The Effect of Subjective Life Expectancy on Financial Decisions

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Abstract

I investigate whether exposure to natural disasters and mass shootings influences subjective life expectancy and affect financial decisions. I show that being exposed to natural disasters and mass shootings significantly decreases an individual's subjective life expectancy relative to life table probabilities. Lifespan optimists become less optimistic with a disaster experience and lifespan pessimists do not react at all. I find that disasters monotonically reduce the share of financial assets in equities and non-government bonds for increasing levels of lifespan optimism. When unrelated to life expectancy, disaster experiences do not matter. My findings provide evidence for the existence of an expectations channel for experiences to affect financial decisions.

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1 Introduction

Standard economic models work under the premise that an agent with stable risk preferences and rational expectations is an apt characterization of the real world. Recent evidence challenges this premise by documenting that personal experiences affect economic decisions (Malmendier and Nagel, 2011). However, little is known about the channels through which experiences affect economic decisions. Experiences may affect economic decisions by influencing risk attitudes, or by altering beliefs and expectations of future events. In this paper, I identify deviations in subjective life expectancy from objective life table probabilities (henceforth known as mortality deviations) as one of the channels for experiences to affect an individual's financial portfolio choice.[1]

I document the causal effect of natural disasters and mass shootings on mortality deviations by using county-level variation in disaster declarations from the Federal Emergency Management Agency (FEMA) and incidents of mass shootings from the Stanford Mass Shootings Database (SMD). After controlling for economic, demographic and spatial differences in life expectancy, I find that individuals exposed to these experience shocks are significantly more pessimistic about their life expectancy. My findings show that exposure to a natural disaster reduces subjective life expectancy by 1.3 percentage points (pp). In terms of economic significance, these revisions in expectations are at least five times larger than rational revisions according to Bayes' rule and about 10 percent of the unconditional average in-sample mortality deviations.

To assess the robustness of this relationship between experiences and expectations, I estimate the impact of mass shootings and find that exposure to mass shootings reduces subjective life expectancy by 2.2 pp. In addition, I find that the disaster effects on individuals residing in neighboring counties to disaster affected regions are equally strong. They

[1] A simple scatter-plot of mortality deviations against the share of financial assets invested in stocks and non-government bonds by individuals (Figure 1a) suggests that investment in risky assets is positively correlated with lifespan optimism.

are more than two-thirds of the impact on those residing in disaster-affected regions. These results lend further support to the conclusion that disaster experiences reduce lifespan expectations. Breaking the sample into lifespan optimists (individuals with positive mortality deviations) and pessimists (individuals with negative mortality deviations), I also find that lifespan optimists become less optimistic when they experience natural disasters and lifespan pessimists do not react at all.

I go on to estimate the impact of natural disasters on the share of financial investments in equities and non-government bonds (risky assets share) by individuals. Exposure to a natural disaster decreases the share of risky assets by 1.29 pp, consistent with evidence in Bharath and Cho (2015). In support of the hypothesis that disaster effects operate through the subjective life expectancy channel, natural disasters reduce risky assets share only when there are deviations between subjective life expectancy and objective life table probabilities. In other words, after controlling for mortality deviations, natural disasters have no unconditional impact on the share of risky assets. I find that a disaster experience lowers the risky asset share by about 1 pp for lifespan optimists and does not affect risky asset share for lifespan pessimists. Extreme optimists with over +20 pp deviation from life table probabilities reduce their risky asset share by about 30 basis points (bps) more than moderate optimists (< 20 pp. positive deviations), presenting a step-wise increase in disaster experience effects. These effects are also persistent – past disaster experiences shape lifespan expectations and affect current investment decisions.

Taken together, these empirical results suggest that personal experiences affect lifespan expectations and investment decisions. In particular, lifespan expectations may be related to risky behavior in at least two ways. First, they potentially alter the individual's expected lifespan, i.e., the time horizon for optimization. I refer to this negative impact on expected lifespan as lifespan pessimism. Second, such experiences may contribute to being generally pessimistic about a range of future events, which is known as dispositional pessimism.[2] Dispositional pessimism may affect both lifespan expectations and average return expectations from investing in financial markets, two of the most relevant expectations in the context of individual economic decision-making.[3]

To distinguish between lifespan pessimism and dispositional pessimism, I set up a canonical life-cycle model. In the first model, the agent is a lifespan pessimist whose expectations in other dimensions are optimal.[4] In the second model, the agent exhibits dispositional pessimism, which I model as positively correlated deviations in lifespan expectations and expectations about average financial returns.

The canonical model follows Cocco, Gomes, and Maenhout (2005) and Love (2013). I introduce lifespan pessimism by increasing the conditional life table mortality probability $(1 - \psi(t))$ by a factor τ, i.e., $(1 - \psi(t))(1 + \tau)$ where $\tau \in [0, 1]$. For dispositional pessimism, I assume that fraction of τ, i.e., lifespan pessimism, affects financial return expectations.

Relative to the baseline profile without any bequest motives, a lifespan pessimist marginally *increases* her share of investment in risky assets, although the extent to which she accumulates wealth is lower (and her saving profile is lower). At reasonably low levels of pessimism (less than 4 percent deviation from rational expectations) the average increase in risky assets share is marginal at 0.16 pp) and at very high levels (over 50 percent deviation from rational expectations) about 1.28pp before retirement. After retirement, the corresponding averages

[2]Several studies in psychology and medicine use psychometric tests to measure dispositional pessimism – the tendency to be generally pessimistic about a range of expectations – and show that it is a significant factor that affects individual decision-making (see, for example, Scheier and Carver, 1985).

[3]For a subset of respondents where I measure both mortality deviations and financial return expectations in the Health and Retirement Study (HRS). I show that financial return expectations are positively correlated with lifespan expectations, suggesting that dispositional pessimism is indeed a plausible mechanism. This is also in line with Puri and Robinson (2007), who show that respondents in the Survey of Consumer Finances who think economic conditions will stay the same or deteriorate are more pessimistic about the age at which they expect to die than those who think that economic conditions will improve.

[4]Recent work by Heimer, Myrseth, and Schoenle (2016) has shown the importance of this mechanism for savings and consumption decisions. By calibrating a canonical life-cycle model with subjective life expectancy, Heimer, Myrseth, and Schoenle (2016) show that the young under save and retirees draw down their assets more slowly.

are marginally higher at lower magnitudes of pessimism (at 0.56 pp) and much higher at higher magnitudes of pessimism at 7.86 pp. This relationship between lifespan pessimism and risky behavior is governed by the changes to the discount rate. As the discount rate increases, wealth accumulation decreases and the expected value of future income decreases. This lowers the wealth to present value of all future income ratio and increase the agent's share of investments in risky assets.[5] Holding fixed risk attitudes, changes in risky behavior due to pure lifespan pessimism is small.

Relative to the baseline profile without any bequest motive, a lifetime dispositional pessimist (where the agent is both a lifespan pessimist and a financial returns pessimist) reduces her share of investment in risky assets throughout her lifetime, although she converges to the baseline level of exposure by the end of her lifetime. This mechanism is more consistent with the empirical findings.

In the presence of a bequest motive, the strength of pure lifespan pessimism is weakened towards the end of an agent's life. Without a bequest motive, an extreme lifespan pessimist (with more than 50 percent deviation from objective life table expectations) increases her risky share by 8.32 pp, whereas with bequest motives, the average increase after retirement is a modest 1.33 pp. Changes in the average effects on risky asset share before retirement move in the same direction although the magnitude of adjustment is not significantly lower. Reasonably strong bequest motive offsets responses to pure lifespan pessimism after retirement. However, the effects of dispositional pessimism are stronger in the presence of bequest motives. An extreme dispositional pessimist under-invests in risky assets by 22.17 pp after retirement in the presence of bequest motives, an addition of 4 pp to the underinvestment without a bequest motive. With bequests, the positive effect of pure lifespan pessimism on risky asset share is dampened and reduction in investments into risky assets through

[5] However, an assumption that the impact of pessimism is *before* savings have adjusted implies that a higher discount rate only lowers the expected value of future labour income. This increases the wealth to income ratio, thereby marginally reducing the share of risky assets.

the dispositional pessimism channel is exacerbated, lending further support to dispositional pessimism as the underlying mechanism to the observed empirical findings.

This paper connects to several strands of literature. The literature on experience effects as in Anagol, Balasubramaniam, and Ramadorai (2015); Giuliano and Spilimbergo (2014); Malmendier and Nagel (2011); Choi, Laibson, Madrian, and Metrick (2009); Kaustia and Knüpfer (2008) and Malmendier and Tate (2005), question standard models in economics with stable risk preferences and expectations that are unaltered by experiences. This paper provides evidence of the expectations channel through which experiences affect economic decisions. Studies such as Puri and Robinson (2007) show that optimism affects economic choices including financial decisions. This paper provides evidence on the mechanisms through which such expectations affect financial decisions.

Additionally, this work relates to the long-standing literature on survival beliefs as explored most recently by Heimer, Myrseth, and Schoenle (2016) and by Rappange, Brouwer, and Exel (2015); Jarnebrant and Myrseth (2013); Gan, Hurd, and McFadden (2005); Hurd and McGarry (2002); Smith, Taylor, and Sloan (2001); Hurd and McGarry (1993); Hamermesh (1985). I show that mortality beliefs are also affected by personal experiences and estimate how such experiences contribute to expectation errors. Finally, this work contributes to the growing corpus of knowledge on household financial behavior, valuation expectations, and the optimality of such expectations (Anagol, Balasubramaniam, and Ramadorai, 2016; Barberis, Greenwood, Jin, and Shleifer, 2015; Campbell, 2006; Brunnermeier and Parker, 2005).

The rest of the paper is organized as follows. Section 2 offers a brief summary of the data and descriptive statistics, Section 3 estimates the effect of natural disasters and mass shootings on mortality deviations, Section 4 presents the role of the mortality deviations channel on the share of investments in risky assets, Section 5 lays out the model framework to assess the role of lifespan pessimism and dispositional pessimism on portfolio choice, and Section 6 concludes.

2 Data and summary statistics

The main data source for this work is the Health and Retirement Study (HRS), a biennial panel survey of about 15,000 respondents since 1992 in the United States with individuals aged 50 and over, and contains 11 waves of data spanning two decades (till 2012).[6] A consolidated panel dataset created by RAND using the raw questions from each wave of the HRS is used for analysis. To identify shocks to mortality deviations, I merge information from the Federal Emergency Management Agency, the Stanford Mass Shootings Database, Uniform Crime Report Statistics from the Federal Bureau of Investigation to the rich set of demographic, social, economic and spatial information in the HRS at the county level. Appendix B presents a detailed description of data used in this study.

Period life table numbers from the U.S. Vital Statistics Tables[7] are used as the benchmark "objective" life expectancy to measure deviations of subjective life expectancy. Let l^s be the agent's subjective expectation of life till target age y and l^p the probabilities from period life tables. The difference, $l^d = l^s - l^p$, measures the direction and magnitude of deviation from life table probabilities. As a percent of life table probabilities, the average deviation is -13.2 percent (median = -3.1 percent). The distribution is left-skewed (Pearson Standardized measure = -0.59).[8] Table 1 provides a breakdown of this variation by age. Although the average respondent in each age category until age 75 underestimate their odds of survival and above age 75 overestimate their odds of survival, this masks the cross-sectional variation observed within each age category. However, at either end of the distribution, a consistent monotonic increase from pessimism to optimism as a function of age is noteworthy.

[6] Several research work use this data. For a comprehensive overview of the data, refer to the user guides at `http://goo.gl/m0ZA38`, especially, Sonnega (2015).

[7] The National Vital Statistics System is the inter-governmental data sharing platform in Public Health. This is run by the National Centre for Health Statistics in the Center for Disease Control and Prevention (CDC).

[8] As pointed out by Gan, Hurd, and McFadden (2005), focal point responses (and other measurement challenges) in expectation surveys make it difficult to assess the true subjective probabilities without a benchmark. Life table probabilities provide a meaningful benchmark for this measure of expectations and thus provide a meaningful transformation of the variable of interest.

Since subjective life expectancy is a function of the target age y, and the current age of the respondents a, Figure 2 presents the comparison of l^s and l^p, across y and a. The nature of the survey question is such that y is fixed for a given set of ages of respondents. If a is the age of the respondent, $x = y - a$ where y is the target age used in the survey. In general, relatively younger respondents (around age 50) are asked about their expectation of surviving 20 - 25 years into the future, whereas the lower end of x primarily covers the oldest respondents, i.e., ages 80 and over. This figure presents the subjective and life table equivalents for a subset of x, between 10 and 15, as a function of the age of the respondent. Across all x, the elderly (> 75 years) consistently over-estimate their expected survival probability, sometimes by 3 times the life table equivalent for their age and gender. The expectation horizon x does have a role in the extent of deviation from life table probabilities and thus is controlled for in any of the subsequent analysis. Arguably, for younger individuals, longer expectation horizon ($x > 14$) matters the most for long-term financial choices of individuals. Middle-aged individuals (≈ 50 years) assess themselves to be about 20 pp less likely (relative to life table probabilities), whereas the old assess themselves (on average) to be many times more likely to survive across all horizons of x. These summary statistics reaffirm the patterns documented in the literature and most recently by Heimer, Myrseth, and Schoenle (2016).

In a sub-sample of respondents in the HRS whose death record is available, Hurd and McGarry (2002) show that their subjective mortality expectations help to predict their death, over and above the life table probabilities. A few other research studies also show that subjective expectations are informative (Rappange, Brouwer, and Exel, 2015; Jarnebrant and Myrseth, 2013; Smith, Taylor, and Sloan, 2001; Hurd and McGarry, 1993). While this strand of literature suggests that the information content in subjective probabilities cannot be ignored, other evidence also points towards the presence of systematic biases in subjective survival expectations (Edwards, 2006; Elder, 2007). The correlation between personal choice (such as smoking) and subjective mortality expectations has been found to be high. However, a causal assessment of how beliefs about mortality are formed is critical to a further analysis of its role in economic decision making. Personal health status changes (as in Smith, Taylor Jr, Sloan, Johnson, and Desvousges (2001)) provide a relatively poor setting for causal analysis as they are often influenced by past behavior. But events that are beyond the control of the individual experiencing them (such as natural disasters and mass shootings) provide an ideal setting for the evaluation of mortality belief formation.

3 Shocks to mortality expectations

For individual i in county c at time t, let $l^d_{i,c,t}$ be the expectation deviation from period life table probability for a target age $y = a + x$, i.e., $l^s_{i,t} - l^p_{i,t}$. Then, the following regression specification forms the baseline for the estimation strategy in this paper:

$$l^d_{i,c,t} = \alpha + X'_{i,t}\beta + \psi_c + \zeta_x + \epsilon_{i,c,t} \tag{1}$$

$X_{i,t}$ is a vector of control variables that explain deviations in subjective expectations. Both objective and subjective life expectancy vary with target age y and the current age of the individual a. Since $l^d_{i,c,t}$ is observed at different y and a, the empirical model also reflects this setting. The current age a, and ζ_x – the survival period fixed-effects, to allow for identification within the same $y - a$ or "survival period" implied by the survey – are the most important control variables in this empirical specification.

The other explanatory variables include net total assets, cognitive abilities, self-assessment of health status, out-of-pocket medical expenditure, bequest motives, education, family characteristics and other variables such as whether parents of the respondent are still alive. Lastly, ψ_c are county fixed-effects that capture possible regional variations in life expectancy.

It is important to note that the adjusted R-squared in this baseline regression analysis, with county fixed-effects, is reasonably high at 26 percent (Appendix Table A.1).[9] That

[9] l^d is strongly correlated with age. Appendix Figure A.1 presents the pessimism profile for individuals as a function of age from equation (1). At age 50, respondents are highly pessimistic (about 50 pp lower than life table probability estimates) whereas respondents at age 85 are highly optimistic estimating their odds of surviving 33 pp more than life table estimates of 12 percent.

said, a significant fraction of mortality deviations is *not* explained by conventional proxies of information about an agent's mortality risk. Adjusting for demographic, socio-economic, and health covariates, systematic miscalibration of subjective life expectancies cannot be ruled out.

3.1 Exogenous experience shocks and mortality deviations

A wide array of personal characteristics is highly correlated with mortality deviations. In this section, I use two sources of exogenous experience shocks (natural disasters and mass shootings) to estimate the causal impact of experiences on mortality deviations.

The first empirical challenge in studying the impact of natural disasters involves potential mediators such as health and wealth losses caused due to a natural disaster. Naturally, an argument about an exogenous shock here is not merely one of changes in expectations, but tangible changes to individual well-being that could, in turn, affect mortality expectations. In this scenario, the effect of a natural disaster is merely another dimension of heterogeneity that is not fully captured in life tables. However, this section measures how *expectations* change with the *experience* that cannot be explained by the *ex-ante* probability of natural disasters. Further, potential mediators of the impact of disasters on life expectancy include health expectations, and other covariates such as whether spouse, parents, and children are alive are controlled for, thus reducing the likelihood of other unobserved channels of impact on mortality deviations.

Modifying equation 1 to include proxies for the role of natural disasters and mass shootings, Tables 2a and 2b present the empirical estimates of the effect of exogenous experience on mortality deviations.

Table 2a presents the regression results using various measures of extreme natural disasters experienced at the county level. Controlling for all other covariates presented in Appendix Table A.1, Column (1) presents the effect of a one percent increase in the number of extreme disaster days in a year on expectation deviations. A one percent increase in the number of days of extreme disaster results in an increase in mortality pessimism by 0.20

percent. However, this effect is asymmetric (Column 2). Estimates suggest that middle-aged individuals (age 50) are likely to be 1.31 percent more pessimistic (relative to life tables), and the effect of a one percent increase in the number of days of extreme disasters in a year wanes as individuals get older. An 85-year-old is not affected by extreme disasters in the same way (point estimate of 0.0079 and statistically insignificant). Columns (3) and (4) present estimates for a one percent increase in the total number of disasters. Again, the effects are asymmetric - middle aged (50 year olds) react sharply with a 3.12 percent decrease in life expectancy relative to life tables, whereas 85-year-olds do not react at all (Figure 3).

Columns (4) and (5) present the effect size for at least one disaster experience in a given year. Individuals in counties with at least one extreme disaster experience are 1.34 pp more pessimistic than their counterparts without such an experience. The average deviation from objective probabilities is -13.23 percent, and hence this effect constitutes nearly 10 percent of the average deviation from objective life table probabilities. The effects are statistically and economically significant. This is primarily driven by middle-aged individuals, as older individuals do not react to such events in forming their expectations. All these suggest that middle-aged individuals are susceptible to pessimistic mortality beliefs due to exogenous experiences.[10]

One potential confounder of the impact of natural disasters on mortality deviations is wealth losses associated with such disasters. To test the robustness of the general relationship between exogenous experience and mortality deviations, I test whether another type of shock that is typically not associated with wealth-losses, mass shootings affect mortality deviations. Table 2b presents the regression results for the effect of mass shootings in the United States on mortality expectations. Controlling for the regularity of events closely associated with

[10]To test whether these shocks are truly exogenous, and the effects obtained are not driven by selection, I test the impact of future natural disasters at $t+1$ on current mortality expectations at t. Appendix Table A.4 suggests that the identification is robust and the effects of natural disasters in the future on current expectation deviations are statistically and economically *insignificant.*

mass shootings (crimes related to arson, gun and murder) at the county level (Column 1 presents the baseline regression) and extreme natural disaster experiences, mass shootings increase mortality pessimism by 2.62 percentage points for individuals in counties where these shootings occur. Importantly, this effect is virtually absent in counties that already have experienced crimes of similar nature (arson, gun violence and murder) in the same year – the interaction term suggests that additional mass shootings have no effect in counties that record such violence. Also, such shootings affect individuals of all age groups, i.e., the effect size is not a function of age and affect the elderly as much as it affects the middle-aged respondents in the HRS sample.[11] This effect size is large (20 percent of the average deviation from objective probabilities).

