	758644	792150.6	683053.9	704699.8	564386.5	517524.1	340882.7
	%	47%	43%	36%	34%	34%	28%	34%	25%	23%	15%
Panel B: By Gender											
Male	Count	905990	1027826	1254534	1536606	1754497	1881030	1784549	2062950	2074390	2161062
	%	40%	46%	56%	69%	75%	78%	86%	91%	91%	96%
Female	Count	1374366	1216730	1005633	683371	579002	535303	301816	215488	196940	84090
	%	60%	54%	44%	31%	25%	22%	14%	9%	9%	4%
Panel C: By Retirement Status											
Retired	Count	581360	729254	624325	487138	443648	357490	294779	227597	229637	268365
	%	25%	32%	28%	22%	19%	15%	14%	10%	10%	12%
Non-Retired	Count	1698996	1515302	1635842	1732839	1889851	2058843	1791585	2050842	2041693	1976786
	%	75%	68%	72%	78%	81%	85%	86%	90%	90%	88%

Table 4-4: Group composition by 2007 decile

This table presents the population distribution in each decile by groups. The decile cut-off points are calculated using the 2007 income data.

Decile		1	2	3	4	5	6	7	8	9	10
Panel A: By Race											
White	Count	1219273	1278994	1446992	1461333	1541349	1733279	1381665	1714052	1753806	1904269
	%	7.9%	8.3%	9.4%	9.5%	10.0%	11.2%	9.0%	11.1%	11.4%	12.3%
	Cumulative %	7.9%	16.2%	25.6%	35.0%	45.0%	56.2%	65.2%	76.3%	87.7%	100.0%
Non-White	Count	1061083	965562	813174	758644	792150	683053	704699	564386	517524	340882
	%	14.7%	13.4%	11.3%	10.5%	11.0%	9.5%	9.8%	7.8%	7.2%	4.7%
	Cumulative %	14.7%	28.1%	39.4%	50.0%	61.0%	70.5%	80.2%	88.1%	95.3%	100.0%
Panel B: By Gender											
Male	Count	905990	1027826	1254534	1536606	1754497	1881030	1784549	2062950	2074390	2161062
	%	5.5%	6.3%	7.6%	9.3%	10.7%	11.4%	10.9%	12.5%	12.6%	13.1%
	Cumulative %	5.5%	11.8%	19.4%	28.7%	39.4%	50.8%	61.7%	74.2%	86.9%	100.0%
Female	Count	1374366	1216730	1005633	683371	579002	535303	301816	215488	196940	84090
	%	22.2%	19.6%	16.2%	11.0%	9.3%	8.6%	4.9%	3.5%	3.2%	1.4%
	Cumulative %	22.2%	41.8%	58.1%	69.1%	78.5%	87.1%	92.0%	95.5%	98.6%	100.0%
Panel C: By Retirement Status											
Retired	Count	581360	729254	624325	487138	443648	357490	294779	227597	229637	268365
	%	13.7%	17.2%	14.7%	11.5%	10.5%	8.4%	6.9%	5.4%	5.4%	6.3%
	Cumulative %	13.7%	30.9%	45.6%	57.1%	67.5%	76.0%	82.9%	88.3%	93.7%	100.0%
Non-Retired	Count	1698996	1515302	1635842	1732839	1889851	2058843	1791585	2050842	2041693	1976786
	%	9.2%	8.2%	8.9%	9.4%	10.3%	11.2%	9.7%	11.2%	11.1%	10.7%
	Cumulative %	9.2%	17.5%	26.4%	35.8%	46.1%	57.3%	67.0%	78.2%	89.3%	100.0%

Table 4-5: Group composition by 2009 decile

This table presents the population distribution in each decile by groups. The decile cut-off points are calculated using the 2009 income data.

