The Effect of Lifespan Expectations on Financial Decisions: Evidence from Mass Shootings and Natural Disaster experiences

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Abstract

I investigate the relationship between lifespan expectations and household investments into risky financial assets. To credibly establish this relationship, I use natural disasters and mass shootings experiences, in the county of the household, their social network and by geographic distance, and show that exposure to such experiences in their own county, neighbouring counties, and in counties with high relative probability of friendship make households more pessimistic. Using these experiences as an instrument, I document a robust negative relationship between lifespan pessimism and investments into risky assets. These results highlight the role of lifespan expectations in explaining household investments in risky financial markets.

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1 Introduction

Standard economic models work under the premise of rational expectations. A mounting body of evidence challenges this premise by showing that individual expectations about the future states of the world deviates from the rational, correct probabilities. These subjective expectations may depart from true probabilities as individuals systematically overweight small probability events (Kahneman and Tversky, 1982), overweight rare events that have salient attributes (Bordalo et al., 2012, 2016), hold extrapolative expectations (Hirshleifer et al., 2015) or simply overweight their recent personal experiences while forming their expectations (Malmendier and Nagel, 2011, 2015; Kuchler and Zafar, 2015).

How do subjective expectations affect financial decisions by individual investors? Early studies such as Chevalier and Ellison (1997); Sirri and Tufano (1998) show that investors in mutual funds react to recent past performance strongly, suggesting an extrapolative behavior on the part of mutual fund investors. In studying individual investor decisions with 401(K) plans, Choi et al. (2009) show that recent positive idiosyncratic excess returns increase contribution rates. Previtero (2014) suggests that extrapolation from past returns in the stock market affect annuitization decisions on retirement savings. These expectations are not necessarily driven only by uninformed, less financially sophisticated agents in the economy as Vissing-Jorgensen (2003) finds that even wealthy investors expect stock returns to remain high when surveyed at the peak of the business cycle. Subjective beliefs and expectations in the other financial markets such as mortgage markets also explain investor decisions (Piazzesi and Schneider, 2009; Bailey et al., 2017). Most research work in this literature attributes such extrapolative behaviour to revisions in an agent's priors as we do not have sound empirical estimates on how an agent's prior expectations change when faced with new incoming information, direct or indirect experiences.

An important empirical observation in the literature on household portfolio choice is that conditional on participating in the stock market, households hold moderate amounts of risky assets as part of their financial holdings (Guiso and Sodini, 2013; Campbell, 2006; Ameriks and Zeldes, 2001). However, most models of life-cycle asset allocation tend to suggest that households invest almost all of their wealth in risky assets.[1] This strand of work has focused its efforts on introducing changes to models to make models more realistic, including non-tradable labour income, borrowing constraints and other such key changes.

One of the core parameters in studies of household investment decisions over the life cycle is survival probabilities. Rational expectations demand that these survival probabilities are no different from life table estimates after taking into account potential age, gender, and spatial variations in such estimates.[2] Yet, lifespan expectations differ from these objective life table probabilities of survival. However, we know little about the role of subjective expectations, and in particular lifespan expectations, and household financial decisions. Heimer et al. (2016) calibrate a life-cycle model with subjective mortality beliefs and show that the young under-save and the retirees draw down their asset much slower than they ought to. Puri and Robinson (2007) use repeated cross-sections of the Survey of Consumer Finances (SCF) and find that optimism relates to how equity wealth is allocated across various equity instruments, but not with allocation decisions between risky and safe assets. Empirically, we do not yet know how these expectations are formed, nor possess a credible estimate of the relationship between subjective lifespan expectations and portfolio choice confronting potential concerns of endogeneity.

In this paper, I present empirical evidence on the relationship between subjective lifespan expectations and risky financial investments. I begin by first presenting evidence on how lifespan expectations for individuals in the United States change with direct or indirect experiences of mass shootings or natural disasters. Direct experiences are shootings incidents

[1]Some work has attempted to reconcile this observation alongside the fact that a large fraction of households tend not to participate in risky asset markets. For instance, Gomes and Michaelides (2004) show that with fixed participation costs, preference heterogeneity and the use of Epstein-Zin preferences can improve the model's ability to match empirical observations.

[2]See Deaton and Lubotsky (2003) for an account on mortality inequality and the spatial variation in survival probabilities.

or natural disasters that affect the county of residence, and indirect experiences are shootings incidents or natural disasters that affect other counties by the degree of proximity in friendship networks – derived from Facebook friendship data as in Bailey et al. (2018, 2017) – and by the degree of geographic proximity.

Most empirical work in assessing how such beliefs are formed have looked at personal characteristics (preference for smoking, Smith et al. (2001)), and economic characteristics (wealth and income, Deaton and Lubotsky (2003)). However, these estimates suffer from non-causal interpretations as often these are endogenously determined. Lifespan expectations may deviate from objective lifetable probabilities due to economic conditions, demography and other heterogeneous factors. In order to get credible estimates of belief formation, I use mass shootings and natural disasters as exogenous shocks.[3] I control for all observable demographic, social, economic and health characteristics, and account for spatial variation in county level lifespan expectations with county fixed effects. After controlling for such variations, mass shootings and natural disasters in the county of residence make individuals life span pessimistic. These revisions cannot be explained by rational bayesian updates to prior expectations. However, this observed revision may be attributed to other unobservable factors such as damage to property during natural disasters, or other changes in domestic economic conditions. Although it is hard to argue for potential unobservable factors with mass shootings incidents[4], I use *indirect* experiences of mass shootings and natural disasters and document its effects on lifespan expectations. I use the social connectedness index measure from Bailey et al. (2018) to construct mass shootings and natural disaster experiences

[3]Mobility and selective migration are obvious natural confounds to a strictly causal interpretation. It may be the case that households who update their prior beliefs about the probability of a natural disaster or mass shootings may choose to relocate, thus reducing the strength of this relationship. However, this biases any estimates of this relationship downwards, thus lending some support to interpreting estimates as a lower bound of the true effect size. Moreover, this study is of an age group that is relatively less prone to migration decisions, as they are much older and I observe that they are nearly immobile from their zipcode information.

[4]The occurrence of such incidents may be positively correlated with violence at the county level. Although I use county fixed effects to address this, I also account for time-varying levels of violence by using data from the Federal Bureau of Investigation and the Department of Justice.

in other counties by low, medium and high level of social connectedness as determined by the tercile cutoffs of this index. Over and above the impact of disasters and mass shootings in one's own county of residence, indirect experiences also increase lifespan pessimism. Social connectedness is nearly isomorphic to geographic distance from the county of residence (Bailey et al., 2018). Hence the observed effect may not necessarily be driven due to social connectedness, but by spatial proximity to such events. To disentangle spatial proximity from social connectedness, I construct indirect experiences by distance terciles to the county of residence for each individual. While spatial proximity drives nearly all of the effect for natural disasters, social connectedness to counties that experienced mass shootings affects lifespan expectations, suggesting that the underlying mechanisms of affecting expectations may be different for different kinds of experiences.

The combined direct and indirect effects of natural disasters (mass shootings) are 3.6 (4.8) percentage points increase in lifespan pessimism. A comparison of the effect size to the actual mortality risk posed by natural disasters and mass shootings provide for a meaningful benchmark for the extent of miscalibration in lifespan expectations. Extremely generous estimates of the rational revisions to the likelihood of death due to future disasters or mass shootings when such events occur is less than 0.72 percentage points, putting the estimated changes *at least* five times more than expected under a rational benchmark. Moreover, these effects are nearly 20 percent of the average difference between subjective and objective survival probabilities. These effects are statistically robust, credible, and meaningfully large.

Direct experiences with natural disasters and mass shootings affect lifespan expectations, but may also affect risk taking behaviour. Early life experiences with the Great Depression are linked to more conservative financial investments into risky assets (Malmendier and Nagel, 2011), suggesting an increased risk aversion or a change in belief about expected return. Risk experiments conducting in conflict-ridden regions, or areas that were affected by natural disasters suggest that a direct exposure may alter risk preferences (Cassar et al., 2017; Voors et al., 2012; Cameron and Shah, 2015; Eckel et al., 2009). Additionally, Callen et al. (2014) conduct a risk elicitation experiment in Afghanistan – a country with a recent violent history – with civilians, and find that the effect of fearful recollections of violent events on risk and certainty preferences are *localized* to those who were directly exposed to it.

In this context, mass shootings and natural disasters in friendship networks and geographically proximate counties provide a good setting for assessing the relationship between lifespan expectations and financial portfolio choice as they are not direct experiences by individuals. With the identifying assumption that *indirect* experiences of mass shootings and natural disasters affect financial decisions only through lifespan expectations, I instrument lifespan expectations with these experiences to assess the relationship between lifespan expectations and the share of risky assets in the financial portfolio of the household.

An increase in lifespan pessimism is strongly negatively associated with investments into risky assets. A one percent increase in lifespan pessimism is associated with a 3.67 percent decrease in the share of risky assets, representing a 1.7 percentage point reduction in the unconditional average share of risky assets ($\tilde{4}5$ percent).

Taken together, these empirical results suggest that an increase in lifespan pessimism decreases investments in risky assets. Lifespan expectations may be related to risky behavior in two ways. First, they potentially alter the individual's expected lifespan, i.e., the time horizon for optimization. Second, such lifespan pessimism may spillover into other dimensions where agents form expectations. Several studies in psychology (see, for example, Heinonen et al., 2005; Carver et al., 2003; Scheier et al., 2001; Scheier and Carver, 1985) show that such dispositional pessimism or optimism – a more generalized expectancy across a range of domains – plays a significant role in individual decision-making.

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.[5]

To distinguish between pure lifespan pessimism and dispositional pessimism empirically is difficult without appropriate psychometric test scores. In order to understand the relative roles of both of these approaches by which lifespan pessimism can affect risky asset share, I set up a canonical life-cycle model. In the first model, the agent is a lifespan pessimist whose expectations in other dimensions are rational. 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 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

[5]For a subset of respondents where I measure both lifespan pessimism 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 may be at play. 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.

share of investments in risky assets. 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 reducing the share of risky assets. Holding fixed risk attitudes, changes in risky behavior due to pure lifespan pessimism is then, consistent with empirical findings.

