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August 6, 2025

Workshop Selection Committee
NBER

Dear Organizers,

I am writing to apply for the Graduate Student Workshop on Climate Finance. I am a rising fifth year Ph.D. candidate in Finance at Columbia Business School, with research interests in climate finance, investments, public finance and corporate finance.

My current focus is on quantifying the limits to effective adaptation to climate change - whether through place based policies, or migration - and using tools from finance to understand and address these limitations. In the paper I attach with this application, I study one key friction: beliefs about climate risk. I develop a framework to examine how different types of experiences – first-time, repeated, or through social networks – as well as individual characteristics, shape belief updating around extreme weather events. I study this in the context of registered investment advisors' portfolio allocations.

My job market paper, which I am currently developing, examines the role of financial constraints in the (mis)allocation of adaptation investments, specifically public investments in flood protection infrastructure in the US, and the resulting impact on local economic outcomes.

Beyond my job market paper, in future research I hope to focus on how to finance adaptation in the low-income and developing countries, given the changing geographies and economies due to the climate transition.

I would be honored to participate in the dissertation-writer workshop to receive feedback on my work, engage with fellow researchers, and contribute to the growing field of climate finance.

The expected completion date of my Ph.D. is May 2027. I will be on the job market in Fall 2026. My faculty advisor, Pari Sastry (psastry@wharton.upenn.edu), is familiar with my research and would be happy to provide a reference.

Sincerely,
Meha Sadasivam

Meha Sadasivam

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Research area

Climate Finance, Investments, Public Finance, Corporate Finance

Education

Columbia Business School — New York, NY
PhD in Finance — 2021 – Present
MS in Financial Economics — 2021

Birla Institute of Technology and Science, Pilani — Hyderabad, India
B.E. Electrical & Electronics Engineering — 2016

Research

Extreme weather and risk perception
Bernstein & Tamer Centers' Joint Doctoral Research Grant (2023)

Different shades of ESG funds
with Simona Abis, Andrea Buffa

Where does the mortgage climate risk go?
with Jack McCoy

Climate Innovation
with Caroline Flammer, Olivier David Zerbib

RA for Pari Sastry — 2024
RA for Jesse Schreger (Country Risk) — 2020 – 2021
RA for Wei Jiang (Appraisal Arbitrage) — 2019 – 2020

Teaching experience

Instructor, MS Math Bootcamp — 2024

TA, MBA Capital Markets (Kent Daniel, Simon Oh) — 2024 – 2025
TA, PhD Big Data and Finance (Harry Mamaysky, Michael Johannes) — 2021 – 2024
TA, MBA Capital Markets (Suresh Sundaresan) — 2022
TA, MBA Advanced Corporate Finance (John Moon) — 2022
TA, MBA Debt Markets (Suresh Sundaresan) — 2021
TA, PhD Computing for Business Research (Kriste Kristovski) — 2020
TA, MS Python Boot Camp (Lira Mota) — 2020

Conferences/Workshops

ARCS 2025 - PhD Workshop — 2025
Princeton Initiative: Macro, Money and Finance — 2023
Yale Summer School in Behavioral Finance — 2022
Stanford Big-Data Initiative in International Macro-Finance — 2021

Scholarships

Doctoral Fellowship (Columbia Business School) — 2021 – 2026
Paul and Sandra Montrone Doctoral Fellowship — 2021, 2024
50% Tuition Scholarship (Columbia Business School) — 2019 – 2021

Work experience

Bank of America, Global Research — New York, NY
Summer Associate - ESG/ Quant Research — 2020

D.E. Shaw & Co — Hyderabad, India
Software Engineer — 2016 – 2019

J.P. Morgan — Mumbai, India
Junior Analyst Intern - M&A — 2016

Other activities

PhD Seminar Organizer — 2024 – 2025
DEI Standing Committee — 2020 – 2021

Basketball Team, Music Club, Department of Sponsorship, Student Welfare Division (BITS Hyderabad) — 2012 – 2015

Volunteering and Outreach
Core Committee member, CSR Club (D.E. Shaw) — 2017 – 2019
Enactus (BITS Hyderabad) — 2014 – 2015
SPICMACAY, Hyderabad — 2013

Personal

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Updated July 2025

Extreme weather and risk perception

Meha Sadasivam*

June 2025

Abstract

This paper examines how investors differentially update their climate risk perceptions following extreme weather events. Studying registered investment advisers' portfolio allocations, I document a significant shift toward safer assets (government bonds) and away from risky assets (equity) following local extreme weather disasters. The magnitude of this portfolio reallocation varies systematically with political ideology, a proxy for heterogeneous prior beliefs about disaster risk. Democratic counties exhibit the most persistent risk-off behavior when directly experiencing disasters, particularly during first-time exposures compared to subsequent events. The updating of beliefs also occurs through social networks, with the strongest effects observed in swing counties, where prior beliefs about disaster probabilities are less firmly anchored. These findings complement the literature that suggests political ideology plays a crucial role in how investors process climate risk information, and provides novel insights on the strength of each step in the belief updating process.

*ms5941@gsb.columbia.edu. I am grateful to Kent Daniel and Pari Sastry for all their advice and encouragement throughout this project, as well as Simona Abis, Caroline Flammer, Stefano Giglio, Harrison Hong, Eric Johnson, Sandra Matz, Simon Oh, Stijn Van Nieuwerburgh, Laura Veldkamp and all participants in the finance seminars, PhD seminars, and the financial economics colloquium at Columbia, and the ARCS Annual Research Conference PhD Workshop for helpful feedback and suggestions. This was supported by the Bernstein and Tamer Centers' joint doctoral research grant (2023).

1 Introduction

In recent years, extreme weather events have become more frequent and have caused increasingly significant damage. Figure 1 from the National Oceanic and Atmospheric Administration illustrates the growing number and frequency of billion-dollar disasters. Another growing issue is the political polarization that inflicts society today. At the intersection, we are faced with an issue that is existential, that relies on a consensus to pave a path forward to try and mitigate losses of such high magnitude in the future.[1]

Extreme weather provides a unique setting where the event on its own can be scarring and push individuals to be pessimistic about the future, as documented in Johnson and Tversky (1983) and Goetzmann, Kim, and Shiller (2024), but it also brings some indisputable evidence about the frequency of occurrence of the disaster experienced and the extent to which one may expect damages in the future that affect their consumption stream. However, the process of updating beliefs about disaster probabilities in response to these experiences varies systematically with individual characteristics, endogenous network preferences, information sources, and inherent biases (Kamenica and Gentzkow (2011), Gentzkow, Wong, and Zhang (2024), Malmendier and Veldkamp (2022)).

Studying this from an investor's point of view allows us to capture some key mechanisms at play - how much do extreme weather events trigger a portfolio choice response? How much of the change can be explained by first hand experiences, and how much does holding on to prior beliefs dampen the response? How does the learning process evolve over time with multiple experiences, and how does it vary by distance from the disaster? In this paper, I shed some light on how investment decisions differ depending on your prior beliefs about an underlying source of risk - specifically climate risk - to your future consumption. I develop a conceptual framework to help formalize how much experiencing public signals mitigate the lack of precision with which an investor is able to observe the "true underlying climate risk process".

[1] See for example, this recent article by the Brookings Institution.

Specifically, I focus on portfolio choice following experiences of extreme weather events that are FEMA presidentially declared disasters, by *Registered Investment Advisers* or RIAs who are *local*, ie they operate out of just one location[2][3]. The assumption here is that these RIAs are representative of the county they operate out of. These RIAs manage around $20 Trillion in assets under management and span over 620 counties. Figure 2 shows the time series of AUM and the number of counties spanned by these local RIAs, as well as multi-office RIAs. They manage less than a quarter of the AUM that the multi office RIAs do, but operate out of more counties.

To capture differences in prior beliefs and asymmetric belief updating on this polarizing topic, I follow the formalization in Meeuwis, Parker, Schoar, and Simester (2022) where these differences are summarized by political ideology. I use the 2016 voteshare of the county to proxy for the political ideology of the RIA, with the key assumption being the RIA firm embodies all the characteristics of the county it operates out of. This is the key source of heterogeneity in the analysis. Using stacked event studies around the FEMA weather disasters among counties with at least one RIA present, I compare the response of the treated counties with counties that have never experienced a disaster since 2013. I track portfolio reallocation across asset classes, specifically focusing on the *risky* asset class - exchange traded equity, and the *safe* asset class - government/ agency bonds, and a unique asset class that captures both the riskiness from local, geographically concentration as well as the safety of a public finance fixed income instrument - state/local bonds. I focus on the extensive margin in this paper, since I am unable to observe the within asset class reallocation using the form ADV.

Using this margin of variation, I shed some light on the learning process about climate risk. I begin by studying responses to the first FEMA weather disaster that hits the county in recent history. I find a persistent shift toward safe assets, driven almost entirely by the democratic county RIAs, with an equal magnitude of a shift away from risky exchange traded

[2]This is measured based on their reported number of 'other offices', from their filed Form ADV

[3]Mamaysky and Zhang (2023) has a detailed description of the data

equity. I next look at the responses to the subsequent disasters, where an extreme weather event in the region is no longer as much of a surprise. This leads to a muted shift toward safe assets, again driven by the democratic county RIAs, which is not as persistent, suggesting the lesser weight being put on the repeat experience. Finally, to capture the network based effect of experiencing the disaster only through friends/family, I focus on distant counties that are more socially connected to the disasters, but do not experience the economic impact or physical damage first hand. I find that the flight to safety in this case is driven by the politically moderate county RIAs, suggesting that there is rational updating through the network when there is less weight placed on priors and the information observed is not as biased.

The results for the state/local bonds are also particularly interesting. Following the first disaster, democratic RIAs shift toward state or local bonds in the subsequent years following the weather disaster. In the case of repeat disasters, the republican RIAs shift toward state or local bonds, which captures an interesting phenomenon of investing more in a region which already has proven to have experienced multiple spells of significant economic damage.

These results suggest that the learning process is asymmetric, and there are marked limitations to the extent to which these public signals mitigate prior beliefs.

Related Literature: This paper contributes to the growing literature at the intersection of climate finance and asset pricing, with an emphasis on the role of subjective beliefs in investment decision making. Specifically, the paper studies a unique setting through local investment advisory firms, captures portfolio choice at the extensive margin, and isolates different channels at play in the learning process about climate risk.

First, this paper contributes to the growing literature on portfolio responses to extreme weather. Alok, Kumar, and Wermers (2020) look at the portfolio responses of mutual fund managers following natural disasters. They focus on a risk salience channel, rather than the belief updating channel, and show that mutual fund managers close to the disaster zone reduce their holdings of stocks in disaster-affected areas, relative to distant fund managers.

Their results go against the home bias channel of having superior information about fundamentals of the local companies, since the stocks most sold seem to outperform over the next two years, which suggests that proximity to disasters can lead to price distortion and negatively affect fund performance. Building on these insights about geographic proximity, Alekseev, Giglio, Maingi, Selgrad, and Stroebel (2022) also study mutual fund managers who experience extreme heat in their area, and find that at the aggregate, managers tilt toward and away from similar industries - which they deem to be hedges against climate risk. The importance of local climate experience extends beyond institutional investors to individual investor portfolio choice. Specifically, Choi, Gao, and Jiang (2020) find that carbon-intensive firms earn lower stock returns following experiencing abnormally warmer temperature, captured through the under-performance of their "Emissions minus Clean" portfolios. They show that these return patterns are not entirely due fundamental information, and find a shift in ownership from retail traders to block-holders (those who own more than 5% of shares outstanding, and are not institutional investors). Similar to these papers, I find that investors' beliefs about climate risk are affected by locally observed extreme weather events. However, studying RIAs allows me to document a distinct extensive margin response - reallocation between stocks and government bonds, rather than within equity holdings - which provides broader insights into how extreme weather experiences shape general risk perceptions.

Beyond direct experience, learning about climate risk through social networks has emerged as an important channel. This is documented in various papers that focus on flooding that is geographically distant but close in terms of network distance, where they observe higher flood insurance uptake (Hu (2022), Ratnadiwakara (2020), Xu and Box-Couillard (2024)). These studies build on the broader social finance literature following Bailey, Cao, Kuchler, Stroebel, and Wong (2018). In this paper, I extend this line of research by studying how extreme weather experiences through social networks affects portfolio choice.

Particularly relevant to my work is Anderson and Robinson (2024), where they show

asymmetric updating of climate risk concerns following a heatwave in Sweden by capturing households retirement portfolio choices through multiple surveys. They find that men in the strong right-wing regions become less concerned about climate change, relative to other areas, and women in general became more concerned. The polarization in beliefs was reflected in their investment behavior - the more concerned actively rebalanced their portfolios toward fossil-fuel exclusion funds. The system's transition toward green investments overall, however, is driven by the funds themselves re-branding and embracing a green label, and not individual active choices to buy into greener funds. This work expanded on their earlier findings in Anderson and Robinson (2019), where they document through a survey around the heatwave in Sweden in 2014, that those who are most concerned about future climate disasters are more likely to hold green mutual funds. Similarly, my paper sheds light on the asymmetric updating of beliefs about underlying climate risk, but through a different lens - observing changes in asset class level holdings through SEC mandated filings of investment advisors. This does not allow me to study the loading of specific assets on physical risk or transition risk.