Decile		1	2	3	4	5	6	7	8	9	10
Panel A: By Race											
White	Count	1249094	1301192	1349647	1468930	1526066	1552331	1669147	1748652	1782662	1828168
	%	8.07%	8.41%	8.72%	9.49%	9.86%	10.03%	10.79%	11.30%	11.52%	11.81%
	Cumulative %	8.07%	16.48%	25.20%	34.69%	44.55%	54.58%	65.37%	76.67%	88.19%	100.00%
Non-White	Count	1034499	983916	767146	884123	706670	631180	675068	555812	480704	441168
	%	14.45%	13.74%	10.71%	12.35%	9.87%	8.82%	9.43%	7.76%	6.71%	6.16%
	Cumulative %	14.45%	28.19%	38.90%	51.25%	61.12%	69.93%	79.36%	87.13%	93.84%	100.00%
Panel B: By Gender											
Male	Count	1028128	1090440	1330348	1637062	1532749	1720845	1841906	2074227	2008307	2179423
	%	6.25%	6.63%	8.09%	9.96%	9.32%	10.47%	11.20%	12.61%	12.21%	13.25%
	Cumulative %	6.25%	12.88%	20.97%	30.93%	40.25%	50.72%	61.92%	74.53%	86.75%	100.00%
Female	Count	1255465	1194668	786445	715992	699986	462665	502308	230236	255058	89914
	%	20.27%	19.29%	12.70%	11.56%	11.30%	7.47%	8.11%	3.72%	4.12%	1.45%
	Cumulative %	20.27%	39.56%	52.26%	63.83%	75.13%	82.60%	90.71%	94.43%	98.55%	100.00%
Panel C: By Retirement Status											
Retired	Count	691663	670328.8	553461.4	657576	362662.8	360751.1	337121.8	251245	153635.5	205149.3
	%	16.30%	15.80%	13.04%	15.50%	8.55%	8.50%	7.94%	5.92%	3.62%	4.83%
	Cumulative %	16.30%	32.10%	45.14%	60.63%	69.18%	77.68%	85.62%	91.55%	95.17%	100.00%
Non-Retired	Count	1591930	1614779	1563332	1695478	1870073	1822760	2007093	2053218	2109730	2064187
	%	8.66%	8.78%	8.50%	9.22%	10.17%	9.91%	10.91%	11.16%	11.47%	11.22%
	Cumulative %	8.66%	17.43%	25.93%	35.15%	45.32%	55.23%	66.14%	77.31%	88.78%	100.00%

Table 4-6: Lorenz ordinates decomposition for the overall sample (2007 vs. 2009)

This table presents the order statistics (upper cutoff values) and the Lorenz ordinates for 2007 and 2009 data from the SCF. The standard error for the Lorenz ordinates are in parentheses.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates 2007										
Order Statistic	13,632	22,577	31,736	39,191	49,841	63,899	77,956	102,238	149,097	-
Overall	0.0098	0.0301	0.0600	0.0992	0.1473	0.2095	0.2884	0.3862	0.5218	1.0000
Sample	(0.0016)	(0.0044)	(0.0085)	(0.0138)	(0.0203)	(0.0286)	(0.0391)	(0.0520)	(0.0697)	
Panel B : Lorenz Ordinates 2009										
Order Statistic	13,947	22,116	29,886	38,851	49,810	61,760	79,696	102,011	147,039	-
Overall	0.0111	0.0335	0.0641	0.1076	0.1608	0.2299	0.3158	0.4285	0.5778	1.0000
Sample	(0.0013)	(0.0034)	(0.0060)	(0.0096)	(0.0140)	(0.0195)	(0.0263)	(0.0349)	(0.0458)	

Table 4-7: Lorenz ordinates and subsample decomposition by race (2007)

Panel A of this table presents the decomposed order statistics and the Lorenz ordinates for the 2007 data by race. The standard errors for the decomposed Lorenz ordinates are in parentheses. Panel B presents the additive decomposition in each decile by race.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates										
Order Statistic	13,632	22,577	31,736	39,191	49,841	63,899	77,956	102,238	149,097	-
Overall Sample	0.0098 (0.0016)	0.0301 (0.0044)	0.0600 (0.0085)	0.0992 (0.0138)	0.1473 (0.0203)	0.2095 (0.0286)	0.2884 (0.0391)	0.3862 (0.0520)	0.5218 (0.0697)	1.0000
White	0.0067 (0.0013)	0.0213 (0.0039)	0.0453 (0.0080)	0.0776 (0.0134)	0.1175 (0.0201)	0.1732 (0.0293)	0.2404 (0.0403)	0.3321 (0.0533)	0.4646 (0.0768)	1.0000
Non-White	0.0222 (0.0040)	0.0643 (0.0101)	0.1167 (0.0174)	0.1827 (0.0261)	0.2621 (0.0364)	0.3495 (0.0474)	0.4738 (0.0625)	0.5951 (0.0766)	0.7422 (0.0926)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
White	53.4%	56.1%	59.9%	62.1%	63.4%	65.7%	66.2%	68.3%	70.7%	79.2%
Non-White	46.6%	43.9%	40.1%	37.9%	36.6%	34.3%	33.8%	31.7%	29.3%	20.8%