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) reduce 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 amplifies the negative effect on risky asset share, and the magnitudes are 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. The effect on risky asset share is modest, and with stronger parameterization of bequest motives, nearly absent. 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, reduction in investments into risky assets through the spillover mechanism is further amplified.

This paper connects to several strands of literature. The literature on experience effects – (see, for instance, Anagol et al., 2018a; Giuliano and Spilimbergo, 2014; Malmendier and Nagel, 2011; Choi et al., 2009; Kaustia and Knüpfer, 2008) – 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.

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 indirect experiences through friendship networks, 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, 2018b; 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 lifespan expectations, Section 4 presents the relationship between lifespan expectations and 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

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 lifespan expectations, 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.

[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).

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, $l^d = l^p - l^s$, 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), i.e., an average survey respondent is pessimistic about their lifespan. The distribution is right-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.

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

[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.

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.

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.

In order to measure disaster and shootings experiences by friendship networks, I make use of the Social Connectedness Index available from Facebook based on Bailey et al. (2018). For each county pair, this index provides a relative measure of the total number of Facebook friendship links between individuals located in the two counties as of April 2016. The data is normalized to have a maximum value of 1,000,000, which is assigned to Los Angeles to Los Angeles connections – the county pair with the largest number of friendship links. This normalized data is then rounded to the nearest 0.0025. Given Facebook's scale (229 million active users, or about 70% of the population in the U.S.), as well as the representativeness of the users to the opulation, this data provides a comprehensive measure of friendship networks between U.S. counties. Facebook mainly serves as a platform for real-world friends and acquaintances to interact online, and people usually only add connections on Facebook to individuals whom they know in the real world (Jones et al., 2013; Gilbert and Karahalios, 2009; Hampton et al., 2011). Since establishing a link on Facebook requires the consent of both parties involved, this serves as an accurate indicator of friendship networks in the U.S. Arguably, this is only a snapshot (in the cross-section) of the friendship links as of April 2016 and does not reflect the time-varying nature of such friendship network. However, this snapshot is sufficient as a conditioning variable as the inroads made by Facebook over time is only capturing the nature of real friendship network on a digital platform with greater precision and representativeness. Lastly, I use data for measuring distance between county pairs from the NBER and the distance is calculated as the great-circle distances using the Haversine formula based on internal points in the geographic area.

3 Shocks to lifespan 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 (Appendix Table A.1). 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. That said, a significant fraction of lifespan expectation deviations are *not* explained by conventional proxies of information, or by county fixed effects. Adjusting for demographic, socio-economic, and health covariates, systematic miscalibration of subjective life expectancies cannot be ruled out.

3.1 Mass shootings and lifespan expectations

In this section, I document the empirical relationship between episodes of mass shootings and lifespan expectations. Modifying equation 1 to include proxies for mass shootings, Table 2a present the empirical estimates of the effect of exogenous experience on lifespan expectations.

Columns 1–3 of Table 2a present the point estimates of three proxies for mass shooting experiences in the county of residence for HRS respondents: log(number of deaths + 1) in Column 1, log(number of shootings + 1) in Column 2 and a dummy variable that takes the value 1 if the county experienced any mass shooting within the calendar year before the surveyed date. All regressions are with controls as in Appendix Table A.1. A one percent increase in the number of deaths due to mass shootings in the county of residence increase lifespan pessmism by 1.2 percentage points, and the effect size is similar for when mass shootings are proxied by the number of shootings taking place. Any mass shooting taking place at the county of residence increases lifespan pessimism by 2.39 percentage points, or about 18 percent of the base rate of lifespan pessimism. These estimates are statistically and economically significant.

Columns 4–6 of Table 2a estimate the relationship between mass shootings experiences in the county of residence, and in other counties sorted by the tercile cutoff points on the social connectedness index from Facebook. In these estiamtes, the in-county experience with mass shootings still matters (with similar magnitudes as in Columns 1–3). Over and above the in-county experience, mass shootings experience in counties with low social connectedness also increase pessimism by 0.59 percentage points (Column 6) and the effect size monotonically increase to 0.64 percentage points for medium levels of social connectedness to 1.23 percentage points for experiences in other counties with high levels of social connectedness. One potential explanation for this relationship may be that spatial proximity matters to belief formation more than social connectedness and the SCI measure is very strongly correlated with spatial proximity. In order to disentangle spatial proximity from social connectedness, I introduce measures of mass shootings by terciles of the great circle distance between counties in Columns 7–9. The coefficient estimates for spatial proximity is positive, however statistically insignificant, while the coefficients for SCI terciles are similar in magnitude to those in Columns 4–6, and statistically significant. This suggests that proximity may not be driving such belief formation but friendship networks transmit such experiences to individuals more strongly.

3.2 Natural disasters and lifespan expectations

In this section, I document the empirical relationship between episodes of natural disasters and lifespan expectations. Modifying equation 1 to include proxies for natural disasters , Table 2b present the empirical estimates of the effect of exogenous experience on lifespan expectations.

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 lifespan expectations.

Table 2b 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, Columns 1–3 present the effect of natural disasters proxied by the log(number of days of disaster in the year + 1), log(number of disasters in the year +1) and by a dummy variable that takes the value 1 if the county experienced a disaster at all.

A one percent increase in the total number of days of natural disaster experience in a given year in the county of residence, increases lifespan pessimism by 0.39 percentage points (Column 1, Table 2b). A one percent increase in the number of diasters experienced in a given year, within the county of residence, increases lifespan pessimism by 1.40 percentage points, and the magnitude is similar with estimates using a dummy variable for any disaster experience in-county for HRS respondents (Columns 2 and 3). These estimates are equivalent to about 10 percent of the base rate of lifespan pessimism.

When a natural disaster strikes a county, a whole range of factors may potentially confound the relationship between lifespan expectations and such experiences. In order to credibly establish this relationship, I use proxies of natural disaster experiences by the terciles of SCI, and by spatial proximity in Columns 4 through 9 of Table 2b. While the estimates for in-county experiences remain similar in magnitude, a monotonic increase in the effect of disasters by the degree of social connectedness is noteworthy (Columns 4–6). Disasters for counties with low levels of social connectedness do not matter to lifespan expectations, whereas the effect from medium levels of SCI is 0.19 percentage points, and high SCI is 0.34 percentage points. The combined effect size through social connectedness is about 4.1

percent of the base rate of lifespan pessimism, about a little less than half of the in-county effect size. Similar to the effects on mass shootings, I explore whether it is spatial proximity to disasters or social connectedness that drives mortality belief formation with natural disaster experiences (Columns 7–9). Unlike mass shootings, natural disasters are strongly explained by spatial proximity, as opposed to social connectedness. Disasters in counties within the short distance tercile on county-county distances, increase lifespan pessimism by 1.43 percentage points, whereas disasters in counties that fall in the long distance tercile increase lifespan pessimism by 0.51 percentage points. While short-distance counties may fall within the range of commute distances for most HRS respondents, it is noteworthy that the point estimates on disasters in counties in medium and large distance bins are positive and statistically significant. The total distance driven effect size on lifespan expectations is about 19 percent of the base rate of lifespan expectations – a robust and meaningful effect size.

3.3 Placebo tests

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 and mass shootings at $t+1$ on current lifespance expectations at t. Table 3 suggests that the identification is robust and the effects of natural disasters and mass shootings in the future on current lifespan expectations are statistically *insignificant.* except in two instances, where the effect sizes go the other way and are significant at the 10 percent level.

3.4 Neighbourhood analysis

To zero in on the spatial effects more carefully, 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 or other potential confounds due to disasters may be at play. Appendix Table A.2 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.

3.5 Are these rational updates to prior expectations?

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

4 Lifespan expectations and risky assets

The extent to which lifespan expectations 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 lifespan expectations and risky behavior.

The measures of disaster and shootings experiences in the social network, and by spatial proximity is appealing as an instrument as it fulfills the assumptions required for a causal interpretation of the IV estimand as detailed in Angrist et al. (1996). The potential outcomes for individuals within a county with spatial and socially proximate disasters and shootings is unrelated to the treatment status of other individuals. Similarly, the treatment assignment, i.e., the experience of natural disasters after accounting for the ex-ante probability of natural disasters is exogenous and random. For instance, a hurricane affecting one county and not another within the state of Florida is assumed to be random. Of course, the exclusion restriction that spatial and socially proximate experiences do not affect investments into risky assets other than through lifespan expectations is difficult to test.

Direct experiences with natural disasters and mass shootings affect lifespan expectations, but may also affect risk taking behaviour. Early life experiences with the Great Depression are linked to more conservative financial investments into risky assets (Malmendier and Nagel, 2011), suggesting an increased risk aversion or a change in belief about expected return. Risk experiments conducting in confict-ridden regions, or areas that were affected by natural disasters suggest that a direct exposure may alter risk preferences (Cassar et al., 2017; Voors et al., 2012; Cameron and Shah, 2015; Eckel et al., 2009). Additionally, Callen et al. (2014) conduct a risk elicitation experiment in Afghanistan – a country with a recent violent history – with civilians, and find that the effect of fearful recollections of violent events on risk and certainty preferences are *localized* to those who were directly exposed to it. Relying on these empirical estimates, this remains a plausible identifying assumption in this setting.

For individual i from county c at time t, let $l^d_{i,c,t}$ be the lifespan 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 coefficient of interest:

$$w_{i,c,t} = \psi_c + \zeta_x + \theta_t + X'_{i,c,t}\beta + \delta_0 l^d_{i,c,t} + \epsilon_{i,c,t} \tag{2}$$

$X_{i,c,t}$ is a vector of control variables such as age, age-squared, wealth, wealth-squared, 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 δ_0 measures the relationship between lifespan expectations and the share of risky assets. I estimate this least-squares relationship, and also instrument for lifespan expectations with log(number of disasters) and log(number of shootings) to provide a more credible, better identified estimate.