The broader literature on belief updating and learning about global warming offers additional context for understanding these investment responses. Deryugina (2013), through survey responses, documents that more extreme temperature deviations lead to larger belief changes, but experiencing a long period of abnormal temperature doesn't have a larger effect, and that conservatives are significantly affected. Sisco, Bosetti, and Weber (2017) find attention to climate change increases after extreme weather events, especially when they are locally abnormal. Recent work by Faralli (2024) finds that analysts rationally look for more information related to physical and transition risks post experiencing disaster which leads them to better forecast the performance of companies not directly hit by the disaster, highlighting the role of beliefs. Further supporting the importance of personal experience, Di Giuli, Garel, Michaely, and Romec (2024) find that fund managers personal experiences with abnormal heat increase their likelihood of supporting climate proposals.

A second important strand of literature focuses on climate beliefs without specific interaction with extreme weather. Ceccarelli and Ramelli (2024) study how a one-time information intervention affects beliefs about the climate transition, rather than experiences. They provide causal evidence to suggest that investors who are more optimistic about the transition to renewable energy and away from fossil fuels, expect higher returns and lower risk and are therefore more likely to invest in green funds, especially for investors without strong environmental preferences. They also highlight the role of second order beliefs - the fact that they expect people to be more worried about climate change in the future makes investors anticipate higher green returns, and show marked differences in optimism by political ideology. Aron-Dine, Beutel, Piazzesi, and Schneider (2024) use a household survey in Germany coupled with a quantitative model to illustrate that there is unmet demand for safe green assets like green bank deposits, which combines households non-pecuniary preferences for greenness along with their general preference for safe assets. My findings complement this work by documenting a flight to safety which aligns with a broader notion of increased risk aversion.

Ultimately, this paper contributes to the literature on the role of beliefs in portfolio choice following Giglio, Maggiori, Stroebel, and Utkus (2021b), and the role of political ideology (Hong and Kostovetsky (2012), Meeuwis, Parker, Schoar, and Simester (2022), Cassidy and Vorsatz (2024)) in shaping investment decisions (Baldauf, Garlappi, and Yannelis (2020) also highlights the role of political ideology in forming beliefs about the underlying climate risk through house prices), with a particular focus on how political ideology drives differential belief updating following extreme weather episodes.

2 Theoretical Framework

The goal of this framework is to formalize how experiencing the same weather disaster — or receiving the same public signal about the underlying climate risk process — can lead

to different responses depending on initial beliefs about disaster probabilities. Gentzkow and Shapiro (2006) provides a theoretical basis for why learning about disaster risks might be distorted by reputational concerns. Building on this foundation, I develop a stylized model of heterogeneous beliefs about climate disaster risk across different political groups, following Meeuwis, Parker, Schoar, and Simester (2022). The model demonstrates how political ideology influences both initial beliefs and the processing of new information about climate risks, ultimately affecting consumption and investment decisions.

Setup and Beliefs: Consider an economy with three types of investors $i \in \{D, R, S\}$, representing Democratic, Republican, and Swing voters respectively. Each type begins with different prior beliefs about the probability of climate disasters, reflecting their political ideology. These initial beliefs for each type i are normally distributed:

$$\lambda_0^i \sim \mathcal{N}(\mu_i, \sigma_i^2) \tag{1}$$

where λ_0^i represents the initial belief about disaster probability, μ_i is the mean belief, and σ_i^2 captures belief uncertainty. The mean beliefs reflect political priors, with Democrats holding the highest probability assessment of climate disasters, Republicans the lowest, and Swing voters in between:

$$\mu_D > \mu_S > \mu_R \tag{2}$$

Both Democrats and Republicans hold their beliefs with high conviction (low σ_D^2 and σ_R^2), while Swing voters exhibit greater uncertainty (high σ_S^2).

Information Structure and Learning: In each period, investors observe public signals about disaster probability. For each type i, these signals take the form:

$$s_i^p = \lambda + \varepsilon_i^p, \quad \text{where } \varepsilon_i^p \sim \mathcal{N}(0, (\sigma_i^p)^2) \tag{3}$$

where λ represents the true probability of a climate disaster and ε_i^p captures noise in the

signal.

Belief Updating and Consumption: Upon observing public signals, investors update their beliefs following Bayes' rule. The posterior mean belief for each type is:

$$\mu_i^{\text{post}} = \frac{\frac{\mu_i}{\sigma_i^2} + \frac{s_i^p}{(\sigma_i^p)^2}}{\frac{1}{\sigma_i^2} + \frac{1}{(\sigma_i^p)^2}} \tag{4}$$

The weight on the prior and the new information through the signal depends on the precision with which investors hold on to their prior - or conviction in their prior belief about the level, and the precision with which they observe the signal. This signal precision also may be influenced by the damage they directly experienced, the level of disruption to daily life, etc. Ultimately, these updated beliefs directly influence consumption expectations. The consumption process incorporates disaster risk as follows, which draws from Giglio, Maggiori, Rao, Stroebel, and Weber (2021a):

$$c_{t+1} = \mu + J_{t+1}, \quad \text{where } J_{t+1} = \begin{cases} -\xi & \text{with probability } \lambda_i \\ 0 & \text{with probability } 1 - \lambda_i \end{cases} \tag{5}$$

Here, μ represents baseline consumption growth, and ξ captures the magnitude of consumption loss in the event of a climate disaster. Through this channel, it enters the investors portfolio optimization problem.

Sequential Disaster Learning: When a second disaster takes place, investors receive another public signal that updates their already-updated beliefs. This creates a compound updating process where beliefs evolve through sequential disaster experiences. After the first disaster at t, agents update their beliefs according to the original structure. Upon experiencing a second disaster at $t + k$, they receive a new signal:

$$s_{i,t+k}^p = \lambda + \varepsilon_{i,t+k}^p, \quad \text{where } \varepsilon_{i,t+k}^p \sim \mathcal{N}(0, (\sigma_{ik}^p)^2) \tag{6}$$

The level of precision of the second signal is determined by two forces. First, given

the repeated nature, there may be more directed information, reinforcement of the higher probabilities of a disaster hitting the region. In contrast, having lived through the disaster once and survived may make it easier to take it less seriously, ie the incurred damage may not be as unmanageable given you know how to deal with it. The subjectivity of this is captured by subscript i, as well as k to capture the time between both disasters experienced. The sequential updating leads to a compound posterior, which is of the form:

$$\mu_i^{\text{second}} = \frac{\frac{\mu_i^{\text{post}}}{(\sigma_i^{\text{post}})^2} + \frac{s_{i,t+k}^p}{(\sigma_i^p)^2}}{\frac{1}{(\sigma_i^{\text{post}})^2} + \frac{1}{(\sigma_{ik}^p)^2}} \tag{7}$$

This sequential structure allows us to trace the evolution of beliefs through multiple disaster experiences. Repeated exposure to disaster signals can lead to belief convergence across political groups, though the rate of convergence varies with initial belief precision. Also, given the level of surprise after the first disaster experience may not be as much, and the added element of having survived multiple episodes of extreme weather events, there could be muted responses to the subsequent disaster.

Learning through the network: When agents learn about disasters through their social networks rather than direct experience, the information transmission becomes subject to network-specific distortions. The network-mediated disaster signal received by region i from region j can be expressed as:

$$s_{ij}^n = \lambda + \nu_{ij}, \quad \text{where } \nu_{ij} \sim \mathcal{N}(0, (\sigma_{ij}^n)^2) \tag{8}$$

The variance of the network-transmitted signal, $(\sigma_{ij}^n)^2$, increases with network distance and ideological difference between regions. This increased noise in network-transmitted information particularly affects regions with strong partisan priors (low σ_i^2), as they discount noisy signals more heavily.[4] Consequently, swing regions (high σ_i^2) may exhibit stronger

[4]This is an extremely simplified and stylized equation that captures many interesting phenomena to do with information being transmitted through the network only through the noise or variance parameter as of now. For example, the network may transmit biased signals which may be far from true as in Bowen, Dmitriev, and Galperti (2023), or may be perceived differently depending on how much the investors identifies

responses to network-transmitted disaster information, as they are more willing to update beliefs based on indirect evidence. This creates a pattern where belief updating from network-transmitted information may be stronger in politically moderate areas than in partisan strongholds.

Model Implications: This framework generates several key implications. First, the heterogeneity in initial beliefs (μ_i) and belief precision (σ_i^2) leads to systematic differences in how different political groups process the same climate-related information. Second, the Bayesian updating mechanism implies that groups with stronger priors (Democrats and Republicans) require more evidence to change their beliefs compared to groups with weaker priors (Swing voters). The additional channel of subjective signal precision adds another layer that could slow learning further despite experiencing the same disaster.

The model generates the following testable predictions. First, following a disaster, we would expect to see a stronger flight-to-safety response in Democratic-leaning investors. This is more muted for the Republican-leaning investors, and is more volatile for the moderates, given the lower weight on their prior. Second, if this is repeat exposure, or the disaster is not as much of a surprise, the response will be of lesser magnitude relative to the first disaster experience. Third, when experiencing through the network, the swing regions (high σ_i^2) may exhibit stronger responses to network-transmitted disaster information as they are more willing to update based on indirect evidence.

Taking it to the data: The model thus provides a framework for understanding how political ideology shapes both the interpretation of climate risk and subsequent economic decisions. In this paper, the extreme weather episodes are public signals, observed only if directly experienced in the county in which the RIA is located, or in a county that the RIA is closely socially connected to. The priors are dependent on the political leaning of the RIA. When a disaster hits, the update in individual beliefs of disaster probabilities and expectations of future consumption growth is captured by changes in portfolio holdings -

with who transmitted the information (Malmendier and Veldkamp (2022)).

since I am unable to directly observe belief changes.

3 Data and Measurement

3.1 Form ADV Data

To obtain information about Registered Investment Advisors located across the country in different counties, I use the Form ADV filings (described in detail in Mamaysky and Zhang (2023)). This is an annual filing, mandated by the SEC for firms that manage over $100 million. Beginning in 2017, they report their share of holdings in 12 asset classes, which is a key variable of interest in my analysis.

To study the effects of extreme weather episodes at the county level, I map investment advisers to their respective counties from the zip-codes provided in the filing, which corresponds to the advisor's principal office and place of business[5]. In the case of multiple counties associated with one zip-code, I map it to the county with the highest residential share. I restrict the sample to investment advisers that operate out of a single location, where the "other offices" is set to 0 explicitly. For the main analysis, I do not distinguish firms by clientele, or size.

3.2 Weather Events

I obtain weather episodes from NOAA's Storm Events database. This is a comprehensive database that consists of 46 weather events across the US from 2000. I convert them to the county-year-month level, and merge with the FEMA Disaster Declaration database. This lists all official FEMA Disaster Declarations starting from 1953, and consists of three disaster declaration types: major disaster, emergency, and fire management assistance. Merging ensures that the disasters are all weather related.

[5]Crosswalk downloaded here.

3.3 Other county variables

To capture the political affiliation of the county, I get the party vote share from the MIT Election data[6]. Specifically, I use the 2016 election vote share. I classify a county as democratic or republican if there the party received above 60% of the votes, and the rest are neutral (40–60% of voteshare in either party). Population is the 2020 census population estimates. Social connectedness at the county level is from Bailey, Cao, Kuchler, Stroebel, and Wong (2018). Distances are from the 2010 county distances data from NBER [7].

4 Portfolio changes and beliefs

4.1 Difference in differences strategy

Portfolio holdings and climate risks present several endogeneity concerns. For one, sophisticated RIAs may already incorporate climate risks into their portfolio strategies through diversification, hedging, or avoiding highly exposed assets. They may locate themselves in less risky areas to start with. Both of these suggest that the results from an analysis of responses to climate shocks would then represent a lower bound. Weather disasters help mitigate endogeneity from anticipation effects by providing plausibly exogenous variation in local conditions, as their precise timing, location, and intensity are determined by complex atmospheric interactions that are effectively random. While certain areas may be more prone to specific types of disasters, the exact occurrence of an event is unpredictable beyond short-term forecasts and occurs independently of economic, social, or political conditions that might affect outcomes of interest.

To capture portfolio responses, I setup the analysis to use stacked event studies.[8] An event is defined as a FEMA weather disaster in a state in a particular month. Each stack is identified by a unique stack id, and has its own treatment and control group. For the main

[6]Downloaded here
[7]Downloaded here
[8]I closely follow the methodology in Hu (2022), and refer to code here to set up the analysis.

analysis, treatment is defined as a county experiencing a FEMA-declared disaster between 2018–2022, having had no such disasters since 2013 - for the first time in recent history. The control group consists of counties that have remained FEMA disaster-free since 2013. The sample is further restricted to RIAs that have not moved in the entire filing period 2017-2023, and have filed the Form ADV every year (2017-2023).

The final sample for this analysis consists of 18 unique months with FEMA episodes, which hit 51 unique counties and 653 RIAs. Table 1 presents summary statistics. [9]. Column 1 describes the control counties, which were never hit by a FEMA disaster since 2013. Column 2 describes the treated counties, hit for the first time since 2013. Columns 3-5 describe the treated counties split by their 2016 voteshare (>60% Democratic votes, >60% Republican votes, 40–60% for either party). *# Events* are the total number of FEMA disasters in the analysis that involved each type of county, *# Counties* is the median number of counties that are a part of each event study, *# RIAs* is the median number of RIAs that are a part of each event, *Total AUM* is the median of the average assets under management of the RIAs that are a part of each event, and the values corresponding to the asset classes are the median of the average percentage of the AUM held in each of them, per event.

