

5. Savings and Portfolio Choice of Pessimistic Agents

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 (C.7), subject to (C.6) is as follows:

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

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

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

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

$$u'_t(c_t) = \beta \psi_t E_t R_{t+1} u'_{t+1}(\Gamma_{t+1} \mathbf{c}_{t+1}) \quad (\text{C.10})$$

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

$$\beta \psi_t E_t (R_{t+1}^e - R^f) a_t u'_{t+1}(\Gamma_{t+1} \mathbf{c}_{t+1}) = 0 \quad (\text{C.11})$$

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

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portfolio choice in period $t - 1$.¹⁶

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

Optimal solution: Figure B.4 shows the average of 20,000 simulated paths of consumption (first row), saving (second row) and portfolio share (third row) for a college graduate without a bequest motive.¹⁸ The life-cycle profile starts at the age of 50, from when estimates of mortality deviations are observed in the data. This has the distinct advantage of studying agents in a setting where from the

¹⁶Following 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.

¹⁷The post-war data series records a higher mean of 7.12 percent and a standard deviation of 6.10 percent.

¹⁸Profiles for high school graduates and others look similar but at different levels of wealth.

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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 B.8 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 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 B.4) increases her consumption profile, although marginally, throughout her life until 80 and reduces consumption dramatically around age 80. Table B.9 presents the magnitude of difference from the baseline profile. Even at very high levels of pessimism ($\tau = 60\text{percent}$), 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

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decreases her saving until retirement, and the rate of draw down from savings is higher until around age 80 after which she sharply decreases the rate of drawing down from savings.¹⁹ At the same time, a lifetime pessimist *increases* her share of investments in risky assets throughout life, and this increase is the highest at old age, after retirement. While this may appear to be counter-intuitive, the role of mortality pessimism on the share of investment in risky assets is related to assumptions about the timing of the impact of pessimism. The discount rate determines savings in a life-cycle model and as it increases, wealth accumulation decreases (as evident in relative saving declines for a lifespan pessimist). This lowers the wealth to present value of all future income ratio, i.e., $\frac{W}{PV(Y)}$, implying that the agent will actually increase her share of investments in risky assets as opposed to decreasing them.²⁰ This assumption relies on understanding the extent to which savings have adjusted within the same year and in a canonical life-cycle model, the assumption goes in the direction of a high degree of adjustment within the same year.

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

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

¹⁹The 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 6.

²⁰However, 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.

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

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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 share of investment in risky assets well throughout her lifetime, although she converges to the baseline level by the end of her lifetime.

Summary of model results:

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

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

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

5.2 Bequests

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

$$V_{T+1} = b \frac{(X_{T+1}/b)^{1-\rho}}{1-\rho} \quad (\text{C.12})$$

For expositional purposes, the bequest function is also assumed to be isoelastic and the strength of this channel is determined by the parameter b . Following Gomes and Michaelides (2005), the importance of bequest motive b is set at 2.5. Intuitively,

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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 B.9 presents the deviations from the baseline scenario with parameters as in Table B.8 but with a strong bequest motive where $b = 2.5$. The extent to which pure lifespan pessimists increase consumption before retirement is indeed reduced, and so savings decline and increase in investment into risky assets due to mortality pessimism. However, the extent to which these pessimists reduce their consumption after retirement is much higher and the increase in risky share is no longer in large magnitudes. During retirement, consumption decreases as a result of both a high effective discount rate (increased expectation of mortality risk) and wealth does not fall towards zero due to the presence of a bequest motive. Since future labour income and financial wealth fall, optimal asset allocation depends on the relative speed at which these factors decrease. This depends on both the discount rate (adjusted for pessimistic survival probabilities) and the strength of the bequest motive. Given these parameter values, during most of the retirement period, they decline at similar rates and therefore the share of wealth in risky assets remains constant (Appendix Figure 1.3). However, it is evident that the effects on portfolio choice, savings and consumption is far stronger in the presence of a bequest motive, suggesting that dispositional pessimists who also have strong bequest motives tend to react sharply to their pessimistic expectations.

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

6 Conclusion

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

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

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

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Table B.1: Summary Statistics: Mortality Deviations

This table reports pooled population-weighted summary statistics for l^d , i.e., deviations of subjective probabilities 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

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

Table B.2a: Impact of Natural Disasters on Mortality Deviations

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

$$l_{i,c,t}^d = \alpha + X_{i,t}'\beta + \omega \text{Natural Disaster Proxy}_{c,t} + \psi_c + \zeta_x + \epsilon_{i,c,t}$$

l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables as in Table 1.1. Columns 1–2 present the results for the natural disaster shock measured as the total number of days of disaster experience in a given year, columns 3–4 for the total number of disaster experiences in a given year and columns 5–6 for an indicator variable equal to 1 if the respondent experienced any disaster in a given year. These estimates are presented for respondents whose age is between 50 and 85, ***, **, * denote 1, 5, and 10 percent significance. All standard errors are robust and clustered at the state level.

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

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Table B.2b: Impact of Mass Shootings on Mortality Deviations

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

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

l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables as in Table 1.1. Column 1 presents the baseline regression without mass shootings experience. Columns 2–4 present the estimated results for the impact of mass shootings. Column 2 is equivalent to Table B.2a for controls, and columns 3–4 estimate it with a stricter requirement with individual fixed effects. These estimates are presented for respondents whose age is between 50 and 85, ***, **, * denote 1, 5, and 10 percent significance. All standard errors are robust and clustered at the state level.

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

Table B.3: Impact of Natural Disasters on Optimists and Pessimists

This table presents the impact of natural disasters on optimists (defined as positive l^d before the natural disaster) and on pessimists (defined as negative l^d before the natural disaster.) l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables as in Table 1.1. These estimates are presented for respondents whose age is between 50 and 85, ***, **, * denote 1, 5, and 10 percent significance. All standard errors are robust and clustered at the state level.

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

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

This table presents the population weighted regression estimates of the impact of natural disasters and l^d on risky asset share. $w_{i,c,t}$ is the share of equity and debt holdings in financial assets. l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables that control for age, wealth, health, demography and other characteristics as in Table 1.1. The coefficients of interest are μ, δ_0 and δ_1 . δ_1 measures the impact on risky share *when* there is a natural disaster and l^d .

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

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

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

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

This table presents the impact of natural disasters, mortality deviations, l^d , on risky-asset share by *quartiles* of optimism. l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables that control for age, wealth, health, demography and other characteristics as in Table 1.1. These estimates are presented for respondents whose age is between 50 and 85, ***, **, * denote 1, 5, and 10 percent significance. Robust standard errors in parenthesis.

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

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Table B.6: Lifetime disaster experience and risky asset share

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

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

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

$w_{i,c,t}$ is the share of equity and debt holdings in the financial assets. l^d is the deviations of subjective life expectancy from life-table probabilities. ψ_c are county fixed effects, ζ_x are survival period fixed effects, and $X_{i,t}$ is a matrix of control variables that control for age, wealth, health, demography and other characteristics as in Table 1.1. These estimates are presented for respondents whose age is between 50 and 85, ***, **, * denote 1, 5, and 10 percent significance. Robust standard errors in parenthesis.

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

Example for λ : Age = 50

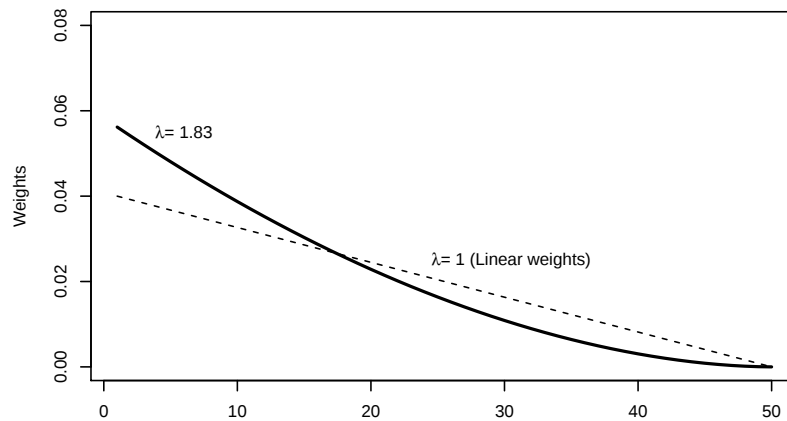


Table B.7: Mortality Deviations and Financial Return Expectations

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

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

Table B.8: Model Parameters: Baseline

This table presents the parameter values in the baseline model.

