Beyond the Crashes: Preferences and Beliefs Shaped by Market Downturns

Abstract

This paper studies how past experiences of stock market downturns shape investors' risk-taking behavior. Using household-level survey data, I document relationships between lifetime downturn experiences, risk preferences, beliefs, and portfolio allocations. Both risk tolerance and pessimistic beliefs exhibit inverted-U relationships with past downturn experiences: moderate exposure is associated with higher reported risk tolerance and more pessimistic expectations, while extremely high exposure weakens these effects. Consistent with these patterns, stock market shares display a similar non-linear relationship with past downturn experiences. A channel decomposition shows that changes in risk tolerance account for part of this relationship, whereas survey-based belief measures explain little. As a complement, I conduct a counterfactual analysis that recovers investors' beliefs and risk preferences from asset prices, showing that investors in the real world are both more risk tolerant and more pessimistic than those in the counterfactual no-downturn world, with the risk tolerance channel accounting for a larger share of the risky portfolio difference.

Keywords: Market Downturn Experiences, Household Portfolio Choice, Heterogeneous Beliefs, Heterogeneous Preferences, Stock Market Participation, Asset Pricing.

JEL Classification Codes: G11, G12, D14, D81

1 Introduction

Investors exhibit substantial heterogeneity in their willingness to take financial risks. While some households allocate a large share of their wealth to risky assets, others avoid the stock market. Understanding the sources of this heterogeneity is central to household finance and asset pricing. One potential driver is individuals' past experiences with financial markets. In particular, experiencing severe market downturns may shape both investors' willingness to bear risk and their expectations about future returns.

Evidence suggests that investors' past experiences with financial markets can have lasting effects on their financial decisions. For example, Malmendier & Nagel (2011) show that past experienced stock market returns influence investors' risk-taking behavior. Individuals who have experienced higher stock market returns in the past are more likely to participate in the stock market and allocate a larger share of their liquid assets to equities. Their analysis focuses on average return experiences accumulated over an individual's lifetime and how these experiences shape participation and portfolio allocation decisions. In contrast, this paper focuses on tail events, specifically experiences of severe market downturns. Moreover, rather than examining investment outcomes alone, this study seeks to disentangle the mechanisms through which experiences affect behavior. In particular, it investigates whether past market downturn experiences primarily operate through changes in investors' risk appetites or through changes in their subjective beliefs about future returns, and which of these channels plays a more important role in shaping observed investment behavior.

This paper examines how experiences of severe stock market downturns influence investors' risk-taking behavior by separately analyzing their effects on risk tolerance and beliefs about future returns. Using household-level data from the Survey of Consumer Finances (SCF), I document systematic relationships between lifetime market downturn experiences, reported risk tolerance, subjective expectations, and portfolio choices.

Focusing first on risk tolerance and beliefs, the results reveal a systematic inverted-U pattern. Moderate exposure to stock market downturns is associated with a higher probability of reporting greater risk tolerance, while very high exposure eventually reduces reported risk tolerance. A similar pattern emerges for beliefs. Households with more downturn experiences tend to report more pessimistic expectations about the economy, particularly at longer horizons, although this effect also weakens for households with extremely high exposure.

I next examine how these differences translate into stock market participation and allocations to stocks. In baseline specifications, past downturn experiences show little direct relationship with stock market participation. However, participation is strongly related to risk tolerance, with more risk-tolerant households being substantially more likely to hold stocks. Once risk tolerance is accounted for, pessimistic beliefs about future returns have limited explanatory power for participation decisions. In addition, the relationship between bad experiences and participation becomes stronger when cash holdings are not controlled for, suggesting that part of the effect of past downturn experiences operates through households' liquidity. These results indicate that downturn experiences influence stock market participation primarily through their impact on risk tolerance and liquidity, rather than through a direct effect on participation itself.

For stock allocations, I examine how downturn experiences affect the share of liquid financial wealth invested in stocks. I find an inverted-U relationship between past downturn experiences and risky portfolio shares: moderate exposure to downturns is associated with higher equity exposure, while very large exposure eventually reduces households' willingness to hold risky assets. Risk tolerance and long-horizon beliefs also play an important role in shaping portfolio allocations. More risk-tolerant households allocate a larger share of their liquid wealth to stocks, whereas households with more pessimistic long-term expectations hold smaller risky shares. Importantly, even after accounting for these differences in risk tolerance and beliefs, the relationship between downturn experiences and stock market shares remains present. These results indicate that past downturn experiences are significantly related to risky portfolio shares, and that differences in risk tolerance and beliefs explain only part of this relationship.

A natural question is which channel primarily drives the relationship between downturn experiences and risky portfolio shares. To address this question, I conduct a regression-based channel decomposition that evaluates how much of the relationship between bad experiences and risky share can be accounted for by changes in risk tolerance and beliefs. Intuitively, the approach compares the strength of the relationship between bad experiences and risky shares before and after introducing these variables into the regression. Evaluated at the mean level of bad experiences, the results show that changes in risk tolerance explain about 18% of the relationship between bad experiences and risky share, while survey-based belief measures explain little of the effect. Even after accounting for both risk tolerance and beliefs, a substantial portion of the relationship remains. Overall, these findings suggest that the effect of downturn experiences on risky portfolio choices operates primarily through changes in risk tolerance, together with an additional component that is not captured by the survey measure of beliefs.

Because the SCF is primarily a repeated cross-sectional survey, it is generally difficult to observe how the same households adjust their preferences and portfolio choices over time. However, the 2007 and 2009 waves form a short panel that makes it possible to track the same households before and after the 2008 financial crisis. I use this panel structure to examine whether households with different lifetime downturn experiences respond differently to this major market crash. The results show that households with more past downturn experiences report significantly higher risk tolerance in 2009, even after controlling for their pre-crisis risk tolerance in 2007. In contrast, past downturn experiences do not lead to differential changes in beliefs, stock market participation, or stock market shares over this period.

Survey-based measures of preferences and beliefs may contain measurement error and typically capture only coarse categories of expectations. To complement the survey evidence, I therefore conduct a price-based counterfactual analysis that recovers investors' risk preferences and beliefs directly from market prices. The analysis compares two representative investor types that differ in their exposure to market downturns. A "Normal" investor has experienced the full history of market returns, while a "Lucky" investor has not experienced the most severe downturns in the sample. To connect this counterfactual exercise with the survey evidence, it is useful to interpret the two investor types through the lens of the SCF results. In the survey data, risk tolerance and pessimistic beliefs exhibit an inverted-U relationship with the number of past downturn experiences. A "Lucky" investor can therefore be viewed as representing the far left of this experience distribution, corresponding to investors with very limited exposure to downturns, whereas the "Normal" investor is closer to the average experience level observed in the population.

Using a semi-parametric Smoothed Empirical Likelihood (SEL) approach, I recover the beliefs and risk preferences that are consistent with observed asset prices for each investor type. The estimates reveal that the Lucky investor appears more risk-averse than the Normal investor, while the Normal investor holds more pessimistic beliefs about future market returns. At first glance, this pattern may appear surprising. A natural explanation is a selection mechanism: investors who become extremely risk-averse after experiencing severe market downturns are more likely to exit the stock market or invest only a very small share of their wealth in risky assets, and therefore have limited influence on market prices. As a result, observed market prices primarily reflect the preferences of investors who remain active in the market, including Lucky investors who continue to participate and Normal investors whose risk tolerance may have increased after moderate exposure to downturns.

The counterfactual exercise further enables a comparison of the relative importance of risk preferences and beliefs in determining portfolio allocation. Adjusting the Lucky investor's risk preferences to match those of the Normal investor increases her optimal risky share by about 40 percentage points, whereas adjusting beliefs reduces it by about 31 percentage points. These results indicate that both channels matter, with risk preferences playing a slightly larger role in shaping portfolio allocation. This finding is qualitatively consistent with the survey evidence documented earlier.

This paper makes three main contributions. First, it documents novel inverted-U effects of stock market downturn experiences on investors' preferences and beliefs. Using household-level data from the SCF, I show that moderate exposure to market downturns is associated with higher reported risk tolerance and more pessimistic beliefs, while extremely severe exposure eventually weakens these effects. These findings reveal a systematic non-linear relationship between past market experiences and investors' attitudes toward risk and expectations about future returns. More importantly, the results suggest that investors' risk preferences are not fixed parameters but can evolve with past market experiences. This finding contributes to the asset pricing literature by providing micro-level evidence that risk preferences may vary systematically with individuals' experience histories.

Second, the paper sheds light on the mechanisms through which downturn experiences affect portfolio allocations. By jointly analyzing preferences, beliefs, and portfolio allocations, I show that the relationship between downturn experiences and risky asset holdings operates primarily through changes in risk preferences rather than through changes in beliefs. A regression-based channel decomposition indicates that risk tolerance accounts for a meaningful portion of the relationship between downturn experiences and stock market shares. More broadly, distinguishing whether downturn experiences affect investment behavior through changes in beliefs or through shifts in risk preferences has important implications for policies aimed at encouraging household participation in financial markets, as these channels may call for different policy responses and informational interventions.

Third, the findings highlight an important selection mechanism driven by downturn experiences. Households with substantial downturn experiences tend to report lower risk tolerance and are more likely to exit the stock market or substantially reduce their risky holdings. As a result, these households are less likely to be marginal investors in the market, and their preferences and beliefs are therefore less likely to be reflected in asset prices. This selection mechanism helps reconcile the survey evidence with the patterns observed in market prices and motivates the price-based counterfactual analysis presented later in the paper.

This paper contributes to the growing literature on how personal experiences shape financial decision-making. A large body of work shows that individuals' past economic experiences influence their beliefs and risk-taking behavior. For example, Malmendier & Nagel (2011) document that investors' lifetime experienced stock market returns affect stock market participation and portfolio allocation. Gomes et al. (2022) show that household forecasts adjust following financial deteriorations. Other studies link early-life experiences to long-run financial attitudes and choices. For instance, Cronqvist et al. (2015) and Giuliano & Spilimbergo (2014) show that individuals exposed to recessions earlier in life adopt more conservative financial and political preferences, while Calvet & Sodini (2014) document that differences in risk-taking may also have genetic components. Related evidence also shows that past experiences influence decision-making in institutional settings. Malmendier et al. (2011) find that managers who lived through the Great Depression exhibit greater caution toward external financing, whereas those who experienced World War II pursue more aggressive financial policies. Bernile et al. (2017) document a U-shaped relationship between early-life exposure to natural disasters and corporate risk-taking. Kaustia & Knüpfer (2008) and Chiang et al. (2011) show that prior investment experiences affect subsequent participation in IPO markets. This paper contributes to this literature by examining how experiences of severe market downturns influence investor behavior through two distinct channels: risk preferences and beliefs about future returns.

This paper is also related to the literature on heterogeneity in investors' beliefs and risk preferences. A central challenge in this literature is disentangling the role of preferences and expectations in shaping observed investment behavior. Some studies focus primarily on heterogeneity in risk preferences. For example, Calvet et al. (2022) study heterogeneity in risk preferences within an Epstein–Zin framework while maintaining homogeneous beliefs. Earlier work such as Pålsson (1996), Barsky et al. (1997), and Halek & Eisenhauer (2001) relates differences in risk tolerance to demographic and biographical characteristics. Other studies emphasize heterogeneity in beliefs. For instance, Meeuwis et al. (2022) study differences in belief updating across investors with different political affiliations, while survey-based studies document substantial heterogeneity in expectations about future returns (see, e.g., Greenwood & Shleifer (2014), Giglio et al. (2021), and Adam et al. (2021)). Survey data have also been widely used to study differences in portfolio allocations across households (e.g., Guiso et al. (2002), Calvet et al. (2007), and Malmendier & Nagel (2011)). However, survey respondents may find it difficult to clearly distinguish between beliefs and risk preferences, and survey questions typically rely on coarse response categories. As a result, separating the roles of preferences and expectations based solely on survey responses can be challenging. This paper contributes to this literature by jointly analyzing risk preferences, beliefs, and portfolio choices, and by complementing survey-based evidence with a price-based counterfactual analysis.

Finally, the paper relates to a literature that uses information-theoretic methods to estimate asset pricing models. The information-theoretic approach was introduced by Stutzer (1995), Stutzer (1996), Kitamura & Stutzer (1997), and Kitamura et al. (2004). Subsequent studies apply these methods to recover pricing kernels (e.g., Almeida & Garcia (2017), Ghosh et al. (2016), and BoroviČka et al. (2016)), evaluate asset pricing models (e.g., Almeida & Garcia (2012)), and assess fund performance (e.g., Almeida et al. (2020)). In particular, Ghosh & Roussellet (2023) and Ghosh et al. (2024) use a semi-parametric framework to recover subjective beliefs and risk preferences from asset prices. While adopting a similar estimation approach, this paper focuses on how differences in investors' past market experiences shape beliefs and risk preferences.

The structure of the paper is as follows. Section 2 describes the survey data and variable construction. Section 3 presents the main empirical results based on the SCF. Section 4 complements the survey evidence with a price-based counterfactual analysis. Section 5 concludes.

2 Data and Variable Construction

The Survey of Consumer Finances (SCF) is a triennial survey of U.S. households conducted by the Federal Reserve Board. It collects detailed information on household finances and biographical characteristics. Importantly, it also asks participants about their risk appetite and beliefs. The question regarding risk appetite is:

> "Which of the following statements comes closest to describing the amount of financial risk that you are willing to take when you save or make investments?"

Participants choose one of the following options:

1. Take substantial financial risks expecting to earn substantial returns
2. Take above average financial risks expecting to earn above average returns
3. Take average financial risks expecting to earn average returns
4. Not willing to take any financial risks

I construct a risk-tolerance factor variable based on the responses to this question by assigning values 0, 1, 2, and 3 to represent risk-tolerance levels from lowest (answer 4) to highest (answer 1).

The SCF also contains information on household beliefs about the economy. In all survey waves, respondents are asked about their expectations for the economy over the next five years. The question is:

> "Over the next five years, do you expect the economy to perform better, worse, or about the same as now?"

Starting in 2010, the survey additionally asked respondents about their expectations for the next year, using the same wording but referring to "over the next year."

For both questions, participants choose one of the following answers:

1. Better
2. Worse
3. About the same

To focus on my research question, I construct a pessimism dummy for both the one-year and five-year belief measures. The dummy equals 1 if the respondent answers "Worse," and 0 if the answer is "Better" or "About the same."