Table 4-8: Lorenz ordinates and subsample decomposition by race (2009)

Panel A of this table presents the decomposed order statistics and the Lorenz ordinates for the 2009 data by race. The standard errors for the decomposed Lorenz ordinates are in parentheses. Panel B presents the additive decomposition in each decile by race.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates										
Order Statistic	13,947	22,116	29,886	38,851	49,810	61,760	79,696	102,011	147,039	-
Overall Sample	0.0111 (0.0013)	0.0335 (0.0034)	0.0641 (0.0060)	0.1076 (0.0096)	0.1608 (0.0140)	0.2299 (0.0195)	0.3158 (0.0263)	0.4285 (0.0349)	0.5778 (0.0458)	1.0000
White	0.0077 (0.0012)	0.0241 (0.0031)	0.0492 (0.0059)	0.0842 (0.0096)	0.1311 (0.0144)	0.1946 (0.0209)	0.2731 (0.0287)	0.3845 (0.0395)	0.5358 (0.0528)	1.0000
Non-White	0.0230 (0.0035)	0.0659 (0.0079)	0.1152 (0.0125)	0.1881 (0.0188)	0.2629 (0.0249)	0.3512 (0.0316)	0.4624 (0.0394)	0.5799 (0.0465)	0.7221 (0.0534)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
Group 1	53.4%	55.7%	59.5%	60.6%	63.2%	65.6%	67.0%	69.5%	71.8%	77.4%
Group 2	46.6%	44.3%	40.5%	39.4%	36.8%	34.4%	33.0%	30.5%	28.2%	22.6%

Table 4-9: Concentration ordinates and subsample decomposition by race (2009)

Panel A of this table presents the decomposed order statistics and the concentration ordinates for the 2009 data by race. The standard errors for the decomposed Concentration ordinates are in parentheses. Panel B presents the additive decomposition in each decile by race.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Concentration Ordinates										
Order Statistic	13,632	22,577	31,736	39,191	49,841	63,899	77,956	102,238	149,097	-
Overall Sample	0.0225 (0.0049)	0.0518 (0.0066)	0.0935 (0.0097)	0.1411 (0.0132)	0.2004 (0.0179)	0.2724 (0.0233)	0.3596 (0.0299)	0.4674 (0.0378)	0.6221 (0.0478)	1.0000
White	0.0176 (0.0059)	0.0387 (0.0072)	0.0722 (0.0101)	0.1134 (0.0138)	0.1668 (0.0191)	0.2326 (0.0254)	0.3106 (0.0328)	0.4158 (0.0427)	0.5743 (0.0562)	1.0000
Non-White	0.0396 (0.0068)	0.0969 (0.0124)	0.1665 (0.0189)	0.2365 (0.0241)	0.3160 (0.0298)	0.4091 (0.0361)	0.5282 (0.0434)	0.6446 (0.0495)	0.7867 (0.0549)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
White	60.4%	57.8%	59.9%	62.2%	64.5%	66.2%	66.9%	68.9%	71.5%	77.4%
Non-White	39.6%	42.2%	40.1%	37.8%	35.5%	33.8%	33.1%	31.1%	28.5%	22.6%

Table 4-10: Lorenz ordinates and subsample decomposition by gender (2007)