Parameter	Value
Risk aversion (ρ)	5
Discount factor (β)	0.98
Risk-free return (R^f)	2%
Equity premium ($R_t^s - R^f$)	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

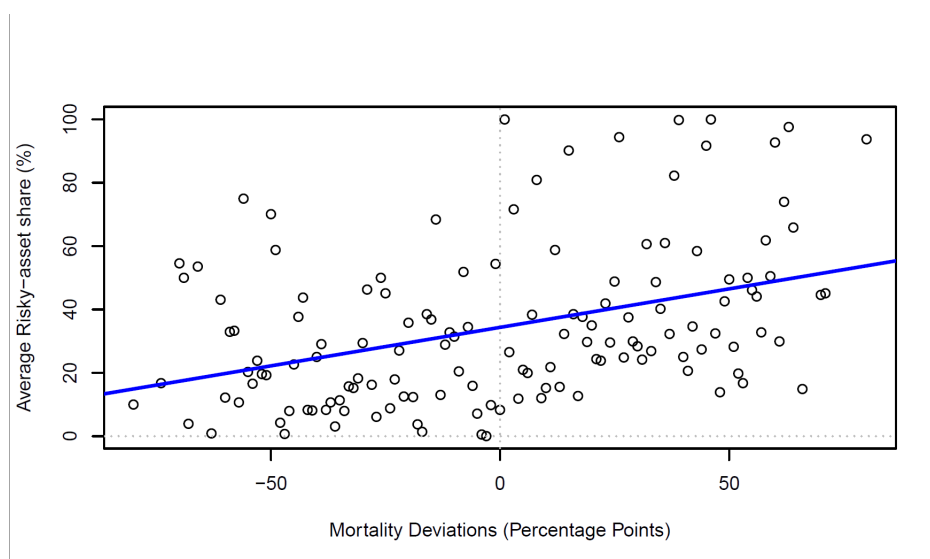
Table B.9: Pre- and post- retirement effects of mortality, and dispositional pessimism

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

Panel A: Deviations from baseline, without bequests												
	Average before retirement, Pessimism Range						Average after retirement, Pessimism Range					
	4%	12%	28%	44%	60%	64%	4%	12%	28%	44%	60%	64%
Consumption												
Units: Percent Difference from baseline												
Mortality Pessimist	0.06	0.71	0.99	1.75	3.05	2.44	-0.24	-0.59	-3.09	-4.15	-5.10	-7.08
Dispositional Pessimist	-0.63	-1.28	-3.31	-4.46	-4.74	-5.48	-1.72	-4.76	-11.35	-15.21	-18.09	-20.07
Savings												
Units: Percent Difference from baseline												
Mortality Pessimist	-0.90	-1.77	-4.43	-6.60	-7.74	-9.25	-1.94	-4.57	-12.02	-17.87	-22.91	-25.13
Dispositional Pessimist	-1.94	-4.85	-11.23	-16.66	-20.72	-22.36	-3.99	-10.29	-23.13	-32.47	-39.74	-41.84
Risky share												
Units: Percentage Points from baseline												
Mortality Pessimist	0.16	0.33	0.58	0.94	1.12	1.28	0.56	1.32	3.20	5.47	7.86	8.32
Dispositional Pessimist	-1.18	-3.91	-10.68	-20.87	-39.69	-46.54	-0.79	-2.82	-7.07	-11.90	-17.75	-19.50
Panel B: Deviations from baseline, with bequests												
	Average before retirement, Pessimism Range						Average after retirement, Pessimism Range					
	4%	12%	28%	44%	60%	64%	4%	12%	28%	44%	60%	64%
Consumption												
Units: Percent Difference from baseline												
Mortality Pessimist	-0.53	-0.42	0.53	1.03	1.28	2.04	-2.43	-4.52	-5.24	-6.83	-9.36	-9.16
Dispositional Pessimist	0.09	-1.27	-2.64	-4.31	-5.59	-5.43	-1.44	-5.88	-11.26	-16.18	-20.12	-20.25
Savings												
Units: Percent Difference from baseline												
Mortality Pessimist	-1.28	-2.90	-5.05	-7.37	-9.87	-9.82	-3.14	-7.70	-13.54	-19.25	-24.97	-25.68
Dispositional Pessimist	-0.84	-4.58	-10.39	-16.42	-21.55	-22.20	-3.21	-10.73	-22.28	-31.80	-39.18	-40.27
Risky share												
Units: Percentage Points from baseline												
Mortality Pessimist	0.06	0.17	0.53	0.76	1.07	1.11	0.09	0.31	0.81	1.12	1.35	1.33

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

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



5. The Effect of Subjective Life Expectancy on Financial Decisions

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

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

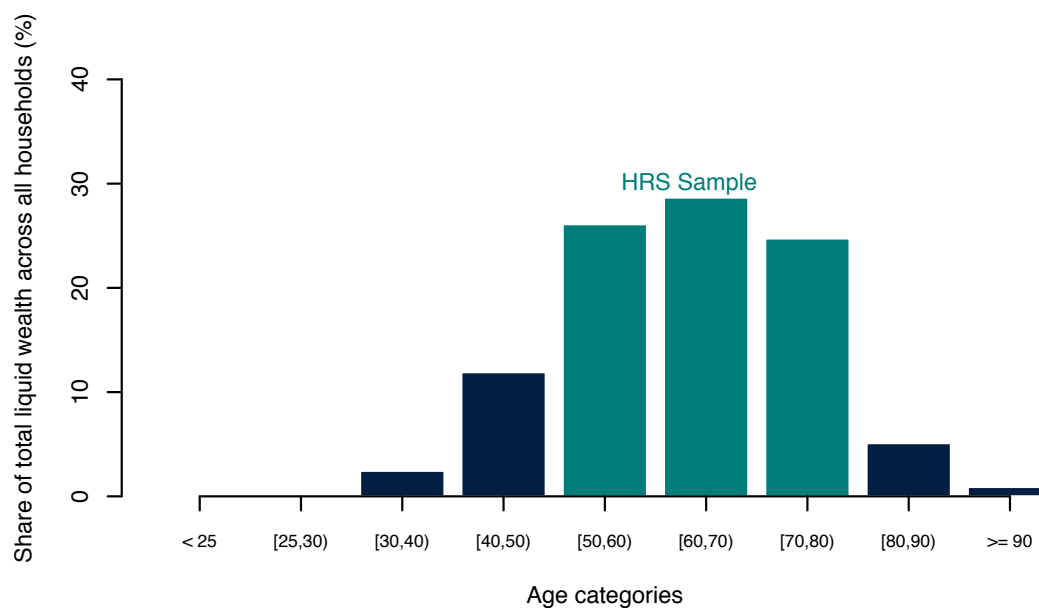
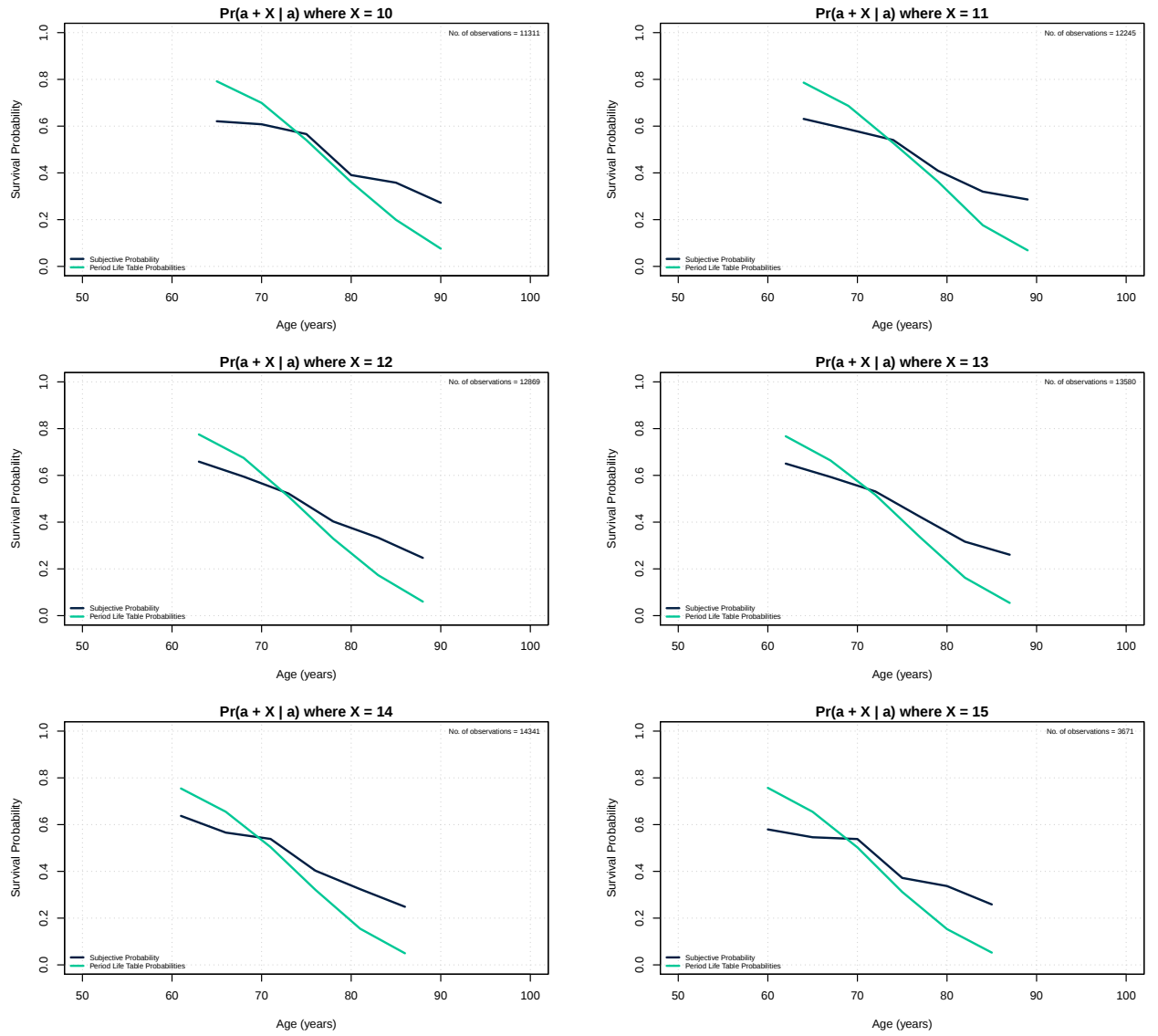