Table 4a presents the regression results. Column 1 presents the OLS estimate of the relationship between lifespan expectations and risky asset share, after controlling for age, wealth, health, demographic, spatial and time characteristics. A one percent increase in lifespan pessimism is associated with a 1.08 percent reduction in the share of risky assets. Columns (2) and (3) of Table 4a present the IV estimates using two stage least squares. In Column 2, I instrument lifespan expectations with all disaster and shooting experiences (including the in-county direct experience) and in Column 3 I instrument only with experiences measured by social and spatial proximity. A one percent increase in lifespan pessimism is associated with a 3.67 percent reduction in the share of risky assets. The standard errors are larger than in the OLS estimates – as is normal with IV regressions. However, the Kleibergen-Paap rK LM Statistic (Kleibergen and Schaffer, 2015), Hansen/Sargan Statistic (Arellano and Bond, 1991), and the Cragg-Donal Wald F statistic (compared against the Stock-Yogo critical values as in, Stock and Yogo, 2002), all present evidence against weak instruments problem.[9]

The HRS does not have detailed break-down of the financial portfolio of its respondents. However, it is possible to further breakdown the total share of risky assets into the share of direct stockholdings in the financial portfolio. Table 4b estimates the relationship between lifespan expectations and direct stockholdings by households.

Column 1 of Table 4b presents the OLS estimate of the relationship between lifespan expectations and direct stockholding share, after controlling for age, wealth, health, demographic, spatial and time characteristics. A one percent increase in lifespan pessimism is associated with a 0.95 percent reduction in the share of risky assets (about 87% of the estimates in Table 4a). Columns (2) and (3) of Table 4b present the IV estimates using two

[9]The estimates in Columns 2 and 3 of Table 4a, interpretted as in Angrist et al. (1996), are Local Average Treatment Effects (LATE), as opposed to Average Treatment Effects, and are thus slightly larger in magnitude than the OLS estimates.

stage least squares. In Column 2, I instrument lifespan expectations with all disaster and shooting experiences (including the in-county direct experience) and in Column 3 I instrument only with experiences measured by social and spatial proximity. A one percent increase in lifespan pessimism is associated with a 3.1 percent reduction (about 86% of the estimates in Table 4a) in the share of direct stockholdings. The Kleibergen-Paap rK LM Statistic (Kleibergen and Schaffer, 2015), Hansen/Sargan Statistic (Arellano and Bond, 1991), and the Cragg-Donal Wald F statistic (compared against the Stock-Yogo critical values as in, Stock and Yogo, 2002), all present evidence against weak instruments problem.

One of the mechanisms by which individuals alter their portfolio composition is through direct investments in risky assets, as opposed to changing their composition in already existing accounts for retirement savings. This "top up your existing exposure to risky assets" approach through direct investments in stocks suggest that households may be operating on different parts of their financial portfolio to adjust for their lifespan expectations.

5 Savings and portfolio choice of pessimistic agents

The empirical estimates suggest that lifespan expectations are related to the share of risky assets in the financial portfolio of individuals. Lifespan expectations may be related to risky behavior in two ways. First, they potentially alter the individual's expected lifespan, i.e., the time horizon for optimization. Second, such lifespan pessimism may spillover into other dimensions where agents form expectations. Several studies in psychology (see, for example, Heinonen et al., 2005; Carver et al., 2003; Scheier et al., 2001; Scheier and Carver, 1985) show that such dispositional pessimism or optimism – a more generalized expectancy across a range of domains – plays a significant role in individual decision-making.

Several challenges limit the possibility of discerning lifespan 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 lifespan expectations spillover into expectations in other domains, 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 Index Fund) will yield positive returns the following year. Table 5 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 lifespan 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:

$$X_t = R_t(X_{t-1} - C_{t-1}) + Y_t \tag{3}$$

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 E 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:

$$U_t = E_t \sum_{i=0}^{T-t} \beta^i \Big\{ \Psi_{t+i,t} u(C_{t+i}) \Big\}, \tag{4}$$

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 (4), subject to (3) is as follows:

$$V_t^*(X_t, P_t) = \underset{C_t,\zeta_t}{max} \big\{ u(C_t) + \beta\psi_t E_t V_{t+1}^*(X_{t+1}, P_{t+1}) \big\} \tag{5}$$

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:

$$v_t^*(x_t) = \max_{c_t,\zeta_t}\{u(c_t) + \beta\psi_t E_t \Gamma_{t+1}^{1-\rho} v_{t+1}^*(a_t R_{t+1} + \Theta_{t+1})\}, \tag{6}$$

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:

$$u_t^{'}(c_t) = \beta\psi_t E_t R_{t+1} u_{t+1}^{'}(\Gamma_{t+1}\boldsymbol{c_{t+1}}) \tag{7}$$

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:

$$\beta\psi_t E_t(R_{t+1}^e - R^f)a_t u_{t+1}^{'}(\Gamma_{t+1}\boldsymbol{c_{t+1}}) = 0 \tag{8}$$

The optimal portfolio choice can be determined by using (8), given end-of-period saving a_t and a decision rule for the next-period consumption. Given the optimal portfolio choice, (7) 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 $t-1$.[10]

Calibration: Table 6 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

[10]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.

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.[11] 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 3 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.[12] 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 6 and no pessimism in the model. The dotted 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

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

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 3) increases her consumption profile, although marginally, throughout her life until 80 and reduces consumption dramatically around age 80. Table 7 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.[13] 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

[13]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 E.

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.[14] 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.[15] 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 3) 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 7), 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 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

[14]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.

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

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 standard 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:

$$V_{T+1} = b\frac{(X_{T+1}/b)^{1-\rho}}{1-\rho} \tag{9}$$

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 7 presents the deviations from the baseline scenario with parameters as in Table 6 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 *direct* and *indirect* experiences through social and spatial proximity affect lifespan expectations in the United States. These effects are at least five times higher than justified by Bayes' rule. Using these experiences as an instrument, I credibly identify a relationship between lifespan expectations and portfolio choice. I show that increases in lifespan pessimism is negatively related to the share of risky assets in the financial portfolio of individuals. These effects translate to a 1.7 percentage point reduction in the unconditional average share of risy assets.

Pessimistic expectations may be indicative of responses that purely affect an individual's lifespan or may also spillover due to dispositional pessimism. In a canonical life-cycle model, with modification to the timing of the shock 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 in a model where I allow for spillovers by allowing for correlated expectations 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 lifespan pessimism may affect portfolio choice.

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Figure 1: 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).

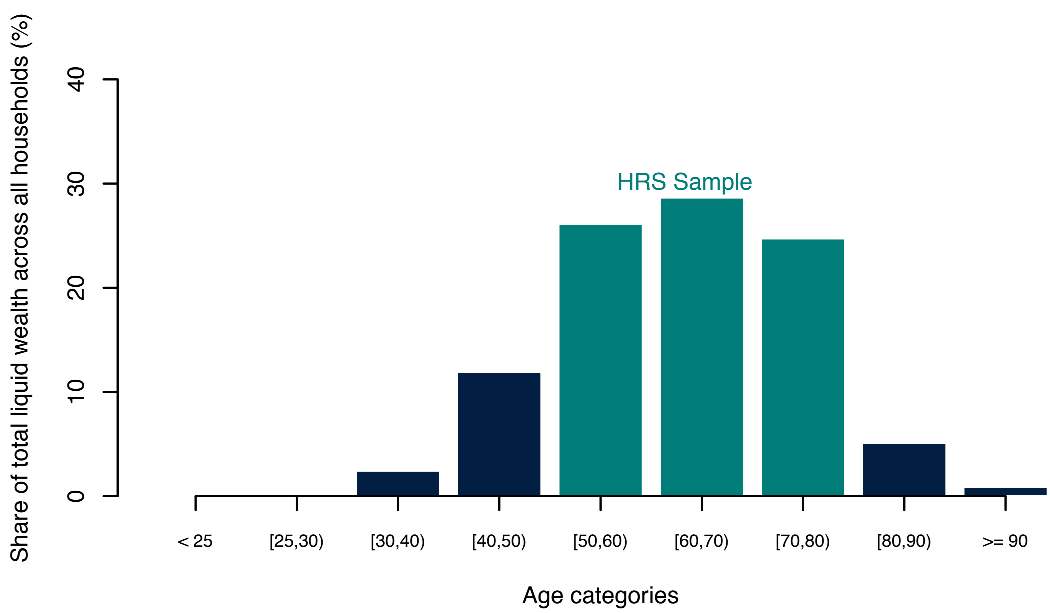


Figure 2: Subjective vs. Life-table probabilities

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.