Unconditionally, individuals are observed to be either optimistic (positive lifespan expectations relative to life tables) or pessimistic (negative lifespan expectations relative to life tables). Hence, the role of exogenous experience may be related to different types of agents. To test whether optimists and pessimists react to disaster shocks differently, I break the sample into optimists and pessimists and analyze the effect of natural disasters on mortality deviations. Table 3 presents the results from this analysis. Columns (1–2) of Table 3 presents the results for optimists (classified as optimists before the disaster occurrence), and Columns (3–4) presents the analysis for pessimists. Natural disasters make optimists less optimistic by 1.32 percentage points, whereas such experiences do not make pessimists more pessimistic.

Robustness 1: One of the concerns with the measure l^d is that these absolute differences in probabilities are not anchored. For instance, an individual aged 75 has a life table likelihood of 0.24 to live an additional 20 years. If the individual's subjective life expectancy for the same period is 0.23, then the measure l^d captures the mortality deviation as -0.01. However,

[11]The last two columns of Table 2b present a far more conservative estimate of the impact of mass shootings and extreme natural disasters, with individual fixed-effects. While the effect sizes are lower than in Columns 1 and 2, the results are qualitatively comparable.

this difference as a percent of the life table probability is -4.1 percent. To overcome concerns that shocks capture mortality deviations in the absolute and not in relative terms, I estimate the specification with l^d measured as the percent deviation from life table probabilities. Appendix Tables A.2 and A.3 present these results. The dependent variable is measured as $\frac{l^s - l^p}{l^p}$, where l^p is the period life table probabilities corresponding to the subjective probability, l^s, reported by the individual. The effects are significant and similar in size to those reported in Tables 2a and 2b suggesting that the relative scales do not influence the analysis.[12]

Robustness 2: Despite explicit controls for wealth and self-assessed health status, one of the concerns may be that such confounders are not well measured and thus influence the effect of natural disasters on mortality deviations. To measure the effect without such concerns, I estimate a specification where I define disaster experience as 1 when an individual resides in a county that has a border with a disaster declared county and 0 when the respondents are in other counties unaffected by disasters and not adjacent to any disaster affected county within the same state (Appendix Figure A.2). This specification has the advantage that no real wealth losses due to disasters may be experienced. Appendix Table A.5 presents the results and are consistent with the main findings with a slight reduction in the magnitude of impact, which is also consistent with the salience of such disaster experiences to individuals.

Economic significance: A comparison of the effect size to the actual mortality risk posed by natural disasters provide for a meaningful benchmark for the extent of miscalibration in mortality expectations. Appendix D presents a benchmark estimate of the rational update to mortality expectations. Revisions to the likelihood of death due to future disasters when a disaster is currently experienced is nearly zero. Most conservatively, the effect of disaster

[12]It is important to note that the effect size is similar because any level effects are captured by control variables such as age in the main specification and are thus effectively controlled for.

experiences on mortality expectations are *at least* five times more than such rational updates to expectations.

4 Mortality deviations and risky behavior

The extent to which such mortality beliefs affect individual decision making is paramount in deciphering the effect of such biased beliefs on individual welfare. Of the many decisions that may relate to biased expectations, I focus on one of the more well measured financial decisions individuals make – the share of total financial assets invested in risky assets. In this section, I evaluate the relationship between mortality expectations and risky behavior.

For individual i from county c at time t, let $l^d_{i,c,t}$ be the expectation deviation from period life table probability till target age $y = a + x$, i.e., $l^s_{i,c,t} - l^p_{i,c,t}$. Then, the following regression specification yields an estimate of the coefficients of interest:

$$\begin{aligned} w_{i,c,t} \quad &= \quad \psi_c + \zeta_x + \theta_t + X^{'}_{i,c,t}\beta + \delta_0 l^d_{i,c,t} \\ &+\delta_1 l^d_{i,c,t} \times I(\text{Experience} > 0)_{c,t} + \mu I(\text{Experience} > 0)_{c,t} + \epsilon_{i,c,t} \qquad (2) \end{aligned}$$

$X_{i,c,t}$ is a vector of control variables such as age, age-squared, wealth, health expectations, out of pocket medical expenditure and cognitive abilities, ψ_c are county fixed-effects, ζ_x are the survival period fixed-effects and θ_t are time fixed-effects. The fraction of total assets in risky markets $w_{i,c,t}$ is measured as the sum total of investments in stocks, mutual funds, investment trusts, non-government bonds and bond funds of individual i from county c at time t divided by all financial assets held by that individual.

The coefficient μ measures the direct impact of natural disasters on risky assets share. δ_0 measures the effect of mortality deviations on risky asset share and δ_1 measures the impact of mortality deviations *when* individual i experiences a disaster on investment share in risky assets.

Table 4 presents the regression results. Column 1 presents the unconditional impact of experiencing a natural disaster on risky assets share, controlling for ageFr, wealth, health, demographic, spatial and time characteristics. Individuals who experience a disaster reduce their risky assets share by 1.29 percentage points.[13] Column 2 presents the relationship between mortality deviations and risky assets share is positive. A one percentage point increase in mortality deviations (optimism) increases risky assets share by 1.5 percent, echoing the unconditional relationship in Figure 1a. Controlling for mortality deviations, Column 3 shows that natural disasters have no unconditional effect on risky assets share when mortality deviations are included in the analysis. Furthermore, as in Column 4, disaster experience lowers the risky share for individuals with positive mortality deviations.[14] This suggests that lifespan optimism is associated with a higher risky share only among individuals who have not experienced a natural disaster.

To further test if the degree of optimism matter to the effect of natural disasters on risky assets share, Table 5 presents the analysis by quartiles of optimism. Column (4) of Table 5 shows that the degree of optimism matters to the extent of adjustment. Individuals who are less optimistic ($0 < l^d \leq 20$) reduce their risky share by a smaller magnitude than those who are extremely optimistic ($l^d > 20$). At the same time, individuals who are pessimistic ($l^d \leq 0$) do not adjust their share of risky assets at all.

Appendix Table A.6 presents the impact of both natural disasters and mass shootings on risky asset share. While both types of personal experiences negatively affect risky assets both directly and mediated through expectation miscalibration, only natural disasters are statistically significant. It is important to note that are issues of statistical power with mass shootings as these are very few events used for statistical identification. However, the direction and magnitudes appear similar to the effects of natural disaster shocks.

[13] These effects are similar and in line with Bharath and Cho (2015).

[14] Although Columns 1–3 in Table 4 provide convincing evidence of a mortality deviations channel through which natural disasters affect risky assets share, the estimation of the indirect effects in the presence of interactions ($l^d \times$ I(Natural Disaster > 0)) require additional statistical tests for assessing the importance of this channel with standard errors and sensitivity tests. Appendix E presents the results of this analysis and suggests that up to one-thirds of the total effect of natural disasters may be attributable to mortality deviations.

4.1 lifetime disaster experience, mortality deviations, and risky asset share

To investigate the relationship between a lifetime of disaster experiences, mortality expectations, and risky asset share, I augment the specification from Malmendier and Nagel (2011) and estimate the following regression specification using non-linear least squares:

$$w_{i,t} = \alpha + \beta N_{i,t}(\lambda) + \omega(N_{i,t}(\lambda) \times l^d_{i,c,t}) + \delta l^d(y)_{i,t} + \gamma^{'} X_{i,t} + \epsilon_{i,t} \tag{3}$$

$$N_{i,t}(\lambda) = \sum_{k=1}^{age-1} \kappa_{i,t}(k,\lambda) \times \text{SHOCK}_{i,t-k} \tag{4}$$

$$\kappa_{i,t}(k,\lambda) = \frac{(age_{i,t} - k)^{\lambda}}{\sum_{k=1}^{age_{i,t}-1}(age_{i,t} - k)^{\lambda}} \tag{5}$$

Here, $w_{i,t}$ is the share of wealth in risky assets, and $l^d_{i,c,t}$ is the difference in the subjective and life table probabilities, and $X_{i,t}$ includes a range of demographic and wealth variables as controls. $\text{SHOCK}_{i,t-k}$ measures the total number of disasters experienced by an individual i at time $t-k$. To allow for different magnitudes of the impact of experiences in the distant past to the immediate, a parsimonious specification involves the estimation of the parameter λ alongside the parameters of interest, β, and ω.[15]

The parameter of interest is ω, which measures the effect size of such disaster experiences and changes to the mortality expectations channel. Table 6 presents the results. I estimate the λ parameter in the baseline specification (column (1) of the table), without age and year fixed-effects in order to minimize the bias caused due to fixed-effects. The parameter λ is statistically significant and suggests that more recent disaster experiences have a much

[15] Alternate specifications for Table 4 without county or state fixed effects yield similar quantitative estimates, suggesting that these shocks are robust to issues of selection in the FEMA database. Therefore, in this specification, they have been omitted for parsimony.

higher weight than in the distant past. For example, for a 50-year old respondent, the weight on disaster experienced the previous year ($k = 1$) is about 6 percent (Bottom panel of Table 6) and reduces to 0 going back to her birth year. Reasonably persistent effects of disaster experiences of the distant past on current portfolio share of risky assets also account for higher estimated magnitudes in Table 6 than in Table 4.

5 Savings and portfolio choice of pessimistic agents

Although the empirical estimates suggest that mortality deviations are related to the share of risky assets in the financial portfolio of individuals, the mapping of the relationship between mortality deviations and risky behavior is not known. In this section, I present a stylized life-cycle model by introducing mortality pessimism and assess the mechanism through which they relate to risky behavior.

Mortality pessimism may affect risky behavior in different ways. They may affect risky behavior by itself, *without* affecting other expectations. I term this as "pure" mortality pessimism. Pure mortality pessimism is noteworthy as it could potentially affect many economic and financial decisions through its multiplicative impact on the agent's discount factor. A decrease in an agent's life expectation alters the time horizon of optimization, which could be modeled as an increase in the discount rate – that is, a strict preference for immediate consumption rather than deferring it to later. Measuring subjective life expectancy and constructing survival curves, Heimer, Myrseth, and Schoenle (2016) find that the young under-save and retirees draw down their assets more slowly. Otherwise, they may also affect risky behavior by affecting other expectations – also known as dispositional pessimism. However, early literature on pessimism (or optimism) suggests that individuals may not solely be pessimistic about mortality, independent of other expectations such as expected returns to investment in risky asset markets, income growth expectations and so on. This dispositional pessimism is the second potential mechanism through which rare events affect economic and financial decisions. While studying the dynamics of subjective mortality expectations on individual decision-making, delineating the role of dispositional pessimism and pure mortality pessimism is important.

Several challenges limit the possibility of discerning mortality expectations from generalized expectations in the data. Firstly, large-scale psychometric assessments of dispositional pessimism are unavailable and are thus largely unobservable. Secondly, creating a benchmark to assess whether such expectations are pessimistic is not straightforward. To the extent mortality expectations are correlated with other expectations such as return expectations revisions in subjective life expectancy plays an important role in affecting financial decisions both by itself and due to dispositional pessimism.

For a subset of respondents for whom I measure both financial return expectations and l^d, following Puri and Robinson (2007), I test whether the measure l^d also captures dispositional pessimism. I compare l^d to the respondents' assessment of the likelihood that mutual funds (such as the Dow Jones Industrial Average) will yield positive returns the following year. Table 7 tests whether this measure of financial returns expectations are correlated with mortality expectation deviations, l^d. Column (1) presents the average expectations of a positive return from mutual funds across quartiles of mortality expectation deviations. Respondents whose mortality expectations are highly pessimistic ($<$ 19 percent deviation from life table probabilities) believe that there is only a 38 percent chance of the Dow Jones yielding positive returns the following year. However, on the other end of the mortality expectations distribution, respondents who are highly optimistic think that the Dow Jones is at least 51 percent likely to turn in positive returns the following year. With more positive expectations about mortality, respondents are also positive about their financial returns the following year. Column (3) presents the coefficient estimates of a regression estimate of this relationship between l^d and financial return expectations. The relationship is positive and increases monotonically (Columns 4 and 5 present confidence intervals that do not overlap). An extreme lifespan pessimist (on average) expects a positive return by 11.48 pp *less* than an extreme lifespan pessimist, suggesting that l^d captures dispositional pessimism, to the extent measured by general financial market expectations.

In this model, I interpret the deviations of subjective life expectancy from life table probabilities as measuring degrees of mortality pessimism and also allow for correlations between mortality expectations and financial return expectations. This forms the basis of the incremental changes to a canonical life-cycle model presented below.

5.1 Model specification

I adopt the model of consumption and portfolio choice in Love (2013) which adopts the canonical model from Cocco, Gomes, and Maenhout (2005) and modify to incorporate pessimism. Time is discrete and the individual lives for a maximum of T periods, retires at date T_R, which is assumed to be exogenous and deterministic for simplicity. This individual lives from one period to the next with probability $\psi(t)$. In each period t, the individual consumes C_t, allocates ζ_t percent of the wealth in the risky asset, which offers a gross rate of return R_t^s, and allocates the remainder in the risk-free asset, whose gross return is a constant R^f. Saving and consumption must be financed out of cash on hand X_t, which consists of saving from the previous period plus current income, Y_t and is governed by the following equation:

$$X_t = R_t(X_{t-1} - C_{t-1}) + Y_t \tag{6}$$

where, R_t is defined as $\zeta_t R_t^s + (1 - \zeta_t)R^f$, the gross portfolio rate of return.

A lifetime lifespan pessimist is one whose mortality expectations are higher than the life table estimates $((1 - \psi(t)))$ by a factor τ, i.e., $(1 - \psi(t))(1 + \tau)$. A lifetime dispositional pessimist is one who has correlated expectations between mortality and financial pessimism, where the financial pessimism is a fraction ι of mortality pessimism τ. Assuming that R_t^s is normally distributed with mean μ^s and standard deviation σ^s, a financial pessimist is one whose return expectations are lower at $\mu^s(1 - \iota\tau)$. I assume that $\iota = 0$ and $\tau = 0$ in the benchmark specification.

I also assume that expected excess returns, i.e., $E(R^s - R^f)$ is zero-lower-bound, i.e.,

$\mu^s(1 - \iota\tau) \geq R^f$. In this approach, a pessimistic investor underweights the positive states of the world to the negative states, and thus is assumed to have a lower expected return. It is also important to note this assumption imposes restrictions on the parameter space for τ, i.e., $\tau \leq \frac{1}{\iota}(1 - \frac{R^f}{\mu^s})$ where $0 < \iota \leq 1$. For example, at 6 percent equity premium, this implies that $\tau \leq 0.66$. A constant τ does not mean that survival curves shifts downwards. Appendix F presents an example of how the survival curve looks when the τ parameter is set at 60 percent, i.e., a large, but not unrealistic number considering empirical evidence. The shape of the survival curve used in the analysis (in terms of the magnitude of pessimism) peaks after retirement.

Following Carroll (1997), the income process is a deterministic function of age, combined with a transitory shock and a random-walk persistent shock. Permanent income, P_t, evolves according to $P_t = P_{t-1}G_tN_t$, where G_t captures the age-earnings profile, and N_t is a log-normally distributed shock. Current income, therefore, is a realized product of permanent income and a log-normally distributed transitory shock, Θ_t: $Y_t = P_{t-1}G_tN_t\Theta_t$. Similarly, retirement income is also considered to be uncertain.

In this setting, the discounted expected lifetime utility in period t is therefore given by:

$$U_t = E_t \sum_{i=0}^{T-t} \beta^i \Big\{ \Psi_{t+i,t} u(C_{t+i}) \Big\}, \tag{7}$$

where β is the time-invariant discount factor, and $\Psi_{t+i,t}$ is the probability of surviving to $t + i$ conditional on being alive in period t. In this baseline specification, there are no bequest motives, and individuals value consumption by the isoelastic CRRA formulation: $u(C_t) = C_t^{1-\rho}/(1 - \rho)$. The assumption that income follows a unit root process and preferences are isoelastic allows for the problem to be normalized by permanent income and solve the model following the method of endogenous grid points as in Carroll (2006).

Solving the life-cycle model: In a rational world without pessimism, the value function for the consumer's problem in (7), subject to (6) is as follows:

$$V_t^*(X_t, P_t) = \max_{C_t, \zeta_t} \{ u(C_t) + \beta \psi_t E_t V_{t+1}^*(X_{t+1}, P_{t+1}) \} \tag{8}$$

Let $x_t = \frac{X_t}{P_t}$, then $c_t(x_t) = C_t(X_t, P_t)/P_t$ and $\zeta_t(x_t) = \zeta_t(X_t, P_t)/P_t$. Similarly, the normalized value function is $v_t(x_t) = P_t^{\rho-1} V_t(X_t, P_t)$. The optimal solution to the problem is given by the value function:

$$v_t^*(x_t) = \max_{c_t, \zeta_t} \{ u(c_t) + \beta \psi_t E_t \Gamma_{t+1}^{1-\rho} v_{t+1}^*(a_t R_{t+1} + \Theta_{t+1}) \}, \tag{9}$$

where $\Gamma_{t+1} = G_{t+1} N_{t+1}$ is the stochastic growth factor, and $a_t = x_t - c_t$ is the end of period saving by the individual. Homogeneity of preferences imply that $\Gamma^{-\rho} u_t^{'}(c_t) = u_t^{'}(\Gamma_t c_t)$, thus making the first-order conditions to be:

$$u_t^{'}(c_t) = \beta \psi_t E_t R_{t+1} u_{t+1}^{'}(\Gamma_{t+1} \boldsymbol{c_{t+1}}) \tag{10}$$

Here, $\boldsymbol{c_{t+1}} = \boldsymbol{c_{t+1}}(R_{t+1} a_t + \Theta_{t+1})$, i.e., the decision rule for consumption in period $t+1$. The first-order condition for portfolio choice is:

$$\beta \psi_t E_t (R_{t+1}^e - R^f) a_t u_{t+1}^{'}(\Gamma_{t+1} \boldsymbol{c_{t+1}}) = 0 \tag{11}$$

The optimal portfolio choice can be determined by using (11), given end-of-period saving a_t and a decision rule for the next-period consumption. Given the optimal portfolio choice, (10) determines the optimal consumption level in period t for every level of a_t. The method of endogenous grid points (as in Carroll, 2006) uses these first order conditions to estimate the normalized cash on hand, $x_t = a_t + c_t(a_t)$. Interpolating between c_t and x_t pairs generates the consumption decision rule which in turn can be used to solve for optimal consumption and portfolio choice in period $t-1$.[16]

[16] Following Love (2013), I use 30-grid points for end of period savings, with triple exponential spacing, and compute the distributions for asset returns and transitory and permanent income shocks using 10-point Gauss-Hermite quadrature.

Calibration: Table 8 lists the set of parameters used to solve this model. The discount factor is set to 0.98, at the higher end of the range estimated in Cagetti (2003). Survival probabilities come from the 2007 Social Security Administration Period Life Tables. The baseline parameterization of the model sets ρ, the coefficient of relative risk aversion at 5, at the higher end of estimates available Inkmann, Lopes, and Michaelides (2011). Campbell and Viceira (2002) estimate the standard deviation and mean of the excess returns of stocks over the risk-free rate using annual data on the S&P 500 for the period 1880-1995. They estimate a mean excess return of 6.24 percent and a standard deviation of 18.11 percent.[17] In this calibration exercise, I set the standard deviation of the stock return to 18 percent, the risk-free rate of 2 percent and the excess return equal to 4 percent. The model also allows for asset returns to be correlated with permanent income. Following Gomes and Michaelides (2005), I set the correlation coefficient between permanent income and excess returns to 10 percent during working life, and zero percent in retirement. The income profiles are taken from estimates by Love (2013) following Cocco, Gomes, and Maenhout (2005), and retirement income is the average income of retired households between ages 65 and 85 from the 1970-2007 waves of the Panel Study of Income Dynamics.