Figure B.2: Subjective vs. Life-table probabilities

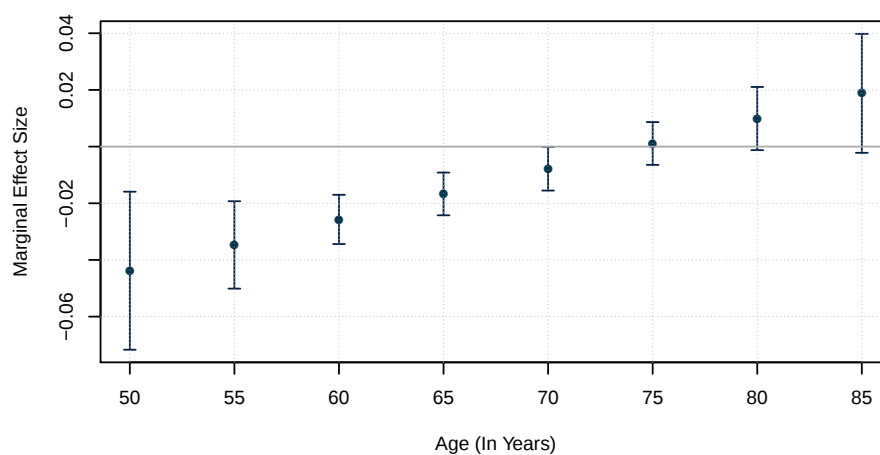
This figure presents six panels of comparison between subjective and life table probabilities. Each panel is different in the survival horizon, i.e., the difference between the target age and current age of the respondent. Across all survival horizons, the dark blue line represents the subjective probability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



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Figure B.3: Effects of Natural Disasters by Age

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



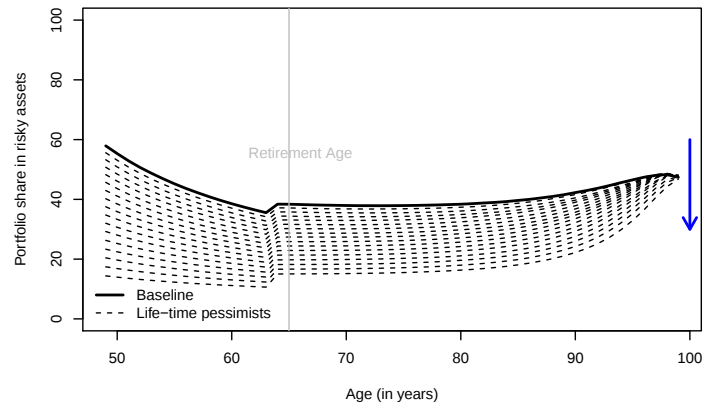
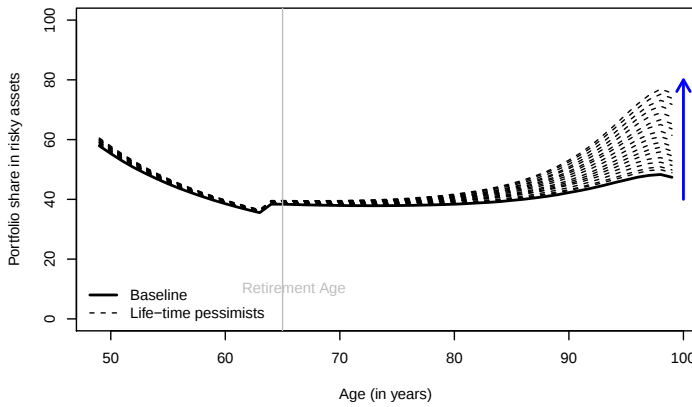
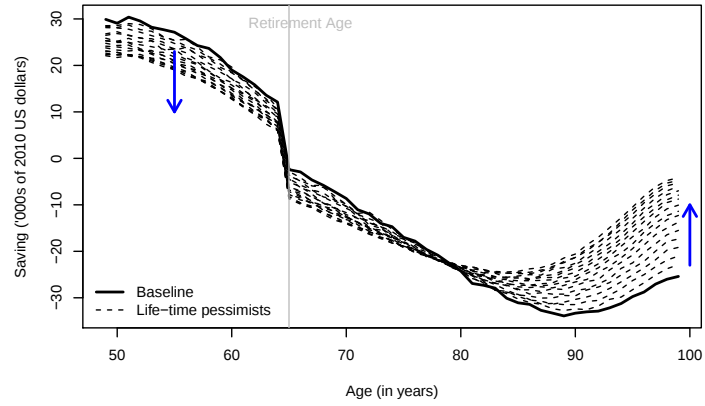
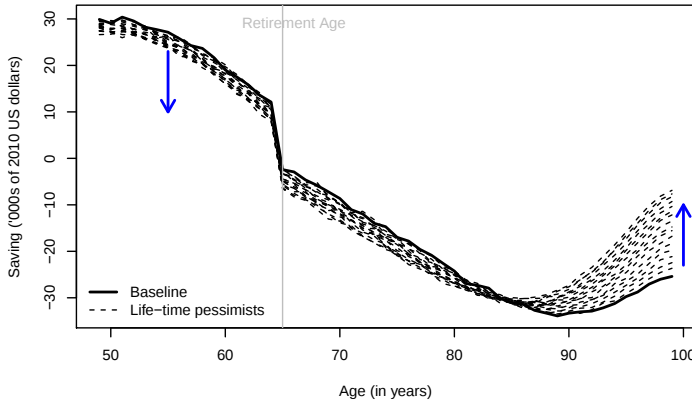
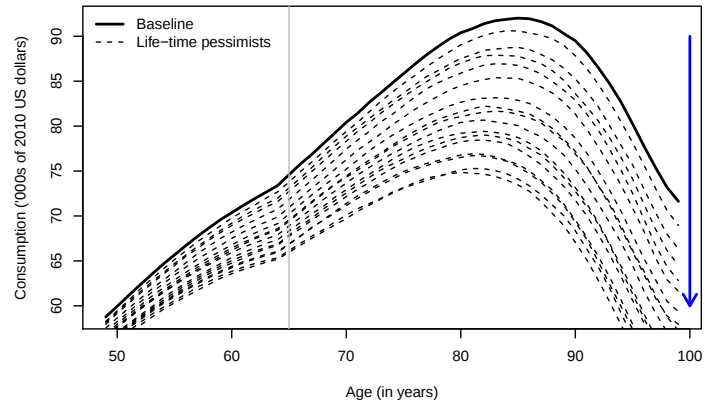
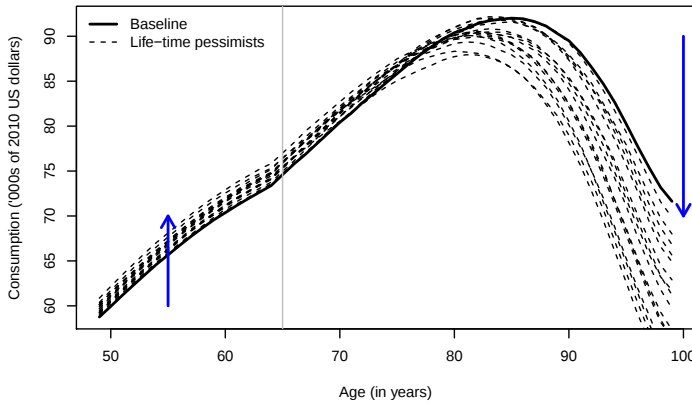
6. Conclusion

Figure B.4: Life-cycle profile for College Graduates

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

Mortality Pessimist

Dispositional Pessimist



1 Appendix Tables and Figures

Table 1.1: 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

1. Appendix Tables and Figures

Table 1.2: Impact of Extreme Natural Disasters on Mortality Deviations: Percent Deviations

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

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

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

Robust Standard Errors, Clustered at the State Level

5. The Effect of Subjective Life Expectancy on Financial Decisions

Table 1.3: Impact of Mass Shootings on Mortality Deviations: Percent Deviations

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

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

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

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

1. Appendix Tables and Figures

Table 1.4: Placebo Analysis: Impact of Natural Disasters on Mortality Deviations

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

	(1)	(2)	(3)
Log(No. of days + 1)	0.0002 (0.001)		
Log(No. of disasters + 1)		0.0046 (0.004)	
I(No. of disasters > 0)			0.0018 (0.004)
Control variables (Incl. Age in levels)	✓	✓	✓
State Fixed Effects	✓	✓	✓
Survival Horizon Fixed Effects	✓	✓	✓
Adjusted R-squared	0.1873	0.1867	0.1832
No. of Observations	57,252	57,252	57,252
***, **, * denote 1, 5 and 10 percent significance			
Robust Standard Errors			

Table 1.5: Robustness: Spatial Effects of Natural Disasters on Mortality Deviations

$$l_{i,c,t}^d = \alpha + X_{i,t}'\beta + \omega \text{Treatment}_{c,t+1} + \psi_c + \zeta_x + \epsilon_{i,c,t}$$