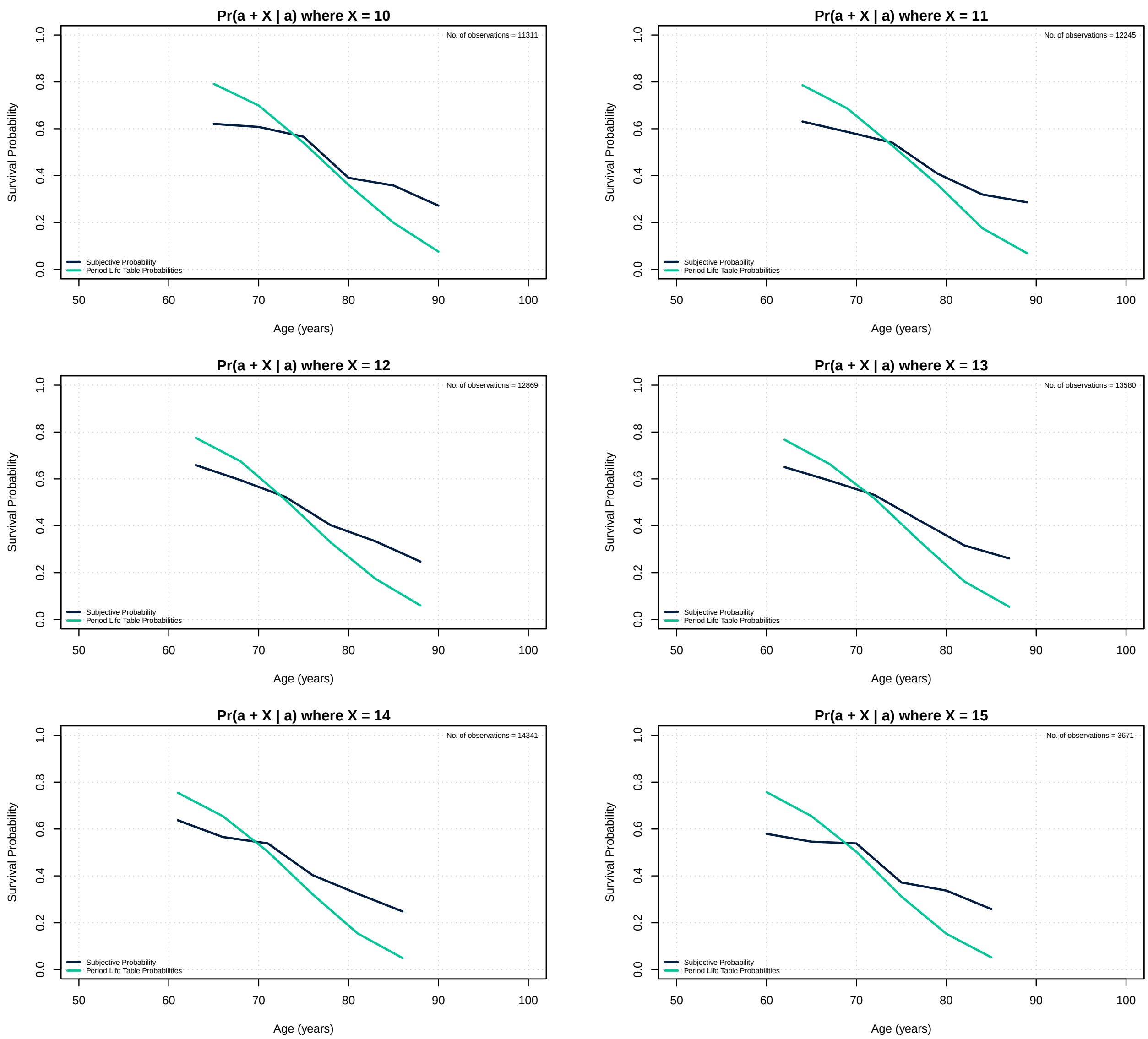


Figure 3: Life-cycle profile for College Graduates

This figure plots the model generated optimal paths for portfolio share in risky assets for a mortality pessimist (Column 1) and a dispositional pessimist (Column 2). Units: percentage points. 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.

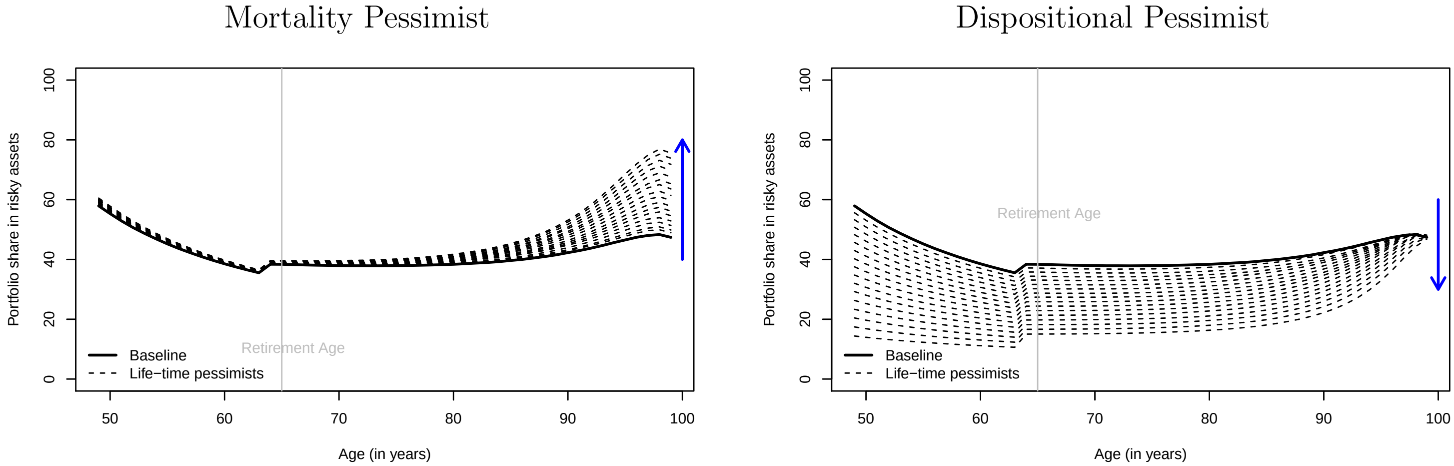


Table 1: Summary Statistics: Mortality Deviations

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
All	0.13	0.42	0.03	-0.27	-0.64	98,402

Table 2a: Impact of Mass Shootings on Mortality Deviations

This table presents the population weighted regression estimates for the impact of mass shootings on subjective lifespan expectations. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(No. of deaths + 1)	0.0122***			0.0157***			0.0162***		
	(0.002)			(0.002)			(0.002)		
Log(No. of shootings + 1)		0.0114***			0.0146***			0.0152**	
		(0.002)			(0.003)			(0.002)	
I(No. of shootings > 0)			0.0239***			0.0249***			0.0255***
			0.0033			(0.003)			(0.004)
By Social Connectedness:									
Low connectedness									
Log(No. of deaths + 1)				0.0048**			0.0046**		
				(0.002)			(0.002)		
Log(No. of shootings + 1)					0.0052**	0.0059*		0.0049**	
					(0.002)	(0.004)		(0.002)	
I(No. of shootings > 0)									0.006
									(0.004)
Medium connectedness									
Log(No. of deaths + 1)				0.0058**			0.0055**		
				(0.002)			(0.004)		
Log(No. of shootings + 1)					0.0061***			0.0058**	
					(0.002)			(0.002)	
I(No. of shootings > 0)						0.0064**			0.0062**
						(0.002)			(0.002)
High connectedness									
Log(No. of deaths + 1)				0.0085**			0.0082**		
				(0.003)			(0.003)		
Log(No. of shootings + 1)					0.0090***			0.0086***	
					(0.003)			(0.003)	
I(No. of shootings > 0)						0.0123**			0.0119**
						(0.006)			(0.006)
By Geographic Distance									
Short distance									
Log(No. of deaths + 1)							0.0004		
							(0.002)		
Log(No. of shootings + 1)								0.0009	
								(0.002)	
I(No. of shootings > 0)									0.0018
									(0.002)
Medium distance									
Log(No. of deaths + 1)							0.0010		
							(0.002)		
Log(No. of shootings + 1)								0.0014	
								(0.002)	
I(No. of shootings > 0)									0.0023
									(0.003)
Long distance									
Log(No. of deaths + 1)							0.0012		
							(0.002)		
Log(No. of shootings + 1)								0.0019	
								(0.002)	
I(No. of shootings > 0)									0.0018
									(0.002)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survival Horizon Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.2438	0.2441	0.2358	0.2361	0.2358	0.2360	0.2361	0.2358	0.2360
No. of Observations	97,708	97,708	97,708	97,708	97,708	97,708	97,708	97,708	97,708

Robust Standard Errors Clustered at the State Level

Table 2b: Impact of Natural Disasters on Mortality Deviations

This table presents the population weighted regression estimates for the impact of natural disasters on subjective lifespan expectations. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(No. of days + 1)	0.0039***			0.0030***			0.0025***		
	(0.001)			(0.001)			(0.001)		
Log(No. of disasters + 1)		0.0140***			0.0081**			0.0064**	
		(0.004)			(0.004)			(0.003)	
I(No. of disasters > 0)			0.0126***			0.0127***			0.0086***
			0.0036			(0.004)			(0.003)
By Social Connectedness									
Low connectedness									
Log(No. of days + 1)				0.000			0.000		
				(0.001)			(0.001)		
Log(No. of disasters + 1)					-0.002			-0.002	
					(0.002)			(0.002)	
I(No. of disasters > 0)						0.003			-0.001
						(0.003)			(0.003)
Medium connectedness									
Log(No. of days + 1)				0.0016*			0.0013*		
				(0.001)			(0.001)		
Log(No. of disasters + 1)					0.0019**			0.0014	
					(0.001)			(0.001)	
I(No. of disasters > 0)						0.0073*			0.0025
						(0.004)			(0.004)
High connectedness									
Log(No. of days + 1)				0.0011**			-0.0002		
				(0.001)			(0.001)		
Log(No. of disasters + 1)					0.0034***			0.0013	
					(0.001)			(0.001)	
I(No. of disasters > 0)						0.0137***			0.0006
						(0.005)			(0.006)
By Geographic Distance									
Short distance									
Log(No. of days + 1)							0.0011**		
							(0.001)		
Log(No. of disasters + 1)								0.0020**	
								(0.001)	
I(No. of disasters > 0)									0.0143**
									(0.003)
Medium distance									
Log(No. of days + 1)							0.0002		
							(0.000)		
Log(No. of disasters + 1)								0.0001	
								(0.001)	
I(No. of disasters > 0)									0.0055**
									(0.002)
Long distance									
Log(No. of days + 1)							0.0008*		
							(0.000)		
Log(No. of disasters + 1)								0.0017**	
								(0.001)	
I(No. of disasters > 0)									0.0051**
									(0.002)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survival Horizon Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.2438	0.2441	0.2358	0.2361	0.2358	0.2360	0.2361	0.2358	0.2360
No. of Observations	97,708	97,708	97,708	97,708	97,708	97,708	97,708	97,708	97,708

Robust Standard Errors Clustered at the State Level

Table 3: Placebo Regression

	Natural Disasters	Mass Shootings
Own county I(shock > 0)	0.0015	-0.0520*
	(0.004)	(0.029)
By Social Connectedness:		
Low connectedness: I(shock > 0)	0.0006	0.0010
	(0.002)	(0.002)
Medium connectedness: I(shock > 0)	-0.0008	0.0023
	(0.002)	(0.002)
High connectedness: I(shock > 0)	0.0077	0.0030
	(0.005)	(0.001)
By Geographic Distance		
Short distance: I(shock > 0)	-0.0011	-0.0004
	(0.009)	(0.001)
Medium distance: I(shock > 0)	0.0000	-0.0008
	(0.001)	(0.002)
Long distance: I(shock > 0)	-0.0040*	-0.0030
	(0.001)	(0.002)
Control variables	Yes	Yes
County Fixed Effects	Yes	Yes
Survival Horizon Fixed Effects	Yes	Yes
Adjusted R-squared	0.2564	0.2339
No. of Observations	59940	59940

Robust Standard Errors Clustered at the State Level

Table 4a: Relationship between lifespan expectations and Risky-asset share

This table presents the population weighted regression estimates of the relationship between lifespan expectations and the share of risky investments in the financial wealth of the household.