Table 1 reports summary statistics for the SCF sample from 1989 to 2019. The sample begins in 1989, the first SCF wave that includes both the risk tolerance measure and survey expectations about future market performance. The sample is restricted to households with a head aged 75 or younger. Panel A presents statistics for the full sample, while Panel B focuses on households that participate in the stock market. All dollar variables are expressed in 2019 dollars.

A household's risky share is defined as the percentage of liquid assets invested in the stock market. Liquid assets include all checking accounts, all savings accounts, certificates of deposit, the market value of bond and stock holdings, and the value of all mutual funds. Cash-like liquid assets include checking accounts, savings accounts, and certificates of deposit. A stock market participant is defined as a household with at least $1 of liquid assets invested in the stock market, either through directly held stocks or through mutual funds. Unlike studies that focus on overall household portfolio allocation, this paper does not include defined contribution pension plans or IRAs in liquid assets or stock market investments. The reason is that the analysis here focuses on the channels of risk aversion and beliefs. The SCF provides belief measures only up to a five-year horizon, while pension plans and IRAs are typically associated with much longer investment horizons.

The table also reports a measure of past market downturns experienced by each household. For each month in the historical data, I compute the trailing three-month return on the U.S. market portfolio using data from the Kenneth French Data Library. A month is classified as a downturn if this return falls below the 10th percentile of the postwar return distribution, which corresponds to a three-month return of -4.21%. I estimate this threshold from the postwar sample and then apply it to all households in the SCF. This choice avoids letting extreme prewar episodes, such as the Great Depression, drive the cutoff and make downturn months too rare for the cohorts that account for most of the analysis sample. It also aligns the downturn definition more closely with the market environment faced by the households in the SCF sample.

Table 1: Summary Statistics

	Obs.	10 pct.	Med.	90 pct.	Mean	Stdev.
Panel A. Full Sample (1989-2019, Age $\leq$ 75)						
Income ($ thousands)	49,350	14.4	56.1	165.7	108.3	376.3
Liquid Asset ($ thousands)	49,350	0	4.6	124.7	139.3	1,125.7
Cash-Like Liquid ($ thousands)	49,350	0	3.7	58.9	43.9	241.2
Stock Market Participation	49,350	0	0	1	0.21	0.42
Risky Share (%)	45,550	0	0	66.8	10.7	27.9
Risk Tolerance	49,350	0	1	2	0.87	0.84
1-Year Pessimism	22,576	0	0	1	0.17	0.38
5-Year Pessimism	49,350	0	0	1	0.21	0.43
Bad Experience	49,350	46.0	82.0	128.0	86.5	30.3
Panel B. Stock Market Participants (1989-2019, Age $\leq$ 75)						
Income ($ thousands)	16,701	36.3	105.7	331.1	238.7	721.8
Liquid Asset ($ thousands)	16,701	6.9	65.6	739.1	585.6	2,337.9
Cash-Like Liquid ($ thousands)	16,701	1.8	17.4	174.4	130.4	445.1
Risky Share (%)	16,701	8.5	56.0	94.7	51.4	31.3
Risk Tolerance	16,701	0	1	2	1.29	0.76
1-Year Pessimism	6,489	0	0	1	0.19	0.39
5-Year Pessimism	16,701	0	0	1	0.20	0.42
Bad Experience	16,701	54.0	88.8	129.2	91.1	28.9

Notes: This table reports summary statistics for households in the Survey of Consumer Finances (SCF) from 1989 to 2019 with household head age $\leq$ 75. Monetary variables are expressed in thousands of 2019 dollars. Summary statistics are computed using SCF survey weights. Liquid assets include checking and savings accounts, certificates of deposit, bonds, stocks, and mutual funds. Risky share is the percentage of liquid assets invested in stocks. Bad experience counts the number of months since birth in which the trailing three-month market return falls below the 10th percentile of its historical distribution.

3 Empirical Results

This section examines how households' past stock market experiences affect their financial preferences and investment behavior. Using data from SCF, I first study how exposure to market downturns relates to households' risk tolerance and beliefs. I then examine whether these preference and belief channels help explain households' decisions to participate in the stock market and the share of liquid assets they allocate to risky assets.

Regressions cannot be simply applied to SCF data. The SCF handles missing data and respondent privacy using five imputations with weights (see Rubin (2004)). The five implicates cannot be simply combined into a single dataset, as this would artificially inflate the sample size to five times the true number of observations and lead to overestimation of statistical significance. As discussed in Hanna et al. (2018), proper inference with multiple implicates must account for both within- and between-imputation uncertainty. Using only one implicate preserves the correct sample size but ignores imputation uncertainty, which may also result in overstated significance. Details are provided in Appendix A.

3.1 Experiences, Preferences, and Beliefs

I begin by examining how households' past exposure to stock market downturns relates to their financial preferences and beliefs. In particular, I study whether households that have experienced more downturn months exhibit different levels of risk tolerance and expectations about the market. Because the SCF measures risk tolerance and return expectations as ordered categorical variables, I estimate ordered response models relating these measures to households' past downturn experiences with the following form:

$$Y_{it} = \alpha + \beta_1 BE_{it} + \beta_2 BE_{it}^2 + X_{it}'\gamma + \delta_t + \varepsilon_{it}, \quad (1)$$

where Y_{it} alternatively denotes risk tolerance, one-year pessimism, or five-year pessimism. BE_{it} denotes the bad experience measure described earlier. The vector X_{it} includes household characteristics and income controls, and δ_t denotes survey year fixed effects.

Table 2 reports the results. Column (2) additionally controls for cash-like liquid assets. I focus on a cash-like liquidity measure because broader liquid asset definitions include marketable securities that may themselves reflect households' portfolio decisions. At the same time, even cash-like liquidity may partly reflect households' preferences and beliefs. For this reason, I report specifications both with and without the liquidity control.

Panel A shows that downturn experiences are significantly related to risk tolerance in a non-monotonic way. The coefficient on bad experiences is positive, while the squared term is

Table 2: How Bad Experiences Affect Risk Tolerance and Beliefs

	(1)	(2)
Panel A. Dependent variable: Risk Tolerance		
Bad Experiences	0.207***	0.240***
	(0.077)	(0.078)
Bad Experiences Squared	−0.158***	−0.193***
	(0.056)	(0.058)
Income control	Yes	Yes
Cash-like liquid assets Control	No	Yes
Household characteristics	Yes	Yes
Year fixed effects	Yes	Yes
Panel B. Dependent variable: Pessimism (1-Year)		
Bad Experiences	0.207	0.187
	(0.146)	(0.148)
Bad Experiences^2	−0.312**	−0.290**
	(0.140)	(0.142)
Income control	Yes	Yes
Cash-like liquid assets Control	No	Yes
Household characteristics	Yes	Yes
Year fixed effects	Yes	Yes
Panel C. Dependent variable: Pessimism (5-Year)		
Bad Experiences	0.247***	0.197**
	(0.095)	(0.095)
Bad Experiences^2	−0.379***	−0.334***
	(0.070)	(0.070)
Income control	Yes	Yes
Cash-like liquid assets Control	No	Yes
Household characteristics	Yes	Yes
Year fixed effects	Yes	Yes

Notes: Panel A is estimated using an ordered probit model, while Panels B and C use ordered logit models. Bad experiences measure the number of downturn months experienced since birth. Column (2) additionally controls for cash-like liquid assets. All specifications include income controls, household controls, and year fixed effects. Income controls include log income and its square. Household controls include age, number of children and its square, education, race, gender, marital status, retirement status, disability status, and defined-benefit pension coverage. Continuous variables are standardized to have mean zero and unit standard deviation. Panels A and C use the 1989-2019 SCF waves, while Panel B uses 2010-2019 because the one-year expectation question is only available starting in 2010. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

negative, indicating an inverted-U pattern. Since the experience variables are standardized to have a mean of zero and unit standard deviation, this implies that the probability of reporting a higher level of risk tolerance initially increases as bad experiences rise above the sample mean, but eventually declines at sufficiently high levels of exposure.

Panel B reports results for one-year pessimism. The linear term is not statistically significant, but the squared term is negative and significant. This suggests a weaker non-linear relationship between bad experiences and short-term beliefs. In particular, the probability of reporting a higher level of one-year pessimism first increases and then declines, with the turning point occurring near the sample mean of bad experiences.

Panel C shows a similar but stronger pattern for five-year pessimism. The coefficient on bad experiences is positive and significant, while the squared term is negative and significant. Thus, the probability of reporting a higher level of five-year pessimism initially rises with bad experiences, but falls once exposure becomes sufficiently high. As in Panel A, the turning point lies above the sample mean.

Taken together, these results suggest that moderate exposure to market downturns is associated with a higher probability of reporting greater risk tolerance and stronger pessimism, while very high levels of exposure attenuate these effects. I obtain similar qualitative patterns when restricting the sample to households that participate in the stock market. These patterns indicate that past market experiences shape households' financial preferences and beliefs, which may in turn influence their decisions to participate in the stock market and their allocation to risky assets.

3.2 Stock Market Participation and Portfolio Allocation

I next examine whether the differences in preferences and beliefs documented in the previous section translate into differences in portfolio choices. In particular, I study how bad market experiences relate to households' decisions to participate in the stock market and to their allocation of liquid assets to risky investments.

I begin by analyzing stock market participation of the following form:

$$SP_{it} = \alpha + \beta_1 BE_{it} + \beta_2 BE_{it}^2 + \theta Z_{it} + X_{it}'\gamma + \delta_t + \varepsilon_{it}, \tag{2}$$

where SP_{it} denotes the household's stock market participation indicator, BE_{it} is the bad experience measure defined earlier, and Z_{it} includes variables capturing households' risk tolerance and/or beliefs. The vector X_{it} includes income and household characteristics, and δ_t denotes survey year fixed effects.

Table 3 reports the results. The specifications are organized to show how the relationship

Table 3: How Bad Experiences Affects Stock Participation Through Preferences and Beliefs

	Dependent variable: Stock Participation					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. With cash-like liquid asset control						
Bad Experiences	0.002	−0.113	0.190	0.003	0.053	−0.112
	(0.104)	(0.104)	(0.156)	(0.104)	(0.143)	(0.104)
Bad Experiences^2	0.083	0.167**	0.066	0.080	0.103	0.167**
	(0.083)	(0.084)	(0.188)	(0.082)	(0.150)	(0.084)
Risk Tolerance		0.437***			0.433***	0.437***
		(0.012)			(0.018)	(0.012)
Pessimism (1-Year)			0.066		0.084	
			(0.049)		(0.051)	
Pessimism (5-Year)				−0.043		−0.011
				(0.029)		(0.029)
Income control	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,350	49,350	22,576	49,350	22,576	49,350
Panel B. Without cash-like liquid asset control						
Bad Experiences	−0.158	−0.266***	−0.106	−0.155	−0.218	−0.264***
	(0.099)	(0.099)	(0.140)	(0.099)	(0.141)	(0.099)
Bad Experiences^2	0.224***	0.305***	0.295**	0.219***	0.366**	0.303***
	(0.081)	(0.081)	(0.147)	(0.081)	(0.146)	(0.081)
Risk Tolerance		0.453***			0.447***	0.453***
		(0.012)			(0.018)	(0.012)
Pessimism (1-Year)			0.052		0.076	
			(0.049)		(0.051)	
Pessimism (5-Year)				−0.074**		−0.039
				(0.029)		(0.029)
Income control	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,350	49,350	22,576	49,350	22,576	49,350

Notes: This table reports ordered-logit regressions of stock market participation on bad experiences, risk tolerance, and pessimism. Bad experiences measure the number of downturn months experienced since birth. Panel A additionally controls for cash-like liquid assets, while Panel B excludes this control. All specifications include income controls, household controls, and year fixed effects. Income controls include log household income and its square. Household controls include age, number of children and its square, education, race, gender, marital status, retirement status, disability status, and defined-benefit pension coverage. Continuous variables are standardized to have mean zero and unit standard deviation. Columns including one-year pessimism use the 2010-2019 SCF waves because this question is only available starting in 2010. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

between bad experiences and stock market participation changes as preference and belief variables are introduced.

Panel A reports specifications that control for cash-like liquid assets. Column (1) includes only the bad experience variables and shows little evidence of a significant relationship between bad experiences and stock market participation. Column (2) adds risk tolerance, which enters strongly and significantly. The coefficient on risk tolerance is large and highly significant across specifications, indicating that households with greater risk tolerance are substantially more likely to participate in the stock market. Importantly, its magnitude remains very stable across specifications, suggesting that the effect of risk tolerance is not simply capturing differences in household financial capacity.

Columns (3) and (4) instead introduce belief measures. The pessimism variables are generally not statistically significant, suggesting that beliefs have limited explanatory power for participation decisions relative to risk preferences.

Finally, Columns (5) and (6) include both risk tolerance and belief measures simultaneously. Risk tolerance remains strongly significant, while the belief variables remain weak. Once risk tolerance is controlled for, the squared term of bad experiences becomes significantly positive, suggesting that households with either relatively high or relatively low levels of bad experiences are more likely to participate in the stock market compared to those with average levels of bad experiences. This pattern is consistent with the earlier finding that bad experiences have an inverted U-shaped effect on pessimism, implying that households with either high or low bad experiences tend to be less pessimistic.

Panel B reports the same specifications without controlling for cash-like liquid assets. In this case, the coefficients on bad experiences become more statistically significant, suggesting that part of the relationship between bad experiences and participation may reflect differences in financial liquidity rather than beliefs. In some specifications, pessimism appears significant, but the effect disappears once risk tolerance is included.

Overall, these results indicate that the effect of bad experiences on stock market participation operates primarily through changes in risk tolerance and financial liquidity, while pessimistic beliefs play a limited role.

I next examine the intensive margin of stock market investment among households that already participate in the stock market. Specifically, I study how past downturn experiences relate to the share of liquid assets invested in stocks (risky share) among stock market participants, with the following regression form:

$$RS_{it} = \alpha + \beta_1 BE_{it} + \beta_2 BE_{it}^2 + \theta Z_{it} + X_{it}'\gamma + \delta_t + \varepsilon_{it}, \tag{3}$$

where RS_{it} denotes the share of liquid assets invested in stocks for household i in year t.

BE_{it} is the bad experience measure defined earlier, and Z_{it} includes variables capturing households' risk tolerance and beliefs. The vector X_{it} includes household characteristics and income controls, and δ_t denotes survey year fixed effects. The sample is restricted to households that participate in the stock market.

Table 4 reports the results. Panel A controls for cash-like liquid assets. Column (1) shows that bad experiences are significantly related to the share of liquid assets invested in stocks. The coefficient on bad experiences is positive while the squared term is negative, indicating an inverted-U relationship between past downturn experiences and risky share. This pattern suggests that moderate exposure to downturns is associated with higher equity exposure, while very large exposure eventually reduces households' willingness to hold risky assets.