Panel A of this table presents the decomposed order statistics and the Lorenz ordinates for the 2007 data by gender. The standard errors for the decomposed Lorenz ordinates are in parentheses. Panel B presents the additive decomposition in each decile by gender.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates										
Order Statistic	13,632	22,577	31,736	39,191	49,841	63,899	77,956	102,238	149,097	-
Overall Sample	0.0098 (0.0016)	0.0301 (0.0044)	0.0600 (0.0085)	0.0992 (0.0138)	0.1473 (0.0203)	0.2095 (0.0286)	0.2884 (0.0391)	0.3862 (0.0520)	0.5218 (0.0697)	1.0000
Male	0.0042 (0.0009)	0.0149 (0.0026)	0.0336 (0.0056)	0.0646 (0.0104)	0.1051 (0.0165)	0.1594 (0.0247)	0.2354 (0.0360)	0.3349 (0.0508)	0.4745 (0.0713)	1.0000
Female	0.0541 (0.0084)	0.1505 (0.0199)	0.2687 (0.0330)	0.3730 (0.0439)	0.4809 (0.0547)	0.6060 (0.0663)	0.7083 (0.0751)	0.7925 (0.0815)	0.8955 (0.0879)	
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
Male	0.3819	0.4402	0.4974	0.5783	0.6338	0.6756	0.7246	0.7699	0.8075	88.7%
Female	0.6181	0.5598	0.5026	0.4217	0.3662	0.3244	0.2754	0.2301	0.1925	11.3%

Table 4-11: Lorenz ordinates and subsample decomposition by gender (2009)

Panel A of this table presents the decomposed order statistics and the Lorenz ordinates for the 2009 data by gender. The standard errors for the decomposed Lorenz ordinates are in parentheses. Panel B presents the additive decomposition in each decile by gender.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates										
Order Statistic	13,947	22,116	29,886	38,851	49,810	61,760	79,696	102,011	147,039	-
Overall Sample	0.0111 (0.0013)	0.0335 (0.0034)	0.0641 (0.0060)	0.1076 (0.0096)	0.1608 (0.0140)	0.2299 (0.0195)	0.3158 (0.0263)	0.4285 (0.0349)	0.5778 (0.0458)	1.0000
Male	0.0055 (0.0009)	0.0180 (0.0023)	0.0401 (0.0046)	0.0751 (0.0080)	0.1171 (0.0120)	0.1797 (0.0178)	0.2576 (0.0249)	0.3743 (0.0352)	0.5268 (0.0482)	1.0000
Female	0.0481 (0.0063)	0.1358 (0.0137)	0.2231 (0.0200)	0.3224 (0.0263)	0.4499 (0.0332)	0.5618 (0.0380)	0.7002 (0.0417)	0.7866 (0.0424)	0.9150 (0.0385)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
Male	0.4313	0.4674	0.5429	0.6063	0.6325	0.6790	0.7087	0.7588	0.7919	86.7%
Female	0.5687	0.5326	0.4571	0.3937	0.3675	0.3210	0.2913	0.2412	0.2081	13.3%

Table 4-12: Concentration ordinates and subsample decomposition by gender (2009)

Panel A of this table presents the decomposed order statistics and the concentration ordinates for the 2009 data by gender. The standard errors for the decomposed concentration ordinates are in parentheses. Panel B presents the additive decomposition in each decile by gender.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Concentration Ordinates										
Order Statistic	13,632	22,577	31,736	39,191	49,841	63,899	77,956	102,238	149,097	-
Overall Sample	0.0225 (0.0049)	0.0518 (0.0066)	0.0935 (0.0097)	0.1411 (0.0132)	0.2004 (0.0179)	0.2724 (0.0233)	0.3596 (0.0299)	0.4674 (0.0378)	0.6221 (0.0478)	1.0000
Male	0.0132 (0.0051)	0.0283 (0.0060)	0.0555 (0.0080)	0.0943 (0.0112)	0.1468 (0.0159)	0.2090 (0.0212)	0.2949 (0.0287)	0.4076 (0.0383)	0.5741 (0.0512)	1.0000
Female	0.0842 (0.0121)	0.2067 (0.0210)	0.3446 (0.0290)	0.4507 (0.0336)	0.5549 (0.0373)	0.6913 (0.0398)	0.7879 (0.0400)	0.8627 (0.0386)	0.9400 (0.0350)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
Male	0.5089	0.4755	0.5156	0.5805	0.6363	0.6666	0.7122	0.7575	0.8015	86.7%
Female	0.4911	0.5245	0.4844	0.4195	0.3637	0.3334	0.2878	0.2425	0.1985	13.3%

Table 4-13: Lorenz ordinates and subsample decomposition by retirement status (2007)

