Propagation of climate disasters through ownership networks*

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Abstract

Climate disasters propagate through common ownership networks. Institutional investors in firms hit by climate-related disasters are more likely to vote in favor of climate proposals at their other portfolio firms. This effect is short-lived, larger in periods of high attention to climate change, and concentrated in carbon-intensive firms. Aggregating investor-level shocks to the firm level, we find that firms with impacted investors exhibit an immediate reduction in climate change sentiment on conference calls. Over time, they lower emissions and energy use, and enhance climate focus in governance. These findings highlight the ripple effects of climate disasters through investment networks, influencing corporate behavior towards environmental responsibility.

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1 Introduction

Climate risk is one of the greatest challenges facing the world today and is quickly becoming a concern for large firms. A 2019 CDP report suggests that the world's largest 215 companies have $250 billion in potential losses to write-offs of assets from climate impacts, with many likely to hit within the next five years.[1] The possibility that these externalities have yet to be fully reflected in asset prices together with regulatory uncertainty in the transition to a low-carbon economy pose a substantial financial risk to investors (Kruger, Sautner, and Starks, 2020; Bansal, Ochoa, and Kiku, 2017; Bolton and Kacperczy, 2021; Hoepner, Oikonomou, Sautner, Starks, and Zhou, 2022; Seltzer, Starks, and Zhu, 2020). Large investors are taking notice of these risks and exerting their influence over environmental, social, and governance (ESG) policies (see e.g., Dyck, Lins, Roth, and Wagner, 2019; Krueger, Sautner, and Starks, 2020).

In this paper, we study climate disasters' propagation through common ownership networks as a particular mechanism through which investors may impact corporate ESG policies. The idea lies at the intersection of studies on salience as a driver of asset prices (e.g., Cosemans and Frehen, 2021; Frydman and Wang, 2020; Bose, Cordes, Nolte, Schneider, and Camerer, 2022; Rehse, Riordan, Rottke, and Zietz, 2019), studies on information transmission through common ownership networks (e.g., Azar, Schmalz, and Tecu, 2018; Edmans, Levit, and Reilly, 2019), and those on investors engagement in corporate ESG performance management (e.g., Kruger et al., 2020; Naaraayanan, Sachdeva, and Sharma, 2021; Doidge, Dyck, Mahmudi, and Virani, 2019; Hoepner, Oikonomou, Sautner, Starks, and Zhou, 2018). Natural disasters are one salient event that impacts corporate managers and asset prices alike (e.g., Kruttli, Roth Tran, and Watugala, 2021; Dessaint and Matray, 2017; Bernile, Bhagwat, and Rau, 2017). In particular, Huang, Jiang, Xuan, and Zhou (2021) and Alok, Kumar, and Wermers (2020) show that directors and fund managers exhibit salience bias with respect to natural disasters.

We conjecture that investors' exposure to climate disasters via one portfolio firm impacts their climate-related voting behavior and in turn the environmental focus of other (non-disaster hit) firms in their portfolio. This idea is supported by anecdotal evidence. For example, in the second quarter of 2017, after nearly 10% of its portfolio holdings were affected by climate disaster shocks, the investment company GMO LLC notably supported voting

[1] CDP is an international environmental NGO. See the report here: https://www.cdp.net/en/articles/media/worlds-biggest-companies-face-1-trillion-in-climate-change-risks.

on climate-related proposals of its portfolio firms like Devon Energy and Marathon Petroleum, even though these firms are not directly hit by climate disaster shocks.

We begin by examining how investors' exposure to climate disasters across their portfolios impacts their ES voting behavior at their other portfolio firms. In our first set of tests, we exploit within firm-time variation in investors' climate disaster exposure and examine how this exposure impacts the propensity of investors to support shareholder ES proposals. Our primary measure of investors' disaster exposure is portfolio-weighted, with each portfolio firm being disaster-exposed if their geographic footprint is hit by more severe disaster activity than their footprint would have been in the 1990s. The inclusion of proposal fixed effects and voter-industry fixed effects absorbs the average voting behavior on a given proposal and the typical voting patterns of specific funds within an industry.

We find that investors are more likely to support shareholder climate proposals at other firms they own following climate disaster shocks. Additional tests indicate that these results are (1) driven by votes for climate proposals at carbon-intensive 'brown' firms, (2) concentrated in periods of high public attention to climate change, and (3) driven by climate disasters occurring in the preceding two quarters. Within the sample of voting shareholders that owned shares during the previous fiscal year, a one standard deviation increase in disaster exposure in the previous two quarters predicts a 6 percentage point increase in the probability of supporting a climate proposal. Given that the average affirmative support for these proposals is under 20% this represents a economically significant change in voting behavior. Moreover, this change in voting behavior is statistically similar across a range of splits on investor characteristics, such as whether the investor is or is not a Big 3 indexer, a large mutual fund, or a signatory of the United Nation's Principles for Responsible Investment.

The dynamics of our voting results support a causal interpretation, as the effect is concentrated in disasters occurring in the two quarters before the vote and there is no evidence of a significant relation between voting behavior and future exposure to climate disasters. This pattern holds across various disaster exposure measures and remains robust even when controlling for disasters at investors' headquarters locations, which, as shown by existing studies (Alok et al., 2020; Fich and Xu, 2023), also influence portfolio allocation and voting decisions. The immediate and short-lived effect of investors' disaster exposure on voting discussions aligns with the concept of salience—investors disproportionately focus on climate issues following a disaster impacting a portfolio firm.

Next, we examine whether these investor-level disaster shocks predict firm-level changes in environmental focus. For these tests, we construct a firm-level indirect climate shock measure by aggregating investors' portfolio climate disaster exposures across all investors in a firm at a given time, weighted by institutional ownership. We begin by examining the immediate effects on climate sentiment in conference call discussions, computed as in Sautner, Van Lent, Vilkov, and Zhang (2023). We find that conference call climate change sentiment is more pessimistic in calls that follow their investors' climate disaster exposure.

Further, we explore whether this heightened investor attention results in tangible changes in corporate environmental policies. Our findings indicate that firms adopt specific governance mechanisms such as linking their executive pay policies to greenhouse gas (GHG) emission reductions and providing their boards with explicit responsibility for climate change in the two-year period following climate shocks to their institutional investors. Concurrently, firm-level greenhouse gas emissions and energy usage cumulatively decline, suggesting that changes in the governance mechanisms incentivize firms to shrink their carbon footprints and internalize some of the negative externalities from their activities (e.g., Cohen, Kadach, Ormazabal, and Reichelstein, 2023). Finally, all of these immediate and long-run firm-level outcomes concentrate in brown industries, which echoes the insight of Hartzmark and Shue (2023) that climate-conscious policies should focus on impact by targeting the firms that drive the most CO2 emissions.

Our paper contributes to ongoing debates on institutional investors' role in enhancing companies' ESG performance. While divestitures and threats of exit could discipline managers to improve ES performance (Gantchev, Giannetti, and Li, 2022), some theoretical works argue that, to make social investing impactful, divestment is not as effective as engagement or holding a brown stock if the firm has taken a corrective action (Berk and van Binsbergen, 2021; Broccardo, Hart, and Zingales, 2022; Edmans, Levit, and Schneemeier, 2022). Existing work highlights that socially responsible funds could make them effective at influencing firm behavior through engagement (e.g., Kruger et al., 2020; Naaraayanan et al., 2021; Doidge et al., 2019; Hoepner et al., 2022), and voting (e.g., Dikolli, Frank, Guo, and Lynch, 2022; He, Kahraman, and Lowry, 2023). Our work implies that, triggered by portfolio climate disaster shocks, institutional shareholders make impactful differences to improve the ESG performance of non-affected firms in the same portfolio.

Additionally, our findings enrich the nascent behavioral corporate finance literature on the impact of salience on individual decision-making. Recent papers document that salience can affect consumer choice (Bordalo, Gennaioli, and Shleifer, 2013), household insurance behavior (Gallagher, 2014), judicial decisions (Bordalo, Gennaioli, and Shleifer, 2015), corporate policies (Dessaint and Matray, 2017), fund allocation decisions (Alok et al., 2020), households' perception of risk (Gao, Liu, and Shi, 2020). Apart from several recent studies (see e.g., Dessaint and Matray, 2017; Alok, Kumar, and Wermers, 2020), limited evidence exists on the role of behavioral aspects of managers. Our paper complements these studies by examining the role of fund managers' behavioral biases in influencing corporate policies, i,e., the transmission of fund managers' perceptions onto their portfolio firms. In particular, we complement Alok et al. (2020) who find that fund managers underweight affected firms' shares following climate disasters. We, on the other hand, show that fund managers also adjust their behavior towards the non-affected firms: they change their voting behavior at non-affected firms, and those firms alter their climate policies.

Our study also adds to a large and growing literature on the impacts of weather and climate risks on corporate behavior. Climate change and weather shocks have been linked to changes in real estate values (Bernstein, Gustafson, and Lewis, 2019; Murfin and Spiegel, 2020; Baldauf, Garlappi, and Yannelis, 2020), corporate cash flows (Addoum, Ng, and Ortiz-Bobea, 2020; Brown, Gustafson, and Ivanov, 2021), institutional investors' attention (Kruger et al., 2020; Alok et al., 2020), corporate loan yields (Correa, He, Herpfer, and Lel, 2022), and municipal bond yields (Painter, 2020; Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2021).[2] We add a propagation channel through common ownership to show the impact of climate change shocks on firms.

Lastly, our findings connect to the common ownership literature by presenting a new type of information that flows through common ownership networks. There is some debate in this literature regarding what policies pass through common ownership networks (see e.g., Azar, Schmalz, and Tecu, 2018; Lewellen and Lowry, 2021; Koch, Panayides, and Thomas, 2021). Our voting results build on the idea in Edmans et al. (2019) that there is a voice and exit channel to governance in a world with common ownership with evidence that the voice of investors changes following their exposure to climate events.

[2]See also Barnett, Brock, and Hansen (2020); Choi, Gao, and Jiang (2020); Engle, Giglio, Kelly, Lee, and Stroebel (2020); Hong, Karolyi, and Scheinkman (2020). This list is by no means exhaustive.

2 Empirical Measures and Sample Construction

In this section, we outline the data sources and methods used to construct each variable of interest as well as present descriptive statistics for the key variables for our study.

2.1 Climate Disaster Exposure through Institutional Ownership

We begin by describing how we construct the primary explanatory variable, which measures investors' exposure to climate disasters across their portfolios.

2.1.1 Natural disaster data and disaster firm identification

We first obtain natural disaster information from SHELDUS, a county-level natural hazard dataset for the United States. This database provides comprehensive county-level details on natural hazards from 1960 to present, including the type of hazard, location, timing, and direct losses (e.g., property and crop losses, injuries, fatalities). This database is widely used in studies on the effects of natural disasters, including studies on financial markets (e.g., Cortés and Strahan, 2017; Correa et al., 2022). To capture shocks created by relatively large disasters, we include disasters that led to Presidential Disaster Declarations by Federal Emergency Management Agency (FEMA) and caused damages exceeding $100 million (adjusted to 2019 U.S. dollars). A county is marked as disaster-hit if it is listed in the state's FEMA request following such a large-scale disaster.

In accordance with the findings of the Intergovernmental Panel on Climate Change (IPCC) reports (e.g., Seneviratne, Nicholls, Easterling, Goodess, Kanae, Kossin, Luo, Marengo, McInnes, Rahimi, et al., 2017),[3] we focus our analysis on hurricanes/storms, floods, and wildfires, which are climate change-related severe weather events. Recent studies attribute the increased severity of these disasters to climate change, we provide more detailed discussions of this evidence in Appendix A.2. Appendix Table IA.1 provides details on these big natural disasters in our sample period. The appendix also discusses other large natural disasters in the United States, including 1) earthquakes, which are clearly not climate change related, and 2) ice storms, snow, and freezing,

[3]The IPCC is an intergovernmental body of the United Nations, which provides policymakers and the public with regular scientific assessments on climate change, its implications, and future risks. The IPCC reports show substantial evidence of a link between climate change, heat waves, and wildfires. The report finds similarly strong evidence for a link between climate change and more severe Atlantic hurricanes as well as extreme precipitation.

which have not crossed the the \$100 million damage threshold since before 2010.

Unlike prior studies that typically focus on disaster exposure based on firms' headquarters, we incorporate information based on firms' geographic footprints. To do so, we rely on the National Establishment Time-Series (NETS) dataset from Walls and Associates, which provides annual snapshots of detailed establishment-level information on geographic location and parent company ownership.[4] Thus, we calculate each firm i's fraction of establishments in a county c in year y as $Operation\ Weight_{i,c,y}$, which is $\frac{Number\ of\ establishment_{i,c,y}}{Total\ number\ of\ establishment_{i,y}}$, and then define a company's exposure to climate disaster risk in each year-quarter q from 2004 to 2019 as:

$$Disaster\ exposure_{i,q} = \sum_{c} Operation\ Weight_{i,c,y-1} \times County\ Exposed_{c,q}, \tag{1}$$

where $County\ Exposed_{c,q}$ is an indicator equal to 1 for counties suffering a climate disaster in calendar quarter q, and 0 otherwise. This time-varying location-weighted measure evaluates a company's exposure to climate disaster shocks.

As climate disasters disproportionately affect large or geographically dispersed firms, $Disaster\ Exposure_{i,q}$ may be be correlated with stable time and spatial characteristics that harm its interpretation as a disaster shock. To guard against this possibility, we construct a measure of excess disaster exposure. Specifically, we start by constructing a quarterly disaster exposure benchmark for each firm in each year using the disaster map in the 1990s:

$$Expected\ Quarterly\ Exposure_{i,q} = \sum_{c} Operation\ Weight_{i,c,y-1} \times County\ Quarterly\ Exposed_{c,90s}, \tag{2}$$

where $County\ Quaterly\ Exposed_{c,90s}$, ranging from 0 to 1, is the fraction of the 40 quarters in the 1990s that county c experienced a climate disaster. This benchmark provides a hypothetical value for firms' quarterly disaster exposure by applying firms' real footprint layout in the latest year $y-1$ but assuming the disaster map remains unchanged from the 1990s.[5] Comparing (1) and (2), we identify an unexpected climate disaster shock to firm i

[4]Our main tests do not apply establishment sales and employee counts from NETS, because both items are often imputed values.

[5]In Appendix Table IA.6, we also show our main voting result remains robust to accounting for any seasonality in the climate disasters from the 1990s.

in year-quarter q if it suffers an excess disaster shock, which is defined as:

$$Excess\ Disaster\ Exposure_{i,q} = Max\{0, Disaster\ Exposure_{i,q} - Expected\ Quarterly\ Exposure_{i,q}\}. \tag{3}$$

$Excess\ Disaster\ Exposure_{i,q}$ measures whether and to what extent a firm has higher $Disaster\ Exposure_{i,q}$ than its benchmark $Expected\ Quarterly\ Exposure_{i,q}$. This value will be greater than zero to the extent that a higher percentage of a firm's footprint is exposed to disasters in a quarter than it would have been in the typical quarter in the 1990s. We use the maximum because a positive difference is an unexpectedly large disaster shock but a negative difference is potentially non-news that includes the many instances of when locations are spared from disasters compared with the 1990s. We also analyze an alternative measure, $I(Excess\ Disaster\ Exposure_{i,q} > 0)$ where $I(.)$ is the indicator function.

Figure 1 illustrates the notable shift in average exposure to climate-related disasters (hurricanes/storms, floods, and wildfires) from the 1990s to the post-2000 period. The comparison reveals a dramatic expansion in the geographic spread of these disasters. Many counties, previously unaffected in the 1990s, have emerged as high-risk areas in recent years. Conversely, a smaller number of regions that experienced these disasters in the 1990s have not been similarly affected during our study period. Detailed analyses of each disaster type are presented separately in Appendix A.3.

[Figure 1 here]

Panel A of Table 1 provides descriptive summaries of the disaster measures for holdings of institutional investors. The true quarterly disaster exposure *Disaster Exposure* is right skewed. For example, the value of *Disaster Exposure* for a median firm and an average firm are 0.00% and 1.7%, respectively, and a firm at the 99% percentile has around 50% of establishments exposed to climate disasters.[6]

The pivotal variable in our analyses is *Excess Disaster Exposure*, which reflects the extent to which a firm's geographic footprint is unexpectedly exposed (based on 1990s) to disasters in a given quarter. The average *Excess Disaster Exposure* is about 1.3% in the entire sample, with 7.2% of firm-quarters recording a positive

[6] An untabulated test of pairing *Disaster Exposure* and the benchmark *Expected Quarterly Exposure* shows their correlation is 0.16 (p-value <0.0001). This confirms that our benchmarking is useful for measuring a disaster shock measure rather than stable time and spatial correlations due to firms' geographic locations and that location's climate disaster likelihood.

Excess Disaster Exposure. In our analysis, we refer to these disaster-hit firms as focal firms. Putting these two numbers together suggests that conditional on being a focal firm, approximately 18% (i.e., 1.3/7.2) of a firm's footprint is hit by a disaster in a given quarter. Appendix Figure IA.4 presents the industry distribution of firms with positive excess disaster exposure. Approximately half of disaster firms are in high-tech, manufacturing, shops, or healthcare. The remainder are spread out across a wide range of industries.

[Table 1 here]

For most of our analyses we use Equation (3) to identify disaster exposed focal firms. In Section 3.3, we further validate the robustness of our results by employing the continuous measure of $Disaster\ exposure_{i,q}$ directly. Additionally, we explore alternative benchmarks, considering factors like firms' size and geographic layout. These robustness checks confirm the strength and consistency of our findings across different methodologies.

2.1.2 Ownership data and measuring indirect natural disaster shocks via common ownership

To translate the firm-level climate disaster shock into investor-level exposures, we use information on institutional investors' quarterly equity holdings from 13F filings as compiled by Thomson/Refinitiv. The Securities and Exchange Commission requires financial institutions that manage investment portfolios of over $100 million in qualified securities to disclose their long-side holdings every quarter in Form 13F. We interchangeably refer to a 13F filer as an institutional investor or fund family as the disclosed positions are not individual portfolios but an aggregated one across funds under the 13F filer's umbrella. We follow standard procedures when constructing portfolio positions and weights. Specifically, to avoid stale data, we use the first chronological filing date (fdate) on each reporting date (rdate) and adjust share holdings for stock splits (using CRSP cumulative adjustment factors) when the fdate and rdate are different. Following Ben-David, Franzoni, Moussawi, and Sedunov (2021), we aggregate the five 13F filers that Blackrock reports under into one entity. Finally, we merge prices from CRSP using historical CUSIPs and quarter to compute the value of holdings and portfolio weights.[7]

Given firm i, institutional investor j, and year-quarter q, we aggregate the climate disaster shock to the

[7]We remove observations when the total portfolio weight is above 100% due to the very rare cases of when shares are double counted.

institutional investor level and construct the investor's indirect disaster exposure in two ways:

$$Portfolio\ Exposed_{j,q} = \sum_i I(Excess\ Disaster\ Exposure_{i,q} > 0) \times w_{i,j,q}, \tag{4}$$

$$Portfolio\ Exposed^{cont.}_{j,q} = \sum_i Excess\ Disaster\ Exposure_{i,q} \times w_{i,j,q}, \tag{5}$$

where $I(.)$ is the indicator function, $w_{i,j,q}$ is the portfolio weight of an investor j's holdings in firm i. For each investor, we sum the portfolio weight of each holding exposed to focal firms so that $Portfolio\ Exposed_{j,q}$ measures the proportion of an investor's portfolio experiencing an excessive natural disaster shock. We also analyze an alternative measure, $Portfolio\ Exposed^{cont}_{j,q}$, which incorporates the magnitude of the excessive natural disaster shocks that each focal firm suffers.

In our regression analyses, we typically focus on using a four-quarter moving average of these measures to account for the seasonality of climate disasters and to match the frequency of the yearly outcomes that we examine. However, we unpack these annual measures into their quarterly components when presenting our main results in figure form.

2.2 Voting Data and Climate-related Shareholder Proposals

The first goal of this paper is to study the relationship between the aforementioned measures of investors' exposure to climate events and investors' voting behavior. Our first set of tests examines voting on shareholder-sponsored proposals[8]. For this analysis, we collect mutual fund voting records from Institutional Shareholder Services (ISS) Voting Analytics. ISS in turn compiles the voting results of mutual funds families from form N-PX that is filed to the SEC. Because Iliev and Lowry (2015) find funds vote in the same direction over 96% of the time as that of the fund family, we proceed to merge this mutual fund-level data to our fund family-level 13F holdings data. We follow He, Huang, and Zhao (2019) in adopting a name-matching algorithm for doing so and then aggregate voting records across funds by fund family for the same proposal.

Similar to the procedure of He et al. (2023), we adopt a rigorous multi-stage screening process to identify three

[8]We focus on shareholder-sponsored as opposed to management-sponsored proposals as the literature has found that the former is more likely to need institutional investors' climate activism and as management rarely sponsors a climate-themed proposal (Cvijanović, Dasgupta, and Zachariadis, 2016).

mutually exclusive categories of shareholder-sponsored proposals: climate-related, environmental, and social. We first filter down to proposals identified by ISS Voting Analytics as SRI and keep categories with a clear association with climate or ES issues. Then, we read through all of the proposals' agenda general descriptions and the more detailed item descriptions to identify keywords associated with each category of proposals. Finally, we search for these keywords within item descriptions among all shareholder proposals to identify any proposals related to these categories. To check for potential inconsistencies and data errors, we manually read through all of the identified proposals. We iterate through this process several times to refine the set of keywords as well as manually remove any false positives. This process results in a initial sample of 428 climate, 537 non-climate environmental, and 1218 social shareholder-sponsored proposals. After requiring the data used in our main voting regression tests, our final sample includes 310 climate, 425 non-climate environmental, and 936 social proposals. This sample of proposals tallies up to 1671 proposals, which is similar to the 1658 ES proposals analyzed by He et al. (2023) over the same 2004 to 2019 sample period.

In our voting regression tests, we consider a vote for a proposal as an indicator variable for when institutional investors do not vote against the proposal, which means they are not actively rejecting a given climate proposal. Therefore, our vote for variable is an upper bound on support for climate proposals. At the same time, we find nearly identical estimates for our main results when defining a vote for a proposal as when the investor affirmatively votes for the proposal. We report these results in the Appendix.