Optimal solution: Figure 4 shows the average of 20,000 simulated paths of consumption (first row), saving (second row) and portfolio share (third row) for a college graduate without a bequest motive.[18] The life-cycle profile starts at the age of 50, from when estimates of mortality deviations are observed in the data. This has the distinct advantage of studying agents in a setting where from the age of 50, after experiencing a shock, they reoptimize by being pessimists for the rest of their lives. Across all graphs, the dark line indicates the baseline profile, with parameters in Table 8 and no pessimism in the model. The dotted

[17]The post-war data series records a higher mean of 7.12 percent and a standard deviation of 6.10 percent.
[18]Profiles for high school graduates and others look similar but at different levels of wealth.

lines are estimates for varying levels of pessimism parameter τ that range from 0 (baseline profile) to 64 percent. The first column refers to a lifetime lifespan pessimist, and the second to a dispositional pessimist whose correlation between mortality and financial pessimism is 1. The estimated optimal paths in the baseline profile are identical to Love (2013). The blue arrows refer to the direction in which the profiles increase / decrease as the parameter τ ranges from 0 to 64 percent. Consumption and savings are presented in thousands of 2010 US dollars while portfolio share in risky assets is presented as a percentage of total financial wealth.

In the baseline profile, consumption continues to grow throughout, albeit at a small rate, and dips towards the end of life due to the higher rate of mortality discounting. The growth rate of consumption is influenced by two factors. Firstly, the portfolio rate of return relative to the discount rate affects the growth rate of consumption. Secondly, in this model, retirement income is uncertain. Therefore, consumption is also influenced by the need for precautionary savings against medical cost shocks in old age. The saving profile also suggests that the accumulation is primarily between ages 20 and 50, after which the agent draws down on financial wealth to finance consumption. The patterns observed echo the work by Bodie, Merton, and Samuelson (1992) where consumption in the early years of life are financed out of human capital and the role of financial wealth is more pronounced in later periods of life.

Compared to the baseline profile, a lifetime lifespan pessimist (Column 1 of Figure 4) increases her consumption profile, although marginally, throughout her life until 80 and reduces consumption dramatically around age 80. Table 9 presents the magnitude of difference from the baseline profile. Even at very high levels of pessimism ($\tau = 60$percent), the average increase in consumption before retirement is about 3 percent of the baseline profile, whereas the decrease in consumption after retirement is high at 5 percent. In terms of saving, a lifetime lifespan pessimist decreases her saving until retirement, and the rate of draw down from savings is higher until around age 80 after which she sharply decreases the rate of drawing down from savings.[19] At the same time, a lifetime pessimist *increases* her share of investments in risky assets throughout life, and this increase is the highest at old age, after retirement. While this may appear to be counter-intuitive, the role of mortality pessimism on the share of investment in risky assets is related to assumptions about the timing of the impact of pessimism. The discount rate determines savings in a life-cycle model and as it increases, wealth accumulation decreases (as evident in relative saving declines for a lifespan pessimist). This lowers the wealth to present value of all future income ratio, i.e., $\frac{W}{PV(Y)}$, implying that the agent will actually increase her share of investments in risky assets as opposed to decreasing them.[20] This assumption relies on understanding the extent to which savings have adjusted within the same year and in a canonical life-cycle model, the assumption goes in the direction of a high degree of adjustment within the same year.

In addition, the magnitude of impact due to pessimistic expectations about mortality are not large. Extreme pessimists (with $\tau > 90$ percent) are rare and do not find empirical support.[21] Even with a modification in the assumption of the timing of the impact of pessimism, the effect on savings and portfolio choice decisions will be small.

On the other hand, relative to the baseline profile, a lifetime dispositional pessimist (Column 2 of Figure 4) decreases her consumption before and after retirement. The estimated decrease in average consumption before retirement for very high levels of pessimism ($\tau =$ 60percent) is 4.7 percent of the baseline profile (Table 9), and the corresponding loss of consumption after retirement is much higher at 18 percent. Similarly, her average saving before retirement is lower by as much as one-fifth of the baseline profile and shrinks the rate at which she draws down on saving for consumption at a higher rate and at least 10

[19] The point at the age profile where this flips sign after retirement is determined by the peak difference in unconditional mortality probabilities as explained in Appendix F.

[20] However, if the impact of pessimism is *before* savings have adjusted, then a higher discount rate only means lower present value of future income, and hence the $\frac{W}{PV(Y)}$ increases. This means that an agent with mortality pessimism will decrease her share of risky investments.

[21] However, extreme optimists, where optimism is as high as 3 times the life table mortality probabilities find empirical support.

years before such a pattern is observed with a lifespan pessimist. More importantly, the distinguishing feature of these two mechanisms is that a dispositional pessimist reduces her share of investment in risky assets well throughout her lifetime, although she converges to the baseline level by the end of her lifetime.

Summary of model results:

	Lifetime lifespan pessimist		Lifetime dispositional pessimist	
	Before retirement	After retirement	Before retirement	After retirement
Consumption	+	−	−	−
Saving	−	Sharp draw down	−	Sharper draw down
Risky assets	+	+	−	−

As the table above shows, the empirical results in Section 4 is most consistent with dispositional pessimism (under standard assumptions in a life-cycle model) as the share of investments into risky assets decreases due to a downward revision in expectation caused by rare events. Predictions about the behavior on saving and consumption from these models cannot be empirically assessed with data from the HRS and are thus beyond the scope of this evaluation.

In summary, the observed empirical findings are consistent with dispositional pessimism whereby the impact of rare events is not only on mortality but also on the generalized expectations of future events.

5.2 Bequests

The presence and strength of bequest motives have an important role to play in determining the policy functions at the end of life. The value function for the last period corresponds to the bequest function and is modeled as:

$$V_{T+1} = b\frac{(X_{T+1}/b)^{1-\rho}}{1-\rho} \tag{12}$$

For expositional purposes, the bequest function is also assumed to be isoelastic and the strength of this channel is determined by the parameter b. Following Gomes and Michaelides (2005), the importance of bequest motive b is set at 2.5. Intuitively, the effect of mortality pessimism on optimal paths of policy functions is offset as b increases since both enter as multiplicative factors in the value function. However, the presence of bequest motives is likely to increase the effect of dispositional pessimism as it dampens opposing effects arising out of correlated mortality and financial returns expectations.

Panel (B) of Table 9 presents the deviations from the baseline scenario with parameters as in Table 8 but with a strong bequest motive where $b = 2.5$. The extent to which pure lifespan pessimists increase consumption before retirement is indeed reduced, and so savings decline and increase in investment into risky assets due to mortality pessimism. However, the extent to which these pessimists reduce their consumption after retirement is much higher and the increase in risky share is no longer in large magnitudes. During retirement, consumption decreases as a result of both a high effective discount rate (increased expectation of mortality risk) and wealth does not fall towards zero due to the presence of a bequest motive. Since future labour income and financial wealth fall, optimal asset allocation depends on the relative speed at which these factors decrease. This depends on both the discount rate (adjusted for pessimistic survival probabilities) and the strength of the bequest motive. Given these parameter values, during most of the retirement period, they decline at similar rates and therefore the share of wealth in risky assets remains constant (Appendix Figure A.3). However, it is evident that the effects on portfolio choice, savings and consumption is far stronger in the presence of a bequest motive, suggesting that dispositional pessimists who also have strong bequest motives tend to react sharply to their pessimistic expectations.

In summary, the effect of dispositional pessimism on portfolio choice is even stronger and the positive effects of pure mortality pessimism on risky asset share is dampened in the presence of a bequest motive. In the presence of a bequest motive, dispositional pessimism as a mechanism is further strengthened.

6 Conclusion

In this paper, I show that exogenous experiences affect mortality beliefs in the United States. Disaster effects on lifespan optimists are economically significant whereas lifespan pessimists do not revise their expectations. These effects are at least five times higher than justified by Bayes' rule. I document that disasters have no unconditional impact on risky asset share once mortality deviations are controlled for. Further, disaster experience lowers the risky asset share by about 1pp for lifespan optimists and does not affect lifespan pessimists – consistent with the experience effects on expectations. These effects monotonically increase in magnitude for increasing levels of lifespan optimism.

Pessimistic expectations may be indicative of responses that purely affect an individual's mortality or alternatively be driven by dispositional pessimism. In a canonical life-cycle model, I show that mortality pessimism increases the share of risky assets. With small departures from traditional assumptions in a canonical model, the effects can be negative, albeit by a small magnitude. However, agents who are both lifespan pessimists and financial returns pessimists leads to a reduction in the share of risky assets, consistent with empirical findings.

Although dispositional pessimism affects a wide range of expectations, this paper only explores correlated expectations across mortality and financial returns. Setting up pessimistic expectations across various future events, including income expectations, and allowing for time-varying return and mortality expectations appears to be important future additions to evaluating the mechanisms by which mortality pessimism may affect portfolio choice.

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Table 1: Summary Statistics: Mortality Deviations

This table reports pooled population-weighted summary statistics for l^d, i.e., deviations of subjective probablities from life table probabilities for different age categories. Each row represents different age categories from the lowest to the highest observed in the Health and Retirement Study. Column (1) presents the average life expectancy deviation and Columns 2–5 presents the cross-sectional distribution within each age category. The last row presents the average for the full sample. Units: Percentage

		Percentile				
Age category	Mean	25	50	75	90	N
50 to 55	-24.82	-40.92	-7.82	17.42	26.39	2,752
56 to 60	-29.08	-48.22	-8.80	18.08	36.23	12,361
61 to 65	-29.02	-57.63	-6.81	22.63	43.11	19,338
66 to 70	-32.01	-39.27	-19.23	10.67	24.35	15,351
71 to 75	-20.07	-34.92	-0.97	27.94	47.52	13,527
76 to 80	0.12	-45.24	25.14	63.08	83.92	9,638
81 to 85	50.44	-13.36	82.05	125.26	149.51	6,011
> 85	142.89	58.64	165.98	226.16	267.63	2,654
All	-0.13	-0.42	-0.03	0.27	0.64	101,056

Table 2a: Impact of Natural Disasters on Mortality Deviations

This table presents the population weighted regression estimates for the following empirical model:

$$l^d_{i,c,t} = \alpha + X^{'}_{i,t}\beta + \omega \text{Natural Disaster Proxy}_{c,t} + \psi_c + \zeta_x + \epsilon_{i,c,t}$$

l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables as in Table A.1. Columns 1–2 present the results for the natural disaster shock measured as the total number of days of disaster experience in a given year, columns 3–4 for the total number of disaster experiences in a given year and columns 5–6 for an indicator variable equal to 1 if the respondent experienced any disaster in a given year. These estimates are presented for respondents whose age is between 50 and 85, ***, **, * denote 1, 5, and 10 percent significance. All standard errors are robust and clustered at the state level.

Dep. Var.: $l^d_{i,c,t}$	(1)	(2)	(3)	(4)	(5)	(6)
Log(No. of days + 1)	-0.002*	-0.043***				
	(0.001)	(0.009)				
Log(No. of disasters + 1)			-0.015***	-0.156***		
			(0.004)	(0.032)		
I(No. of disasters > 0)					-0.013***	-0.133***
					(0.004)	(0.031)
Age ×						
Log(No. of days + 1)		0.001***				
		(0.000)				
Log(No. of disasters + 1)				0.002***		
				(0.000)		
I(No. of disasters > 0)						0.002***
						(0.000)
Control variables (Incl. Age in levels)	✓	✓	✓	✓	✓	✓
County Fixed Effects	✓	✓	✓	✓	✓	✓
Survival Horizon Fixed Effects	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.2438	0.2441	0.2358	0.2361	0.2358	0.2360
No. of Observations	78,917	78,917	78,917	78,917	78,917	78,917

Table 2b: Impact of Mass Shootings on Mortality Deviations

This table presents the population weighted regression estimates for the following empirical model:

$$\begin{aligned} l^{d}_{i,c,t} \quad = \quad & \alpha + X^{'}_{i,t}\beta + \omega \text{Natural Disaster Proxy}_{c,t} + \rho I(\text{Arson+ Gun + Murder} > 0)_{c,t} + \\ & \mu I(\text{Mass Shootings} > 0)_{c,t} + \mu_2 I(\text{Mass Shootings} > 0)_{c,t} \times I(\text{Arson + Gun + Murder} > 0)_{c,t} \\ & + \psi_c + \zeta_x + \epsilon_{i,c,t} \end{aligned}$$

l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables as in Table A.1. Column 1 presents the baseline regression without mass shootings experience. Columns 2–4 present the estimated results for the impact of mass shootings. Column 2 is equivalent to Table 2a for controls, and columns 3–4 estimate it with a stricter requirement with individual fixed effects. These estimates are presented for respondents whose age is between 50 and 85, ***, **, * denote 1, 5, and 10 percent significance. All standard errors are robust and clustered at the state level.

Dep. Var.: $l^{d}_{i,c,t}$	(1)	(2)	(3)	(4)
I(Arson+Gun+Murder > 0)	-0.0170	-0.0171	0.0013	0.0012
	(0.015)	(0.015)	(0.007)	(0.007)
I(Mass Shootings> 0)		-0.0262***		-0.0229***
		(0.008)		(0.004)
I(Arson+Gun+Murder > 0) x I(Mass Shootings > 0)		0.0299***		0.0280***
		(0.008)		(0.008)
I(No. of disasters > 0)	-0.1088***	-0.1090***	-0.0782***	-0.0784***
	(0.034)	(0.034)	(0.027)	(0.027)
Age ×				
I(No. of disasters > 0)	0.0016***	0.0016***	0.0011***	0.0011***
	(0.000)	(0.000)	(0.000)	(0.000)
Control variables (Incl. Age in levels)	✓	✓	✓	✓
Individual Fixed Effects	×	×	✓	✓
County Fixed Effects	✓	✓	×	×
Survival Horizon Fixed Effects	✓	✓	✓	✓
Adjusted R-squared	0.2438	0.2441	0.5523	0.5523
No. of Observations	78,917	78,917	78,917	78,917

Table 3: Impact of Natural Disasters on Optimists and Pessimists

This table presents the impact of natural disasters on optimists (defined as positive l^d *before* the natural disaster) and on pessimists (defined as negative l^d *before* the natural disaster.) l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables as in Table A.1. These estimates are presented for respondents whose age is between 50 and 85, ***, **, * denote 1, 5, and 10 percent significance. All standard errors are robust and clustered at the state level.

Dep. Var.: $l^d_{i,c,t}$	(1)	(2)	(3)	(4)
	Optimists		Pessimists	
I(No. of disasters > 0)	-0.0132***	-0.0148***	-0.0034	-0.0042
	(0.004)	(0.004)	(0.014)	(0.014)
Control variables (Incl. Age in levels)	Yes	Yes	Yes	Yes
State Fixed Effects	No	Yes	No	Yes
County Fixed Effects	Yes	No	Yes	No
Survival Horizon Fixed Effects	Yes	Yes	Yes	Yes
No. of Observations	44,761	44,761	34,156	34,156

Table 4: Impact of Natural Disasters on Risky-asset share

This table presents the population weighted regression estimates of the impact of natural disasters *and* l^d on risky asset share. $w_{i,c,t}$ is the share of equity and debt holdings in financial assets. l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables that control for age, wealth, health, demography and other charactersitics as in Table A.1. The coefficients of interest are μ,δ_0 and δ_1. δ_1 measures the impact on risky share *when* there is a natural disaster and l^d.

$$w_{i,c,t} = \psi_c + \zeta_x + \theta_t + X'_{i,c,t}\beta + \delta_0 l^d_{i,c,t} + \delta_1 l^d_{i,c,t} \times I(\text{Experience} > 0)_{c,t} + \mu I(\text{Experience} > 0)_{c,t} + \epsilon_{i,c,t}$$

These estimates are presented for respondents whose age is between 50 and 85, ***, **, * denote 1, 5, and 10 percent significance. All standard errors are robust. The standard errors are clustered at the state level when county fixed effects are used.

Dep. Var.: $w_{i,t}$	(1)	(2)	(3)	(4)
I(No. Disaster > 0)	-0.0129***		-0.0008	-0.0020
	(0.004)		(0.004)	(0.004)
l^d		0.0156***	0.0156***	0.0184***
		(0.005)	(0.005)	(0.005)
$l^d\times$ I(No. Disaster > 0)				-0.0274**
				(0.014)
Age controls	Yes	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes	Yes
Health controls	Yes	Yes	Yes	Yes
Demography + Family Controls	Yes	Yes	Yes	Yes
Survival Period FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
No. of observations	78,917	78,917	78,917	78,917

Table 5: Impact of Natural Disasters on Risky-asset Share by Optimism Quartiles

This table presents the impact of natural disasters, mortality deviations, l^d, on risky-asset share by *quartiles* of optimism. l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables that control for age, wealth, health, demography and other charactersitics as in Table A.1. These estimates are presented for respondents whose age is between 50 and 85, ***, **, * denote 1, 5, and 10 percent significance. Robust standard errors in parenthesis.

Dep. Var.: $w_{i,t}$	(1)	(2)	(3)	(4)
I(No. Disaster > 0)	-0.0129***		-0.0008	0.0093
	(0.004)		(0.004)	(0.007)
l^d				
< -0.15		..	..	..
		..	..	..
$(-0.15, 0]$		0.0018	0.0019	0.0031
		(0.003)	(0.003)	(0.003)
$(0, 0.20]$		0.0074***	0.0074***	0.0089***
		(0.003)	(0.003)	(0.003)
> 0.20		0.0117***	0.0118***	0.0137***
		(0.004)	(0.004)	(0.004)
$l^d\times$ I(No. Disaster > 0)				
< -0.15				..
				..
$(-0.15, 0]$				-0.0123
				(0.011)
$(0, 0.20]$				-0.0144**
				(0.007)
> 0.20				-0.0210*
				(0.011)
Age controls	Yes	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes	Yes
Health controls	Yes	Yes	Yes	Yes
Demography + Family Controls	Yes	Yes	Yes	Yes
Survival Period FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
No. of observations	78,917	78,917	78,917	78,917

Table 6: Lifetime disaster experience and risky asset share

This table presents the regression estimates of a lifetime of disaster experiences on risky asset share. The graph below illustrates the weighting function for a respondent who is 50 years old.

$$w_{i,t} = \alpha + \beta N_{i,t}(\lambda) + \omega(N_{i,t}(\lambda) \times l^d_{i,t}) + \delta l^d_{i,t} + \gamma^{'} X_{i,t} + \theta_t + \epsilon_{i,t}$$

$$N_{i,t}(\lambda) = \sum_{k=1}^{age-1} \kappa_{i,t}(k,\lambda) \times \text{SHOCK}_{i,t-k} \qquad \kappa_{i,t}(k,\lambda) = \frac{(age_{i,t}-k)^{\lambda}}{\sum_{k=1}^{age_{i,t}-1}(age_{i,t}-k)^{\lambda}}$$

$w_{i,c,t}$ is the share of equity and debt holdings in the financial assets. l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables that control for age, wealth, health, demography and other charactersitics as in Table A.1. These estimates are presented for respondents whose age is between 50 and 85, ***, **, * denote 1, 5, and 10 percent significance. Robust standard errors in parenthesis.

