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EXTREME WEATHER AND RETIREMENT SAVINGS

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In this paper, we discuss the impact of extreme weather on US families with a specific focus on household finances. We first derive a life-cycle model of consumption, then introduce climate change-oriented consumption shocks as an additional expense which is proportional to labor income. Our key finding is that exposure to shocks associated with natural disasters may lower lifetime wealth by interrupting savings contributions. We test this model by demonstrating that households living in counties which experience a high amount of natural disasters suffer lower contributions to long-term savings between 1970 and 2020. We suggest this is driven in part by temporarily lowered income and increased labor market turnover. We conclude with a discussion on how climate change may accelerate a retirement crisis and recommend suggestions for how the financial industry can help households address this challenge.

1 Introduction

The impact of natural disasters on household finances has become an increasingly important topic of study.[1] A recent poll from the Harvard T.H. Chan School of Public Health, The Robert Wood Johnson Foundation, and National Public Radio (2022) found that 78% of US Adults have been personally affected by one or more extreme weather events over the past five years. Amongst those impacted, 17% reported serious financial problems often stemming from rising sea levels and flooding. The Federal Reserve's Survey of Household Economics and Decisionmaking (2023) similarly found that 13% of adults experienced a financial disruption from severe weather events, driven either by income loss, property damage, temporary evacuation, long-term displacement from home, or bodily harm. Impacted Americans tended to have lower incomes and responded to natural disasters by exploring migration, altering their property to reduce risk, or purchasing additional insurance—each of which may drain savings and negatively impact utility. The market response to the risk profile of natural disasters has shifted as well, with insurers like State Farm pulling out of both business and personal lines of property and casualty insurance

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in California "due to the historic increases in construction costs outpacing inflation, rapidly growing catastrophe exposure, and a challenging reinsurance market" (State Farm General Insurance Company, 2023).

While the financial hardships of extreme weather are numerous, we propose to explore an underappreciated channel of interest to finance practitioners: long-term savings. In this paper, we examine the impact on retirement savings from extreme weather events, including income challenges, labor market turnover, and drops in employer contributions to pensions.

To motivate our analysis, we build a lifecycle investment model designed to maximize consistent consumption over an investor's lifetime. This framework attempts to demonstrate that negative savings shocks associated with natural disaster exposure have important implications for long-term consumption drawn from retirement savings, particularly for younger investors. As a result, the uncertainty facing households with fragile safety nets may demand a wider range of financial tools to help vulnerable communities cope with the spillover effects from climate change.

To explore this challenge empirically, we run fixed effects panel regressions over county-level data from the US Bureau of Economic Analysis (BEA) to measure household finances and Federal Emergency Management Agency (FEMA) disaster declarations as a proxy for extreme weather events. We regress income, unemployment, and retirement contributions on disasters between 1970 and 2020 and find negative implications of extreme weather on income and retirement as well as evidence of labor market turnover.

We propose several mitigating solutions, including overlaying catastrophe bond-like products to a core portfolio and incorporating additional active "alpha-seeking" strategies within a retirement savings plan as potential mitigants to help offset drops in contributions. We show that even a modest incremental uplift in returns through "alpha" can help to offset the negative impact on consumption in retirement.

The remainder of our paper is organized as follows: we first provide an overview on the relationship between natural disasters and savings, as well as discuss lifecycle consumption and portfolio choice. We then build our model of lifetime consumption and introduce natural disasters as a tax to income. After discussing the model's implications, we present our empirical analysis. We conclude with a discussion on the implications of this work for the financial industry and academic research.

2 Background

2.1 Economic impact of natural disasters

The relationship between natural disasters and economic well-being of households has been analyzed across a range of topics, often with mixed results based on the event, time period, or unit of analysis. Large disasters, like Hurricane Katrina, often serve as an event study for exploring these types of exogenous shocks.

Bleemer and Klaauw (2019) find higher rates of insolvency and lower rates of home-ownership for New Orleans residents impacted by flooding 10 years after Hurricane Katrina—though residents of mostly-white neighborhoods were more likely to migrate out of the city when compared to residents of mostly-black neighborhoods. Racial disparities in the impact of disasters on household finance were also found in a panel of disasters from 2011 to 2014, particularly in declining credit scores and mortgage delinquencies in communities of color (Ratcliffe *et al.*, 2020). Basker and Miranda (2018) investigated the effects of Katrina on business activity and found that young and small firms were disproportionately afflicted by the hurricane, with many permanently shutting down. Brown *et al.* found that unemployment claims rose dramatically following Katrina, with women and young claimants posting the most dramatic increases. Clayton and Spletzer (2006) find that the number of jobs in the New Orleans Metropolitan Statistical Area (MSA) fell significantly following Katrina and displaced workers who found work quickly had lower earnings and earnings growth than a sample from the prior year. Fussell *et al.* (2009) analyze the displaced population of New Orleans through racial and socioeconomic lenses, finding that black residents returned to the city slower than white residents; these racial disparities disappeared once the authors controlled for housing damages, suggesting a racial imbalance in exposure to flooding damage.

In contrast, Gallagher and Hartley (2017) argue that Hurricane Katrina flooding resulted in a general reduction in total debt balances as households used public assistance to pay down mortgages. Deryugina (2011) saw no effect on US county earnings 10 years after hurricanes—instead seeing most of the costs absorbed by government transfers and social safety nets. Similarly, Deryugina (2017) uses differences-in-differences methods to find county resilience to hurricanes, with average earnings not falling systematically and employment rate only falling years later.

Kousky *et al.* (2020) use Fannie Mae data to investigate how flood insurance impacted loan performance following Hurricane Harvey, finding that property damage increases mortgage delinquency in the short term and increases the likelihood of obtaining forbearance. Outside the United States, Christian *et al.* (2018) found that Cyclone Phailin reduced consumption and food expenditure in Odisha, India. Using war registry data, Karbownik and Wray (2019) suggest that Americans who were exposed to low-intensity hurricanes in the late 19th century suffered lifetime decreases in income—with negative effects resulting from prolonged stress for pregnant women or children in infancy. Belasen and Polachek (2008) find that average worker wages rise and employment drops in Floridian counties experiencing a hurricane between 1988 and 2005, with opposite earnings effects in neighboring counties. In particular, they see positive demand shocks to construction with negative demand shocks for manufacturing, services, finance, and trade.[2]

Public policy research has generally confirmed challenges in data availability for the pricing for flood risk. A 2017 Department of Homeland Security Office of Inspector General (OIG) report showed that more than 50% of FEMA National Flood Insurance Program (NFIP) flood maps are considered out of date (Kelly, 2017).[3] Furthermore, a 2020 OIG report underscored FEMA's own lack of accurate information on Severe Repetitive Loss properties used in mitigation efforts (Cuffari, 2020). A study by Hino and Burke (2021) found little evidence that housing markets fully priced in flood risks for at least 3.8 million US floodplain homes based on assessed property values in 2016–2017. Bakkensen and Barrage (2022) find similar mispricing for coastal properties in Rhode Island.

In Wildfires, Liao and Kousky (2022) find that wildfires lead to declining budgets and increased probability of deficits at California municipalities—though smaller spending in comparison to state and federal governments. These impacts can appear as an increase in revenues due to higher property turnover as households sell property after the disaster, as well as deepening costs due to increased local spending on fire suppression and community development.

Disasters can also span pollution and biological based shocks. Christensen *et al.* (2023) find that the 2014–2015 drinking water crisis in Flint, Michigan led to a substantial decline in house values lasting well beyond the initial crisis. Yue *et al.* (2020) found that Chinese households who became aware of having a COVID-19 infection became less confident in the economy and increased their risk aversion in investment decisions. Meanwhile, Derby *et al.* (2022) find that while the COVID-19 pandemic did not meaningfully reduce individual contributions to retirement savings; employer-plan withdrawals increased for Americans those under the age of 60, likely driven by a temporary exemption of early distribution penalties.

Across disasters in general, Wu *et al.* (2022) find that natural disasters reduce household income, wealth, and health using individual-level studies with health impacts exacerbating negative impacts on savings outcomes. Okuyama (2003) observes that heightened uncertainty due to natural disasters can create serious impacts on economic activity and production planning, particularly during the immediate recovery from a shock. Hallegatte and Dumas (2009) suggest that reconstruction quality and embodied technical change that might come from accelerated replacement of capital after a disaster cannot turn disasters into positive events.

Research on worker displacement conducted by Fallick (1996) observes that displaced workers experience more non-employment, and while the difference eventually fades after four years, their earnings losses are large and persistent often averaging 14% or more. In contrast, Tran and Wilson (2023) see initial declines but longer-run boosts to income through an employment boost and longer run higher wages 0.6% above baseline trend eight years after a disaster, though with negative spillover effects to neighboring counties.

Physical science, public policy, and economic literature have all wrestled with the relationship among climate change, natural disasters, and human economic wellbeing. The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report highlights the relationship between climate change and increased incidence of natural disasters (2021). The report's key points suggested meaningful scientific evidence of an observed increase in extreme events, such as droughts, cyclones, heatwaves, heavy precipitation since 1950 and its link to human-induced climate change as the most likely driver. Similarly, Kossin *et al.* (2017) note a general increased intensity in tropical cyclones based on both theory and numerical modeling simulations generally indicate an increase in tropical cyclone associated with rising average temperatures. Sweet and Park (2014) suggest that there has been an increase in coastal flooding events, explained by a meaningful rise in the sea level, driven by a warming planet.

Climate Change as a global externality has been studied by Nordhaus (2019) through integrated assessment models (IAMs), profiling the relationship among economic growth, emissions, climate system impacts, and policy. Houser *et al.* (2015) used risk-assessment models to profile likely impacts of climate change on various sectors of the US economy such as agriculture, labor productivity, and crime rates. Bhola *et al.* (2023) find a strong correlation among economic burden of natural disasters, emissions, and temperature, between 1980 and 2021. The International Monetary Fund (2017) has also profiled the macroeconomic impacts of Climate Change, suggesting that uneven impacts of temperature shocks across high- and low-income countries necessitate adaptation and mitigation efforts; financial markets are cited as a potential tool to help disperse catastrophic weather risk, hinging on the further development of weather-related insurance instruments and proper pricing of weather-related risks. For a detailed report on climate science, potential impacts, and avenues for economic analysis, please see Hsiang and Kopp (2018).

In this paper, we initially describe natural disasters as a tax on income and long-term savings, then later incorporate climate change as an extension of our base model by increasing the frequency and severity of natural disaster implications to income.

2.2 *Lifecycle consumption and portfolio choice*

An extensive body of literature explores studying optimal consumption and portfolio choice over the lifecycle in the face of uncertainty. Cocco *et al.* (2005) provide an example of a realistically calibrated model of lifetime consumption and portfolio choice under labor income uncertainty, including an analysis of the impacts of potentially catastrophic labor income shocks. O'Hara and Daverman (2015) apply a similar model to design optimal target-date fund glidepaths and draw conclusions about the characteristics of optimal portfolios for the individual retirement savings and investment problem.

Many researchers extend and vary the basic lifecycle model described in Cocco *et al.* (2005). For example, Gomes and Michaelides (2003) incorporate fixed costs of equity market participation and incorporate internal habit formation in individual preferences. Chai *et al.* (2011) incorporate flexibility into work hours and the timing of retirement, as well as the impact from including annuities in the investment opportunity set. Galvez and Paz-Pardo (2023) incorporate a richer and more flexible description of labor income risk.

In a lifecycle investment context, one of the key drivers of the dynamics of optimal portfolio decision-making is uninsurable non-investment risk embedded in the cash flows received as an individual's labor income. A number of papers examine how disaster risk impacts decision-making. Bharath and Cho (2021) use longitudinal survey data to analyze how natural disasters, even those of a fleeting nature, influence individual's risk aversion and forward-looking return expectations. Alan (2012) examines disasters as they relate to the equity premium puzzle and associated implications for portfolio choice for households of different income levels.

While much of the current literature focuses on the impact of rare disasters insofar as they impact individual's incomes, in our model we incorporate natural disaster risks into the lifetime consumption and portfolio choice problem as rare but high-impact exogenous expenses (for example, residential rebuilding expenses following a devastating storm). Our model is described in detail in the next section.