Combining this direct relationship with the earlier results on risk tolerance and pessimism suggests that the effect of bad experiences on risky share is more closely aligned with the risk tolerance channel than with the belief channel. In particular, households with either relatively high or relatively low levels of bad experiences tend to be both more risk averse and less pessimistic. While lower pessimism would generally predict greater stock market investment, higher risk aversion is associated with lower risky share, consistent with the inverted-U pattern observed here.

Column (2) introduces risk tolerance. Risk tolerance enters strongly and positively, indicating that more risk-tolerant households allocate a larger share of their liquid wealth to stocks. The coefficient remains highly significant and stable across specifications, confirming that risk preferences play a central role in determining risky portfolio allocations.

Columns (3) and (4) instead introduce belief measures. One-year pessimism is not statistically significant, while five-year pessimism enters negatively and significantly, indicating that more pessimistic long-term beliefs are associated with a lower risky share. One possible explanation is that short-term expectations are more sensitive to transitory information and therefore less informative about longer-horizon portfolio decisions.

Columns (5) and (6) include both risk tolerance and belief measures simultaneously. Risk tolerance remains strongly significant, and five-year pessimism remains negative and significant. At the same time, the coefficients on bad experiences become smaller relative to the baseline specification, suggesting that part of the effect of past downturn experiences on risky share operates through changes in households' preferences and beliefs. The remaining direct effect may reflect additional channels not fully captured by the survey measures of risk tolerance and expectations, or measurement error in these variables.

Panel B reports the same specifications without controlling for cash-like liquid assets. The results are qualitatively similar. The inverted-U relationship between bad experiences

Table 4: How Bad Experiences Affect Risky Share Through Preferences and Beliefs

	Dependent variable: Risky Share (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. With cash-like liquid asset control						
Bad Experiences	4.011*	3.286	6.651**	4.047*	5.990*	3.326
	(2.193)	(2.182)	(3.297)	(2.193)	(3.290)	(2.181)
Bad Experiences^2	−4.139**	−3.543**	−4.083	−4.288***	−3.445	−3.689**
	(1.630)	(1.624)	(3.169)	(1.632)	(3.160)	(1.626)
Risk Tolerance		2.382***			2.067***	2.361***
		(0.261)			(0.438)	(0.261)
Pessimism (1-Year)			−0.676		−0.570	
			(0.964)		(0.957)	
Pessimism (5-Year)				−2.285***		−2.168***
				(0.619)		(0.614)
Income control	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,701	16,701	6,489	16,701	6,489	16,701
Panel B. Without cash-like liquid asset control						
Bad Experiences	5.177**	4.514*	6.627*	5.232**	6.025	4.574*
	(2.395)	(2.391)	(3.885)	(2.396)	(3.873)	(2.392)
Bad Experiences^2	−6.861***	−6.329***	−4.210	−7.028***	−3.609	−6.494***
	(1.811)	(1.808)	(3.677)	(1.817)	(3.666)	(1.813)
Risk Tolerance		2.158***			1.833***	2.135***
		(0.301)			(0.500)	(0.302)
Pessimism (1-Year)			−0.771		−0.677	
			(1.106)		(1.099)	
Pessimism (5-Year)				−2.534***		−2.427***
				(0.721)		(0.719)
Income control	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,701	16,701	6,489	16,701	6,489	16,701

Notes: This table reports OLS regressions of risky share on bad experiences, risk tolerance, and pessimism. The sample includes only households that participate in the stock market. Risky share is defined as the percentage of liquid assets invested in stocks. Bad experiences measure the number of downturn months experienced since birth. Panel A additionally controls for cash-like liquid assets, while Panel B excludes this control. All specifications include income controls, household controls, and year fixed effects. Income controls include log household income and its square. Household controls include age, number of children and its square, education, race, gender, marital status, retirement status, disability status, and defined-benefit pension coverage. Continuous variables are standardized to have mean zero and unit standard deviation. Columns including one-year pessimism use the 2010-2019 SCF waves because this question is only available starting in 2010. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

and risky share remains strong, while risk tolerance continues to be a powerful predictor of risky portfolio allocations, and five-year pessimism remains negatively related to risky share.

To quantify the relative importance of different channels, I conduct a regression-based channel decomposition that examines how the marginal effect of bad experiences changes when preference and belief variables are introduced into the regression. Intuitively, this approach measures how much of the reduced-form relationship between bad experiences and risky share is absorbed once a potential channel variable is included in the specification. Because the specification includes a quadratic term in bad experiences, the marginal effect of bad experiences on risky share depends on the level of bad experiences and is given by

$$ME \equiv \frac{\partial RS}{\partial BE} = \beta_1 + 2\beta_2 BE. \tag{4}$$

I evaluate this marginal effect at the sample mean of bad experience, $BE = 0$. Because bad experiences are standardized in the regressions, $BE = 0$ corresponds to the sample mean rather than to the absence of bad experiences. At this value, the marginal effect reduces to β_1.

I then compare the marginal effects across specifications in Table 4. Let $ME^{(1)}$ denote the marginal effect from regression (1), which includes only bad experiences. Let $ME^{(2)}$ denote the marginal effect from regression (2), which additionally includes risk tolerance, $ME^{(4)}$ the marginal effect from regression (4), which additionally includes five-year pessimistic beliefs, and $ME^{(6)}$ the marginal effect from regression (6), which includes both risk tolerance and five-year pessimism.

The contribution of each channel is measured by the extent to which the marginal effect of bad experiences declines once the corresponding channel variable is introduced. Formally, the contribution of the risk-tolerance channel is defined as

$$\text{Risk Tolerance Contribution} = \frac{ME^{(1)} - ME^{(2)}}{ME^{(1)}}, \tag{5}$$

and the contribution of the belief channel is defined as

$$\text{Belief Contribution} = \frac{ME^{(1)} - ME^{(4)}}{ME^{(1)}}. \tag{6}$$

Finally, the joint contribution of the two channels is defined as

$$\text{Joint Contribution} = \frac{ME^{(1)} - ME^{(6)}}{ME^{(1)}}. \tag{7}$$

I focus on five-year pessimistic beliefs rather than one-year pessimistic beliefs because the former is statistically significant in the risky-share regressions. It is therefore more meaningful to assess how much of the bad-experience effect on risky share operates through this belief measure.

Using the estimates in Panel A of Table 4, the baseline marginal effect at $BE = 0$ is 4.011. After introducing risk tolerance, the marginal effect declines to 3.286, implying that approximately 18% of the relationship between bad experiences and risky share is associated with changes in risk tolerance. In contrast, introducing belief measures produces virtually no change in the marginal effect. When both risk tolerance and beliefs are included, the marginal effect declines to 3.326, implying that roughly 17% of the baseline relationship is explained jointly by these variables.

These findings provide insight into the mechanisms through which bad experiences affect household portfolio choices. The results suggest that the impact of bad experiences on risky share operates primarily through changes in risk tolerance, together with a direct effect that is not mediated by the measure of survey belief.

While pessimistic beliefs are themselves associated with lower risky shares, the decomposition indicates that they do not account for a meaningful portion of the relationship between bad experiences and risky shares. This suggests that pessimistic beliefs may be driven more by contemporaneous market conditions or external information than by past bad experiences.

Finally, even after accounting for both risk tolerance and pessimistic beliefs, a substantial fraction of the relationship between bad experiences and risky shares remains unexplained. Several mechanisms may contribute to this residual component. First, survey-based measures may contain measurement error, which could weaken the estimated role of risk tolerance or beliefs in the regressions. Second, the belief measures themselves may not fully capture the dimensions of expectations that are most relevant for portfolio choice. For example, the survey questions focus on expected returns, but households' investment decisions may also reflect perceptions of crash risk or other downside risks that are not directly measured by the survey question. Alternatively, bad experiences may influence portfolio choices through other channels beyond risk tolerance and beliefs that are not directly measured in the survey, such as reduced trust in financial institutions or limited attention to financial markets.

3.3 Household Responses to the 2008 Financial Crisis

The baseline results are obtained from repeated cross-sectional SCF samples and relate households' portfolio choices to cumulative bad experiences over the life cycle. In contrast, the 2007-2009 SCF provides a short panel that follows the same households before and after the 2008 financial crisis. The panel structure allows us to examine within-household changes in beliefs, risk tolerance, and portfolio choices around this episode.

Importantly, the 2008 financial crisis represents a single large market downturn, which differs conceptually from the life-cycle measure of bad experiences used in the baseline analysis. While the baseline measure captures the accumulation of adverse market outcomes over many years, the crisis can be viewed as a new negative shock affecting households simultaneously. Using the panel data, I examine whether households with more adverse prior experiences responded differently to this shock. In particular, whether they exhibited larger changes in beliefs, risk tolerance, or portfolio allocation following the crisis.

Table 5 reports summary statistics for households observed in both the 2007 and 2009 waves of the SCF panel. To ensure comparability over time, the sample is restricted to households with the same household head and respondent in both waves. The panel questionnaire does not include the question on one-year-ahead expectations. Instead, it only reports households' expectations over a five-year horizon. Therefore, this subsection uses the five-year belief measure throughout.

In addition, because the 2009 survey was conducted after the most acute phase of the financial crisis, reported expectations appear somewhat more optimistic than in the 2007 wave. For this reason, rather than constructing a pessimism dummy as in the baseline analysis, I use the original categorical responses to the survey question, where values of 1, 2, and 3 correspond to pessimistic, neutral, and optimistic expectations, respectively.

The table reports weighted means in each year, together with the average change between 2009 and 2007. Panel A includes all households in the panel sample, while Panels B and C focus on subsamples defined by stock market participation. Panel B restricts the sample to households that participated in the stock market in 2007, allowing us to examine exit from the market during the crisis. Panel C further restricts the sample to households that participated in both years, which allows us to study portfolio adjustments among continuing participants.

Several patterns emerge from the table. In the full panel sample, average risk tolerance declines significantly between 2007 and 2009, while reported optimism increases substantially. As noted above, this likely reflects that the 2009 survey captures households' expectations after the most acute phase of the crisis and over a five-year horizon rather than at the peak of the downturn. Income also falls significantly over this period, reflecting the broader economic downturn during the financial crisis. In contrast, average stock market participation increases slightly, and the average risky share among all households remains largely unchanged.

Focusing on households that held stocks in 2007 reveals a different pattern. A substantial fraction of these households exited the stock market by 2009, with participation falling by

Table 5: Summary Statistics for the 2007–2009 Panel

	2007	2009	Change
Panel A. Full Panel Households (N=3,188)			
Stock market participation	0.248	0.265	0.017**
			(0.008)
Risky share (%)	10.93	11.10	0.174
			(0.398)
Risk tolerance	0.955	0.834	−0.121***
			(0.016)
Optimism	1.982	2.354	0.371***
			(0.016)
Income ($ thousands)	119.8	110.7	−9.14***
			(2.05)
Cash-like liquid assets ($ thousands)	40.9	42.0	1.02
			(2.18)
Panel B. Households Participating in the Stock Market in 2007 (N=1,159)			
Stock market participation	1.000	0.720	−0.280***
			(0.013)
Risky share (%)	43.99	30.78	−13.22***
			(1.13)
Risk tolerance	1.323	1.141	−0.182***
			(0.028)
Optimism	2.009	2.358	0.349***
			(0.037)
Income ($ thousands)	231.6	194.7	−36.9***
			(7.00)
Cash-like liquid assets ($ thousands)	95.9	101.7	5.74
			(8.39)
Panel C. Households Participating in the Stock Market in Both 2007 and 2009 (N=913)			
Risky share (%)	44.83	42.77	−2.06*
			(1.19)
Risk tolerance	1.369	1.228	−0.141***
			(0.034)
Optimism	2.002	2.376	0.374***
			(0.041)
Income ($ thousands)	262.8	221.7	−41.2***
			(8.72)
Cash-like liquid assets ($ thousands)	111.1	120.8	9.74
			(11.0)

Notes: This table reports weighted means for households observed in both the 2007 and 2009 waves of the panel Survey of Consumer Finances. The sample is restricted to households whose head is age 75 or younger in 2009. The last column reports the weighted mean change between 2009 and 2007, with standard errors in parentheses. Panel A includes all households in the analysis sample. Panel B includes households that participate in the stock market in 2007. Panel C includes households that participate in the stock market in both 2007 and 2009. Risky share is measured as the percentage of liquid financial assets invested in risky assets. Monetary variables are expressed in thousands of 2019 dollars. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

28 percentage points. Among these households, the average risky share declines sharply, indicating a large reduction in exposure to risky assets during the crisis and its aftermath. Risk tolerance also declines significantly, while reported optimism about future stock returns increases on average.

Among households that remained in the stock market in both years, the adjustment in risky share is more moderate but still significantly negative. Risk tolerance again declines significantly, while reported optimism about future stock returns increases.

The three panels reveal several patterns in households' responses to the crisis. First, across both the full sample and the subsamples, households exhibit a significant decline in risk tolerance between 2007 and 2009, indicating a broad shift toward more conservative risk attitudes following the market downturn. Second, households that participated in the stock market in 2007 either reduced their exposure to risky assets or exited the market altogether by 2009. At the same time, Panel A shows that stock market participation in the full panel sample increases slightly between 2007 and 2009. This suggests that while many existing participants reduced risk or exited the market, a nontrivial number of households that were not participating in 2007 entered the stock market by 2009. Overall, these patterns point to substantial heterogeneity in household responses to the crisis, with both exit and entry occurring alongside adjustments in portfolio allocation and risk attitudes.

Table 6 examines whether households with different lifetime bad experiences responded differently to the financial crisis. Following the baseline analysis, I first examine whether bad experiences predict risk tolerance, beliefs, and stock market participation. In each regression, the dependent variable is measured in 2009, while the corresponding baseline value measured in 2007 is included as a control. This specification allows us to capture how prior bad experiences relate to changes in preferences, beliefs, and participation during the crisis period.

Panel A reports results for risk tolerance and beliefs using the full panel sample. Columns (1)-(2) show that bad experiences are positively associated with risk tolerance in 2009, although the quadratic term is not statistically significant. The coefficient on baseline risk tolerance is positive and highly significant, indicating strong persistence in households' risk attitudes. Conditional on baseline risk tolerance, households with more lifetime bad experiences exhibit a larger increase (or smaller decline) in risk tolerance following the crisis. In contrast, columns (3)-(4) show no significant relationship between bad experiences and optimism about future stock market returns.