2.3 Describing the climate proposal sample

The top five most frequent climate-related proposal item descriptions all pertain to adopting greenhouse gas targets or goals, with the next two most popular being reports on global warming and the financial risks of climate change. In contrast, the most popular non-climate environmental proposals' item descriptions relate to preparing sustainability reports or adding sustainability as a metric for executive compensation. Lastly, the most popular social proposals are related to gender, sexual orientation, or diversity.

Panel B of Table 1 reports on characteristics of climate proposals over time. We first see a slight uptick in the number of such proposals starting in 2015, which is the year of the Paris Agreement on climate change. The number of investors voting on climate proposals have also increased, which either reflects more interest in climate governance or the secular increase in institutional ownership over time. Digging into the voting support, we observe that average share of votes outstanding that not opposing climate proposals has remained steady, while the percentage of affirmative votes has nearly doubled from 9.24% to 18.91%. Similarly, more climate proposals have passed in recent years, but, overall, such proposals almost never pass, consistent with the broader finding by He et al. (2023) that ES proposals almost always fail.

Panel C of Table 1 displays summary statistics for the climate proposal sample at the fund family-proposal level, covering the period from 2004 to 2019. All variables are calculated as defined in Appendix A.1. The average support from institutional investors for climate-related shareholder proposals is 37.67%.[9] Among fund families that vote on climate-related shareholder proposals, the average of $Portfolio\ Exposed_{j,t}$ is 2.95%, namely the average portfolio weight of firms suffering excess climate shocks is 2.95%. $Portfolio\ Exposed_{j,t}$ is an upper bound when we treat all excess disaster exposures the same; but when we account for the magnitude of the disaster (normalized to be between 0 and 1), the average disaster-weighted portfolio weight ($Portfolio\ Exposed^{cont.}$) is now 0.0018%. We also compute a generic measure of the voting influence of an investor in a firm as a specific investor's institutional ownership (IFO). We find that IFO is 20.73 basis points, which indicates that on average an investor owns 0.2073% of shares outstanding of firms in our sample. The average portfolio value of $99.95 billion, compared to the median of $13.33 billion, suggests a skew towards larger investors. Lastly, these investors experience an average prior quarter's portfolio return of 2.79%. The summary statistics of the variables above are similar for environmental- or social-related shareholder proposals (see Panel A of the Appendix Table IA.2).

3 Immediate Impacts: Voting

Our central research question is the extent to which climate events propagate through common ownership networks to impact corporate climate and environmental outcomes. To address this, we conduct our analysis in two distinct stages. In this section, we delve into the immediate impacts of investors' natural disaster exposure on their voting behavior. In the subsequent section, we examine firm-level effects, focusing on conference call discussions and

[9] We note that this average computed at the investor-proposal level differs from the "Vote Not Against" average in Panel B of Table 1 because the number there is based on aggregate voting tallies comparing share support divided by shares outstanding at the company-proposal level. At the proposal-investor level, the ISS data only contains labels for if the fund votes a certain way i.e., it is not weighted by shares. Thus, the difference in Panel B and C can be explained by the fact that funds that support climate proposals have relatively more voting shares than those that do not.

longer-run environmental and governance outcomes.

3.1 Voting analyses

We first analyze how natural disasters propagate through the common ownership network in the form of institutional investors' voting on climate, environmental, and social shareholder-sponsored proposals. Our regression sample includes all shareholder-sponsored proposals with available portfolio exposure computed from 13F data at the investor and year-quarter level and focuses on the spillover effect i.e., the voting at firms that have no contemporaneous disaster exposure. We then estimate the following regression,

$$Vote\ for\ Proposal_{i,j,k,t} = \gamma_1 Portfolio\ Exposed_{j,t-1} + \gamma_2 IFO_{i,j,t-1} + \gamma_3 X_{j,t-1} + \text{FEs} + \epsilon_{i,j,k,t}, \tag{6}$$

where $Vote\ for\ Proposal_{i,j,k,t}$ is the voting support by fund family j for proposal k as of the shareholder meeting held by firm i in year t. $Portfolio\ Exposed_{j,t-1}$ is the four-quarter moving average of the two fund family level portfolio exposure measures to climate disasters based on Equations (4)–(5), and $IFO_{i,j,t-1}$ is the four-quarter moving average of institutional ownership by fund family j in firm i. Both moving averages end in the quarter of the record date when shareholders are recorded to have a right to vote in the subsequent shareholder meeting.[10]

The unit of observation in Equation (6) is at the fund family-proposal-year-level as a proposal can only be filed by one firm as of its shareholder meeting date. This allows us to include proposal fixed effects that absorb all time-specific firm-level attributes and focuses our coefficient estimates on how different investors vote on the same proposal. We also include fund family by industry fixed effects to capture a fund family's typical support for proposals. Thus, the coefficient on $Portfolio\ Exposed_{j,t-1}$ identifies how fund families vote differently in periods when they experience a climate disaster at their other portfolio firms, relative to both their own typical voting patterns and the voting patterns of other, untreated, investors at the same time. $X_{j,t-1}$ further controls for time-varying determinants of their voting such as investors' portfolio size and past performance.

The estimates on γ_1 provide evidence on how climate disasters at other portfolio firms affect investor voting

[10] To properly compute moving averages, we account for gaps in the 13F history from investors entering and exiting positions. So for each investor, we create a non-missing quarterly time index starting from the first available holding of a firm and to the last available holding. We assume that quarterly IFO and $Portfolio\ Exposed_{j,t-1}$ is zero when there is a gap in the data.

behavior, especially on climate and other ES proposals. We posit that investors may update their beliefs on (or pay more attention to) climate issues following a climate disaster shock. If natural disaster exposure changes investors' voting patterns similarly across all of the other firms in the portfolio, it will be captured by a significant γ_1. Our control for $IFO_{i,j,t-1}$ accounts for any simultaneous effect of large shareholders' differential monitoring role in firms (see e.g., Alchian and Demsetz, 1972; Shleifer and Vishny, 1986).

[Table 2 here]

Columns (1) and (2) of Table 2 indicate a positive relation between climate disasters among other portfolio firms and the propensity to support climate shareholder proposals of firms. Columns (3) and (4) restrict the sample to investors that we observe holding the firm at which the vote occurs during the year of our disaster measurement. We find similarly significant estimates using this restricted sample, suggesting that our findings persist within the set of longer-term shareholders. Within this sample of longer-term shareholders, a one standard deviation increase in $Portfolio\ Exposed_{j,t-1}$ (or $Portfolio\ Exposed^{cont}_{j,t-1}$ that accounts for the magnitude of the disaster exposure) is associated with an increase by 3.49 (or 2.98) in voting for climate proposals.

We also document a significant negative relationship between the level of institutional ownership by an investor in a specific firm (IFO) and the probability of them supporting climate-related shareholder proposals. For example, in Column (3), a one standard deviation increase in $\text{IFO}_{i,j,t}$ results in approximately 2.40 percentage points lower support for climate-related shareholder proposals. This is consistent with the large literature suggesting a negative relation between institutional ownership and ESG proposal voting outcomes. According to He et al. (2023), environmental and social (ES) proposals nearly always fail with shareholder support almost never crossing the 50% threshold. Consistent with this finding, in our sample, the levels of support among investors on ES proposals remain lower than 30%.

Columns (4) through (8) show that this result is specific to climate-related shareholder proposals. We find no spillover voting effects of investors' natural disaster exposure with respect to votes on other environmental or social shareholder proposals. All four of the coefficients in these columns corresponding to the effect of investors' disaster exposure on voting behavior are statistically insignificant with t-statistics less than 1.19 in magnitude.

3.2 Dynamic Impact of Climate Disasters on Voting

In Table 3 we study the timing over which disasters relate to voting behavior by splitting our disaster exposure measure into recent and more distant disasters over the past year. The estimates indicate that the relation between investors' disaster exposure and their voting behavior is concentrated in disasters that occur in the most recent half of the year. This result is consistent with either salience driving investors' voting behavior or management adjusting over the course of the year so as to preempt investors' desire to support shareholder climate proposals over six months after the disaster event.

[Table 3 here]

To study these alternatives more closely, Panel A of Figure 2 provides a graphical representation of Columns (3) and (4) of Table 2, with our disaster shock measure decomposed into its quarterly components. Specifically, the figure provides the relation between disasters that occur in quarters relative to the shareholder vote quarter, which we denote time 0. For ease of interpretation, Panel B of the figure is restricted to firms with a December 31 fiscal year end, although the figure is similar to the full sample version in Panel A.[11] Since shareholder votes typically are scheduled in the quarter after fiscal year end, time -1 is the final quarter that determines the annual fiscal results (i.e., October 1 - December 31 the previous year). Time -2 through -8 reflect earlier periods, while times 0 to 3 reflect the year after the current fiscal year.

[Figure 2 here]

The results in Figure 2 are consistent with climate disasters temporarily impacting institutional investors' propensity to support shareholder climate proposals. Disasters occurring two quarters before the vote have the most impact and correspond to the only statistically significant estimate across the twelve quarters examined. The next most positive coefficients correspond to disasters one and zero quarters before the vote date, which is just less than half the magnitude of the time -2 estimate. Importantly, we find no significant effects in the quarters after the vote, suggesting that our findings are not primarily due to a correlation between our disaster and stable investor characteristics.

[11] The similarity is because in the ISS data for shareholder-sponsored proposals, 84% of proposals are for firms that have a December 31 fiscal year end, for which the shareholder meeting is in calendar quarter Q2.

Figure 2 thus helps to clarify the timing of events. Specifically, we can fix calendar quarter Q2 of the current year as event time 0 given a vast majority of proposals in the sample are voted on then in the data. The record date, when lists of shareholders with the right to vote are compiled, occurs about half a quarter (i.e., about 57 days in our data) before the shareholder meeting. Given, our disaster portfolio exposure shock is merged according to the quarter of the record date, then the significant effect at -2 occurs about 2.5 quarters before the vote in calendar quarter Q2, which in turn is somewhere between Q3 and Q4 of the previous year. In our disaster data, we unsurprisingly find that 69% of excess disaster shocks occur in Q3 and Q4. Thus, investors appear to be influenced by seasonal disasters in Q3 and Q4 of the previous year, which affects their voting behavior in the subsequent year's shareholder meeting. This short-lived impact of climate disasters in investors' portfolios and their voting behavior is consistent with salience driving investors' voting decisions. In the coming sets of analyses, we aggregate across firms' investor base to see if this translates into actual changes in firm behavior.

3.3 Robustness and Interpretation

3.3.1 Alternative Benchmarks and Constructions of the Spillover

The dynamic illustration in Figure 2 is consistent with a causal interpretation whereby investors vote differently when their portfolio is more significantly affected by disasters in the preceding two quarters. Even if our estimates represent a plausibly causal relation between portfolio firm disaster exposure and voting outcomes, questions remain about the precise driving mechanism. Our baseline disaster exposure measure normalizes an area's exposure using a benchmark that reflects what would have happened to that area based on 1990s disasters. To a large degree, this controls for the obvious correlation between a portfolio's disaster exposure and holdings in large or geographically dispersed firms. But, large or dispersed firms will still be predisposed to take on higher disaster measures to the extent adverse climate events have risen over the past several decades. In many ways, this is exactly what we want to capture, however, it is also important to understand the extent to which our disaster shocks matter exclusively through their relation with firm size or geographic dispersion.

In Table 4 we first show that the use of the 1990s benchmark does not drive our main results. The first few rows of Column 1 indicate qualitatively similar effects to those in our main results tables with somewhat larger magnitudes using non-benchmarked disaster exposure measure, *Disaster exposure*, defined in Equation (1). This measure will consider disaster exposure that is attributable to the firm's geographic footprint. The similar to slightly larger magnitude suggests that most of what drives our main result is unexpected disaster exposure.

[Table 4 here]

In Columns (2) and (3), we construct new disaster exposure benchmarks based on firms' size and geographic footprint. Here, we only consider a firm disaster exposed if it experiences *Disaster exposure* above its size- or size & geographic footprint-matched benchmark. For the size benchmarks, each year, we follow the NYSE breakpoints of the 30th and the 70th percentiles to put all firms into three size groups, and apply the average *Disaster exposure* in each group as the size-based benchmark. Similarly, each year, we rank firms based on the size of their geographic footprints, then use the breakpoints of the 30th and 70th percentiles in this ranking to put firms into three groups. Together, we have 3×3 sorts on size and footprints, thus getting nine size & footprint-adjusted benchmarks. In Column (4), we combine the 1990s benchmark with the 3×3 sorts above, apply the average of $Disaster\ exposure_{i,q}^{90s-bk}$ in each size-footprint group as the benchmark, and consider a firm suffering climate shocks if its *Disaster exposure* is above this all-adjusted benchmark.

The results in Columns (2) through (4) of Table 4 report results with magnitudes similar to either the 1990s benchmarked estimates in Table 2 or the unbenchmarked estimates in Column (1). To the extent that these tests appropriately account for size and footprint effects, these results suggests that our main results are predominantly driven by abnormal or unexpected disaster exposure.

The remaining rows in Table 4 combined with Appendix Table IA.5 show that our findings are driven by the weight of an investor portfolio that is exposed to disasters, and not particularly by large or small firms being exposed. The remainder of Table 4 presents qualitatively similar results scaling investors portfolio weights by either the market capitalization of the exposed firm, the inverse of market capitalization, or conditioning on whether the exposed firm is above or below the NYSE median market capitalization. Thus, whether we focus on variation generated from large or small firms being hit by large or small disasters, we reach similar conclusions. Conversely, Appendix Table IA.5 shows that if we just measure the extent to which large or small firms in an investor's portfolio are hit, with no regard to how much the investor owns in those firms, we find no significant relation with voting behavior. Likewise, if we deviate from linear portfolio weight measures, which best represent the impact on portfolio returns, we find no significance. These findings are consistent with investors adjusting their voting behavior on climate proposals at other firms they own only to the extent that a meaningful part of their portfolio is hit by climate disasters in the previous period.

3.3.2 A Simulated Placebo Test

The relation between disaster-related portfolio exposure and the predisposition of large or geographically dispersed to be portfolio exposed also raises statistical issues. While our dynamic tests indicate that disaster-related portfolio exposure is a time-series shock, there remains the possibility that our 1990s benchmark does not adequately address potential bias or improperly estimated standard errors due to spatial correlation as disasters or disaster-related spillovers likely always hit firms that are geographically dispersed. Bias may result from the correlation between the disaster spillover shock and stable spatial characteristics related to location, while underestimated standard errors may result from not fully accounting for the spatial correlation across firms with our investor- and year-quarter double-clustered standard errors. Both issues may potentially inflate our t-statistics.

To address these issues, we conduct simulated placebo tests under the null hypothesis that randomized placebo disasters should have no effect on climate voting. The key assumption is that with placebo disasters, a placebo portfolio exposure measure would still inherit any spatial correlation from the geographic distribution of firms at a point in time. Specifically, we replace the actual $\textit{County exposed}_{c,q}$ in Eq. (1) with random placebo disasters, re-construct our main portfolio exposure measure, and repeat our regression tests with this placebo portfolio exposure measure. The placebo measure would still remain a time-series shock as our randomization is iid over time. We repeat this randomization 1000 times in order to generate a simulated distribution of t-statistics under the null hypothesis.

Figure 3 reports on the results. The black dots at each lag represent the simulated t-statistics under the placebo disaster null, while the larger blue dot represents the actual t-statistic from Figure 2. Strikingly, we observe that the blue dots are all within the distribution of black dots at every lead or lag, except for at -2. At time -2 relative to the vote, the actual t-statistic is extreme relative to the simulated distribution under placebo disasters, a rejection of the null hypothesis. Therefore, we can conclude that there is a robust effect from actual disasters on climate voting.

Table IA.7 in the Appendix conducts the analysis more formally. For the coefficients of interest in Tables 2 and 3, we compute the proportion of its respective simulated p-values that are below the nominal 5% level. This measures the statistical size of our hypothesis tests as, under the null hypothesis of random placebo disasters, a properly sized test would have a false positive rate of 5%. We observe that in the "Al" sample, inference based on our main portfolio exposure measure is properly size at 4.7%, while the version constructed from the recent two quarters is slightly oversized. In the "IFO>0" sample, the main measure is slightly oversizes, but the recent version is properly sized. In any case, following Huang, Li, Wang, and Zhou (2020), we use the 97.5 percentile of the simulated t-statistics as an adjusted critical value at the 5% level for our hypothesis tests. We observe that our actual t-statistics in Tables 2 and 3 are above this adjusted critical value. Therefore, we again can reject the null of placebo disasters, and conclude that there is an effect related to the actual excess disaster shock.

3.3.3 Comparison with Direct Investor Exposure

Finally, we consider the possibility that the location and disaster exposure of investors' headquarters may affect our findings. Alok et al. (2020) find that managers adjust their investment decisions in response to natural disasters that hit their investment firms' headquarters, while Fich and Xu (2023) further shows that hurricanes around investors' headquarters lead to changes in voting behavior. The intuition underlying our findings is distinct in that it relies on common ownership propagation of natural disaster exposures in investors' portfolios. However, the two results may be correlated to the extent that investors concentrate their holdings in firms with geographically proximate headquarters (Coval and Moskowitz, 1999).

The most direct way that we address any lingering overlap between these effects and our findings in our main tests is by controlling for firms' own disaster exposure via proposal fixed effects. Notably, these fixed effects also subsume any effect of firm-level characteristics, such as customer or supplier linkages (Pankratz and Schiller, 2023). However, we also directly add control for investor-level disaster exposure at their headquarters. To compute this measure, we scrape institutional investor's historical headquarter addresses from the universe of 13F filings, and construct a flag, $Investor\ Disaster\ Exposure_{j,t}$, for when the county of an investor headquarter is hit by a disaster. Across the four columns of Table IA.8 we find little evidence that investors home location disaster exposure affects their votes on climate proposals. Columns (3) and (4) show that the inclusion of this control also has little effect on the main results in our paper.

3.4 Heterogeneity

We next study how the portfolio disaster-voting relation varies over time and across firm and investor types.

3.4.1 Attention to climate change

We first examine how the relationship between natural disaster exposure and voting behavior relates to attention to climate change. We predict that the relation will be stronger when climate change awareness is high because that is when investors will be most likely to extrapolate future events from current climate-related disasters. To measure attention to climate news, we follow Engle et al. (2020) by constructing two indices. WSJ CC is based on climate news coverage in the *The Wall Street Journal* (WSJ) from January 1984 to June 2017, and Neg. CC is based on negative climate news from over one trillion news articles and social media posts from May 2008 to May 2018. Figures 2 and 3 in Engle et al. (2020) show that both indices peak surrounding climate events such as United Nations climate-related meetings or the Paris Climate Agreement, but do not exhibit any noticeable trend over time.

In Table 5 we interact our investor-level disaster exposure measure with a standardized version of these two climate attention indices. The persistent significance of the baseline disaster measure shows that under typical levels of climate change attention there is a significant relation between investors' disaster exposure and their voting behavior on climate-related proposals.

[Table 5 here]

The positive and statistically significant interaction between both climate change attention indices and investors' disaster exposure indicates that the impact of owning disaster hit firms on investors' voting behavior is especially pronounced when attention to climate change is high. The magnitude of this estimate indicates that the disaster exposure-voting relation approximately doubles when climate change is elevated by one standard deviation and is approximately zero when climate change attention is one standard deviation below its typical level. This result holds whether or not we control for the interaction between an investor's stake in the firm and climate change attention, which we find to be but positive but marginal in terms of statistical significance.

The results in Table 5 further corroborate our preferred interpretation of our results as evidence that investors factor in their recent exposure to climate-related disasters when considering future climate policy. The results embed two levels of investor attention. First, as in all of our voting analyses, proposal fixed effects absorb the aggregate effect of climate attention on voting behavior, requiring that investors respond differently to disasters when they are portfolio affected compared to when other firms are affected. Second, the Table 5 results further show that elevated climate attention changes the way that investors interpret these disasters that disproportionately affect their portfolio. Although salience is a likely driver of these findings, they could also be consistent with rational stories involving diversification tactics and/or expected differences in policy that relate to aggregate climate attention.

3.4.2 Brown versus green firms

An interesting feature of climate proposals in our data is that many of them target oil and energy firms, and to a lesser extent automobile companies. For example, the top two climate proposal targeted firms are Dominion Energy and Exxon Mobile with 25 each. Other firms in the top 20 include Chevron, Ford Motor, Berkshire Hathaway, Amazon, and Kroger. Thus, climate proposals appear to be targeted at brown industry firms with high GHG emissions. The natural following question is whether the climate voting effect we document concentrates in green or brown firms. Ex-ante, such a question is uncertain as the literature debates which firms climate activism should target. On one hand, green firms are where green policies are more easily adopted. On the other hand, brown firms are where such policies may be most impactful.

The primary way we test this is by interacting the explanatory variable of interest with the extent of emissions produced by the firm to which the climate proposal relates. We consider two emissions measures: the natural log of CO2 emissions and CO2 scaled by sales. Thus, we employ continuous measures of emissions instead of bifurcating firms into green and brown firms based on whether they are above or below median emissions as in Hartzmark and Shue (2023).[12] Columns (1) and (2) of Table 6 reproduce our voting analyses including this additional interaction term within the sample of emitting firms. The results suggest that the impact of investors'

[12] We do not find similar results when we classify firms as green or brown based on median emissions by year. We posit this is because climate proposals concentrate in brown firms already. Therefore, the median cutoff roughly compares brown firms with brown firms. We instead use the continuous measure to specifically examine if climate voting is related to the level of emissions among brown firms.

portfolio disaster exposure on their voting behavior is more pronounced when voting on climate proposals at brown firms. Column (3) shows that our main results hold in the 47% of our voting sample without emissions data. Thus, while high emissions is one driver of our results, we continue to find effects for non-emitting firms.

[Table 6 here]

In Appendix Table IA.9 we consider an industry-level measure of green and brown firms. Following Choi et al. (2020), we label industries as brown based on the five major industries identified by IPCC: energy, transport, buildings, chemicals & metals, and AFOLU (agriculture, forestry, and other land use); we otherwise label as green. Using this industry classification, 7,099 of the 8,594 voting sample observations are classified as brown firms, consistent with the business models of the firms we observe in the data. Column (1) shows that there is no effect on the 1,495 firms in green industries. Column (2) further shows that the entire effect is driven by brown industries, although the interaction in Column (3) is statistically insignificant due to the small population of green firms in our sample.

A benefit to the industry-based definitions of green and brown firms is that we retain the entire sample. A downside is that industry classifications are inherently noisy and may overlook important aspects of the firm. For instance, SIC code 8711 is for "Engineering Services," and contains petroleum engineering services as well as companies developing green technologies.