3 Model

In this section we propose a model for quantifying and analyzing the impact of extreme weather-related shocks on lifetime consumption.[4] Our model is an extension of the lifecycle model of consumption and portfolio choice from Cocco *et al.* (2005), which solves for optimal consumption decisions and equity allocations as functions of age and wealth. We extend the model by allowing for the possibility of natural disasters which result in required additional consumption which is proportional to income.[5] These consumption shocks can be interpreted as extra spending due to disaster shock-related damages or negative income shocks due to lost wages and employment because of natural disasters.

We let t denote age, and we assume an investor lives to be T. Let be the probability that an investor lives to be $t+1$, conditional on living to age t. Let $t+1$ be the probability of an extreme weather shock. We assume an investor's preferences are described by Epstein–Zin utility as follows:

$$V_{i,t}(X_{i,t}, Y_{i,t+1}) = \Big\{(1-\delta)C_{i,t}^{1-1\psi} + \delta E_t\big[p_t(1-\pi_t)V_{i,t+1}(X_{i,t+1}^{noshock}, Y_{i,t+1})^{1-\gamma} + p_t\pi_t V_{i,t+1}\ (X_{i,t+1}^{shock}, Y_{i,t+1})^{1-\gamma}\big]^{\frac{1-1/\psi}{1-\gamma}}\Big\}^{\frac{1}{1-1/\psi}} \tag{1}$$

where δ is the discount factor, ψ is the elasticity of intertemporal substitution, and γ is the risk aversion parameter. Consumption at age t is given by $C_{i,t}$, and wealth at time is given by $X_{i,t}$. Wealth from period $t+1$ to evolves differently depending on whether there is an extreme weather shock. Specifically in the event of a natural disaster there is an additional expense equal to κ_t percent of income $Y_{i,t}$; the two possible laws of motion that govern how wealth evolves are:

$$X_{i,t+1}^{shock} = (1-\kappa_t)Y_{i,t+1} + (X_{i,t} - C_{i,t}) \times (1 + \alpha_{i,t}R_{t+1}^S + (1-\alpha_{i,t})R_{t+1}^B) \tag{2}$$

$$X_{i,t+1}^{noshock} = Y_{i,t+1} + (X_{i,t} - C_{i,t}) \times (1 + \alpha_{i,t}R_{t+1}^S + (1-\alpha_{i,t})R_{t+1}^B) \tag{3}$$

We assume that an investor i's labor income $Y_{i,t}$ in their working years is given by:

$$\log(Y_{i,t}) = f(t) + \eta_i + v_{i,t} + \epsilon_{i,t} \tag{4}$$

where $f(t)$ is a deterministic function of age,[6] $\eta_i \sim N(0, \sigma_\eta^2)$ is an individual-specific fixed effect, $\epsilon_{i,t} \sim N(0, \sigma_\epsilon^2)$ is a transitory income shock, and $v_{i,t}$ is the cumulative sum of permanent income shocks and is given by:

$$v_{i,t} = v_{i,t-1} + u_{i,t} \tag{5}$$

with $u_{i,t} \sim N(\sigma_u^2)$. The allocation to equity is given by $\alpha_{i,t}$. The returns on stocks and bonds between periods t and $t+1$ are given by $(\mu_{R^S} - \sigma_S^2/2, \sigma_S^2)$ and $(\mu_{R^S} - \sigma_S^2/2, \sigma_S^2)$ respectively, with log returns distributed according to $N(\mu_{R^S} - \sigma_S^2/2, \sigma_S^2)$ and $N(\mu_{R^B} - \sigma_B^2/2, \sigma_B^2)$. We assume at the terminal age all wealth is consumed and utility is given by:

$$V_{i,T+1}(X_{i,T+1}, Y_{i,T+1}) = (1-\delta)X_{i,T} \tag{6}$$

We do not allow short selling and assume no borrowing[7]:

$$0 \le \alpha_{i,t} \le 1 \tag{7}$$

and

$$C_{i,t} \le X_{i,t} \tag{8}$$

We will present several different versions of the model described above, where we make different assumptions about the extreme weather shock-related parameters and related to climate change.

3.1 The optimization problem

In each period t the investor must decide how much to consume $C_{i,t}$ and how much to invest in the equity asset $\alpha_{i,t}$, conditional on their wealth $X_{i,t}$, and labor income $Y_{i,t}$. After they make these two decisions, the random variables R_{t+1}^S, R_{t+1}^B, η_i, $v_{i,t}$, $\epsilon_{i,t}$, and the extreme weather shock are realized. The optimization problem for the investor is to maximize the expected utility of consumption over the entire lifecycle:

$$\underset{\max\{c_{i,t},\alpha_{i,t}\}_{t=1}^T}{E[V_0]} \tag{9}$$

subject to Equations (2)–(8). Since analytical solutions to this problem do not exist, we solve the problem via backward induction and rely on numerical solution methods.

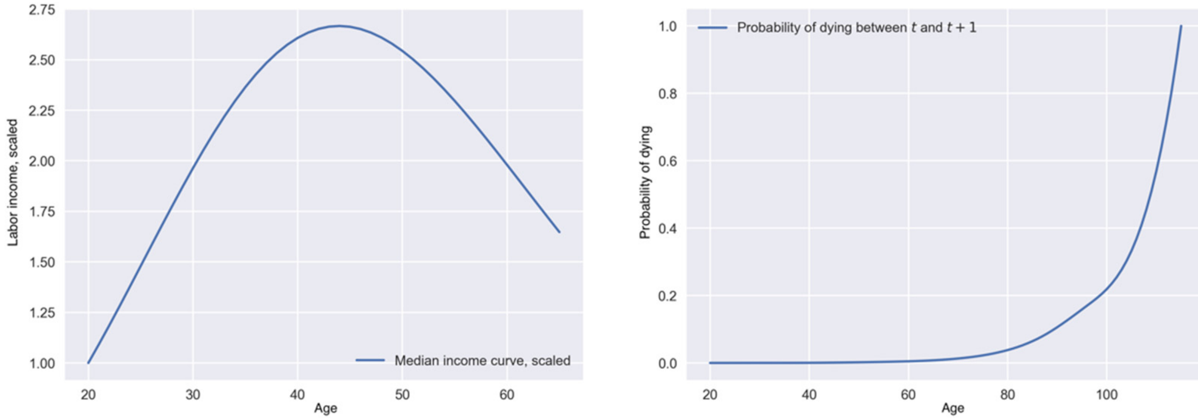


Figure 1 Median income curve fitted using data from the Panel Study of Income Dynamics (PSID) (left), and mortality probabilities from the Society of Actuaries (right).

Table 1 Benchmark parameter values used in life-cycle model.

Parameter	Description	Value
δ	Discount factor	0.96
γ	Risk aversion parameter	3.68
ψ	Elasticity of intertemporal substitution	0.27
μ_S	Expected (real) return on equities	0.0415
σ_S	Standard deviation of equity returns	0.16
μ_B	Expected (real) return on bonds	0.01
σ_B	Standard deviation of bond returns	0.045
σ_η	Standard deviation of individual fixed effect	0.25
σ_ϵ	Standard deviation of transitory income shocks	0.3
σ_u	Standard deviation of permanent income shocks	0.1

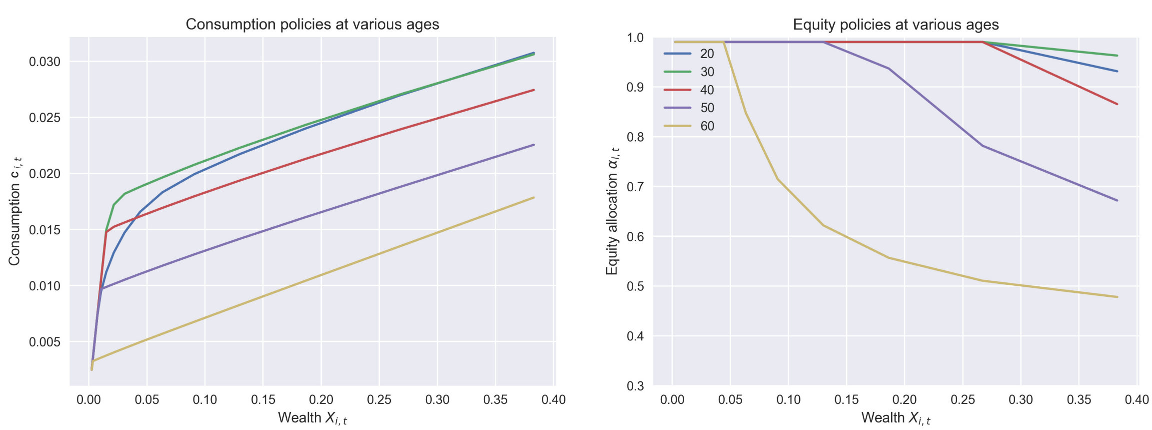


Figure 2 Sample consumption policies (left) and equity policies (right) from the baseline model, i.e. where there is no chance of extreme weather shocks. Note that consumption is scaled by permanent income.

3.2 Calibration

We calibrate the labor income model in Equations (4) to (5) using data from the Panel Study of Income Dynamics; the average income curve is plotted in Figure 1. We assume t begins at age 20, and that investors live to maximum of $T = 115$. Mortality rates p_t are taken from the Blended Annuity 2000 Mortality table from the Society of Actuaries and are plotted in Figure 1. Other key parameters and assumptions are presented in Table 1.[8]

3.3 Results

3.3.1 Benchmark model results

To begin, we present results from solving our baseline model, where the probability of a

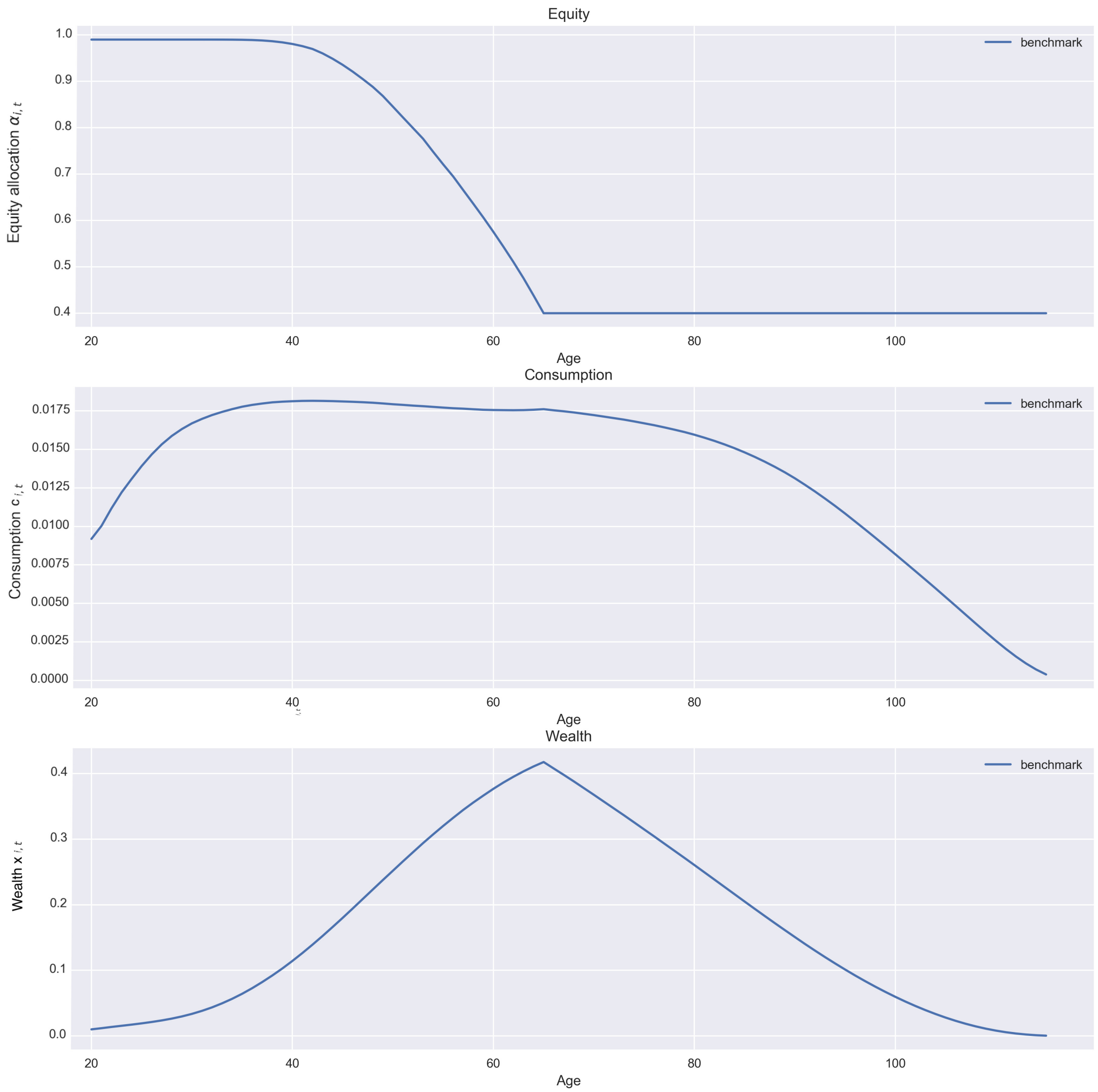


Figure 3 Average equity (top), consumption (middle) and wealth (bottom) as a function of age in the benchmark model when there are no extreme weather shocks. Note that both consumption and wealth are scaled by permanent income $N_{i,t}$.

extreme weather shock is zero for all t. Optimal consumption and equity policies for select ages are plotted in Figure 2.[9] We see that:

- For a given age, optimal consumption is an increasing function of wealth.
- For a given age, optimal equity is a decreasing function of wealth.