The summary statistics suggest that across all counties, RIAs hold the most of their AUM in exchange traded equity and mutual funds/ETFs, followed by cash and fixed income (government bonds, state/local bonds, investment grade corporate bonds). The median control county's AUM is much higher than the rest. While the treatment and control sample are not tightly matched, restricting the counties to the ones that have an RIA present might mitigate some of the systematic differences that could exist across these different counties. Also, to the extent that there is no unobservable time-varying differences across counties, the county fixed effects should capture any other systematic differences that might exist.

[9]Table C.6 lists the FEMA disasters that are a part of the main analysis

I use the following regression specification to capture the average treatment effect:

$$Y_{it} = \beta_1 \text{Treated}_{c(i)} \times \text{Post}_{it} + \beta_2 \text{Treated}_{c(i)} + \beta_3 \text{Post}_{it} + \alpha_{c(i)e} + \alpha_{te} + \alpha_i + \epsilon_{it} \tag{9}$$

Y_{it} is the percentage in AUM held in any of the asset class buckets reported by RIA i on the Form ADV at time t, $\text{Treated}_{c(i)}$ is a dummy variable for a county c that RIA i belongs to, which equals 1 if the county was hit between 2018–2022 by a FEMA declared weather disaster for the first time since 2013, and equals 0 if never hit since 2013. Post_{it} is dummy variable for time t and RIA i that equals 1 if $t >$ time of the event taking place. This depends on the RIA i since the date of the form ADV filing can be different across RIAs. $\alpha_{c(i)e}$ are county $c(i)$ x event e fixed effects, α_{te} are time t x event e fixed effects, and α_i are RIA i fixed effects. Standard errors are clustered at the county x event level. The county x event and time x event fixed effects are required to absorb any other event specific variation, since the same control counties might appear in multiple panels, and each stack contains overlapping time periods.

The main focus of this paper is on the differential updating of beliefs depending on political ideology as proxied for buy differential portfolio responses, holding all else equal. To study this, I add an interaction term to equation (9).

$$Y_{it} = \beta_1 \text{Treated}_{c(i)} \times \text{Post}_{it} \times \text{Party}_{c(i)} + \beta_2 \text{Treated}_{c(i)} \times \text{Post}_{it} + \cdots + \alpha_{c(i)e} + \alpha_{te} + \alpha_i + \epsilon_{ict} \tag{10}$$

where $\text{Party}_{c(i)}$ is the political affiliation of the county, measured by 2016 voteshare ($>$ 60% would be Democratic or Republican, 40–60% are "neither"). The interaction term $\text{Treated}_{c(i)} \times \text{Post}_{it} \times \text{Party}_{c(i)}$ is the key variable of interest.

The difference-in-differences framework relies on three key identifying assumptions within each event stack: first, treated and control counties would have followed parallel trends in outcomes absent treatment; second, the Stable Unit Treatment Value Assumption (SUTVA)

must hold, meaning disasters in treated counties do not spillover to affect neighboring control counties; and third, the estimated coefficients represent weighted averages of event-specific effects, with weights determined by the number of treated units in each disaster event. Considering the counties are restricted to those where there is at least one RIA present, there is a certain amount of selection that could help mitigate concerns about systematic differences across treatment and control counties. Spillovers are harder to measure, but FEMA disaster declarations are comprehensive and cover all the counties that were badly hit. To ensure parallel trends, I modify the specification in (10) to capture the dynamic treatment effect.

$$Y_{it} = \beta_0 + \sum_{\tau=-3,\tau\neq-1}^{3} \beta_{1\tau}\text{Treated}_{c(i)} \times \text{Relative Year}_{i,\tau} \times \text{Party}_{c(i)} + \cdots + \alpha_{c(i)e} + \alpha_{te} + \alpha_i + \epsilon_{it} \tag{11}$$

where Relative $\text{Year}_{i,\tau}$ is dummy variable that equals 1 at $t+\tau$ years for RIA i if t is the time of the filing closest to the event taking place, after the event.

4.2 Predictions/ Hypotheses

The analysis enables us to test some of the predictions of the theoretical framework developed in Section 2. I capture the flight-to-safety highlighted in the model in the narrowest sense, as a shift toward safe government bonds, and away from risky exchange traded equity.[10] The third asset class is the state or local bonds, which might be considered safe, but due to its loading on spatially concentrated assets may be perceived as more risky if there is a higher likelihood of weather disasters in the future. These are the key dependent variables in the analysis. This leads to the following hypotheses:

Hypothesis 1: Democratic RIAs tilt towards government debt and away from equity

[10] An extension would be to look at shifts into money market mutual funds or other equivalent safe assets.

following their first extreme weather event. The effect is persistent, highlighting the role of shifted beliefs.

Hypothesis 2: Republican RIAs show a much more muted response, maybe even in the opposite direction. The effects will not be persistent.

It is unclear which direction the moderates will tilt. If they see the signal with a high precision, they may tilt toward safer assets.

4.3 Results

Table 2 reports the results from running the specification in (10), restricting the sample such that treatment and control are within the same state for an event. This was in order to reduce the impact of unobservable confounders, like the differences in taxes across states.[11] The results confirm Hypotheses 1 and 2 described above: following a surprising extreme weather episode, Democratic county RIAs strongly tilt their portfolios toward government and agency bonds, by 3%, significant at the 1% level, with an equal decrease in share of AUM in equity in terms of economic magnitude, although the result is not statistically significant. Republican county RIAs show a weaker increase of about 1.2% toward government bonds, although these results are quite noisy given the small sample size and the lack of sample prior to t-1 (the disasters were all earlier in the sample for the Republican RIAs). Surprisingly, Democratic RIAs also increase their tilt toward State/Local bonds by 0.8%, also significant at the 1% level. This suggests that they are not as worried about loading on increasing risk in a particular location, and to the extent that these bonds are of the state/county they operate out of, may suggest that they anticipate rebuilding in the future and a boost to economic activity and growth.

The dynamic treatment plots in Figure 3 suggest a persistent large shift toward gov-

[11] The results for the average treatment with similar state restrictions are reported in Table A.1. Following experiencing a FEMA disasters, RIAs tilt their portfolios by 0.65% toward government bonds which is significant at the 10% level, and by 0.33% toward state or local bonds, significant at the 5% level, relative to RIAs in the control counties. They also tilt their portfolios away from exchange traded equity by -0.7%, which is not statistically significant but the magnitude almost exactly offsets the tilt toward government bonds.

ernment bonds for the democratic RIAs, reaching around 5% in year 3 post disaster. Surprisingly, there is a strong opposite effect in the neutral RIAs. It is hard to interpret the republican RIA results given the small sample size, and missing data pre t-1 for the events, but the immediate temporary increase in the share of government bonds suggests that they might be temporarily driven to safer assets, so the shift in beliefs was temporary or not enough to significantly update their posterior beliefs about disaster probabilities. The dynamic average treatment effects are plotted in Figure A.1. These plots suggest that there are no parallel trends, and a persistent shift away from equity, and into government and agency bonds, as well as state and local bonds, suggesting that overall there is a flight to safety, which we can attribute to being driven almost entirely by democratic RIAs. The persistence also helps confirm the hypothesis that this could indeed be a shift in beliefs about a systematic risk in the long run, and not a temporary reaction to an extreme one-off event.

4.4 Subsequent Disasters

In order to shed some more light on the learning process, and understand how responses differ when the weather disaster is not as much of a surprise, I repeat the analysis above, but change the treatment to now include be disasters that weren't the first FEMA extreme weather disaster in the county since 2013. This means that the county had experienced at least 1 such event from 2013 until the disaster used for the stacked event study. The control counties remain the same, which are those that have not experienced a FEMA weather episode since 2013. The conceptual framework highlights how the learning process with subsequent disasters may be different depending on how affected you were the first time, the fact that you aren't as surprised about it, but ultimately could be pushing up your belief about underlying probability of another disaster taking place soon, given you have experienced multiple of these in a short span of time.

Table 3 reports the results from running the same specification as in (10) but now with

the modified treatment variable.[12] The results align with the predictions from the model, in the sense that the response is not as strong as in the case of the first disaster. Democratic RIAs increase their share in government or agency bonds by 0.65%, significant at the 5% level, which is less than a third of the magnitude observed in the case of the first disaster. Democratic RIAs also decrease their share in Equity by 0.45%, which is not statistically significant but also somewhat offsets the increase into government and agency bonds, and seem to weakly decrease their share in state/local bonds. This is consistent with the idea that you may not want to continue to invest in a region that has now experiences multiple weather episodes.

Also consistent with the model are the results for the Republican RIAs, who do not increase their share in government bonds, suggesting that they may not updating their beliefs as strongly as they might have following the first disaster. Surprisingly, Figure 4 suggests that they seem to persistently increase their share in state or local bonds in the years following the disaster. Given the limitations to the data currently, I am unable to observe what these bonds actually are, but to the extent that these are the bonds of your locality, this result might mirror the choices to continue to live in an area despite facing multiple extreme weather episodes.

4.5 Experiencing disasters through the social network

The final analysis studies how disasters are perceived when experienced through the social network, which is as good as experiencing it first hand, but without the direct economic impact, if someone very close to you experienced an extreme weather disaster. To capture this, I modify the treatment variable to be equal to 1 if a county at least 750 miles away, that has not experienced a disaster of its own in the sample period, is more *socially connected* to the region hit by a disaster relative to other counties within the state it belongs to, following

[12]Note that the current specification doesn't limit the sample to include ones that only experience their second disaster within the window 2018-2022, which would be a cleaner way to capture the effect of a second (subsequent) disaster, and then potentially expand this to the third or fourth if there are such cases.

Hu (2022). Socially connected is measured using the Social Connectedness Index from Bailey et al. (2018) which provides a ranking of county-county pairs based on the number of facebook friends one county has in the other county. I weight these ranks by the population of the counties hit by the disaster, to capture the intensity with which the effect of the disaster might be disseminated through the network. The goal is to isolate the network channel, such that the only way these connected counties experience a weather disaster is through their network.

Table 4 reports the results from running the specification in (10), however without the state restriction, and now with this modified treatment variable to capture high social connectedness. These connected counties may have experienced multiple weather episodes in the sample period from 2018-2022, which potentially confounds the results given that an earlier treated county may show up in a control county. The results as of now will therefore be noisy estimates. The results suggest that the neutral counties are the ones to drive the flight to safety when experiencing disasters through the network, which aligns with the model – since neutral counties have noisier priors, and they are likely to observe signals with the least noise or bias, they update most strongly. The average treatment effects presented in Table A.3 also suggest that these neutral counties are the ones driving these results.

Figure 5 suggests that there are issues with the pre-trends for the democratic and republican counties especially, but the results are strongly driven by the neutral counties.

5 Conclusion

This paper quantifies the forces driving belief updating about climate risk through the lens of portfolio responses. While heterogeneous learning across individual characteristics is well-documented in the literature, the setting of local investment advisory firms offers unique insights into how people assess consumption risks from contentious issues like climate change. Understanding how beliefs evolve, update, and influence investment decisions is particularly

crucial given that much of this process operates through expectations.

Using asset class data from Form ADV, this paper demonstrates a heterogeneous flight to safety that varies with political ideology. However, given the limitations of the data, in this paper I do not look at the intensive margins within equity, or the specific holdings of mutual funds or ETFs that might also be perceived as safe assets.

Greater data granularity would allow us to distinguish between general increases in risk aversion and climate-specific risk responses. Moreover, if post-disaster flights to safety create persistent demand for safer assets, there may be untapped potential for green safe assets, such as bank deposits earmarked for climate mitigation projects, as suggested by Aron-Dine et al. (2024).

Beyond climate change, our increasingly polarized society demands a unified framework for understanding how personal beliefs shape investment decisions. By examining the interplay between network-based preferences—particularly political ideology as an anchor for prior beliefs—and signals that challenge these beliefs, we can better comprehend complex social phenomena. This paper presents a framework that enhances our understanding of policy implementation in contexts where endogenous biases persist. Future research could extend this framework to examine how varying intensities of network effects and information signals influence belief updating across different demographic groups and policy domains.