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

Table 1.6: Impact of Mass Shootings on Risky-asset Share

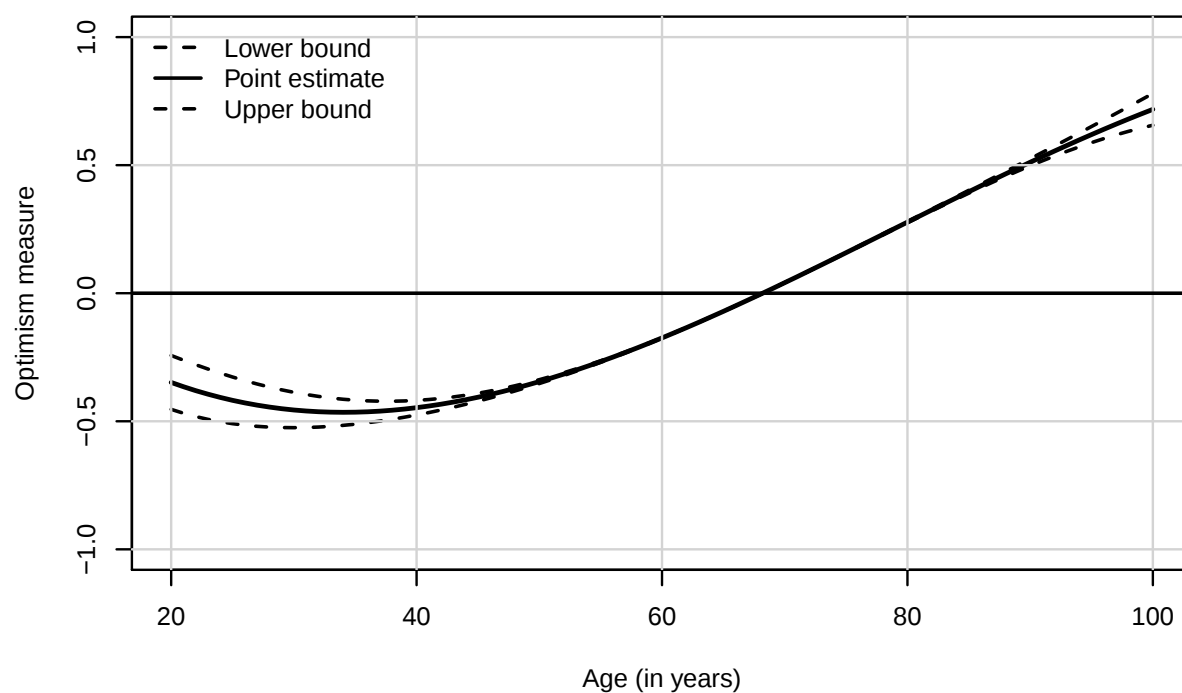
This table presents the population weighted regression estimates of the impact of mass shootings *and* l^d on risky asset share. The coefficients of interest are μ, δ_0 and δ_1 . δ_1 measures the impact on risky share *when* there is a natural disaster and a change in l^d is observed.

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

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

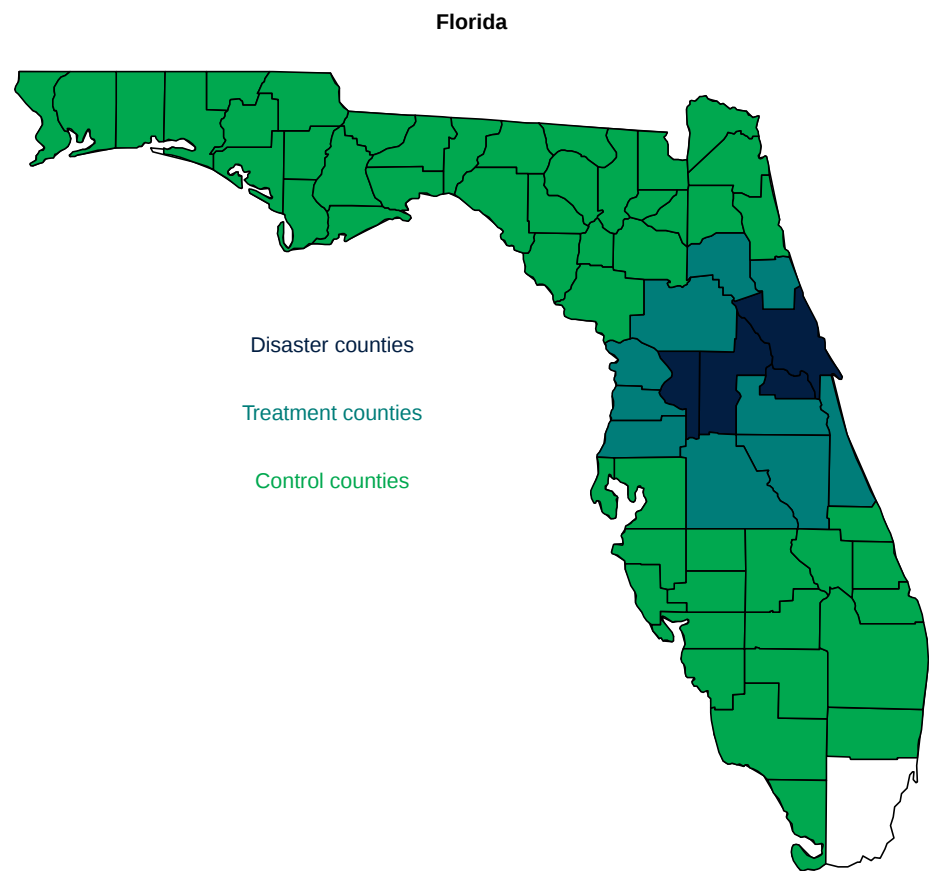
Figure 1.1: Estimates of age-wise pessimism profile: τ_t

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



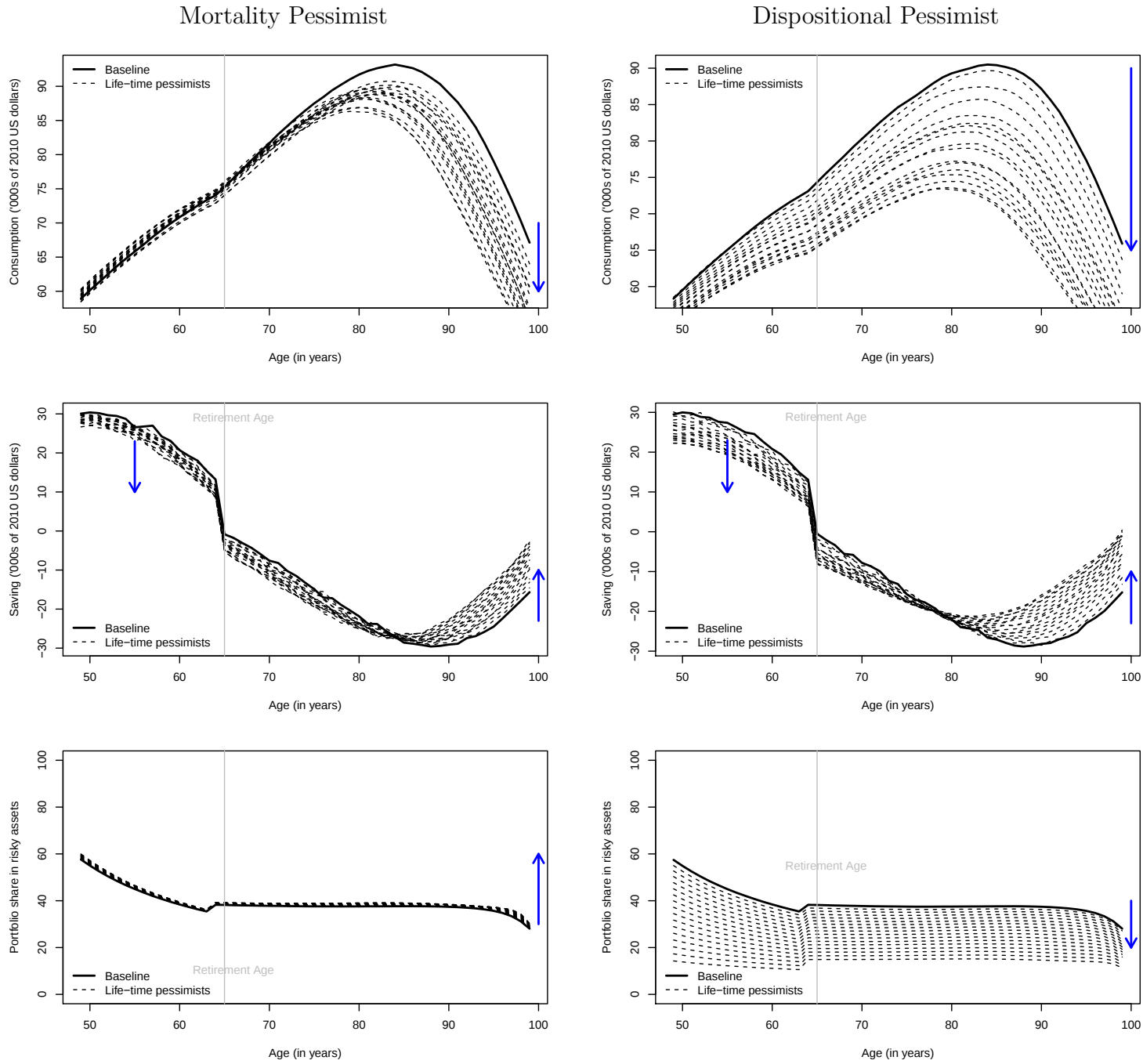
5. *The Effect of Subjective Life Expectancy on Financial Decisions*

Figure 1.2: Identification Strategy for Neighbourhood effects



1. Appendix Tables and Figures

Figure 1.3: Life-cycle profile for College Graduates With Bequest Motive



2 Data description

Health and Retirement Study

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

Regarding mortality expectation, the question in the HRS is framed as the expected probability of living till age y . If a respondent is aged a and $a \leq 65$, the HRS poses the following question: “What is the percent chance that you will live to be 75 or more?”. When a respondent is at least sixty-five years old, to accommodate older respondents, the question asks the probability of living to an age from 80 to 100 depending on the respondent’s age: “What is the percent chance that you will live to be [80 (if $65 \leq a \leq 69$) / 85 (if $70 \leq a \leq 74$) / 90 (if $75 \leq a \leq 79$) / 95 (if $80 \leq a \leq 84$) / 100 (if $85 \leq a \leq 89$)]?” 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

²²Several 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)

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

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

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

²³This definition is the same as in studies such as Brunnermeier and Nagel (2008) and Puri and Robinson (2007) but different from Badarinsa, 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.