Table 2 Parameter values used in the first extreme weather shock extension of the model.

Parameter	Description	Value
π_t	Probability of extreme weather shock	$0.2\ \forall\, t$
κ_t	Magnitude of extreme weather shock	$0.2\ \forall\, t$

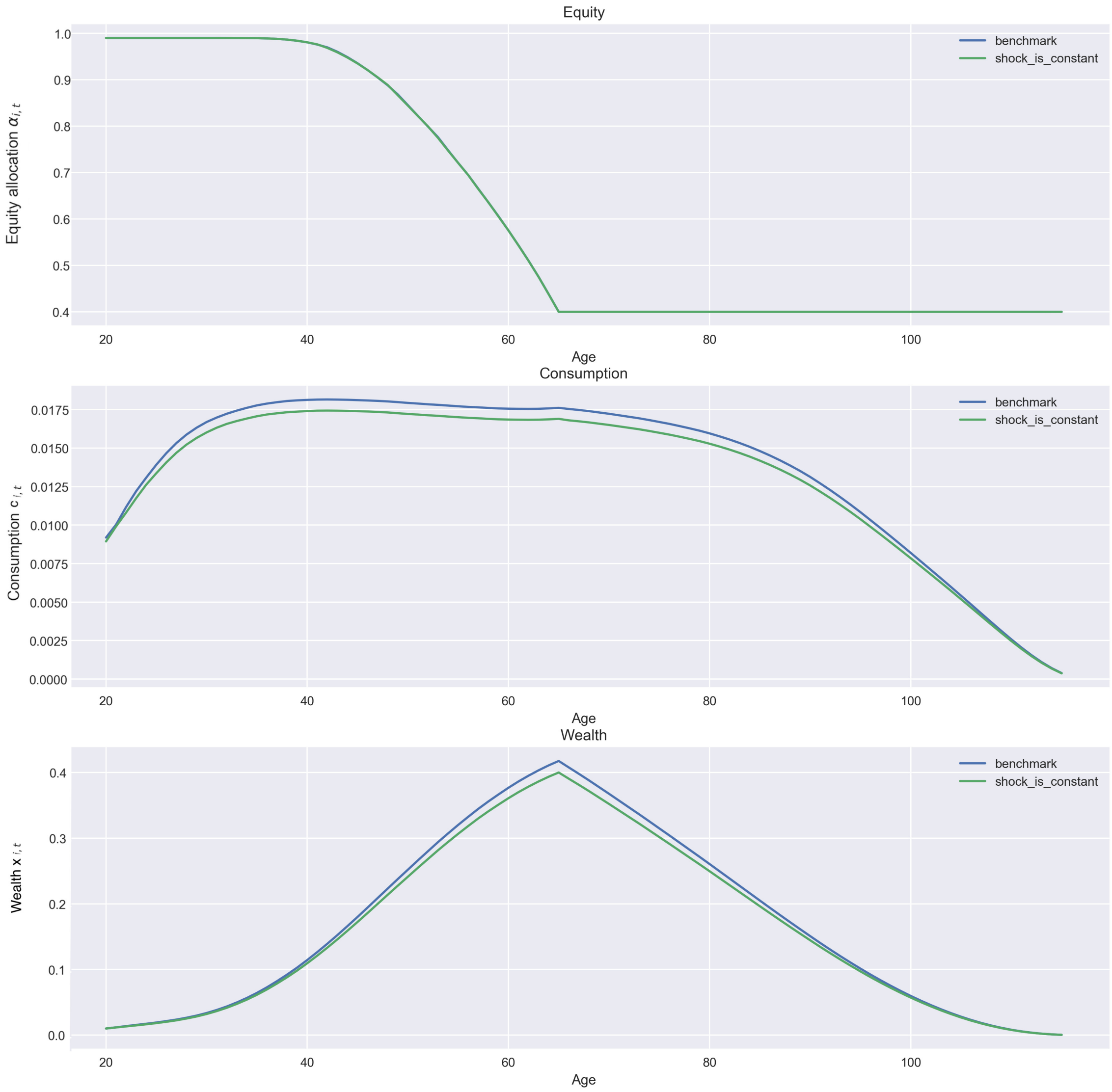


Figure 4 Average equity (top), consumption (middle), and wealth (bottom) as a function of age in first extreme weather shock extension. Note that both consumption and wealth are scaled by permanent income $N_{i,t}$.

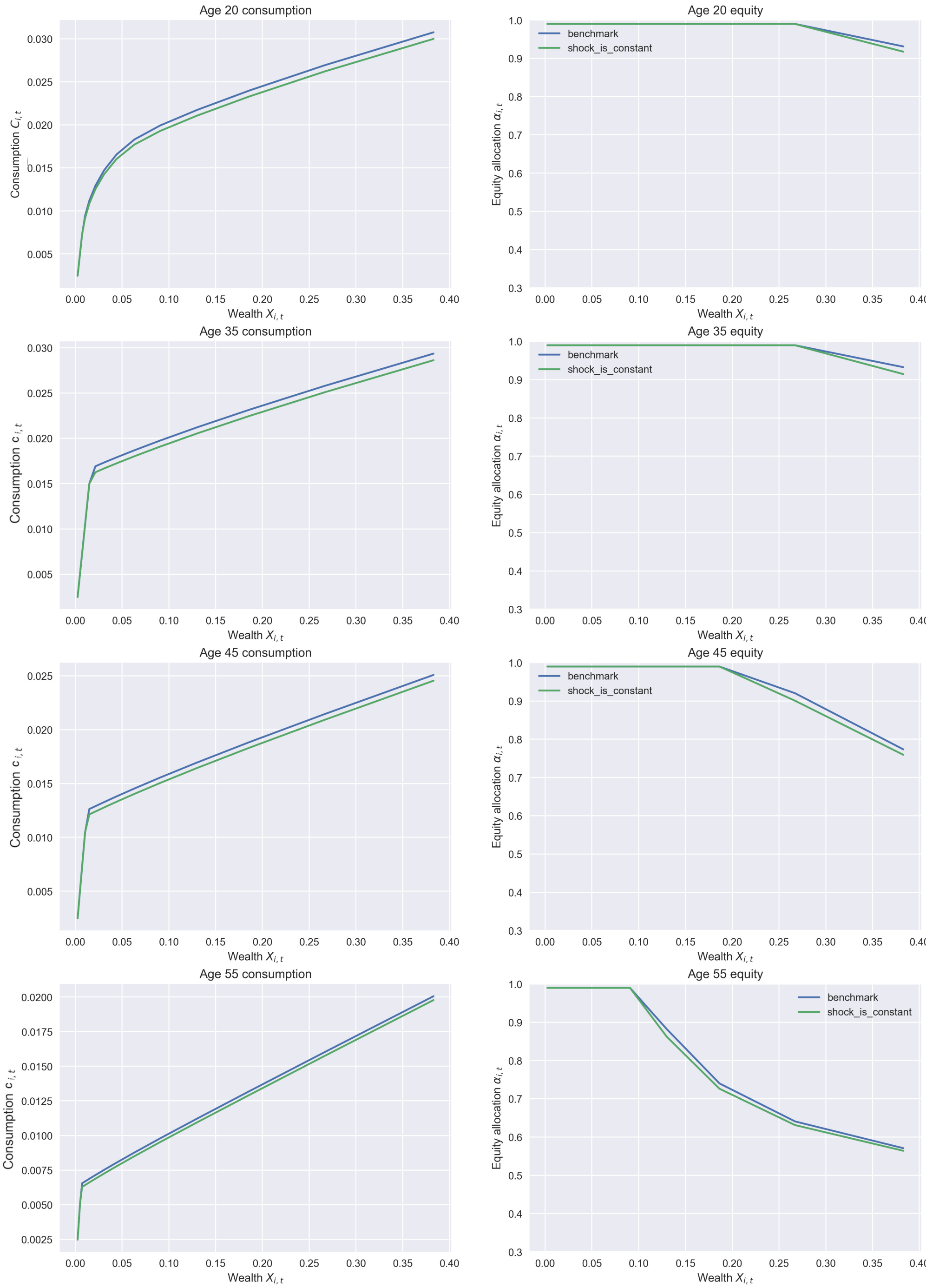


Figure 5 Consumption and equity policy comparison in benchmark case and the first version of the extreme weather shock model where there is a constant probability of a constant magnitude shock. Note that both consumption and wealth are scaled by permanent income $N_{i,t}$.

- For a given level of wealth, optimal consumption decreases with age.
- For a given level of wealth, optimal equity decreases with age.

While the policy functions are interesting in their own right, to understand what they actually mean for an investor, it is helpful to use them alongside Monte Carlo simulations.[10] We generate sample investor consumption, equity and wealth paths by simulating labor income and financial returns and assuming decisions on consumption and equity are made optimally according to the policy functions. Taking the mean across these sample paths in the benchmark case gives us the average consumption, equity, and wealth by age as shown in Figure 3. As we will see, these average curves are a useful way to compare different models and understand the impact of extreme weather shocks on consumption and savings.

3.3.2 *Extension* 1: *Probability of shock and magnitude of consumption hit are constant*

We next present results from the first extension of the benchmark model. In this extension at every age there is the probability of an extreme weather shock which requires spending of income; the values we test are given in Table 2. We solve this model via backward induction to generate a new set of policy functions. Then, running the same simulation exercise described in the previous section, we get the average consumption, equity and wealth curves shown in Figure 4, which we plot alongside the benchmark results from Section 3.3.1.

We see that equity allocations are basically the same across the two cases, while consumption and wealth are notably lower when we model extreme weather shocks. The similar equity allocations are interesting because if we look at the policy functions for equity in Figure 5, we can see that at a given age and for a given level of wealth, the optimal equity allocation is higher in the benchmark case.

This is because the potential of an extreme weather shock reduces an investor's capacity to take risk within their portfolio. This effect is somewhat netted-out by the fact that investors accumulate less wealth when there are extreme weather shocks (as evidenced by the lower wealth accumulation in Figure 5) and this lower wealth results in higher equity allocation.

3.3.3 *Extension* 2: *Probability of shock is constant, magnitude is normally distributed*

In the second extension, we assume that is normally distributed according to $N \sim (\mu_\kappa, \sigma_\kappa^2)$. The parameters we use in the results presented here are in Table 3. Again running the simulation exercise, we get the average consumption, equity and wealth curves shown in Figure 6. While not shown here, the policy functions exhibit similar behavior to that discussed in the previous section.