Dep. Var.: $w_{i,t}$	(1)	(2)	(3)
λ (weighting parameter)	1.8332***	1.83	1.83
	(0.270)	[fixed]	[fixed]
β	-0.1670***	-0.0478***	-0.0422***
	(0.015)	(0.016)	(0.016)
ω	-0.0930***	-0.0890***	-0.1149***
	(0.049)	(0.048)	(0.047)
Demographic Controls	Yes	Yes	Yes
Wealth Controls	Yes	Yes	Yes
Year Dummies	No	Yes	Yes
Age Dummies	No	No	Yes
R-squared	0.08	0.08	0.08
No. of observations	78,917	78,917	78,917

Example for λ: Age = 50

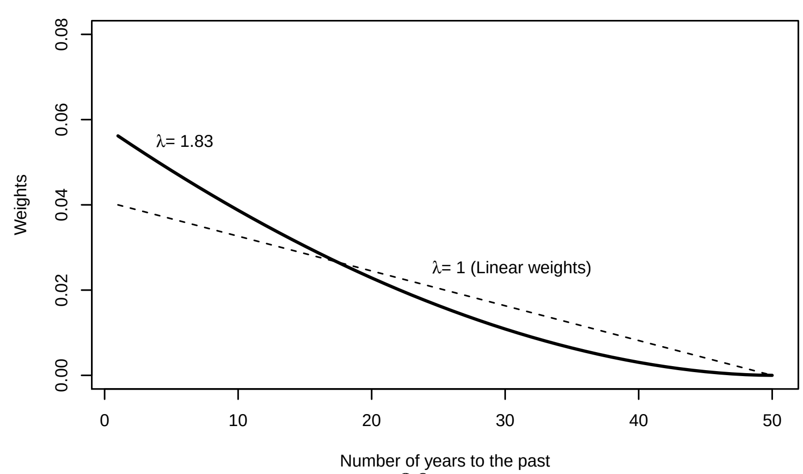


Table 7: Mortality Deviations and Financial Return Expectations

This table presents the correlation between life expectancy deviations and the likelihood respondents think that Mutual Funds (such as the Dow Jones Industrial Average) will go up the following year. These statistics are reported only for a subset of respondents for whom these questions were asked. Column (1) in this table reports the average reported likelihood across the four quartiles of life expectancy deviations (in rows). Column (3) estimates the statistical difference in reported likelihood as agents become more optimistic about life expectancy. Columns (4–5) report the confidence intervals.

Correlations between Mortality Deviations and Financial Return Expectations					
1^d Quartiles	Summary Statistics		Regression Estimates		
	Mean	N	Estimate	95% confidence interval	
	(1)	(2)	(3)	(4)	(5)
< -19%	38.55	8,340	[omitted]		
-18.99% to 0	44.25	7,802	5.09***	4.01	6.17
0.01% to 19%	48.21	8,223	8.63***	7.56	9.69
> 19%	50.67	8,454	11.48***	10.40	12.56
Mean Dep. Var.			41.14%		

Table 8: Model Parameters: Baseline

This table presents the parameter values in the baseline model.

Parameter	Value
Risk aversion (ρ)	5
Discount factor (β)	0.98
Risk-free return (R^f)	2%
Equity premium ($R^s_t - R^f$)	4%
Retirement age (T^R)	65
Correlation between equities and permanent income	
Before retirement	0.10
After retirement	0
Maximum age (T)	100
Pessimism factor (τ)	0.00
Correlation across expectations (ι)	0.00
Uncertain income in retirement	Yes
Bequest Motive	No

Table 9: Pre- and post- retirement effects of mortality, and dispositional pessimism

Panel (A) presents the differences in consumption, savings and risky share from the baseline for various levels of pessimism before and after retirement. Panel (B) presents the same table with the strength of the bequest motive set to 2.5.

Panel A: Deviations from baseline, without bequests

	Average before retirement, Pessimism Range						Average after retirement, Pessimism Range					
	4%	12%	28%	44%	60%	64%	4%	12%	28%	44%	60%	64%
Consumption												
Units: Percent Difference from baseline												
Mortality Pessimist	0.06	0.71	0.99	1.75	3.05	2.44	-0.24	-0.59	-3.09	-4.15	-5.10	-7.08
Dispositional Pessimist	-0.63	-1.28	-3.31	-4.46	-4.74	-5.48	-1.72	-4.76	-11.35	-15.21	-18.09	-20.07
Savings												
Units: Percent Difference from baseline												
Mortality Pessimist	-0.90	-1.77	-4.43	-6.60	-7.74	-9.25	-1.94	-4.57	-12.02	-17.87	-22.91	-25.13
Dispositional Pessimist	-1.94	-4.85	-11.23	-16.66	-20.72	-22.36	-3.99	-10.29	-23.13	-32.47	-39.74	-41.84
Risky share												
Units: Percentage Points from baseline												
Mortality Pessimist	0.16	0.33	0.58	0.94	1.12	1.28	0.56	1.32	3.20	5.47	7.86	8.32
Dispositional Pessimist	-1.18	-3.91	-10.68	-20.87	-39.69	-46.54	-0.79	-2.82	-7.07	-11.90	-17.75	-19.50

Panel B: Deviations from baseline, with bequests

	Average before retirement, Pessimism Range						Average after retirement, Pessimism Range					
	4%	12%	28%	44%	60%	64%	4%	12%	28%	44%	60%	64%
Consumption												
Units: Percent Difference from baseline												
Mortality Pessimist	-0.53	-0.42	0.53	1.03	1.28	2.04	-2.43	-4.52	-5.24	-6.83	-9.36	-9.16
Dispositional Pessimist	0.09	-1.27	-2.64	-4.31	-5.59	-5.43	-1.44	-5.88	-11.26	-16.18	-20.12	-20.25
Savings												
Units: Percent Difference from baseline												
Mortality Pessimist	-1.28	-2.90	-5.05	-7.37	-9.87	-9.82	-3.14	-7.70	-13.54	-19.25	-24.97	-25.68
Dispositional Pessimist	-0.84	-4.58	-10.39	-16.42	-21.55	-22.20	-3.21	-10.73	-22.28	-31.80	-39.18	-40.27
Risky share												
Units: Percentage Points from baseline												
Mortality Pessimist	0.06	0.17	0.53	0.76	1.07	1.11	0.09	0.31	0.81	1.12	1.35	1.33
Dispositional Pessimist	-1.29	-3.99	-10.84	-21.77	-41.93	-48.48	-1.16	-3.58	-8.77	-14.49	-20.58	-22.17

Figure 1a: Unconditional Relationship Between Mortality Deviations and Risky-asset Share

This figure presents a scatter-plot of the average risky-asset share (y-axis) held by individuals in the Health and Retirement Study at each level of mortality deviation (x-axis). Mortality deviations are measured as the difference between the subjective life expectancy and life-table equivalents. Positive deviations denote "optimism", and negative deviations denote "pessimism" relative to life-table estimates.

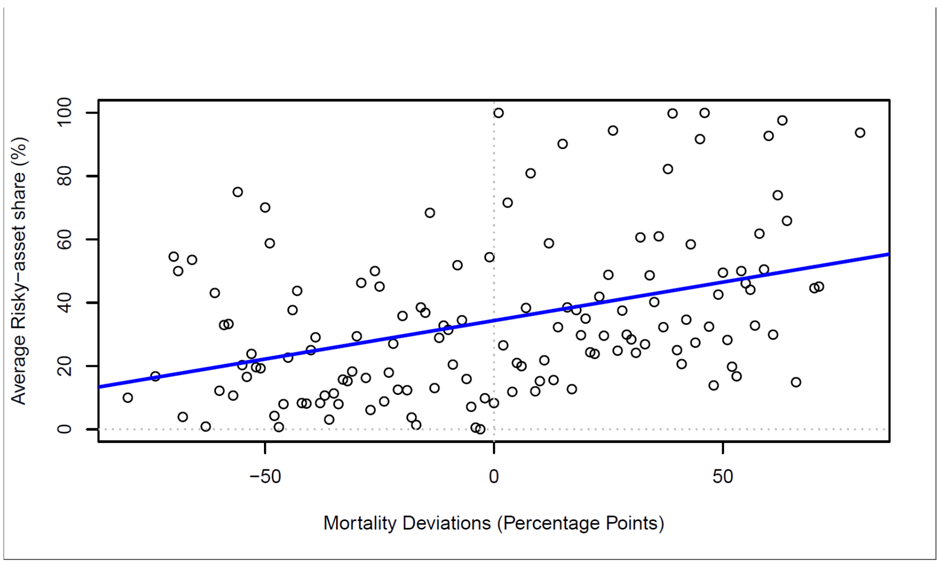


Figure 1b: Share of Aggregate Liquid Financial Wealth Across Age-groups

This figure presents the share of aggregate liquid financial wealth amongst households in the United States by different age-categories. The data is from the 2013 Survey of Consumer Finances. Liquid assets are defined as the sum of total value of directly held pooled investment funds, deposits (in various accounts and certificate of deposits), total value of savings bonds, total value of directly held stocks and bonds, other financial and managed assets, and cash value of whole life insurance. This measure does not include the total value of quasi-liquid assets (IRAs, Keoghs, thrift-type accounts, and future and current account-type pensions).

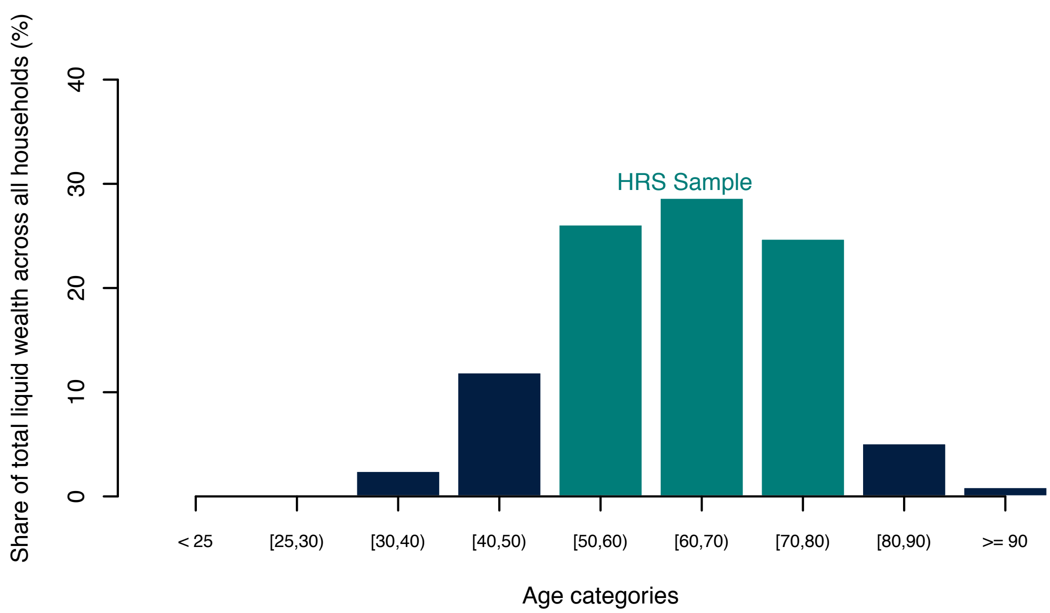


Figure 2: Subjective vs. Life-table probabilities

This figure presents six panels of comparison between subjective and life table probabilities. Each panel is different in the survival horizon, i.e., the difference between the target age and current age of the respondent. Across all survival horizons, the dark blue line represents the subjective probability and the line in teal refer to the corresponding life-table probabilities from the Vital Statistics Tables.

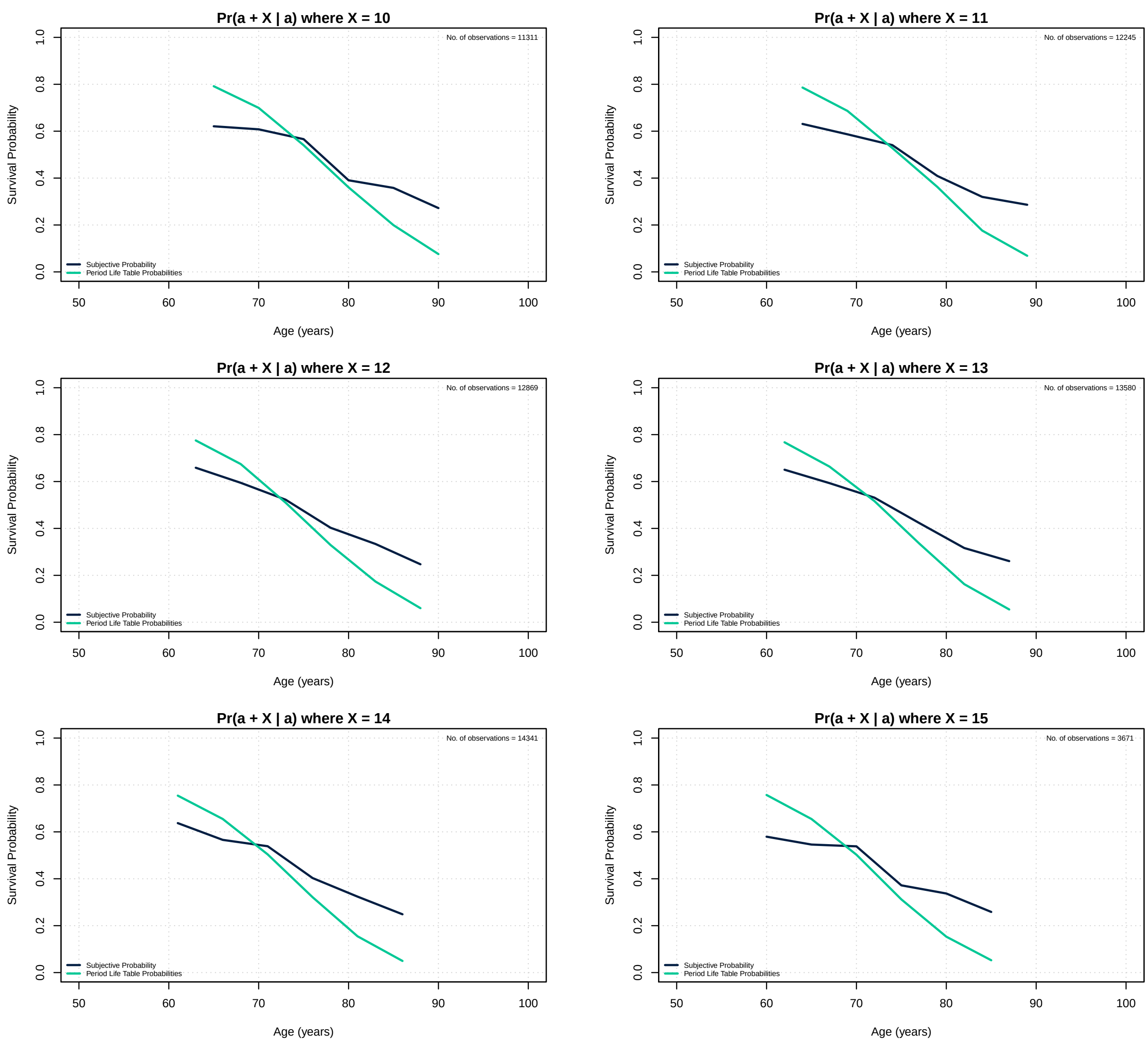


Figure 3: Effects of Natural Disasters by Age

This figure plots the average marginal effects of experiencing a natural disaster across different ages from Column (6) of Table 2a. Standard errors are computed using the delta method and the empirical specification is evaluated at different age points, 50, 55, 60 and so on.

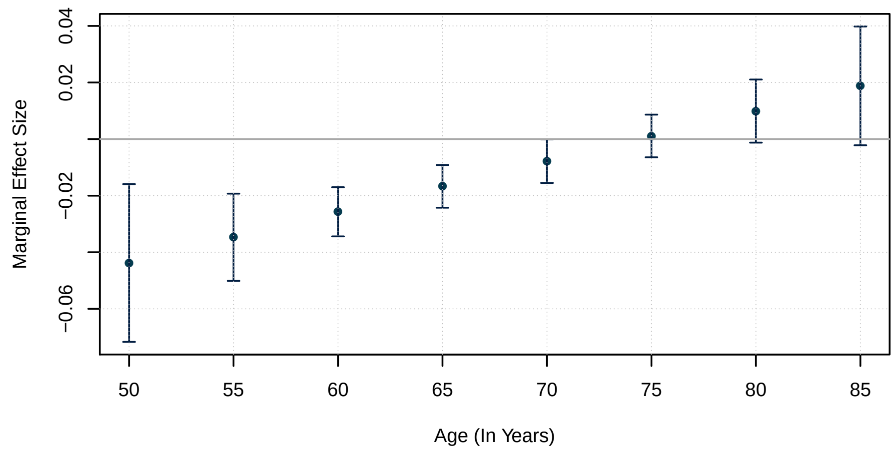
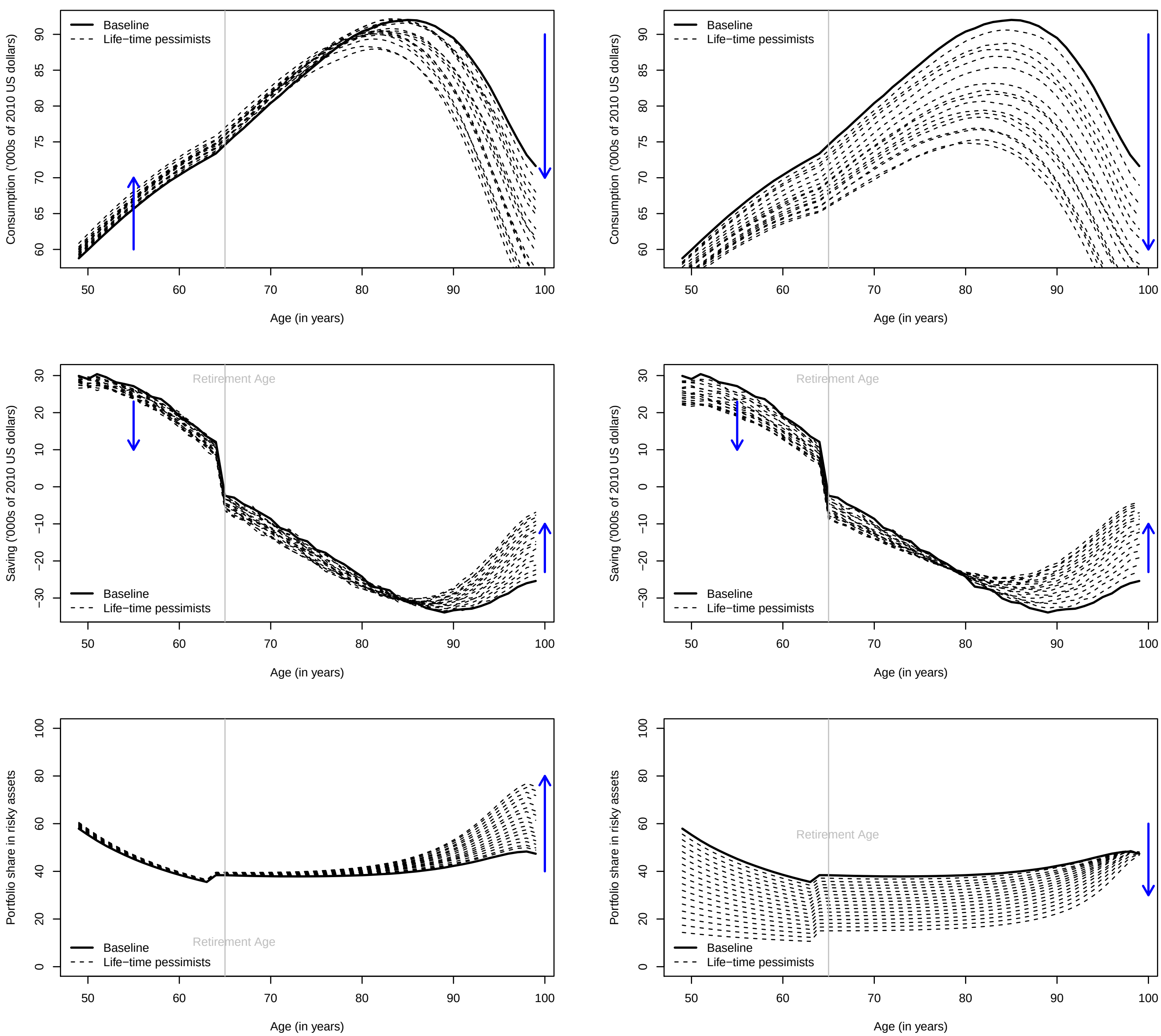


Figure 4: Life-cycle profile for College Graduates

This figure plots the model generated optimal paths for consumption (Row 1), savings (Row 2) and portfolio share in risky assets (Row 3) for a mortality pessimist (Column 1) and a dispositional pessimist (Column 2). Units: thousands of 2010 US dollars (Rows 1 and 2) and percentage points (Row 3). The dark line is the baseline optimal path and the dotted lines are at various levels of pessimism, τ at which the life-cycle model was estimated.