Panel A of this table presents the decomposed order statistics and the Lorenz ordinates for the 2007 data by retirement status. The standard errors for the decomposed Lorenz ordinates are in parentheses. Panel B presents the additive decomposition in each decile by retirement status.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates										
Order Statistic	13,632	22,577	31,736	39,191	49,841	63,899	77,956	102,238	149,097	-
Overall Sample	0.0098 (0.0016)	0.0301 (0.0044)	0.0600 (0.0085)	0.0992 (0.0138)	0.1473 (0.0203)	0.2095 (0.0286)	0.2884 (0.0391)	0.3862 (0.0520)	0.5218 (0.0697)	1.0000
Retired	0.0183 (0.0067)	0.0621 (0.0214)	0.1160 (0.0392)	0.1740 (0.0583)	0.2334 (0.0583)	0.2945 (0.0777)	0.3677 (0.0977)	0.4348 (0.1214)	0.5218 (0.1430)	1.0000
Non-Retired	0.0083 (0.0015)	0.0245 (0.0040)	0.0500 (0.0079)	0.0860 (0.0132)	0.1320 (0.0200)	0.1944 (0.0292)	0.2744 (0.0408)	0.3776 (0.0557)	0.5217 (0.0762)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
Retired	0.2807	0.3097	0.2910	0.2638	0.2384	0.2115	0.1918	0.1694	0.1504	15.0%
Non-Retired	0.7193	0.6903	0.7090	0.7362	0.7616	0.7885	0.8082	0.8306	0.8496	85.0%

Table 4-14: Lorenz ordinates and subsample decomposition by retirement status (2009)

Panel A of this table presents the decomposed order statistics and the Lorenz ordinates for the 2009 data by retirement status. The standard errors for the decomposed Lorenz ordinates are in parentheses. Panel B presents the additive decomposition in each decile by retirement status.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates										
Order Statistic	13,947	22,116	29,886	38,851	49,810	61,760	79,696	102,011	147,039	-
Overall Sample	0.0111 (0.0013)	0.0335 (0.0034)	0.0641 (0.0060)	0.1076 (0.0096)	0.1608 (0.0140)	0.2299 (0.0195)	0.3158 (0.0263)	0.4285 (0.0349)	0.5778 (0.0458)	1.0000
Retired	0.0240 (0.0068)	0.0703 (0.0182)	0.1278 (0.0322)	0.2120 (0.0522)	0.2723 (0.0664)	0.3523 (0.0851)	0.4381 (0.1049)	0.5255 (0.1248)	0.5971 (0.1407)	1.0000
Non-Retired	0.0090 (0.0012)	0.0273 (0.0030)	0.0535 (0.0055)	0.0901 (0.0088)	0.1422 (0.0133)	0.2094 (0.0191)	0.2953 (0.0262)	0.4123 (0.0356)	0.5745 (0.0482)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
Retired	0.3096	0.3006	0.2853	0.2821	0.2424	0.2194	0.1986	0.1756	0.1479	14.3%
Non-Retired	0.6904	0.6994	0.7147	0.7179	0.7576	0.7806	0.8014	0.8244	0.8521	85.7%

Table 4-15: Concentration ordinates and subsample decomposition by retirement status (2009)

Panel A of this table presents the decomposed order statistics and the concentration ordinates for the 2009 data by retirement status. The standard errors for the decomposed concentration ordinates are in parentheses. Panel B presents the additive decomposition in each decile by retirement status.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Concentration Ordinates										
Order Statistic	13,632	22,577	31,736	39,191	49,841	63,899	77,956	102,238	149,097	-
Overall Sample	0.0225 (0.0049)	0.0518 (0.0066)	0.0935 (0.0097)	0.1411 (0.0132)	0.2004 (0.0179)	0.2724 (0.0233)	0.3596 (0.0299)	0.4674 (0.0378)	0.6221 (0.0478)	1.0000
Retired	0.0365 (0.0270)	0.0935 (0.0336)	0.1588 (0.0452)	0.2310 (0.0602)	0.3076 (0.0772)	0.3764 (0.0921)	0.4542 (0.1090)	0.5168 (0.1227)	0.6582 (0.1305)	1.0000
Non-Retired	0.0202 (0.0035)	0.0448 (0.0056)	0.0825 (0.0090)	0.1261 (0.0126)	0.1825 (0.0173)	0.2550 (0.0232)	0.3438 (0.0304)	0.4591 (0.0394)	0.6161 (0.0511)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
Retired	0.2319	0.2586	0.2432	0.2342	0.2197	0.1978	0.1808	0.1583	0.1514	14.3%
Non-Retired	0.7681	0.7414	0.7568	0.7658	0.7803	0.8022	0.8192	0.8417	0.8486	85.7%