3.3.4 *Extension* 3: *Probability of shock changes over time, magnitude is constant*

Finally, in the third extension we set the magnitude of the shock to a constant while allowing

Table 3 Parameter values used in the second extreme weather shock extension of the model.

Parameter	Description	Value
π_t	Probability of extreme weather shock	0.2
μ_k	Mean magnitude of extreme weather shock	0.3
σ_k	Standard deviation of magnitude of extreme weather shock	0.1

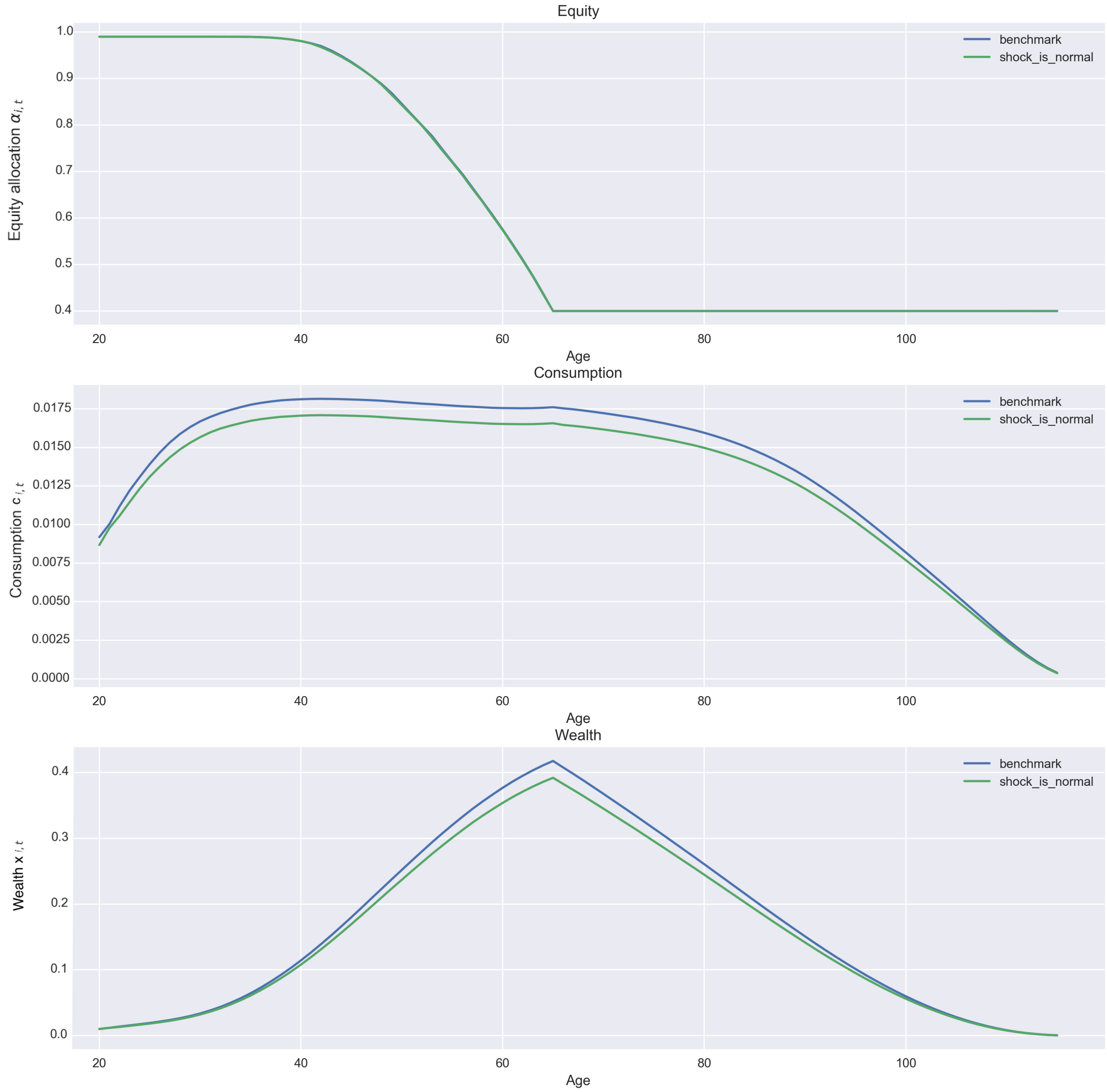


Figure 6 Average equity (top), consumption (middle) and wealth (bottom) as a function of age in the second extension when the magnitude of the consumption shock is normally distributed. Note both consumption and wealth are scaled by permanent income.

the probability of a shock to vary over time; specifically, we assume that the probability of a shock increases with time. The assumed probabilities are shown in Figure 7. The intuition behind this extension is closest to the concept of a "climate shock", namely, that natural disasters may increase in frequency over time due to climate change, consistent with the possible climate futures specified in the IPCC (2021). The simulation results are shown in Figure 8.

3.4 *Quantifying the impact of extreme weather shocks on different age groups*

In the results we have presented so far, we have simulated investors paths across their entire lifecycle; i.e. from $t = 20$ to $T = 115$. The implicit assumption for these investors then is that there is the possibility of an extreme weather shock in every year of their adult life. While this is probably a reasonable assumption for an investor who

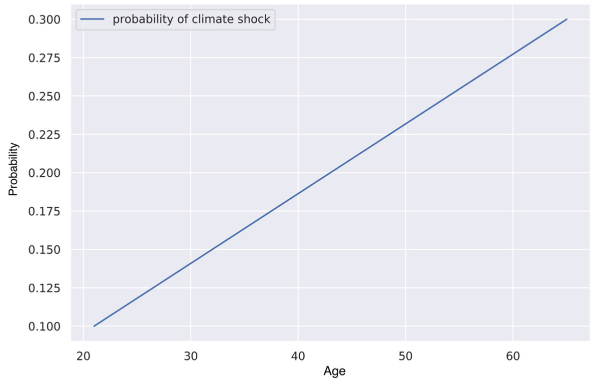


Figure 7 Probability of extreme weather shock as a function of time.

is currently 20 years old, it is not for a 60-year-old who has, up until relatively recently, experienced a world where extreme weather shocks were less frequent and less severe. In this section we therefore vary the starting age of the problem, which allows us to analyze the cumulative impact of extreme weather shocks for people in different age groups, with different savings horizons.

Using the version of the extreme weather shock model described in Section 3.3.4, we plot average consumption, wealth, and equity as functions of age for different starting ages as shown in Figure 9. We include both the benchmark case where there is no possibility of a shock and the case where the shock magnitude is assumed to be constant, and where the probability of a shock is time dependent. Note that the assumed starting wealth is the same for both cases. In order to look more closely at the impact of extreme weather shocks on wealth and retirement savings, we also plot consumption at age 66 for both the benchmark and no shock cases in the final two columns.

What is clear from Figure 9 is that investors who experience extreme weather shocks throughout their entire lives see a bigger hit to their lifetime consumption and overall wealth compared to those who are older and have not had to pay for extreme weather-related expenses for most of their lives. Young people today face on average many more extreme weather shocks than those who are in retirement, both because they have many more years of potential shocks and the likelihood of those shocks is likely to increase with climate change. These shocks compound and mean younger investors both have less capacity to save in their accumulation years, and they end up with less savings in their decumulation years.

3.5 Plugging the savings shortfall

In the previous section, we saw that extreme weather shocks negatively impact an individual's ability to save for retirement. In this section, we seek to understand just how much extra return would be required to fully close the consumption and wealth gaps that result from extreme weather shocks. To explore this question, we begin by analyzing the impact of adding "alpha", or additional uncorrelated return, to our benchmark fixed income and equity returns. Specifically, we compare consumption and wealth across the life-cycle for three cases:

- Our standard benchmark case, with no extreme weather shocks. This is the level of consumption we hope to achieve by adding alpha.
- Extension 3.3.2 where we include extreme weather shocks, with a constant probability and constant magnitude in every period. These wealth and consumption paths illustrate the shortfall that results from extreme weather shocks, when no mitigating or compensating actions are taken.
- Extension 3.3.2 but with 25 bps of active return and 2% active risk for both the fixed income and equity asset in the simulations, and assumed zero correlations between the alpha stream and equity and bond asset classes. This increases return and only modestly increases risk, given

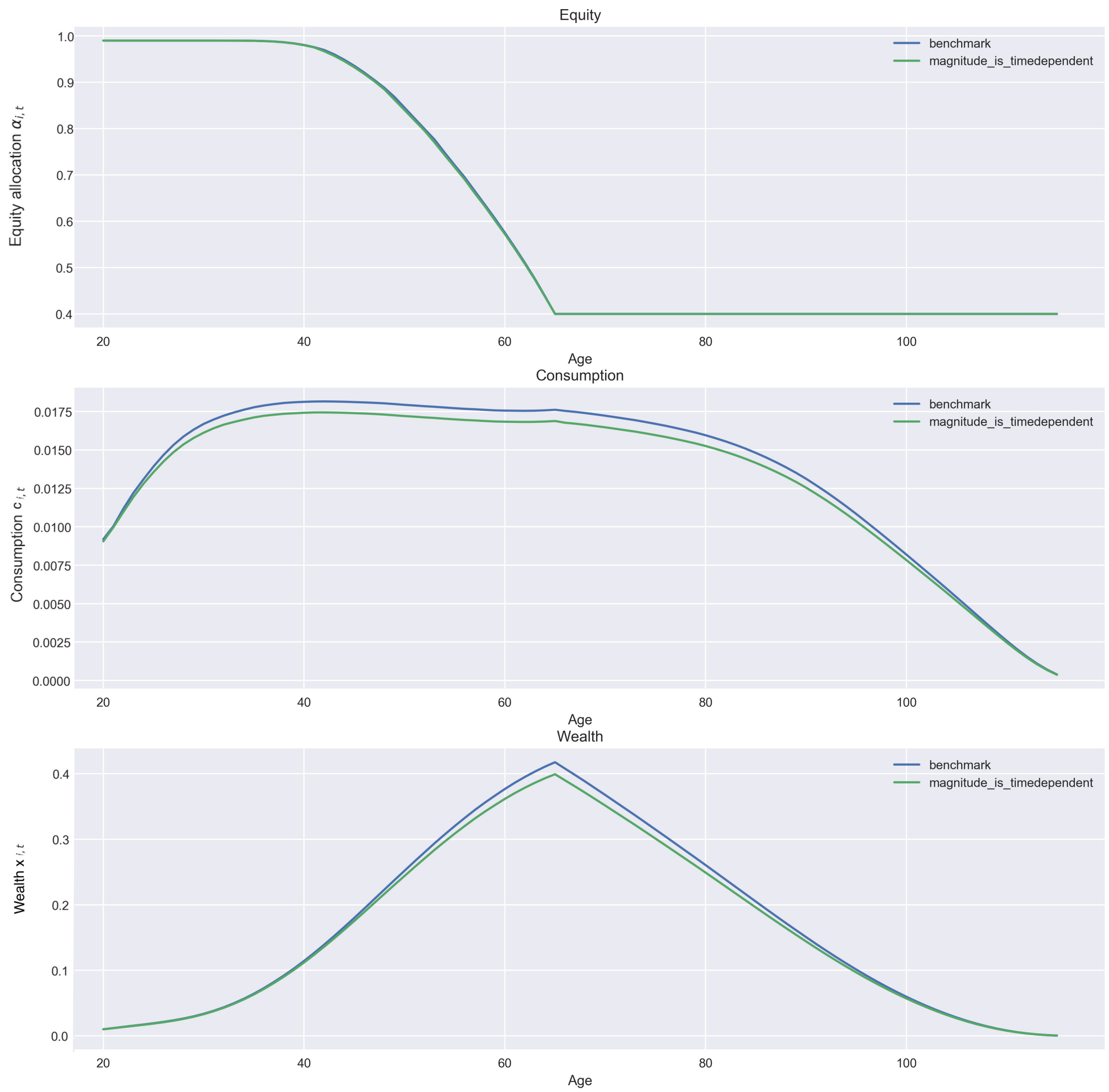


Figure 8 Average equity (top), consumption (middle), and wealth (bottom) as a function of age in the third extension when there is an increasing probability of a extreme weather shock that requires spending a constant amount of income. Note that both consumption and wealth are scaled by permanent income $N_{i,t}$.

the uncorrelated nature of the "active returns" or "alpha".