5. The Effect of Subjective Life Expectancy on Financial Decisions

Table 2.1: 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 ≥ 10,000 US dollars) > 0	0.822	0.812	0.778	0.747	0.821
Prob(Bequest ≥ 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.

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

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

Federal Emergency Management Agency (FEMA)

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

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

Natural disasters by themselves are exogenous and not under the influence of any one individual. However, FEMA declarations are themselves not guaranteed when a disaster occurs and thus introduces concerns of selection. The Stafford Act²⁶ 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

²⁴Wealth 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.

²⁵The 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.

²⁶Section 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>

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process (by including state fixed effects) will pick up additional effects due to selection issues across states in the US.

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

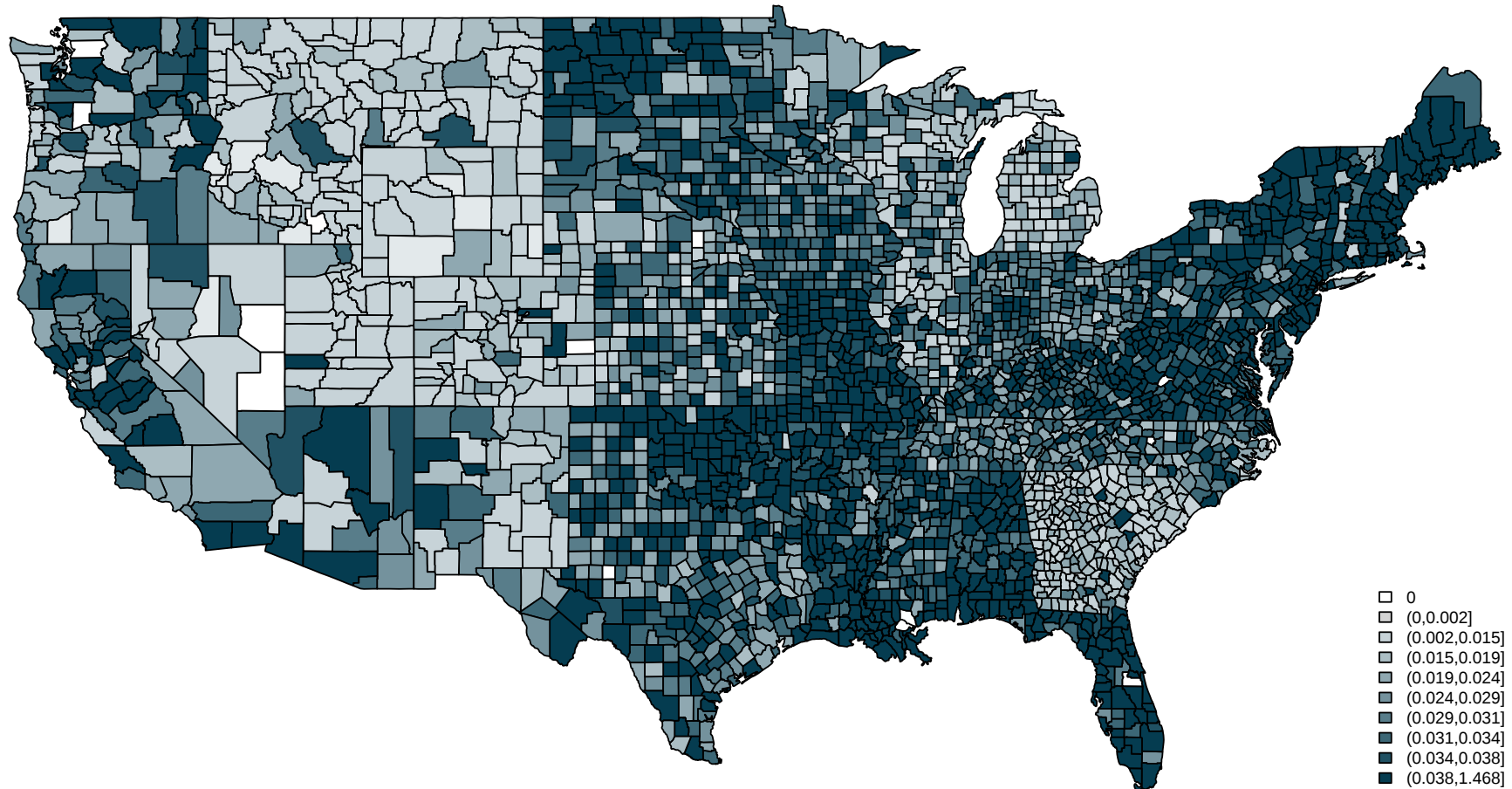
Appendix 3 also provides evidence that differences in state propensities on FEMA declarations with its neighbouring states, although not always statistically significant, are economically meaningful and large for most states for the range of disasters used for analysis in this paper. Merging this data with the HRS data at the county level (using State and County FIPS codes)²⁸, and identifying effects *within* states forms the basis of the empirical analyses.

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

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

Figure 2.1: All Declared Disasters in the United States

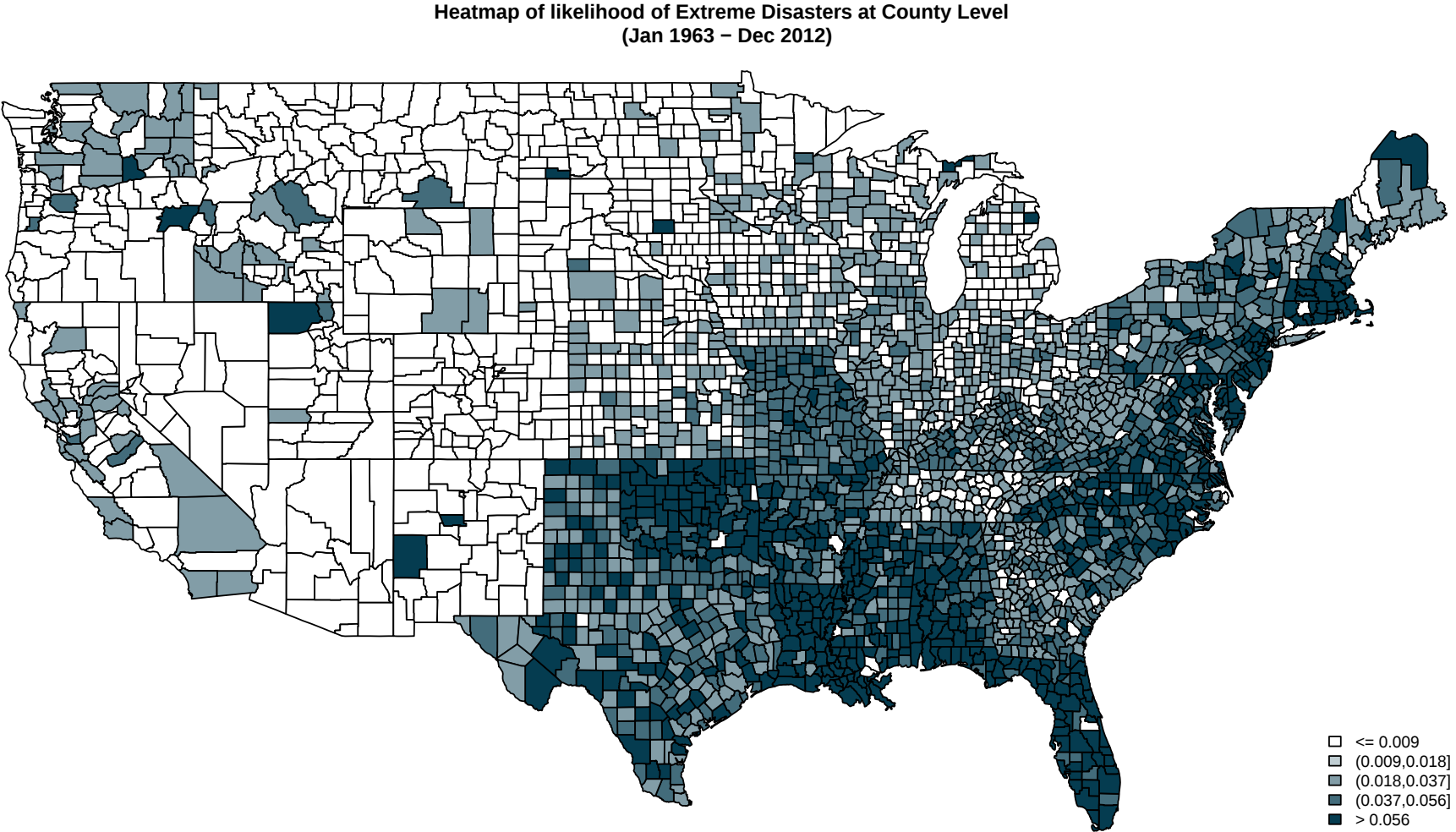
**Heatmap of likelihood of Declared Disasters at County Level
(Jan 1963 – Dec 2012)**



2. Data description

Source: Federal Emergency Management Agency (FEMA)