Panel B examines stock market participation in 2009 among households that participated in the market in 2007. Columns (5)–(6) show that bad experiences do not significantly predict whether households remain in the stock market during the crisis. Columns (7)–(8) addition-

Table 6: Bad Experiences and Crisis-Period Preferences and Participation

	RT 2009		OPT 2009		SP 2009			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Risk Preferences and Beliefs (Full Sample)								
Bad Experiences	0.189***	0.183***	−0.028	−0.020				
	(0.065)	(0.065)	(0.082)	(0.083)				
Bad Experiences^2	−0.036	−0.031	0.071	0.064				
	(0.065)	(0.066)	(0.073)	(0.073)				
Baseline Value	0.318***	0.320***	0.223***	0.222***				
	(0.017)	(0.017)	(0.013)	(0.013)				
Panel B. Stock Participation (Households in the Stock Market in 2007)								
Bad Experiences					−0.006	−0.001	−0.027	−0.023
					(0.098)	(0.097)	(0.101)	(0.100)
Bad Experiences^2					0.086	0.090	0.102	0.108
					(0.095)	(0.095)	(0.095)	(0.095)
Risk Tolerance 2007							0.041*	0.041*
							(0.022)	(0.022)
Optimism 2007							−0.012	−0.015
							(0.025)	(0.025)
Income control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cash-like liquid assets control	Yes	No	Yes	No	Yes	No	Yes	No
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,188	3,188	3,188	3,188	1,159	1,159	1,159	1,159

Notes: This table reports regressions of 2009 household outcomes on prior bad experiences measured in 2007. RT 2009 denotes 2009 risk tolerance, OPT 2009 denotes 2009 optimism, and SP 2009 denotes 2009 stock market participation. Bad Experience is measured by the number of downturn months experienced since birth until 2007. Baseline value is the value of the corresponding dependent variable in 2007. Income controls include log household income and its square. Household controls include age, number of children and its square, education, race, gender, marital status, retirement status, disability status, and defined-benefit pension coverage in 2007. Continuous variables are standardized to have a mean of zero and unit standard deviation. Standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

ally control for baseline risk tolerance and optimism, and the results remain qualitatively similar.

Overall, these results suggest that while lifetime bad experiences are associated with changes in risk tolerance during the crisis, they do not directly predict stock market participation decisions over this period.

Table 7: Bad Experiences and Crisis-Period Risky Portfolio Shares

	Dependent variable: Risky Share (%)			
	(1)	(2)	(3)	(4)
Bad Experiences	−5.333	−4.783	−7.434	−6.996
	(7.000)	(6.922)	(6.814)	(6.746)
Bad Experiences^2	7.875	8.275	9.679*	10.142*
	(5.397)	(5.417)	(5.410)	(5.452)
Risky Share (%) 2007	0.328***	0.320***	0.327***	0.319***
	(0.041)	(0.036)	(0.041)	(0.036)
Risk Tolerance 2007			2.698*	2.734*
			(1.464)	(1.463)
Optimism 2007			−2.460*	−2.650*
			(1.442)	(1.451)
Income control	Yes	Yes	Yes	Yes
Cash-like liquid assets	Yes	No	Yes	No
Household characteristics	Yes	Yes	Yes	Yes
Observations	1,159	1,159	1,159	1,159

Notes: This table reports regressions of 2009 risky portfolio shares on prior bad experiences measured in 2007 for households participating in the stock market in 2007. Income controls include log household income and its square. Household controls include age, number of children and its square, education, race, gender, marital status, retirement status, disability status, and defined-benefit pension coverage in 2007. Continuous variables are standardized to have a mean of zero and unit standard deviation. Standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7 examines whether lifetime bad experiences predict changes in households' risky portfolio shares during the crisis period. The sample is restricted to households that participated in the stock market in 2007, and the dependent variable is the risky share of liquid financial assets invested in risky assets in 2009. As in the previous specifications, the regressions control for the corresponding baseline outcome measured in 2007.

Columns (1)–(2) show that bad experiences do not significantly predict risky portfolio shares in 2009. The coefficient on baseline risky share is positive and highly significant, indicating substantial persistence in households' portfolio allocations. Columns (3)–(4) additionally control for baseline risk tolerance and optimism. Higher pre-crisis risk tolerance predicts larger risky portfolio shares in 2009. In contrast, optimism in 2007 is negatively associated with risky exposure in 2009. In other words, households with higher pre-crisis risk tolerance tend to hold larger risky shares after the crisis, whereas households reporting more optimistic expectations prior to the crisis tend to hold smaller risky shares in 2009. At the same time, the squared term of bad experiences remains positive and significant. This result suggests that, conditional on pre-crisis risk tolerance, beliefs, and baseline risky share in 2007, households with either relatively high or relatively low levels of early-life bad experiences tend to increase their stock market investment following the 2008 crisis.

In summary, these results suggest that lifetime bad experiences significantly predict changes in risk tolerance between the pre- and post-crisis periods, but do not directly predict changes in optimism, stock market participation, or risky portfolio shares.

4 Counterfactual Analysis

The baseline results show that bad experiences are associated with systematic changes in households' risk appetites. In particular, risk tolerance initially increases with the number of bad experiences but declines once bad experiences become sufficiently severe. At the same time, risk tolerance is strongly associated with the probability of stock market participation. These patterns imply that households with a substantial level of bad experiences are more likely to exit the stock market, while those who remain invested may be relatively more risk-tolerant.

Motivated by this selection, this section focuses on the beliefs and risk preferences reflected in market prices, which primarily incorporate the preferences of investors who remain active in the stock market. In addition, the survey-based measures used in the baseline analysis may contain measurement error. Survey questions typically rely on discrete response categories and may therefore introduce imprecision. Moreover, households may find it difficult to clearly distinguish between their risk appetite and beliefs about future returns. Empirical evidence (e.g., Charles et al. (2024)) also documents a relatively weak transmission from reported beliefs to actual investment behavior. Another limitation is that the survey questions only elicit coarse categories of beliefs (e.g., optimistic, neutral, or pessimistic) rather than the full distribution of expected returns.

For these reasons, this section complements the survey-based evidence by turning to market prices. Specifically, I conduct a counterfactual analysis to examine how bad experiences affect investors' price-implied beliefs and risk aversion.

4.1 Framework and Investor Types

This section outlines the general framework used to assess the influence of personal experiences on financial decisions. To assess the impact of personal experiences on risk-taking behaviors, I classify investors into two distinct categories: (1) the "Type Normal" investor, and (2) the "Type Lucky" investor (hereafter referred to as the "Normal" and "Lucky" investor). The Normal investor has experienced the complete history of the stock market in the sample. In contrast, the Lucky investor has not experienced certain market downturns. While this investor acknowledges the presence of market downturns, the severity is often underestimated due to a lack of direct experience. To model the Lucky investor's experience, I adjust the market returns during market crashes to a less severe value. In the baseline scenario, the Lucky investor is shielded from the lowest 10th percentile of quarterly market returns, specifically quarterly returns below -7.48% (annualized -29.92%). Such returns in the sample are replaced with the threshold itself[1]. For additional robustness, Section 4.3 presents results derived from alternative threshold values.

The framework is initiated with the no-arbitrage assumption. For investor type $k \in \{\text{Normal, Lucky}\}$, it is posited that the conditional Euler equation is satisfied and given by:

$$\mathbb{E}^{P^{(k)}}\left[M_{t+1}^{(k)}\mathbf{R}_{t+1}^{(k)}|\mathcal{F}_t^{(k)}\right] = \mathbf{1}_n, \tag{8}$$

where $M_{t+1}^{(k)}$ summarizes the SDF of type-k investor, $\mathbf{R}_{t+1}^{(k)} \in \mathbb{R}^n$ is the vector of gross returns of the n traded assets in the sample of type-k, and $\mathcal{F}_t^{(k)}$ denotes type-k investor's information set at time t. Note that the Euler equation satisfies under investors' subjective beliefs $P^{(k)}$, which could be distorted from the objective measure.

The investor's risk preferences are reflected in the SDF, and I assume the SDF is exponentially affine in the investor's wealth portfolio return: $\forall k \in \{\text{Normal, Lucky}\}$

$$M_{t+1}^{(k)} = \beta^{(k)} e^{-\theta^{(k)} \log\left(R_{t+1}^{W,(k)}\right)}, \tag{9}$$

where $\theta^{(k)}$ is the relative risk aversion coefficient (CRRA) of the type-k investor. Investors are assumed to allocate their wealth between the market portfolio and a risk-free asset, without shorting:

$$R_{t+1}^{W,(k)} = w^{(k)} R_{t+1}^{m,(k)} + \left(1 - w^{(k)}\right) R_{t+1}^{f}, \tag{10}$$

[1]The adjusted quarters include: 1948:Q3, 1957:Q3, 1962:Q2, 1966:Q3, 1970:Q2, 1973:Q1, 1973:Q2, 1973:Q4, 1974:Q2, 1974:Q3, 1975:Q3, 1981:Q3, 1982:Q1, 1986:Q2, 1987:Q4, 1990:Q3, 1998:Q3, 2000:Q4, 2001:Q1, 2001:Q3, 2002:Q2, 2002:Q3, 2008:Q1, 2008:Q3, 2008:Q4, 2009:Q1, 2010:Q2, 2011:Q3, 2015:Q3, and 2018:Q4.

where $0 < w^{(k)} < 1$. Given the diversity of experiences, it is reasonable to assume that the Normal and Lucky investors may possess different subjective beliefs $P^{(k)}$ and SDFs $M_{t+1}^{(k)}$. Since the Lucky investor has distorted memory, her information set $\mathcal{F}_t^{(k)}$ also differs from that of the Normal investor.

In order to disentangle the effect of risk preferences and beliefs, I estimate $P^{(k)}$ and $\theta^{(k)}$ simultaneously with the maximized smoothed empirical likelihood (SEL) approach as described in Kitamura et al. (2004). Denote $X_t^{(k)} \in \mathbb{R}^m$ as a random variable that describes the economic state that type-k investor perceived at time t with m selected variables. Assume the subjective beliefs $P^{(k)}$ has a $T \times T$ matrix form, where T is the length of the sample. $p_{i,j}^{(k)}$ is the element of matrix $P^{(k)}$ at row i and column j, and it can be formally written as: $\forall i, j = 1, \ldots T$,

$$p_{i,j}^{(k)} = Prob\left\{X_{t+1}^{(k)} = x_j^{(k)} | X_t^{(k)} = x_i^{(k)}\right\}. \tag{11}$$

A kernel weight $\omega_{i,j}^{(k)}$ is assigned to each entry $p_{i,j}^{(k)}$ for smoothing the objective function in a conditional setting. It is a measure of the distance between two states, thus an estimate of the objective data-generating process. In particular, $\forall i, j = 1, \ldots T$,

$$\omega_{i,j}^{(k)} = \frac{\mathcal{K}\left(\frac{x_i^{(k)} - x_j^{(k)}}{b_T}\right)}{\sum_{l=1}^{T} \mathcal{K}\left(\frac{x_i^{(k)} - x_l^{(k)}}{b_T}\right)}, \tag{12}$$

where $\mathcal{K}(\cdot)$ is a symmetric positive kernel function and b_T is a chosen bandwidth parameter. As a result, for each current state, ω assigns a weight to any possible state for the next period based on their distance from the current state. A future state with greater similarity to the current state receives a higher weight. States that are far outside the neighborhood of the current state receive a weight of zero. The size of the neighborhood depends on the bandwidth b_T.

The estimation of $\theta^{(k)}$ and $p_{i,j}^{(k)}$ is to maximize the following smoothed empirical likelihood:

$$\max_{\theta^{(k)}, \left\{p_{i,j}^{(k)}\right\}_{i,j=1}^{T}} \sum_{i=1}^{T} \sum_{j=1}^{T} \omega_{i,j}^{(k)} \log\left(\frac{p_{i,j}^{(k)}}{\omega_{i,j}^{(k)}}\right), \tag{13}$$

subject to: $\forall i = 1, \ldots T$

$$\begin{cases} \sum_{j=1}^{T} p_{i,j}^{(k)} M_j^{(k)} \mathbf{R}_j^{(k)} = \mathbf{1} \\ \sum_{j=1}^{T} p_{i,j}^{(k)} = 1 \\ 0 \leq p_{i,j}^{(k)} \leq 1 \end{cases} \tag{14}$$

The subjective beliefs $p_{i,j}^{(k)}$ can be solved as a function of $\theta^{(k)}$: $\forall i, j = 1, \dots T$

$$\hat{p}_{i,j}^{(k)}\left(\theta^{(k)}\right) = \frac{\omega_{i,j}^{(k)}}{1 + \hat{\boldsymbol{\lambda}}_i^{(k)\prime}\left(M_j^{(k)}\mathbf{R}_j^{(k)} - \mathbf{1}\right)}. \tag{15}$$

With the solution of the subjective probabilities above, the risk preference parameter $\theta^{(k)}$ is defined as the value that maximize the SEL (13):

$$\hat{\theta}^{(k)} = \arg\max_{\theta^{(k)}} \sum_{i=1}^{T}\sum_{j=1}^{T} \omega_{i,j}^{(k)} \log\left(\frac{p_{i,j}^{(k)}}{\omega_{i,j}^{(k)}}\right). \tag{16}$$

The SEL estimation requires the following inputs: (1) time series of the test assets, (2) information variables, and (3) investors' wealth portfolios. In the baseline scenario in this counterfactual analysis, the test assets consist of the quarterly gross returns of both the market portfolio and the risk-free asset spanning from 1947:Q1 to 2019:Q4. The information variables contain the exponentially weighted moving averages of historical excess market returns, while the wealth portfolio is a composite of the market and risk-free assets. Market returns are sourced from the Kenneth French library, with risk-free returns derived from the 90-day T-bills dataset from CRSP.

Table 8: Sample Statistics $1947:Q1 - 2019:Q4$

	Normal	Lucky
Real Market returns		
Mean	8.69%	10.95%
Min	−108.41%	−41.62%
1st qtl.	−8.84%	−8.84%
Median	11.46%	11.46%
3rd qtl.	27.96%	27.96%
Max	91.62%	91.62%
Std. dev	16.13%	13.79%

Notes: The sample covers from 1947:Q1 to 2019:Q4. The Normal investor possesses accurate information throughout the sample period. For the Lucky investor, the cutoff threshold of the nominal annualized market return is −29.92%. All returns are annualized real returns.