3.4.3 Investor type

As a final heterogeneity test, we study the role of investor type. We have no clear prior on the type of investor most impacted, since the most intuitive dimensions would most directly predict an investors average support for climate proposals as opposed to the marginal change in this average in response to a disaster shock. For example, an ESG-focused investor may support climate proposals and be focused on doing so and therefore not respond as significantly to disaster shocks across their portfolio. Nevertheless, any observed heterogeneous effects across the investor base speak to the likelihood of the voting effects we observe aggregating to meaningful firm-level impacts.

Given our diffuse prior we consider a wide range of investor characteristics. Across the five columns of Table 7, we interact an investors disaster exposure with indicators for: the Big 3 indexers (i.e., Blackrock, State Street, and Vanguard), the Top 10 investors in a quarter based on portfolio value, indicators for mutual funds (banks) that are larger than the 75th percentile of all investors by portfolio value, and investors who signed on to the UN Principles for Responsible Investment. Across all five columns, we see the baseline measure of disaster exposure to continue to be statistically significant. This indicates that excluding any of these groups does not affect our inferences. We also find statistically insignificant interactions in all cases. Thus, we cannot reject the hypothesis that the effect we estimate is consistent across investors of all types we examine. At the same time, in the last row, we report Wald tests for the total effect for these five types of investors, and find that all of them, except that of large banks, have a statistically significant and positive coefficient. So, a byproduct of this result is that disaster exposure affects the most impactful voters, as well as smaller shareholders.

[Table 7 here]

3.5 Exit versus Voice

Our focus on voting speaks to voice i.e., engagement as the mechanism for investors to change firms' climate policies. At the same time, firms may exercise exit i.e., the boycotting of "brown" holdings via selling or even divestment. We analyze this remaining possibility in Appendix Table IA.10.

We use the same brown versus green industry classifcation as before. In Column (1), we regress investors' brown industry portfolio weight in the current year on their previous years' portfolio exposure to climate disasters. Given the inclusion of investor fixed effects, we see that time-variation in portfolio exposure to climate disasters does not predict brown industry portfolio weight. In Columns (2) and (3), we analyze the change in brown portfolio (i.e., the extensive margin) and the change in high CO2 portfolio weight within the brown industry (i.e., the intensive margin). As both outcomes are uncorrelated with exposure to climate disasters, we conclude investors neither rebalance out of brown industries nor out of high CO2 emitters within brown industries. Moreover, in Columns (4)–(6), these results are robust to using the percentage of brown shares in a portfolio, which addresses the concern that changes in share prices after disasters offsets investors' rebalancing.

Overall, these results demonstrate the relative importance of engagement versus exit in our setting (e.g., Azar, Duro, Kadach, and Ormazabal, 2021; Kruger et al., 2020). Theoretically, Broccardo et al. (2022) demonstrate that this trade-off depends on the proportion of socially responsible investors in the economy, and that voice is optimal when a majority of investors care about social responsibility. Thus, our voting evidence contrasted with the lack of evidence for any selling and divestment of brown firms supports a model where social responsibility is the majority's preference.

4 Firm-level Spillover Effects

Our investor-level findings thus far indicate that investors' voting behaviors are affected by climate disaster exposure across other firms in their portfolios. This relation extends to a variety types of investors, including those with the most impact. With that said, it is unclear *ex-ante* whether these differential voting preferences will manifest in significant adjustments when aggregated to the firm level. On the one hand, the number of climate-related shareholder proposals are relatively small, the sample on the margin of passing is even smaller, and such proposals typically target "brown" firms. On the other hand, the changes in voter preferences we observe may reflect broader shifts in investors' preferences that impact firms through additional channels.

This tension motivates our next set of tests, in which we study whether the aggregate exposure of a firm's investor base impacts firm level outcomes. Furthermore, we delve into whether potential firm impacts concentrate among brown industries, as suggested by our voting analysis. For this set of tests, we aggregate the investor-level measure of their portfolio's disaster exposure to the firm level. Specifically, we value-weight investors' climate disaster exposures across all investors in a firm i in a given year-quarter q by,

$$VW(Portfolio\ Exposed)_{i,q} = \sum_{j \in S_{i,q}} IFO_{i,j,q} \times Portfolio\ Exposed_{j,q}, \tag{7}$$

where $j \in S_{i,q}$ is the set of firm i's institutional investors, and $IFO_{i,j,q}$ is an investor's ownership in this firm. We value-weight using $IFO_{i,j,q}$ since theoretical and empirical models of common ownership typically assume that institutional ownership in a specific firm captures the influence of investors voting for their preferred managerial policies (e.g. Gilje, Gormley, and Levit (2020)). Lastly, to focus on the portfolio spillover interpretation, we compute this measure for firms without direct contemporaneous climate disaster exposure. The summary statistics of $VW(Portfolio\ Exposed)_{i,q}$ and our firm-level outcomes are reported in Panel B of Appendix Table IA.2.

4.1 Conference Call Discussion

We begin our firm level analyses by examining whether an investor base's disaster exposure affects firms' quarterly conference call discussion of climate change. Our dependent variable is based on time-varying text-based measures of firm-level attention to climate change issues constructed by Sautner et al. (2023) (SLVZ). SLVZ extract words related to climate change from transcripts of quarterly earnings conference calls of publicly-listed firms.[13] Adapting a machine learning keyword discovery algorithm, they first produce climate change bigrams and then construct an aggregate firm-level measure of climate change exposure via word counts and climate change sentiment by counting the number of climate change bigrams after conditioning on the presence of the positive and negative tone words. Our outcome variable of interest ($CC\ Sentiment_{i,q}$) is the difference between the positive and negative tone climate sentiment scaled by overall climate attention. We also separately study the positive and negative decomposition of $CC\ Sentiment_{i,q}$ and the effect for brown versus green industries.

Our regression specification for detecting firm-level spillover effects is,

$$CC\ Sentiment_{i,q} = \beta_1 VW(Portfolio\ Exposed)_{i,q-1} + \beta_2 Disaster\ Exposure_{i,q-1} + Controls_{i,q-1} + \epsilon_{i,q}. \quad (8)$$

The coefficient of interest, β_1 on $VW(Portfolio\ Exposed)_{i,q-1}$, measures the spillover effect of climate disasters that institutional investors face at their other portfolio firms in the previous calendar quarter on a firm's conference call climate sentiment the current quarter q. $Disaster\ Exposure_{i,q-1}$ controls for the effect of firms being directly hit by disasters in the previous quarter. Results are similar dropping firms that are substantially hit by disasters or including an interaction between a firm's own disaster exposure and that of their investor base. The other controls include the previous year's log assets (to account for firm size), the overall institutional ownership, and the number of institutional blockholders (to account for underlying ownership structure at the firm level).

We also include a rich set of fixed effects. First, we add firm fixed effects to focus our inference on the effect from the spillover shock within firm over time, and to control for unobserved constant differences across firms. State × year fixed effects control for unobserved time-varying trends across states (e.g., disasters often cause spatial clustering by affecting geographic areas differently over time), while Industry × year fixed effects control

[13] SLVZ measures are available on https://osf.io/fd6jq/.

for potential product market trends over time (e.g., several studies find common ownership is often associated with product market competition). For inference, we use robust standard errors double-clustered by firm and year-quarter.

Table 8 reports on the conference call results. Column (1) suggests that the climate disasters that institutional shareholders have faced at other portfolio firms during the past year have a significant negative effect on climate change sentiment during conference calls.[14] Columns (2) and (3) show that the effect manifests primarily through increases in negative sentiment. Since all the coefficients of interest in Table 8 are normalized by their full-sample standard deviations, the coefficient estimate of -0.39 in Column (1) suggests that a one standard deviation increase in portfolio disaster exposure leads to an approximate 0.39 percentage reduction in net climate change sentiment. Lastly, Column (4) reports on the results of comparing the effects on sentiment for brown versus green industries. While sentiment drops significantly in both brown and green industries with no statistical difference based on the interaction, we do observe that the average sentiment coefficient among brown industries is about 78% larger than that of green industries.

[Table 8 here]

Figure 4 dynamically illustrates the relation between the disaster exposure of firms' investor base and their conference call climate sentiment. We find that the significant negative relation concentrates in disasters one quarter before and on the quarter of the conference call. Our estimate of this relation between one quarter ago disaster shocks and conference call climate sentiment is larger in magnitude compared with any other coefficient in the eleven surrounding quarters. Importantly, we again find no evidence of pre-trends, which is consistent with a causal interpretation of our results. Thus, the aggregate exposure of a firm's investor base to climate disasters appears to be a significant determinant of the the firm's dialogue with investors.

[Figure 4 here]

[14] Appendix Tables IA.11 and IA.12 also reports results for firm-level indirect exposure constructed within different investor types, for Big-3 indexers, and for UN PRI signatories. Consistent with the overall effect, we generally find that the conference call effect across different subsets of investors is negative, with the strongest and statistically significant effects showing up for investment advisors and mutual funds.

4.2 Long-run Environmental Outcomes

We next examine if firms respond to indirect exposure to disasters in the long-run by adjusting their climate policies. Such an objective is important in light of our earlier findings that formal voting mechanisms tend to fail despite garnering increased voting support while less formal conference call discussion increase. Our aim is to understand the relation between investors' disaster exposure and both longer-run physical outcomes and climate-related governance initiatives.

4.2.1 Emissions and Energy Use

For our analysis of physical outcomes, we obtain greenhouse gas emission and total energy use data from the Refinitiv ESG (Asset4) database. The former is measured as the total amount of CO2 and CO2 equivalent emissions in metric tons (MTs), and includes both direct (scope 1) and indirect (scope 2) emissions. The latter is the total energy consumption by firms in gigajoules (GJs).

We report results from these long-run effects in Panel A of Table 9 for up to two years into the future following the indirect climate-change exposure shocks. Each row in this table corresponds to a separate outcome variable. To capture these effects, we modify Equation (8) to include a two-year lagged window, a contemporaneous window, and a one-year lead of indirect exposure relative to the year of the specific outcome variable where all control variables such as firm size and fixed effects remain the same. To be comparable to the annual outcomes, we compute the average indirect exposure over four quarters as the variable of interest. This approach allows us to systematically assess the impact of climate-related exposure on emissions and energy use over a substantial period. Panel B of Table 9 further compares these effects for brown versus green industries.

[Table 9 here]

We start our long-run analysis by examining how carbon emissions (CO2) respond to indirect exposure to climate-change related disasters. Carbon emissions are at the center of international treaties on climate change (e.g., the Paris Agreement of 2015), state regulations (e.g., California's cap-and-trade program of 2013), regional alliances (e.g., the Regional Greenhouse Gas Initiative), disclosure standards (e.g., Task Force on Climate-related Financial Disclosures), and investor-led initiatives (e.g., Climate Action 100+). Research on climate finance also heavily involves carbon emissions and their perception by investors (e.g., Bolton and Kacperczy, 2021; Kumar and Purnanandam, 2023; Ivanov, Kruttli, and Watugala, 2023).

The first row of Panel A in Table 9 shows no sign of a significant change in CO2 emissions in the period preceding the indirect exposure shocks. On the other hand, we observe a substantial cumulative decline in CO2 emissions in the two-year period after a positive shock to indirect exposure to climate-change disasters, which is both economically and statistically significant as reported in Column (3). For a one standard deviation increase in indirect portfolio exposure to climate disasters results in a drop in CO2 emissions of 0.908 millions of metric tons. Economically, this is very large compared with the average CO2 of 5.639 millions of metric tons and represents about 16% of average firm-level CO2 emissions in our sample. This effect over time is also apparent in Panel A of Figure IA.5. In untabulated tests, when we break down the total CO2 emissions into scope 1 and scope 2 emissions, we find the drop in total CO2 emissions is coming mostly from scope 1 emissions, which are under the direct control of firms unlike scope 2 emissions (not reported). The fact that scope 1 emissions are the driving component of the reduction in CO2 emissions reinforces the notion that firms are cutting down on their emissions as scope 1 emissions are directly attributable to firm-specific actions.

The next row indicates that the drop in CO2 emissions is robust to when scaling by sales. This is important as the level of CO2 is largely explained by firms' sales, providing a confounding interpretation (Zhang (2023)). When we scale by sales, we find that there is again no pre-trend or contemporaneous effect, but there remains a drop in carbon intensity in the subsequent two-year period. This reinforces the initial findings and suggests a genuine shift in firms' environmental impact.

[Figure IA.5 here]

In the third row, we also show that firms reduce another critical climate factor, their total energy use. There is no change in energy use for firms immediately prior to a shock to indirect exposure as shown in Column (1). However, firms start reducing their energy use within two years after their indirect exposure to climate change disasters via common ownership networks. Column (3) reports a significant drop in energy use, which is 44% of average energy use in our sample. As energy usage is a significant driver of CO2 emissions, this evidence complements the findings in Row 1. Panel B of Figure IA.5 shows the large drop in energy use by firms in the aftermath of indirect exposure to climate change disasters. Further, we find the changes in CO2 emissions and energy usage are concentrated in brown industries, consistent with the higher support on climate proposals for this subset of firms in Table 6 (not reported). This suggests that institutional investors target firms that are responsible for a significant portion of CO2 emissions following indirect shocks. Taken together, these results suggest that the indirectly exposed firms take drastic actions to mitigate their carbon print in the form of lower carbon emissions and energy usage compared to themselves prior to the indirect climate-change shocks and to other firms.

4.2.2 Climate related Governance Provisions

In light of the transient nature of the voting effects identified in Table 2, a pertinent question arises: how can these short-term shifts translate into relatively longer-lived effects in real climate-change policies? In the final two rows of Panel A of Table 9, we address this question by examining whether firms adjust their climate-change related governance mechanisms in the aftermath of indirect exposure to climate change disasters. Such governance changes, once implemented, tend to have more lasting impacts than fluctuating voting support, given their stickier nature.

Linking executive pay to GHG emissions is one such mechanism that can encourage firms to take actions. For example, Cohen et al. (2023) show that ESG-based pay is accompanied by reductions in meaningful GHG emissions. We obtain climate-related governance mechanisms variables from the Carbon Disclosure Project (CDP) survey, which collects data from companies to disclose their climate impact. Our analysis zeroes in on firms that affirmatively respond to integrating monetary incentives for executives to manage climate policies, including achieving GHG emission targets, and placing the highest responsibility for climate change with the board of directors.[15] Specifically, we encode an indicator equal to 1 and 0 otherwise when firms' executives are incentivized to manage the climate and when the board of directors holds responsibility for climate change.

Table 9 row 3 shows a notable trend that firms are increasingly likely to incorporate GHG emission reduction goals into their executive compensation policies within the two-year window following being indirectly exposed to

[15] Specifically, the survey questions are (in the same order): 1) "Do you provide incentives for the management of climate change issues, including the attainment of greenhouse gas targets?" with a follow-up answer of "Executive/office/manager" to the question of "Who is entitled to benefit from those incentives?" and a follow-up answer of "Recognition (non-monetary)" to the question "The type of incentives: Do you provide incentives for the management of climate change issues, including the attainment of greenhouse gas targets?" and 2) answer of "Board" to the question of "Where is the highest level of responsibility for climate change within your company? Please specify who is responsible."

climate change disasters. This corresponds to a 3.89% increase in the likelihood of the adoption of climate-based executive pay policies in our sample for a one standard deviation increase in our disaster measures.[16] Panel C of Figure IA.5 shows this uptick in the growing tendency among firms to adopt climate-focused executive pay policies.

Another crucial governance mechanism is the board of directors (Adams, Hermalin, and Weisbach, 2010). The final row of Table 9 shows that boards are increasingly tasked with explicit responsibility for climate change after being indirectly exposed to climate change disasters. The statistically significant coefficient estimate of 0.06 within the initial two-year period represents a 11.53% increase in this board responsibility for a typical firm in our sample. This heightened accountability of boards in climate governance is also depicted in Panel D of Figure IA.5. Altogether, these findings suggest that the surge in investor support for climate proposals immediately after climate-related disasters has a tangible impact on corporate governance. Such shifts in governance likely contribute to the subsequent reductions in CO2 emissions and energy use, demonstrating a direct link between investor actions following disasters and concrete corporate climate initiatives.

4.2.3 Where is the most long-run impact? A Comparison of Brown versus Green Industries.

Finally, Panel B of Table 9 reports the results when interacting $VW(Portfolio\ Exposed)$ with Green industry. It shows that *all* of the long-run outcomes concentrate in brown industries with little effect on green industries. For example, the first row of the top half of Panel B reports that a one standard deviation increase in indirect climate disaster portfolio exposure results in a drop in CO2 emissions of 1.342 millions of metric tons within brown industries. In the first row of the bottom half, the interaction term with green industry is not only statistically significant, indicating a sharp difference in associated CO2 emissions, but also nearly the same magnitude in the opposite direction. As a result, indirectly exposed firms in green industries do not experience a drop in total CO2 emissions. In the remaining rows, we see similar contrasting patterns for CO2 per unit of sales, energy use, and pay incentives and board responsibility for climate management. Hence, these results echo the insight of Hartzmark and Shue (2023) that green policies targeting brown industries have the largest impact while already green industries have little to improve on in terms of sustainability.

[16] We also observe that these firms are more likely to provide non-monetary incentives within the two-year period for executives who reduce their firms' carbon prints (not reported).

5 Conclusion

We provide the first evidence that the salience effect of climate disasters on institutional investors flows through to affect corporate ESG policies. We find that climate-change related disasters increase institutional investors' awareness of climate change issues and accordingly these investors engage with the unaffected firms in their portfolios to influence corporate climate policies. In particular, we observe that such institutional investors vote in greater support of climate-related shareholder proposals at unaffected firms only after getting hit by climate change disasters in their portfolios and compared to other institutional investors. There is no such effect for other types of ES proposals. These unaffected firms also exhibit significantly negative sentiment on climate change during conference calls. Both of these effects are temporary, in support of salience potentially being the main driver behind the change in these effects. In the long-run, firm-level GHG emissions and energy usage cumulatively decline at the same time as the unaffected firms adopt specific governance mechanisms such as linking their executive pay policies to GHG emission reductions, suggesting that changes in governance mechanisms potentially incentivize firms to internalize some of the negative externalities from their activities. We also find evidence that institutional investors target firms that are responsible for a significant portion of CO2 emissions, as our results are more pronounced in brown industries.

These findings are particularly important in the current context of increasing awareness and action against climate change. Our work contributes to the growing literature on climate finance and the role of institutional investors in addressing the challenges posed by climate change, providing a new perspective on how indirect exposure to climate events can drive corporate change. While our study offers a comprehensive analysis, it also opens avenues for further exploration. Future research could investigate the long-term sustainability of these changes or assess whether similar patterns hold across different sectors, regions, and other types of environmental crises. Overall, our study contributes to the understanding of the ripple effects that climate disasters have on corporate behavior and policies. Our findings suggest that market-based solutions in the form of common ownership networks can encourage firms to reduce their carbon print, likely in tandem with coordinated regulatory actions.

References

Adams, R., Hermalin, B., Weisbach, M., 2010. The role of boards of directors in corporate governance: a conceptual framework and survey. Journal of Economic Literature 48, 58–107.

Addoum, J., Ng, D., Ortiz-Bobea, A., 2020. Temperature shocks and establishment sales. Review of Financial Studies 33, 1331–1366.

Alchian, A. A., Demsetz, H., 1972. Production, information costs, and economic organization. American Economic Review 62, 777–795.

Alok, S., Kumar, N., Wermers, R., 2020. Do fund managers misestimate climatic disaster risk. The Review of Financial Studies 33, 1146–1183.

Azar, J., Duro, M., Kadach, I., Ormazabal, G., 2021. The big three and corporate carbon emissions around the world 142, 674–696.

Azar, J., Schmalz, M. C., Tecu, I., 2018. Anticompetitive effects of common ownership. The Journal of Finance 73, 1513–1565.

Baldauf, M., Garlappi, L., Yannelis, C., 2020. Does climate change affect real estate prices? only if you believe in it. The Review of Financial Studies 33, 1256–1295.

Bansal, R., Ochoa, M., Kiku, D., 2017. Climate change and growth risk. NBER Working Paper 23009.

Barnett, M., Brock, W., Hansen, L. P., 2020. Pricing uncertainty induced by climate change. The Review of Financial Studies 33, 1024–1066.

Ben-David, I., Franzoni, F., Moussawi, R., Sedunov, J., 2021. The granular nature of large institutional investors. Management Science 67, 6629–6659.

Bender, M. A., Knutson, T. R., Tuleya, R. E., Sirutis, J. J., Vecchi, G. A., Garner, S. T., Held, I. M., 2010. Modeled impact of anthropogenic warming on the frequency of intense atlantic hurricanes. Science 327, 454–458.

Berk, J., van Binsbergen, J. H., 2021. The impact of impact investing .

Bernile, G., Bhagwat, V., Rau, P. R., 2017. What doesn't kill you will only make you more risk-loving: Early-life disasters and ceo behavior. The Journal of Finance 72, 167–206.

Bernstein, A., Gustafson, M. T., Lewis, R., 2019. Disaster on the horizon: The price effect of sea level rise. Journal of financial economics 134, 253–272.

Bolton, P., Kacperczy, M., 2021. Do investors care about carbon risk? Journal of Financial Economics 142, 517–549.

Bordalo, P., Gennaioli, N., Shleifer, A., 2013. Salience and consumer choice. Journal of Legal Studies 121, 803–8433.

Bordalo, P., Gennaioli, N., Shleifer, A., 2015. Salience theory of judicial decisions. Journal of Legal Studies 44, S7–S33.

Bose, D., Cordes, H., Nolte, S., Schneider, J. C., Camerer, C. F., 2022. Decision weights for experimental asset prices based on visual salience. Review of Financial Studies 35, 5094–5126.

Broccardo, E., Hart, O., Zingales, L., 2022. Exit versus voice. Journal of Political Economy 130, 3101–3145.

Brown, J. R., Gustafson, M. T., Ivanov, I. T., 2021. Weathering cash flow shocks. The Journal of Finance 76, 1731–1772.

Choi, D., Gao, Z., Jiang, W., 2020. Attention to global warming. The Review of Financial Studies 33, 1112–1145.

Cohen, S., Kadach, I., Ormazabal, G., Reichelstein, S., 2023. Executive compensation tied to esg performance: international evidence .

Correa, R., He, A., Herpfer, C., Lel, U., 2022. The rising tide lifts some interest rates: Climate change, natural disasters and loan pricing. Working paper .