The results from this exercise are shown in Figures 10 and 11. We see that adding 25 bps of alpha when extreme weather shocks are incorporated results (on average) in wealth accumulation like the standard case. Similarly, while the consumption paths have different shapes due to different consumption policy functions for the standard case and the case with extreme weather shocks, we see that adding 25 bps of alpha results in a level of consumption like the standard case at the point of retirement. It should also be noted that the level of consumption is actually higher through retirement in the case with 25 bps of alpha.[11] It should also be noted that the equity allocations are the same in each of these cases.

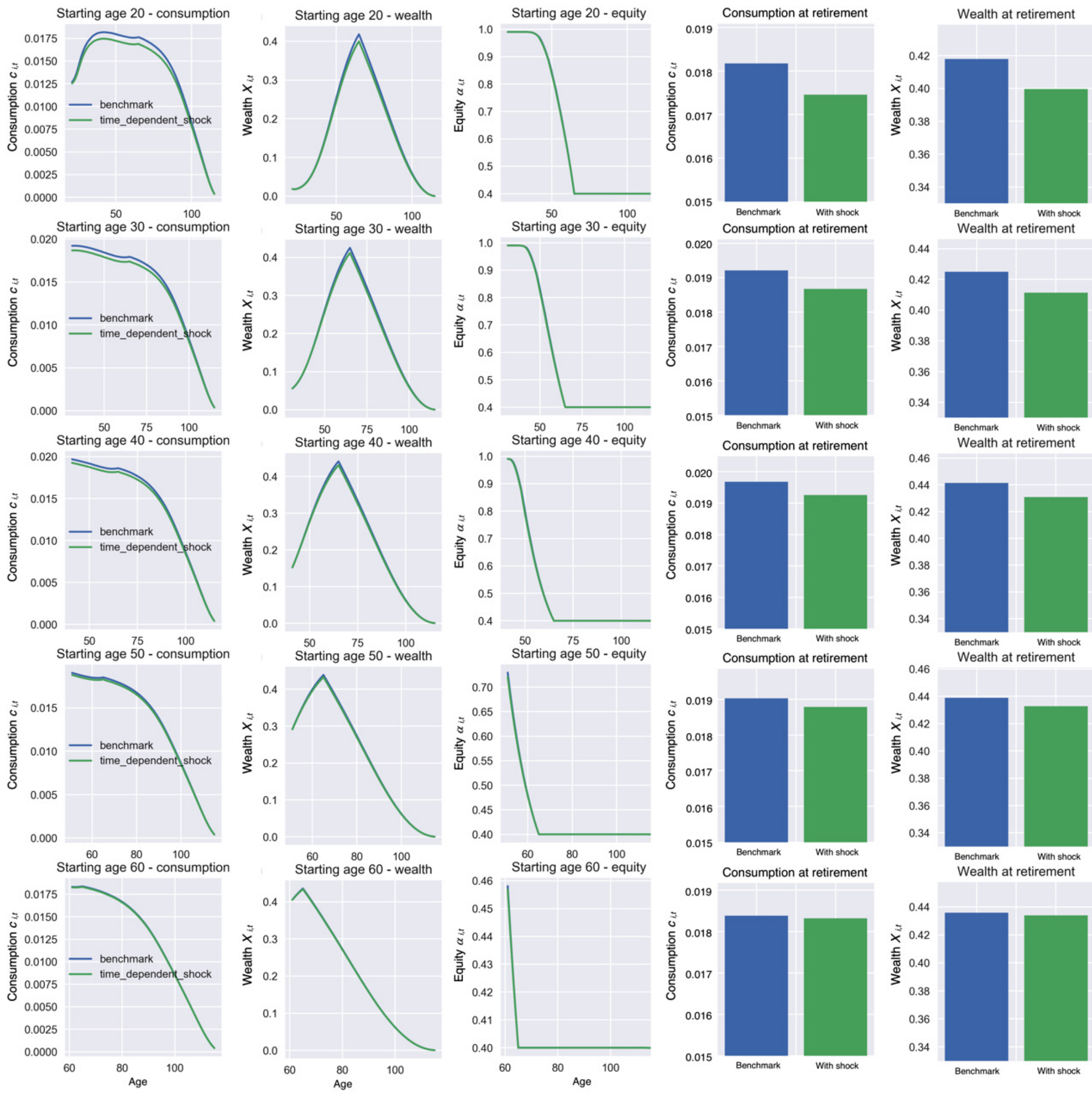


Figure 9 Each row has results for a different starting age. For each starting age we show (in order) average consumption, average wealth, average equity, consumption in the first year of retirement and wealth in the first year of retirement. Note that consumption and wealth are scaled by permanent income $N_{i,t}$.

In Figure 12 we quantify the relationship between alpha and consumption, by plotting different amounts of alpha against their respective consumption gaps in our simulation. In the figure, the gap is the percentage difference between consumption in the standard case without shocks, and the case with shocks but with added alpha. Of course, the higher the alpha is, the smaller the shortfall, and with higher levels of alpha, the more improved the level of consumption.

In general, any increase in return would have a positive benefit for consumption, so the result above is meant to show the scale of the relationship between negative shocks to contributions and returns necessary to restore lifetime consumption.

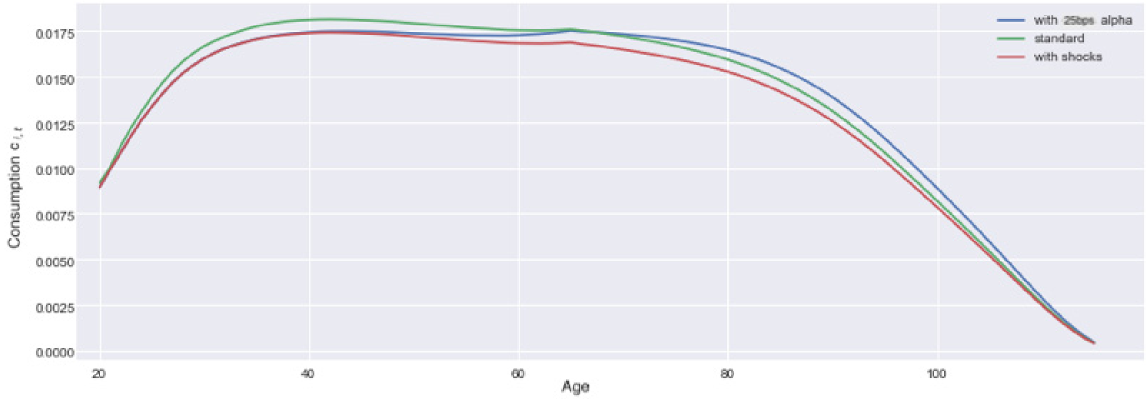


Figure 10 Consumption by age in standard case, with shocks, and with shocks + alpha. Note that consumption is scaled by permanent income $N_{i,t}$.

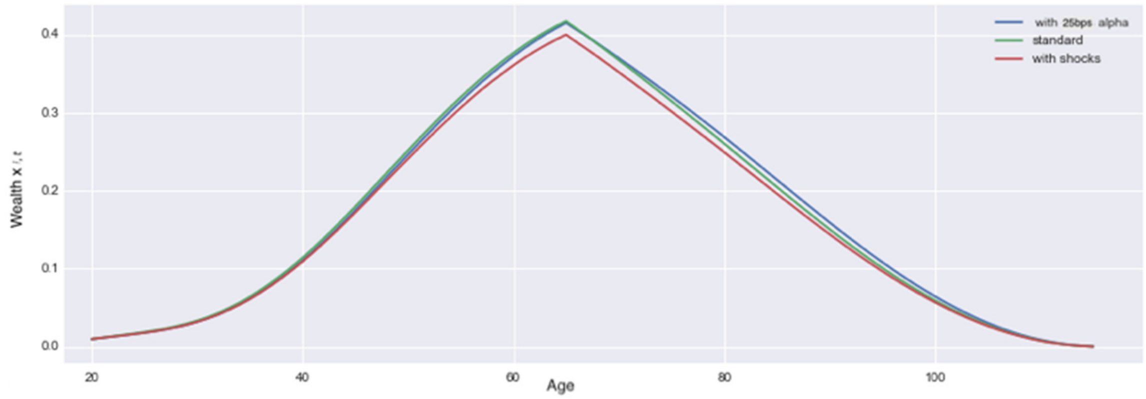


Figure 11 Wealth by age in standard case, with shocks, and with shocks + alpha. Note that wealth is scaled by permanent income $N_{i,t}$.

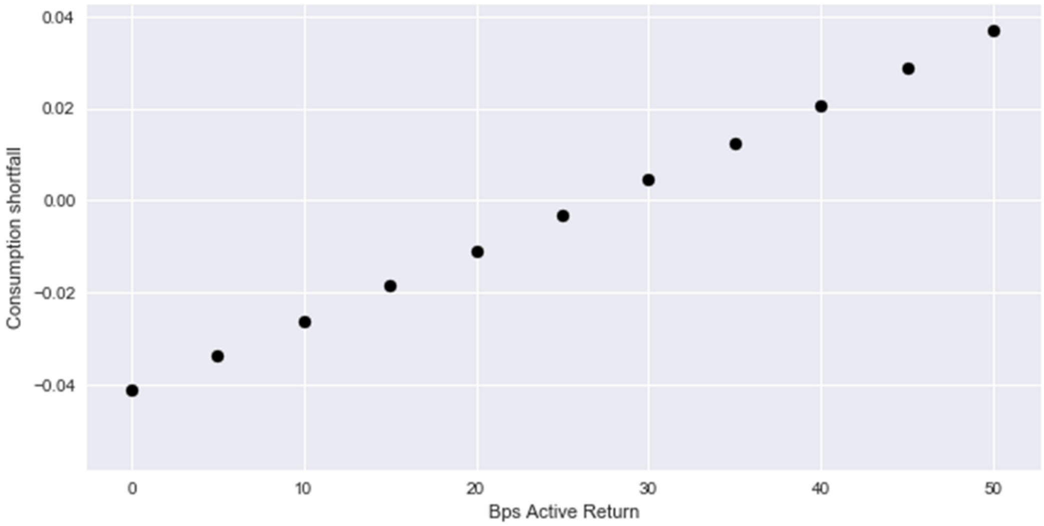


Figure 12 Consumption shortfall when testing out different active return amounts.

We discuss broader options for practitioners and policy in the Discussion section.

4 Empirical Approach

We have just constructed a model of portfolio choice which suggests that climate change-related shocks to future income can negatively impact long-term wealth through lower retirement savings. Next, we will test this model through a series of panel regressions focused on the relationship between extreme disasters and several economic variables: income, unemployment insurance, hiring, and employer contributions to pensions. We will first give a description of the data, the structure of the tests, and a discussion of initial results.

4.1 Data

In this paper we rely on two main datasets: (1) disaster records from the Federal Emergency Management Agency (FEMA) and (2) the Regional Economic Accounts datasets from the Bureau of Economic Analysis (BEA). We describe each of these datasets below in turn.

4.2 Federal emergency management agency (FEMA) data

We obtain the disaster data from the OpenFEMA API[12] which provides granular historical datasets with detail on natural disasters that rose to needing Federal Government Support in the United States, supported by the Federal Emergency Management Agency. The agency was created by President Jimmy Carter on April 1, 1979, merging disaster relief functions from the Dept. of Housing and Urban Development (HUD) and Dept. of Defence. The department is primarily focused on on-the-ground support for disaster recovery and currently falls under the Department of Homeland Security (DHS). The process for disaster declaration is as follows:

A disaster occurs in a state, most commonly natural although other types may be covered (e.g. biological).

The Governor's request is made through the regional FEMA office. State and Federal officials conduct a preliminary damage assessment (PDA) to estimate the extent of the disaster and its impact on individuals and public facilities.

Based on the Governor's request, the President may declare that a major disaster or emergency exists, thus activating an array of Federal programs to assist in the response and recovery effort.