Table 8 presents the sample statistics of the annualized market returns observed by the two investor types. The Lucky investor is characterized as one who has never encountered the lowest 10th percentile of quarterly market returns throughout the sample period. Consequently, annualized nominal market returns below −29.92% are substituted with −29.92%. This adjustment leads to a higher average experienced annualized market return of 10.95%

for the Lucky investor, compared to 8.69% for the Normal investor. For the Normal investor, the minimum experienced market return is −108.41%, whereas it stands at −41.62% for the Lucky investor. Since the Lucky investor's experience is modified only for the lowest 10th percentile, the first quartile, median, third quartile, and maximum remain identical to those of the Normal investor. Furthermore, the Lucky investor experiences a lower standard deviation of market returns.

4.2 Counterfactual Results

4.2.1 Impact of Downturn Experiences on Preferences and Beliefs

This subsection presents the main results of the counterfactual analysis. Specifically, I compare the recovered risk preferences and price-consistent beliefs of the Normal and Lucky investors. By contrasting these two types of investors, I assess how the absence of exposure to bad states affects the risk aversion and beliefs implied by market prices.

Table 9 presents the SEL estimations for the risk aversion coefficient, denoted as θ. Within this context, both agents allocate a predetermined portion of their wealth between the market portfolio and the risk-free asset. Panel A provides results for risky shares at 10%, 30%, 50%, 70%, and 90%. As observed, both types of investors display diminishing risk aversion as they commit more of their wealth to the stock market, which is consistent with investors' behaviors from well-known portfolio choice frameworks, for instance, the mean-variance portfolio theory. At any given level of risky share, the Lucky investor consistently demonstrates a greater degree of risk aversion. In essence, the Lucky investor is comparatively more risk-averse when she dedicates an equivalent wealth proportion to the stock market as the Normal investor.

Panel B outlines estimations for risky shares based on regression coefficients from Malmendier & Nagel (2011). They use the following regression model:

$$y_{it} = \alpha + \beta A_{it}(\lambda) + \gamma' x_{it} + \epsilon_{it}, \tag{17}$$

where y_{it} stands for the fraction of liquid assets invested in stocks, $A_{it}(\lambda)$ is the experienced stock return that depends on λ, a parameter that controls the shape for the weighting function. A positive λ implies that recent returns receive a higher weight than past returns. x_{it} are the control variables including household characteristics. Using the Survey of Consumer Finances panel data, they estimate β at 1.668 and λ at 1.166. I assume that Normal investors allocate risk in the same manner as the average participants from this survey (47%). The experienced stock returns (A_{it}) of Normal and Lucky investors are 9.70% and 11.69%,

Table 9: Estimated Risk Preferences Coefficients with Different Risky Share Levels

	NORMAL		LUCKY	
	θ	β	θ	β
Panel A: Fixed risky shares				
$w = 10\%$	32.4	1.10	52.8	1.19
	(0.770)	(0.002)	(1.675)	(0.005)
$w = 30\%$	10.2	1.05	20.0	1.12
	(0.122)	(0.002)	(0.830)	(0.003)
$w = 50\%$	6.3	1.04	11.4	1.09
	(0.092)	(0.001)	(0.089)	(0.002)
$w = 70\%$	4.2	1.03	8.1	1.08
	(0.061)	(0.001)	(0.048)	(0.002)
$w = 90\%$	3.5	1.03	6.6	1.08
	(0.047)	(0.001)	(0.036)	(0.001)
Panel B: MN2011-implied risky shares				
w	47%		50%	
	6.6	1.04	11.4	1.09
	(0.068)	(0.001)	(0.089)	(0.002)

Notes: The sample covers from 1947:Q1 to 2019:Q4. The Normal investor possesses accurate information throughout the sample period. For the Lucky investor, the cutoff threshold is -29.92%. The test assets consist of the quarterly gross market returns and the gross risk-free returns. The information variable is the exponentially-weighted average of the excess market returns. The weight for computing exponentially-weighted moving average is 0.28. Values in the parentheses are the bootstrapped standard errors of the risk preference coefficients. Panel A adopts fixed risky share levels for both investor types. Panel B uses the regression coefficients ($\lambda = 1.166, \beta = 1.668$) from Malmendier & Nagel (2011) to compute the risky shares.

respectively. Therefore, the regression in Equation (17) implies that Lucky investors, sharing the same characteristics (x_{it}) except for stock return experience, allocate risk at 50%. Note that the risky-share measure used here follows the definition in Malmendier & Nagel (2011), since the regression estimates employed in this counterfactual exercise are taken from their specification. In the baseline survey analysis, I instead exclude defined-contribution retirement accounts because the beliefs questions refer to relatively short horizons. With this risk allocation input, the SEL-estimated risk aversion coefficient stands at 6.6 for the Normal investor and 11.4 for the Lucky investor. This suggests that individuals who have been shielded from more adverse market events tend to be more risk-averse. A plausible reason for this somewhat surprising outcome might be that the most risk-averse investors, after enduring stock market downturns, are no longer the marginal investors of the market - either having exited the market or having committed such a minimal investment as to minimally impact market prices. The remaining stock market participants are the ones who have higher risk tolerance. This is described by the phrase 'what doesn't kill you only makes you more risk-loving' by Bernile et al. (2017).

In addition to the coefficients of risk preference, SEL also recovers the subjective beliefs held by both investor types. Figure 1 plots the time series of the annualized moments of the market returns, as perceived by the Normal (solid black lines) and Lucky (red-dashed lines) investor types. The dotted blue lines describe the conditional moments under the objective measure given by the kernel density matrix ω in Equation (12).

Panel A depicts the conditional mean of these subjectively forecasted market returns. Notably, the Lucky investor consistently anticipates superior market returns, with average expected returns standing at 8.7% for the Normal investor compared to 10.7% for the Lucky investor. Interestingly, economic downturns tend to narrow the gap in subjective beliefs between the two, as evidenced by a correlation of -9.4% between their differences and a recession indicator. However, compared to the average market returns under objective measures, the Normal investor generally does not show strong pessimism.

Panel B highlights the conditional volatility linked to subjective beliefs about market returns. The Normal type persistently expects a higher market return volatility, averaging 15.3%, in contrast to the Lucky investor's more optimistic estimate of 13.5%. This disparity in volatility predictions becomes even more pronounced during economic recessions, underlined by a 33.3% correlation with the recession indicator. Compared with the objective measure, both investors expect lower volatility in the stock market during economic recessions.

Turning to Panel C, it underscores the conditional skewness of the beliefs. The Normal investor typically exhibits a negative skewness, averaging -0.48. Conversely, the Lucky investor leans towards a positive skewness, with an average of 0.19. This suggests that while the Normal investor is more inclined to assign higher probabilities to unfavorable outcomes, the Lucky type tends to be more optimistic, focusing on the positive scenarios. Compared to the objective measure, the Normal investor's conditional skewness is similar. However, during economic recessions, the Normal investor shows a less negative conditional skewness than the objective measure.

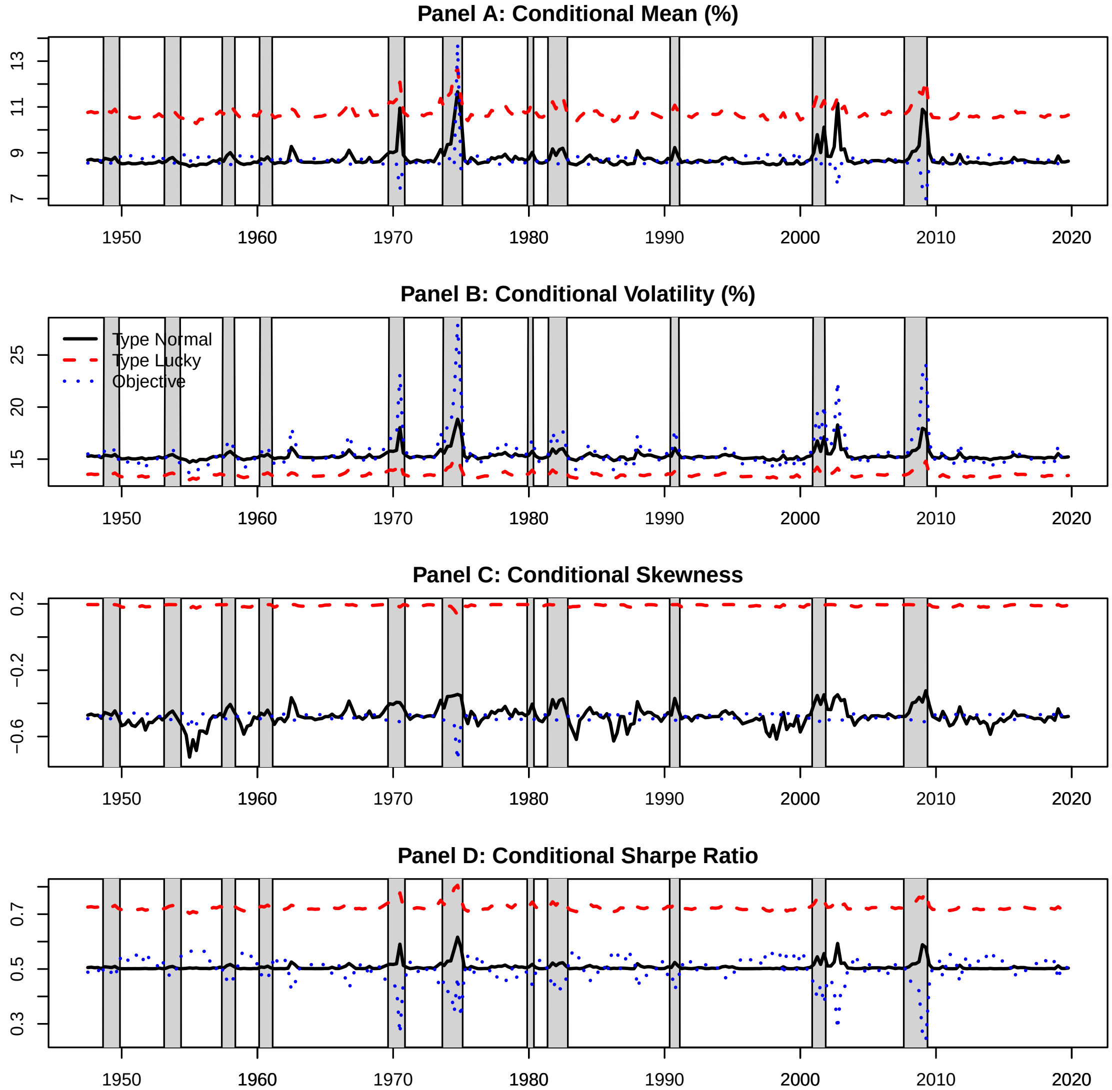
Panel D elaborates on the conditional Sharpe ratio. Owing to a greater conditional mean coupled with diminished conditional volatility, the Lucky investor invariably forecasts a more favorable conditional Sharpe ratio than the Normal investor. Specifically, their average conditional Sharpe ratios are 0.72 and 0.50, respectively.

In summary, experiencing economic downturns often makes investors more pessimistic about future market returns. They expect lower mean returns, higher volatility, and more negative skewness. While the Normal investor is more pessimistic than the Lucky investor, she is not more pessimistic compared to the objective measure.

Figure 2 plots the conditional distributions of the annualized market returns, as perceived by the Normal (solid black lines) and Lucky (red-dashed lines) investor types, in two very different states of the world. The left panels depict the densities following quarters characterized by high market returns. Specifically, the top-left panel represents beliefs in 1975:Q2, a period marked by recovery from a two-year recession, where the preceding quarter had an impressive market return of 24.8%. The middle panel focuses on the start of 1999, a high point after a long stretch of good economic times in the 1990s, with the market going up by almost 22% just before then. Meanwhile, the bottom-left panel mirrors the scenario in 1983:Q1, during the recovery of the early 1980s recession, when the market return of the preceding quarter reached 19.3%. Across these three left panels, a consistent pattern emerges: in these positive economic conditions, the Lucky investor's density is almost indistinguishable from that of the Normal investor towards the right tail. However, she assigns lower probabilities to extreme negative outcomes, skewing her beliefs more towards annualized real returns ranging from -50% to -10%. This implies that the Lucky investor does not merely allocate the probabilities supposedly for market crash states to the truncation threshold state. Instead, she exhibits a slight optimism by allocating the additional probabilities to less severe states. Additionally, the Normal investor's density is almost identical to the objective in good economic states.

The right panels depict densities following a significant market downturn. The top-right panel reveals belief densities for 1974:Q4, situated at the trough of the 1973-1974 stock market crash, recording a stark quarterly market return of -24.7%. The middle-right panel reflects the worst period of the 2007-2008 financial crisis, with the preceding

Figure 1: Subjective Beliefs About Market Returns



Notes: The figure plots the time series of the conditional moments computed by the SEL estimated probabilities (subjective beliefs) of the market returns. The black solid lines describe the beliefs of the Normal investor, the red dashed lines correspond to the Lucky investor, and the blue dotted lines are the conditional moments associated with the objective distribution. The grey-shaded areas are the NBER recession periods. The sample period covers from 1947:Q1 to 2019:Q4. The Lucky type of investor has never experienced the lowest 10 percentile of the market returns (-29.92%). The test assets consist of the gross market portfolio and the risk-free asset. The information variables are the exponentially weighted moving average of the past market returns in excess of the risk-free returns. The pricing kernel is exponentially affine to the wealth portfolio. The wealth portfolio of both investors is assumed to be a combination of the market portfolio and a risk-free asset. This figure assumes that the percentage invested in the market portfolio is implied by the Malmendier & Nagel (2011) regression coefficients. In particular, the Normal (Lucky) investor allocates 47% (50%) of her wealth in the stock market.

quarter experiencing a return of -22.3%. Meanwhile, the bottom-right panel illuminates the period succeeding the "Black Monday" stock market crash on October 19, 1987, when the market plunged by 23.2%. Observations from the right panels suggest that, in adverse states, the Lucky investor assigns diminished weights to both extremities compared to the Normal type. This trend appears less pronounced in the bottom-right panel, likely due to the unpredictability of the "Black Monday" crash. Compared to the objective measure, both investors give less weight to extreme events.