Mortality Pessimist | Dispositional Pessimist



Online Appendix

A Appendix Tables and Figures

Table A.1: Correlates of Subjective Life Expectancy

This table presents the baseline state-county fixed effects regression specification. All variables reported are used as control variables in all subsequent analyses presented in this paper.

	Coefficient	Standard error
Age	0.006**	(0.003)
Age-Squared	0.001***	(0.000)
Wealth Bins		
43,000 – 141,400	0.001	(0.004)
141,401 – 372,000	0.006	(0.005)
> 372,000	0.012***	(0.005)
Log(Out of Pocket Medical Expenditure + 1)	-0.001***	(0.000)
Self-reported Health Status		
Very good	-0.056***	(0.005)
Good	-0.121***	(0.004)
Fair	-0.181***	(0.006)
Poor	-0.223***	(0.010)
Cognitive Skills (Backward Counting)		
Correct (1st try / 2nd try)	0.033**	(0.015)
Race: Black/African American	0.043***	(0.006)
Gender: Female	-0.0687***	(0.005)
Parents:		
I(Mother lives currently)	0.031***	(0.006)
I(Mother lives currently) x Gender: Female	0.033***	(0.008)
I(Father lives currently)	0.066***	(0.008)
I(Father lives currently) x Gender: Female	-0.033***	(0.011)
Education Qualification:		
GED	-0.002	(0.007)
High-school graduate	0.007	(0.005)
Some college	0.022***	(0.006)
Marriage Status:		
I(Married)	0.0023	(0.011)
I(Divorced at least once)	0.011***	(0.003)
I(Widowed at least once)	-0.009**	(0.003)
County Fixed Effects	Yes	
Survival Horizon Fixed Effects	Yes	
Adjusted R-squared	0.2685	
No. of Observations	78,917	

***, **, * denote 1, 5 and 10 percent significance

Robust Standard Errors Clustered at the State Level

Table A.2: Impact of Extreme Natural Disasters on Mortality Deviations: Percent Deviations

$$\text{percent}(l^d_{i,c,t}) = \alpha + X^{'}_{i,t}\beta + \omega \text{Natural Disaster Proxy}_{c,t} + \psi_c + \zeta_x + \epsilon_{i,c,t}$$

	(1)	(2)	(3)	(4)	(5)	(6)
Log(No. of days + 1)	-0.0033*	-0.0908***				
	(0.002)	(0.033)				
Log(No. of disasters + 1)			-0.0225*	-0.2982***		
			(0.012)	(0.102)		
I(No. of disasters > 0)					-0.0275**	-0.2822***
					(0.013)	(0.095)
Age ×						
Log(No. of days + 1)		0.0013***				
		(0.000)				
Log(No. of disasters + 1)				0.0041***		
				(0.001)		
I(No. of disasters > 0)						0.0039***
						(0.001)
Control variables (Incl. Age in levels)	✓	✓	✓	✓	✓	✓
County Fixed Effects	✓	✓	✓	✓	✓	✓
Survival Horizon Fixed Effects	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.1873	0.1867	0.1832	0.1839	0.1863	0.1782
No. of Observations	78,917	78,917	78,917	78,917	78,917	78,917

***, **, * denote 1, 5 and 10 percent significance

Robust Standard Errors, Clustered at the State Level

Table A.3: Impact of Mass Shootings on Mortality Deviations: Percent Deviations

$$
\begin{aligned}
\text{percent}(l^d_{i,c,t}) \quad = \quad & \alpha + X^{'}_{i,t}\beta + \omega \text{Natural Disaster Proxy}_{c,t} + \rho I(\text{Arson+ Gun + Murder} > 0)_{c,t} + \\
& \mu I(\text{Mass Shootings} > 0)_{c,t} + \mu_2 I(\text{Mass Shootings} > 0)_{c,t} \times I(\text{Arson + Gun + Murder} > 0)_{c,t} \\
& + \psi_c + \zeta_x + \epsilon_{i,c,t}
\end{aligned}
$$

	(1)	(2)	(3)	(4)
I(Arson+Gun+Murder > 0)	-0.0260	-0.0266	-0.0019	-0.0022
	(0.041)	(0.041)	(0.022)	(0.022)
I(Mass Shootings > 0)		-0.0766***		-0.0432***
		(0.009)		(0.010)
I(Arson+Gun+Murder > 0) x I(Mass Shootings > 0)		0.0991***		0.0643***
		(0.039)		(0.028)
I(No. of disasters > 0)	-0.2316***	-0.2323***	-0.2471***	-0.2480***
	(0.101)	(0.101)	(0.110)	(0.110)
Age ×				
I(No. of disasters > 0)	0.0034***	0.0034***	0.0035***	0.0035***
	(0.001)	(0.001)	(0.002)	(0.002)
Control variables (Incl. Age in levels)	✓	✓	✓	✓
Individual Fixed Effects	×	×	✓	✓
State Fixed Effects	✓	✓	×	×
Survival Horizon Fixed Effects	✓	✓	✓	✓
Adjusted R-squared	0.2438	0.2441	0.5523	0.5523
No. of Observations	78,917	78,917	78,917	78,917

***, **, * denote 1, 5 and 10 percent significance

Robust Standard Errors (Columns 3,4, Clustered at the State Level)

Table A.4: Placebo Analysis: Impact of Natural Disasters on Mortality Deviations

$$l^d_{i,c,t} = \alpha + X^{'}_{i,t}\beta + \omega \text{Natural Disaster Proxy}_{c,t+1} + \psi_c + \zeta_x + \epsilon_{i,c,t}$$

	(1)	(2)	(3)
Log(No. of days + 1)	0.0002		
	(0.001)		
Log(No. of disasters + 1)		0.0046	
		(0.004)	
I(No. of disasters > 0)			0.0018
			(0.004)
Control variables (Incl. Age in levels)	✓	✓	✓
State Fixed Effects	✓	✓	✓
Survival Horizon Fixed Effects	✓	✓	✓
Adjusted R-squared	0.1873	0.1867	0.1832
No. of Observations	57,252	57,252	57,252

***, **, * denote 1, 5 and 10 percent significance

Robust Standard Errors

Table A.5: Robustness: Spatial Effects of Natural Disasters on Mortality Deviations

$$l^d_{i,c,t} = \alpha + X^{'}_{i,t}\beta + \omega \text{Treatment}_{c,t+1} + \psi_c + \zeta_x + \epsilon_{i,c,t}$$

	(1)	(2)	(3)	(4)
I(No. of disasters > 0)	-0.0101**	-0.0072*	-0.0612*	-0.0512*
	(0.005)	(0.004)	(0.037)	(0.029)
	-2.1042	-1.8462	-1.6630	-1.7902
Age ×				
I(No. of disasters > 0)			0.0008*	0.0007*
			(0.001)	(0.000)
			1.6000	1.7500
Control variables (Incl. Age in levels)	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	No	Yes	No
State Fixed Effects	No	Yes	No	Yes
Survival Horizon Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.2477	0.2477	0.2477	0.2477
No. of Observations	26,955	26,955	26,955	26,955

Robust Standard Errors

Table A.6: Impact of Mass Shootings on Risky-asset Share

This table presents the population weighted regression estimates of the impact of mass shootings *and* l^d on risky asset share. The coefficients of interest are μ,δ_0 and δ_1. δ_1 measures the impact on risky share *when* there is a natural disaster and a change in l^d is observed.

$$w_{i,c,t} = \psi_c + \zeta_x + \theta_t + X^{'}_{i,c,t}\beta + \delta_0 l^d_{i,c,t} + \delta_1 l^d_{i,c,t} \times I(\text{Experience} > 0)_{c,t} + \mu I(\text{Experience} > 0)_{c,t} + \epsilon_{i,c,t}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l^d	0.020***	0.018***	0.014***	0.012**	0.024*	0.023	0.017	0.016
	(0.005)	(0.004)	(0.004)	(0.005)	(0.013)	(0.013)	(0.013)	(0.013)
I(No. Disaster > 0)	-0.014***	-0.002	-0.010***	0.001	-0.014***	-0.002	-0.011***	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
l^d × I(No. Disaster > 0)	-0.033**	-0.027**	-0.029**	-0.023*	-0.032**	-0.026*	-0.028**	-0.022
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
I(Arson + Gun + Murder > 0)					0.012	0.008	-0.024*	-0.024*
					(0.008)	(0.008)	(0.015)	(0.015)
I(Mass Shootings > 0)					-0.003	0.007	-0.044	-0.030
					(0.040)	(0.040)	(0.044)	(0.044)
l^d × I(Arson + Gun + Murder > 0)					-0.005	-0.007	-0.005	-0.005
					(0.013)	(0.014)	(0.014)	(0.013)
l^d × I(Mass Shootings > 0)					-0.047	-0.032	-0.039	-0.025
					(0.133)	(0.133)	(0.046)	(0.134)
I(Arson + Gun + Murder > 0) x I(Mass Shootings > 0)					0.018	0.018	0.039	0.045
					(0.043)	(0.043)	(0.134)	(0.047)
l^d × I(Arson + Gun + Murder > 0) × I(Mass Shootings > 0)					0.177	0.160	0.180	0.164
					(0.140)	(0.140)	(0.141)	(0.141)
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wealth Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Health Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demography + Family Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survival Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	No	No	Yes	Yes	No	No
County Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Time Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R-squared	0.16	0.17	0.19	0.20	0.16	0.17	0.19	0.20
No. of observations	78,917	78,917	78,917	78,917	78,917	78,917	78,917	78,917

***, **, * denote 1, 5 and 10 percent significance, Robust Standard Errors in parenthesis

Figure A.1: Estimates of age-wise pessimism profile: τ_t

This figure presents the age-wise optimism profile estimates from the regression specification in Table 2a. Standard errors are computed using the delta method. Estimates for ages 20-50 and 96-100 are extrapolated from an empirical model that uses data only for individuals between 50 and 96 as the Health and Retirement Study covers individuals over 50, and do not have observations of individuals over 96.

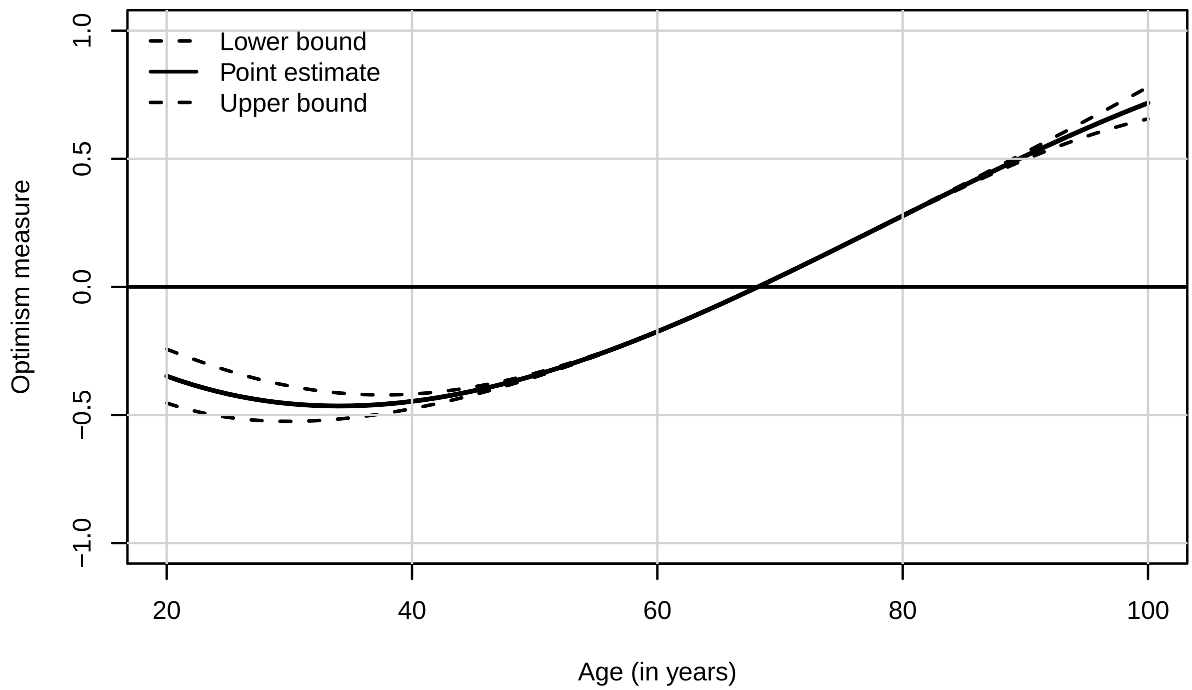


Figure A.2: Identification Strategy for Neighbourhood effects

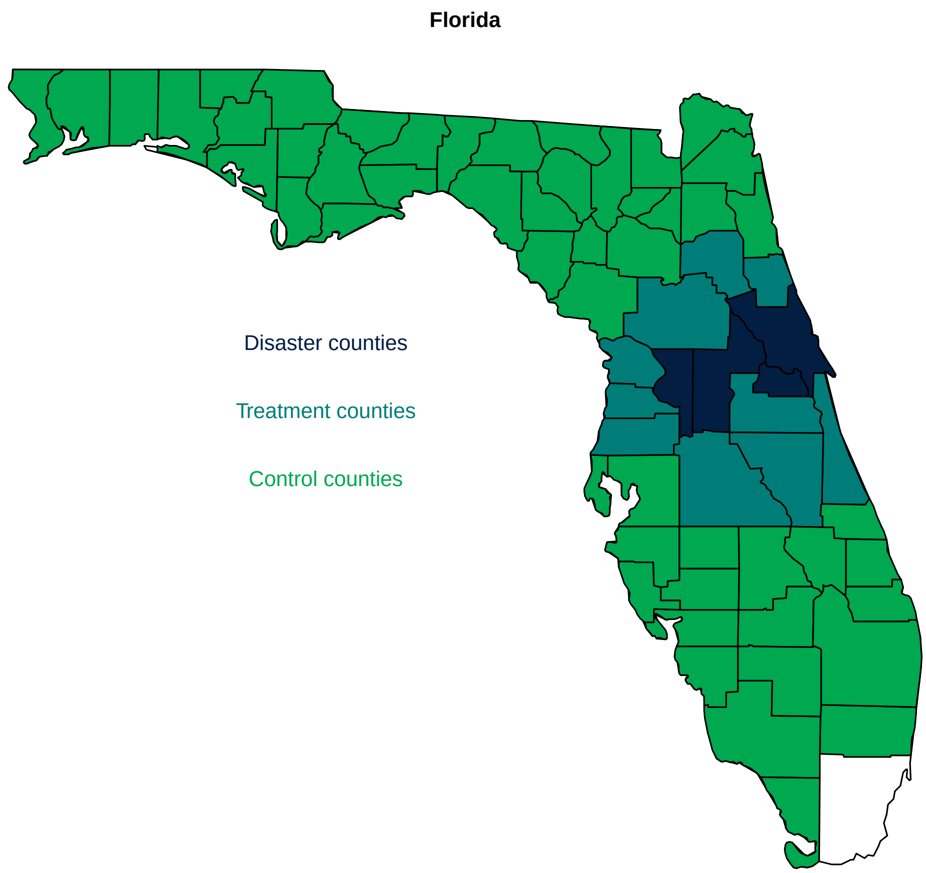
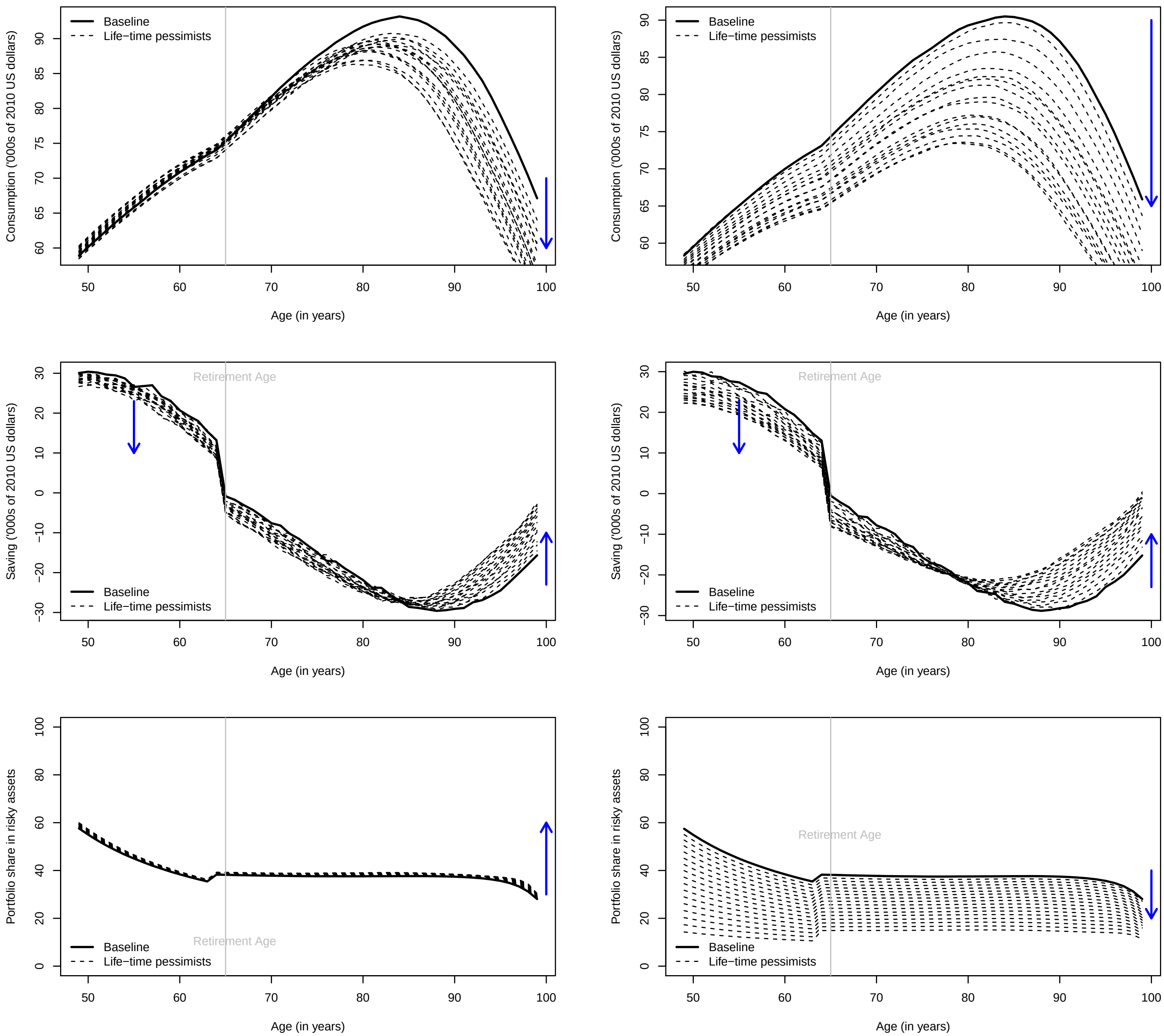


Figure A.3: Life-cycle profile for College Graduates With Bequest Motive

Mortality Pessimist

Dispositional Pessimist



B Data description

Health and Retirement Study

The main data source for this paper is the Health and Retirement Study (HRS), a biennial panel survey since 1992 in the United States with individuals aged 50 and over, and contains 11 waves of data spanning two decades (till 2012).[22] A consolidated panel dataset created by RAND using the raw questions from each wave of the HRS is used for analysis. While the most comprehensive empirical exercise could potentially use all eleven waves of the HRS data, there have been some changes to the questions on subjective life expectancy over time. These questions are fully consistent since 1996 and hence for all analyses presented the first few waves of study are not utilised.