There are many datasets within the FEMA database. Within our statistical tests, we focus on two key tables:

(1) **FEMA Web Disaster Declarations**: This table contains one record per disaster, applying a unique disaster identifier. This dataset identifies the key state associated with the disaster, its nature, as well as the time stamps for declaration, begin and end dates. See Figure 13a for an example.
(2) **FEMA Web Declaration Areas**: This table provides detail about the areas that have been designated for FEMA assistance. The dataset has one line per designated area (typically county, occasionally entire state), meaning the more designated counties, typically the larger the geographic area impacted by the disaster. The table also has US Census geographic identifiers (GEOIDs) that are related to Federal Information Processing Series (FIPS) codes for Counties and States.[13] A small proportion of the records within the table reflect pure "Statewide" designations, meaning that every county within the state is designated for potential assistance. In our data treatment, we copy Statewide designations to individual country records to ensure that we appropriately capture and

Disaster Number	3390
Declaration Date	2017-09-18T00:00:00.000Z
Disaster Name	HURRICANE MARIA
Incident Begin Date	2017-09-16T00:00:00.000Z
Incident End Date	2017-09-22T00:00:00.000Z
Declaration Type	Emergency
State Code	VI
State Name	Virgin Islands of the U.S.
Incident Type	Hurricane
Entry Date	2017-09-18T00:00:00.000Z
Update Date	2018-09-07T00:00:00.000Z
Closeout Date	2018-09-07T00:00:00.000Z
Region	2
IH Program Declared	0.0
IA Program Declared	0.0
PA Program Declared	1.0
HM Program Declared	0.0
ID	0b1556f2-f32d-4313-9aa0-aac454e708cb
Hash	88f309a79696aa61bec889b76989e511e0a5cb90
Last Refresh	2023-09-28T23:41:26.075Z

(a) Sample "Disaster Declaration" record from OpenFEMA API

FEMA Declaration String	FM-5250-CA
Disaster Number	5250
State	CA
Declaration Type	FM
Declaration Date	2018-07-05T00:00:00.000Z
FY Declared	2018
Incident Type	Fire
Declaration Title	KLAMATHON FIRE
IH Program Declared	0
IA Program Declared	0
PA Program Declared	1
HM Program Declared	1
Incident Begin Date	2018-07-05T00:00:00.000Z
Incident End Date	2018-07-16T00:00:00.000Z
Disaster Closeout Date	NaN
Tribal Request	0
FIPS State Code	6
FIPS County Code	93
Place Code	99093
Designated Area	Siskiyou (County)
Declaration Request Number	18054
Last IA Filing Date	NaN
Last Refresh	2023-05-22T03:41:22.800Z
Hash	422f5c9511415d85c1cda35c8b824eb4fd104f33
ID	8b185107-eea2-4897-b981-ee9e80687d7f

(b) Sample "Disaster Designated Areas" record from OpenFEMA API

Figure 13 Sample records from OpenFEMA API.

count all designations at the county level. See Figure 13b for an example of the features of the dataset.

The FEMA dataset contains rich information on the location, time, and characteristics of the disasters that have occurred. Table 4 provides some summary statistics of the disaster declarations within the data from 1970 to 2020. Over this time, there have been approximately 80 disasters per year, with Fires, Severe Storms, and Hurricanes making up the majority of the disaster counts.

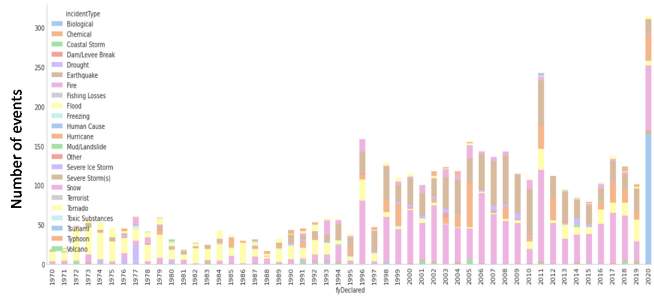
Table 4 FEMA Disaster Declarations—Summary statistics from 1970 to 2020.

	Total	Per Year	
Sample	Number	Mean	St. dev
Disaster Declarations			
Declared	4233	83	58.46
Declaration Type			
Major Disaster	2294	44.98	20.17
Fire Management	919	48.36	25.41
Emergency	557	14.65	22.96
Fire Suppression	463	14.93	22.14
Incident Type			
Fire	1462	29.24	29.4
Severe Storms	975	20.77	18.19
Hurricane	674	13.48	9.92
Tornado	137	3.34	2.66
Snow	164	4.97	4.84
Biological[a]	164	—	—
Severe Ice Storm	62	2.95	2.44
Typhoon	56	2.8	1.47
Drought	39	4.88	1.47
Earthquake	31	1.41	0.59
Coastal Storm	29	1.71	1.36
Other	18	1.8	1.55
Disaster Summaries			
Designation Area			
Non Statewide	3940	1145.09	1446.4
Statewide	283	6.9	1446.54

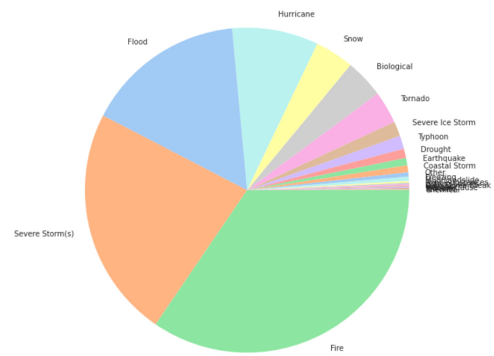
Notes: The table shows summary statistics for FEMA's Disaster Declarations Summaries and FEMA Web Declaration Areas datasets.
[a]Biological refers to COVID-19 related FEMA declarations.

About 1,100 counties are designated for assistance on an annual basis with seven disasters on average designated statewide.

Figure 14 shows the summary statistics across disasters and over time, demonstrating that disaster counts have increased over time, having risen approximately threefold from the 1970s to the 2010s. Also, the nature of the recorded

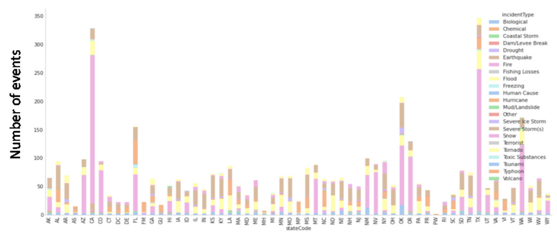


Incident Type Over Time

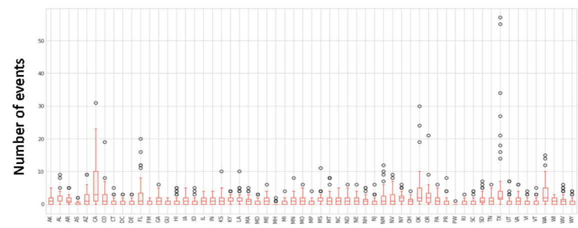


Full Sample

Figure 14 Unique disaster declarations over time and by incident type, 1970–2020.



Incident Type by State



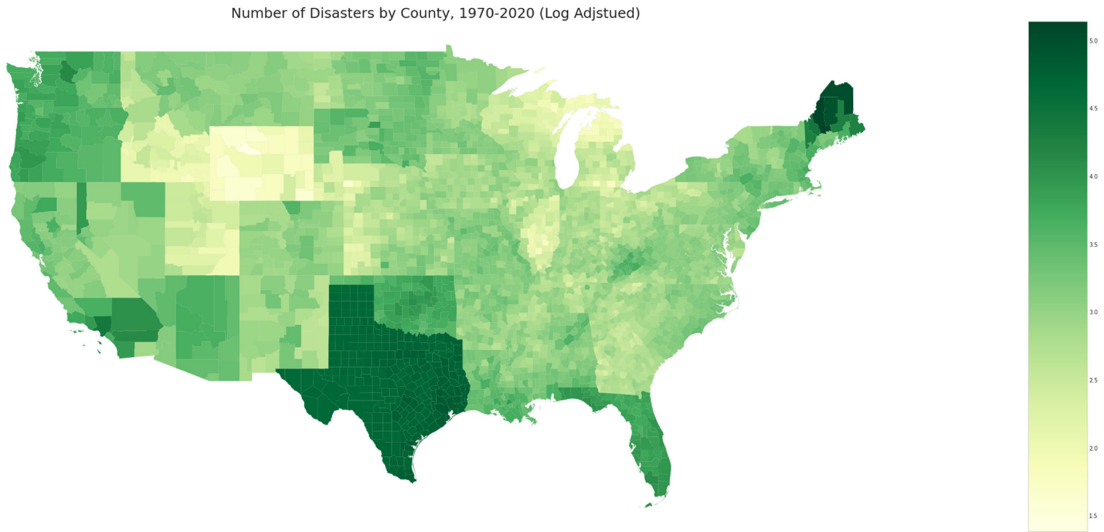
Annual Distribution of Events by State

Figure 15 Disaster events by state and type.

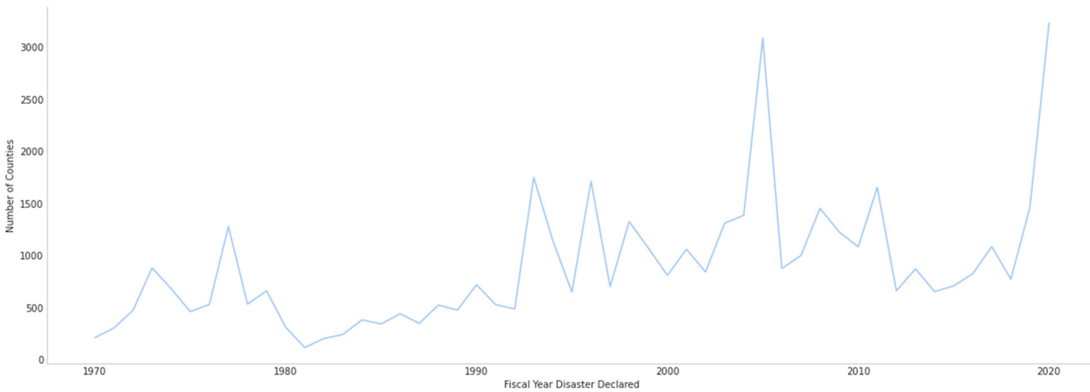
disasters has also changed, with the Fires and Severe Storms much more common in the recent periods.[14]

Figure 15 breaks down the number of incidents by state and type, as well as displays the annual distribution of disaster counts by state. California and Texas stand out as having the most disasters, while Oklahoma, Florida and Washington are in the next tier. Importantly, the distribution of disaster counts per year is right-skewed, with fewer than 10 disasters on average per state and some years with significantly more events.

The number of affected counties per year has increased over time. Figure 16 shows that while not uniform, most states have high propensity for disasters. Texas stands out as having more frequent Statewide' designations and hence more consistently high disaster designations. Wyoming, Idaho and Utah have larger geographic areas with fewer designations. Figure 16a highlights that the number of unique counties affected by one or more disaster per year has increased over time, particularly since the 1980s (darker tones correspond to more events). With the average over the last 10 years at approximately 1,200 counties affected by at least one disaster per year, the unconditional likelihood that a county is affected by a disaster in a year in any year stands at approximately 40%, notably even higher than the 20–30% assumption used in the shocks within our lifecycle model in Section 3. Figure 16b shows the geographic distribution of events by incident type. Fires tend to affect the Western part of the United States relatively more often, while Hurricanes are more prominent in the Southeast. Severe storms and floods are more dispersed geographically, but have pockets of concentration (for example, severe storm events tend to be more prevalent in the Midwest).



(a) Distribution of Events by County



(b) Number of Unique Counties Affected by a Disaster per Month

Figure 16 Geographic distribution of disaster declarations by county.