Table 4-16: Lorenz ordinates decomposition for the overall sample (2006 vs. 2012)

This table presents the order statistics (upper cutoff values) and the Lorenz ordinates for the 2006 and 2012 PSID data. The standard errors for the Lorenz ordinates are in parentheses.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates 2006										
Order Statistic	14553	24387	34234	45801	57576	72294	89427	114259	159054	-
Overall Sample	0.0099	0.0340	0.0705	0.1205	0.1851	0.2656	0.3655	0.4906	0.6577	1.0000
Panel B : Lorenz Ordinates 2012										
Order Statistic	13633	23129	32849	43423	56958	70403	87696	111595	154945	-
Overall Sample	0.0097	0.0329	0.0689	0.1179	0.1820	0.2627	0.3631	0.4896	0.6559	1.0000

Table 4-17: Lorenz ordinates and subsample decomposition by race (2006)

Panel A of this table presents the decomposed order statistics and the Lorenz ordinates for the 2006 PSID data by race. The standard errors for the decomposed Lorenz ordinates are in parentheses. Panel B presents the additive decomposition in each decile by race.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates										
Order Statistic	14553	24387	34234	45801	57576	72294	89427	114259	159054	-
Overall Sample	0.0099 (0.0012)	0.0340 (0.0029)	0.0705 (0.0051)	0.1205 (0.0078)	0.1851 (0.0110)	0.2656 (0.0146)	0.3655 (0.0186)	0.4906 (0.0228)	0.6577 (0.0270)	1.0000
White	0.0072 (0.0011)	0.0283 (0.0028)	0.0597 (0.0050)	0.1030 (0.0077)	0.1651 (0.0112)	0.2402 (0.0150)	0.3373 (0.0194)	0.4651 (0.0244)	0.6369 (0.0294)	1.0000
Non-White	0.0268 (0.0053)	0.0695 (0.0112)	0.1378 (0.0192)	0.2298 (0.0286)	0.3098 (0.0359)	0.4246 (0.0449)	0.5416 (0.0523)	0.6498 (0.0573)	0.7874 (0.0594)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
White	62.7%	71.8%	73.1%	73.7%	76.9%	78.0%	79.6%	81.7%	83.5%	86.2%
Non-White	37.3%	28.2%	26.9%	26.3%	23.1%	22.0%	20.4%	18.3%	16.5%	13.8%

Table 4-18: Lorenz ordinates and subsample decomposition by race (2012)

Panel A of this table presents the decomposed order statistics and the Lorenz ordinates for the 2012 PSID data by race. The standard errors for the decomposed Lorenz ordinates are in parentheses. Panel B presents the additive decomposition in each decile by race.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates										
Order Statistic	13633	23129	32849	43423	56958	70403	87696	111595	154945	-
Overall Sample	0.0097 (0.0012)	0.0329 (0.0030)	0.0689 (0.0054)	0.1179 (0.0083)	0.1820 (0.0119)	0.2627 (0.0161)	0.3631 (0.0209)	0.4896 (0.0263)	0.6559 (0.0322)	1.0000
White	0.0072 (0.0012)	0.0258 (0.0028)	0.0561 (0.0051)	0.1000 (0.0082)	0.1609 (0.0082)	0.2368 (0.0082)	0.3365 (0.0121)	0.4649 (0.0166)	0.6307 (0.0220)	1.0000
Non-White	0.0263 (0.0051)	0.0792 (0.0121)	0.1532 (0.0121)	0.2361 (0.0203)	0.3205 (0.0284)	0.4332 (0.0358)	0.5381 (0.0440)	0.6519 (0.0500)	0.8219 (0.0543)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
Group 1	64.3%	68.2%	70.7%	73.6%	76.8%	78.2%	80.4%	82.4%	83.5%	86.8%
Group 2	35.7%	31.8%	29.3%	26.4%	23.2%	21.8%	19.6%	17.6%	16.5%	13.2%