Regarding mortality expectation, the question in the HRS is framed as the expected probability of living till age y. If a respondent is aged a and $a \leq 65$, the HRS poses the following question: "What is the percent chance that you will live to be 75 or more?". When a respondent is at least sixty-five years old, to accommodate older respondents, the question asks the probability of living to an age from 80 to 100 depending on the respondent's age: "What is the percent chance that you will live to be [80 (if 65 <= a <= 69) / 85 (if 70 <= a <= 74) / 90 (if 75 <= a <= 79) / 95 (if 80 <= a <= 84) / 100 (if 85 <= a <= 89)]?" Notationally, the question posed is the probability that a respondent will live till age y (the target age) conditional on being age a, i.e., $\Pr(a + x|a)$ where $x = y - a$. The incremental number of years of life expected in the question posed to respondents (x) is effectively a function of their current age (henceforth known as the Survival Period). The survey also records information about health, family structure, health care costs, income (including pensions or annuities), assets, housing, job status (and history), and health insurance. All other important observed characteristics used in this paper primarily come from modules on

[22] Several research work use this data. For a comprehensive overview of the data, refer to the user guides at `http://goo.gl/m0ZA38`, especially, Sonnega (2015)

income, assets, cognition, and expectations. Since some of these variables are only available at the household level, this paper uses only the primary respondents (and not their spouses) for analysis.

Table B.1 presents summary statistics for the respondents under study. Of those in the age group 50-56, nearly 47 percent of the sample are men, although this attenuates to 40 percent for the 76-85 age group. The life expectancy of Blacks and others (Hispanic and Asians) are lower than that of Whites, leading to an attenuation in the sample from 9.5 percent (age group 50–56) to 5.8 percent (age group 76-85) for Blacks and 6.1 percent to 2 percent for Hispanics and Asians for the same age groups. This paper does not study individuals older than 85 as a large proportion of them use proxies for completing the survey.

Decline in cognitive functioning and onset of cognitive impairment pose serious challenges to survey design especially with questions on expectations and probabilities. Any assessment of the role such subjective expectations play on economic decisions will have to control for the cognitive ability to answer such survey questions. Using survey questions on cognition, a summary score of cognitive capabilities developed in Herzog and Wallace (1997) is deployed to control for cognitive impairment. To a large extent, individuals score highly on the cognitive measures and are fairly in control of their cognitive skills even when over 76 years old. That said, the onset and decline of cognitive capabilities after age 76 is captured by a decline in the score developed by Herzog and Wallace (1997).

Risky share is defined as the fraction of all *financial* assets directly held in Stocks, Mutual Funds and Investment Trusts and non-governmental Bonds and Bond Funds.[23] On average, the middle-aged cohort (50-56) have 10 percent of their assets in IRA/Keogh Accounts, and this diminishes to about 6 percent for the very old. The fraction of investments in stocks, funds and trust, however, does not decline and remains stable around 6.5 percent of

[23]This definition is the same as in studies such as Brunnermeier and Nagel (2008) and Puri and Robinson (2007) but different from Badarinza, Campbell, and Ramadorai (2016) as it is difficult in the HRS to assume that values in the IRA and Keogh Accounts are not primarily in money-market and treasury bonds.

Table B.1: Summary Statistics: Demography, Cognition, Assets and Bequest

	Age distribution				
	50-56	57-61	62-68	69-75	76-85
Demography					
Male (fraction)	0.469	0.462	0.457	0.445	0.402
Race (fraction):					
Black	0.095	0.091	0.085	0.071	0.054
White	0.844	0.863	0.872	0.900	0.926
Other	0.061	0.045	0.042	0.028	0.020
Cognition (fraction)					
Poor (0-10 points)	0.004	0.005	0.010	0.003	0.033
Fair (11-20 points)	0.193	0.192	0.251	0.143	0.409
Good (21 - 35 points)	0.803	0.804	0.739	0.854	0.559
Wealth					
Share of Total Assets (average)					
Risky Financial Assets					
Stocks, Funds, Trusts	0.064	0.062	0.064	0.065	0.082
Non-government Bond and Bond Funds	0.005	0.005	0.007	0.008	0.011
IRA/Keogh Accounts	0.104	0.121	0.121	0.101	0.059
Non-Risky Financial Assets					
CDs, T-Bills, Checking, MM accounts	0.104	0.104	0.114	0.126	0.181
Housing and Real Estate					
Primary residence	0.398	0.377	0.401	0.362	0.337
Real Estate	0.029	0.029	0.031	0.026	0.016
Net Wealth (fraction)					
0 - 50,000	0.245	0.213	0.190	0.183	0.214
50,001 - 100,000	0.143	0.123	0.108	0.111	0.121
100,001 - 500,000	0.419	0.426	0.412	0.431	0.435
500,001 - 1,000,000	0.109	0.137	0.163	0.153	0.130
$>$ 1,000,000	0.084	0.101	0.127	0.122	0.101
Share of Financial Assets (average)					
Risky Assets	0.423	0.450	0.448	0.411	0.325
Bequest Motive (fraction)					
Prob(Any bequest at all) $>$ 0	0.880	0.869	0.840	0.822	0.877
Prob(Bequest $\geq$ 10,000 US dollars) $>$ 0	0.822	0.812	0.778	0.747	0.821
Prob(Bequest $\geq$ 100,000 US dollars) $>$ 0	0.733	0.722	0.647	0.581	0.742
No. of Observations: Total respondents	33,227	29,859	24,840	30,458	27,577

Notes: This table reports the summary statistics for respondents in the Health and Retirement Study (HRS) for all waves from 1992-2012, across five age-groups: 50-56, 57-61, 62-68,69-75 and 76-85. The reported statistics are weighted by the individual sampling weights provided in the RAND HRS dataset. "(fraction)" denotes the fraction of respondents within each age-bin of the characteristic reported in rows. "(average)" denotes the mean value of the characteristic reported in the rows. This table includes all respondents, and not just those who have reported subjective life expectancy in the survey.

total assets (financial and non-financial) of the individual. In an alternate measure of risky share that includes IRA and Keogh Account as part of risky assets, there is a reduction in the share as individuals get older. This however may just be mechanical: IRA and Keogh accounts require withdrawals after holders turn 70.5. Therefore, this paper uses the share of stocks, mutual funds, investment trusts and non-governmental bonds and bond funds to total financial assets as the measure of risky share of an investor's financial portfolio.

The next few rows in the table present the role of housing, bequest and the wealth distribution of the population under study. The modal age group is between 55-60 with an average (net) wealth of about 162,000 dollars.[24]

Federal Emergency Management Agency (FEMA)

Natural disasters have been utilized as a source of exogenous variation in many studies. To estimate changes in subjective life expectancy due to exogenous shocks, I use the spatial information from the HRS and map hand-collected data from FEMA's Disaster Declaration Database at the county level.

The FEMA database dates back to 1953, and documents details for each disaster declaration including declaration date, begin and end dates for disaster, type of disaster, and location (state and county) of the disaster. From 1963 through the end of 2013, a total of 3215 separate disasters were declared across the United States.[25]

Natural disasters by themselves are exogenous and not under the influence of any one individual. However, FEMA declarations are themselves not guaranteed when a disaster occurs and thus introduces concerns of selection. The Stafford Act[26] and prior to that the

[24]Wealth is computed as the total net wealth including investments in stocks, bonds, retirement accounts, primary and secondary housing, net of secured and unsecured loans of the household. The HRS does not have individual wealth details, but only for the household as a whole. Hence, this paper only uses the primary respondent and not their spouses in any of the analyses.

[25]The first ten years of this database (till 1963) does not contain county level geographic classification of disasters. Hence this paper uses disaster declarations since 1963 at the county level to measure exogenous natural disaster experiences.

[26]Section 401 of the Stafford Act can be accessed here: `https://www.fema.gov/robert-t-stafford-disaster-relief-and-emergency-assistance-act-public-law-93-288-amended`

Disaster Relief Act requires that "all requests for a declaration by the President that a major disaster exists shall be made by the Governor of the affected State." Different states in the US have varied propensity to declare disasters, and thus any study that does not control for this selection process (by including state fixed effects) will pick up additional effects due to selection issues across states in the US.

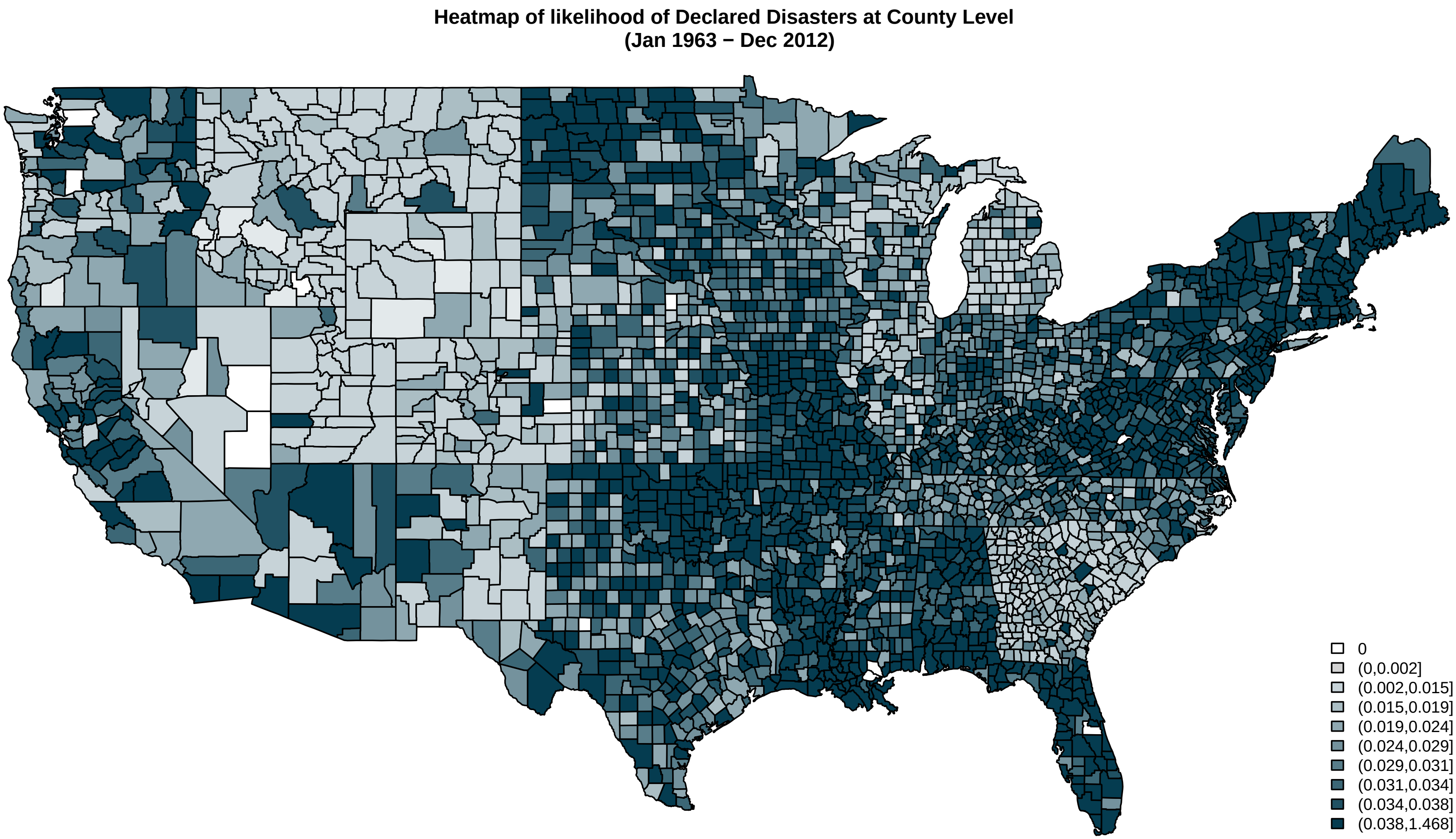
In order to be conservative, this paper uses only those disasters that inevitably require federal assistance. In this study, only those disasters that are least likely in the FEMA database are used. [27] Disaster declarations for floods, heavy rain, snow storms and alike are excluded from the analysis. In other words, the identifying assumption is that disasters such as Hurricane Katrina will always be declared a disaster under FEMA, and are not influenced unduly by state-level propensities to seek federal assistance.

Appendix C also provides evidence that differences in state propensities on FEMA declarations with its neighbouring states, although not always statistically significant, are economically meaningful and large for most states for the range of disasters used for analysis in this paper. Merging this data with the HRS data at the county level (using State and County FIPS codes)[28], and identifying effects *within* states forms the basis of the empirical analyses.

[27] Following classification types from the FEMA database are considered: Earthquake, Hurricane, Severe Ice Storm, Severe storm(s), Tornado, Tsunami, Typhoon, and Volcano.

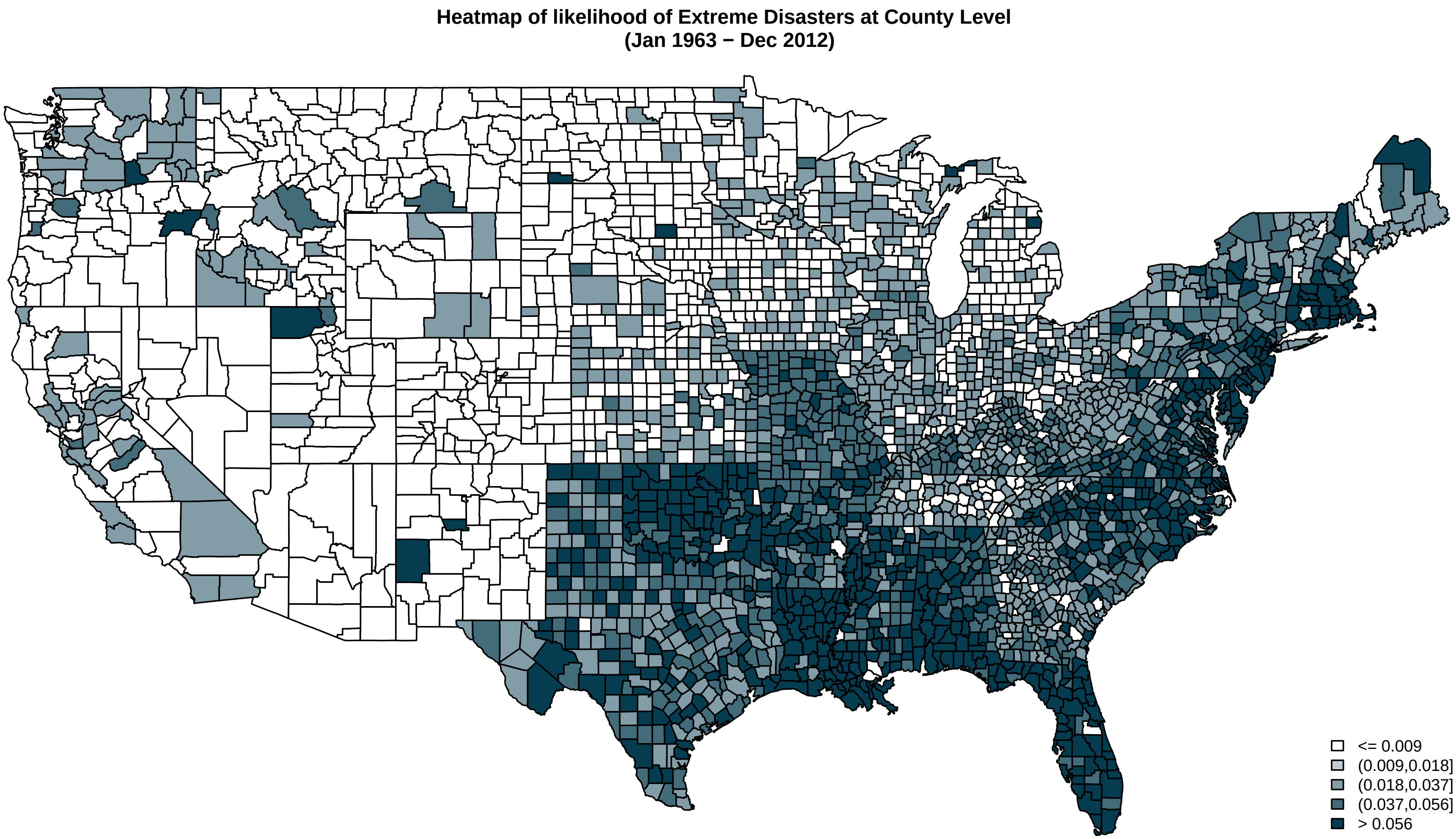
[28] The Federal Information Processing Standard (FIPS) code $6-4$ uniquely identifies counties and county equivalents in the United States.

Figure B.1: All Declared Disasters in the United States



Source: Federal Emergency Management Agency (FEMA)

Figure B.2: Extreme Disasters in the United States

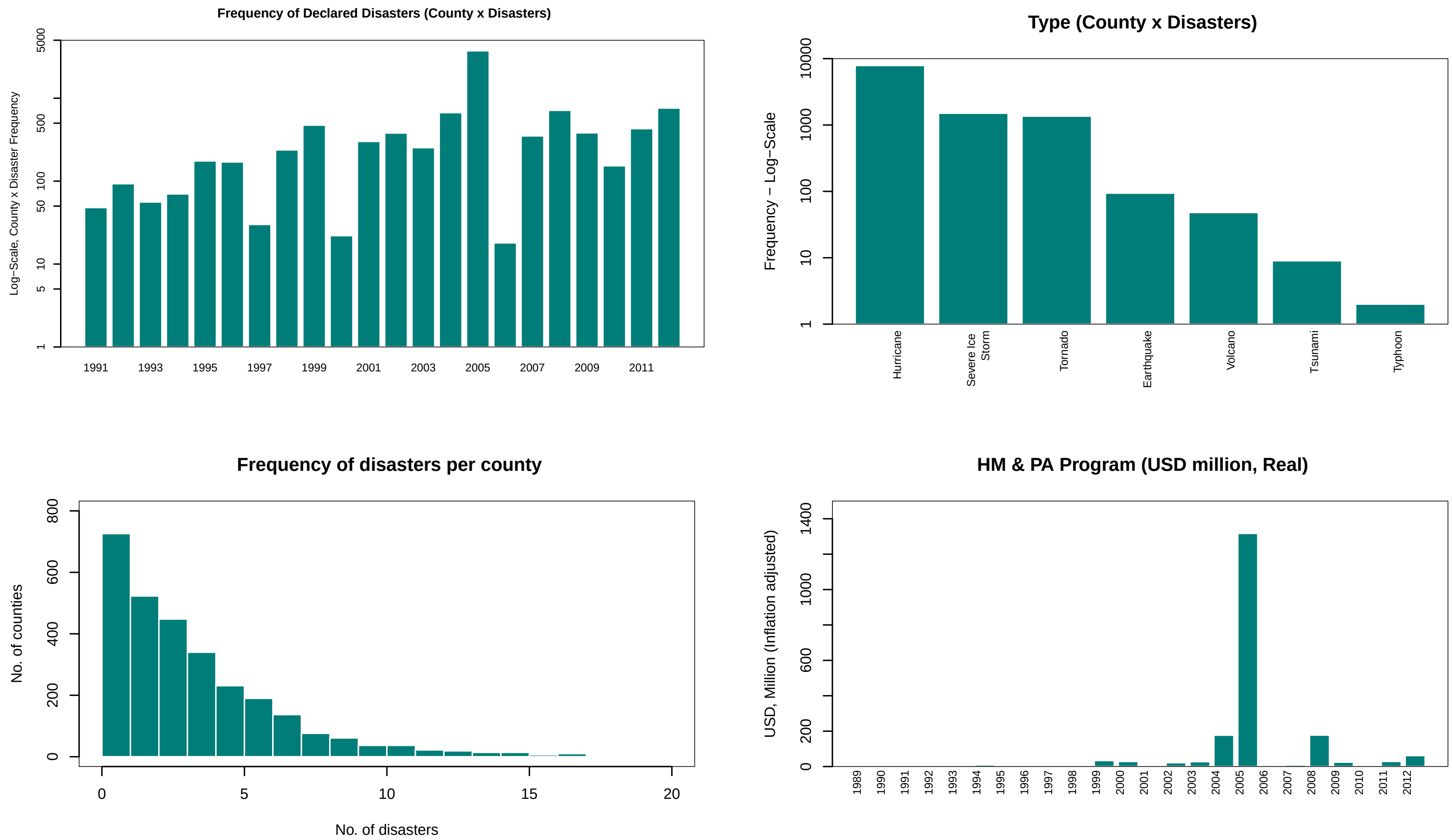


Source: Federal Emergency Management Agency (FEMA)

Figure B.1 presents the geographical variation in all disasters declared in the United States since 1963. The variation in exposure to likelihood of disasters across counties and states suggests that while disasters may be a regular occurrence for some of the counties, they are not so regular and "rare" in other counties. Further, events such as severe ice storms, earthquake, hurricane, tsunami, typhoon and volcanoes are truly exogenous and do not occur often in the past – their prevalence is less likely as can be seen in Figure B.2. These are referred to as extreme disasters and are used as disaster shocks in the paper.