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Figure 1: More damages in the recent years. Source: NCEI-NOAA

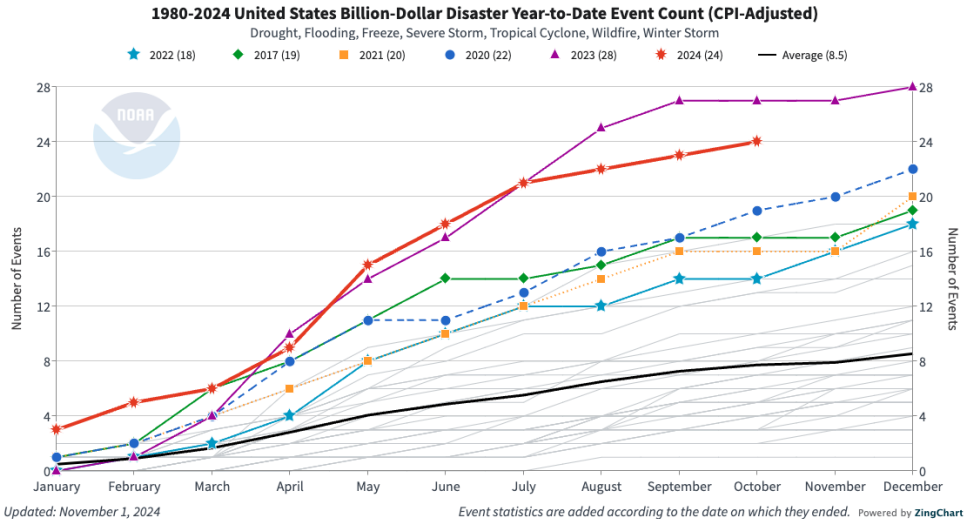
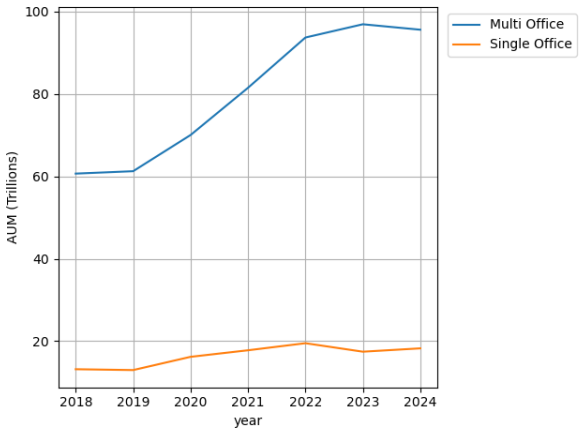
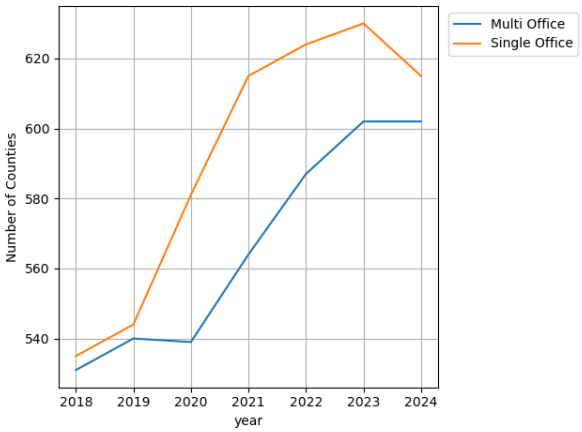


Figure 2: Local (single office) vs multi office RIAs

These graphs present the differences of the Local RIAs vs the Multi Office RIAs in the time series. Panel (a) plots the time series of the total AUM of both types of RIAs and panel (b) plots the number of counties they are present in, for the period 2018–Aug 2024. Both are taken from the Form ADV, filed annually by the RIAs. Local is defined as having 0 other offices according to their filing.



(a) Total AUM



(b) Number of counties covered

Table 1: Summary statistics for treated and control counties

This table presents the summary statistics for the preliminary analysis, where treated counties are those that were hit with a FEMA disaster for the first time since 2013. Column 1 describes the control counties, which were never hit by a FEMA disaster since 2013. Column 2 describes all the treated counties. Columns 3-5 are the treated counties split by their 2016 voteshare (>60% Democratic votes, >60% Republican votes, 40-60% for either party). *# Events* are the total number of FEMA disasters in the analysis that involved each type of county, *# Counties* is the median number of counties that are a part of each event study, *# RIAs* is the median number of RIAs that are a part of each event, *Total AUM* is the median average assets under management of the RIAs that are a part of each event, and the values corresponding to the asset classes are the median average percentage of the AUM held in each of them, per event.

	All Control	All Treated	Dem Treated	Rep Treated	Neither Treated
# Events	18.00	18.00	8.00	5.00	14.00
# Counties	122.00	1.50	1.00	1.00	1.50
# RIAs	691.00	5.50	18.00	1.00	4.50
Total AUM ($ Million)	2,565.42	553.46	822.10	216.56	393.56
Equity (Exch) (%)	39.23	34.01	38.25	34.50	33.56
Equity (Non-Exch) (%)	2.43	0.74	0.77	0.00	0.45
Govt/Agency Bonds (%)	3.24	3.45	5.03	0.50	1.59
State/Local Bonds (%)	3.49	2.20	2.59	0.75	2.32
Sovr Bonds (%)	0.05	0.00	0.00	0.00	0.00
Corp Bonds (IG) (%)	3.01	2.15	3.18	1.58	1.73
Corp Bonds (NIG) (%)	0.57	0.09	0.08	0.23	0.07
Derivatives (%)	0.56	0.00	0.29	0.00	0.00
MF/ETF (%)	34.14	41.42	25.95	40.67	45.82
Hedge Funds/PE (%)	2.55	0.47	1.53	0.00	0.66
Cash (%)	6.65	7.76	8.29	8.58	5.50
Other Assets (%)	4.12	1.50	5.03	0.53	0.95

Table 2: Portfolio responses to first disaster experiences first-hand by political affiliation

This table presents results from the stacked event study analysis of RIA portfolio responses to FEMA weather disasters by political affiliation, using the following regression

$$Y_{it} = \beta_1 \text{Treated}_{c(i)} \times \text{Post}_{it} \times \text{Party}_{c(i)} + \beta_2 \text{Treated}_{c(i)} \times \text{Post}_{it} + \cdots + \alpha_{c(i)e} + \alpha_{te} + \alpha_i + \epsilon_{ict}$$

Y_{it} is the percentage in AUM held in {Equity + Government Bonds + State/Local Bonds, Equity, Government Bonds, State/Local Bonds} reported by RIA i on the Form ADV at time t, $\text{Treated}_{c(i)}$ is a dummy variable for a county c that RIA i belongs to, which equals 1 if the county was hit between 2018–2022 by a FEMA declared weather disaster for the first time since 2013, and equals 0 if never hit since 2013. Post_{it} is a dummy variable for time t and RIA i that equals 1 if $t >$ time of the event taking place. This depends on the RIA i since the date of the form ADV filing can be different across RIAs. $\text{Party}_{c(i)}$ is the political affiliation of the county, measured by 2016 voteshare ($> 60\%$ would be Democratic or Republican, 40–60% are "neither"). $\alpha_{c(i)e}$ are county $c(i)$ x event e fixed effects, α_{te} are time t x event e fixed effects, and α_i are RIA i fixed effects. The interaction term $\text{Treated}_{c(i)} \times \text{Post}_{it} \times \text{Party}_{c(i)}$ is the key variable of interest. Standard errors are clustered at the county x event level. The results are from a single regression, that shows results relative to the moderate RIAs.

	(1)	(2)	(3)	(4)
	Equity+Govt+Local	Equity	Govt/Agen	State/Loc
Treated x Post	0.28	0.91	-0.70	0.07
	(1.90)	(1.95)	(0.46)	(0.22)
Treated x Post x Dem	0.98	-2.80	2.99***	0.79***
	(1.97)	(1.82)	(0.65)	(0.28)
Treated x Post x Rep	1.75	0.96	1.20**	-0.41
	(8.30)	(8.50)	(0.60)	(0.42)
Observations	14009	14009	14009	14009
Adjusted R^2	0.88	0.88	0.89	0.95
AdvisorFE	Yes	Yes	Yes	Yes
CountyxEventFE	Yes	Yes	Yes	Yes
YearxEventFE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3: Portfolio response dynamics to first disaster experienced first-hand by political affiliation

This figure shows the dynamic effects of extreme weather events on portfolio allocations of RIAs, separated by the political affiliation of their local county. Each row represents a different political affiliation (Democratic, Neither, or Republican counties), while columns show different asset classes: exchange-traded equity, government/agency bonds, and state/local municipal bonds. The specification estimates:

$$Y_{it} = \sum_{\tau=-3,\tau\neq-1}^{3} \beta_{1\tau}\text{Treated}_{c(i)} \times \text{Relative Year}_{i,\tau} \times \text{Party}_{c(i)} + \cdots + \alpha_{c(i)e} + \alpha_{te} + \alpha_i + \epsilon_{it}$$

Y_{it} is the percentage in AUM held in {Equity + Government Bonds + State/Local Bonds, Equity, Government Bonds, State/Local Bonds} reported by RIA i on the Form ADV at time t, $\text{Treated}_{c(i)}$ is a dummy variable for a county c that RIA i belongs to, which equals 1 if the county was hit between 2018–2022 by a FEMA declared weather disaster for the first time since 2013, and equals 0 if never hit since 2013. $\text{Relative Year}_{i,\tau}$ is dummy variable that equals 1 at $t+\tau$ years for RIA i if t is the time of the filing closest to the event taking place. $\text{Party}_{c(i)}$ is the political affiliation of the county, measured by 2016 voteshare ($> 60\%$ would be Democratic or Republican, 40–60% are "neither"). Again, this t depends on the RIA i since the date of the form ADV filing can be different across RIAs. $\alpha_{c(i)e}$ are county $c(i)$ x event e fixed effects, α_{te} are time t x event e fixed effects, and α_i are RIA i fixed effects. The interaction term $\text{Treated}_{c(i)} \times \text{Relative Year}_{i,\tau} \times \text{Party}_{c(i)}$ captures the dynamic effect. The figures plot the coefficients on the interaction terms from independent regressions with each party included as an interaction term, relative to year (-1), and the shaded region represents the 95% confidence interval.

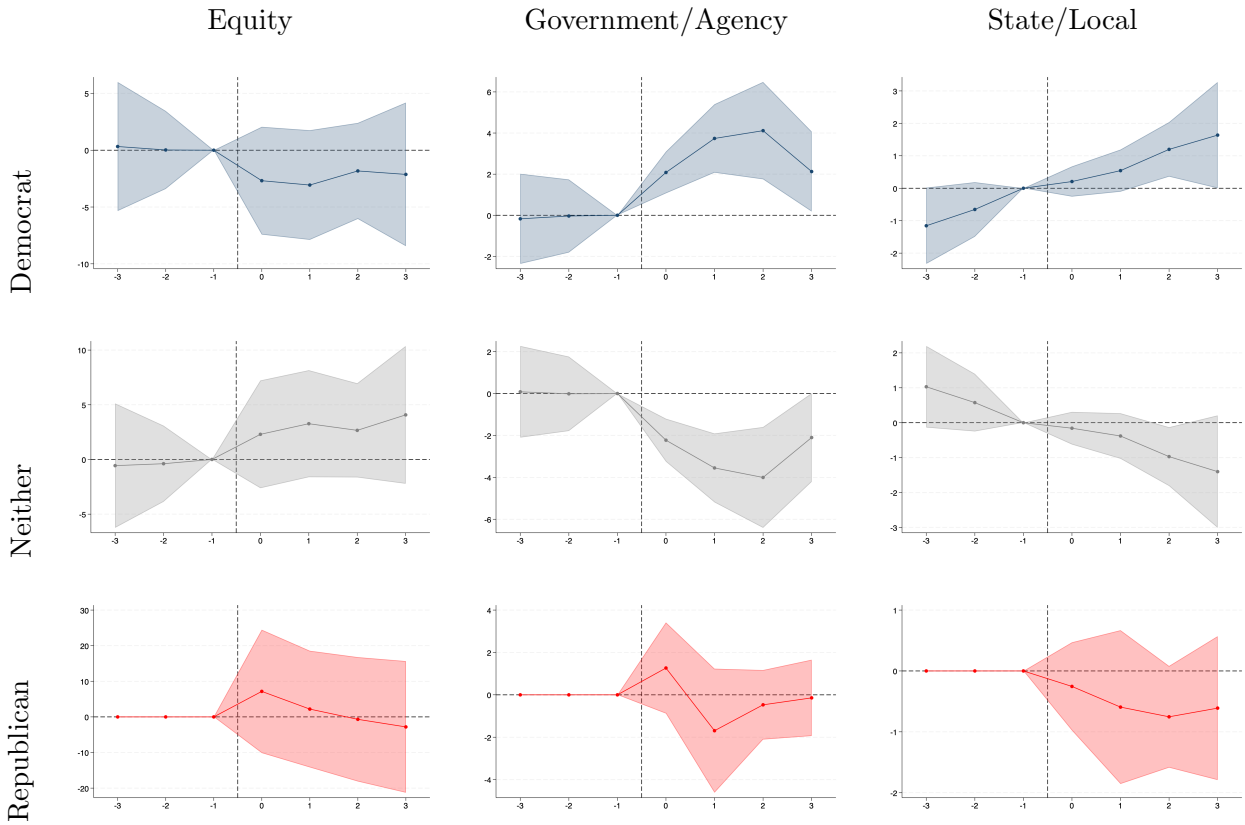


Table 3: Portfolio responses to subsequent disasters experienced first-hand

This table presents results from the stacked event study analysis of RIA portfolio responses to subsequent FEMA weather disasters by political affiliation, using the following regression

$$Y_{it} = \beta_1 \text{Repeat Treated}_{c(i)} \times \text{Post}_{it} \times \text{Party}_{c(i)} + \beta_2 \text{Repeat Treated}_{c(i)} \times \text{Post}_{it} + \cdots + \alpha_{c(i)e} + \alpha_{te} + \alpha_i + \epsilon_{ict}$$

Y_{it} is the percentage in AUM held in {Equity + Government Bonds + State/Local Bonds, Equity, Government Bonds, State/Local Bonds} reported by RIA i on the Form ADV at time t, $\text{Repeat Treated}_{c(i)}$ is a dummy variable for a county c that RIA i belongs to, which equals 1 if the county was hit between 2018–2022 by a FEMA declared weather disaster and had previously experienced at least one disaster since 2013, and equals 0 if never hit since 2013. Post_{it} is dummy variable for time t and RIA i that equals 1 if $t >$ time of the event taking place. This depends on the RIA i since the date of the form ADV filing can be different across RIAs. $\text{Party}_{c(i)}$ is the political affiliation of the county, measured by 2016 voteshare ($> 60\%$ would be Democratic or Republican, 40–60% are "neither". $\alpha_{c(i)e}$ are county $c(i)$ x event e fixed effects, α_{te} are time t x event e fixed effects, and α_i are RIA i fixed effects. The interaction term $\text{Repeat Treated}_{c(i)} \times \text{Post}_{it} \times \text{Party}_{c(i)}$ is the key variable of interest. Standard errors are reported in parentheses and are clustered at the county x event level.