Cortés, K. R., Strahan, P. E., 2017. Tracing out capital flows: How financially integrated banks respond to natural disasters. Journal of Financial Economics 125, 182–199.

Cosemans, M., Frehen, R., 2021. Salience theory and stock prices: Empirical evidence. Journal of Financial Economics 140, 460–483.

Coval, J. D., Moskowitz, T. J., 1999. Home bias at home: Local equity preference in domestic portfolios. The Journal of Finance 54, 2045–2073.

Cvijanović, D., Dasgupta, A., Zachariadis, K. E., 2016. Ties that bind: How business connections affect mutual fund activism. The Journal of Finance 71, 2933–2966.

Dessaint, O., Matray, A., 2017. Do managers overreact to salient risks? evidence from hurricane strikes. Journal of Financial Economics 126, 97–121.

Dikolli, S. S., Frank, M. M., Guo, Z. M., Lynch, L. J., 2022. Walk the talk: Esg mutual fund voting on shareholder proposals. Review of Accounting Studies 27, 864–896.

Doidge, C., Dyck, A., Mahmudi, H., Virani, A., 2019. Collective action and governance activism. Review of Finance 23, 893–933.

Dyck, A., Lins, K. V., Roth, L., Wagner, H. F., 2019. Do institutional investors drive corporate social responsibility? international evidence. Journal of financial economics 131, 693–714.

Edmans, A., Levit, D., Reilly, D., 2019. Governance under common ownership. The Review of Financial Studies 32, 2673–2719.

Edmans, A., Levit, D., Schneemeier, J., 2022. Socially responsible divestment. European Corporate Governance Institute–Finance Working Paper .

Elsner, J. B., Jagger, T. H., et al., 2009. Hurricanes and climate change. Springer.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., Stroebel, J., 2020. Hedging climate change news. The Review of Financial Studies 33, 1184–1216.

Fich, E. M., Xu, G., 2023. Do salient climatic risks affect shareholder voting? Available at SSRN 4262927 .

Frydman, C., Wang, B., 2020. The impact of salience on investor behavior: Evidence from a natural experiment. The Journal of Finance 75, 229–276.

Gallagher, J., 2014. Learning about an infrequent event: evidence from flood insurance take-up in the united states. Journal of Applied Economics 6, 206–233.

Gantchev, N., Giannetti, M., Li, R., 2022. Does money talk? divestitures and corporate environmental and social policies. Review of Finance 26, 1469–1508.

Gao, M., Liu, Y., Shi, Y., 2020. Do people feel less at risk? evidence from disaster experience. Journal of Financial Economics 138, 866–888.

Gilje, E. P., Gormley, T. A., Levit, D., 2020. Who's paying attention? measuring common ownership and its impact on managerial incentives. Journal of Financial Economics 137, 152–178.

Goldsmith-Pinkham, P. S., Gustafson, M., Lewis, R., Schwert, M., 2021. Sea level rise exposure and municipal bond yields. Jacobs Levy Equity Management Center for Quantitative Financial Research Paper .

Grinsted, A., Ditlevsen, P., Christensen, J. H., 2019. Normalized us hurricane damage estimates using area of total destruction, 1900- 2018. Proceedings of the National Academy of Sciences 116, 23942–23946.

Hartzmark, S. M., Shue, K., 2023. Counterproductive impact investing: The impact elasticity of brown and green firms. Available at SSRN 4359282 .

He, J. J., Huang, J., Zhao, S., 2019. Internalizing governance externalities: The role of institutional cross-ownership. Journal of Financial Economics 134, 400–418.

He, Y., Kahraman, B., Lowry, M., 2023. Es risks and shareholder voice. The Review of Financial Studies, Forthcoming .

Hoepner, A., Oikonomou, I., Sautner, Z., Starks, L., Zhou, X., 2022. Esg shareholder engagement and downside risk. working paper .

Hoepner, A. G., Oikonomou, I., Sautner, Z., Starks, L. T., Zhou, X., 2018. Esg shareholder engagement and downside risk .

Hong, H., Karolyi, G. A., Scheinkman, J. A., 2020. Climate finance. The Review of Financial Studies 33, 1011–1023.

Huang, D., Li, J., Wang, L., Zhou, G., 2020. Time series momentum: Is it there? Journal of financial economics 135, 774–794.

Huang, Q., Jiang, F., Xuan, Y., Zhou, X., 2021. Director personal experience and corporate environmental performance. Working paper .

Iliev, P., Lowry, M., 2015. Are mutual funds active voters? The Review of Financial Studies 28, 446–485.

Ivanov, I., Kruttli, S., Watugala, S., 2023. Banking on carbon: Corporate lending and cap-and-trade policy. Review of Financial Studies forthcoming.

Koch, A., Panayides, M., Thomas, S., 2021. Common ownership and competition in product markets. Journal of Financial Economics 139, 109–137.

Krueger, P., Sautner, Z., Starks, L. T., 2020. The importance of climate risks for institutional investors. The Review of Financial Studies 33, 1067–1111.

Kruger, P., Sautner, Z., Starks, L., 2020. The importance of climate risks for institutional investors. Review of Financial Studies 33, 1067–1111.

Kruttli, M. S., Roth Tran, B., Watugala, S. W., 2021. Pricing poseidon: Extreme weather uncertainty and firm return dynamics .

Kumar, M., Purnanandam, A., 2023. Carbon emissions and shareholder value: causal evidence from the u.s. power utilities. working papers .

Lewellen, K., Lowry, M., 2021. Does common ownership really increase firm coordination? Journal of Financial Economics 141, 322–344.

Murfin, J., Spiegel, M., 2020. Is the risk of sea level rise capitalized in residential real estate? The Review of Financial Studies 33, 1217–1255.

Naaraayanan, S. L., Sachdeva, K., Sharma, V., 2021. The real effects of environmental activist investing. European Corporate Governance Institute–Finance Working Paper .

Painter, M., 2020. An inconvenient cost: The effects of climate change on municipal bonds. Journal of Financial Economics 135, 468–482.

Pankratz, N., Schiller, C., 2023. Climate change and adaptation in global supply-chain networks. Review of Financial Studies, accepted .

Rehse, D., Riordan, R., Rottke, N., Zietz, J., 2019. The effects of uncertainty on market liquidity: evidence from hurricane sandy. Journal of Financial Economics 134, 318–332.

Sautner, Z., Van Lent, L., Vilkov, G., Zhang, R., 2023. Firm-level climate change exposure. The Journal of Finance 78, 1449–1498.

Seltzer, L., Starks, L., Zhu, Q., 2020. Climate regulatory risks and corporate bonds. working paper .

Seneviratne, S. I., Nicholls, N., Easterling, D., Goodess, C. M., Kanae, S., Kossin, J., Luo, Y., Marengo, J., McInnes, K., Rahimi, M., et al., 2017. Changes in climate extremes and their impacts on the natural physical environment .

Shleifer, A., Vishny, R. W., 1986. Large shareholders and corporate control. Journal of Political Economy 94, 461–488.

Smith, A. B., Katz, R. W., 2013. Us billion-dollar weather and climate disasters: data sources, trends, accuracy and biases. Natural Hazards 67, 387–410.

Wuebbles, D. J., Fahey, D. W., Hibbard, K. A., Arnold, J. R., DeAngelo, B., Doherty, S., Easterling, D. R., Edmonds, J., Edmonds, T., Hall, T., et al., 2017. Climate science special report: Fourth national climate assessment, volume i .

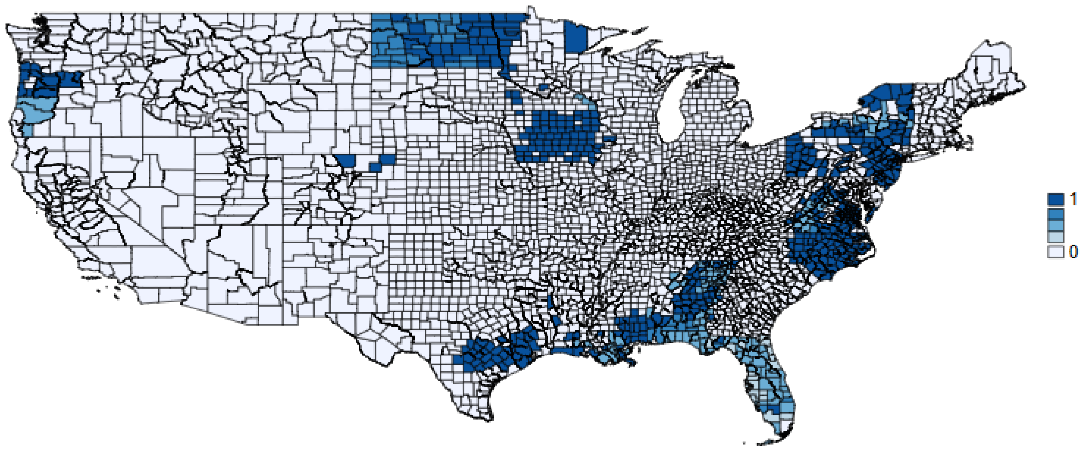
Zhang, S., 2023. Carbon returns across the globe. Available at SSRN 4378464 .

Figures

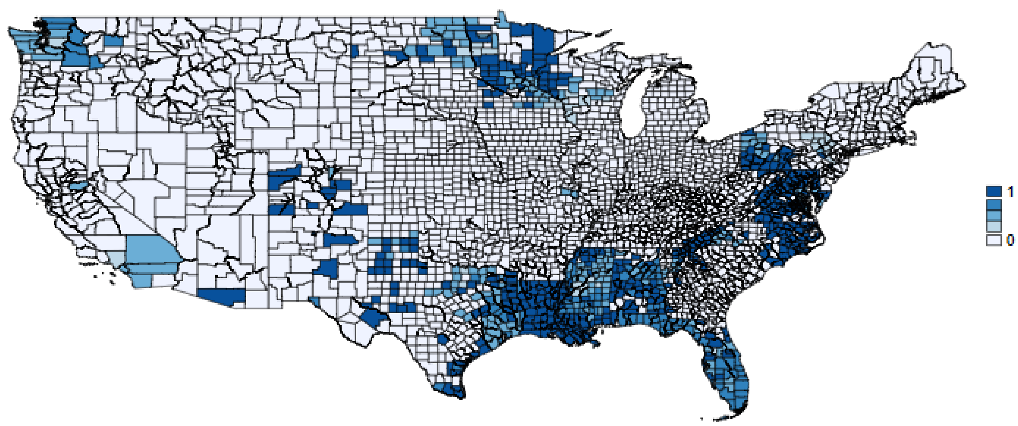
Figure 1: Climate disasters maps: from 1990 to 2019

This figure shows the frequency of climate disasters in counties on the U.S. mainland in each decade from 1990 to 2019.The maps are based on disaster records in the SHELDUS database for hurricanes/storms, floods, and wildfires.

Panel A: Counties hit by climate disasters during the 1990s



Panel B: Counties hit by climate disasters during the 2000s



Panel C: Counties hit by climate disasters during the 2010s

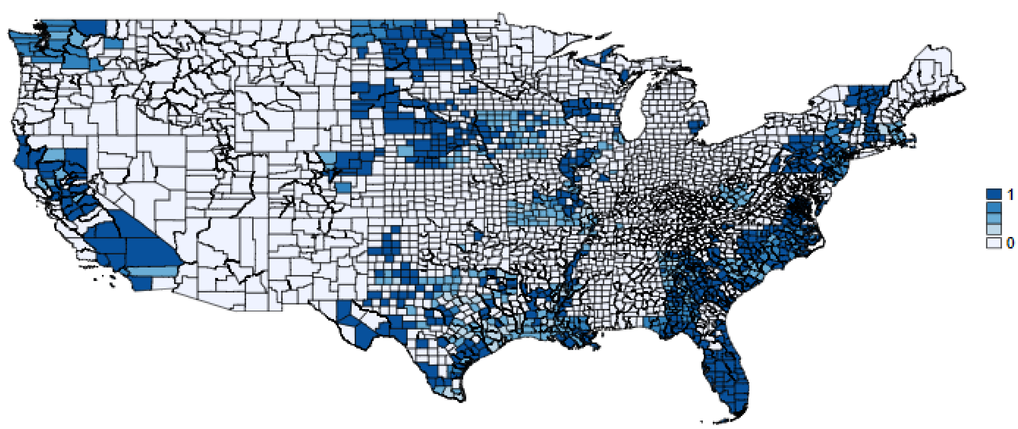
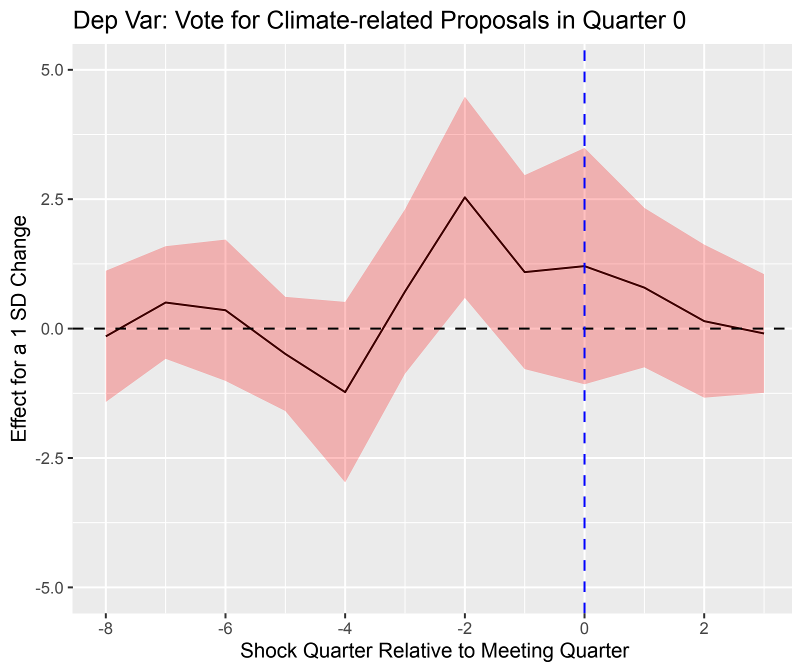


Figure 2: Dynamics of the voting effect

This figure presents the quarterly dynamics of the voting for climate-related proposals by institutional investors associated with indirect exposure to climate-related disasters via their equity ownership. The plot shows γ_1 from estimating Equation (6) in the main text, except we use the quarterly (instead of the 4-quarter moving average) explanatory variable and we progressively lag (or lead) it by up to eight (or three) quarters. γ_1 is interpreted as the percentage point increase in voting for a proposal associated with a one standard deviation increase in Portfolio Exposure$j, t-1$. In Panel A, we report the full-sample results. In Panel B, to facilitate the discussion of the event timing, we focus on the sub-sample of firms that have a December fiscal year end. The shaded areas are 95% confidence intervals based on robust standard errors clustered by institutional investor and year.

Panel A: Full-sample



Panel B: December fiscal year end sample

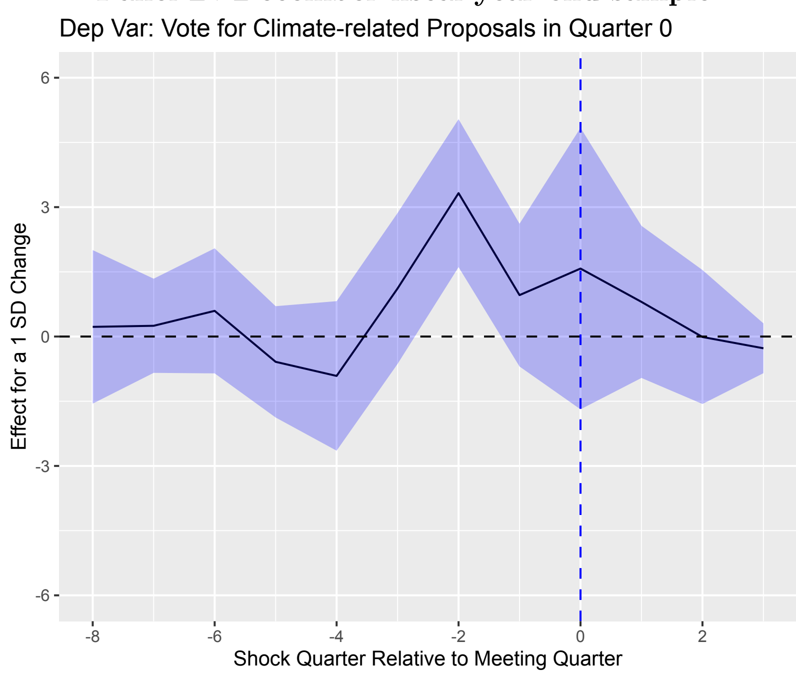


Figure 3: Placebo Tests

This figure presents placebo tests analyzing the timing of disaster spillover shocks' via common ownership on climate voting behavior. At each quarterly lead or lag relative to the shareholder meeting event time 0, we simulate the distribution of t-statistics under the null hypothesis that randomly generated placebo disasters should have no effect on climate voting. Specifically, we replace the actual $County\ exposed_{c,q}$ in Eq. (1) with random placebo disasters, re-construct our main portfolio exposure measure, and repeat our regression tests with this placebo portfolio exposure measure. At each lead or lag, the black dots report on the distribution of the 1000 simulated t-statistics, while the larger blue dot represents the t-statistic under actual disasters.

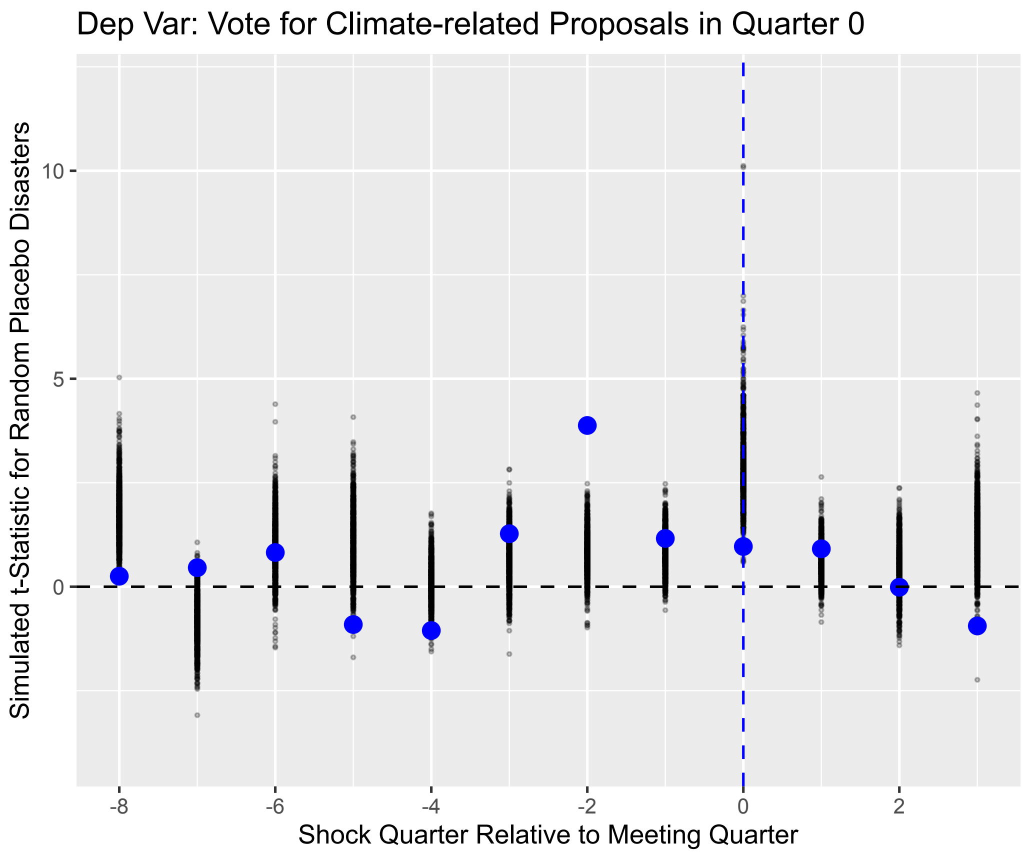
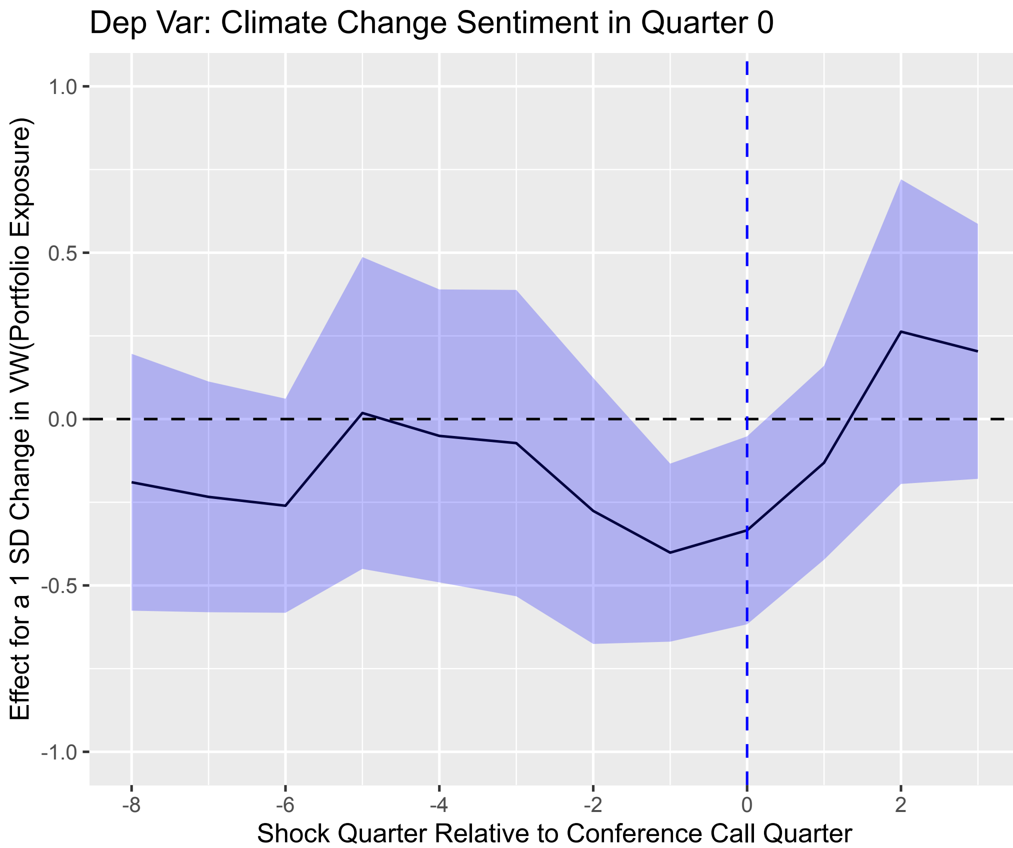


Figure 4: Dynamics of the effect on earnings call climate change sentiment

This figure presents the dynamic effects of firm-level indirect exposure to disasters via common ownership on climate change sentiment in earnings conference calls. The plot shows β_1 from estimating Equation (8) in the main text, except we progressively lag (or lead) it by up to eight (or three) quarters. β_1 is interpreted as the change in climate change sentiment associated with a one standard deviation increase in our indirect exposure measures. The shaded areas are 95% confidence intervals based on standard errors clustered by firm and year.