Figure 2.2: Extreme Disasters in the United States



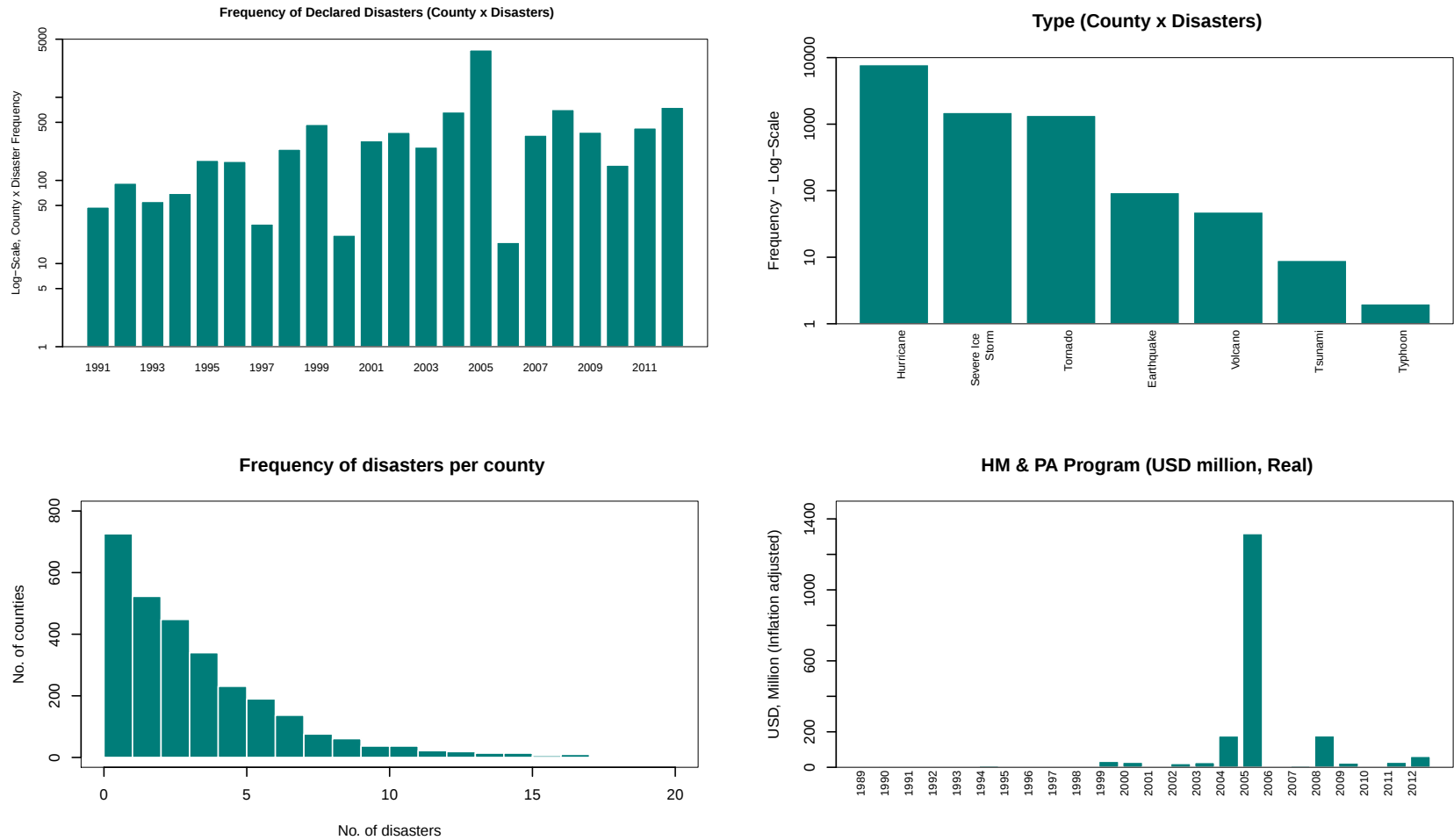
Source: Federal Emergency Management Agency (FEMA)

2. Data description

Figure 2.1 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 2.2. These are referred to as extreme disasters and are used as disaster shocks in the paper.

The top left panel of Figure 2.3 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 2.3: 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 2.3 plots the histogram of the number of counties that have experienced different disaster frequencies. A large proportion of counties in the United States have experienced less than 5 extreme disasters since 1963, whereas some counties have had nearly 16 extreme disasters in its history. The severity of such disasters (measured by the total federal financing received for recovery) have increased over time (bottom left panel).

Stanford Mass Shootings Database (MSA)

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

The Stanford Mass Shootings Data (MSA) puts together a repository for any event where there are three or more victims (not necessarily fatal and not including the shooter) unrelated to drugs or gang rivalry, thus enabling this study to assess the impact of a “man-made” but exogenous disaster on subjective mortality expectations. Only those events that are classified as “Mass Shooting”, “Mass Murder” and “Spree Killing” in the database are used in this paper for identification.³¹ I have hand-collected the county information for every reported mass shooting in the Stanford

²⁹The 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.

³⁰A 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>.

³¹Mass 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.

5. *The Effect of Subjective Life Expectancy on Financial Decisions*

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

³²The 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 2.4: Mass Shootings in the USA

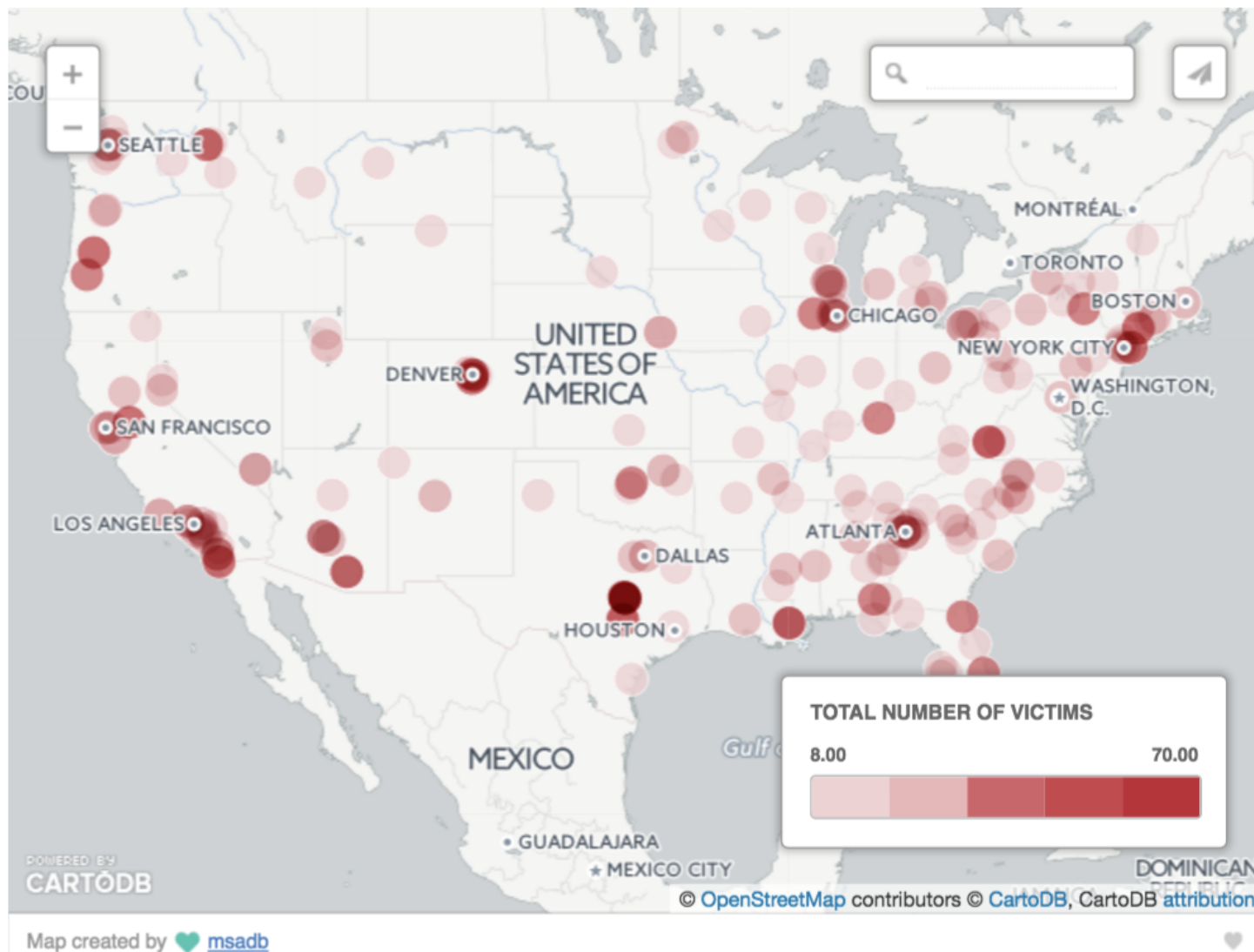
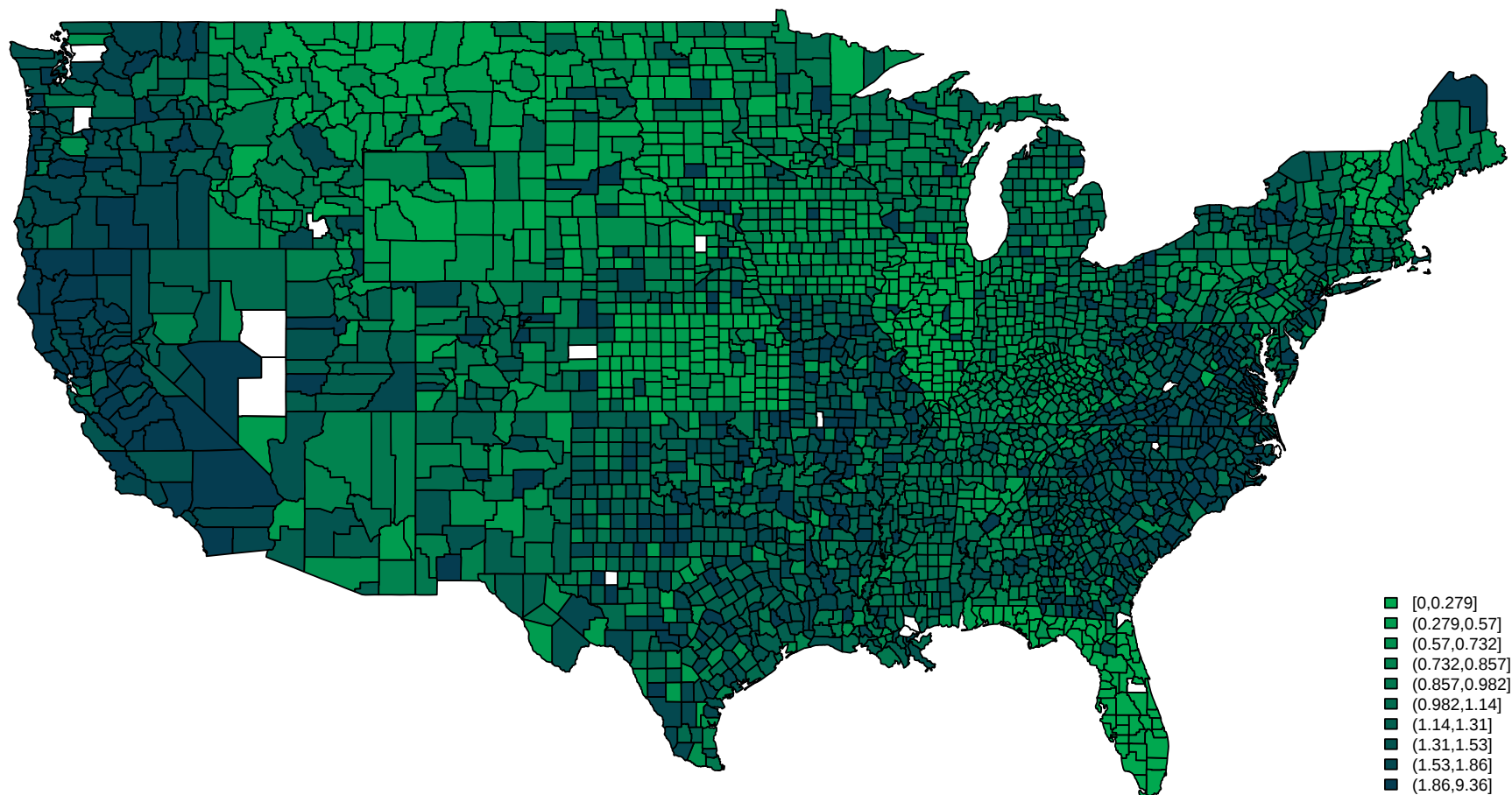