	(1)	(2)	(3)	(4)
	Equity+Govt+Local	Equity	Govt/Agen	State/Loc
Repeat Treated x Post	-0.27	-0.20	-0.04	-0.04
	(0.42)	(0.38)	(0.16)	(0.12)
Repeat Treated x Post x Dem	0.11	-0.45	0.65**	-0.08
	(0.58)	(0.54)	(0.28)	(0.18)
Repeat Treated x Post x Rep	-0.27	-0.59	-0.19	0.51*
	(1.33)	(1.25)	(0.24)	(0.30)
Observations	102069	102069	102069	102069
Adjusted R^2	0.88	0.89	0.90	0.89
AdvisorFE	Yes	Yes	Yes	Yes
CountyxEventFE	Yes	Yes	Yes	Yes
YearxEventFE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4: Portfolio response dynamics to subsequent disasters experienced first-hand

This figure replicates the analysis from Figure 3 but focuses on counties that have experienced multiple extreme weather events during the sample period. The specification and control variables remain the same, but the treatment group is now defined as counties that have experienced more than one disaster in recent history - since 2013. This analysis helps understand whether repeated exposure to climate risks leads to different portfolio allocation strategies, and whether these differences vary by political affiliation. Each row represents a different political affiliation (Democratic, Neither, or Republican counties), while columns show different asset classes: exchange-traded equity, government/agency bonds, and state/local municipal bonds.

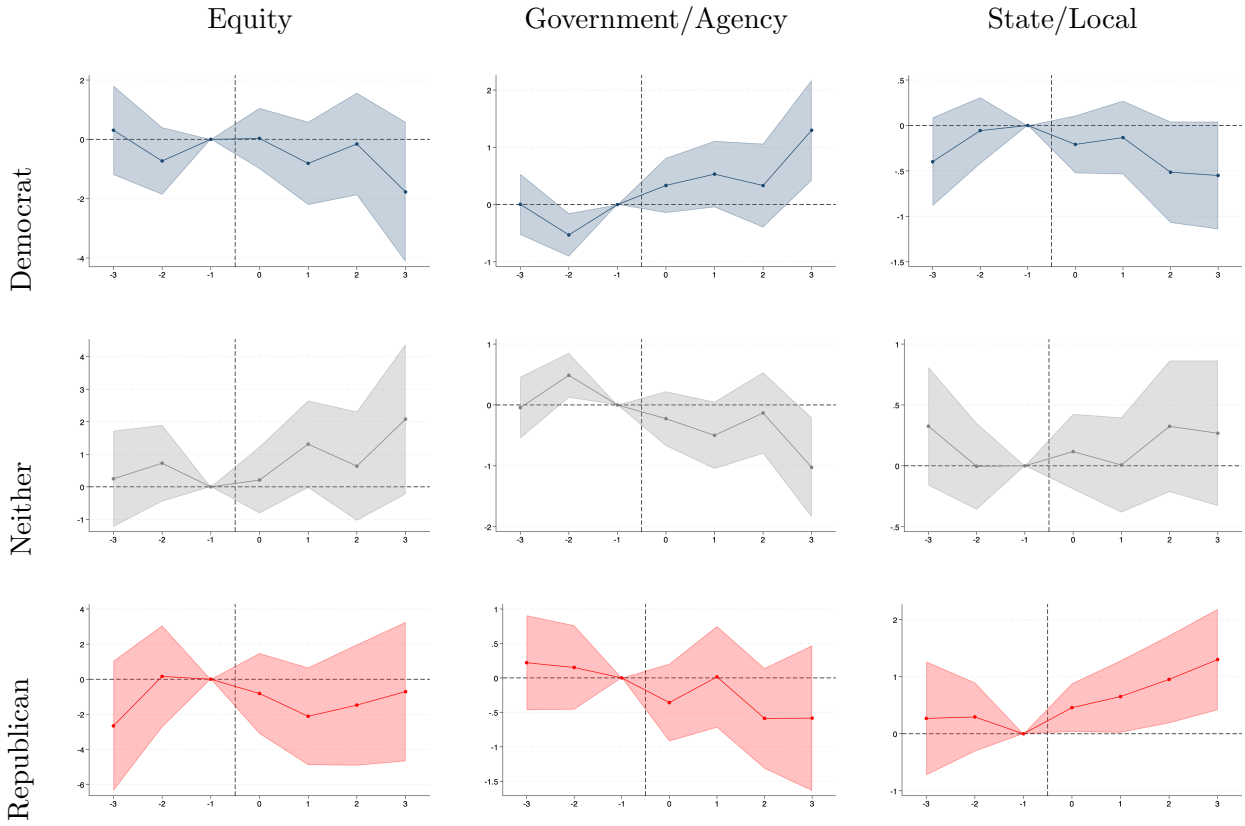


Table 4: Portfolio responses to disasters experienced through social networks

This table presents results from a stacked event study analyzing how RIA portfolios respond to FEMA weather disasters experienced through their network, by political affiliation, using the following regression

$$Y_{it} = \beta_1 \text{Connected}_{c(i)} \times \text{Post}_{it} \times \text{Party}_{c(i)} + \beta_2 \text{Connected}_{c(i)} \times \text{Post}_{it} + \cdots + \alpha_{c(i)e} + \alpha_{te} + \alpha_i + \epsilon_{ict}$$

Y_{it} is the percentage in AUM held in {Equity + Government Bonds + State/Local Bonds, Equity, Government Bonds, State/Local Bonds} reported by RIA i on the Form ADV at time t, $\text{Connected}_{c(i)}$ is a dummy variable for a county c that RIA i belongs to, which equals 1 if the county is above state median socially connected to a county hit by a FEMA declared weather disaster equals 0 if not as closely connected, and has never directly been hit by such a disaster. Post_{it} is dummy variable for time t and RIA i that equals 1 if $t >$ time of the event taking place. This depends on the RIA i since the date of the form ADV filing can be different across RIAs. $\text{Party}_{c(i)}$ is the political affiliation of the county, measured by 2016 voteshare ($> 60\%$ would be Democratic or Republican, 40–60% are "neither". $\alpha_{c(i)e}$ are county $c(i)$ x event e fixed effects, α_{te} are time t x event e fixed effects, and α_i are RIA i fixed effects. The interaction term $\text{Connected}_{c(i)} \times \text{Post}_{it} \times \text{Party}_{c(i)}$ is the key variable of interest. Standard errors are clustered at the county x event level.

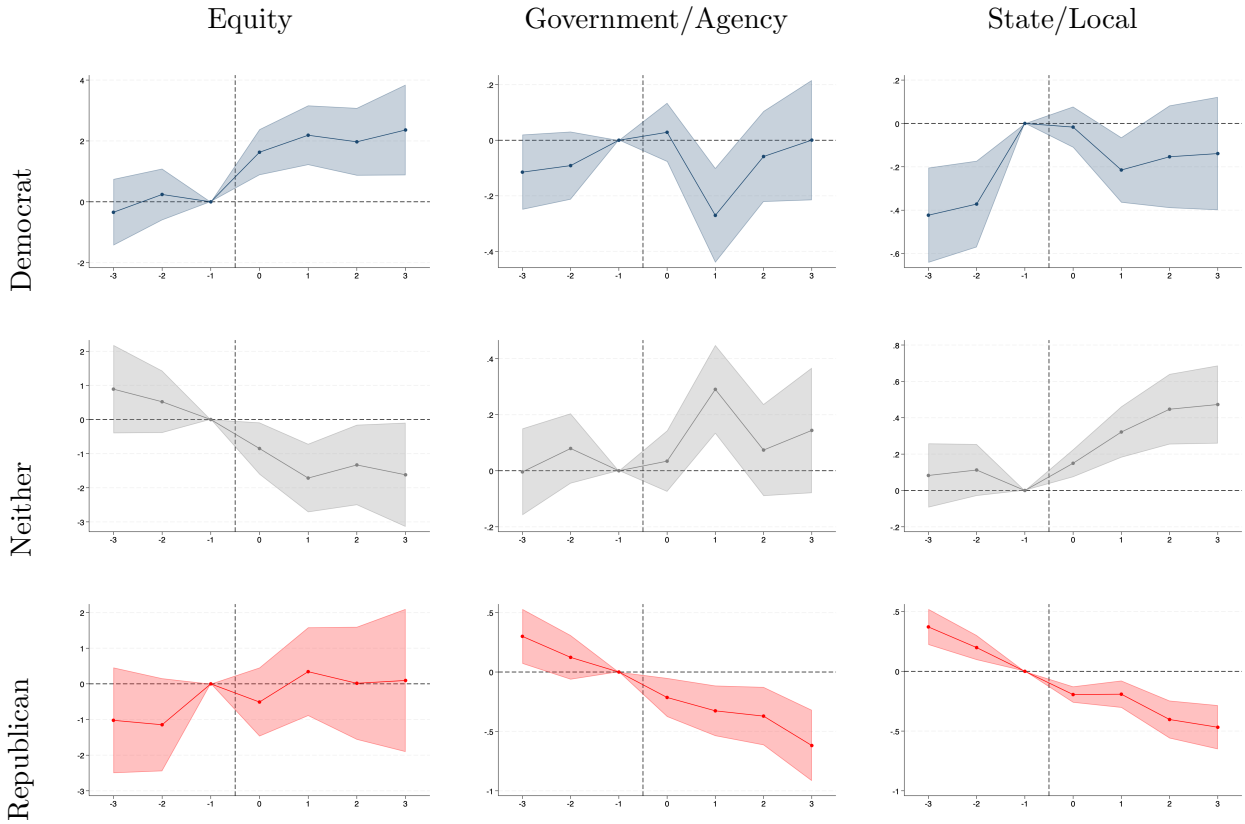
	(1)	(2)	(3)	(4)
	Equity+Govt+Local	Equity	Govt/Agen	State/Loc
Connected x Post	-1.33***	-1.61***	0.12***	0.15***
	(0.39)	(0.36)	(0.03)	(0.05)
Connected x Post x Dem	2.09***	2.20***	-0.07*	-0.05
	(0.52)	(0.48)	(0.04)	(0.07)
Connected x Post x Rep	0.53	1.36**	-0.41***	-0.41***
	(0.65)	(0.65)	(0.09)	(0.06)
Observations	135633	135633	135633	135633
Adjusted R^2	0.87	0.87	0.93	0.64
AdvisorFE	Yes	Yes	Yes	Yes
CountyxEventFE	Yes	Yes	Yes	Yes
YearxEventFE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 5: Dynamic treatment - socially connected with state controls - political leaning

This figure examines how experiencing extreme weather disasters through the social network affects portfolio decisions. The treatment variable is now the population weighted degree of social connectedness (measured by the Social Connectedness Index from Bailey, Cao, Kuchler, Stroebel, and Wong (2018) to the disaster affected-counties, where a county is treated if it has above state-median connectedness. This analysis helps understand whether information and experience sharing through social networks affects institutional investment responses to climate risks, and whether these effects vary by political affiliation. All other aspects of the specification remain unchanged.



Appendix A Average treatment effects

Table A.1: Direct experiences - state controls

This table presents results from the stacked event study analysis of RIA portfolio responses to FEMA weather disasters, using the following regression specification:

$$Y_{it} = \beta_1 \text{Treated}_{c(i)} \times \text{Post}_{it} + \beta_2 \text{Treated}_{c(i)} + \beta_3 \text{Post}_{it} + \alpha_{c(i)e} + \alpha_{te} + \alpha_i + \epsilon_{it}$$

Y_{it} is the percentage in AUM held in {Equity + Government Bonds + State/Local Bonds, Equity, Government Bonds, State/Local Bonds} reported by RIA i on the Form ADV at time t, $\text{Treated}_{c(i)}$ is a dummy variable for a county c that RIA i belongs to, which equals 1 if the county was hit between 2018–2022 by a FEMA declared weather disaster for the first time since 2013, and equals 0 if never hit since 2013. Post_{it} is dummy variable for time t and RIA i that equals 1 if $t >$ time of the event taking place. This depends on the RIA i since the date of the form ADV filing can be different across RIAs. $\alpha_{c(i)e}$ are county $c(i)$ x event e fixed effects, α_{te} are time t x event e fixed effects, and α_i are RIA i fixed effects. The interaction term $\text{Treated}_{c(i)} \times \text{Post}_{it}$ is the key variable of interest.