Dep. Var. : Fraction(Risky Assets)	(1)	(3)	(5)
Type:	OLS	IV	IV
Instruments:		All	Non-own
l^d	-0.0108**	-0.0367**	-0.0385**
	(0.004)	(0.019)	(0.019)
Control variables	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes
Survival Horizon Fixed Effects	Yes	Yes	Yes
Adjusted R-squared	0.1961	0.1575	0.1582
Kleibergen-Paap rK LM Statistic		2839.313	2835.9
Chi-sq P-val:		0.00	0.00
Hansen J Statistic		47.793	44.454
Chi-sq P-val:		0.15	0.15
Weak identification test			
Cragg-Donald Wald F Statistic		79.951	85.364
Stock-Yogo critical value (Relative Bias)(5%)		21.38	21.39
No. of Observations	86,200	86,200	86,200

Robust standard errors in parenthesis

Table 4b: Relationship between lifespan expectations and share of direct stock holdings

This table presents the population weighted regression estimates of the relationship between lifespan expectations and the share of direct stock holdings in the financial wealth of the household.

Dep. Var. : Fraction(Equity holding)	(1)	(3)	(5)
Type:	OLS	IV	IV
Instruments:		All	Non-own
l(d)	-0.0095**	-0.0310*	-0.0331**
	(0.005)	(0.018)	(0.018)
Control variables	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes
Survival Horizon Fixed Effects	Yes	Yes	Yes
Adjusted R-squared	0.1811	0.1390	0.1394
Kleibergen-Paap rK LM Statistic		2799.24	2835.9
Chi-sq P-val:		0.00	0.00
Hansen J Statistic		50.603	48.129
Chi-sq P-val:		0.16	0.16
Weak identification test			
Cragg-Donald Wald F Statistic		77.945	85.364
Stock-Yogo critical value (Relative Bias)(5%)		21.39	21.39
No. of Observations	86,200	86,200	86,200

Robust standard errors in parenthesis

Table 5: Mortality Deviations and Financial Return Expectations

This table presents the correlation between life expectancy deviations and the likelihood respondents think that 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%	50.69	8,353	[omitted]		
-18.99% to 0	48.22	8,324	2.88***	1.80	3.95
0.01% to 19%	44.23	7,761	6.43***	5.35	7.52
> 19%	38.60	8,381	11.47***	10.39	12.56
Mean Dep. Var.			41.14%		

Table 6: 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 7: 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

Online Appendix

A Appendix Tables and Figures

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 2b. 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.

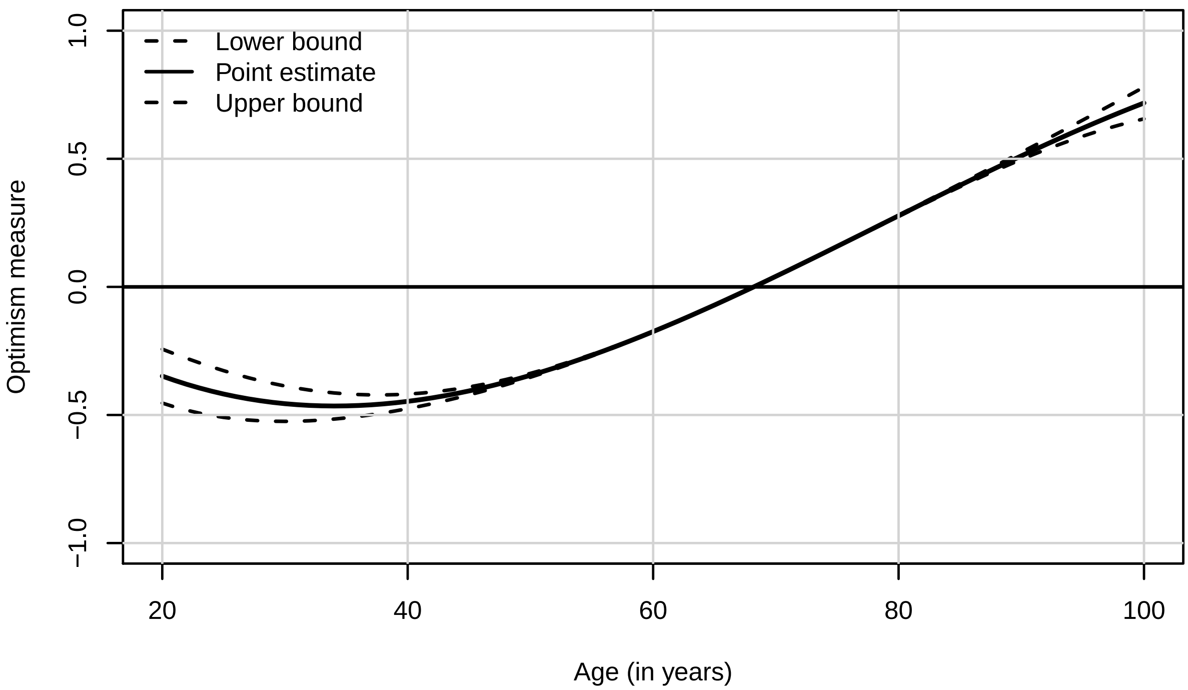


Figure A.2: Identification Strategy for Neighbourhood effects

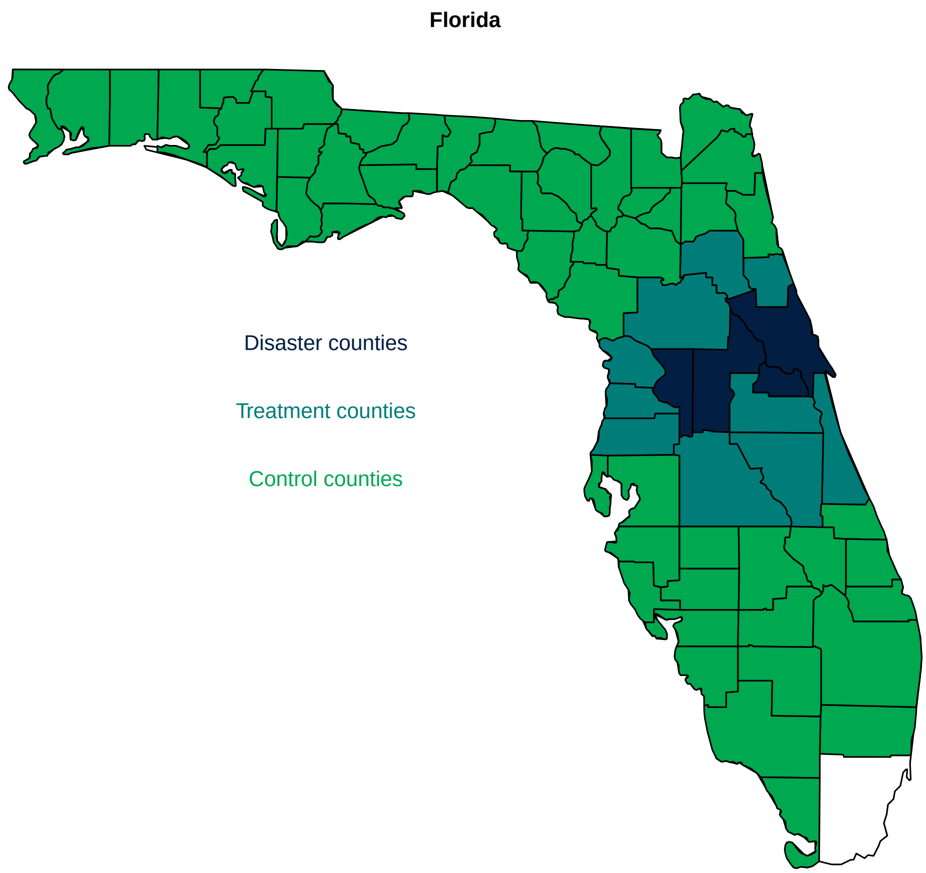


Figure A.3: Life-cycle profile for College Graduates With Bequest Motive

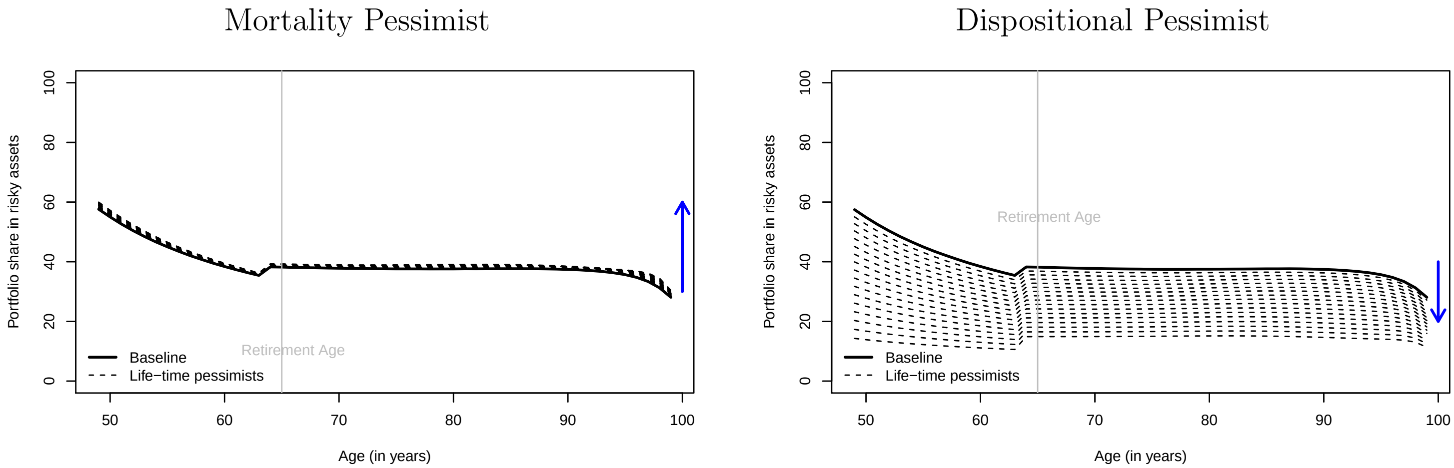


Table A.1: Correlates of Subjective Life Expectancy

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: 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

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).[16] 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.