The top left panel of Figure B.3 plots the frequency with which extreme disasters occurred in the United States. Nearly every wave has been preceded by a large number of disasters, thus providing ample variation for the purposes of this study. The top right panel plots the distribution of extreme disasters by its type. Hurricanes are a lot more common than Typhoons though much less common than other declared emergencies such as heavy rainfall, and forest fires.

Figure B.3: Summary Statistics: Disaster Declarations in the United States



Source: Federal Emergency Management Agency (FEMA)

The frequency of disasters (or its probability of occurrence) experienced may affect individual expectations. The bottom left panel of Figure B.3 plots the histogram of the number of counties that have experienced different disaster frequencies. A large proportion of counties in the United States have experienced less than 5 extreme disasters since 1963, whereas some counties have had nearly 16 extreme disasters in its history. The severity of such disasters (measured by the total federal financing received for recovery) have increased over time (bottom left panel).

Stanford Mass Shootings Database (MSA)

Mass shootings in the United States is another example of well identified shocks that have very low base rate of mortality. This additional measure of exogenous shock is important in a few ways. Unlike natural disasters, the long-run mortality implications of such shocks are non-existent.[29] While gun violence are directly related to prevailing socio-economic sentiments, to the extent shootings are identifiably not gang or drug related, and the motive is indiscriminate killing, they are exogenous at the level of an individual. This measure exogenous experience does not suffer from selection problems as in the case of FEMA disaster declarations.[30]

The Stanford Mass Shootings Data (MSA) puts together a repository for any event where there are three or more victims (not necessarily fatal and not including the shooter) unrelated to drugs or gang rivalry, thus enabling this study to assess the impact of a "man-made" but exogenous disaster on subjective mortality expectations. Only those events that are classified as "Mass Shooting", "Mass Murder" and "Spree Killing" in the database are used in this

[29]The long-run mortality of a mass-shooting is non-existent. However, another potential channel that may affect mortality expectations is an expected increase in such incidents, which is beyond the scope of measurement.

[30]A minority of U.S. states have bans on a category of guns, i.e., "assault weapons". However, there are no restrictions on travel for those who own guns and most mass shootings occur in locations *different* from where these guns are purchased. For recent work, refer to the New York Times article by Gregor Aisch and Josh Keller dated November 13, 2015 at `http://goo.gl/oYqvoX`.

paper for identification.[31] I have hand-collected the county information for every reported mass shooting in the Stanford database, making it possible to merge this with the HRS data at the county level (using State and County FIPS codes).

Uniform Crime Reporting Program Data

Arguably, an important factor to control for is the prevailing level of crime where respondents in the HRS live. If mass shootings have higher probability of occurrence in geographies where the base rate of crimes due to violence (defined as arson, gun related and murder crimes) is high, controlling for crime rates at the county level becomes important. Since these types of events are also subject to policy solutions that could vary over time, merely controlling for time-invariant unobservables through county fixed-effects do not provide the necessary identification. Controlling for time-varying gun violence across the U.S. allows for better identification of the impact of mass shootings on subjective life expectancy. This is made possible through the Uniform Crime Reporting Program Data made available by the Inter-University Consortium for Political and Social Research (ICPSR) in conjunction with the Department of Justice.

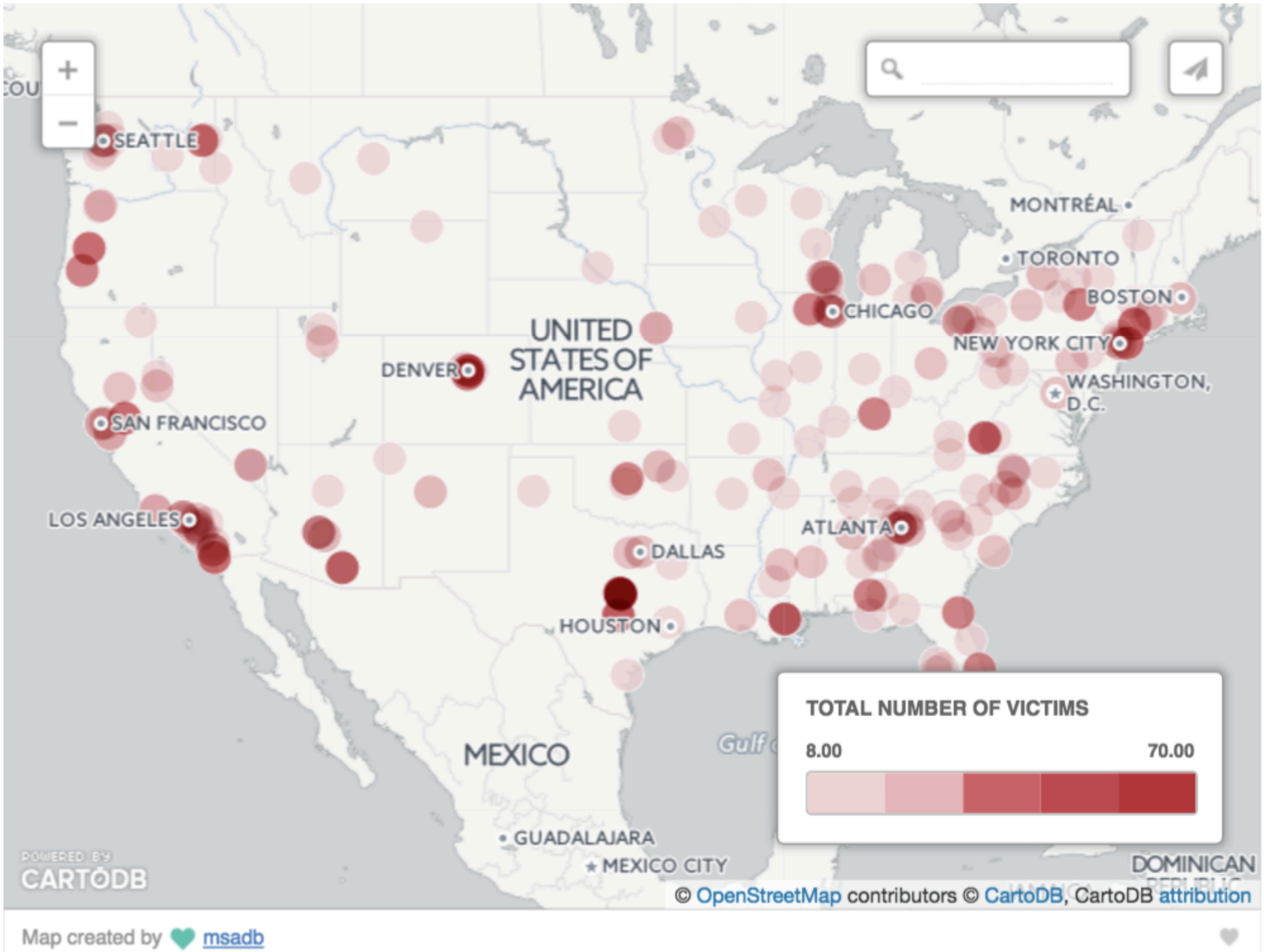
The Uniform Crime Reporting (UCR) program reports counts of arrests and offenses at the county level since 1994 (till 2012). Originally, this data is collected by the Federal Bureau of Investigation (FBI) from reports submitted by agencies and states participating in the UCR Program. The Inter-University Consortium for Political and Social Research (ICPSR), (for the Department of Justice) consolidate this information in a consistent fashion (along with measures assessing the extent of coverage in each county) across all counties in the US,

[31]Mass Shooting is where 3 or more people are shot. Usually this is in a single location and occurs within a single day. Mass Murder is where there are 4 or more fatalities in a single location within a single day. Spree Killing is defined as cases where 4 or more fatalities occur in multiple locations within a short span of time and there are no "cooling off period" between shootings. All these events appear to be indiscriminate (no specific cause from the exact victim) and are not identified as gang or drug related by the media.

every year.[32] Additionally, county-fixed effects allow for controlling other unobserved factors such as institutional histories, efficiency and administrative track record that vary across different geographies.

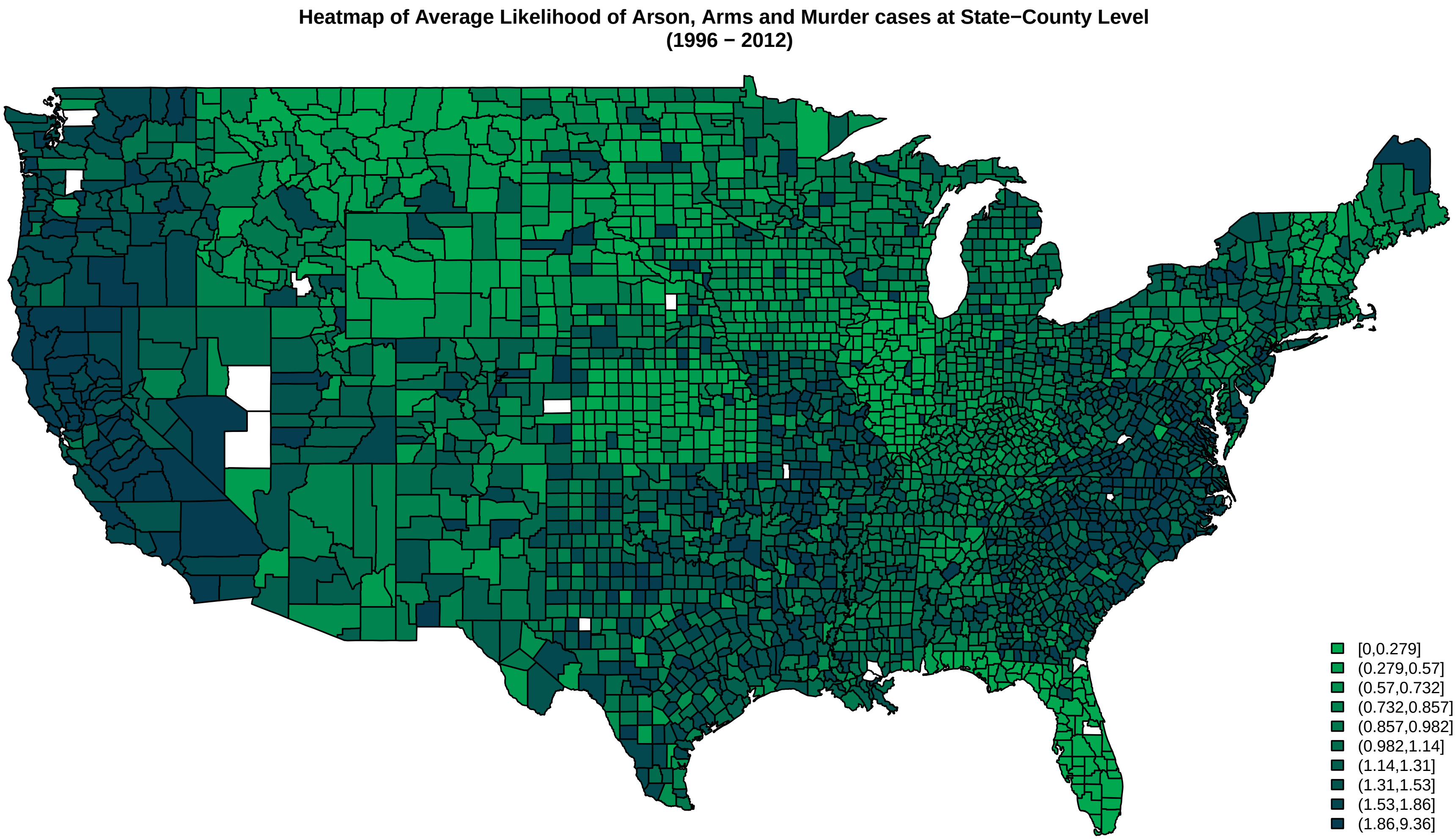
[32]The details of reporting procedures of crime statistics can be found in the Uniform Crime Reporting Handbook (Washington, DC: U.S. Government Printing Office, 1980), and in the codebooks for the ICPSR's Agency-level UCR data collection available upon request.

Figure B.4: Mass Shootings in the USA



Source: `https://library.stanford.edu/projects/mass-shootings-america`

Figure B.5: Percent of crimes involving Arson, Guns and Murder in the United States



Source: Department of Justice, United States, ICPSR (Various Datasets)

Mass Shootings in the United States are not concentrated in any one state over time. Almost every state in the sample has had one mass shooting or the other where the motive may be influenced by socio-economic and racial beliefs, but the victims were chosen at random. Each of the cases in the database is documented in detail to determine whether the victim was random. For instance, on April 6, 2012, a 19-year old and a 32-year old man went on a shooting spree in Tulsa, Oklahoma, shooting black men at random. Three men died and two were wounded in this attack. Similarly, on July 20, 2012, a 24-year old student set off several gas or smoke canisters at a movie theatre (in Denver, Colorado) before opening fire at the audience. Figure B.4 presents a screenshot of the mass shootings database as of 2015: The number of victims in different locations of the shoot out range from 8 to 70, and 43 percent of the events occur between 1996-2012 – the sample period for this study.

In 2012, 1.2 percent of all reported crimes in the United States were related to murder. Tennessee being the state with the highest violent crime rate (643.6 per 100,000), has nearly 1 percent of its crimes as murder. The statistical odds of homicide using a firearm in a given year is 0.4%.[33] Figure B.5 presents the heat-map of the average likelihood of arson, arms and murder crimes at the county level in the United States. At its highest (winsorized at 99th percentile), the reported value is 2.76 percent of all crimes in a county. The variation across counties (and states) is noteworthy and the likelihood of arson, arms and murder crimes and mass shootings are low.[34]

[33]CDC, Vital Statistics: `http://www.cdc.gov/nchs/data/nvsr/nvsr64/nvsr64_02.pdf`, accessed on 22 April, 2016.

[34]It must also be noted that there is substantial discrepancy between the statistics about mortality due to firearms from the CDC and reported crimes for homicide using firearms from the FBI. However, the author does not have disaggregated information at the county level from the CDC and hence use data from the FBI.

C State Propensity to Seek Federal Disaster Declaration

Disasters appear in the FEMA database only if the disaster occuring is officially declared by the state. In mathematical terms, this would mean:

$$Pr(\text{Declared}|\text{Disaster}) = \frac{Pr(\text{Disaster}|\text{Declared})Pr(\text{Declared})}{Pr(\text{Disaster})} \tag{13}$$

When a disaster is declared, it is assumed that it is indeed a disaster. Therefore, Pr(Disaster|Declared) = 1. Then, the conditional likelihood becomes:

$$Pr(\text{Declared}|\text{Disaster}) = \frac{Pr(\text{Declared})}{Pr(\text{Disaster})} \tag{14}$$

In this section, I estimate the propensity for states to declare a disaster. This is important because the true likelihood of a disaster is determined by both the likelihood of the disaster occurring and the propensity for states to declare it to be a disaster. If the propensity to declare a disaster is similar across states, then we can deduce that the FEMA database is a *good* proxy for the true set of natural disasters that have occurred in the United States.

Estimating State-wise Marginal Propensities to Declare a Disaster

Natural disasters do not care about political boundaries. Assuming that the differences in propensities between two *contiguous* counties across different states at the borders are due to variation in state propensities to declare a disaster, I estimate the extent of differences in the likelihood of a disaster being declared because of variations in state propensities.

For example, Florida has two neighbouring states, Alabama and Georgia. In Florida, there are six counties bordering Alabama and nine counties bordering Georgia. Let $D = 1$ for these 15 counties and $D = 0$ for the counties in Alabama and Georgia that border Florida. The disaster dummy $I(\text{Disaster} > 0)_{c,t}$ takes the value 1 if there was a disaster in any of these counties (c) at time t. So, the regression strategy for estimating the propensity to declare a disaster in the state of Florida will be:

$$I(\text{Disaster} > 0)_{c,t} = D\tau + \gamma_t + \epsilon_{c,t} \tag{15}$$

Here, τ is the estimate of Florida's (marginal) propensity to declare a disaster relative to its neighbouring states for counties that share a border with Florida. Importantly, the identification strategy requires that there be more than one state with which a state (s) shares its borders, as the estimated τ cannot be attributed to the state s if there is only one other state with which it shares its borders.

Using this framework, I now estimate state-wise propensity to declare a disaster relative to its neighbouring states, all in one regression:

$$I(\text{Disaster} > 0)_{c,s,t} = D\tau + I(S) + \tau_s I(S) \times D + \lambda_t + \sum_{k=1}^{K} I(\text{Disaster type}_k) + \epsilon_{c,s,t} \tag{16}$$

Equation (16) estimates the the propensity for state s choosing to seek federal assistance, after controlling for potential state level differences in disaster declaration due to unobserved factors such as alignment of political parties at the federal and state level, and within different disaster categories in FEMA. τ_s is the estimate of interest.

The variation used to estimate this regression comes from two sources: (1) Counties within each state; (2) The state boundary with more than one other state (used as a discontinuity). In this regression, I drop the states of Maine, Alaska and the island state of Hawaii. Maine shares a border with only one state, i.e., New Hampshire and has an international border (Canada). Alaska does not have any contiguous U.S. State, and Hawaii is an island.

Two important caveats in this estimation strategy are to be noted. Firstly, estimation of marginal propensities for states assume that states do not collude while making these decisions to apply for federal assistance. To a large extent putting in state and time fixed-

Table C.1: State-level Propensity to Seek Federal Assistance during Natural Disasters

	Disaster Type	Year FE	State FE	Year,State FE	N
		(A)	(B)	(C)	
(1)	Hurricanes	-0.012	0.072	0.072	120,816
		(0.165)	(0.237)	(0.164)	
(2)	Tornados	0.008	-0.016	-0.016	120,816
		(0.069)	(0.072)	(0.072)	
(3)	Earthquakes	0.003	0.013	0.013	120,816
		(0.022)	(0.019)	(0.019)	
(4)	Severe Ice Storms	-0.007	-0.029	-0.029	120,816
		(0.107)	(0.115)	(0.112)	

effects removes this unobserved variation. Secondly, disaster in county A in state s_1 will most likely mean the neighbouring county B in State s_2 will also have experienced the disaster may not necessarily be true. At best, this is an over-estimation of the marginal state propensity to declare a disaster, and hence the results obtained are the lower-bound of the true effect.