4.2.1 Bureau of economic analysis—regional economic accounts

We use annual county-level data economic data provided by the US Bureau of Economic Analysis' Regional Economic Accounts (BEA). Within the BEA data, we use two main tables: Personal Income and Employment by Major Component by County (CAINC4) and the Economic Profile by County (CAINC30). For each table, the data is annual and starts reporting at 1969. Definitions for each major data item are given from the BEA as follows:

(1) **Per Capita Personal Income**. It consists of the income that persons receive in return for their provision of labor, land, and capital used in current production as well as other income, such as personal current transfer receipts. In the state and local personal income accounts the personal income of an area represents the income received by or on behalf of the persons residing in that area. It is calculated as the sum of wages and salaries, supplements to wages and salaries, proprietors' income with inventory valuation (IVA) and capital consumption adjustments (CCAdj),

rental income of persons with capital consumption adjustment (CCAdj), personal dividend income, personal interest income, and personal current transfer receipts, less contributions for government social insurance plus the adjustment for residence. Income is divided by the resident population of the area.

(2) **Employer contributions for employee pension and insurance funds**. It consists of employer payments to private and government pension plans and to private insurance funds such as for group health and life insurance; workers' compensation; and supplemental unemployment insurance.

(3) **Total employment**. A count of jobs, both full-time and part-time. It includes wage and salary jobs, sole proprietorships, and individual general partners, but not unpaid family workers nor volunteers.

(4) **Population (persons)**. The number of individuals (both civilian and military) who reside in a given area.

(5) **Unemployment insurance compensation**. It is made up of the following: State unemployment compensation are benefits consisting mainly of the payments received by individuals under state—administered unemployment insurance (UI) programs, but they include the special benefits authorized by federal legislation for periods of high unemployment. The provisions that govern the eligibility, timing, and amount of benefit payments vary among the states, but the provisions that govern the coverage and financing are uniform nationally. Unemployment compensation of Federal civilian employees are benefits which are received by former federal civilian employees under a federal program administered by the state employment security agencies acting as agents for the US Government. Unemployment compensation of railroad employees are benefits which are received by railroad workers who are unemployed because of sickness or because work is unavailable in the railroad industry and in related industries, such as carrier affiliates. This UI program is administered by the Railroad Retirement Board (RRB) under a federal formula that is applicable throughout the Nation. Unemployment compensation of veterans are benefits which are received by unemployed veterans who have recently separated from military service and who are not eligible for military retirement benefits. Trade adjustment assistance are benefits received by workers who are unemployed because of the adverse economic effects of international trade arrangements. Per capita is defined as Unemployment insurance compensation of a given area divided by the resident population of the area.

4.3 Regression setup

To begin our empirical tests, we use a standard panel fixed-effects regression specification like many of the cited academic studies:

$$\begin{aligned} \text{econ}_{i,t} &= \alpha + \beta \text{Disaster Count}_{i,t} + \beta \text{Controls}_{i,t} \\ &\quad + \text{Year}_{i,t} + \text{State}_{i,t} + \varepsilon_{i,t} \end{aligned}$$

Here $\text{econ}_{i,t}$ is the target economic variable (e.g. income, employer contributions), $\text{Disaster Count}_{i,t}$ is the number of FEMA disasters declared in that county-year, $\text{Controls}_{i,t}$ are controls specific to the target economic variable (employment growth for income, contributions, unemployment; population growth for employment). We also run our tests with fixed effects for year ($\text{Year}_{i,t}$) and state ($\text{State}_{i,t}$). Standard errors ($\varepsilon_{i,t}$) are heteroskedasticity-robust and clustered at the county-year level. All variables are log adjusted.

Initially, we filter FEMA disasters to declarations that are focused on specific counties instead of

Table 5 Impact of disasters on personal income growth.

	Per Capita Personal Income Growth			
Dependent Variable	(1)	(2)	(3)	(4)
Intercept	0.0555***	0.0509***	0.0791***	0.0782***
	(0.0001)	(0.0002)	(0.0014)	(0.0014)
Diaster Count	−0.0069***	−0.0039***	−0.0032***	−0.0037***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Total Employment Growth		0.3865***		0.3277***
		(0.0096)		(0.0098)
Fixed Effect	N	N	Y	Y
Number of Observations				
FIPS	3090			
Years	51			
Total Observations	157051			
Date Range	1970–2020			
R^2	0.0015	0.0508	0.2041	0.2342

Notes: The table shows regression estimates of the impact of extreme weather, measured by FEMA disaster declarations, on per capita personal income growth at the county level. All variables have been log adjusted. Variables labeled “Growth" have Year-on-Year changes taken. Fixed effects include State and Year. Standard Errors are clustered by County and Year. Tests are run annually. Point estimates marked ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

state-wide disaster declarations. In our robustness section, we include all FEMA disasters and project state-wide declarations down to the county level. Our conclusions are the same across the variations in the setup.

4.4 Results

4.4.1 Personal income

For our first test, we explore the relationship between personal income growth and natural disasters. As discussed by Bakkensen and Barrage (2022), results in the academic literature have been mixed depending on whether cross-sectional regressions or panel regressions are used, with the latter attempting to control for omitted variable bias at the geographic level. For completeness, we include both results with and without fixed effects below. Indeed, we observe that income growth is negatively impacted when extreme disasters are high in the county, even after controlling for employment growth and geographic/time fixed effects.

4.5 Unemployment

Next, we explore the impact disasters have on unemployment through government transfers (i.e. unemployment insurance) as well as overall hiring. As with Tran and Wilson (2022), we expect to see overall turnover increase—both as certain industries increase hiring to rebuild damaged physical capital, such as construction, as well as overall economic activity being disrupted increasing layoffs and government transfers (i.e. unemployment claims). We control for population growth with total employment to account for net-migration that may happen between counties during extreme disasters.

Table 6 Impact of disasters on unemployment compensation.

	Per Capita Unemp. Comp. Growth			
Dependent Variable	(1)	(2)	(3)	(4)
Intercept	0.0286***	0.0770***	0.4803***	0.4831***
	(0.0007)	(0.0018)	(0.0069)	(0.0069)
Disaster Count	0.3297***	0.2978***	0.0084***	0.0100***
	(0.0033)	(0.0034)	(0.0019)	(0.0019)
Total Employment Growth		−4.0206***		−1.1135***
		(0.1239)		(0.0462)
Fixed Effect	N	N	Y	Y
Number of Observations				
FIPS	3090			
Years	51			
Total Observations	156863			
Date Range	1970–2020			
R^2	0.0507	0.1313	0.7571	0.7623

Notes: The table shows regression estimates of the impact of extreme weather, measured by FEMA disaster declarations, on unemployment compensation at the county level. All variables have been log adjusted. Variables labeled "Growth" have Year-on-Year changes taken. Fixed effects include State and Year. Standard Errors are clustered by County and Year. Tests are run annually. Point estimates marked ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

We observe evidence for both below, suggesting both employment disruption and new job creation. Namely, we see that disasters tend to drive up unemployment claims while also being associated with increases in total employment after controlling for Year and State fixed effects. Both unemployment claims and increases in total employment are likely driving offsetting impacts to total lifetime savings, as tenure-based pension savings may also be interrupted.[15]

4.6 *Retirement contributions*

Lastly, we look at retirement contributions through employer contributions for employee pension and insurance funds. Notably, over the full sample there has been a change in employer defined benefit (DB) versus employee defined contribution (DC) plans. According to the Employee Benefit Research Institute, defined benefit pensions were overtaken by defined contribution assets in 1996 and by IRAs in 1998—about halfway through our sample. Both types of plans should be implicated by extreme disasters, either through slowdowns in income growth or labor market turnover.

Indeed, we observe a significant drop in employer contributions to pensions in counties that experience an abnormal amount of natural disasters after controlling for employment growth. This only covers employer contributions, which may occur via direct pension allocations or employee matching contributions; this would not cover additional behavior in savings and investing. However, we believe that this observation helps establish an underappreciated channel by which long-term savings of Americans are negatively implicated by extreme weather shocks. We discuss the implications of this finding in the discussion section.

Table 7 Impact of disasters on total employment.

	Total Employment Growth			
Dependent Variable	(1)	(2)	(3)	(4)
Intercept	0.0120***	0.0076***	0.0028***	0.0002
	(0.0002)	(0.0002)	(0.0014)	(0.0010)
Disaster Count	−0.0079***	−0.0068***	0.0015***	0.0013***
	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Population Growth		0.6682***		0.6082***
		(0.0196)		(0.0199)
Fixed Effect	N	N	Y	Y
Number of Observations				
FIPS	3090			
Years	51			
Total Observations	157051			
Date Range	1970–2020			
R^2	0.0058	0.1296	0.1543	0.2422

Notes: The table shows regression estimates of the impact of extreme weather, measured by FEMA disaster declarations, on total employment at the county level. All variables have been log adjusted. Variables labeled "Growth" have Year-on-Year changes taken. Fixed effects include State and Year. Standard Errors are clustered by County and Year. Tests are run annually. Point estimates marked ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

4.7 Robustness

Several papers in the academic literature point to certain challenges in which data source to use to identify extreme natural disasters (Hsiang and Jina, 2014; Bakkensen and Barrage, 2022). Government-based disaster datasets may be biased based on the political alignment between a governor that requests assistance and the federal government which grants FEMA assistance. Furthermore, certain types of disasters may be more or less likely to get tagged as needing FEMA attention based on the population constituency impacted, either as a full state-wide emergency or as a local-county emergency.

Below, we include results across all FEMA disasters—not just county-specific—to see how state level declarations impact the in-sample results. Indeed, the relationship between disasters and each economic variable exhibits the same sign and statistical significance after controlling for geographic-year fixed effects.

5 Discussion

As demonstrated in this paper, households experience a material hardship to both short- and long-term savings during natural disasters through income challenges, labor market turnover, and drops in employer contributions to pensions. Future work may extend this analysis across demographic and income to explore how financial resilience to natural disasters may vary across subgroups. While financial advisers have a fiduciary responsibility to warn households about the long-term repercussions to decumulating retirement savings early—or to halting retirement contributions temporarily—the

Table 8 Impact of disasters on employer contribution to pension and insurance funds.

	Total Employer Contrib. Growth			
Dependent Variable	(1)	(2)	(3)	(4)
Intercept	0.0795***	0.06676***	0.1262***	0.1232***
	(0.0003)	(0.0003)	(0.0020)	(0.0014)
Disaster Count	−0.0308***	−0.0223***	0.0005***	−0.0011***
	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Total Employment Growth		1.0693***		1.0990***
		(0.0143)		(0.0153)
Fixed Effect	N	N	Y	Y
Number of Observations				
FIPS	3090			
Years	51			
Total Observations	157051			
Date Range	1970–2020			
R^2	0.0223	0.3101	0.3753	0.6339

Notes: The table shows regression estimates of the impact of extreme weather, measured by FEMA disaster declarations, on employer contribution growth at the county level. All variables have been log adjusted. Variables labeled “Growth" have Year-on-Year changes taken. Fixed effects include State and Year. Standard Errors are clustered by County and Year. Tests are run annually. Point estimates marked ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

uncertainty facing households with fragile safety nets may demand a wider range of financial tools to help vulnerable communities cope with the spillover effects from climate change.

In this section, we briefly discuss options that market participants and policymakers may consider to address retirement savings shortfalls resulting from extreme weather events: insurance, hedging, adding alpha, improving transparency, and adaptation and mitigation.[16] The first three are available to private market participants and focus on taking the contribution interruption as given, while the last two suggest policy to help arrest the interruption.

5.1 *Natural disaster income insurance*

One of the main contributions of this paper is to highlight the impact of disasters on retirement savings through decreases in contributions to deferred compensation. A similar phenomenon occurred during the COVID-19 pandemic, albeit for different reasons; as noted by Derby *et al.* (2022), the CARES Act temporarily waved the 10% early withdrawal penalty for families with a member diagnosed with COVID-19, were furloughed, laid-off, or suffered a decrease in income as a result of the coronavirus.[17] While this may provide a framework for optional disaster income, a broader income-replacement insurance program might be warranted as the effects of climate change become increasingly frequent and severe. This would allow for costs of natural disasters to be relatively smaller and spread out.

An income insurance product with risk diversified by pooling premiums within and between

Table 9 Tests using county-specific and state-level disaster declarations.