[16] 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)

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 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

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.

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.[17] 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 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.[18]

Federal Emergency Management Agency (FEMA)

Natural disasters have been utilized as a source of exogenous variation in many studies. To

[17]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.

[18]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.

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.[19]

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[20] and prior to that the 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. [21] 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.

[19]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.

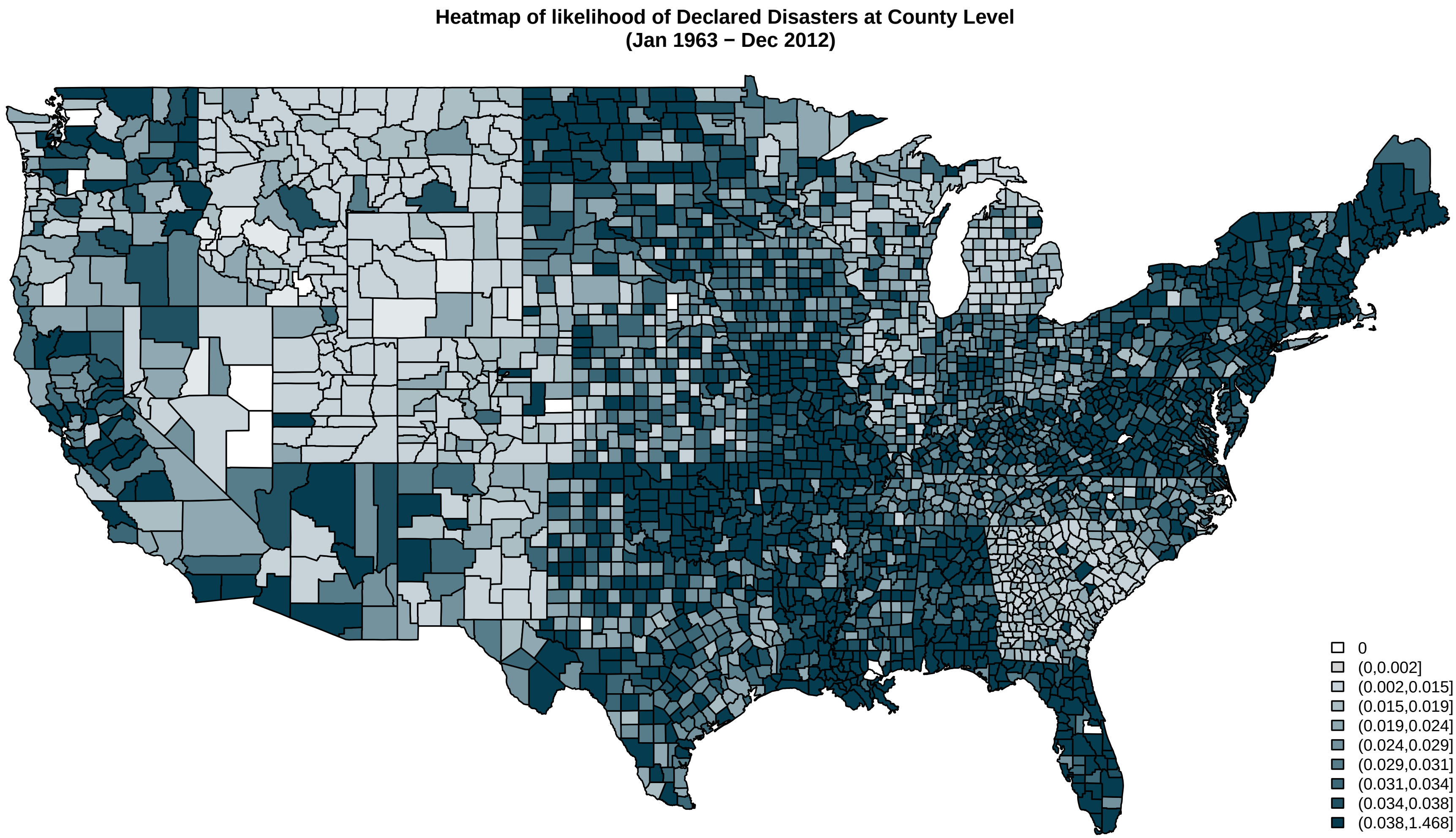
[20]Section 401 of the Stafford Act can be accessed here: `https://www.fema.gov/robert-t-stafford-disaster-relief-and-emergency-assistance-act-public-law-93-288-amended`

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

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)[22], and identifying effects *within* states forms the basis of the empirical analyses.

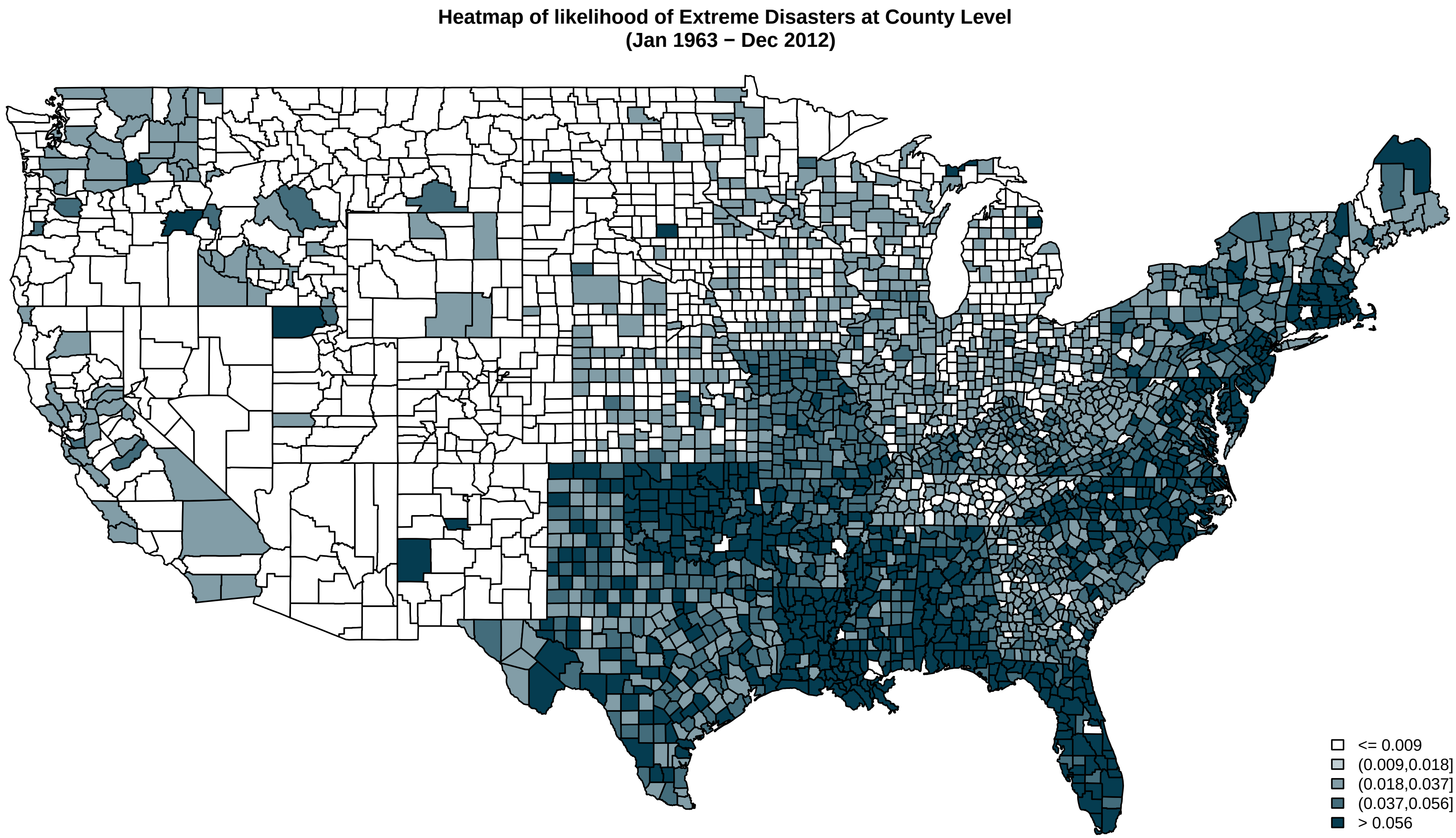
[22]The Federal Information Processing Standard (FIPS) code $6-4$ uniquely identifies counties and county equivalents in the United States.