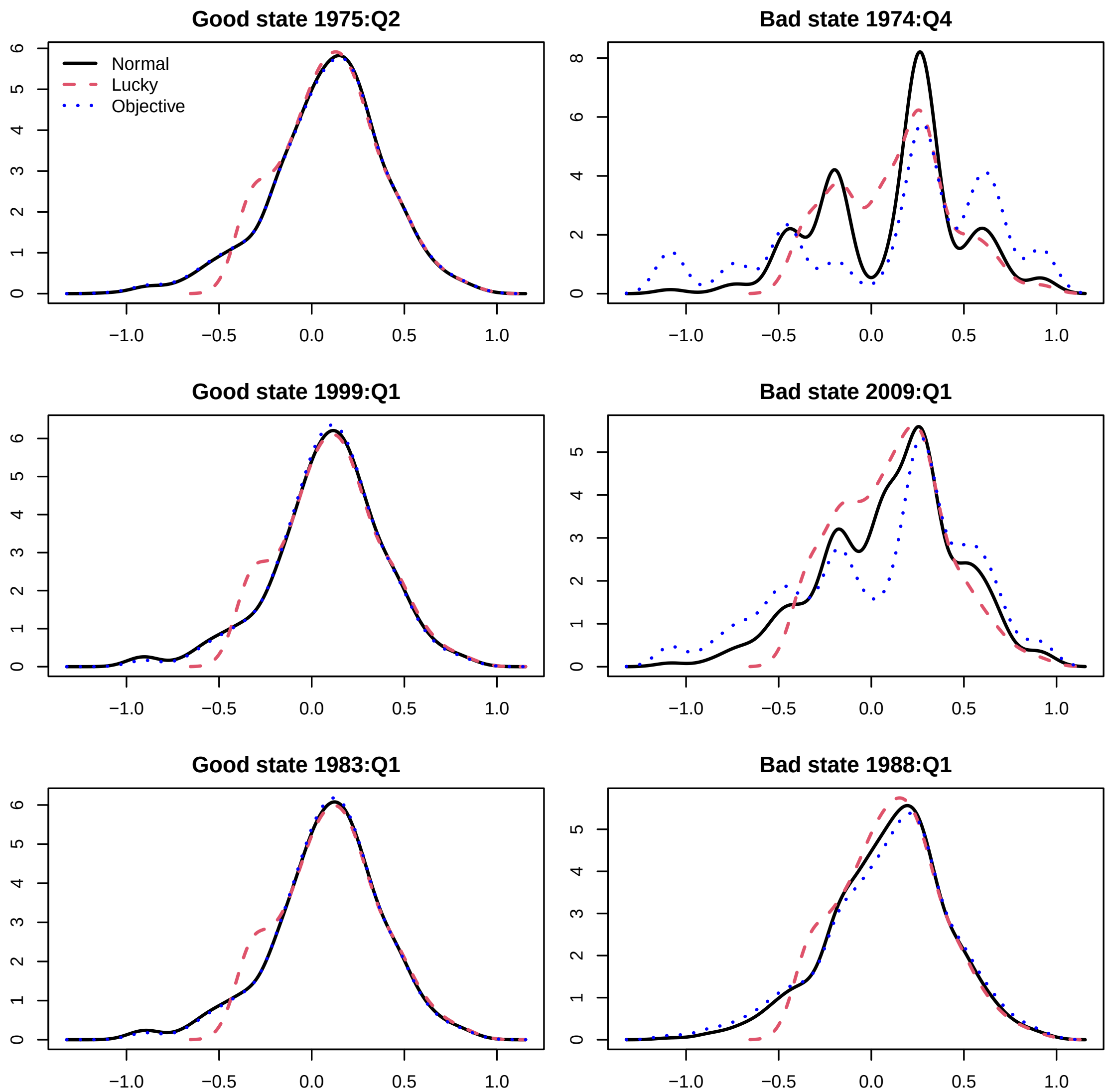
4.2.2 Extreme Events or Overall Lower Returns?

The Normal investor consistently displays both reduced risk aversion and expected market returns when compared to the Lucky investor. This divergence might stem from the former's adverse experiences, or it could be a consequence of persistently lower market returns observed throughout her investment history. To clarify this, I modify the market returns for the Lucky investor so that the average market returns in her dataset align with that of the Normal investor while keeping the standard deviation unchanged.

Table 10 offers a comparison of risk aversion estimations for both pre and post-adjustments. Upon reducing the market returns in the Lucky investor's dataset, the time-weighted experienced market returns (as defined in Malmendier & Nagel (2011)) diminish as well. Consequently, her proportion of risky shares decreases from 50% to 46%, which is almost identical to that of the Normal investor's 47%. Nevertheless, even at this similar level of risky share, the Lucky investor maintains a higher degree of risk aversion. This highlights the conclusion that the Normal investor's willingness to take on risk is more a result of having weathered extreme market downturns in the past instead of just having a consistently mild experience with market returns.

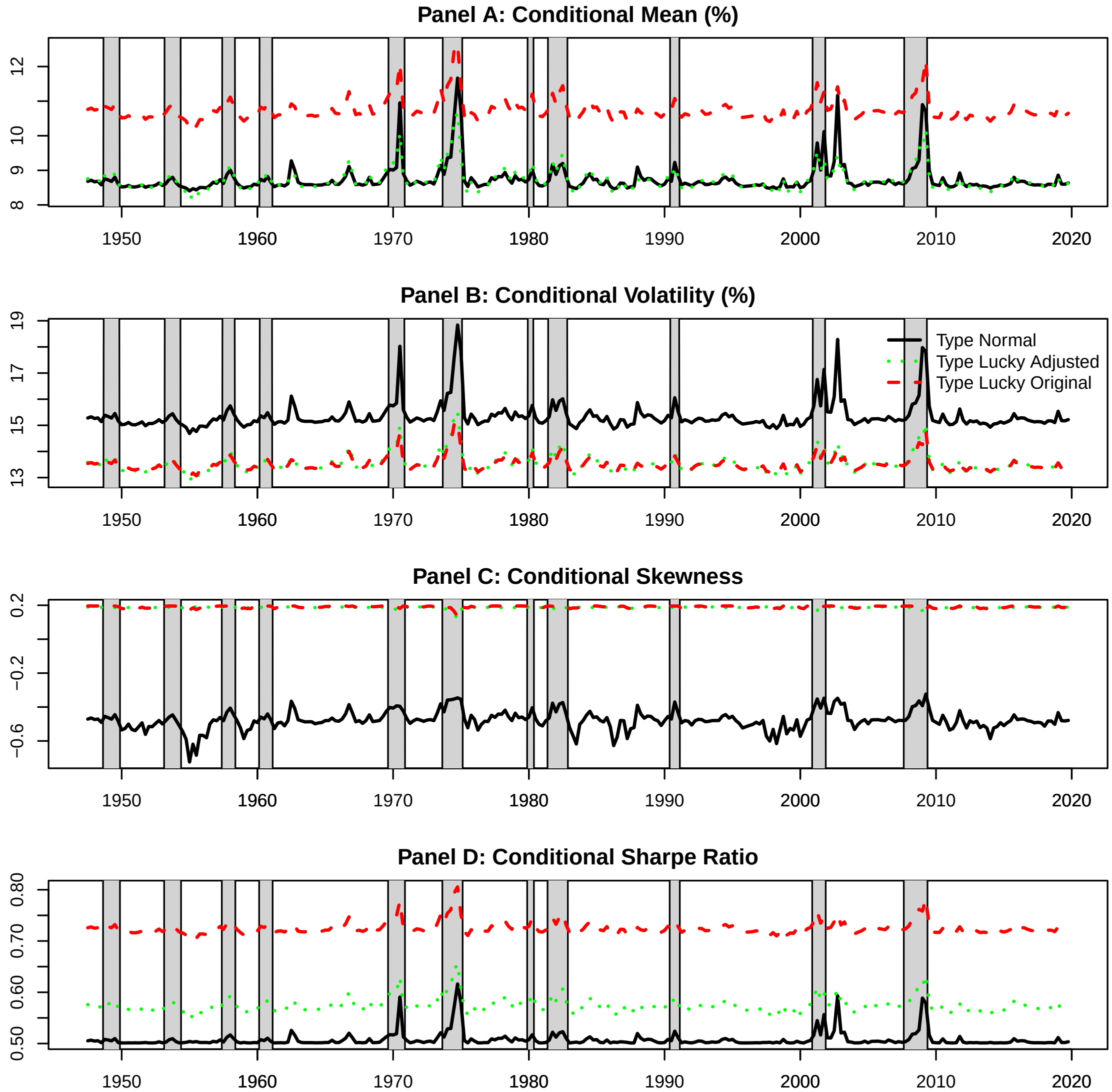
In Figure 3, I examine the beliefs of both the Normal and adjusted Lucky investors. The beliefs of the Normal investor are denoted by black solid lines, while green dotted lines represent the beliefs of the Lucky investor after adjusting her market returns to match the mean of the Normal investor. The original beliefs of the Lucky investor are shown with red dashed lines for reference. Notably, the conditional volatility and skewness for the Lucky investor remain consistent. The primary divergence appears in Panel A, where the gap in the conditional mean between the Normal and Lucky investors narrows considerably. Their beliefs align closely during economic expansions. Yet, during downturns, the Normal investor expects higher returns. This suggests that generally lower experienced returns induce pessimism throughout both economic growth and decline, while economic disasters lead investors to require higher returns during bad times.

Figure 2: Density Plots of the Subjective Beliefs about Annualized Real Market Returns in Bull and Bear Markets



Notes: The figure plots the density of the SEL estimated probabilities (subjective beliefs) of the market returns in good and bad market states. The black solid lines describe the beliefs of the Normal investor, the red dashed lines correspond to the Lucky investor, and the blue dotted lines are the objective densities. The sample period covers from 1947:Q1 to 2019:Q4. The Lucky type of investor has never experienced the lowest 10 percentile of the market returns (-29.92%). The test assets consist of the gross market portfolio and the risk-free asset. The information variables are the exponentially weighted moving average of the past market returns in excess of the risk-free returns. The pricing kernel is exponentially affine to the wealth portfolio. The wealth portfolio of both investors is assumed to be a combination of the market portfolio and a risk-free asset. This figure assumes that the percentage invested in the market portfolio is implied by the Malmendier & Nagel (2011) regression coefficients. In particular, the Normal (Lucky) investor allocates 47% (50%) of her wealth in the stock market. The left panels are the density plots of the beliefs right after economic boosts with quarterly returns at around 20%. The right panels show density plots of the beliefs right after economic disasters with more than 20% drop in market returns.

Figure 3: Beliefs About Market Returns for Normal and Lucky Investor with Adjusted Market Returns



Notes: The figure plots the time series of the conditional moments computed by the SEL estimated probabilities (subjective beliefs) of the market returns. The black solid lines describe the beliefs of the Normal investor, the green dotted lines correspond to the adjusted Lucky investor, and the red dashed lines are the beliefs of the original Lucky investor. The grey-shaded areas are the NBER recession periods. The sample period covers from 1947:Q1 to 2019:Q4. The Lucky type investor has never experienced the lowest 10 percentile of the market returns (−29.92%), and the market returns in her sample are adjusted such that the mean is identical to that of the Normal investor. The test assets consist of the gross market portfolio and the risk-free asset. The information variables are the exponentially weighted moving average of the past market returns in excess of the risk-free returns. The pricing kernel is exponentially affine to the wealth portfolio. The wealth portfolio of both investors is assumed to be a combination of the market portfolio and a risk-free asset. This figure assumes that the percentage invested in the market portfolio is implied by the Malmendier & Nagel (2011) regression coefficients. In particular, the Normal (adjusted Lucky) investor allocates 47% (46%) of her wealth in the stock market.

Table 10: Risk Preferences Before and After Mean Market Return Adjustment

	Normal	Lucky
Panel A: Before Adjustment		
w	47%	50%
θ	6.6	11.4
Panel B: After Adjustment		
w	–	46%
θ	–	9.7

Notes: The sample covers from 1947:Q1 to 2019:Q4. The Normal investor possesses accurate information throughout the sample period. For the Lucky investor, the cutoff threshold is -29.92%. The test assets consist of the quarterly gross market returns and the gross risk-free returns. The information variable is the exponentially-weighted average of the excess market returns. Panel A uses the regression coefficients ($\lambda = 1.166, \beta = 1.668$) from Malmendier & Nagel (2011) to compute the risky shares. Panel B adjusts the mean of the market returns for the Lucky type investor to be identical as the Normal type.

4.2.3 Which Channel Has Higher Impact on Risky Shares?

Experiences of market downturns result in reduced risk aversion and diminished return expectations. Together, these effects contribute to decreased allocations to risky assets in the stock market. This section aims to dissect these intertwined impacts to determine which factor has a more pronounced influence on investment decisions in risky assets. Specifically, I address two main questions:

1. Which channel explains the difference in risk allocations between the Normal and the Lucky investor more?

2. Which channel has a stronger influence on an individual's personal risk allocation?

Addressing the first question, since the Normal investor shows more risk tolerance yet also more pessimism, her smaller allocation to risky assets is more influenced by her pessimism than her estimated risk aversion level. This is because increased risk tolerance generally drives larger allocations to risky assets. To address the second question, I examine the separate effects of risk preferences and beliefs to shed light on their respective roles in observable investment behavior.

To examine the influence of subjective beliefs, I set the risk aversion coefficients of both investors to $\theta = 6.6$, mirroring the risk aversion level of the Normal investor. Following this modification, the estimated risky share w for the Lucky investor shifts dramatically from 50% to 90%. Figure 4 presents the beliefs of both the Normal and the Lucky investors when their risk aversion levels are aligned. The beliefs of the Normal investor are illustrated by the black solid lines. The red dashed lines depict the beliefs of the Lucky investor when her risk aversion aligns with the Normal investor at $\theta = 6.6$, while the blue dotted lines represent the beliefs of the Lucky investor based on her optimal risk aversion coefficient, $\theta = 11.4$.

Panel A plots the time series of the expected market returns perceived by the different investor types. When the risk aversion coefficient is reduced, the mean of the expected market returns for the Lucky investor rises to 11.3%, up from 10.7%. During economic growth, this investor expects even more significant returns with lower risk aversion. Notably, during downturns, her expectations decrease when the risk aversion coefficient is set at $\theta = 6.6$. Consequently, as θ transitions from 11.4 to 6.6, the correlation between the Lucky investor's beliefs and the overall economic trend diminishes. Panels B and C describe the conditional volatility and skewness of both investors' beliefs. Notably, the shift in θ from 11.4 to 6.6 has minimal effect on the conditional volatility and skewness of the Lucky investor's beliefs. Lastly, Panel D displays the conditional Sharpe ratios. As the adjusted Lucky investor expects more returns without added risk, their Sharpe ratio increases.