	(1)	(2)	(3)	(4)
	Equity+Govt+Local	Equity	Govt/Agen	State/Loc
Post	0.35	0.66	-0.01	-0.29***
	(0.73)	(0.74)	(0.11)	(0.09)
Treated x Post	0.26	-0.72	0.65*	0.33**
	(1.51)	(1.58)	(0.38)	(0.13)
Observations	14009	14009	14009	14009
Adjusted R^2	0.88	0.88	0.89	0.95
AdvisorFE	Yes	Yes	Yes	Yes
CountyxEventFE	Yes	Yes	Yes	Yes
YearxEventFE	Yes	Yes	Yes	Yes

Standard errors in parentheses

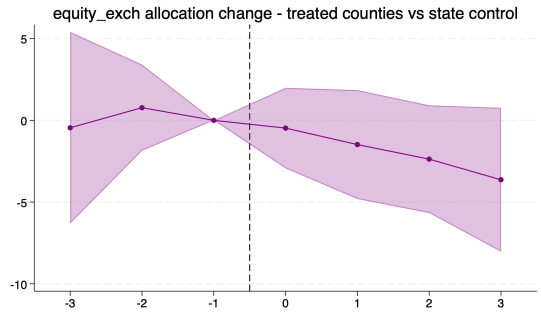
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.1: Dynamic treatment plots - direct experiences with state controls

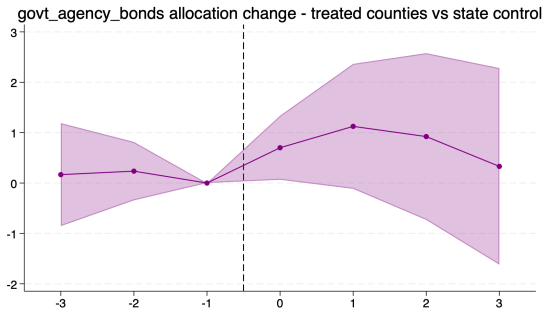
These graphs presents the dynamic treatment effect from the stacked event study analysis of RIA portfolio responses to FEMA weather disasters, using the following regression specification:

$$Y_{it} = \sum_{\tau=-3,\tau\neq-1}^{3} \beta_{1\tau}\text{Treated}_{c(i)} \times \text{Relative Year}_{i,\tau} + \cdots + \alpha_{c(i)e} + \alpha_{te} + \alpha_i + \epsilon_{it}$$

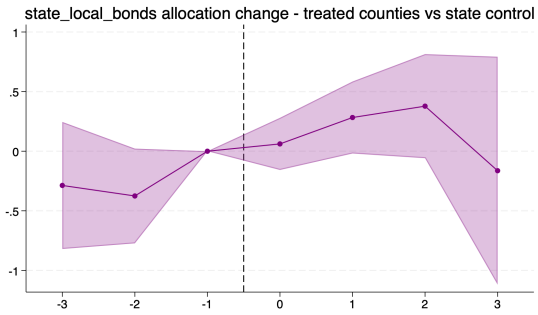
Y_{it} is the percentage in AUM held in {Equity + Government Bonds + State/Local Bonds, Equity, Government Bonds, State/Local Bonds} reported by RIA i on the Form ADV at time t, $\text{Treated}_{c(i)}$ is a dummy variable for a county c that RIA i belongs to, which equals 1 if the county was hit between 2018–2022 by a FEMA declared weather disaster for the first time since 2013, and equals 0 if never hit since 2013. $\text{Relative Year}_{i,\tau}$ is dummy variable that equals 1 at $t+\tau$ years for RIA i if t is the time of the filing closest to the event taking place. Again, this t depends on the RIA i since the date of the form ADV filing can be different across RIAs. $\alpha_{c(i)e}$ are county $c(i)$ x event e fixed effects, α_{te} are time t x event e fixed effects, and α_i are RIA i fixed effects. The interaction term $\text{Treated}_{c(i)} \times \text{Relative Year}_{i,\tau}$ captures the dynamic effect. The figures plot the coefficient on the interaction terms for each year, relative to year (-1), and the shaded region represents the 95% confidence interval.



(a) Equity



(b) Government Agency Bonds



(c) State and Local Bonds

Table A.2: Repeat experiences - state controls

This table presents results from the stacked event study analysis of RIA portfolio responses to FEMA weather disasters, using the following regression specification:

$$Y_{it} = \beta_1 \text{Repeat Treated}_{c(i)} \times \text{Post}_{it} + \beta_2 \text{Repeat Treated}_{c(i)} + \beta_3 \text{Post}_{it} + \alpha_{c(i)e} + \alpha_{te} + \alpha_i + \epsilon_{it}$$

Y_{it} is the percentage in AUM held in {Equity + Government Bonds + State/Local Bonds, Equity, Government Bonds, State/Local Bonds} reported by RIA i on the Form ADV at time t, Repeat Treated$_{c(i)}$ is a dummy variable for a county c that RIA i belongs to, which equals 1 if the county was hit between 2018–2022 by a FEMA declared weather disaster and was hit at least once since 2013, and equals 0 if never hit since 2013. Post$_{it}$ is dummy variable for time t and RIA i that equals 1 if $t >$ time of the event taking place. This depends on the RIA i since the date of the form ADV filing can be different across RIAs. $\alpha_{c(i)e}$ are county $c(i)$ x event e fixed effects, α_{te} are time t x event e fixed effects, and α_i are RIA i fixed effects. The interaction term Repeat Treated$_{c(i)} \times$ Post$_{it}$ is the key variable of interest.

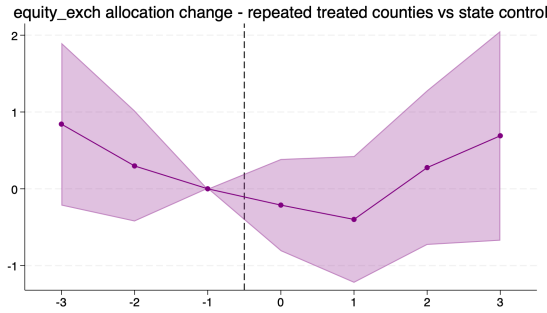
	(1)	(2)	(3)	(4)
	Equity+Govt+Local	Equity	Govt/Agen	State/Loc
Post	-0.45**	-0.42**	-0.06	0.04
	(0.22)	(0.21)	(0.06)	(0.06)
Repeat Treated x Post	-0.19	-0.37	0.20	-0.02
	(0.36)	(0.34)	(0.13)	(0.10)
Observations	102069	102069	102069	102069
Adjusted R^2	0.88	0.89	0.90	0.89
AdvisorFE	Yes	Yes	Yes	Yes
CountyxEventFE	Yes	Yes	Yes	Yes
YearxEventFE	Yes	Yes	Yes	Yes

Standard errors in parentheses

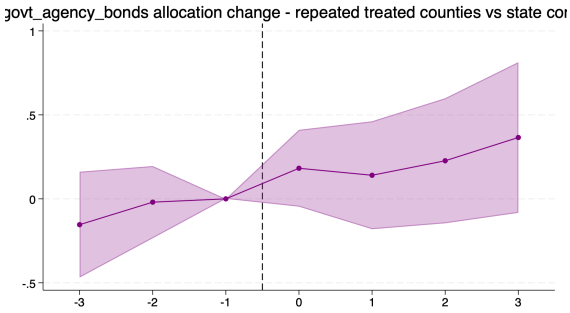
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.2: Dynamic treatment plots - repeat experiences with state controls

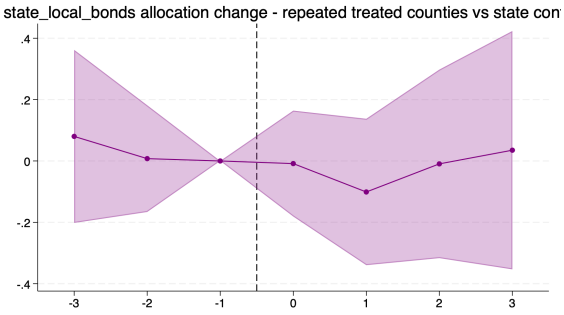
This figure replicates the analysis from Figure A.1 but focuses on counties that have experienced multiple extreme weather events during the sample period. The specification and control variables remain the same, but the treatment group is now defined as counties that have experienced more than one disaster in recent history - since 2013. This analysis helps understand whether repeated exposure to climate risks leads to different portfolio allocation strategies. Plot (a) is for exchange traded equity, (b) for government and agency bonds and (c) for state/ local bonds. The asset class shares are taken from the Form ADV, which reports the AUM as of the date of filing.



(a) Equity



(b) Government Agency Bonds



(c) State and Local Bonds

Table A.3: Experienced through the network - state controls

This table presents results from a similar stacked event study as in A.1 but now examines how experiencing extreme weather disasters through the social network affects portfolio decisions. The treatment variable is now the population weighted degree of social connectedness (measured by the Social Connectedness Index from Bailey, Cao, Kuchler, Stroebel, and Wong (2018) to the disaster affected-counties, where a county is treated if it has above state-median connectedness. This analysis helps understand whether information and experience sharing through social networks affects institutional investment responses to climate risks on average. All other aspects of the specification remain unchanged.

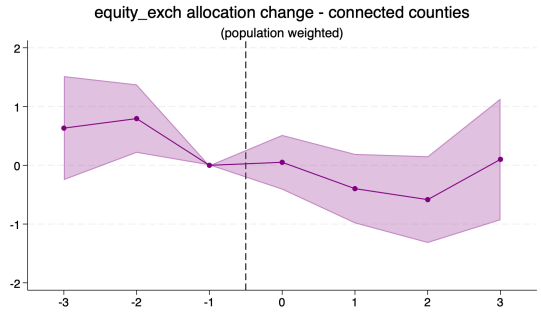
	(1)	(2)	(3)	(4)
	Equity+Govt+Local	Equity	Govt/Agen	State/Loc
Post	1.98***	2.29***	-0.08***	-0.23***
	(0.26)	(0.25)	(0.03)	(0.04)
Connected x Post	-0.67**	-0.79***	0.10***	0.02
	(0.28)	(0.26)	(0.03)	(0.03)
Observations	135633	135633	135633	135633
Adjusted R^2	0.87	0.87	0.93	0.64
AdvisorFE	Yes	Yes	Yes	Yes
CountyxEventFE	Yes	Yes	Yes	Yes
YearxEventFE	Yes	Yes	Yes	Yes

Standard errors in parentheses

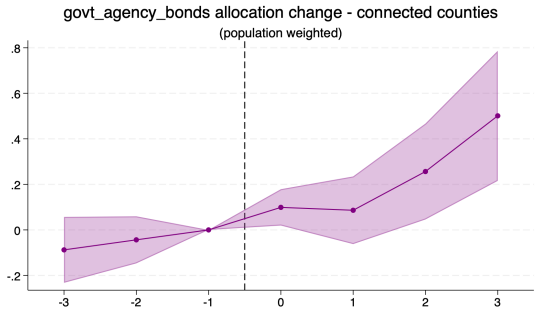
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.3: Dynamic treatment plots - direct experiences with state controls

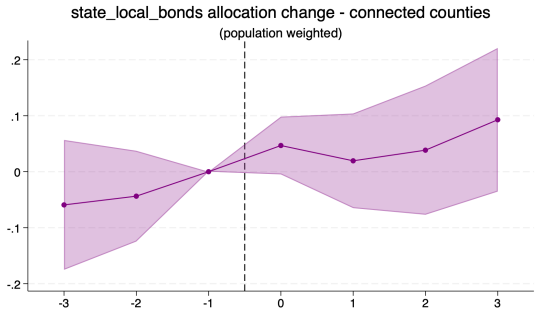
These plots examine how experiencing extreme weather disasters through the social network affects portfolio decisions, following a similar setup as in Figure A.1. The treatment variable is now the population weighted degree of social connectedness (measured by the Social Connectedness Index from Bailey, Cao, Kuchler, Stroebel, and Wong (2018) to the disaster affected-counties, where a county is treated if it has above state-median connectedness. This analysis helps understand whether information and experience sharing through social networks affects investment responses to climate risks on average. All other aspects of the specification remain unchanged.



(a) Equity



(b) Government Agency Bonds



(c) State and Local Bonds

Appendix B Belief evolution

B.1 Local news

Various measures exist in the literature that capture attention to climate change. Choi et al. (2020) use Google search activity in 70 cities globally on the topic "global warming". Google searches are also used in Alekseev et al. (2022) to show the heightened awareness of climate change following extreme heat. Various climate risk news indices developed in Engle et al. (2020), Ardia et al. (2022), Faccini et al. (2023) look at news articles using different climate-related vocabulary to capture different risks [13]. Sautner et al. (2023), the climate change exposure measure is the "relative frequency with which bigrams related to climate change occur in the transcripts of earnings conference calls". Also commonly used in the literature is the Yale Climate Change Opinion Survey, conducted bi-annually since 2008. Howe et al. (2015) disaggregates these national values into county-level estimates, the values for which are publicly available in 2014, 2016, and 2018–2023.

To capture local beliefs about climate change in the context of extreme weather, I construct a zip-code level measure of the number of local publications that mention 'climate change' or related words [14] within extreme weather reporting from 2010-2024[15]. Examples of these articles are in Appendix B.1.1. The measure is constructed as follows:

$$\text{Worry}_t = \left(\frac{\text{Articles}_{\text{climate} \cap \text{extreme weather},t}}{\text{Articles}_{\text{extreme weather},t}} \right) \times 100$$

In order to get a continuous measure at the zip-level, I construct a distance-weighted average of the measure, within the same state, for each month (t) . This is then aggregated to the county level, to match the analysis in the paper. Figure B.4 presents a binscatter,

[13] See Table 1 of Ardia et al. (2022) for a detailed comparison of these sources, as well as a few other climate risk news series

[14] phrases searched for: climate change, climate crisis, global warming, caused by the climate, caused by climate

[15] specifically, for extreme weather reporting, I look for articles with the words: heat wave, excessive heat, high temperature, extreme heat, drought, wildfire, flooding, tropical storm, hurricane

binned by relative time pre/post a FEMA weather disaster. The plot suggests there is an increase in worry about climate change, as captured through the attribution of climate change through extreme weather reporting in the months following the disaster. The maroon line represents the treated counties - those that directly experienced a weather disaster for the first time in recent history, and the navy line represents the control counties. Figure B.5 gets to the core message of the paper, that captures the heterogeneity by political ideology as well as by type of experience. Figure B.6 splits the sample by political ideology only and plots the changes in beliefs by party, regardless of treatment status, pre and post disaster. This graph essentially captures the differences in priors assumed in the model.