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

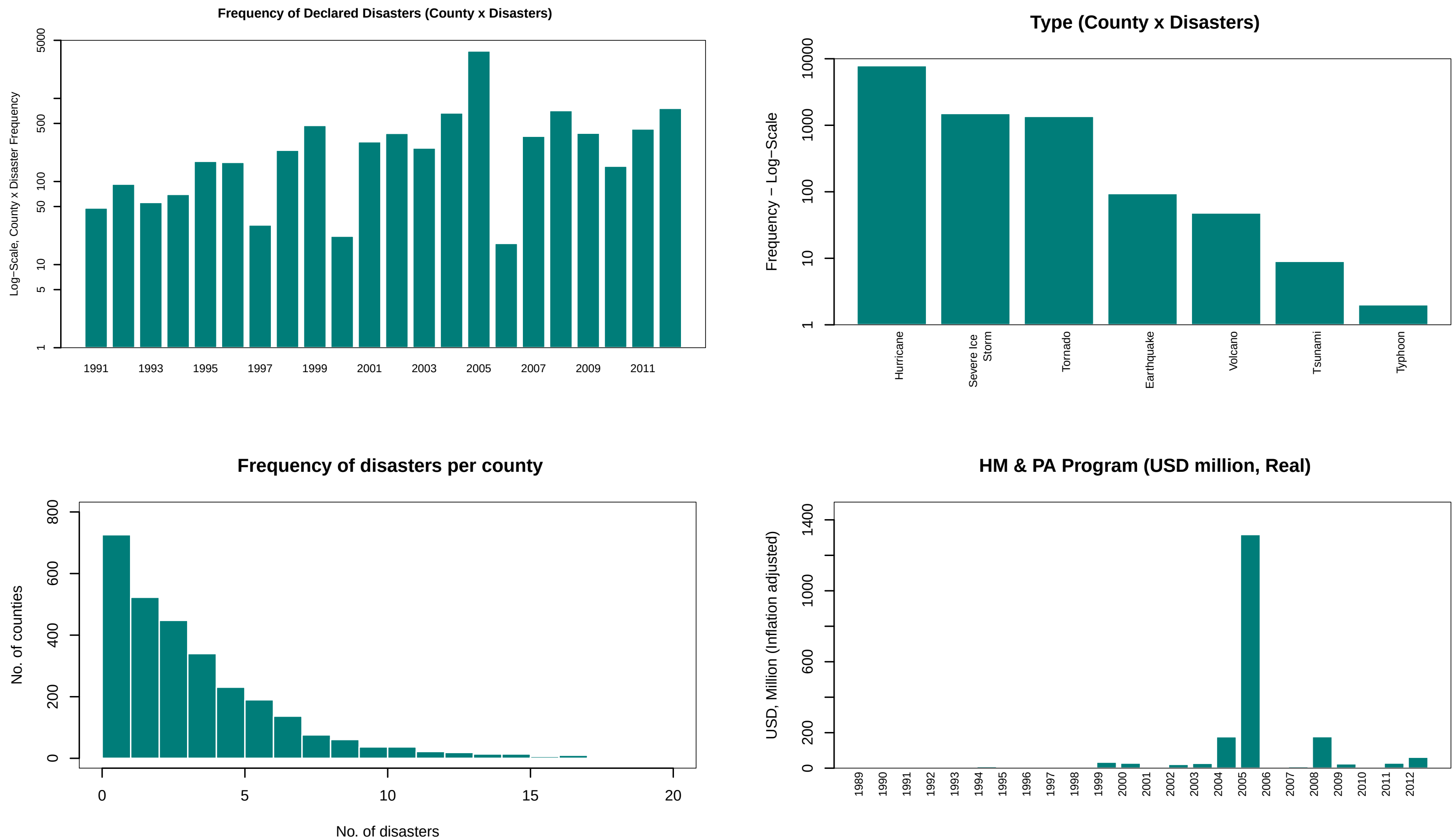


Source: Federal Emergency Management Agency (FEMA)

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.[23] 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.[24]

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

[23]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.

[24]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.[25] 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.

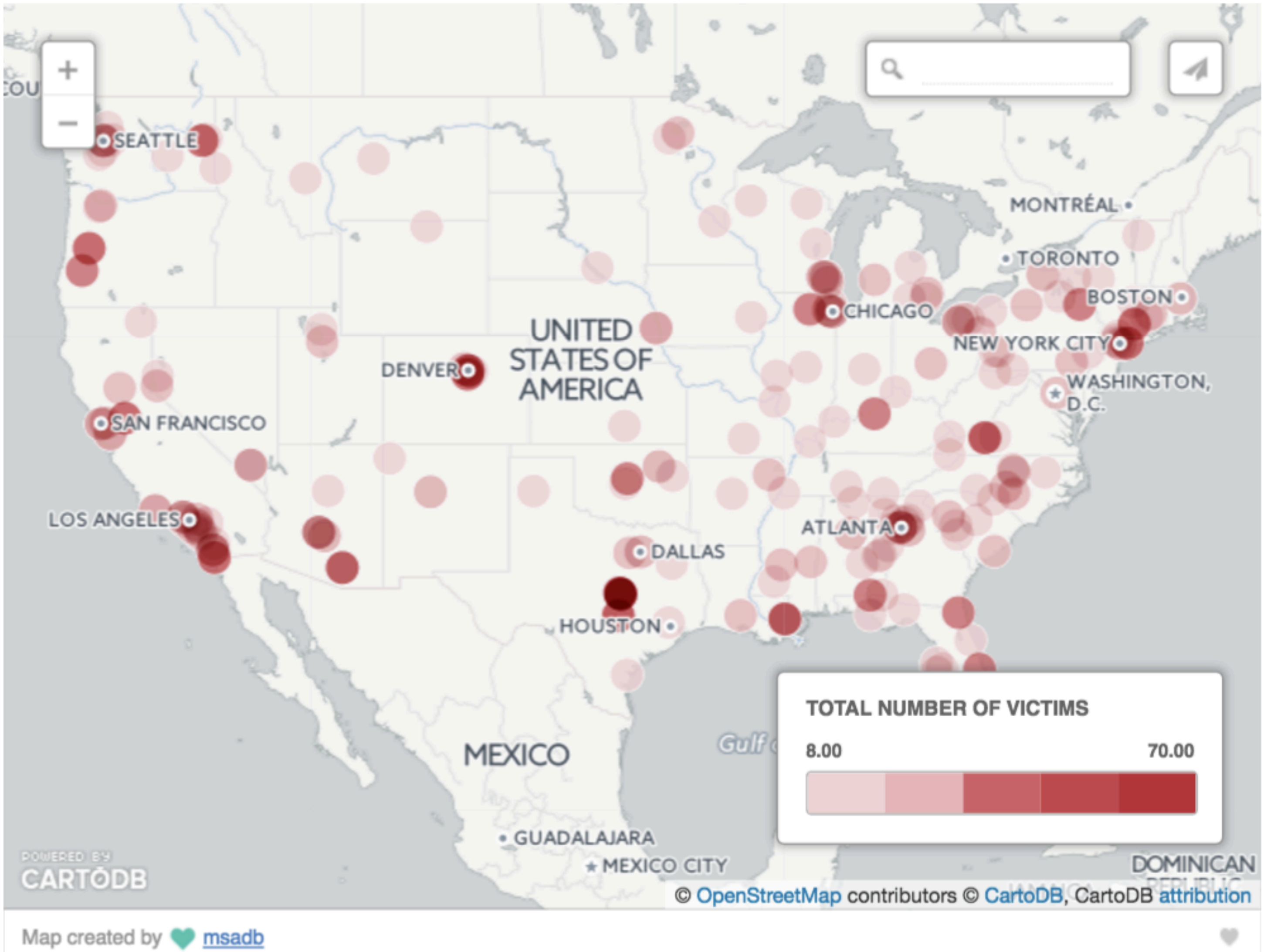
The Uniform Crime Reporting (UCR) program reports counts of arrests and offenses at the county level since 1994 (till 2012). Originally, this data is collected by the Federal Bureau of Investigation (FBI) from reports submitted by agencies and states participating in the UCR Program. The Inter-University 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,

[25] 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.[26] Additionally, county-fixed effects allow for controlling other unobserved factors such as institutional histories, efficiency and administrative track record that vary across different geographies.

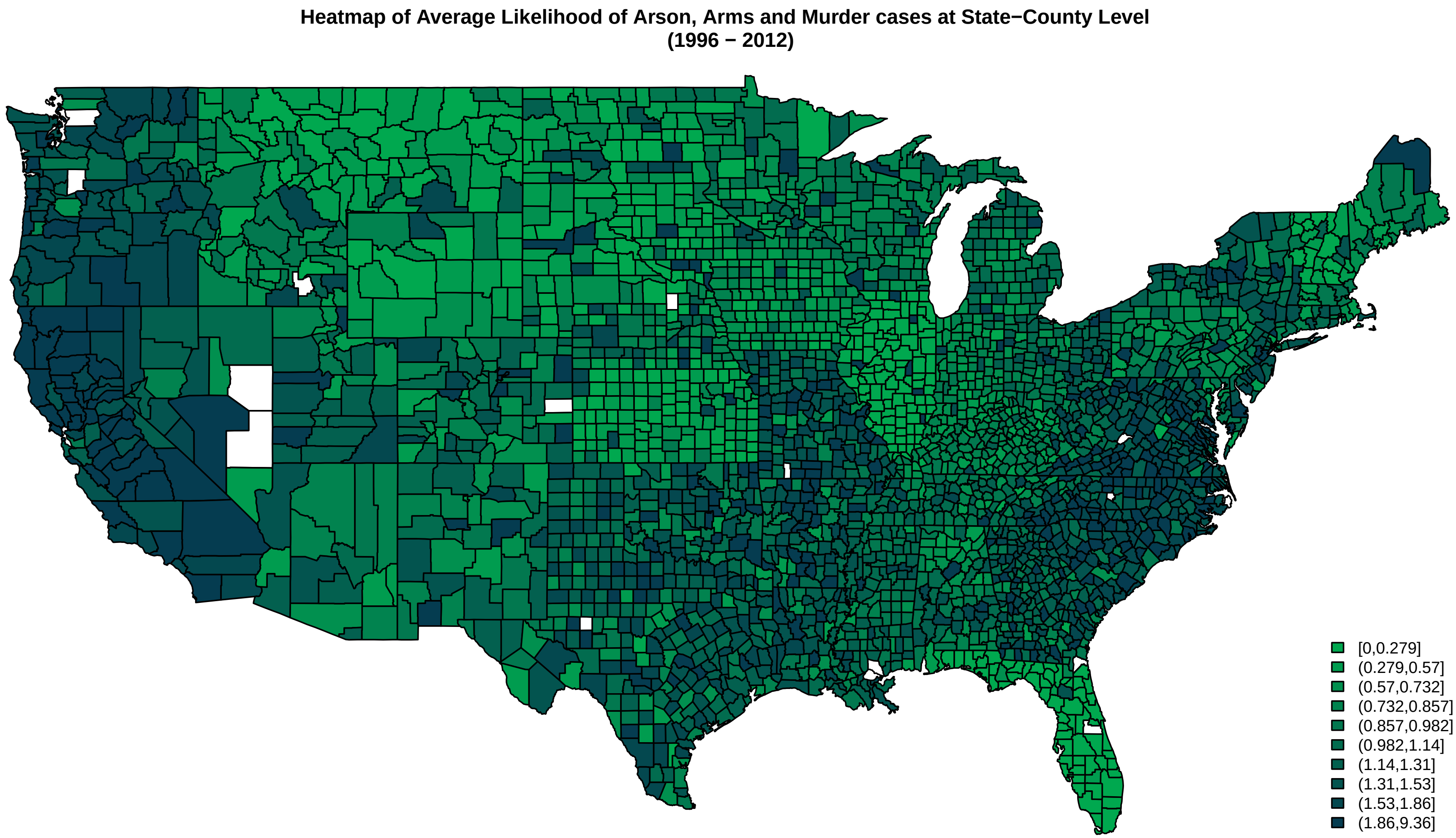
[26] The details of reporting procedures of crime statistics can be found in the Uniform Crime Reporting Handbook (Washington, DC: U.S. Government Printing Office, 1980), and in the codebooks for the ICPSR's Agency-level UCR data collection available upon request.