Figure 2.5: Percent of crimes involving Arson, Guns and Murder in the United States

**Heatmap of Average Likelihood of Arson, Arms and Murder cases at State-County Level
(1996 – 2012)**



2. Data description

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 2.4 presents a screenshot of the mass shootings database as of 2015: The number of victims in different locations of the shoot out range from 8 to 70, and 43 percent of the events occur between 1996-2012 – the sample period for this study.

In 2012, 1.2 percent of all reported crimes in the United States were related to murder. Tennessee being the state with the highest violent crime rate (643.6 per 100,000), has nearly 1 percent of its crimes as murder. The statistical odds of homicide using a firearm in a given year is 0.4%.³³ Figure 2.5 presents the heat-map of the average likelihood of arson, arms and murder crimes at the county level in the United States. At its highest (winsorized at 99th percentile), the reported value is 2.76 percent of all crimes in a county. The variation across counties (and states) is noteworthy and the likelihood of arson, arms and murder crimes and mass shootings are low.³⁴

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

³⁴It 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.

3 State Propensity to Seek Federal Disaster Declaration

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

$$Pr(\text{Declared}|\text{Disaster}) = \frac{Pr(\text{Disaster}|\text{Declared})Pr(\text{Declared})}{Pr(\text{Disaster})} \quad (\text{C.0})$$

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

$$Pr(\text{Declared}|\text{Disaster}) = \frac{Pr(\text{Declared})}{Pr(\text{Disaster})} \quad (\text{C.1})$$

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

3. State Propensity to Seek Federal Disaster Declaration

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:

$$I(\text{Disaster} > 0)_{c,t} = D\tau + \gamma_t + \epsilon_{c,t} \quad (\text{C.2})$$

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:

$$I(\text{Disaster} > 0)_{c,s,t} = D\tau + I(S) + \tau_s I(S) \times D + \lambda_t + \sum_{k=1}^K I(\text{Disaster type}_k) + \epsilon_{c,s,t} \quad (\text{C.3})$$

Equation (C.3) 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-effects removes this unobserved variation. Secondly,

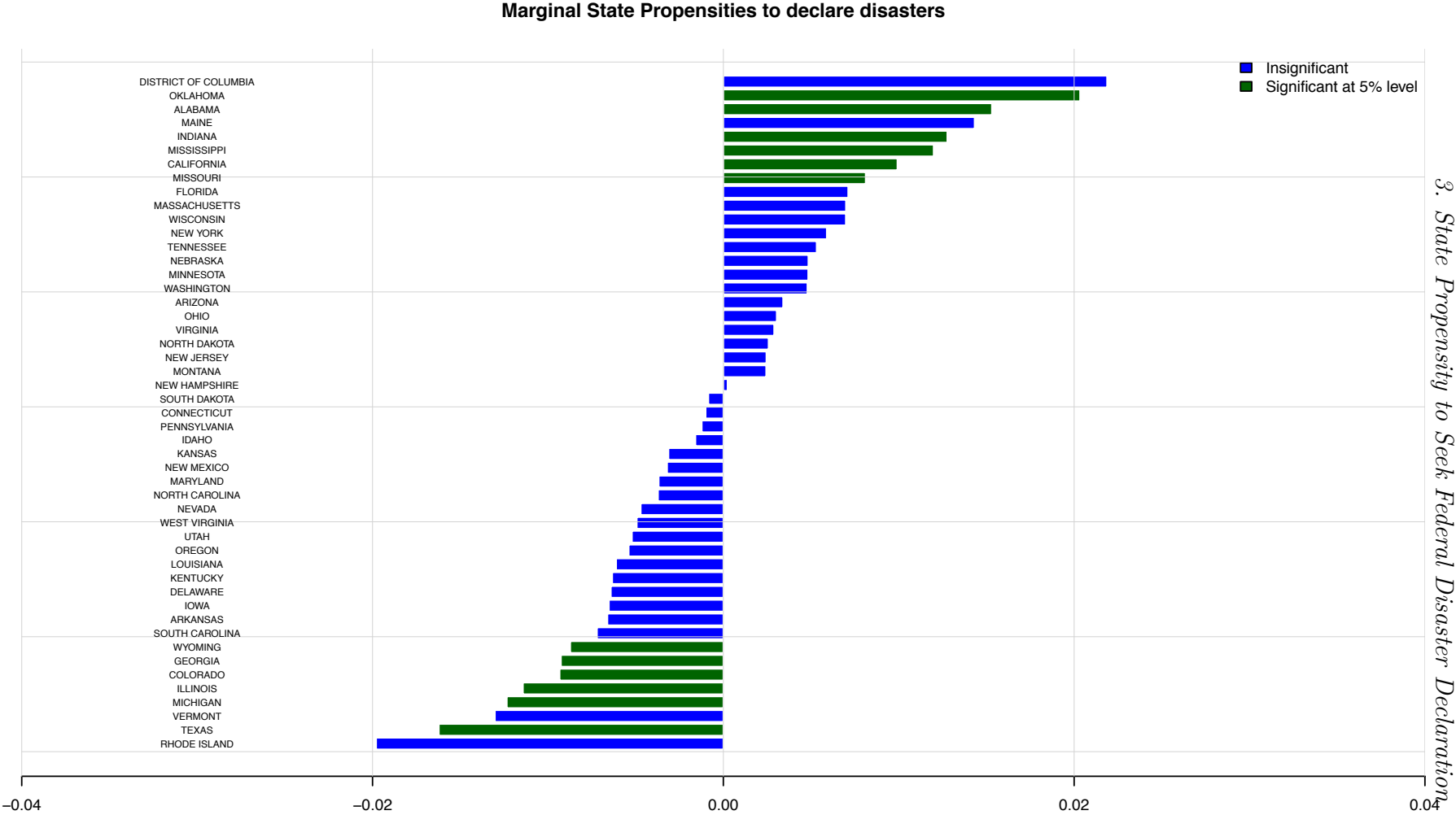
5. The Effect of Subjective Life Expectancy on Financial Decisions

Table 3.1: 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 (0.165)	0.072 (0.237)	0.072 (0.164)	120,816
(2)	Tornados	0.008 (0.069)	-0.016 (0.072)	-0.016 (0.072)	120,816
(3)	Earthquakes	0.003 (0.022)	0.013 (0.019)	0.013 (0.019)	120,816
(4)	Severe Ice Storms	-0.007 (0.107)	-0.029 (0.115)	-0.029 (0.112)	120,816

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 3.1: Variation in State-level Propensity to Seek Federal Assistance during disasters



5. *The Effect of Subjective Life Expectancy on Financial Decisions*

Table 3.1 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 3.1 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.

4 Updates according to Bayes' rule

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

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

$$\Pr(\text{Death}_{c,t+1} \mid \text{Disaster}_{c,t+1}) = \frac{\Pr(\text{Disaster}_{c,t+1} \mid \text{Death}_{c,t+1}) \times \Pr(\text{Death})_{t+1}}{\Pr(\text{Disaster})_{c,t+1}} \quad (\text{C.4})$$

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

³⁵0.4 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.