Isolating the role of risk preferences necessitates that both investors possess identical beliefs. Nonetheless, the SEL struggles with belief customization. As a workaround, I choose the risk preference parameter for the Lucky investor in such a way that her subjective beliefs matrix most closely aligns with that of the Normal investor. A risk aversion value of $\theta = 31.2$ yields a subjective beliefs matrix for the Lucky investor that minimizes the squared error relative to the beliefs of the Normal investor. Upon fixing beliefs, the Lucky investor's risky share shifts from 50% to 19%. Figure 5 depicts the expected market returns for both the Normal and Lucky investors after this alignment of subjective beliefs.

Table 11 presents a comparative analysis of the resulting risky shares when either preferences or beliefs are held constant. Panel A details the risky shares and the derived risk preferences without any imposed constraints. In Panel B, the Lucky investor's risk preference coefficient, θ, is set equal to the Normal investor's value of 6.6. This adjustment causes her risky share to surge from 50% to 90%, indicating that the risk preferences from before and after downturn experiences lead to a 40 percentage points change in her risky share. Conversely, Panel C outlines the scenario where the Lucky investor's beliefs align closely with those of the Normal investor. This alignment leads to a decline in her risky share from 50% to 19%. Hence, the beliefs from before and after downturn experiences cause a 31 percentage point change in her risky share.

In addition, Table 11 provides evidence for heterogeneity in both risk preferences and beliefs. Homogenizing either of these across the investor groups leads to unrealistic outcomes. For example, if both investor types share the same risk preferences, it implies that Lucky investors, as a group, would need to invest an unrealistic proportion (90%) of their wealth in the stock market, disregard their characteristics such as age and income. On the other hand, if the beliefs are homogeneous, Lucky investors would appear to have an unreasonably high risk aversion at 31.2.

Table 11: Risky Preferences with Fixing Channels

	NORMAL	LUCKY
Panel A: Original		
w	47%	50%
θ	6.6	11.4
Panel B: Fix Risk Preference		
w	–	90%
θ	–	6.6
Panel C: Fix Beliefs		
w	–	19%
θ	–	31.2

Notes: The sample covers from 1947:Q1 to 2019:Q4. The Normal investor has the correct information during the sample period, and the Lucky investor has never experienced the lowest 10 percentile of the market returns (-29.92%). The test assets consist of the quarterly gross market returns and the gross risk-free returns. The information variable is the exponentially-weighted average of the excess market returns. Panel A shows the estimated risk preferences when both investors allocate their wealth according to Malmendier & Nagel (2011) estimates. Panel B forces the Lucky investor to have identical risk preferences as the Normal investor. Panel C matches the Lucky investor's beliefs to be as similar as possible to the Normal investor.

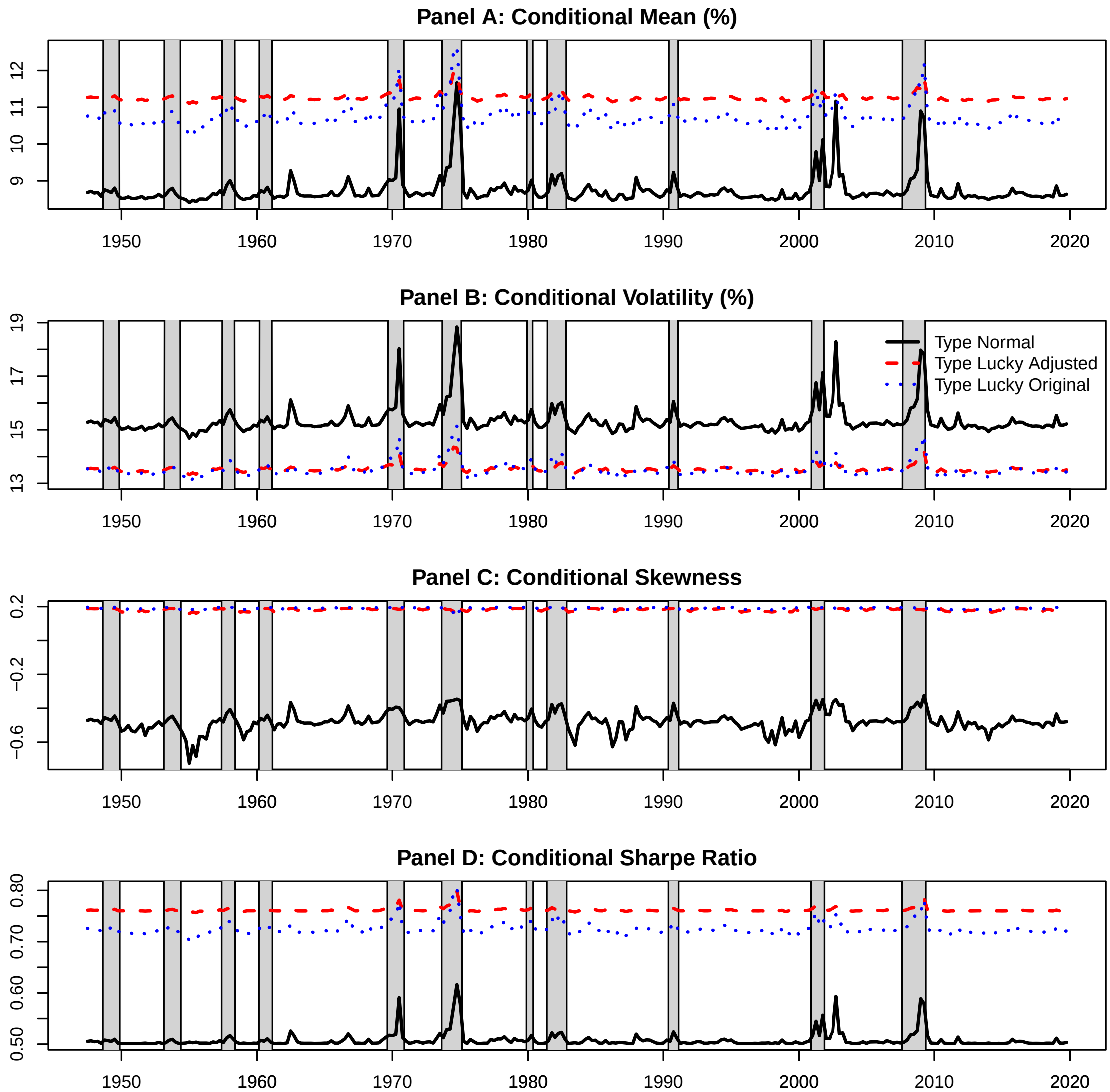
4.3 Robustness

In this section, I present the robustness checks to validate the main findings of the counterfactual analysis. I test the results using various conditioning variables and different thresholds to define the Lucky investor. Additionally, I conduct an out-of-sample test using a rolling-window estimation to further assess the stability and generalizability of the results across different time periods.

Conditioning Variables:

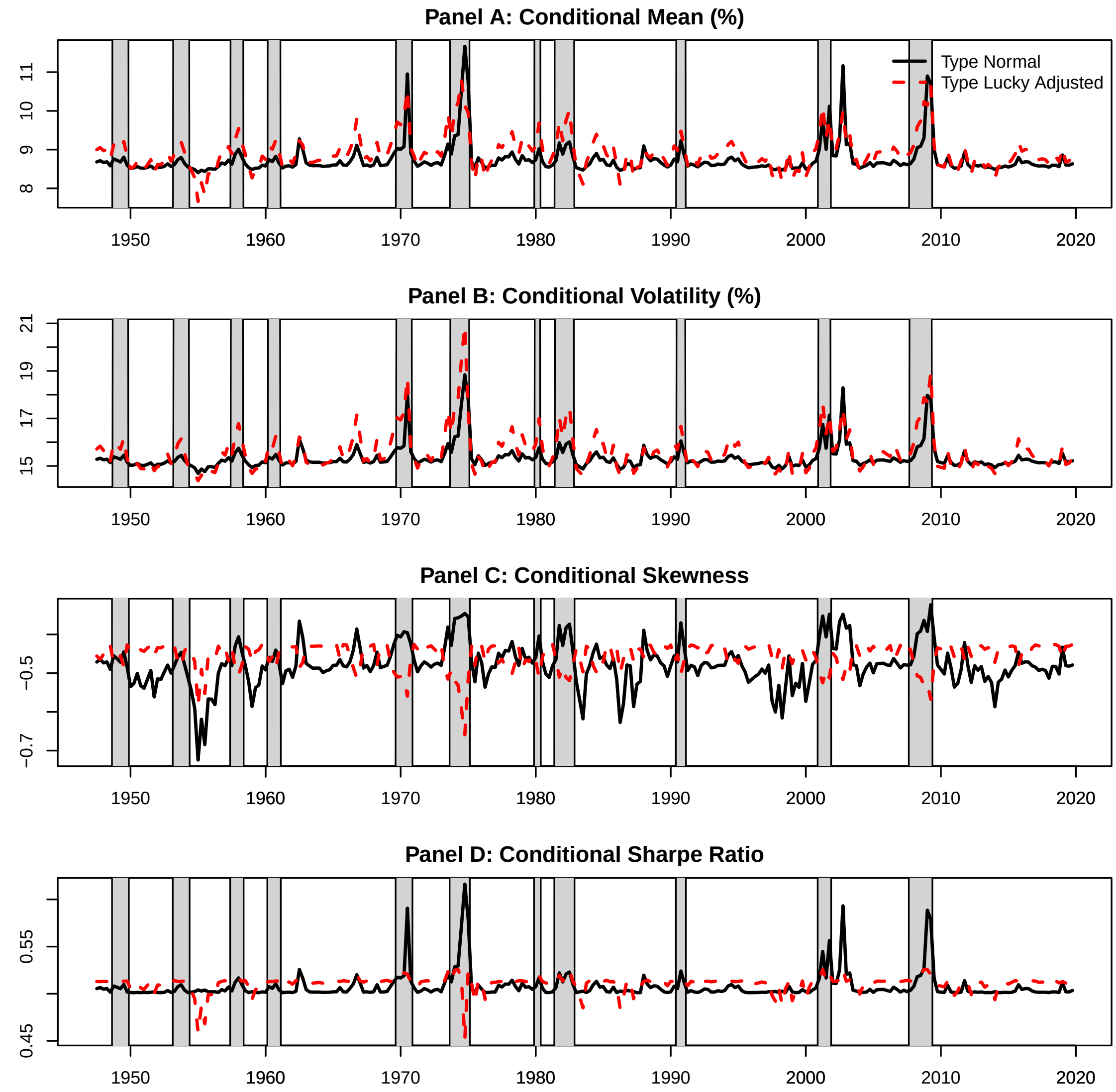
Table 12 shows the estimated risk preference coefficients using various conditioning variables. The main counterfactual analysis uses the exponentially weighted moving average of market returns in excess of the risk-free rate as the conditioning variable. To check robustness, I include macroeconomic factors like consumption growth and inflation in the information variables. Besides the exponentially weighted moving average, I also examine the outcomes

Figure 4: Beliefs About Market Returns for Normal and Lucky Investor with $\theta = 6.6$



Notes: The figure plots the time series of the conditional moments computed by the SEL estimated probabilities (subjective beliefs) of the market returns. The black solid lines describe the beliefs of the Normal investor, and the red dashed lines correspond to the adjusted Lucky investor. The grey-shaded areas are the NBER recession periods. The sample period covers from 1947:Q1 to 2019:Q4. The Lucky investor has never experienced the lowest 10 percentile of the market returns (-29.92%), and her risk preference coefficient is forced to be identical to the Normal investor at 6.6. The test assets consist of the gross market portfolio and the risk-free asset. The information variables are the exponentially weighted moving average of the past market returns in excess of the risk-free returns. The pricing kernel is exponentially affine to the wealth portfolio. The wealth portfolio of both investors is assumed to be a combination of the market portfolio and a risk-free asset. As a result, the Normal (Lucky) investor optimally allocates 47% (90%) of her wealth in the stock market.

Figure 5: Beliefs About Market Returns for Normal and Lucky Investor with Minimized Probability Differences



Notes: The figure plots the time series of the conditional moments computed by the SEL estimated probabilities (subjective beliefs) of the market returns. The black solid lines describe the beliefs of the Normal investor, and the red dashed lines correspond to the adjusted Lucky investor. The grey-shaded areas are the NBER recession periods. The sample period covers from 1947:Q1 to 2019:Q4. The Lucky type investor has never experienced the lowest 10 percentile of the quarterly market returns, and her beliefs are selected to be as close to the Normal investor as possible. The test assets consist of the gross market portfolio and the risk-free asset. The information variables are the exponentially weighted moving average of the past market returns in excess of the risk-free returns. The pricing kernel is exponentially affine to the wealth portfolio. The wealth portfolio of both investors is assumed to be a combination of the market portfolio and a risk-free asset. As a result, the Normal (Lucky) investor optimally allocates 47% (19%) of her wealth in the stock market.

when investors consider information from only the last four quarters. The findings are consistent with the main analysis.

Table 12: Robustness: Conditioning Variables

Conditioning Variables	Normal	Lucky
Average of previous four quarters: Excess market return	6.5	11.4
Average of previous four quarters: Excess market return, consumption growth, inflation	6.6	13.0
Exponentially weighted moving average: Excess market return, consumption growth, inflation	6.7	12.5

Notes: The sample covers from 1947:Q1 to 2019:Q4. The Normal investor possesses accurate information throughout the sample period. The Lucky investor never experienced quarters with an annualized market return below −29.92%. The test assets consist of the quarterly gross market returns and the gross risk-free returns. The weight for computing the exponentially weighted moving average is 0.28.