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%.[27] 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.[28]

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

[28]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:

$$Pr(\text{Declared}|\text{Disaster}) = \frac{Pr(\text{Disaster}|\text{Declared})Pr(\text{Declared})}{Pr(\text{Disaster})} \tag{10}$$

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

$$Pr(\text{Declared}|\text{Disaster}) = \frac{Pr(\text{Declared})}{Pr(\text{Disaster})} \tag{11}$$

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:

$$I(\text{Disaster} > 0)_{c,t} = D\tau + \gamma_t + \epsilon_{c,t} \tag{12}$$

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:

$$I(\text{Disaster} > 0)_{c,s,t} = D\tau + I(S) + \tau_s I(S) \times D + \lambda_t + \sum_{k=1}^{K} I(\text{Disaster type}_k) + \epsilon_{c,s,t} \tag{13}$$

Equation (13) 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 (A)	State FE (B)	Year,State FE (C)	N
(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

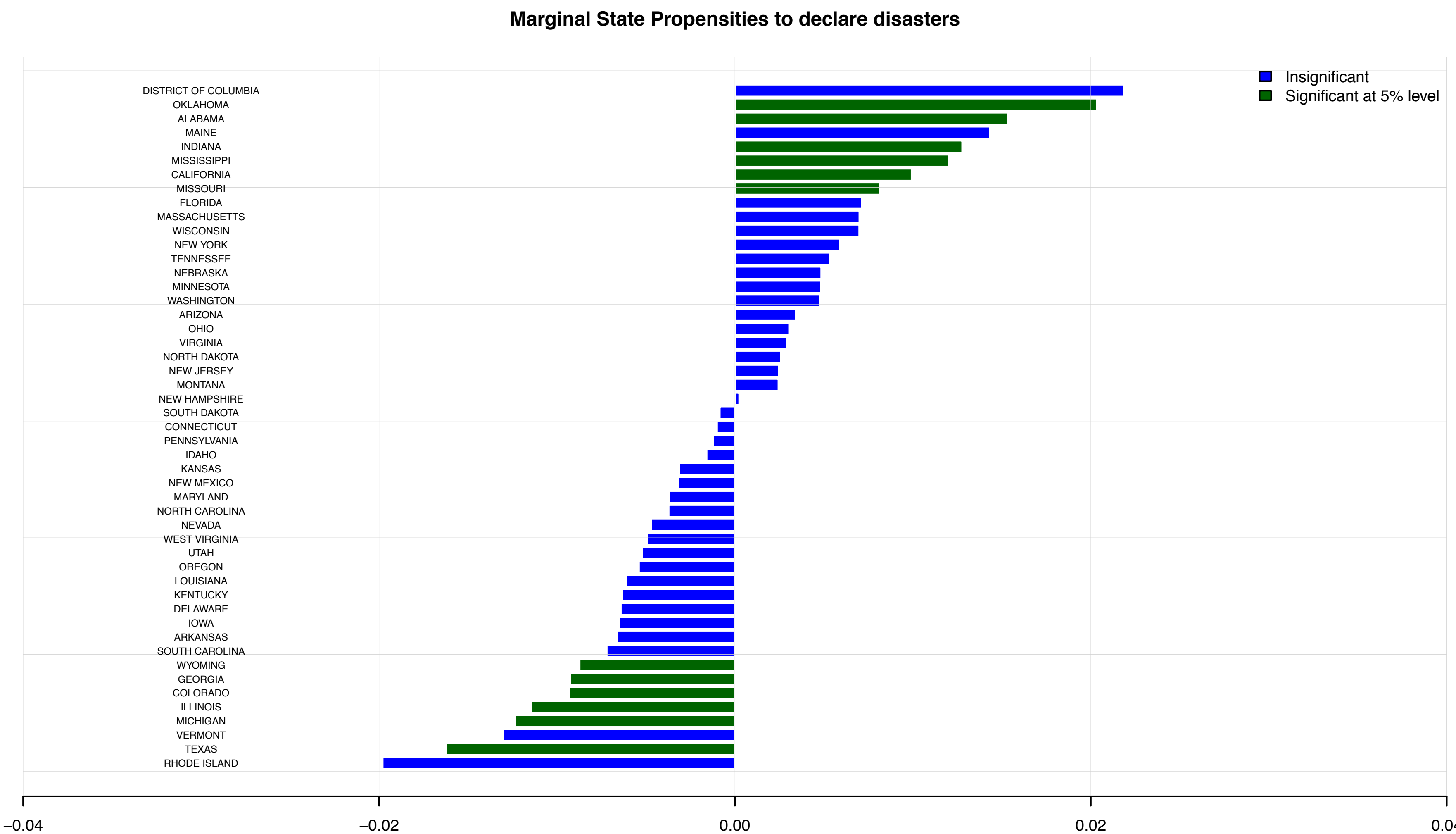


Table C.1 presents the results across all states. Each estimated coefficient is the overall propensity to declare disasters across all states, after controlling for state level variations and time variations. Column (A) presents the coefficients from a specification that only contains year fixed-effects, 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).[29] In relative terms, mortality risks due to natural disasters or gun violence are nearly 120 times lower than health risks and unintentional injuries.[30] 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).[31]

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:

$$\Pr(\text{Death}_{c,t+1} \mid \text{Disaster}_{c,t+1}) = \frac{Pr(\text{Disaster}_{c,t+1} \mid \text{Death}_{c,t+1}) \times Pr(\text{Death})_{t+1}}{Pr(\text{Disaster})_{c,t+1}} \tag{14}$$

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

[29] 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.

[30] 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.

[31] 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.

$$\Pr(\text{Disaster}_{c,t+1} \mid \text{Death}_{c,t+1}) \approx \Pr(\text{Disaster}_{c,t+1}) \tag{15}$$

Assumption (15) 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.[32] Given this assumption, equation (14) 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:

$$y_{c,t} = \alpha_c + \omega_t + \sum_{k=1}^{K} \gamma_{t-k} I(\text{Disaster} > 0)_{c,t-k} + \epsilon_{c,t} \tag{16}$$

$y_{c,t}$ 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

[32] 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.[33]

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.[34] 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.

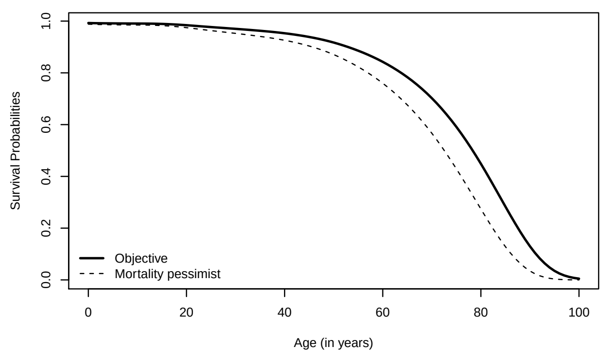
[33]One way to consider the negative coefficients is that post-disaster responses to public health concerns, if anything, reduces mortality rates as opposed to increase them.

[34]Interestingly, a back of the envelope calculation yields similar conservative estimates. The highest value (across counties) for Pr(Natural Disaster) is 0.16 percent. Estimates of Pr(Disaster|Death) range from 0.01 percent[35] to 0.05 percent (Goklany, 2009). Since the highest impact is when middle-aged, Pr(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.[36] 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.

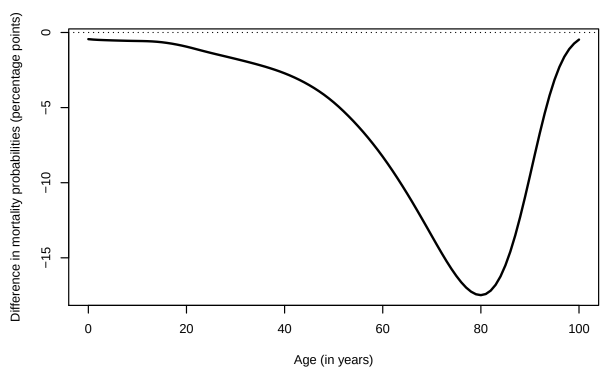
E Mortality pessimism

Figure E.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 E.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 E.1 B).