Table 4-19: Concentration ordinates and subsample decomposition by race (2012)

Panel A of this table presents the decomposed order statistics and the concentration ordinates for the 2012 PSID data by race. The standard errors for the decomposed concentration ordinates are in parentheses. Panel B presents the additive decomposition in each decile by race.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Concentration Ordinates										
Order Statistic	14553	24387	34234	45801	57576	72294	89427	114259	159054	-
Overall Sample	0.0309 (0.0056)	0.0685 (0.0080)	0.1122 (0.0099)	0.1679 (0.0126)	0.2386 (0.0126)	0.3231 (0.0160)	0.4271 (0.0197)	0.5517 (0.0240)	0.7084 (0.0285)	1.0000
White	0.0259 (0.0060)	0.0610 (0.0085)	0.0996 (0.0104)	0.1484 (0.0130)	0.2176 (0.0168)	0.2965 (0.0207)	0.3988 (0.0256)	0.5250 (0.0309)	0.6868 (0.0365)	1.0000
Non-White	0.0640 (0.0143)	0.1178 (0.0217)	0.1951 (0.0284)	0.2963 (0.0361)	0.3765 (0.0414)	0.4977 (0.0479)	0.6131 (0.0520)	0.7276 (0.0531)	0.8502 (0.0502)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
White	72.7%	77.3%	77.1%	76.7%	79.2%	79.7%	81.1%	82.6%	84.2%	86.8%
Non-White	27.3%	22.7%	22.9%	23.3%	20.8%	20.3%	18.9%	17.4%	15.8%	13.2%

Table 4-20: Lorenz ordinates and subsample decomposition by race (1986)

Panel A of this table presents the decomposed order statistics and the Lorenz ordinates for the 1986 PSID data by race. The standard errors for the decomposed Lorenz ordinates are in parentheses. Panel B presents the additive decomposition in each decile by race.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates										
Order Statistic	12975	23489	32580	43215	52616	64992	78647	96000	126048	-
Overall Sample	0.0035 (0.0006)	0.0248 (0.0025)	0.0641 (0.0051)	0.1195 (0.0082)	0.1928 (0.0118)	0.2827 (0.0155)	0.3940 (0.0194)	0.5275 (0.0230)	0.7005 (0.0259)	1.0000
White	0.0017 (0.0005)	0.0170 (0.0021)	0.0478 (0.0046)	0.0953 (0.0077)	0.1652 (0.0116)	0.2529 (0.0157)	0.3628 (0.0201)	0.4990 (0.0244)	0.6783 (0.0280)	1.0000
Non-White	0.0175 (0.0043)	0.0871 (0.0141)	0.1939 (0.0261)	0.3126 (0.0367)	0.4121 (0.0440)	0.5196 (0.0499)	0.6424 (0.0537)	0.7540 (0.0534)	0.8772 (0.0464)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
White	44.0%	60.8%	66.2%	70.8%	76.1%	79.5%	81.8%	84.0%	86.0%	88.3%
Non-White	56.0%	39.2%	33.8%	29.2%	23.9%	20.5%	18.2%	16.0%	14.0%	11.2%

Table 4-21: Lorenz ordinates and subsample decomposition by race (1988)

Panel A of this table presents the decomposed order statistics and the Lorenz ordinates for the 1988 PSID data by race. The standard errors for the decomposed Lorenz ordinates are in parentheses. Panel B presents the additive decomposition in each decile by race.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Lorenz Ordinates										
Order Statistic	12573	21876	32347	42016	51966	64343	78358	96690	132546	1.0000
Overall Sample	0.0116 (0.0014)	0.0382 (0.0034)	0.0806 (0.0061)	0.1376 (0.0094)	0.2097 (0.0130)	0.2987 (0.0170)	0.4055 (0.0212)	0.5308 (0.0253)	0.6961 (0.0295)	
White	0.0071 (0.0012)	0.0264 (0.0030)	0.0583 (0.0055)	0.1085 (0.0089)	0.1736 (0.0128)	0.2561 (0.0172)	0.3631 (0.0221)	0.4906 (0.0272)	0.6624 (0.0326)	1.0000
Non-White	0.0385 (0.0065)	0.1092 (0.0147)	0.2144 (0.0244)	0.3127 (0.0318)	0.4262 (0.0386)	0.5545 (0.0439)	0.6604 (0.0460)	0.7727 (0.0451)	0.8985 (0.0373)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
White	52.7%	59.2%	62.0%	67.6%	71.0%	73.5%	76.8%	79.2%	81.6%	85.7%
Non-white	47.3%	40.8%	38.0%	32.4%	29.0%	26.5%	23.2%	20.8%	18.4%	14.3%