Figure B.4: Binscatter of the local publication based belief measure, in the months before and after a FEMA weather episode - by treatment group

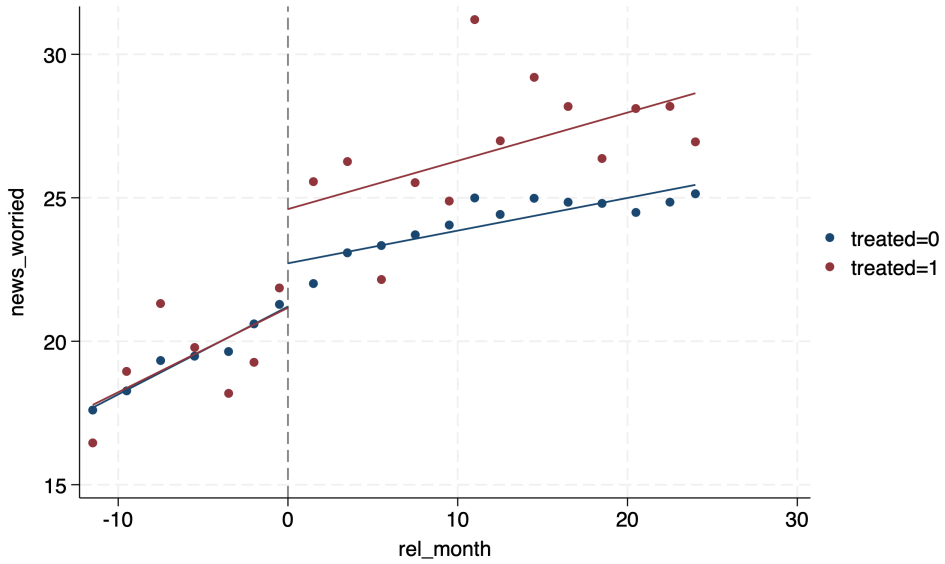


Figure B.5: Binscatter of the local publication based belief measure, in the months before and after a FEMA weather episode - by party and treatment

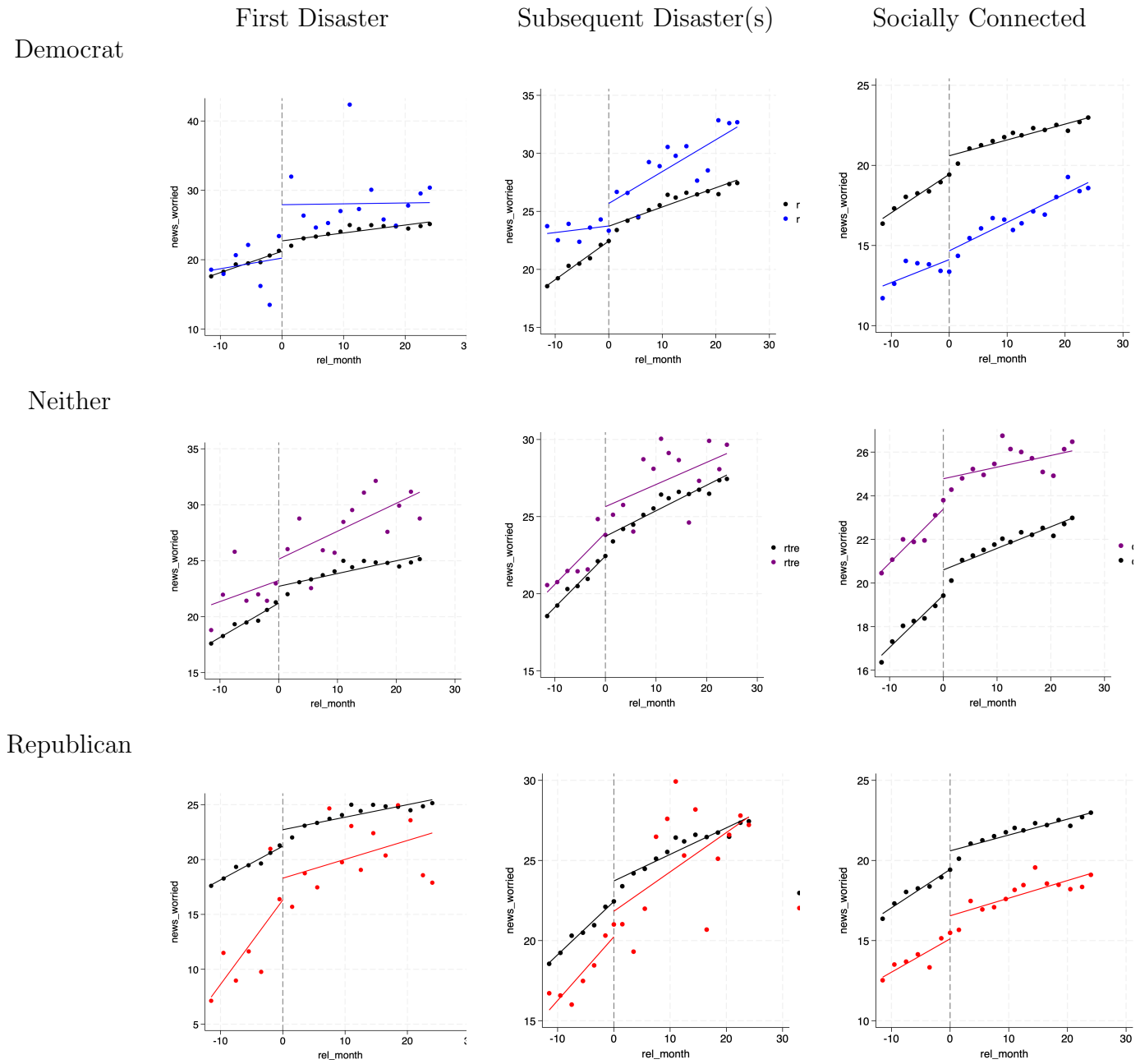
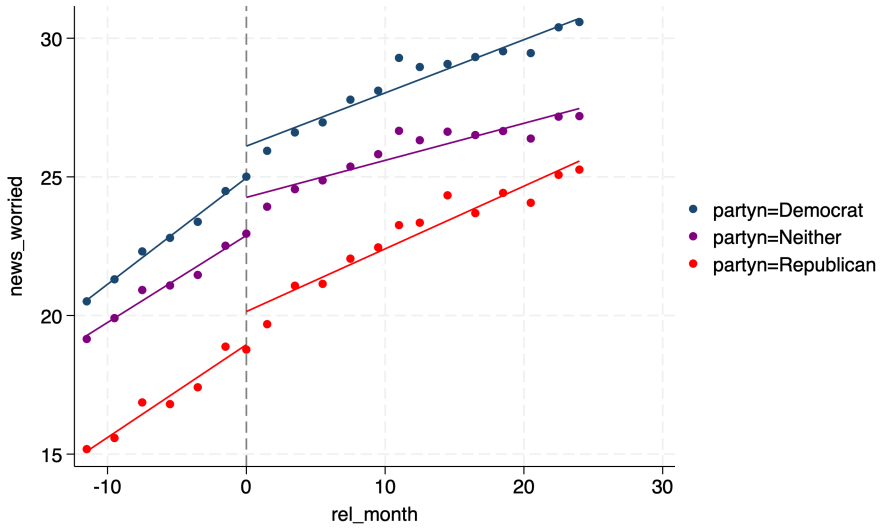


Figure B.6: Binscatter of the local publication based belief measure, in the months before and after a FEMA weather episode - by party



B.1.1 Examples of articles

GOID 1240325865

Title Power gear in NYC may move higher

Date 2012-12-13T00:00:00.000000000

Publisher Gannett Media Corp

Text NEW YORK – A major push is on to move New York City's electrical infrastructure to higher ground or upper floors after Superstorm Sandy sent seawater pouring into low-lying substations and skyscraper basements and plunged half of Manhattan into darkness for four days. The effort, likely to be enormously costly, will center partly on two old weaknesses brought into sharp relief by the surge: power distribution stations built yards from the water's edge, and electrical components in vulnerable basements. Moving all that equipment isn't going to be cheap. Consolidated Edison, the city's main power utility, made a preliminary estimate that it would cost $800 million to rebuild its flood-zone substations in a way that would put sensitive equipment out of the water's reach in a storm like Sandy. Reconfiguring the city's high-rises to move electrical equipment out of vulnerable basement areas will cost many millions of dollars more, and that's just in construction costs. Building owners also will lose large amounts of revenue when rentable floors are converted into mechanical space. In the past, maybe all of those costs would have been considered prohibitive, *but Sandy – coming on top of years of warnings about global warming and the threat of rising seas – changed a lot of minds.* Even before the storm, Con Edison had resolved that any new substations would be elevated enough to be untouched in either a Category 2 hurricane or the type of flood the Federal Emergency Management Agency expects to occur only once every 100 years. It isn't clear yet whether older stations in flood zones should be rebuilt to also raise them out of the flood zone, said John Miksad, Con Edison's vice president of electric operations.

PrintLocation

ZipCode 22108

Country United States

Attributed to Climate Change 1

Extreme Weather ['hurricane']

GOID 3078766701

Title Hurricane Beryl barreling toward Jamaica

Date 2024-07-03T00:00:00.000000000

Publisher Miami Times

Text Hurricane Beryl roared through open waters on Tuesday as a monstrous Category 5 storm on a path that would take it near Jamaica and the Cayman Islands after earlier making landfall in the southeast Caribbean, killing at least four people. A hurricane warning was in effect for Jamaica and a hurricane watch for Grand Cayman, Little Cayman, Cayman Brae and for Haiti's entire southern coast. Beryl was forecast to still be near major hurricane strength when it passes near Jamaica on Wednesday, the Cayman Islands on Thursday and Mexico's Yucatan Peninsula on Friday, according to the National Hurricane Center. The center warned that Beryl was expected to bring life-threatening winds and storm surge to Jamaica, where officials warned residents in flood-prone areas to prepare for evacuation. "I am encouraging all Jamaicans to take the hurricane as a serious threat," Prime Minister Andrew Holness said in a public address late Monday. "It is, however, not a time to panic." Beryl is the earliest Category 5 storm ever to form in the Atlantic, fueled by record warm waters. Early Tuesday, the storm was located about 235 miles (375 kilometers) southeast of Isla Beata in the Dominican Republic. It had top winds of 160 mph (260 kph) and was moving west-northwest at 22 mph (35 kph). "Beryl remains an impressive Category 5 hurricane," the National Hurricane I felt the wind whistling and then for about two hours straight, it was really, really terrifying at times." - Roy O'Neale, Grenadian Resident Center said. A tropical storm warning was in place for the entire southern coast of Hispanio-la, an island shared by Haiti and the Dominican Republic. As the storm barreled through the Caribbean Sea, rescue crews in the southeast Caribbean fanned out across the region to determine the extent of the damage that Hurricane Beryl inflicted after landing on Carriacou, an island in Grenada, as a Category 4 storm. Three people were reported killed in Grenada and Carriacou and another in St. Vincent and the Grenadines, officials said. One fatality in Grenada occurred after a tree fell on a house, Kerryne James, minister of climate resilience, environment and renewable energy, told The Associated Press. She said the nearby islands of Carriacou and Petit Martinique sustained the greatest damage, with water, food and baby formula a priority. "The situation is grim," Grenadian Prime Minister Dickon Mitchell told a news conference Tuesday. "There is no power, and there is almost complete destruction of homes and buildings on the island. The roads are not passable, and in many instances, they are cut off because of the large quantity of debris strewn all over the streets." Meanwhile, Ralph Gon-salves, prime minister of St. Vincent and the Grenadines, promised in a statement to rebuild the archipelago. He noted that 90% of homes on Union Island were destroyed, and that "similar levels of devastation" were expected on the islands of Myreau and Canouan. The last strong hurricane to hit the southeast Caribbean was Hurricane Ivan 20 years ago, which killed dozens of people in Grenada. Grenadian resident Roy O'Neale, 77, recalled how he lost his home to Ivan and built back stronger, with his current home sustaining minimal damage from Hurricane Beryl. "I felt the wind whistling, and then for about two hours straight, it was really, really terrifying at times," he said by phone. "Branches of trees were flying all over the place." One of the homes that Beryl damaged belongs to the parents of U.N. Climate Change Executive Secretary Simon Stiell, who is from Carriacou. The storm also destroyed the home of his late grandmother. *In a statement, Stiell said that the climate crisis is going from bad to worse, and faster than expected. "Whether in my homeland of Carriacou ... hammered by Hurricane Beryl, or in the heatwaves and floods crippling communities in some of the world's largest economies, it's clear that the climate crisis is pushing disasters to record-breaking new levels of destruction," he said.* Grenada, known as the "spice isle," is one of the world's top exporters of nutmeg. Mitchell noted that the bulk of spices are grown in the northern part of the island, which was hit hardest by Beryl. "We certainly expect that we'll take a beating," he said. Beryl has broken several records, including marking the farthest east that a hurricane has formed in the tropical Atlantic in June, according to one hurricane researcher. The storm strengthened from a tropical depression to a major hurricane in just 42 hours, which only six other Atlantic hurricanes have done, and never before September.