Tables

Table 1: Summary statistics

This table reports summary statistics for the disaster-exposed portfolio holdings in Panel A, climate proposals in Panel B, and the investor-proposal sample in Panel C. See Appendix A.1 for variable definitions. N is the number of observations used in our tests. Mean, SD, Median, Q0.10, Q0.25, Q0.75, Q0.90, and Q0.99 report on the sample average, standard deviation, median, the 10th, 25th, 75th, 90th, and 99th percentiles of the sample distribution, respectively. The sample period is 2004 to 2019.

Panel A: Matched sample of NETS and Compustat

Variable	Mean	SD	Median	Q0.10	Q0.25	Q0.75	Q0.99
Disaster Exposure$_{i,q}$	0.017	0.091	0.00	0.00	0.00	0.00	0.50
I(Excess Disaster Exposure$_{i,q}$>0)	0.072	0.258	0.00	0.00	0.00	0.00	1
Excess Disaster Exposure$_{i,q}$	0.013	0.083	0.00	0.00	0.00	0.000	0.42

Panel B: Climate Proposal Sample (310 Proposals)

Year	Proposals	Investors	Investors Per Proposal	Vote Not Against (%)	Vote For (%)	Passed (%)
2004–2009	104	190	39.47	50.89	9.24	0.96
2010–2014	87	215	48.25	52.09	11.05	0.00
2015–2019	119	287	63.82	50.19	18.91	3.36

Panel C: Institutional Investor-Proposal Sample - Climate Proposals

Variable	N	Mean	SD	Median	Q0.10	Q0.25	Q0.75	Q0.90
Vote for Proposals (%)	15,842	37.67	46.16	0.00	0.00	0.00	100.00	100.00
Portfolio Exposed ($\times$ 100)	15,842	2.95	6.03	0.16	0.00	0.00	2.85	10.12
Portfolio Exposed$^{cont.}$ ($\times$ 100)	15,842	0.18	0.50	0.00	0.00	0.00	0.11	0.47
IFO ($\times$ 10000)	15,842	20.73	87.02	0.05	0.00	0.00	3.12	28.55
Portfolio Value ($Bil)	15,842	99.95	263.53	13.33	0.37	1.83	59.61	245.00
Portfolio Return (%)	15,842	2.79	8.92	4.35	-8.32	0.65	8.06	11.39

Table 2: Effect on shareholder voting for proposals

This table reports results from regressions of institutional investors' voting on shareholder proposals on their indirect exposure to disasters as in Equation (6). The unit of observation is at the investor-proposal level, i.e., firm i's proposal k is being voted by an institutional investor j. The dependent variable at time t is the voting outcome measured as an investor's percentage vote on a shareholder (S/H) proposal. Columns (1)–(2), (3)–(4), and (5)–(6) focus on the the mutually exclusive sets of climate-related, environmental-related, and social-related shareholder proposals, respectively. At time time $t-1$, institutional indirect disaster exposure is measured by $Weight$ or $Weight \times MCAP$ as these measures' four-quarter moving average ending in the quarter of the record date before the shareholder meeting and then standardized by the full-sample standard deviation. t-statistics in parentheses are computed from the variance-covariance matrix double clustered by fund-family and year-quarter. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: Vote for Proposals$_{i,j,k,t}$							
	Climate				Environmental		Social	
	All		IFO>0					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolio Exposed$_{j,t-1}$	2.38**		3.49**		1.19		0.60	
	(2.38)		(2.72)		(0.78)		(0.62)	
Portfolio Exposed$^{cont.}_{j,t-1}$		2.31***		2.98**		1.08		0.93
		(3.54)		(2.64)		(0.89)		(1.19)
IFO$_{i,j,t-1}$	−2.75***	−2.71***	−2.40**	−2.38**	−2.12**	−2.10**	−1.25***	−1.24***
	(−2.89)	(−2.87)	(−2.25)	(−2.25)	(−2.54)	(−2.55)	(−2.82)	(−2.84)
Log(Portfolio Value)$_{j,t-1}$	−3.57*	−3.55*	−4.02*	−3.91*	−3.91**	−3.87**	−1.10	−1.09
	(−1.88)	(−1.87)	(−1.80)	(−1.77)	(−2.27)	(−2.28)	(−0.72)	(−0.71)
Portfolio Ret$_{j,t-1}$	−24.77	−23.68	−65.81***	−62.87***	−5.68	−5.24	0.09	0.49
	(−1.37)	(−1.31)	(−5.29)	(−4.72)	(−0.36)	(−0.32)	(0.01)	(0.03)
Proposal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,842	15,842	8,594	8,593	11,223	11,223	20,809	20,808
Adjusted R^2	0.54	0.54	0.56	0.56	0.54	0.54	0.46	0.46

Table 3: Dynamics of voting effect

This table reports on the dynamics of the voting effect when we split the investor spillover measure based on recency to the vote. Because Portfolio $\text{Exposed}_{j,t-1}$ is a 4-quarter moving average, we decompose it into the part driven by the recent two quarters (Portfolio $\text{Exposed}_{j,t-1,q-1:q-2}$) and the latter two quarters (Portfolio $\text{Exposed}_{j,t-1,q-3:q-4}$). We then repeat our voting tests using the decomposed measures individually and together. Columns (1)–(2) report the results for the full sample, while Columns (3)–(4) focus on the IFO>0 sample. Standard errors are double clustered by fund-family and year-quarter. t-statistics in parentheses are computed from the variance-covariance matrix double clustered by fund-family and year-quarter. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: Vote for Climate $\text{Proposals}_{i,j,k,t}$			
	All		IFO>0	
	(1)	(2)	(3)	(4)
Portfolio $\text{Exposed}_{j,t-1,q-1:q-2}$	4.12***		6.21**	
	(2.78)		(2.71)	
Portfolio $\text{Exposed}_{j,t-1,q-3:q-4}$	0.46		0.22	
	(0.31)		(0.15)	
Portfolio $\text{Exposed}^{cont.}_{j,t-1,q-1:q-2}$		2.55**		4.62***
		(2.56)		(3.06)
Portfolio $\text{Exposed}^{cont.}_{j,t-1,q-3:q-4}$		2.02*		1.29
		(1.75)		(1.22)
$\text{IFO}_{i,j,t-1}$	−2.18***	−2.71***	−1.90***	−2.39**
	(−5.92)	(−2.87)	(−4.89)	(−2.25)
Log(Portfolio $\text{Value})_{j,t-1}$	−2.69	−3.54*	−3.04	−3.88*
	(−1.61)	(−1.87)	(−1.44)	(−1.75)
Portfolio $\text{Ret}_{j,t-1}$	−29.69**	−23.54	−55.12***	−61.23***
	(−2.13)	(−1.31)	(−4.11)	(−4.36)
Proposal FE	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes
N	15,842	15,842	8,594	8,593
Adjusted R^2	0.57	0.54	0.59	0.56

Table 4: Robustness: Alternative measures and adjustments

This table reports on the voting results from using 1) alternative functional forms for investors' exposure to disasters in Eq. (1) and 2) unadjusted and alternatively adjusted indirect disaster exposure measures as in Eqs. (2) and (3). See Section 3.3 for a description of the alternative functional forms. For brevity, we report coefficients only on the variables of interest. Column (1) reports the results for the unadjusted measure which considers any firm with positive *Disaster Exposure*. Columns (2) and (3) focus on firms with disaster exposures above the average disaster exposure in their NYSE firm size group or NYSE firm size plus NETs footprint group, respectively. Column (4) combines the adjustments in Column (3) with the 1990s benchmark used in our main measure. t-statistics in parentheses are computed from the variance-covariance matrix double clustered by fund-family and year-quarter. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively. See the results of other alternative measures in Appendix Table IA.5.

	Unadjusted	Size-adjusted	Size & Footprint -adjusted	All -adjusted
	(1)	(2)	(3)	(4)
Portfolio exposed$_{j,t-1,q-1:q-2}$	8.34***	5.66**	5.65**	8.39***
	(2.79)	(2.47)	(2.55)	(3.59)
Portfolio exposed$_{j,t-1,q-3:q-4}$	−2.81*	−0.88	−0.86	0.43
	(−1.76)	(−0.45)	(−0.42)	(0.24)
(Portfolio Exposed × MCAP)$_{j,t-1,q-1:q-2}$	7.56**	5.01**	4.99**	7.26***
	(2.56)	(2.15)	(2.23)	(2.93)
(Portfolio Exposed × MCAP)$_{j,t-1,q-3:q-4}$	−2.89*	−0.84	−0.72	0.59
	(−1.81)	(−0.43)	(−0.36)	(0.34)
(Portfolio Exposed × 1/MCAP)$_{j,t-1,q-1:q-2}$	9.15***	6.35***	6.35**	9.44***
	(3.02)	(2.80)	(2.88)	(4.26)
(Portfolio Exposed × 1/MCAP)$_{j,t-1,q-3:q-4}$	−2.70	−0.91	−1.01	0.25
	(−1.69)	(−0.47)	(−0.50)	(0.14)
(Portfolio Exposed | Large Disaster Firm)$_{j,t-1,q-1:q-2}$	8.08**	5.20**	5.29**	7.76***
	(2.76)	(2.35)	(2.45)	(3.31)
(Portfolio Exposed | Large Disaster Firm)$_{j,t-1,q-3:q-4}$	−2.97*	−1.05	−0.64	0.50
	(−1.77)	(−0.51)	(−0.31)	(0.28)
(Portfolio Exposed | Small Disaster Firm)$_{j,t-1,q-1:q-2}$	3.01**	3.08**	3.02**	3.02**
	(2.10)	(2.21)	(2.12)	(2.34)
(Portfolio Exposed | Small Disaster Firm)$_{j,t-1,q-3:q-4}$	0.78	0.34	−1.03	−0.51
	(0.66)	(0.30)	(−1.07)	(−0.35)

Table 5: Voting effect and attention to climate change
This table examines how the public attention to climate change affects the voting tests in Equation (6). WSJ CC and Neg. CC are standardized attention indices constructed through textual analysis of newspapers by Engle et al. (2020). WSJ CC is based on climate news coverage in *The Wall Street Journal* (WSJ) from January 1984 to June 2017, Neg. CC is based on negative climate news over one trillion news articles and social media posts from May 2008 to May 2018, both variables alone are absorbed by the proposal fixed effect. t-statistics in parentheses are computed from the variance-covariance matrix double clustered by fund-family and year-quarter. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: Vote for Climate Proposals$_{i,j,k,t}$			
	WSJ CC News Matched		Neg. CC News Matched	
	(1)	(2)	(3)	(4)
Portfolio Exposed$_{j,t-1}\times$ WSJ CC$_{t-1}$	3.76**	3.10*		
	(2.43)	(2.00)		
IFO$_{i,j,t-1}$ $\times$ WSJ CC$_{t-1}$		1.48		
		(1.64)		
Portfolio Exposed$_{j,t-1}\times$ Neg. CC$_{t-1}$			3.77***	3.76***
			(3.07)	(3.10)
IFO$_{i,j,t-1}$ $\times$ Neg. CC$_{t-1}$				0.04
				(0.04)
Portfolio exposed$_{j,t-1}$	2.74*	2.98*	4.08***	4.07***
	(1.77)	(1.88)	(3.73)	(3.80)
IFO$_{i,j,t-1}$	-2.37^{**}	-2.92^{**}	-1.96^{*}	-1.96^{*}
	(-2.25)	(-2.36)	(-1.86)	(-2.02)
Log(Portfolio Value)$_{j,t-1}$	-4.74^{**}	-4.64^{**}	-4.58	-4.58
	(-2.11)	(-2.11)	(-1.26)	(-1.28)
Portfolio Ret$_{j,t-1}$	-64.76^{***}	-59.78^{***}	-38.65^{**}	-38.60^{**}
	(-4.94)	(-4.08)	(-2.11)	(-2.15)
Proposal FE	Yes	Yes	Yes	Yes
Fund Family $\times$ Industry FE	Yes	Yes	Yes	Yes
N	8,420	8,420	7,172	7,172
Adjusted R^2	0.56	0.56	0.60	0.60

Table 6: Heterogeneity of spillover firms: Green versus brown

This table examines how firms' greenness affects the voting tests in Equation (6). We proxy for greenness using either (the log of) total CO2 emissions or CO2 emissions scaled by sales, similar to Hartzmark and Shue (2023). t-statistics in parentheses are computed from the variance-covariance matrix double clustered by fund-family and year-quarter. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: Vote for Climate Proposals$_{i,j,t}$		
	Available CO2 Data		No CO2 Data
	(1)	(2)	(3)
Portfolio Exposed$_{j,t-1}$ × Log(Total CO2)$_{i,t-1}$	1.62***		
	(3.22)		
Portfolio Exposed$_{j,t-1}$ × Total CO2/Sales$_{i,t-1}$		1.39*	
		(1.76)	
Portfolio Exposed$_{j,t-1}$	−24.65**	−1.86	4.39***
	(−2.74)	(−0.60)	(2.78)
IFO$_{i,j,t-1}$	−4.14*	−4.20*	−1.81**
	(−1.80)	(−1.81)	(−2.50)
Log(Portfolio Value)$_{j,t-1}$	−2.57	−2.50	−7.37**
	(−1.15)	(−1.12)	(−2.41)
Portfolio Ret$_{j,t-1}$	−54.47**	−55.81**	−72.82
	(−2.70)	(−2.73)	(−1.46)
Proposal FE	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes
N	4,583	4,583	4,008
Adjusted R^2	0.57	0.57	0.54

Table 7: Heterogeneity of Funds

This table examines how different types of investors affect the voting tests in Equation (6). Big 3 indexers are Vanguard, State Street, and Blackrock. Top 10 Investors are the top 10 investors each quarter by total portfolio value. Large MFs (Banks) are mutual funds (banks) above the 75th percentile of the total portfolio value distribution each quarter. UN PRI Signees are the investors that have signed the United Nation's Principles for Responsible Investment. In the last row, we report the estimate and associated F-statistic for the total investor type effect from summing the coefficients on $Weight_{j,t-1}$ and its interaction with investor type. t- and F-statistics in parentheses are computed from the variance-covariance matrix double clustered by fund-family and year-quarter. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: Vote for Climate Proposals$_{i,j,t}$				
Investor Type:	Big 3 Indexers	Top 10 Investors	Large MFs	Large Banks	UN PRI Signees
	(1)	(2)	(3)	(4)	(5)
Portfolio Exposed$_{j,t-1}$	3.19*	3.10**	3.00**	3.66**	3.37**
	(1.88)	(2.34)	(2.28)	(2.39)	(2.43)
Portfolio Exposed$_{j,t-1}$ × Investor Type$_{j,t}$	0.36	2.19	1.37	−2.80	1.32
	(0.29)	(1.50)	(1.04)	(−1.17)	(0.71)
Investor Type$_{j,t}$		−16.26**	−5.03	1.40	−7.05
		(−2.39)	(−1.62)	(0.19)	(−1.35)
IFO$_{i,j,t-1}$	−2.39**	−2.36*	−2.36**	−2.37**	−2.29**
	(−2.16)	(−2.01)	(−2.24)	(−2.06)	(−2.23)
Log(Portfolio Value)$_{j,t-1}$	−4.06*	−2.66	−3.98*	−4.03*	−3.66*
	(−1.80)	(−1.12)	(−1.82)	(−1.79)	(−1.76)
Portfolio Ret$_{j,t-1}$	−65.96***	−65.22***	−63.09***	−65.86***	−62.24***
	(−5.24)	(−4.58)	(−4.90)	(−4.54)	(−5.20)
Proposal FE	Yes	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes	Yes
N	8,594	8,594	8,594	8,594	8,594
Adjusted R^2	0.56	0.56	0.56	0.56	0.56
Total Investor Type Effect	3.55***	5.29***	4.37***	0.85	4.69**
$F-$stat	(7.49)	(8.39)	(6.91)	(0.17)	(5.75)

Table 8: Short-run firm effects: Climate change discussions

This table reports results from regressions of climate-change sentiment extracted from quarterly earnings conference calls by Sautner et al. (2023) on firms' indirect exposure to disasters via common ownership. The dependent variable is the net climate change sentiment (Positive minus Negative) in Columns (1) and (4), the positive climate change sentiment in Columns (2), and the negative climate change sentiment in Columns (3) , all scaled by overall climate change attention (CC Attention). We label SIC2 industries as Brown based on the five major industries identified by the intergovernmental Panel on Climate Change (IPCC), and Green otherwise, following Choi et al. (2020). In the last row, we report the estimate and associated F-statistic for the total green industry effect from summing the coefficients on VW(Portfolio Exposed)$_{j,t-1}$ and its interaction with green industry. t-statistics and F-statistics in parentheses are computed from the variance covariance matrix double clustered by firm and year. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: CC Sentiment$_{i,q}$			
	Pos. − Neg.	Positive	Negative	Pos. − Neg.
	(1)	(2)	(3)	(4)
VW(Portfolio Exposed)$_{i,q-1}$	−0.39***	−0.12	0.27**	−0.57**
	(−2.92)	(−0.77)	(2.39)	(−2.64)
Disaster Exposure$_{i,q-1}$	−0.67	0.10	0.56	−0.60
	(−0.46)	(0.09)	(0.62)	(−0.42)
Log(Assets)$_{i,t-1}$	0.29	0.69**	0.47**	−0.14
	(0.87)	(2.35)	(2.54)	(−0.40)
InstOwn$_{i,q-1}$	−0.08***	−0.05***	0.04***	−0.06***
	(−5.42)	(−5.51)	(3.62)	(−4.53)
NBlocks$_{i,t-1}$	0.01	0.11	0.12	0.04
	(0.04)	(0.93)	(1.06)	(0.29)
VW(Portfolio Exposed)$_{i,q-1}$ × Green Industry				0.25
				(0.94)
Green Industry				−0.28
				(−0.19)
Firm FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	No
N	139,532	139,532	139,532	139,532
Adjusted R^2	0.07	0.12	0.06	0.06
Total Green Industry Effect				−0.32**
F−stat				(4.44)

Table 9: Long-run effects

This table reports results from regressions with the dependent variable being firms' total and sales-scaled CO2 emissions (rows 1 and 2), total energy use (row 3), a dummy indicating if firms' executives are provided pay incentives (row 4), or if the board of directors holds the highest level of responsibility within the firm (row 5), for managing climate issues, respectively. The dependent variables of firm i are measured in year $t-1$ (Column (1)), t (Column (2)), and $t+1$ to $t+2$ (Column (3)), respectively. The independent variable is firm i's indirect exposure, VW(Portfolio Exposed), which is standardized by its full-sample standard deviation. Firm Controls include firm i's Log(Assets), Institutional Ownership, and Number of Institutional Blockholders in $t-1$. Panel A focuses on the aforementioned baseline specification, while Panel B reports the results when including an interaction of VW(Portfolio Exposed) with Green industry. This table summarizes the coefficients of VW(Portfolio Exposed) and VW(Portfolio Exposed)×Green, the detailed reports of each regression are reported in Appendix Table IA.13 to IA.15. We label SIC2 industries as Brown based on the five major industries identified by the intergovernmental Panel on Climate Change (IPCC), and Green otherwise, following Choi et al. (2020). t-statistics in parentheses are computed from the variance covariance matrix double clustered by firm and year. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

Panel A: Baseline Specifications

	Independent Var: VW(Portfolio Exposed)$_{i,t-1}$		
	$k=-1$	$k=0$	$k \in [+1,+2]$
	(1)	(2)	(3)
Total CO2$_{i,t+k}$	−47.23	−176.72	−908.31**
	(−0.38)	(−1.42)	(−2.57)
Total CO2/Sales$_{i,t+k}$	0.01	−0.01	−0.06**
	(0.40)	(−1.00)	(−2.69)
Energy Use$_{i,t+k}$	0.59	8.13	−19.58**
	(0.15)	(1.63)	(−2.43)
Pay Incentive$_{i,t+k}$	−0.004	−0.02	0.03*
	(−0.30)	(−1.45)	(1.98)
Board Responsibility$_{i,t+k}$	0.001	−0.004	0.06*
	(0.08)	(−0.25)	(1.95)
Firm Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes

Panel B: Brown versus Green Interaction

	$k=-1$	$k=0$	$k \in [+1,+2]$
	(1)	(2)	(3)
	Independent Var: VW(Portfolio Exposed)$_{i,t-1}$		
Total CO2$_{i,t+k}$	-61.16	-268.50	$-1{,}342.32^{***}$
	(-0.31)	(-1.47)	(-3.02)
Total CO2/Sales$_{i,t+k}$	0.01	-0.02	-0.07^{**}
	(0.49)	(-1.11)	(-2.49)
Energy Use$_{i,t+k}$	1.82	13.00^{*}	-27.04^{**}
	(0.29)	(1.87)	$(-2.37))$
Pay Incentive$_{i,t+k}$	-0.01	-0.003	0.04^{*}
	(-0.90)	(-0.29)	(1.85)
Board Responsibility$_{i,t+k}$	-0.01	0.01	0.04
	(-0.34)	(0.74)	(1.15)
	Independent Var: VW(Portfolio Exposed)$_{i,t-1}\times$ Green Industry		
Total CO2$_{i,t+k}$	41.57	257.56	$1{,}303.96^{***}$
	(0.17)	(1.23)	(3.17)
Total CO2/Sales$_{i,t+k}$	-0.01	0.02	0.08^{**}
	(-0.61)	(1.05)	(2.40)
Energy Use$_{i,t+k}$	-4.02	-14.46^{**}	25.62^{**}
	(-0.52)	(-2.14)	(2.27)
Pay Incentive$_{i,t+k}$	-0.005	0.003	-0.001
	(-0.25)	(0.21)	(-0.02)
Board Responsibility$_{i,t+k}$	0.0002	-0.04	-0.06^{*}
	(0.01)	(-1.70)	(-1.93)
Firm Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes

Appendix for
"Propagation of climate disasters through ownership networks"

A.1 Variable Definitions

Disaster Measures	
Disaster Exposure$_{i,q}$	See, Eq(1). Firm i's exposure to climate disaster risk in each year-quarter q.
Excess Disaster Exposure$_{i,q}$	See, Eq(3). A measure of unexpected climate disaster shocks to firm i in year-quarter q by comparing Disaster exposure$_{i,q}$ and Expected Quarterly Exposure$_{i,q}$.
Expected Quarterly Exposure$_{i,q}$	See, Eq(2). Firm i's disaster exposure benchmark to climate disaster risk in each year y. This benchmark provides a hypothetical value for firms' disaster exposure by applying firms' real footprint layout in the latest year $y-1$ but assuming the disaster map remains unchanged from the 1990s.
I(Excess Disaster Exposure$_{i,q}$>0)	A dummy variable to identify if a firm i in year-quarter q experienced unexpected climate disaster shocks, namely it has higher Disaster exposure$_{i,q}$ than the benchmark Disaster exposure$^{bm}_{i,y}$. $I(.)$ is the indicator function.
Portfolio Exposed$_{j,q}$	See, Eq.(4). The proportion of an investor j's portfolio experiencing a climate disaster shock in quarter q.
Portfolio Exposed$^{cont.}_{j,q}$	See, Eq.(5). An alternative measure of the proportion of an investor j's portfolio experiencing a climate disaster shock in quarter q, this measure incorporates the magnitude of the excessive natural disaster shocks that each focal firm suffers.
VW(Portfolio Exposed)$_{i,q}$	See, Eq (7). The measure of the spillover effect of climate disasters that firm i experienced through its common institutional investors that hold disaster firms in quarter q.
Fund-Family Variables	

$\text{IFO}_{i,j,q}$	The quarterly institutional ownership computed as $IFO_{i,j,q} = \frac{Shares_{i,j,q}}{Shares\ Outstanding_{i,q}}$, namely shares owned by institutional investor j in firm i divided by total shares outstanding.
Portfolio Value (\$Bil)$_{j,q}$	The total portfolio value of fund family j in quarter q.
Portfolio Return (%)$_{j,q}$	The total portfolio return of fund family j in quarter q.
Vote for Proposal$_{i,j,k,t}$ (%)	The voting support by fund family j for proposal k as of the shareholder meeting held by firm i in year t. Voting support is computed as $100 \times (1 - I(fundvote \in$ "Against")), where $fundvote$ is a label in the ISS Voting Analytics taking on values, "For", "Against", "Abstain", "Do Not", "None", "Withhold" and I(.) is the indicator function. We also alternatively compute voting support as $100 \times (I(fundvote \in$ "For")), the results of which are reported in the Appendix.
Other Variables	
Assets$_{i,t}$	Annual total assets (at) from Compustat. We winsorize at the 1% tail each year in the full Compustat panel.
Board Responsibility$_{i,t}$	A dummy equals one if firm i's board of directors holds the highest level of responsibility within the firm for managing climate issues in year$t$.
CC Sentiment$_{i,q}$	The firm-level net climate change sentiment extracted from quarterly earnings call conference transcripts by Sautner et al. (2023), calculated as the positive sentiment minus the negative sentiment, scaled by total climate change exposure measured by CC Attention$_{i,q}$.
Energy Use$_{i,t}$	Firm i's energy use in year t.
Green Industry	An indicator equal to 1 if an industry is not a Brown Industry and 0 otherwise. Brown industries have SIC2 codes of 1-2, 9-10, 12-17, 20-21, 24, 26-30, 32-36, 37, 39-47, and 49, following Choi et al. (2020).
Industry$_{i,t}$	The 2 digit standard industry classification (SIC2) of the firm from Compustat.
InstOwn$_{i,t}$	The most recent quarterly percentage institutional ownership from the WRDS 13F database.

$\text{MCAP}_{i,q}$	The quarter-end market capitalization of the firm computed as price times shares outstanding from CRSP.
$\text{NBlocks}_{i,t}$	The most recent quarterly number of 5% blockholders from the WRDS 13F database.
Neg. CC_q	The standardized quarterly average of the monthly CH Negative Climate Change News Index from Engle et al. (2020), which is based on textual analysis of negative climate news over one trillion news articles and social media posts from May 2008 to May 2018.
Pay $\text{Incentive}_{i,t}$	A dummy equals one if firm i' executives are provided pay incentives in year t for managing climate issues.
Total $\text{CO2}_{i,t}$	Firm i' total CO2 emissions in year t.
Total $\text{CO2/Sales}_{i,t}$	Firm i' total CO2 emissions scaled its sales in year t.
WSJ CC_q	The standardized quarterly average of the monthly WSJ climate change Index from Engle et al. (2020), which is based on textual analysis of climate news coverage in *The Wall Street Journal* (WSJ) from January 1984 to June 2017.

A.2 Evidence on disasters and climate change

This appendix provides a detailed discussion about why we classify hurricanes, wildfires, and floods as climate-related.

We begin by reviewing the evidence on the severity and frequency of certain natural disasters. The scientific view on natural disasters and their connection to climate change has changed drastically in recent decades. We mostly rely on the aggregation of evidence presented in the most recent National Oceanic and Atmospheric Administration's (NOAA) climate special report (Wuebbles, Fahey, Hibbard, Arnold, DeAngelo, Doherty, Easterling, Edmonds, Edmonds, Hall, et al., 2017) to survey the vast literature on climate change and natural disasters in the United States.

There is a strong distinction between the trends affecting North Atlantic hurricanes threatening the US on the one hand, and the global tropical storm (Cyclone) activity on the other. Outdated models predicted declines in hurricanes globally, but these models were missing geographically heterogeneous patterns. A new generation of models predicts **global** fall in cyclones, but an increase in intense north Atlantic hurricanes (Bender, Knutson, Tuleya, Sirutis, Vecchi, Garner, and Held, 2010). While evidence is mixed for an increasing trend in the severity (or damages) of hurricanes over much of the early 20th century, there is a distinct trend towards more intense and severe hurricanes in recent decades (Grinsted, Ditlevsen, and Christensen, 2019; Smith and Katz, 2013). Though some uncertainty about the precise degree to which climate change impacts these trends (for an early debate between these viewpoints, see, for example, Elsner, Jagger, et al. (2009)), the overall evidence in the last 20 years clearly shows an increasing threat from hurricanes.

Wuebbles et al. (2017) summarizes the state of the literature on hurricanes, wildfires, and floods, as such:

For hurricanes:

"**For Atlantic and eastern North Pacific hurricanes and western North Pacific typhoons, increases are projected in precipitation rates (high confidence) and intensity (medium confidence). The frequency of the most intense of these storms is projected to increase in the Atlantic and western North Pacific (low confidence) and in the eastern North Pacific (medium confidence)**".

For floods:

"**Recent analysis of annual maximum stream- -flow shows statistically significant trends in the upper Mississippi River valley (increasing) and in the Northwest (decreasing). In fact, across the midwestern United States, statistically significant increases in flooding are well documented. These increases in flood risk and severity are not attributed to 20th-century changes in agricultural practices but instead are attributed mostly to the observed increases in precipitation. [... The main conclusion] states that the frequency and intensity of heavy precipitation events are projected to continue to increase over the 21st century with high confidence. Given the connection between extreme precipitation and flooding and the complexities of other relevant factors, we concur with the IPCC Special Report on Extremes (SREX) assessment of "medium confidence (based on physical reasoning) that projected increases in heavy rainfall would contribute to increases in local flooding in some catchments or regions**".

The evidence on wildfires comes to a similar conclusion:

"**The incidence of large forest fires in the western United States and Alaska has increased since the early 1980s (high confidence) and is projected to further increase in those regions as the climate warms, with profound changes to certain ecosystems (medium confidence). [...] Nonetheless, there is medium confidence for a human-caused climate change contribution to increased forest fire activity in Alaska in recent decades, with a likely further increase as the climate continues to**

warm, and low to medium confidence for a detectable human climate change contribution in the western United States based on existing studies. Recent literature does not contain a complete robust detection and attribution analysis of forest fires, including estimates of natural decadal and multidecadal variability, as described in Chapter 3: Detection and Attribution, nor separate the contributions to observed trends from climate change and forest management".

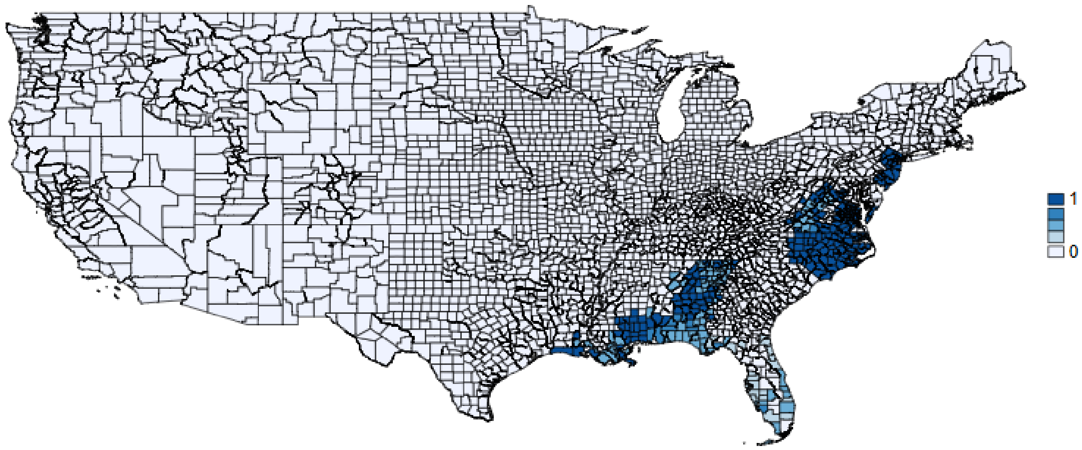
Overall, the scientific evidence strongly points towards a relationship between climate change and the increasing severity and frequency of North Atlantic hurricanes, wildfires, and floods.

A.3 Appendix Figures

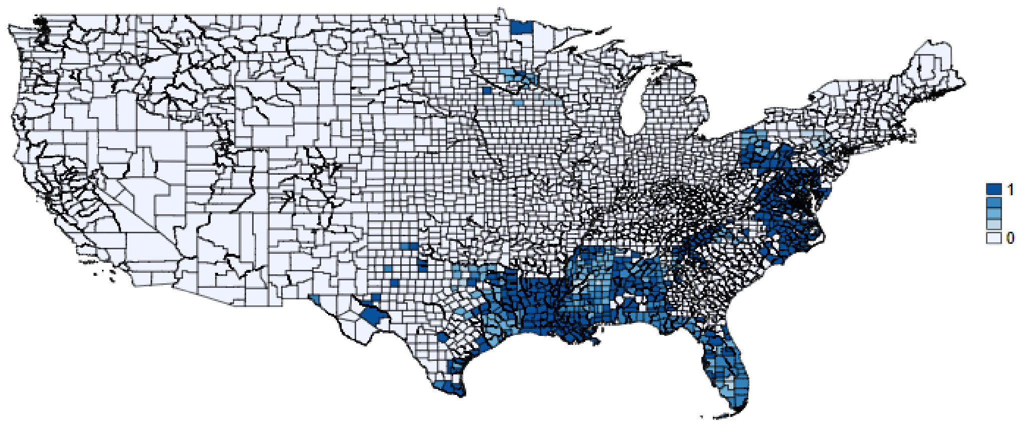
Figure IA.1: Hurricane/storm maps: from 1990 to 2019

This figure shows the frequency of hurricanes/storms in counties on the U.S. mainland in each decade from 1990 to 2019. The maps are based on disaster records in the SHELDUS database.

Panel A: Counties hit by hurricanes/storms during the 1990s



Panel B: Counties hit by hurricanes/storms during the 2000s



Panel C: Counties hit by hurricanes/storms during the 2010s

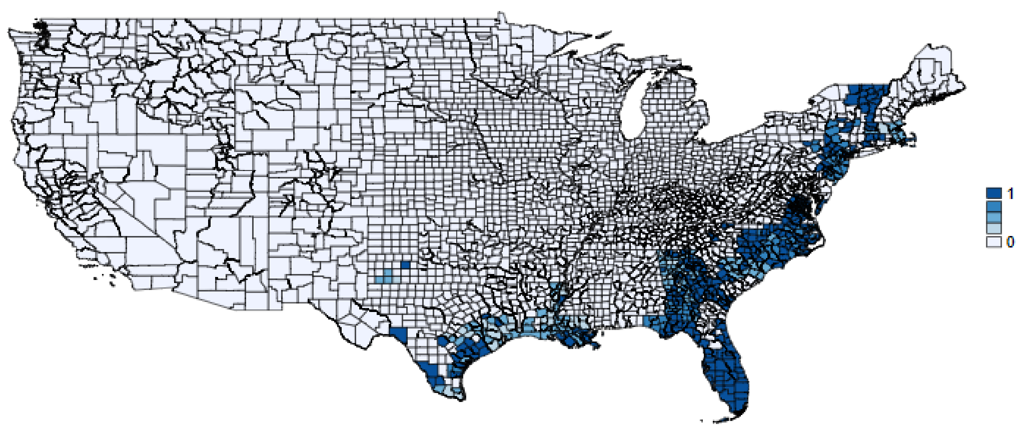
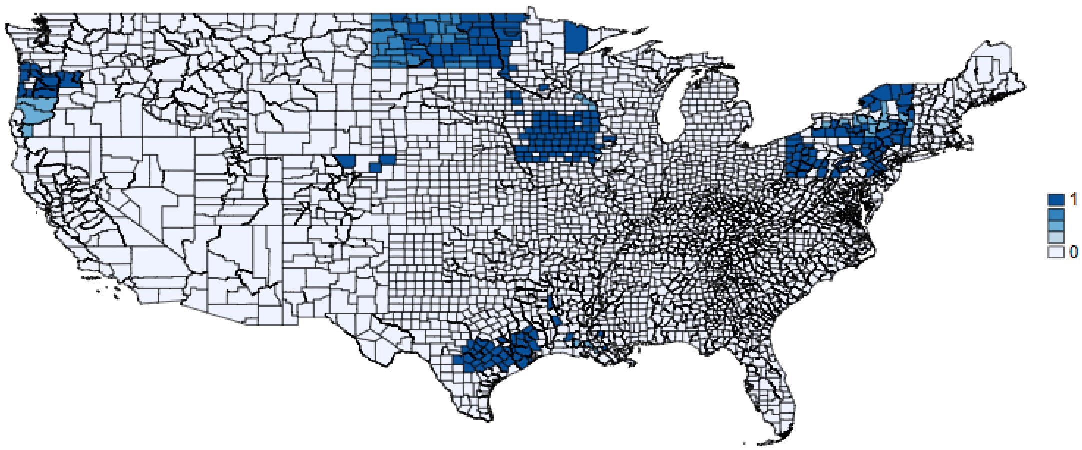


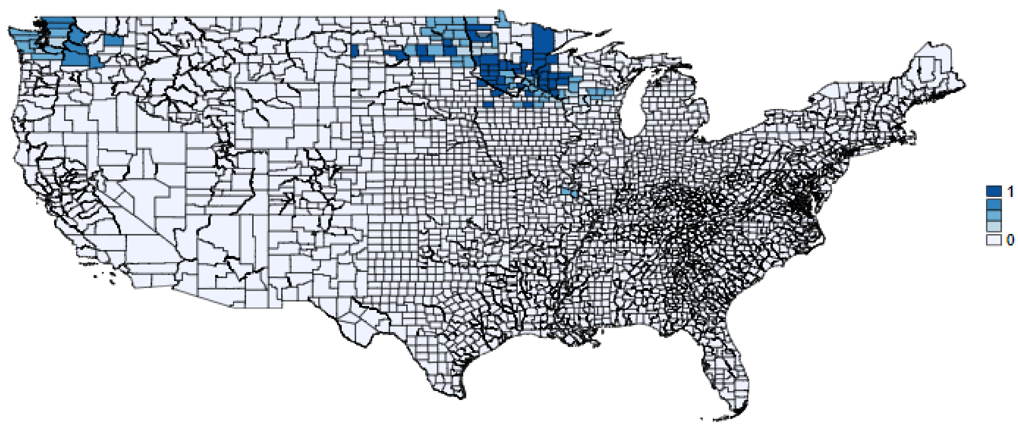
Figure IA.2: Flood maps: from 1990 to 2019

This figure shows the frequency of floods in counties on the U.S. mainland in each decade from 1990 to 2019. The maps are based on disaster records in the SHELDUS database.

Panel A: Counties hit by floods during the 1990s



Panel B: Counties hit by floods during the 2000s



Panel C: Counties hit by floods during the 2010s

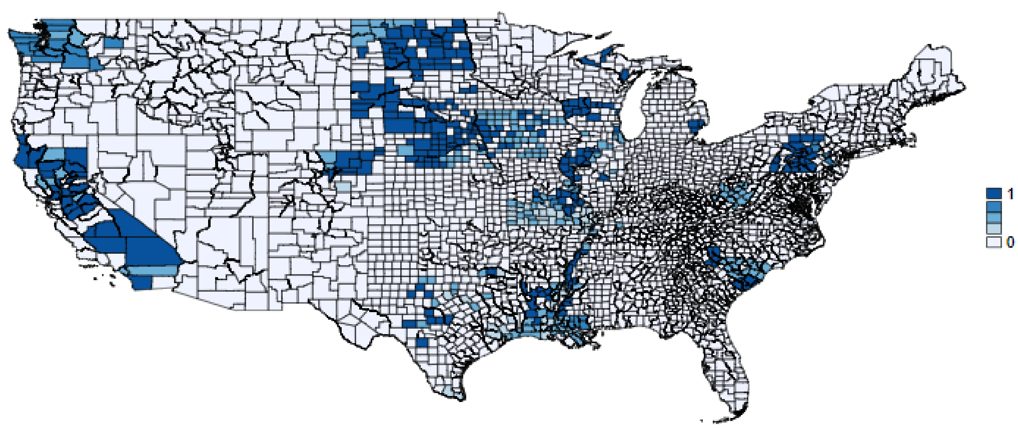
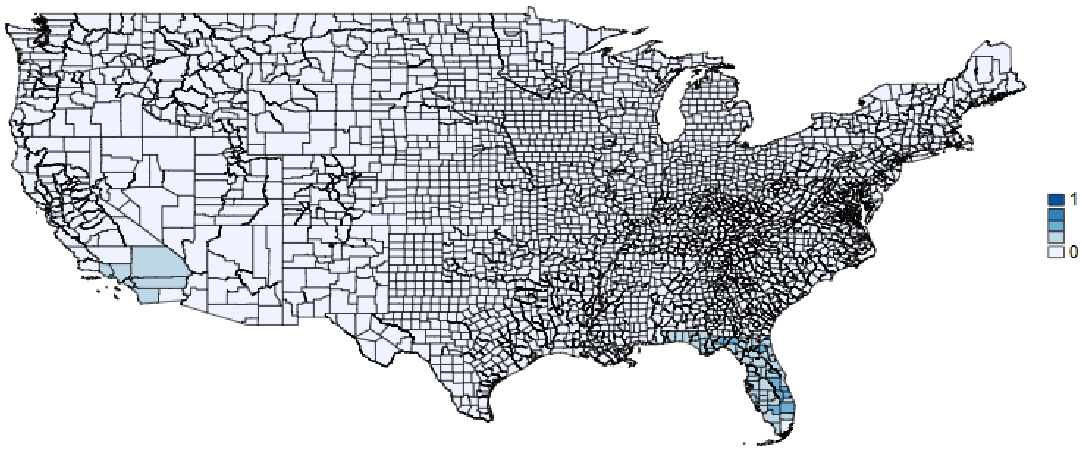


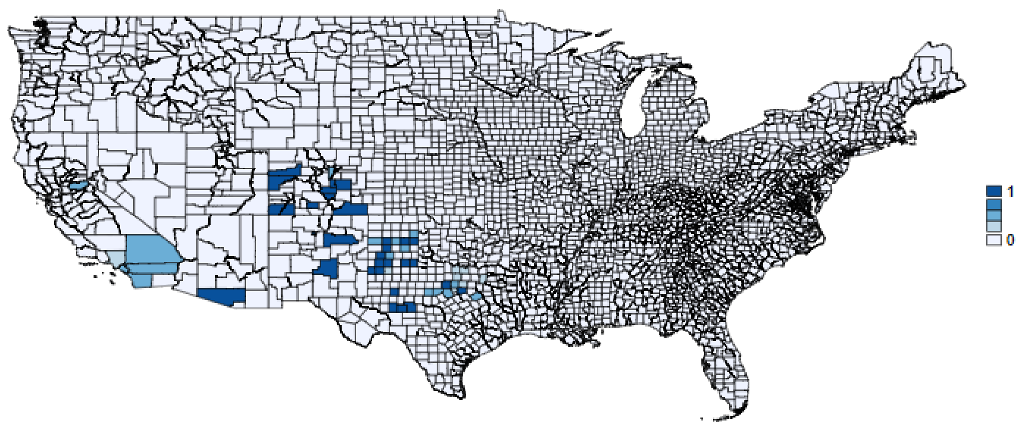
Figure IA.3: Wildfire maps: from 1990 to 2019

This figure shows the frequency of wildfires in counties on the U.S. mainland in each decade from 1990 to 2019. The maps are based on disaster records in the SHELDUS database.

Panel A: Counties hit by wildfires during the 1990s



Panel B: Counties hit by wildfires during the 2000s



Panel B: Counties hit by wildfires during the 2010s

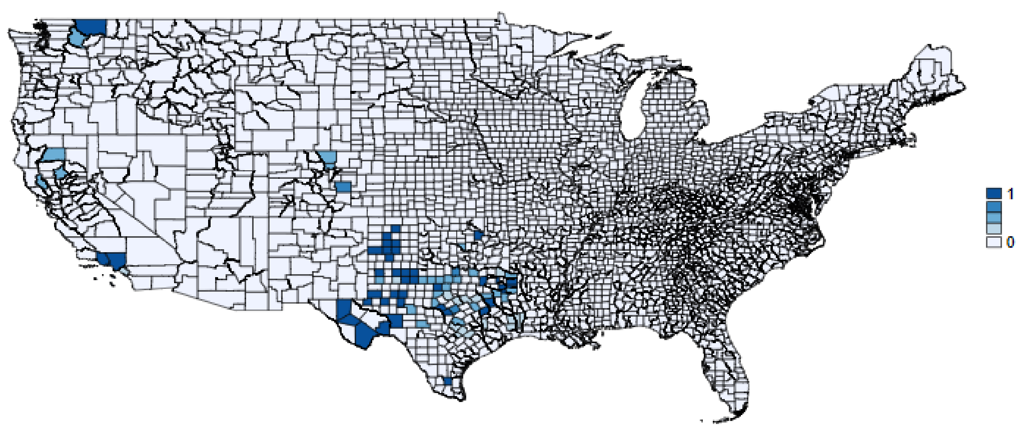


Figure IA.4: Industries for firms with *Excess disaster exposure*>0

This pie chart shows the proportion of different industries for firms with positive *Excess disaster exposure* in the matched sample of NETS and Compustat from 2003 to 2019. We use the Fama French 10-industry classification.