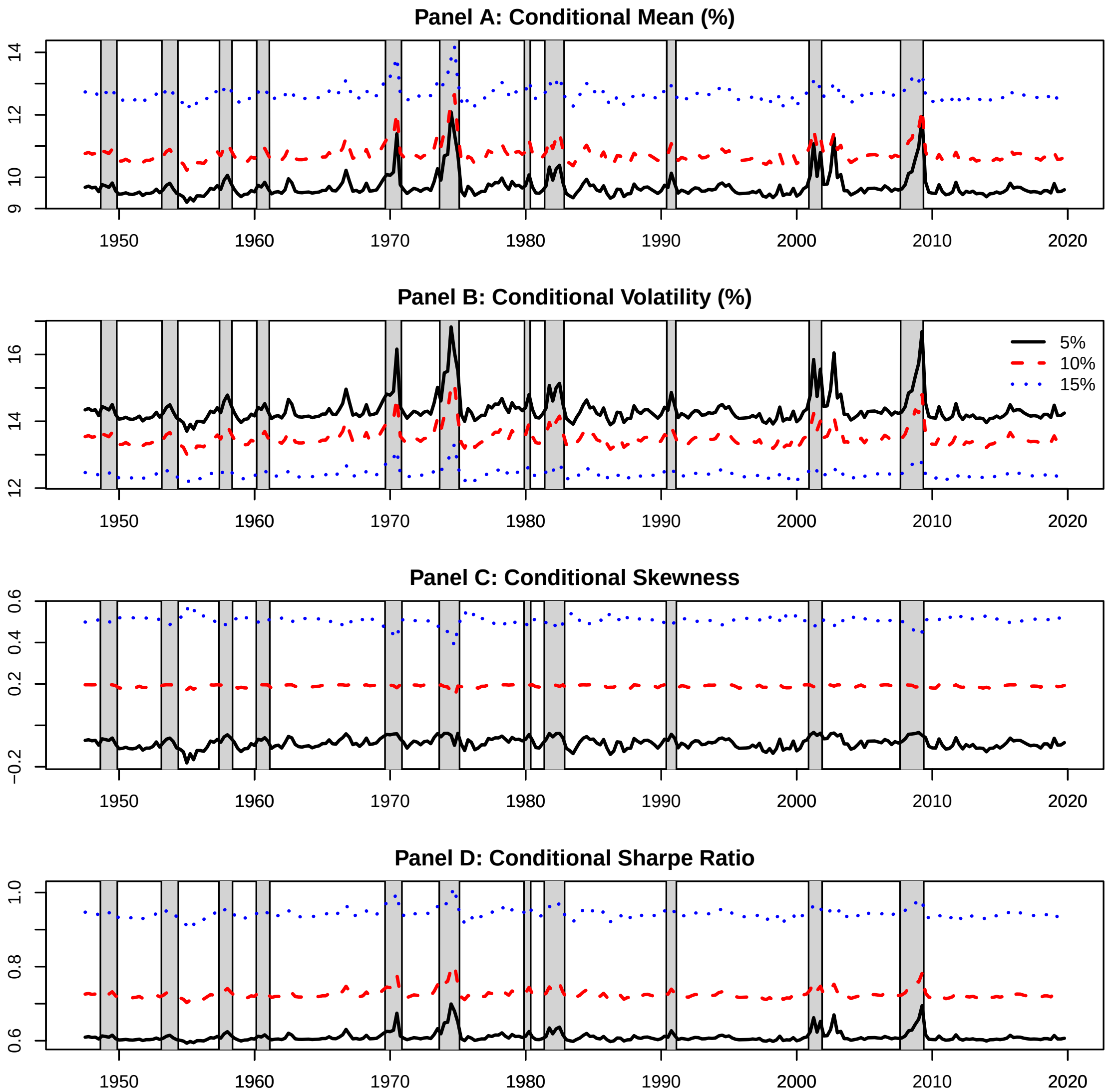
Threshold for Type Lucky:

Table 13 presents the risk aversion coefficients of Lucky investors with different thresholds when defining bad experiences. Figure 6 plots the subjective beliefs of Lucky investors with a truncating threshold at the lowest 5th, 10th, and 15th percentile of the sample.

Out-of-Sample Test:

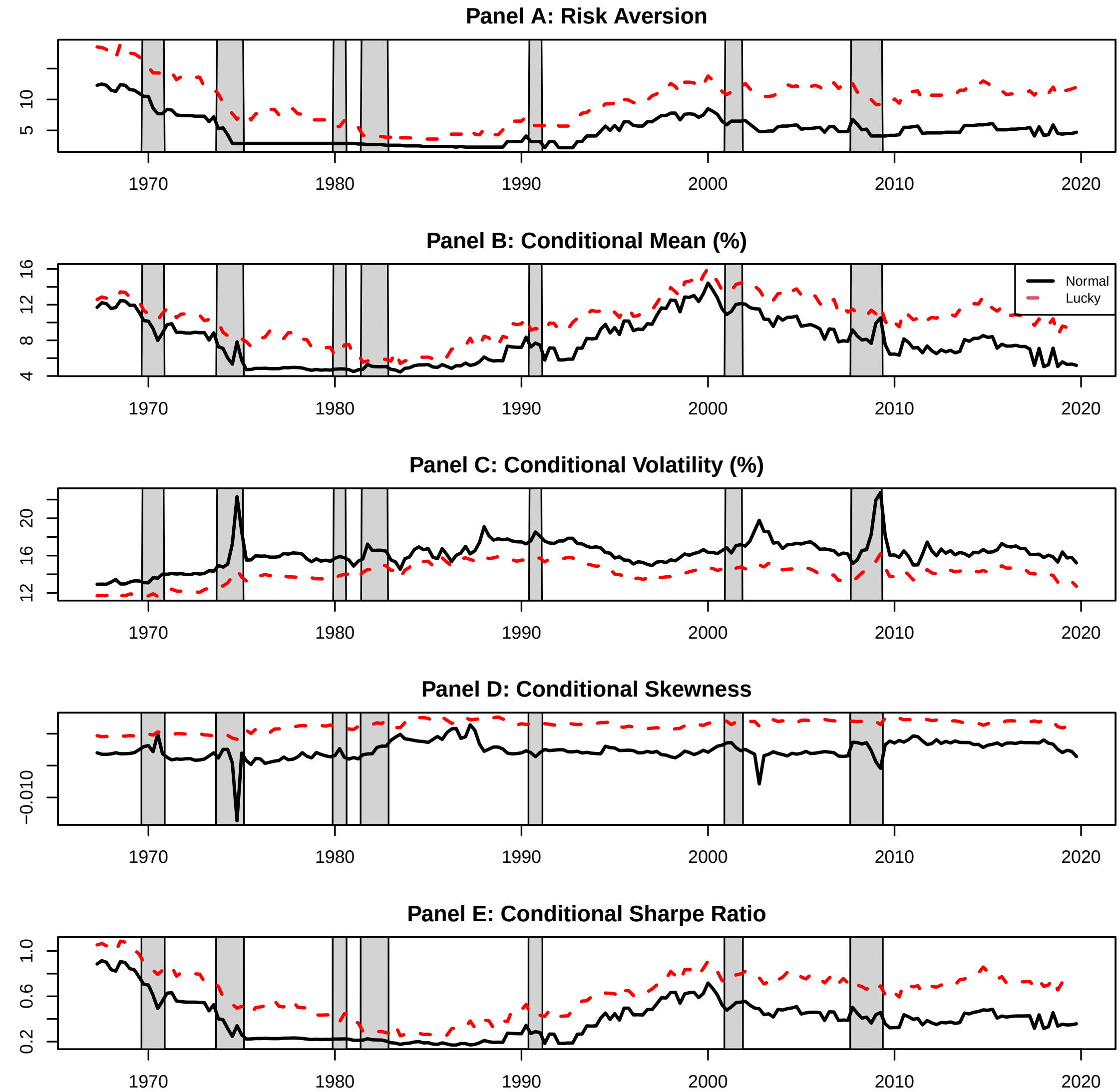
Figure 7 presents the rolling-window estimated risk preference parameter and market beliefs for the Normal and Lucky investors over a 20-year window. The black solid lines represent the Normal investor, who has experienced all historical market crashes, while the red dashed lines depict the Lucky investor, who has never experienced the lowest 10th percentile of returns. Panel A shows that the Normal investor exhibits higher risk aversion, indicating lower risk tolerance compared to the Lucky investor. Panels B through E reveal that the Normal investor consistently exhibits more pessimistic market beliefs compared to the Lucky investor, with lower conditional mean returns (Panel B), higher conditional volatility (Panel C), more negative conditional skewness (Panel D), and a lower conditional Sharpe ratio (Panel E). These out-of-sample estimates align closely with the in-sample results, reinforcing the conclusion that investor experiences significantly shape risk preferences and market expectations.

Figure 6: Lucky Investor Beliefs About Market Returns with Different Truncation Thresholds



Notes: The figure plots the time series of the conditional moments computed by the SEL estimated probabilities (subjective beliefs) of the market returns. The black solid lines describe the beliefs of the Lucky investor who has never experienced the lowest 5th percentile of the market, the red dashed lines correspond to a threshold of the lowest 10th percentile, and the blue dotted lines are associated with the 15th percentile. The grey-shaded areas are the NBER recession periods. The sample period covers from 1947:Q1 to 2019:Q4. The test assets consist of the gross market portfolio and the risk-free asset. The information variables are the exponentially weighted moving average of the past market returns in excess of the risk-free returns. The pricing kernel is exponentially affine to the wealth portfolio. The wealth portfolio of both investors is assumed to be a combination of the market portfolio and a risk-free asset. This figure assumes that the percentage invested in the market portfolio is implied by the Malmendier & Nagel (2011) regression coefficients. In particular, the Lucky investor allocates 50% of her wealth in the stock market.

Figure 7: Rolling-Window Estimated Risk Preference Parameter and Market Beliefs



Notes: The figure shows the time series of the risk preference parameter and conditional moments of market returns, estimated using SEL-derived subjective beliefs with a 20-year rolling window. The black solid lines represent the Normal investor, who has experienced all historical market crashes, while the red dashed lines depict the Lucky investor, who has never encountered the lowest 10th percentile of market returns (annualized at -29.92%). Grey-shaded areas indicate NBER recession periods. The analysis covers the entire sample period from 1947 to 2019, with each estimation based on a 20-year rolling window. The test assets include the gross market portfolio and the risk-free asset. Information variables are the exponentially weighted moving average of past excess market returns. The pricing kernel is modeled as exponentially affine to a wealth portfolio composed of the market portfolio and a risk-free asset. The Lucky investor allocates 50% of her wealth to the stock market, while the Normal investor allocates 47%, based on the coefficients from Malmendier & Nagel (2011).

Table 13: Robustness: Risk Preferences for Type Lucky with Different Thresholds

Threshold	Type Lucky
Lowest 5 percentile (−45.72%)	8.5
Lowest 10 percentile (−29.92%)	11.4
Lowest 15 percentile (−15.72%)	18.2

Notes: The sample covers from 1947:Q1 to 2019:Q4. The Normal investor possesses accurate information throughout the sample period. The Lucky investor never experienced quarters with market returns below a certain threshold. The values in the parentheses are the threshold values in quarterly nominal market returns. The test assets consist of the quarterly gross market returns and the gross risk-free returns. The weight for computing the exponentially weighted moving average is 0.28.

5 Conclusion

This study investigates how lifetime exposure to stock market downturns shapes investors' risk preferences, beliefs, and portfolio choices. Using the SCF, I construct a measure of lifetime bad experiences based on the number of months in which investors were exposed to severely negative stock market returns in their lives.

The empirical results reveal a systematic non-linear relationship between past market experiences and both risk preferences and beliefs. Specifically, both risk tolerance and pessimistic beliefs exhibit an inverted-U relationship with lifetime bad experiences. Investors with a moderate number of bad experiences tend to report higher risk tolerance and stronger pessimistic beliefs. However, once bad experiences become sufficiently severe, both risk tolerance and pessimism decline.

Consistent with these patterns in preferences and beliefs, lifetime bad experiences are also associated with differences in portfolio allocations. Conditional on stock market participation, the share of liquid financial wealth invested in risky assets exhibits a similar inverted-U relationship with bad experiences. Investors with a moderate level of bad experiences tend to allocate a larger fraction of their portfolios to risky assets, while those with very high levels of bad experiences reduce their risky exposure. Importantly, this pattern remains statistically significant even after controlling for survey-based measures of risk tolerance and beliefs, suggesting that bad experiences influence portfolio allocations not only through risk preferences and expectations but also through additional direct channels.

To further assess the relative importance of different channels, I conduct a decomposition analysis of the effect of bad experiences on risky portfolio shares. The results indicate that the primary channel operates through changes in risk preferences. Although bad experiences also affect beliefs about future market returns, the contribution of beliefs to the overall relationship between bad experiences and risky portfolio allocations is comparatively small.

Finally, I complement the survey-based evidence with a counterfactual analysis based on the SEL framework, which recovers investors' risk preferences and beliefs from asset prices. The results indicate that investors who have never experienced severe market downturns appear more risk-averse, whereas investors who have experienced market downturns exhibit a higher willingness to bear risk. At the same time, investors with more negative experiences tend to hold more pessimistic beliefs about future market returns.

Overall, the evidence highlights the important role of lifetime market experiences in shaping investor behavior. Past market downturns influence not only investors' beliefs about future returns but also their risk preferences and participation decisions, thereby contributing to persistent heterogeneity in portfolio choices and market outcomes.

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A Appendix: Repeated-Imputation Inference

Montalto & Sung (1996) describes the Repeated-Imputation Inference (RII) that uses all five implicates of the SCF data, and corrects the extra variability generated by missing values. The RII technique requires the computation of the mean and variance of each of the five implicates. Denote $Q_1, Q_2, \ldots, Q_I$ as the means of a variable, and $U_1, U_2, \ldots, U_I$ as the variances of the same variable from the implicate $1, 2, \ldots, I$, respectively. In the case of the SCF data that has five implicates, $I = 5$.

The RII mean of the variable of interest is the average of the means from each implicate

$$\overline{Q_I} = \frac{\sum_{i=1}^{I} Q_i}{I}. \tag{18}$$

The variance of the variable consists of two components: (1) the average variance of the five samples (the sampling variance, or the "within" imputation variance), and (2) the variance caused by imputation (the "between" imputation variance).

The "within" imputation variance is written as

$$\overline{U_I} = \frac{\sum_{i}^{I} U_i}{I}. \tag{19}$$

The "between" imputation variance is

$$B_I = \frac{\sum_{i=1}^{I} \left(Q_i - \overline{Q_I}\right)^2}{I - 1}. \tag{20}$$

The total variance and the standard deviation of the estimate are

$$\begin{aligned} T_I &= \overline{U_I} + \left(1 + I^{-1}\right) B_I \\ \sigma_I &= \sqrt{T_I}, \end{aligned} \tag{21}$$

where $(1 + I^{-1})$ is an adjustment factor inversely related to the number of implicates. As the number of implicates increases, the weight of the "between" imputation variance decreases.

For testing the null hypothesis $\overline{Q_I} = Q_0$, the RII test statistic

$$t = \frac{\overline{Q_I} - Q_0}{\sqrt{T_I}} \tag{22}$$

has a t-distribution with degrees of freedom v defined as

$$v = (I - 1)\left(1 + r_I^{-1}\right)^2, \tag{23}$$

where

$$r_I = \frac{\left(1 + I^{-1}\right) B_I}{\overline{U_I}}. \tag{24}$$

is the relative increase in variance due to missing data.