³⁶Leading 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.

³⁷For 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.

5. The Effect of Subjective Life Expectancy on Financial Decisions

$$\Pr(\text{Disaster}_{c,t+1} \mid \text{Death}_{c,t+1}) \approx \Pr(\text{Disaster}_{c,t+1}) \quad (\text{C.5})$$

Assumption (C.5) sets the conditional probability of observing a disaster when deaths are recorded at the unconditional disaster probability for county c . This is conservative as the unconditional probability is the upper bound of any estimates of this conditional probability.³⁸ Given this assumption, equation (C.4) 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:

$$y_{c,t} = \alpha_c + \omega_t + \sum_{k=1}^K \gamma_{t-k} I(\text{Disaster} > 0)_{c,t-k} + \epsilon_{c,t} \quad (\text{C.6})$$

$y_{c,t}$ 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 4.1 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 4.1 suggests that there is no discernible pattern to the estimated coefficients across different age categories for mortality rates, and most point estimates that are significant are negative.³⁹

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

³⁹One 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.

4. Updates according to Bayes' rule

Table 4.1: 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 (0.001)	-0.0114*** (0.003)	0.0028 (0.012)	0.0047 (0.003)	0.0020* (0.001)	0.0020*** (0.001)
$t - 2$	-0.0024 (0.002)	-0.0126*** (0.004)	0.0028 (0.007)	0.0045 (0.003)	0.0003 (0.001)	-0.0002 (0.001)
$t - 3$	-0.0025 (0.002)	-0.0002 (0.005)	0.0068 (0.018)	-0.0002 (0.003)	0.0014 (0.001)	0.0005 (0.001)
$t - 4$	-0.0014 (0.002)	0.0021 (0.003)	0.0141 (0.012)	-0.0008 (0.002)	-0.0012 (0.001)	-0.0010 (0.001)
$t - 5$	-0.0010 (0.002)	0.0045 (0.005)	0.0228 (0.012)	-0.0066 (0.005)	-0.0009 (0.001)	-0.0011 (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** (0.001)	-0.0001 (0.000)	-0.0002 (0.000)	-0.0004** (0.000)	0.0001 (0.000)
$t - 2$	0.0003 (0.001)	-0.0002*** (0.000)	-0.0002 (0.000)	-0.0004** (0.000)	-0.0005** (0.000)
$t - 3$	-0.0016 (0.001)	-0.0001 (0.000)	-0.0003 (0.000)	-0.0004* (0.000)	0.0002 (0.000)
$t - 4$	0.0014 (0.001)	-0.0003*** (0.000)	-0.0001 (0.000)	0.0001 (0.000)	-0.0002 (0.000)
$t - 5$	0.0005 (0.001)	0.0001 (0.000)	0.0003 (0.000)		-0.0002 (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

5. *The Effect of Subjective Life Expectancy on Financial Decisions*

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

⁴⁰Interestingly, a back of the envelope calculation yields similar conservative estimates. The highest value (across counties) for $Pr(\text{Natural Disaster})$ is 0.16 percent. Estimates of $Pr(\text{Disaster}|\text{Death})$ range from 0.01 percent⁴¹ to 0.05 percent (Goklany, 2009). Since the highest impact is when middle-aged, $Pr(\text{Death})$ for an individual aged 65, in the next year, is about 1.71 percent. On average, the probability of death across the United States has dropped from 0.85 percent in 1999 to 0.82 percent in 2012 and these trends are reflected across all ages.⁴² Using, Bayes' rule, the probability of death due to natural disasters for a 65 year old in the following year is 0.53 percent. Similarly, mortality risk due to mass shootings is approximately 0.55 percent, nearly as likely as natural disasters at its highest frequency of occurrence. These estimates use the likelihood of arson, gun and murder crimes in the US as a proxy for mass shootings.

5 Indirect Effects of Disasters on Risky-asset Share

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

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

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

This measures the change in the outcome Y (risky asset share) corresponding to a change in the mediator M (expectation deviations), from the value that would be realized had there been no natural disasters, $M_i(0)$, to one where natural disasters are realized, $M_i(1)$. Estimates from Section 3 shows that that $M_i(1)$ and $M_i(0)$ are different, i.e., natural disasters make individuals who experience them more pessimistic. The treatment, experiencing natural disasters, is important because it allows for studying the extent to which the mediator variable matters under well identified conditions.

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

5. *The Effect of Subjective Life Expectancy on Financial Decisions*

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

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

An important property of this approach is that the total effect of natural disasters on risky behaviour decomposes into the natural direct effect and mediated effect (Pearl, 2001). Thus, an estimation of this decomposition would allow for the evaluation of the mediating role played by subjective expectations. The parametric inference follows a four step procedure. First, I fit the models for observed outcome and mediator variables (Section 3 and Section 4). Then, I simulate model parameters from their sampling distribution. I then repeat the following steps for each draw of model parameters: (a) simulate the potential values of the mediator; (b) simulate the potential outcomes given the simulated values of the mediator; and (c) compute the quantities of interest. And lastly, I use these simulations to obtain point estimates as an average of all runs and 95 percent confidence intervals. The procedures

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

5. Indirect Effects of Disasters on Risky-asset Share

Table 5.1: Causal Mediation Effect

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

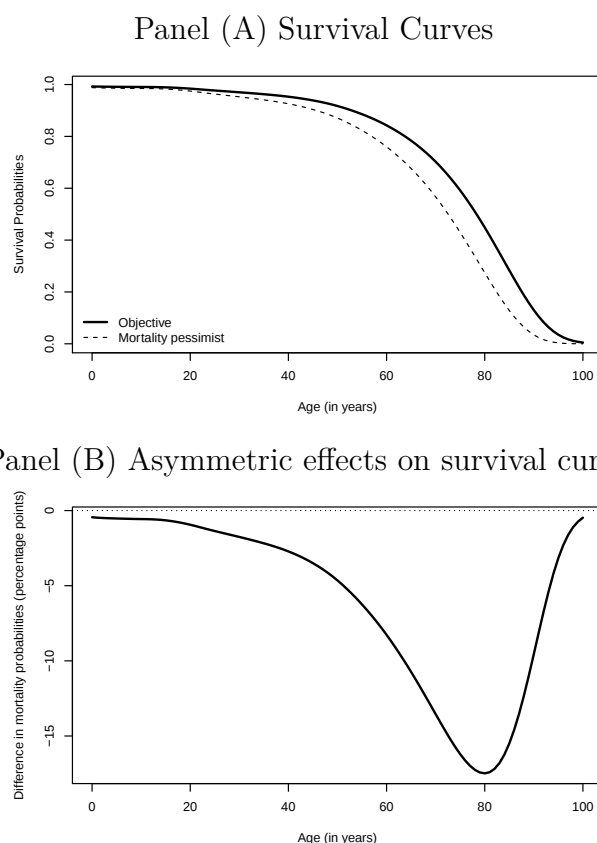
	Point Estimate	95% Confidence Interval	
		Lower-bound	Upper-bound
Mediation Effect	-0.169	-0.204	-0.096
Direct Effect	-1.151	-1.940	-0.353
Proportion Mediated	0.147	0.105	0.272
Sensitivity analysis			
Rho at which Mediation Effect = 0	0.12		
Rho at which Direct Effect = 0	-0.7		
Sample size	78,917		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

used for estimation are described in detail in Imai, Keele, Tingley and Yamamoto (2010c); Imai, Keele and Tingley (2010a); Imai, Keele and Yamamoto (2010b) and implemented in R and Stata by Hicks and Tingley (2011).

Table 5.1 presents the decomposition results for the most conservative case, with time fixed-effects as in Column (4) in Table B.4. The Average Mediation is estimated to be a -0.169 percent. As a percent of the total effect, this is 14.7 percent of the total effect of natural disasters on risky asset share.

6 Mortality pessimism

Figure 6.1: Survival Probabilities: Objective vs. Pessimist



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 6.1 (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 6.1 B).

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6 | Conclusion

In this dissertation, I propose three empirical analyses that document systematic “mistakes” made by individuals and households in financial markets, and the potential sources of such mistakes. The common idea of these studies is that household financial decisions are affected by a greater range of factors than those traditionally incorporated in models of rational, full-information agents who optimize their current consumption and portfolio choice based on stable beliefs and preferences.

Chapter 1 of this thesis introduces the three papers and the broad field of household finance within which these papers contribute specifically on different dimensions. In Chapter 2, I review the extant state of the literature, and the specific areas of household finance that each of the paper pushes the frontier at.

The first paper – joint work with Santosh Anagol and Tarun Ramadorai – exploits a natural experiment in which investors in the Indian initial public offerings are randomly allotted stocks. This paper provides further credence to the growing body of literature on the presence of the endowment effect with risky gambles.

The second paper – joint work with Santosh Anagol and Tarun Ramadorai – exploits the same natural experiment, but to provide precise, *causal* estimates of experience effects on short-term individual investment decisions. This paper sharply identifies the experience effects without any unobserved confounds, and provides for a setting whereby empirical estimates in the literature that cannot account for unobserved confounds can be understood in this light. Statistically, we also contribute to the literature by finding that the causal effects can be closely estimated under specific panel data settings.

The third paper looks at whether exposure to natural disasters and mass shootings influences subjective life expectancy and affect financial decisions. It

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

Taken together, these three empirical papers contribute to our understanding better, systematic deviations of household financial behaviour from normative, rational benchmarks. Specifically, this thesis contributes to the literature on experience effects broadly, and hopefully, will open the door to further research within this and the broader field of household finance.