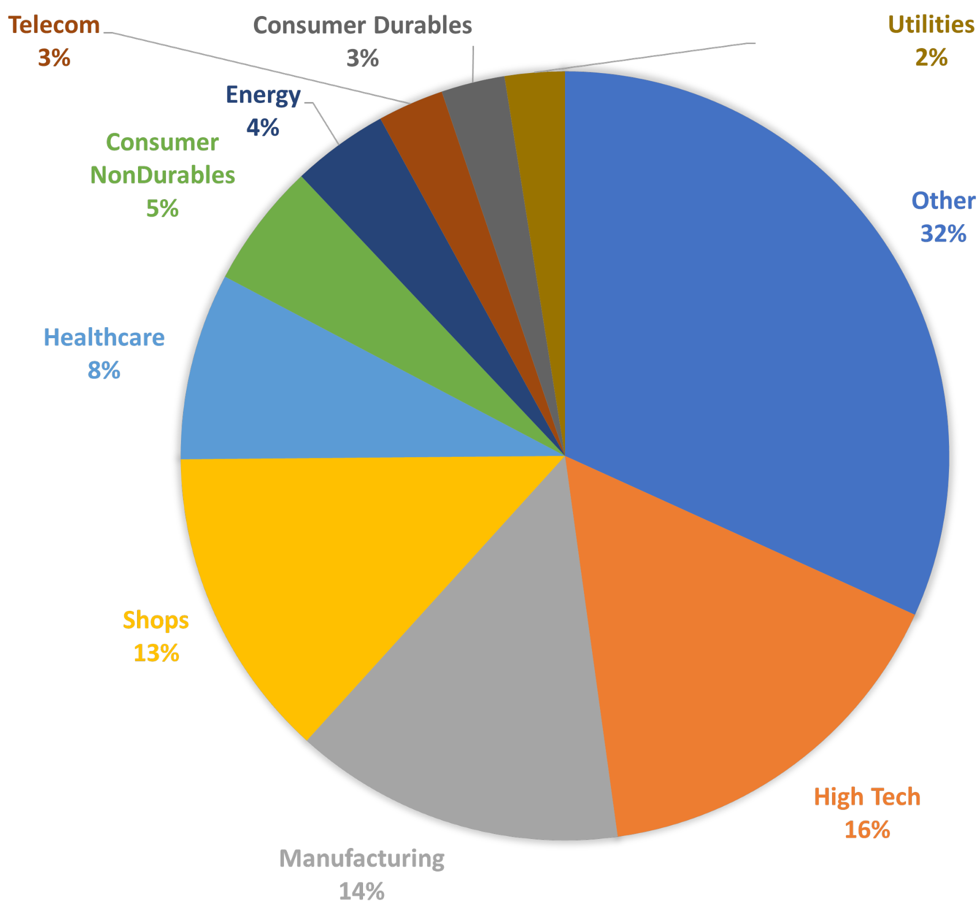
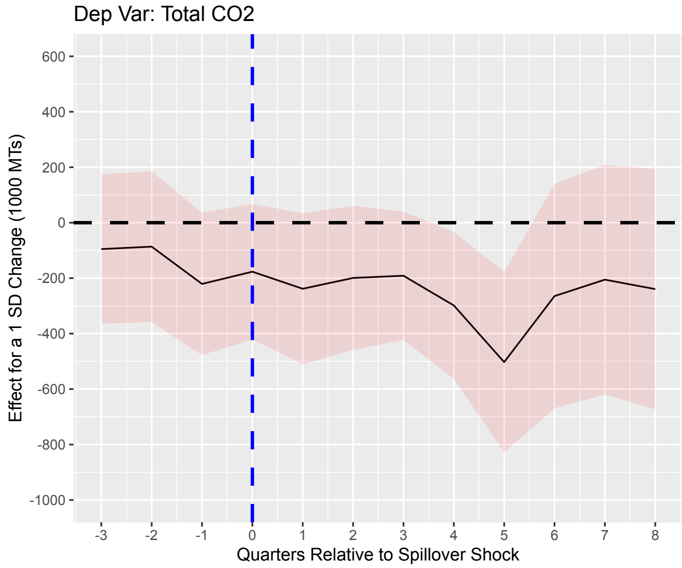


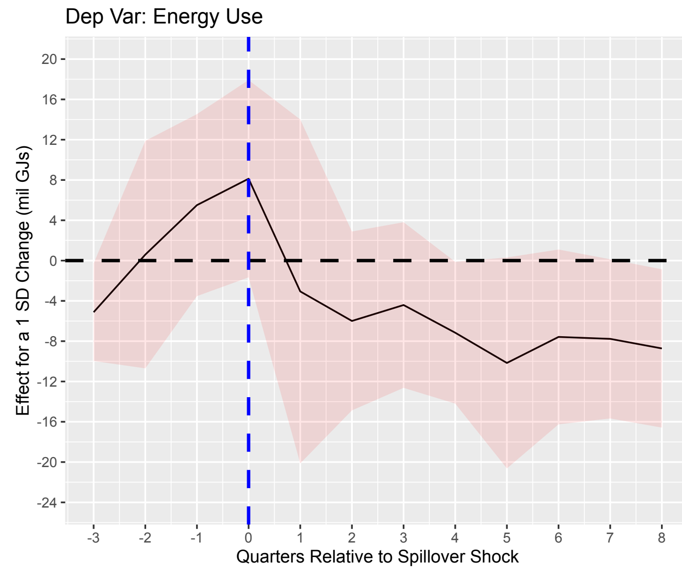
Figure IA.5: Dynamics of effects on firms' climate-change-related outcomes

This figure presents the dynamic effects of firm-level indirect exposure to disasters via common ownership on firms' climate-change-related outcomes. The plot shows β_1 from tests similar to Equation (8) in the main text, except we progressively lag (or lead) the explanatory variable by up to eight (or three) quarters, and we use firms' total CO2 emissions (Panel A), energy use (Panel B), executive pay incentives for climate management (Panel C), and board responsibility for climate management (Panel D) as dependent variables, respectively. The independent variable $MA\ exposure$ is the four-quarter moving average of firms' indirect disaster exposure $VW(Weight)$. The shaded areas are 95% confidence intervals based on standard errors clustered by firm and year.

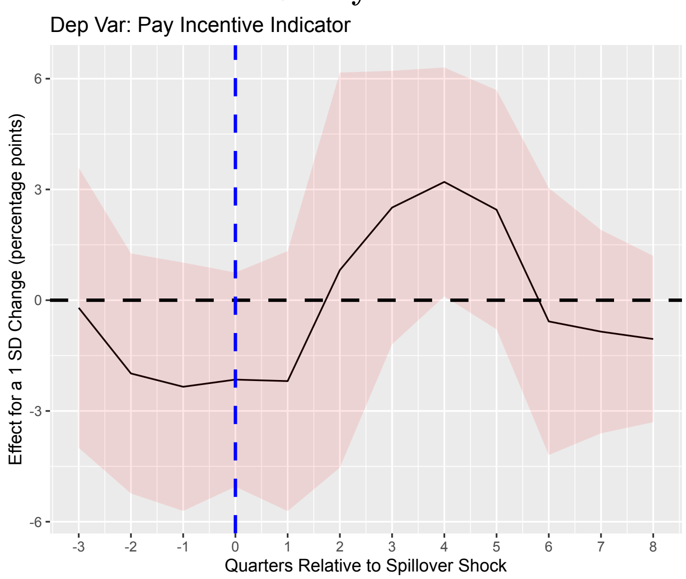
Panel A: Total CO2 Emission



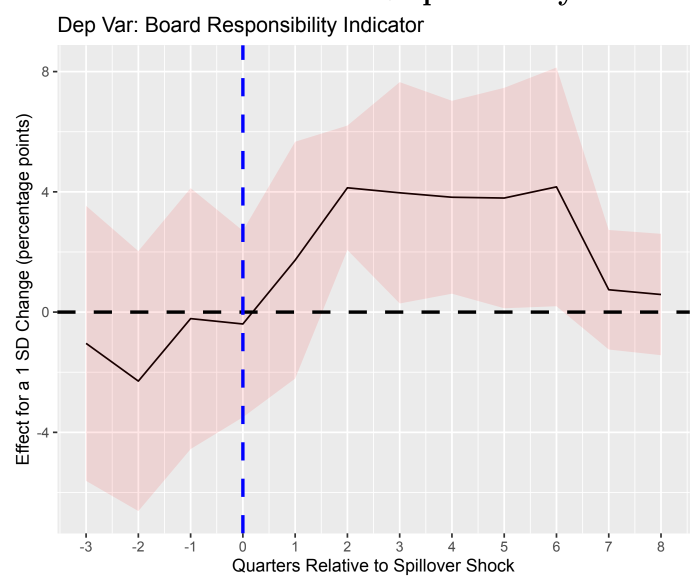
Panel B: Energy Use



Panel C: Pay Incentive



Panel D: Board Responsibility



A.4 Appendix Tables

Table IA.1: Overviews of big natural disasters from 2003 to 2019
This table provides overviews of natural disasters from 2003 to 2019 that resulted in Presidential Disaster Declarations for the Federal Emergency Management Agency (FEMA) and caused total damage exceeding 100 million 2019 U.S. dollars.

Panel A: Climate-change-related disasters

Disasters	Averge total damage per disaster ($M)	Average number of affected counties per disaster
Wildfire	2049.80	4.47
Flood	1116.97	21.30
Hurricane/Storm	5812.23	25.58

Panel B: Other disasters

Disasters	Averge total damage per disaster ($M)	Average number of affected counties per disaster	Diaaster Names
Earthquake	594.41	1.00	2003 San Simeon Earthquake 2014 South Napa Earthquake
Severe Ice Storm	1163.67	33.86	2007 January North American Ice Storm 2007 January Ice Storm in Oklahoma 2009 North American Ice Storm
Snow	124.92	7.00	2003 Denver Blizzard 2010 Snowmageddon
Freezing	1550.19	14.00	2007 California Freeze

Table IA.2: Summary statistics: environmental and social proposals

This table reports summary statistics at the investor-proposal level. See Appendix A.1 for variable definitions. Next to the variables, we display the scaling factor that we convert the original variable into for readability. We use the original variable's units in our tests. N is the number of observations used in our tests. Mean, SD, Median, Q0.10, Q0.25, Q0.75, and Q0.90 report on the sample average, standard deviation, median, the 10th, 25th, 75th, and 90th percentiles of the sample distribution, respectively. The sample period is 2004 to 2019.

Panel A: Institutional Investor-Proposal Samples

Variable	N	Mean	SD	Median	Q0.10	Q0.25	Q0.75	Q0.90
	Climate Proposals, IFO>0							
Vote for Proposals (%)	8,594	39.73	46.69	0.00	0.00	0.00	100.00	100.00
Portfolio Exposed (× 100)	8,594	5.44	7.31	2.21	0.22	0.61	8.64	13.33
Portfolio Exposed$^{cont.}$ (× 100)	8,593	0.32	0.64	0.08	0.01	0.02	0.36	0.76
IFO (× 10000)	8,594	38.21	115.30	2.26	0.06	0.30	16.55	88.38
Portfolio Value ($Bil)	8,594	121.86	297.22	16.53	0.51	2.82	75.73	313.43
Portfolio Return (%)	8,594	3.95	7.68	4.76	-4.64	1.88	8.34	11.46
	Environmental Proposals							
Vote for Proposals (%)	11,223	33.88	44.87	0.00	0.00	0.00	100.00	100.00
Portfolio Exposed (× 100)	11,223	5.76	8.71	1.97	0.10	0.32	7.97	14.64
IFO (× 100)	11,223	35.31	106.17	2.19	0.06	0.26	15.90	82.80
Portfolio Value ($Bil)	11,223	111.26	277.93	14.92	0.46	2.11	69.19	301.86
Portfolio Return (%)	11,223	5.39	7.71	5.58	-1.46	2.61	9.72	14.19
	Social Proposals							
Vote for Proposals (%)	20,809	32.92	44.63	0.00	0.00	0.00	100.00	100.00
Portfolio Exposed (× 100)	20,809	5.63	8.53	1.84	0.10	0.34	7.96	14.75
IFO (× 10000)	20,809	30.83	94.26	2.28	0.06	0.28	15.19	74.00
Portfolio Value ($Bil)	20,809	105.88	262.22	16.95	0.47	2.42	71.14	298.84
Portfolio Return (%)	20,809	4.26	10.20	4.83	-8.60	1.18	10.89	15.02

Panel B: Spillover Firm Sample

Variable	N	Mean	SD	Median	Q0.10	Q0.25	Q0.75	Q0.90
		Quarterly Conference Call Sample						
VW(Portfolio Exposed) (%)	139,532	5.41	9.93	0.76	0.00	0.00	6.33	16.90
Firm Disaster Exposure (%)	139,532	2.86	9.55	0.00	0.00	0.00	1.21	7.51
CC Sentiment (%)	139,532	8.99	40.88	0.00	0.00	0.00	0.00	81.25
CC Positive (%)	139,532	18.60	35.06	0.00	0.00	0.00	20.00	100
CC Negative (%)	139,532	9.83	25.51	0.00	0.00	0.00	0.00	40.00
Assets ($Bil)	139,532	8.75	26.73	1.36	0.12	0.36	4.86	17.77
Institutional Ownership (%)	139,532	70.36	127.75	75.08	30.50	53.50	89.23	97.79
Number of Blockholders	139,532	2.71	1.61	2.75	0.50	1.50	3.75	4.75
		Annual Long-run Outcomes Sample						
Total CO2 (per 1000 MTs)	5,084	5638.70	16738.32	462.28	31.85	98.35	2716.77	14407.00
Total CO2/Sales (× 100)	5,084	50.80	143.23	5.08	0.61	1.76	26.50	102.60
Energy Use (Million GJs)	3,758	44.48	223.98	3.74	0.29	0.91	14.87	74.00
Pay Incentive Indicator (%)	2,438	76.78	42.23	100.00	0.00	100.00	100.00	100.00
Board Responsibility (%)	2,438	37.78	48.49	0.00	0.00	0.00	100.00	100.00
VW(Portfolio Exposed) (%)	5,084	3.06	4.64	1.05	0.00	0.13	4.16	9.18
Firm Disaster Exposure (%)	5,084	2.30	3.40	1.26	0.00	0.00	2.94	5.91
Assets ($Bil)	5,084	34.18	53.66	12.70	2.42	4.94	34.62	102.94
Institutional Ownership (%)	5,084	78.06	16.24	80.21	58.50	68.81	89.04	95.72
Number of Blockholders	5,084	2.57	1.40	2.50	0.75	1.75	3.50	4.25

Table IA.3: Robustness: Results using "Vote For" instead of "Not Vote Against"
This table reports on our main voting tests when we use "Vote For" a proposal as the dependent variable. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: Vote for $\text{Proposals}_{i,j,k,t}$							
	Climate				Environmental		Social	
	All		IFO>0					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolio $\text{Exposed}_{j,t-1}$	2.37^{**}		3.48^{**}		1.17		1.20	
	(2.37)		(2.71)		(0.75)		(1.14)	
Portfolio $\text{Exposed}^{cont}_{j,t-1}$		2.31^{***}		2.98^{**}		1.17		1.33
		(3.55)		(2.64)		(0.93)		(1.67)
$\text{IFO}_{i,j,t-1}$	-2.71^{***}	-2.68^{***}	-2.36^{**}	-2.34^{**}	-2.08^{**}	-2.07^{**}	-1.02^{**}	-1.00^{**}
	(−2.85)	(−2.83)	(−2.20)	(−2.19)	(−2.47)	(−2.49)	(−2.27)	(−2.26)
Log(Portfolio $\text{Value})_{j,t-1}$	-3.59^{*}	-3.56^{*}	-4.05^{*}	-3.94^{*}	-4.02^{**}	-3.99^{**}	−1.04	−1.01
	(−1.89)	(−1.88)	(−1.82)	(−1.78)	(−2.35)	(−2.36)	(−0.69)	(−0.67)
Portfolio $\text{Ret}_{j,t-1}$	−24.30	−23.21	-64.45^{***}	-61.50^{***}	−5.44	−4.96	2.11	2.40
	(−1.35)	(−1.28)	(−5.33)	(−4.75)	(−0.35)	(−0.31)	(0.15)	(0.17)
Proposal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,842	15,842	8,594	8,593	11,223	11,223	20,809	20,808
Adjusted R^2	0.54	0.54	0.56	0.55	0.53	0.53	0.44	0.44

Table IA.4: Robustness: Results for Investors that Held in the Previous Quarter
This table reports on voting results for the sample of investors that with holdings in the prior quarter. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: Vote for Climate Proposals$_{i,j,k,t}$	
	(1)	(2)
Portfolio Exposed$_{j,t-1}$	3.17^{**}	
	(2.16)	
Portfolio Exposed$^{cont.}_{j,t-1}$		2.83^{**}
		(2.77)
IFO$_{i,j,t-1}$	-2.15^{**}	-2.15^{**}
	(-2.27)	(-2.28)
Log(Portfolio Value)$_{j,t-1}$	-5.38^{*}	-5.22^{*}
	(-2.01)	(-1.97)
Portfolio Ret$_{j,t-1}$	-98.24^{***}	-93.50^{***}
	(-5.61)	(-5.48)
Proposal FE	Yes	Yes
Fund Family × Industry FE	Yes	Yes
N	4,559	4,559
Adjusted R^2	0.53	0.53

Table IA.5: Robustness: Alternative Measures and Adjustments

This table reports on voting results from using unadjusted and alternatively adjusted indirect disaster exposure measures. For brevity, we report coefficients only on the variables of interest. Column (1) reports the results for the unadjusted measure which considers any firm with positive *Disaster Exposure*. Columns (2) and (3) focus on firms with disaster exposures above the average disaster exposure in their NYSE firm size group or NYSE firm size plus NETs footprint group, respectively. In Panel B, we report on the results Table 2 in the main paper using the 1990s benchmark accounting for disaster seasonality within a year. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Unadjusted	Size-adjusted	Size & Footprint -adjusted	All -adjusted
	(1)	(2)	(3)	(4)
Portfolio $\text{Exposed}^2_{j,t-1,Q-1:Q-2}$	-0.20	-0.50	0.25	0.51
	(-0.17)	(-0.40)	(0.27)	(0.67)
Portfolio $\text{Exposed}^2_{j,t-1,Q-3:Q-4}$	0.20	-0.02	-1.45	0.22
	(0.18)	(-0.02)	(-1.38)	(0.27)
$\sqrt{\text{Portfolio Exposed}}_{j,t-1,Q-1:Q-2}$	5.65	3.65	3.75	3.49
	(1.73)	(1.41)	(1.46)	(1.55)
$\sqrt{\text{Portfolio Exposed}}_{j,t-1,Q-3:Q-4}$	-0.24	1.70	1.78	1.82
	(-0.14)	(1.41)	(1.09)	(1.22)
$\text{MCAP}_{j,t-1,Q-1:Q-2}$	6.92	6.61	5.57	-1.89
	(0.80)	(0.76)	(0.74)	(-1.00)
$\text{MCAP}_{j,t-1,Q-3:Q-4}$	-2.13	-1.83	-1.56	0.81
	(-0.38)	(-0.32)	(-0.28)	(0.20)
$1/\text{MCAP}_{j,t-1,Q-1:Q-2}$	0.84	0.34	0.37	-0.26
	((0.39)	(0.19)	(0.20)	(-0.14)
$1/\text{MCAP}_{j,t-1,Q-3:Q-4}$	0.95	2.06	2.43	1.68
	(0.52)	(1.29)	(1.67)	(0.89)

Table IA.6: Robustness: 1990s Benchmark Adjusted for Seasonality

This table reports on voting results from Table 2 in the main paper using the 1990s benchmark accounting for disaster seasonality within a year. Specifically, we use the average of Q1, Q2, Q3, or Q4 in the 1990s when constructing the benchmark for the same calendar quarter of the unadjusted measure. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: Vote for Proposals$_{i,j,k,t}$							
	Climate				Environmental		Social	
	All		IFO>0					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolio Exposed$_{j,t-1}$	2.38**		4.18***		1.49		1.01	
	(2.31)		(3.26)		(0.88)		(1.09)	
Portfolio Exposed$^{cont.}_{j,t-1}$		2.26***		2.94**		1.22		0.91
		(3.53)		(2.57)		(1.01)		(1.19)
IFO$_{i,j,t-1}$	−2.77***	−2.72***	−2.47**	−2.43**	−2.14**	−2.12**	−1.26***	−1.24***
	(−2.90)	(−2.88)	(−2.29)	(−2.29)	(−2.55)	(−2.56)	(−2.80)	(−2.81)
Log(Portfolio Value)$_{j,t-1}$	−3.57*	−3.54*	−3.81*	−3.67	−3.48*	−3.44*	−1.00	−0.96
	(−1.88)	(−1.87)	(−1.70)	(−1.66)	(−2.00)	(−1.99)	(−0.64)	(−0.62)
Portfolio Ret$_{j,t-1}$	−25.06	−23.65	−64.49***	−60.52***	−12.39	−11.73	−0.07	−0.02
	(−1.39)	(−1.31)	(−5.59)	(−4.86)	(−0.74)	(−0.69)	(−0.004)	(−0.001)
Proposal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,842	15,842	8,567	8,567	11,059	11,059	20,540	20,540
Adjusted R^2	0.54	0.54	0.55	0.55	0.53	0.53	0.46	0.46

Table IA.7: Robustness: Statistical Size and Adjusted Critical Values

This table reports on the statistical size of the voting tests for climate proposals when using Portfolio Exposure$_{j,t}$ as the variable of interest. Using placebo disasers, we simulate 1000 iterations of the tests in Tables 2 and 3. Specifically, each iteration, we use randomly assigned placebo disasters instead of the actual disasters in Eq. (1) under the null hypothesis that placebo disasters have no effect on climate voting. Size of Test is the proportion of p-values below 0.05. $t_{adj,0.025}$ and $t_{adj,0.975}$ are the 2.5 and 97.5 quantiles of the bootstrap distribution of t-statistics, respectively, and are the adjusted critical values for a two-sided test at the 5% level.