	Income	Unemp	Employ	Retire
Dependent Variable	(1)	(2)	(3)	(4)
Intercept	0.0517***	0.0885***	0.0071***	0.0666***
	(0.0002)	(0.0019)	(0.0002)	(0.0002)
Disaster Count	−0.0066***	0.2068***	−0.0037***	−0.0187***
	(0.0004)	(0.0036)	(0.0002)	(0.0003)
Total Employment Growth	0.3878***	−4.0207***		1.0753***
	(0.0096)	(0.0096)		(0.0139)
Population Growth			0.6760***	
			(0.0205)	
Fixed Effect	N	N	Y	Y
R^2	0.0542	0.1160	0.1262	0.3153
	(5)	(6)	(7)	(8)
Intercept	0.0785***	0.4830***	0.0002	0.1232***
	(0.0014)	(0.0069)	(0.0010)	(0.0014)
Disaster Count	−0.0061***	0.0097***	−0.0010***	−0.0005*
	(0.0005)	(0.0015)	(0.0002)	(0.0003)
Total Employment Growth	0.3313***	−1.0945***		1.0964***
	(0.0098)	(0.0449)		(0.0150)
Population Growth			0.6137***	
			(0.0212)	
Fixed Effect	Y	Y	Y	Y
R^2	0.2370	0.7619	0.2377	0.6358
Number of Observations				
FIPS	3138			
Years	51			
Total Observations	158551			
Date Range	1970–2020			

Notes: The table shows regression estimates including Statewide declarations projected to counties. All variables have been log adjusted. Variables labeled "Growth" have Year-on-Year changes taken. Fixed effects include State and Year. Standard Errors are clustered by County and Year. Tests are run annually. Point estimates marked ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

States segmented by regions that are more likely to exhibit one type of environmental disaster (e.g. hurricane vs. wildfire) could be a viable option market participants can provide households. However, if businesses react to economic stress by cutting benefits in light of income insurance, then government policy might need an alternative set of tools to offset cuts in deferred compensation while discouraging employer moral hazard for benefit decreases.

5.2 Portfolio hedging

Another option to deal with a drop in contributions is to hedge long-term savings with investments that do particularly well in disaster scenarios. Products that generate income during an extreme weather event, such as structuring retirement portfolios with catastrophe bonds might be appropriate as a preventive measure to balance current consumption needs during an emergency with long-term savings requirements.

This could function similarly to a covered-call options writing strategy, where income is generated by the selling of out-of-the-money call options on an investor's equity allocation. Here, income is not required in every period—just during climate events which may impact the economic well-being of the household. Thus, geographically-appropriate insurance contracts could be financed out of a small portion of the portfolio. The optimal amount may be estimated by calculating the likely present value loss of retirement contributions necessary to generate a target supplemental income, then calculate how much catastrophe insurance is necessary to generate the equivalent income in the target period.

Additionally, asset managers may want to consider extreme weather risks in the construction of retirement-oriented portfolios to build resilience for asset volatility during periods where shocks to household wealth are particularly expensive.

5.3 Adding alpha to retirement portfolios

As we discussed in the Model section, one practical way to mitigate the retirement savings shortfall is for individuals to include investments in assets with higher risk-adjusted returns in their longer-term retirement savings—especially if insurance is not available or hedging is too difficult. Increasing return per unit of risk should be agnostic to risk aversion or the focus on balance versus growth. While an ideal structure would incorporate alpha that is more likely to outperform during the extreme weather shock the specific saver might experience, a workable option would be including a general "alpha" overlay scaled to the expected income contribution loss due to natural disasters.

Including an allocation to alpha strategies in long-term savings can be a powerful tool for advisors to help individual clients offset the negative shocks to retirement savings, potentially plugging the gap that lower contributions from natural disasters create in terms of lost compounded returns. Importantly, however, alpha cannot be the answer for the broad population as the net supply of alpha is zero.

5.4 Improving market transparency

For financial markets to price risk appropriately, market participants need access to up-to-date information on the likelihood and damage estimates for natural disasters. Helping home prices properly reflect the likelihood of natural disasters might better guide families to geographies less likely to be severely impacted by climate change. Several options are available to the Federal government to improve the information prospective home-buyers have to understand the climate risks of their prospective home. A reasonable place to start is improving disclosure around flood vulnerability. Joel Scata of the National Resources Defense Council (NRDC) suggests requiring states to enact real estate disclosure laws that provide historical flood damage, costs, floodplain risk, and acknowledgement if previous owners received federal disaster aid to participate in the National Flood Insurance Program (Brody *et al.*, 2019). This could help facilitate a broader set of national guidelines on climate risk disclosures (FEMA, 2022).

To help impose price discipline on mortgage origination, Benjamin Keys from the University of Pennsylvania suggests having the Federal Housing Finance Agency (FHFA) formally study Fannie Mae and Freddie Mac's exposure to climate change risks to help encourage accurate pricing and management of environmental hazards (Wharton Risk Management and Decision Process Center, 2019). Indeed, Ouazad and Kahn (2022) suggest that currently the Government Sponsored Entities partially act as a *de facto* substitute for NFIP outside mandated flood insurance zones. Lastly, a recent Commodity Futures Trading Commission report on climate risk in the US Financial System proposes using Treasury's Financial Stability Oversight Council (FSOC) to accelerating monitoring the impact of climate risk on financial stability and facilitate coordination on rule-making between federal agencies (Behnam *et al.*, 2020).[18]

5.5 Adaptation and mitigation

Lastly, policymakers could explore policies focused on adaptation to help Americans deal with the risks associated with an increased propensity for natural disasters noted in this report alongside reducing emissions to mitigate the amplification and uncertainty of extreme weather events in the future. Formally, adaptation and mitigation would show up in our model as a lower probability and penalty to future income. As the public considers the form these measures should take, we encourage all stakeholders to explore the economic ramifications of extreme weather events and policy options on American families' long-term economic well-being.

6 Conclusion

This report examines the effect of extreme weather events on household finances, with a focus on drivers of long-term savings. We derive a life-cycle model of consumption and demonstrate that representing natural disasters as a shock to income may lower lifetime wealth. Statistical tests using various climate disaster datasets and economic drivers of household wealth suggests that retirement savings may have been penalized historically during extreme weather events. Both challenges leave American families in a precarious financial position—especially when considering the loss of compounded future retirement income.

The policy suggestions of the report for both market participants and policymakers are a natural extension of the initial findings, but are subject to uncertainty and can benefit from greater analysis. Diving into the industry differences of retirement penalties and distinguishing worker or management choices remains an important area for research.[19] However, progress in developing national guidance for climate change risks in the mortgage origination and valuation process would benefit both consumers and investors, helping households better understand the risk of where they live and work. The more information the American public has about the economic risks of natural disasters, the faster the country can move to address it.

Risk Warnings

Capital at risk. The value of investments and the income from them can fall as well as rise and are not guaranteed.

Investors may not get back the amount originally invested.

Past performance is not a reliable indicator of current or future results and should not be the sole factor of consideration when selecting a product or strategy.

Changes in the rates of exchange between currencies may cause the value of investments to diminish or increase.

Fluctuation may be particularly marked in the case of a higher volatility fund and the value.

Important Information

This material is for distribution to Professional Clients (as defined by the Financial Conduct Authority or MiFID Rules) only and should not be relied upon by any other persons.

Endnote

1 We use the terms "natural disasters" and "extreme weather" interchangeably throughout this paper. Natural disasters can cover events unrelated to weather or climate change, such as volcanic eruptions, and are included in the FEMA Disaster Declaration dataset. For the purposes of this analysis, the framework we propose can address both non-climate change drivers and climate change induced interruptions to retirement contributions.

2 Neighboring counties appeared to experience negative spillover effects in trade as well.

3 FEMA's target metric for Database assessment is New, Valid, or Updated Engineering (NVUE) percent attained. There exist private data vendors that offer more comprehensive flood map data for catastrophe modeling, such as Verisk, Fathom, and Reask.

4 Please note that this list of assumptions does not include all assumptions that may have been applied to a particular model and that the models themselves do not reflect every factor that can have a significant impact on results. Any changes to the model assumptions would affect the results shown in this material. The model is shown for informational purposes only. It is provided to quantify and analyze the impact of extreme weather-related shocks on lifetime consumption. Actual returns may vary. The model is based purely on assumptions using available data, based on past and current market conditions, and assumptions relating to available investment opportunities, each of which are subject to change. The underlying assumptions in the model do not include all assumptions that may have been applied to a particular model, and the model itself does not include every factor that can have a significant impact on the model. The model's simulated results have inherent limitations such as material economic and market factors that may have had an impact on actual results. No representation is made that the results shown will come to pass.

5 A "climate shock" commonly refers to a change in the probability distribution from which extreme weather events are drawn. Changes in the probability and magnitude of a disaster are explored later in our model.

6 Log income is typically modeled as a third-degree polynomial of age, i.e. so that if age is given by then $f(t) = \alpha + \beta_1 t + \beta_2 t^2 + \beta_3 t^3$. An example of a typical income curve is in Figure 1.

7 The optimal policy without a short-selling and borrowing constraint is to employ leverage early in life, which many people do via taking out a mortgage to purchase a house. While we exclude housing assets from our analysis for simplicity, presumably housing is one of the things most likely to be impacted by a negative extreme weather shock, and in the presence of such risks, a rational agent may choose to lever up less than they otherwise would in a leverage-unconstrained problem, given the higher exposure to climate shocks of the collateral used by individuals (i.e. a house) to secure a loan.

8 The parameterization of the discount factor value is in line with what is used in Cocco *et al.* (2005). The risk aversion parameter is set so that the equity allocation at the point of retirement is 40%. We set the elasticity of substitution ψ to be the inverse of γ, so in fact our utility function collapses to a power utility function. Capital market assumptions are in line with long-term estimates across a range of models. The labor income risk parameters are estimated using the same approach as in Cocco *et al.* (2005), using data from the Panel Study of Income Dynamics.

9 Note that in all results plotted here, consumption and wealth are scaled by permanent income. Permanent income at time is the cumulative sum of all permanent income shocks up until that point plus the individual specific fixed effect, i.e. so permanent income at time t is given by $N_{i,t} = exp\left(\sum_{n=20}^{t} u_{i,n} + \eta_i\right)$ with scaled consumption given by $c_{i,t} = \frac{C_{i,t}}{N_{i,t}}$ and scaled wealth given by $x_{i,t} = \frac{X_{i,t}}{N_{i,t}}$ This scaling allows us to collapse two state variables (wealth $X_{i,t}$ and income $Y_{i,t}$) into one.

10 For illustrative purposes only. The results shown are hypothetical estimates generated using Monte Carlo simulation, which is a statistical modeling technique that forecasts a set of potential future outcomes based

on the variability or randomness associated with historical occurrences. These estimates are projections used to understand the potential impact of policy functions on investment results. Projections are hypothetical in nature, do not reflect actual investment results and are not guarantees of future results. No representation is made that an investor will achieve results similar to those shown. Actual results could be higher or lower based upon a number of factors and circumstances not addressed herein.

11 The reason for the additional consumption post-retirement is entirely due to the additional alpha. In the decumulation phase, consumption rates are fully dependent on capital market assumptions, and the rate of consumption is independent of the level of wealth (whereas in the accumulation phase, consumption rates are dependent on labor income). The fact that wealth is growing at a higher rate when we have additional wealth directly corresponds to extra consumption.

12 The URL for OpenFEMA is as follows: https://www.fema.gov/openfema

13 For more on US Census Geographic Identifiers, see https://www.census.gov/programs-surveys/geography/guidance/geo-identifiers.html

14 COVID 2019 was recorded as a "Biological" disaster in the 2020 FEMA data, a type that rarely occurs in the data historically.

15 Thank you to Galina Hale for highlighting this possibility.

16 Thank you to Ronald Kahn for helping frame the discussion options.

17 Public Law 116–136: "Coronavirus Aid, Relief, and Economic Security Act" Sec. 2202–2203 (Enacted Mar. 27, 2020).

18 Regulations for insurance on mortgages and real estate development may also be helpful to reduce moral hazard and increase transparency on how the costs of natural disasters may impact households.

19 IRS Form 5500 changes may shed light on business management changes to worker benefits.

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