Table 4-22: Concentration ordinates and subsample decomposition by race (1988)

Panel A of this table presents the decomposed order statistics and the concentration ordinates for the 1988 PSID data by race. The standard errors for the decomposed concentration ordinates are in parentheses. Panel B presents the additive decomposition in each decile by race.

	Bottom Decile	2	3	4	5	6	7	8	9	Total Sample
Panel A: Concentration Ordinates										
Order Statistic	12573	21876	32347	42016	51966	64343	78358	96690	132546	1.0000
Overall Sample	0.0448 (0.0062)	0.0707 (0.0072)	0.1169 (0.0095)	0.1765 (0.0123)	0.2492 (0.0154)	0.3374 (0.0189)	0.4439 (0.0227)	0.5629 (0.0262)	0.7248 (0.0295)	1.0000
White	0.0047 (0.0015)	0.0253 (0.0037)	0.0656 (0.0072)	0.1191 (0.0106)	0.1918 (0.0146)	0.2809 (0.0189)	0.3913 (0.0236)	0.5179 (0.0282)	0.6925 (0.0329)	1.0000
Non-White	0.2863 (0.0364)	0.3433 (0.0377)	0.4249 (0.0399)	0.5217 (0.0425)	0.5943 (0.0439)	0.6770 (0.0441)	0.7598 (0.0432)	0.8336 (0.0405)	0.9189 (0.0328)	1.0000
Panel B: Additive Decomposition by Subsample – Percentage Contribution										
White	8.9%	30.7%	48.1%	57.8%	66.0%	71.4%	75.6%	78.9%	81.9%	85.7%
Non-White	91.1%	69.3%	51.9%	42.2%	34.0%	28.6%	24.4%	21.1%	18.1%	14.3%

Table 4-23: Chi-Squared test results by race (2007 vs. 2009)

This table provides the chi-squared test results for the differences in the decomposition ordinates by race.

Comparison of Lorenz Ordinates across Subgroups in 2007	Test Statistics:
White vs. Non-White	32,602
Comparison of Lorenz Ordinates across Subgroups in 2009	Test Statistics:
White vs. Non-White	50,321
Comparison of Concentration Ordinates within Subgroups (2007 vs.) 2009	Test Statistics:
White	22,360
Non-White	38,641

Table 4-24: Chi-Squared test results by gender (2007 vs. 2009)

This table provides the chi-squared test results for the differences in the decomposition ordinates by gender.

Comparison of Lorenz Ordinates across Subgroups in 2007	Test Statistics:
Male vs. Female	92,704
Comparison of Lorenz Ordinates across Subgroups in 2009	Test Statistics:
Male vs. Female	17,414
Comparison of Concentration Ordinates within Subgroups (2007 vs.) 2009	Test Statistics:
Male	24,579
Female	48,990

Table 4-25: Chi-Squared test results by retirement status (2007 vs. 2009)

This table provides the chi-squared test results for the differences in the decomposition ordinates by retirement status.

Comparison of Lorenz Ordinates across Subgroups in 2007	Test Statistics:
Retired vs. Non-Retired	33,536
Comparison of Lorenz Ordinates across Subgroups in 2009	Test Statistics:
Retired vs. Non-Retired	52,042
Comparison of Concentration Ordinates within Subgroups (2007 vs.) 2009	Test Statistics:
Retired	14,831
Non-Retired	48,256

Figure 4-1 : Decomposed Lorenz ordinates by race (2007)

This figure displays the overall and the decomposed Lorenz ordinates for the 2007 data by race.

Figure 4-2: Decomposition histogram (by race)

This figure displays the contribution to each income decile by the white group and the non-white group for the 2007 and 2009 data, respectively.

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