PrintLocation

ZipCode 33127

Country United States

Attributed to Climate Change 1

Extreme Weather ['tropicalstorm']

GOID 2120008722

Title Suds shortage? Warming climate threatens world's beer supply

Date 2018-10-15T00:00:00.000000000

Publisher USA Today, a division of Gannett Satellite Information Network, Inc.

Text Now this is getting serious. Worldwide, over the next few decades, beer could become more scarce and thus more expensive because of human-caused *global warming*, a study reported Monday. The production of barley, the main ingredient in beer, is likely to drop substantially *because severe droughts and heat extremes will become more frequent as the climate changes, the study says.* "Average yield losses (of barley) range from 3 percent to 17 percent, depending on the severity of the conditions," the study says. In the USA, beer shortages could reduce the amount Americans consume each year by as much as 900 million gallons. That's (gulp) about 9 billion bottles of beer. "Future climate and pricing conditions could put beer out of reach for hundreds of millions of people around the world," said study co-author Nathan Mueller of the University of California-Irvine. This is the first study to quantify the effect of climate change on beer, the world's most popular alcoholic beverage. "While the effects on beer may seem modest in comparison to many of the other impacts of climate change, there is nonetheless something fundamental in the cross-cultural appreciation of beer," said study lead author Dabo Guan of the U. K. 's University of East Anglia. Researchers used computer models to predict the possible effects of extreme climates on barley yields in 34 regions around the world. They examined the effects of the resulting barley supply shock on the supply and price of beer in each region under several climate scenarios. On average, beer prices are likely to double as less barley becomes available, according to the study. One of the most affected countries would be Ireland – where beer prices could increase by as much as 338 percent by 2099 under the most severe scenario. As for consumption, the global amount of beer consumed could fall by as much as 16 percent. In the worst-case climate scenario, parts of the world where barley is grown – including the northern Great Plains, Canadian prairies, Europe, Australia and the Asian steppe – were projected to experience more frequent droughts and heat waves. "Current levels of fossil-fuel consumption and carbon dioxide pollution – business as usual – will result in this worst-case scenario, with more weather extremes negatively impacting the world's beer basket," Mueller said. "Our study showed that even modest warming will lead to increases in drought and excessive heat events in barley-growing areas. " The likelihood of weather conditions hurting barley production would increase from about once a decade before 2050 to once every other year by the end of the century, the research showed. Scientists have long known that barley "is one of the most heat-sensitive crops globally," but the new study connects that to something that people care about – the price of beer – so it's valuable, said David Lobell, a Stanford University agriculture ecologist who was not involved in the study. "Increasingly, research has begun to project the impacts of climate change on world food production, focusing on staple crops such as wheat, maize, soybean and rice," study lead author Guan said. "However, if adaptation efforts prioritize necessities, climate change may undermine the availability, stability and access to 'luxury' goods to a greater extent than staple foods. " The study was published in the peer-reviewed British journal Nature Plants. Contributing: The Associated Press

PrintLocation

ZipCode 22108

Country United States

Attributed to Climate Change 1

Extreme Weather ['heat', 'drought']

B.2 Tweets by local advisory firms

Another direct way to capture attitudes or beliefs of the RIAs is to look at their social media activity. The Form ADV requires RIAs to report their website and/or social media accounts. Using their reported X handles, I scrape tweets weekly from X for the time period July 24, 2024 – November 13, 2024, by accessing the X v2 API through their Basic plan. Within the local RIAs tweets, I identify climate tweets as those that contain any of the words ['climate', 'renewable', 'green energy', 'sustainable', 'carbon', 'environmental', 'emissions', 'clean energy', 'global warming'], suggested by Claude AI. I also gauge political ideology through the tweets by looking for specific words suggested by Claude AI[16]. The approach incorporates both general keyword frequency analysis and the detection of strong ideological signals through specific phrases, with each RIA's ideology ultimately classified based on the relative prevalence of conservative versus progressive markers. When the frequencies of conservative and progressive indicators are equal, the RIA is classified as ideologically neutral, though this systematic approach admittedly simplifies the complex nature of political ideology into discrete categories and can be greatly enhanced using LLMs.

I also use the political leaning proxied by the 2016 voteshare to classify the RIAs as is done in the main analysis. Table B.4 presents summary stats for the local RIAs and their tweets, looking at the period pre - Hurricane Helene, between Helene and Milton, and post Milton split by voteshare. Table B.5 presents the same but now through tweet-inferred political ideology. Hurricanes Helene and Milton hit parts of the eastern coast of the US from September 24, 2024 – September 27, 2024, and Oct 5, 2024 – Oct 10, 2024 respectively.

[16]Specifically I use these words, conservative keywords = ['trump', 'maga', 'republican', 'gop', 'conservatives', 'woke', 'political games', 'biden failure', 'climate hoax', 'liberal agenda', 'radical left', 'socialism', 'fake news', 'government overreach', 'big government', 'freedom', 'liberty', 'foxnews', 'tucker', 'hannity'],
progressive keywords = ['democrat', 'biden', 'progressive', 'liberal', 'leftist', 'climate action', 'renewable transition', 'clean energy future', 'environmental justice', 'green new deal', 'climate crisis', 'sustainability', 'social justice', 'equity', 'renewable energy', 'msnbc', 'infrastructure bill', 'build back better']

Table B.4: Summary statistics for tweets based on RIA political affiliation, by county vote-share (July 24, 2024 – November 13, 2024)

Period	Group Type	Group	% Climate	% Hurricane	Tweet Count	Unique RIAs
Pre	party	Democrat	0.73%	0.12%	3433	88
Pre	party	Neither	0.36%	0.45%	2203	69
Pre	party	Republican	0.15%	0.44%	685	10
Between	party	Democrat	0.36%	1.9%	1105	70
Between	party	Neither	0.66%	0.66%	605	62
Between	party	Republican	1.42%	0.0%	211	8
Post	party	Democrat	0.49%	0.36%	3850	82
Post	party	Neither	0.38%	0.44%	1825	70
Post	party	Republican	0.89%	0.44%	676	8

Table B.5: Summary statistics for tweets based on RIA inferred ideology through Tweets (July 24, 2024 – November 13, 2024)

Period	Group Type	Group	% Climate	% Hurricane	Tweet Count	Unique RIAs
Pre	ideology	neutral	0.58%	0.24%	2061	103
Pre	ideology	progressive	2.3%	0.86%	696	26
Pre	ideology	conservative	0.17%	0.17%	3564	38
Between	ideology	neutral	0.19%	0.57%	526	79
Between	ideology	progressive	5.07%	0.72%	138	25
Between	ideology	conservative	0.24%	1.67%	1257	36
Post	ideology	neutral	0.21%	0.27%	1456	94
Post	ideology	progressive	2.87%	1.15%	522	27
Post	ideology	conservative	0.32%	0.34%	4373	39

Some examples of tweets by different local RIAs are listed below:

> "The Corporate Climate Trap. CEOs continue to fall for the 'climate trap,'... following a letter from a group of Republican attorneys general warning that companies that make grandiose climate pledges may be violating consumer protection laws..."
> – Strive (Ohio), Oct 3, 2024

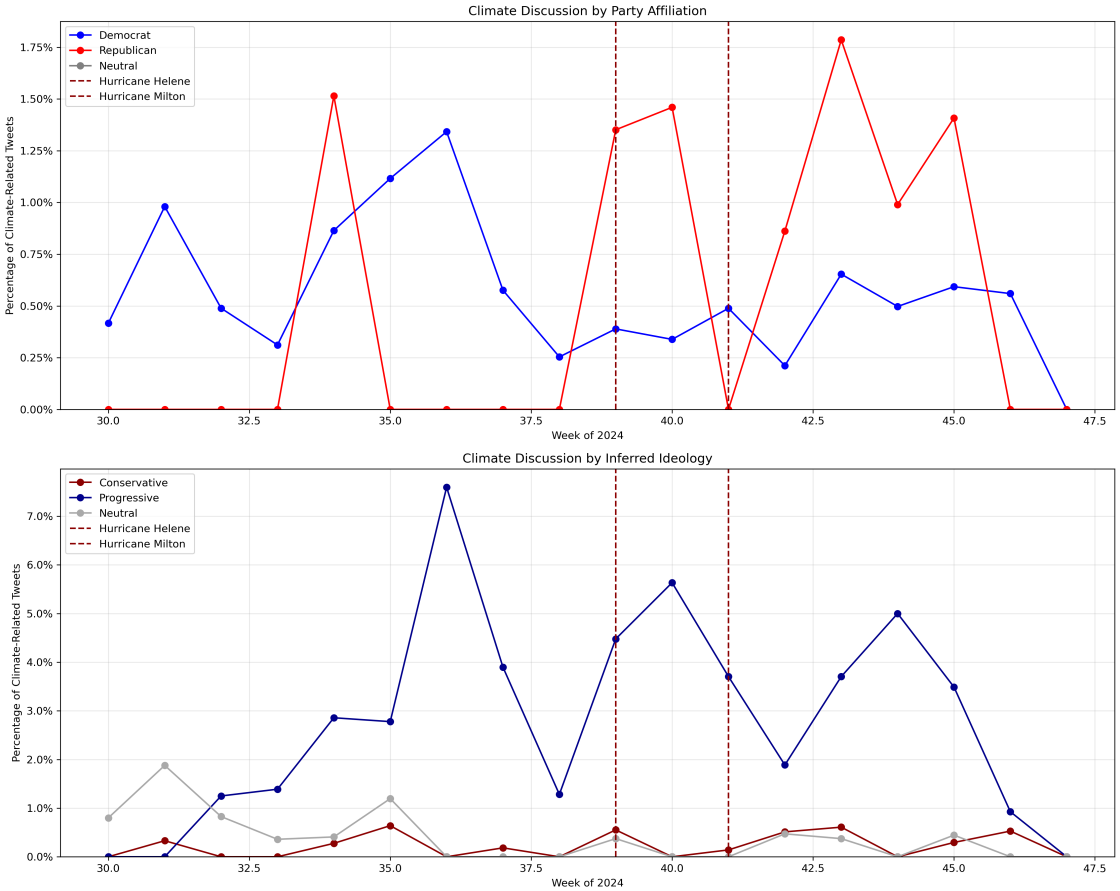
> "Climate change clearly warmed the Gulf waters that fueled Milton's development, likely supercharging its rapid intensification & making this hurricane much more dangerous... Fossil fuel pollution is amplifying this threat."
> – Beyond Investing (Florida), Oct 10, 2024

> "Rebuilding after the hurricanes will take time, but the impacted communities have ample resources to support their recovery and help them come back stronger than before, says Franklin Templeton Fixed Income's Municipal Bond Research Director."
> – Franklin Templeton, Oct 17, 2024

The evolution of tweets that mention climate is presented in Figure B.7

There are some interesting dynamics that potentially capture differential updating of beliefs, even with the crude measure of classification.

Figure B.7: Evolution of tweets by RIAs of different political ideology during hurricane season 2024



Appendix C FEMA Disasters

Year-Month	Disaster Title	Counties	Parties	RIAs
201802	Severe Storms, Tornadoes, Flooding, Landslides,...	1	[Republican]	1
201804	Severe Storms, Flooding, Landslides, And Mudslides	1	[Democrat]	7
201806	Severe Storms, Tornadoes, Straight-Line Winds, ...	1	[Neither]	5
201808	Severe Storms And Flooding	1	[Neither]	2
201809	Hurricane Florence	8	[Democrat, Neither, Republican]	40
201903	Severe Storms And Flooding	2	[Neither, Republican]	4
201903	Severe Storms, Straight-Line Winds, And Flooding	1	[Neither]	1
201903	Severe Winter Storm, Straight-Line Winds, And F...	1	[Republican]	1
201905	Severe Storms, Straight-Line Winds, Tornadoes, ...	2	[Neither]	6
201905	Tornadoes And Flooding	1	[Democrat]	1
201907	Severe Storms, Tornadoes, Straight-Line Winds, ...	2	[Neither]	3
202001	Severe Winter Storm And Flooding	1	[Neither]	1
202002	Severe Storms, Flooding, And Mudslides	1	[Democrat]	5
202006	Knolls Fire	1	[Neither]	3
202008	Tropical Storm Isaias	8	[Neither, Democrat, Republican]	84
202009	Beachie Creek Lionshead Fire Complex	1	[Neither]	4
202009	Creek Fire	2	[Neither]	5
202009	Wildfires	3	[Neither]	9
202009	Wildfires And Straight-Line Winds	1	[Neither]	4
202102	Severe Winter Storm	1	[Republican]	1
202102	Severe Winter Storms	1	[Republican]	1
202102	Severe, Storms, Flooding, Landslides, And Mudsl...	1	[Neither]	6
202106	Severe Storms, Flooding, And Tornadoes	1	[Democrat]	3
202108	Hurricane Henri	3	[Democrat, Neither]	375
202108	Parleys Canyon Fire	1	[Neither]	19
202108	Remnants Of Tropical Storm Fred	1	[Neither]	9
202112	Severe Winter Storms, Snowstorms, Straight-Line...	1	[Neither]	1
202212	Severe Winter Storms, Flooding, Landslides, And...	2	[Democrat, Neither]	52

Table C.6: Disasters in the treatment sample