Sample	Independent Variable	Size of Test	$t^{adj}_{0.025}$	$t^{adj}_{0.975}$
All	Portfolio Exposed$_{j,t-1}$	0.047	1.048	2.100
All	Portfolio Exposed$_{j,t-1,q-1,q-2}$	0.073	0.164	2.233
All	Portfolio Exposed$_{j,t-1,q-3,q-4}$	0.000	-0.443	1.510
IFO>0	Portfolio Exposed$_{j,t-1}$	0.091	0.799	2.396
IFO>0	Portfolio Exposed$_{j,t-1,q-1,q-2}$	0.051	0.417	2.191
IFO>0	Portfolio Exposed$_{j,t-1,q-3,q-4}$	0.003	-0.397	1.639

Table IA.8: Robustness: Investors' Direct Disaster Exposure

This table tests the effects of indirect investor disaster exposure via common ownership in Table 2 controlling for investors' being directly hit by climate shocks. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: Vote for Climate Proposals$_{i,j,t}$			
	All		IFO>0	
	(1)	(2)	(3)	(4)
Direct Investor Disaster Exposure$_{j,t-1}$	0.77	0.76	0.61	0.58
	(1.25)	(1.24)	(0.74)	(0.71)
Portfolio Exposed$_{j,t-1}$		2.37**		3.47**
		(2.35)		(2.68)
IFO$_{i,j,t-1}$	−2.66***	−2.75***	−2.36**	−2.40**
	(−2.84)	(−2.88)	(−2.23)	(−2.25)
Log(Portfolio Value)$_{j,t-1}$	−3.60*	−3.62*	−3.88*	−4.06*
	(−1.91)	(−1.91)	(−1.78)	(−1.83)
Portfolio Ret$_{j,t-1}$	−24.78	−25.11	−64.28***	−65.57***
	(−1.37)	(−1.41)	(−5.52)	(−5.40)
Proposal FE	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes
N	15,842	15,842	8,594	8,594
Adjusted R^2	0.54	0.54	0.55	0.56

Table IA.9: Heterogeneity of Spillover Firms: Green versus Brown Industries

This table examines how firms' greenness affects the voting and sentiment tests in Equation (6) and (8), respectively. We label SIC2 industries as Brown based on the five major industries identified by the intergovernmental Panel on Climate Change (IPCC), and Green otherwise, following Choi et al. (2020). *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: Vote for Climate Proposals$_{i,j,k,t}$		
	Green Industry	Brown Industry	Interaction
	(1)	(2)	(3)
Portfolio Exposed$_{j,t-1}$	0.47	3.22*	3.22*
	(0.21)	(2.03)	(2.03)
IFO$_{i,j,t-1}$	−2.64	−1.82***	−1.82***
	(−1.00)	(−4.80)	(−4.80)
Log(Portfolio Value)$_{j,t-1}$	3.76*	−3.77*	−3.77*
	(1.89)	(−1.84)	(−1.84)
Portfolio Ret$_{j,t-1}$	−121.91**	−53.36***	−53.36***
	(−2.86)	(−3.04)	(−3.04)
Weight$_{j,t-1}$ × Green			−2.75
			(−0.97)
IFO$_{i,j,t-1}$×Green			−0.82
			(−0.30)
Log(Portfolio Value)$_{j,t-1}$×Green			7.53***
			(3.15)
Portfolio Ret$_{j,t-1}$×Green			−68.55
			(−1.72)
Proposal FE	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes
N	1,495	7,099	8,594
Adjusted R^2	0.66	0.58	0.59

Table IA.10: Examining the Exit Channel

This table tests examines whether investors rebalance after portfolio exposure to climate disaster shocks. In Columns (1) and (4), we focus on Brown Portfolio (Share) Weight at the end of year t for investor j, which is the total value (shares) of brown industry portfolio holdings divided by total portfolio value (shares). Columns (2) and (5) focus on the change in weight, while Columns (3) and (6) examines the change in the brown weight with above median (by year) CO2 emissions. The variable of interest is the prior year's Portfolio Exposed$_{j,t-1}$. We label SIC2 industries as Brown based on the five major industries identified by the intergovernmental Panel on Climate Change (IPCC), and Green otherwise, following Choi et al. (2020). We (do not) include investor fixed effects when analyzing the level of (changes in) the weights. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: Portfolio Weight			Dep Var: Share Weight		
	Brown $w_{j,t}$	ΔBrown $w_{j,t}$	ΔBrown $w_{j,t}^{\text{High CO2}}$	Brown $s_{j,t}$	ΔBrown $s_{j,t}$	ΔBrown $s_{j,t}^{\text{High CO2}}$
	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio Exposed$_{j,t-1}$	−0.52	−0.15	0.10	−0.04	−0.13	−1.22
	(−0.83)	(−0.41)	(0.26)	(−0.15)	(−0.67)	(−1.51)
Log(Portfolio Value)$_{j,t-1}$	−0.11	−0.20	−0.05	0.27*	−0.16	0.07
	(−0.48)	(−1.55)	(−0.53)	(1.81)	(−1.33)	(1.06)
Portfolio Ret$_{j,t-1}$	3.84	0.83	−3.73	2.08	1.64	1.27
	(0.63)	(0.47)	(−1.64)	(0.91)	(1.49)	(0.23)
Constant		3.31	3.37		2.41	−0.92
		(1.33)	(1.42)		(0.95)	(−0.34)
Investor FE	Yes	No	No	Yes	No	No
N	51,228	51,228	45,687	51,228	51,228	45,687
Adjusted R^2	0.72	0.001	0.002	0.70	0.001	0.004

Table IA.11: Conference Call Reaction by 13F Investor Type

This table examines how the conference call reaction varies by the investor type. The variable of interest is the firm-level measure constructed from exclusively Banks, Insurance Companies, Investment Advisors, Mutual Funds, or Pension Funds. Panel B focuses on the measure constructed from the Big 3 Indexers, investors excluding the Big-3 Indexers, UN PRI Signatories, and investors excluding UN PRI Signatories. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: CC Sentiment$_{i,q}$				
	(1)	(2)	(3)	(4)	(5)
VW(Portfolio Exposed | Banks)$_{i,q-1}$	-0.13				
	(-0.83)				
VW(Portfolio Exposed | Insurance)$_{i,q-1}$		-0.24			
		(-1.34)			
VW(Portfolio Exposed | Investment Advisors)$_{i,q-1}$			-0.46^{***}		
			(-3.15)		
VW(Portfolio Exposed | Mutual Funds)$_{i,q-1}$				-0.32^{**}	
				(-2.44)	
VW(Portfolio Exposed | Pension Funds)$_{i,q-1}$					-0.30
					(-1.53)
Disaster Exposure$_{i,q-1}$	-0.48	-0.49	-0.69	-0.61	-0.54
	(-0.33)	(-0.35)	(-0.47)	(-0.42)	(-0.38)
Log(Assets)$_{i,t-1}$	0.29	0.29	0.28	0.28	0.30
	(0.87)	(0.88)	(0.85)	(0.86)	(0.91)
InstOwn$_{i,q-1}$	-0.08^{***}	-0.08^{***}	-0.08^{***}	-0.08^{***}	-0.08^{***}
	(-5.15)	(-5.22)	(-5.46)	(-5.35)	(-5.23)
NBlocks$_{i,t-1}$	-0.01	-0.01	0.01	0.004	-0.01
	(-0.09)	(-0.09)	(0.04)	(0.03)	(-0.07)
Firm FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
N	139,532	139,532	139,532	139,532	139,532
Adjusted R^2	0.07	0.07	0.07	0.07	0.07

Table IA.12: Conference Call Reaction by Big-3 and UN PRI Signatories

This table examines how the conference call reaction varies by the investor type. The variable of interest is the firm-level measure constructed from exclusively the Big 3 Indexers, investors excluding the Big-3 Indexers, UN PRI Signatories, and investors excluding UN PRI Signatories. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

	Dep Var: CC Sentiment$_{i,q}$			
	(1)	(2)	(3)	(4)
VW(Portfolio Exposed | Big-3 Indexers)$_{i,q-1}$	-0.23			
	(-1.64)			
VW(Portfolio Exposed | Excluding Big-3 Indexers)$_{i,q-1}$		-0.41^{***}		
		(-3.01)		
VW(Portfolio Exposed | UN PRI Signatories)$_{i,q-1}$			0.02	
			(0.14)	
VW(Portfolio Exposed | Excluding UN PRI Signatories)$_{i,q-1}$				-0.44^{***}
				(-2.98)
Disaster Exposure$_{i,q-1}$	-0.54	-0.68	-0.40	-0.69
	(-0.37)	(-0.47)	(-0.28)	(-0.48)
Log(Assets)$_{i,t-1}$	0.30	0.28	0.28	0.28
	(0.91)	(0.85)	(0.84)	(0.84)
InstOwn$_{i,q-1}$	-0.08^{***}	-0.08^{***}	-0.08^{***}	-0.08^{***}
	(-5.26)	(-5.43)	(-5.07)	(-5.41)
NBlocks$_{i,t-1}$	-0.01	0.01	-0.02	0.01
	(-0.05)	(0.05)	(-0.13)	(0.04)
Firm FE	Yes	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes
N	139,532	139,532	139,532	139,532
Adjusted R^2	0.07	0.07	0.07	0.07

Table IA.13: Effect on long-run CO2 emissions

This table reports results from regressions of firms' CO2 emissions on firms' indirect exposure to disasters via common ownership. In Panel A and B, the dependent variable is the total CO2 emissions in thousands of metric tons or scaled by sales, respectively, for firm i in year $t-1$ (Column (1)), t (Column (2)), and $t+1$ to $t+2$ (Column (3)), respectively. In Panels C and D, we include an interaction with an indicator for Green industry. We label SIC2 industries as Brown based on the five major industries identified by the intergovernmental Panel on Climate Change (IPCC), and Green otherwise, following Choi et al. (2020). The variable of interest is firms' indirect exposure, VW(Portfolio Exposed), which is standardized by its full-sample standard deviation. Standard errors are double clustered by firm and year. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

Panel A: Baseline Specification - Total CO2

	Dep Var: Total CO2		
	$k=-1$	$k=0$	$k\in[+1,+2]$
	(1)	(2)	(3)
VW(Portfolio Exposed)$_{i,t-1}$	-47.23	-176.72	-908.31^{**}
	(-0.38)	(-1.42)	(-2.57)
Disaster Exposure$_{i,t-1}$	3,737.64	$-2{,}166.07$	$-1{,}229.26$
	(1.22)	(-0.71)	(-0.13)
Log(Assets)$_{i,t-1}$	$1{,}625.74^{***}$	$1{,}456.24^{***}$	$2{,}366.54^{***}$
	(3.16)	(3.29)	(3.01)
InstOwn$_{i,t-1}$	-117.43	-670.70	-259.80
	(-0.08)	(-0.47)	(-0.09)
NBlocks$_{i,t-1}$	84.79	98.06	255.74
	(0.88)	(1.14)	(1.53)
Firm FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
N	4,362	5,084	5,023
Adjusted R^2	0.96	0.96	0.97

Panel B: Baseline Specification - Total CO2/Sales

	Dep Var: Total CO2/Sales		
	$k=-1$	$k=0$	$k \in [+1,+2]$
	(1)	(2)	(3)
VW(Portfolio Exposed)$_{i,t-1}$	0.01	−0.01	−0.06**
	(0.40)	(−1.00)	(−2.69)
Disaster Exposure$_{i,t-1}$	0.14	−0.26	0.05
	(0.48)	(−0.95)	(0.06)
Log(Assets)$_{i,t-1}$	−0.05	−0.07**	−0.16**
	(−1.71)	(−2.23)	(−2.65)
InstOwn$_{i,t-1}$	0.17	−0.21	0.29
	(0.68)	(−0.68)	(0.80)
NBlocks$_{i,t-1}$	−0.01	−0.004	−0.01
	(−0.55)	(−0.32)	(−0.47)
Firm FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
N	4,362	5,084	4,416
Adjusted R^2	0.95	0.94	0.96

Panel C: Green versus Brown - Total CO2

	Dep Var: Total CO2		
	$k=-1$	$k=0$	$k \in [+1,+2]$
	(1)	(2)	(3)
VW(Portfolio Exposed)$_{i,t-1}$	-61.16	-268.50	$-1{,}342.32^{***}$
	(-0.31)	(-1.47)	(-3.02)
VW(Portfolio Exposed)$_{i,t-1}$ × Green Industry	41.57	257.56	$1{,}303.96^{***}$
	(0.17)	(1.23)	(3.17)
Disaster Exposure$_{i,t-1}$	3,706.18	$-2{,}286.88$	$-1{,}482.59$
	(1.17)	(-0.73)	(-0.16)
Log(Assets)$_{i,t-1}$	$1{,}622.82^{***}$	$1{,}447.59^{***}$	$2{,}327.00^{***}$
	(3.17)	(3.27)	(2.96)
InstOwn$_{i,t-1}$	-113.31	-671.22	-384.66
	(-0.07)	(-0.47)	(-0.13)
NBlocks$_{i,t-1}$	85.22	101.56	255.80
	(0.89)	(1.17)	(1.51)
Firm FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
N	4,362	5,084	5,023
Adjusted R^2	0.96	0.96	0.97

Panel D: Green versus Brown - Total CO2/Sales

	Dep Var: Total CO2/Sales		
	$k = -1$	$k = 0$	$k \in [+1, +2]$
	(1)	(2)	(3)
VW(Portfolio Exposed)$_{i,t-1}$	0.01	-0.02	-0.07^{**}
	(0.49)	(-1.11)	(-2.49)
VW(Portfolio Exposed)$_{i,t-1}$ $\times$ Green Industry	-0.01	0.02	0.08^{**}
	(-0.61)	(1.05)	(2.40)
Disaster Exposure$_{i,t-1}$	0.15	-0.27	0.21
	(0.50)	(-0.97)	(0.36)
Log(Assets)$_{i,t-1}$	-0.05	-0.07^{**}	-0.14^{**}
	(-1.67)	(-2.23)	(-2.48)
InstOwn$_{i,t-1}$	0.17	-0.21	0.35
	(0.68)	(-0.68)	(0.97)
NBlocks$_{i,t-1}$	-0.01	-0.004	-0.01
	(-0.55)	(-0.30)	(-0.63)
Firm FE	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes
N	4,362	5,084	5,023
Adjusted R^2	0.95	0.94	0.95

Table IA.14: Effect on long-run Energy Use

This table reports results from regressions of firms' energy use on firms' indirect exposure to disasters via common ownership. The dependent variable is the total energy use in millions of gigajoules by firm i in year $t-1$ (Column (1)), t (Column (2)), and $t+1$ to $t+2$ (Column (3)), respectively. Panel A focuses on the aforementioned baseline specification, while Panel B includes an interaction with Green industry. We label SIC2 industries as Brown based on the five major industries identified by the intergovernmental Panel on Climate Change (IPCC), and Green otherwise, following Choi et al. (2020). Firms' indirect exposure, VW(Portfolio Exposed), is standardized by the full-sample standard deviation. Standard errors are double clustered by firm and year. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

Panel A: Baseline Specification - Energy Use

	Dep Var: Energy Use$_{i,t+k}$		
	$k=-1$	$k=0$	$k\in[+1,+2]$
	(1)	(2)	(3)
VW(Portfolio Exposed)$_{i,t-1}$	0.59	8.13	-19.58^{**}
	(0.15)	(1.63)	(-2.43)
Disaster Exposure$_{i,t-1}$	-224.45	-158.63	-187.06
	(-1.45)	(-1.44)	(-1.41)
Log(Assets)$_{i,t-1}$	7.74	7.47	17.46
	(0.80)	(1.00)	(1.10)
InstOwn$_{i,t-1}$	10.36	0.85	8.98
	(0.39)	(0.03)	(0.17)
NBlocks$_{i,t-1}$	-4.33	-5.08	-10.99^{*}
	(-1.27)	(-1.55)	(-1.97)
Firm FE	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes
N	3,163	3,768	3,291
Adjusted R^2	0.85	0.88	0.89

Panel B: Green versus Brown - Energy Use

	Dep Var: Energy Use		
	$k = -1$	$k = 0$	$k \in [+1, +2]$
	(1)	(2)	(3)
VW(Portfolio Exposed)$_{i,t-1}$	1.82	13.00*	−27.04**
	(0.29)	(1.87)	(−2.37)
VW(Portfolio Exposed)$_{i,t-1}$ × Green Industry	−4.02	−14.46**	25.62**
	(−0.52)	(−2.14)	(2.27)
Disaster Exposure$_{i,t-1}$	−222.15	−152.36	−195.05
	(−1.47)	(−1.40)	(−1.49)
Log(Assets)$_{i,t-1}$	7.91	8.41	16.01
	(0.83)	(1.22)	(0.98)
InstOwn$_{i,t-1}$	10.16	0.37	8.72
	(0.38)	(0.01)	(0.16)
NBlocks$_{i,t-1}$	−4.36	−5.22	−10.72*
	(−1.26)	(−1.59)	(−1.97)
Firm FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
N	3,163	3,768	3,291
Adjusted R^2	0.85	0.88	0.89

Table IA.15: Effect on long-run Climate Governance

This table reports results from regressions of firms' climate governance on firms' indirect exposure to disasters via common ownership. The dependent variable is an indicator for climate governance by firm i in year $t-1$ (Column (1)), t (Column (2)), and $t+1$ to $t+2$ (Column (3)), respectively. In Panel A, climate governance is measured by if firms' executives are provided pay incentives for managing the climate, including hitting greenhouse gas emissions targets. In Panel B, climate governance is measured by if the board of directors holds the highest level of responsibility within the firm for managing the climate. Panels C and D include an interaction with Green industry. We label SIC2 industries as Brown based on the five major industries identified by the intergovernmental Panel on Climate Change (IPCC), and Green otherwise, following Choi et al. (2020). Standard errors are double clustered by firm and year. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

Panel A: Baseline Specification - Executive Pay Incentives

	Dep Var: Pay Incentive$_{i,t+k}$		
	$k=-1$	$k=0$	$k \in [+1,+2]$
	(1)	(2)	(3)
VW(Portfolio Exposed)$_{i,t-1}$	−0.004	−0.02	0.03*
	(−0.30)	(−1.45)	(1.98)
Disaster Exposure$_{i,t-1}$	−0.22	0.20	0.42
	(−0.94)	(0.44)	(0.70)
Log(Assets)$_{i,t-1}$	0.07	0.07	0.18
	(1.28)	(1.32)	(1.65)
InstOwn$_{i,t-1}$	0.44	0.41	0.30
	(1.77)	(1.77)	(0.89)
NBlocks$_{i,t-1}$	−0.01	−0.01	−0.005
	(−0.48)	(−0.45)	(−0.18)
Firm FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
N	2,402	2,438	1,905
Adjusted R^2	0.41	0.42	0.63

Panel B: Baseline Specification - Board Responsibility

	Dep Var: Board Responsibility$_{i,t+k}$		
	$k=-1$	$k=0$	$k \in [+1,+2]$
	(1)	(2)	(3)
VW(Portfolio Exposed)$_{i,t-1}$	0.001	-0.004	0.06*
	(0.08)	(-0.25)	(1.95)
Disaster Exposure$_{i,t-1}$	-0.48	1.26*	1.47*
	(-1.01)	(1.88)	(2.07)
Log(Assets)$_{i,t-1}$	-0.05	-0.04	-0.03
	(-0.66)	(-0.67)	(-0.23)
InstOwn$_{i,t-1}$	-0.17	-0.20	-0.47
	(-0.75)	(-0.93)	(-1.05)
NBlocks$_{i,t-1}$	-0.01	-0.01	0.01
	(-0.56)	(-0.64)	(0.16)
Firm FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
N	2,402	2,438	1,905
Adjusted R^2	0.27	0.27	0.50

Panel C: Green versus Brown - Executive Pay Incentives

	Dep Var: Pay Incentive		
	$k = -1$	$k = 0$	$k \in [+1, +2]$
	(1)	(2)	(3)
VW(Portfolio Exposed)$_{i,t-1}$	-0.01	-0.003	0.04^{*}
	(-0.90)	(-0.29)	(1.85)
VW(Portfolio Exposed)$_{i,t-1}$ $\times$ Green Industry	-0.005	0.003	-0.001
	(-0.25)	(0.21)	(-0.02)
Disaster Exposure$_{i,t-1}$	-0.56	0.50	0.17
	(-1.79)	(1.40)	(0.24)
Log(Assets)$_{i,t-1}$	0.04	0.04	0.10
	(0.90)	(0.94)	(1.18)
InstOwn$_{i,t-1}$	0.39	0.38	0.40
	(1.68)	(1.76)	(1.33)
NBlocks$_{i,t-1}$	-0.004	-0.004	-0.01
	(-0.19)	(-0.18)	(-0.41)
Firm FE	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes
N	2,402	2,438	1,905
Adjusted R^2	0.43	0.44	0.64

Panel D: Green versus Brown - Boards Responsibility

	Dep Var: Board Responsibility		
	$k = -1$	$k = 0$	$k \in [+1, +2]$
	(1)	(2)	(3)
VW(Portfolio Exposed)$_{i,t-1}$	-0.01	0.01	0.04
	(-0.34)	(0.74)	(1.15)
VW(Portfolio Exposed)$_{i,t-1}$ × Green Industry	0.0002	-0.04	-0.06^{*}
	(0.01)	(-1.70)	(-1.93)
Disaster Exposure$_{i,t-1}$	-0.60	1.13^{**}	1.13
	(-1.22)	(2.29)	(1.42)
Log(Assets)$_{i,t-1}$	0.0005	0.01	0.05
	(0.01)	(0.26)	(0.42)
InstOwn$_{i,t-1}$	-0.16	-0.18	-0.21
	(-0.82)	(-0.97)	(-0.48)
NBlocks$_{i,t-1}$	-0.01	-0.02	-0.03
	(-0.95)	(-0.96)	(-0.73)
Firm FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
N	2,402	2,438	1,905
Adjusted R^2	0.29	0.29	0.53