Figure C.1: Variation in State-level Propensity to Seek Federal Assistance during disasters

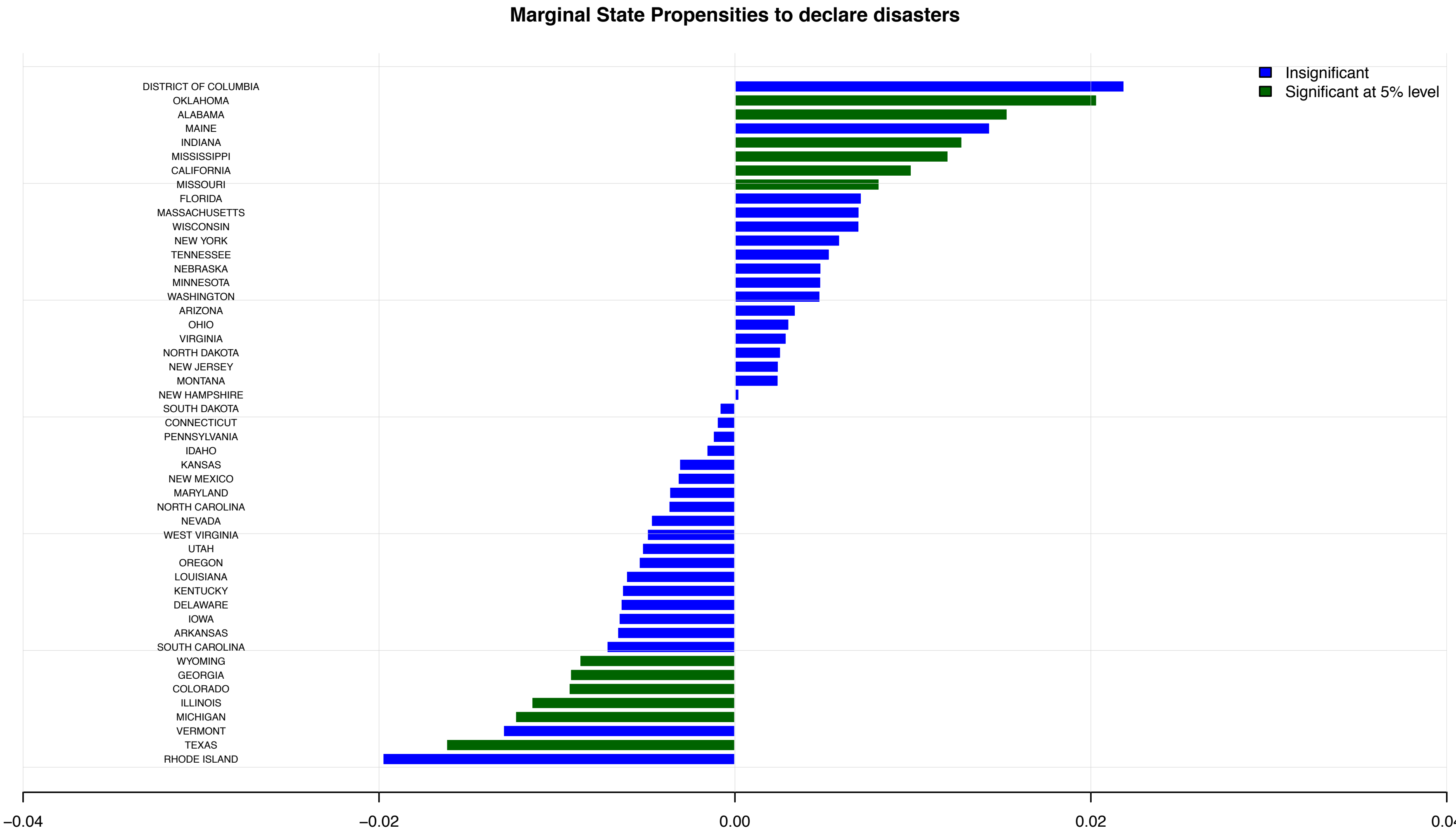


Table C.1 presents the results across all states. Each estimated coefficient is the overall propensity to declare disasters across all states, after controlling for state level variations and time variations. Column (A) presents the coefficients from a specification that only contains year fixed-effects, column (B) with state fixed effects and column (C) with both state and year fixed effects. Across all four disaster types used in the paper (rows 1 – 4), the overall propensity to declare disasters is small and statistically insignificant. However, this masks the heterogeneity across different states. Figure C.1 presents the marginal state propensities to declare disasters compared to its neighbouring states. Only six of the states have estimates that are positive and statistically significant, and the marginal propensities are reasonably large relative to their neighbouring states. This suggests that using FEMA declarations require explicit controls for this additional source of variation.

D Updates according to Bayes' rule

Despite the press given to natural disasters and mass shootings, their contribution to U.S mortality is 0.06 percent for both natural disasters and mass shootings (Goklany, 2009).[35] In relative terms, mortality risks due to natural disasters or gun violence are nearly 120 times lower than health risks and unintentional injuries.[36] These events provide a good setting to measure the impact of a marginal change in disaster occurrence on mortality expectations as changes in base rate of mortality risk due to such events are low (or even negative).[37]

A comparison of the effect size to the actual mortality risk posed by such events provide for a meaningful benchmark of the extent of miscalibration with the impact of an extreme event. Although the general trend has been one of decline in the likelihood of death due to natural disasters and gun violence, Bayesian updating provides a useful benchmark for this analysis, that is, the effect of a disaster on the probability of death by future disasters. The probability of death in county c at time $t+1$ is governed by Bayes' rule:

$$\Pr(\text{Death}_{c,t+1} \mid \text{Disaster}_{c,t+1}) = \frac{Pr(\text{Disaster}_{c,t+1} \mid \text{Death}_{c,t+1}) \times Pr(\text{Death})_{t+1}}{Pr(\text{Disaster})_{c,t+1}} \tag{17}$$

Since data on actual mortality due to disasters is unavailable, I estimate the second-best benchmark under the following assumption.

[35]0.4 percent of all deaths are due to homicide by discharge of firearms (CDC, 2013). Mass shootings constitute a significantly smaller proportion of all gun related deaths in the United States. However, official data do not exist for mass shootings as a separate category. Taking the total for 2015, at 1430, the probability of death due to mass shooting stands at 0.06 percent.

[36]Leading causes of death in the United States in 2013 were heart diseases, cancer, respiratory diseases, stroke and unintentional injuries (CDC, 2013). Unintentional injuries comprise of transport accidents, falls, accidental discharge of firearms, drowning and submersion, accidental suffocation and strangulation and other unspecified accidents.

[37]For instance, changes in mortality risks due to homicide by firearms, for instance, has come down from 0.45 percent in 2002 to 0.43 percent in 2012, a reduction of about 5 percent (CDC, 2002 and 2012). Arguably, there are substantial variations in this rate over time across different geographies within the US. I am working towards obtaining the National Longitudinal Mortality survey to measure these changes at the county level and will be reflected in the subsequent drafts of this paper.

$$\Pr(\text{Disaster}_{c,t+1} \mid \text{Death}_{c,t+1}) \approx \Pr(\text{Disaster}_{c,t+1}) \tag{18}$$

Assumption (18) sets the conditional probability of observing a disaster when deaths are recorded at the unconditional disaster probability for county c. This is conservative as the unconditional probability is the upper bound of any estimates of this conditional probability.[38] Given this assumption, equation (17) is modified as its natural upper bound, i.e., the unconditional probability of deaths at time $t+1$ in county c.

Therefore, the second-best estimate of the effect of current disaster event on the probability of death due to a future disaster is the effect of current disaster on future deaths. To estimate the long-term mortality consequences, using county-level mortality rate estimates from the Center for Disease Control, I estimate a predictive regression over different horizons. The estimation strategy is as follows:

$$y_{c,t} = \alpha_c + \omega_t + \sum_{k=1}^{K} \gamma_{t-k} I(\text{Disaster} > 0)_{c,t-k} + \epsilon_{c,t} \tag{19}$$

$y_{c,t}$ measures the mortality rate in county c at time t, α_c are county fixed-effects, ω_t are time fixed-effects and the coefficient of interest are the various lags of γ_{t-k}, i.e., the coefficient on lags of disasters that have occurred in county c at different years in the past. The estimation is limited by data availability, as the CDC only makes data from 1999 to 2014 publicly available at the county level.

Panel (A) in Table D.1 presents the results for each type of extreme disasters used in this study. To a large extent, the impact of disaster on mortality rates into the future is weak and statistically insignificant, except at the first lag, where the point estimate is 0.2 percent. Panel (B) in Table D.1 suggests that there is no discernible pattern to the estimated

[38] The implicit underlying assumption in this calculation is that disaster occurrences are independent of one another. That is, $\Pr(\text{Disaster}_{c,t+1} \mid \text{Disaster}_{c,t}) = \Pr(\text{Disaster}_{c,t+1})$.

Table D.1: Future Mortality Expectations Due to Natural Disasters

Panel (A) presents the impact of past disasters such as Hurricanes, Tornadoes, Earthquakes, Severe Ice Storms, and Severe Storms (in columns) on current mortality rates at the county level. Data for this regression is from the Centre for Disease Control (CDC) from their county level mortality files and are from years 1992 - 2012. Panel (B) presents the impact of all natural disasters across different age-groups.

Panel (A)

	Hurricanes	Tornados	Earthquakes	Severe Ice Storms	Severe Storms	All
I(Disaster > 0)						
$t-1$	-0.0001	-0.0114***	0.0028	0.0047	0.0020*	0.0020***
	(0.001)	(0.003)	(0.012)	(0.003)	(0.001)	(0.001)
$t-2$	-0.0024	-0.0126***	0.0028	0.0045	0.0003	-0.0002
	(0.002)	(0.004)	(0.007)	(0.003)	(0.001)	(0.001)
$t-3$	-0.0025	-0.0002	0.0068	-0.0002	0.0014	0.0005
	(0.002)	(0.005)	(0.018)	(0.003)	(0.001)	(0.001)
$t-4$	-0.0014	0.0021	0.0141	-0.0008	-0.0012	-0.0010
	(0.002)	(0.003)	(0.012)	(0.002)	(0.001)	(0.001)
$t-5$	-0.0010	0.0045	0.0228	-0.0066	-0.0009	-0.0011
	(0.002)	(0.005)	(0.012)	(0.005)	(0.001)	(0.001)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.67	0.67	0.67	0.67	0.67	0.67
No. of Observations	45,043	45,043	45,043	45,043	45,043	45,043

Panel (B)

	Age Group-wise Mortality Rate				
	45-54	55-64	65-74	75-84	≥ 85
I(Disaster > 0)					
$t-1$	-0.0022**	-0.0001	-0.0002	-0.0004**	0.0001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$t-2$	0.0003	-0.0002***	-0.0002	-0.0004**	-0.0005**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$t-3$	-0.0016	-0.0001	-0.0003	-0.0004*	0.0002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$t-4$	0.0014	-0.0003***	-0.0001	0.0001	-0.0002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$t-5$	0.0005	0.0001	0.0003		-0.0002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.67	0.67	0.67	0.67	0.67
No. of Observations	45,043	45,043	45,043	45,043	45,043

coefficients across different age categories for mortality rates, and most point estimates that are significant are negative.[39]

This result suggests that the Bayesian update to mortality expectations due to a disaster experience is nearly zero. However, the largest magnitude in the estimates (although statistically insignificant) is 0.4 percent.[40] Taking this as the highest possible Bayesian update, the estimated effect on subjective life expectancy due to natural disasters (mass shootings) are at least 3 to 5 times higher than the update suggested by Bayes' rule. The effect of natural disasters and mass-shootings on individual subjective life expectancy is large.

[39] One way to consider the negative coefficients is that post-disaster responses to public health concerns, if anything, reduces mortality rates as opposed to increase them.

[40] Interestingly, a back of the envelope calculation yields similar conservative estimates. The highest value (across counties) for $Pr(\text{Natural Disaster})$ is 0.16 percent. Estimates of $Pr(\text{Disaster}|\text{Death})$ range from 0.01 percent[41] to 0.05 percent (Goklany, 2009). Since the highest impact is when middle-aged, $Pr(\text{Death})$ for an individual aged 65, in the next year, is about 1.71 percent. On average, the probability of death across the United States has dropped from 0.85 percent in 1999 to 0.82 percent in 2012 and these trends are reflected across all ages.[42] Using, Bayes' rule, the probability of death due to natural disasters for a 65 year old in the following year is 0.53 percent. Similarly, mortality risk due to mass shootings is approximately 0.55 percent, nearly as likely as natural disasters at its highest frequency of occurrence. These estimates use the likelihood of arson, gun and murder crimes in the US as a proxy for mass shootings.

E Indirect Effects of Disasters on Risky-asset Share

In the presence of interaction, i.e., $l^d \times$ I(Natural Disaster > 0), decomposing the total effect of natural disasters on risky share into direct and indirect (through mortality deviations) effects and obtaining confidence intervals for such estimates require additional statistical tests. Such an interaction is important because the extent to which l^d "mediates" may depend on whether individuals experienced a natural disaster in the first place.

In order to estimate the extent to which the effect of Z on Y is through X, I appeal to the counterfactual approach to mediation analysis as in VanderWeele (2015) and Baron and Kenny (1986) and argue that X, or mortality deviations, *mediate* effects of natural disasters (Z) on financial decisions (Y).[43] While such approaches are more common in the presence of non-linearities, they are model agnostic – the methods can also be used for linear models. I use this approach because it allows for precise estimates of the relative importance of the mortality deviations channel. Since $\delta_1 \neq 0$ Table 4, following Pearl (2012) and Robins and Greenland (1992) indirect effects, also known as causal mediation effects, for an individual i can be defined as follows:

$$\delta_i(\text{Natural Disasters}) \equiv Y_i \left\{\text{Natural Disasters}, M_i(1)\right\} - Y_i \left\{\text{Natural Disasters}, M_i(0)\right\}$$

This measures the change in the outcome Y (risky asset share) corresponding to a change in the mediator M (expectation deviations), from the value that would be realized had there been no natural disasters, $M_i(0)$, to one where natural disasters are realized, $M_i(1)$. Estimates from Section 3 shows that that $M_i(1)$ and $M_i(0)$ are different, i.e., natural disasters

[43] For a detailed treatment of the econometrics of mediation analysis, see VanderWeele (2015).

make individuals who experience htem more pessimistic. The treatment, experiencing natural disasters, is important because it allows for studying the extent to which the mediator variable matters under well identified conditions.

By virtue of randomized experience of natural disasters, only two of the four traditional assumptions about confounding factors are required for a causal interpretation.[44]

The first assumption is that there are no unmeasured factors that affect the mortality expectations – risky asset share relationship. Factors such as geographic location, and health status may affect both mortality expectations and share of risky assets in the financial portfolio. The rich set of characteristics from the HRS is used to explicitly control for potential confounders of this relationship. The second assumption is that there are no unobserved factors that affect the mortality expectations – risky asset share relationship that are also affected by natural disasters. For example, it may be argued that individuals lose a lot of wealth during disasters, which may, in turn, reduce investment in risky assets and therefore enable pessimistic responses to expectations. The HRS, however, covers a range of questions, including self-assessments of health status, any record of physical disabilities that may have occurred over time and detailed measures of wealth and I use them to minimize the extent to which the effects are confounded.

An important property of this approach is that the total effect of natural disasters on risky behaviour decomposes into the natural direct effect and mediated effect (Pearl, 2001). Thus, an estimation of this decomposition would allow for the evaluation of the mediating role played by subjective expectations. The parametric inference follows a four step procedure. First, I fit the models for observed outcome and mediator variables (Section 3 and Section 4). Then, I simulate model parameters from their sampling distribution. I then repeat the following steps for each draw of model parameters: (a) simulate the potential values of the

[44] Detailed proofs are in Appendix A.2 of VanderWeele (2015). These assumptions also implicitly assume a temporal ordering of effects: Natural disasters affect subjective expectations *before*, directly or indirectly, affecting the risky asset share. For more details see Imai, Keele, and Tingley (2010) and VanderWeele (2015).

Table E.1: Causal Mediation Effect

This table presents the relative importance of the mortality deviations channel for mediating the impact of exogenous disaster experiences on risky-asset share in the presence of interactions. The estimates follow VanderWeele (2015) and Imai, Keele, and Tingley (2010).

		95% Confidence Interval	
	Point Estimate	Lower-bound	Upper-bound
Mediation Effect	-0.169	-0.204	-0.096
Direct Effect	-1.151	-1.940	-0.353
Proportion Mediated	0.147	0.105	0.272
Sensitivity analysis			
Rho at which Mediation Effect = 0	0.12		
Rho at which Direct Effect = 0	-0.7		
Sample size	78,917		
Simulations	1000		

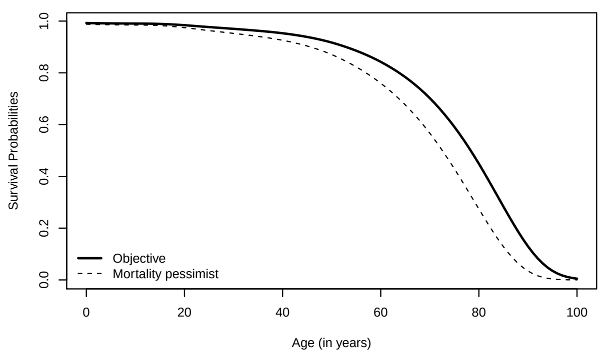
mediator; (b) simulate the potential outcomes given the simulated values of the mediator; and (c) compute the quantities of interest. And lastly, I use these simulations to obtain point estimates as an average of all runs and 95 percent confidence intervals. The procedures used for estimation are described in detail in Imai, Keele, Tingley, and Yamamoto (2010); Imai, Keele, and Tingley (2010); Imai, Keele, and Yamamoto (2010) and implemented in R and Stata by Hicks and Tingley (2011).

Table E.1 presents the decomposition results for the most conservative case, with time fixed-effects as in Column (4) in Table 4. The Average Mediation is estimated to be a -0.169 percent. As a percent of the total effect, this is 14.7 percent of the total effect of natural disasters on risky asset share.

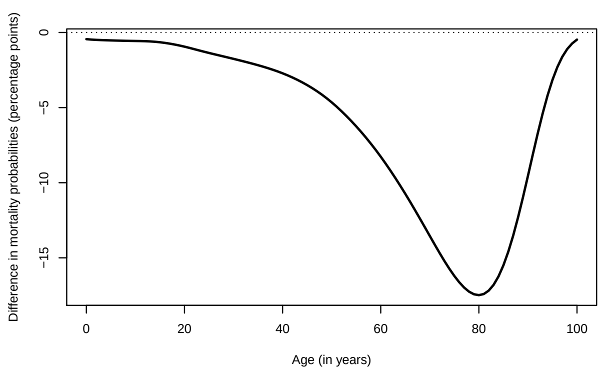
F Mortality pessimism

Figure F.1: Survival Probabilities: Objective vs. Pessimist

Panel (A) Survival Curves



Panel (B) Asymmetric effects on survival curves



In this appendix, I assume that $\tau = 60\%$ and estimate the survival curve to illustrate the difference between a survival curve using life table probabilities ("Objective") and for a pessimist whose subjective mortality expectations are higher by 60%. Figure F.1 (A) presents the results. It is important to note that although τ is a constant on a year by year basis, this translates into an asymmetric effect on the survival curve – it compounds rapidly to deliver the highest difference in conditional probabilities from life tables at age 80 and then (as life tables probabilities of death rapidly rise) wanes to 0 (Figure F.1 B).