Propagation of Climate Disasters Through Ownership Networks

Finance Working Paper N° 941/2023
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Abstract

Institutional investors holding firms hit by climate-related disasters vote more in favor of climate-related shareholder proposals at their other portfolio firms. This relation arises via investors becoming more active voters on climate-related proposals and is strongest following recent exposure to large value-relevant disasters, during periods of elevated attention to climate risks, and for votes occurring at carbon-intensive firms. Aggregating to the firm level, firms with impacted investors exhibit lower climate change sentiment on conference calls and a longer-term decrease in emissions. Thus, climate disasters ripple through ownership networks to influence corporate behavior toward environmental responsibility.

Keywords: institutional ownership networks, shareholder voting, climate change

JEL Classifications: G11, Q54, M14, G3

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Propagation of climate disasters through ownership networks*

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November 10, 2024

Abstract

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1 Introduction

Climate impacts and the associated uncertainty surrounding the transition to a low-carbon economy pose substantial risk to investors (Krueger, Sautner, and Starks, 2020; Bansal, Ochoa, and Kiku, 2017; Bolton and Kacperczy, 2021; Hoepner, Oikonomou, Sautner, Starks, and Zhou, 2024; Seltzer, Starks, and Zhu, 2022). Large investors are taking notice of these risks and exerting influence over environmental, social, and governance (ESG) policies (see e.g., Dyck, Lins, Roth, and Wagner, 2019; Krueger, Sautner, and Starks, 2020). A growing literature documents a variety of static fund characteristics and managerial experiences that predict ESG attention and engagement (Bolton, Li, Ravina, and Rosenthal, 2020; Fich and Xu, 2023).[1] We propose a new time-varying portfolio level driver of investors' ESG attention and engagement, conjecturing that investors' exposure to climate disasters via one portfolio firm impacts the way investors engage on climate-related issues at other (non-disaster hit) firms in their portfolios.

We use shareholder climate proposal votes as a setting to understand the extent to which investors react to their portfolios' climate disaster exposure when engaging with other firms. Shareholder activism is one important avenue through which investors can affect governance structure and in turn shareholder value that has become increasingly linked to environmental and social (ES) issues in recent decades (Dimson, Karakaş, and Li, 2015; Grewal, Serafeim, and Yoon, 2016). Although ES proposals rarely pass or are implemented, the extent of support for these proposals is informative about future ES policies and risks (Flammer, Toffel, and Viswanathan, 2021; He, Kahraman, and Lowry, 2023).[2]

Our analysis of how investors' climate disaster exposure relates to their voting behavior on shareholder proposals is well-suited to identify whether climate disasters in an investor's portfolio affect their outlook on ES issues at non-disaster hit firms because all investors are voting on the same firm's proposal at the same time. Thus, the inclusion of proposal fixed effects allows us to identify off of within firm-time variation in investors' value-weighted portfolio exposure to climate disasters. The inclusion of voter-industry fixed effects further absorbs 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

[1] Also see Alok, Kumar, and Wermers (2020); Foroughi, Marcus, and Nguyen (2023); Di Giuli, Garel, Michaely, and Romec (2024).

[2] This parallels the literature on directorial elections in which support rates are 90%, but the extent of support is predictive about future outcomes (Cai, Garner, and Walkling, 2009; Aggarwal, Dahiya, and Prabhala, 2019).

following climate disaster shocks. 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 (or approximately 30%) increase in the probability of supporting a climate proposal. 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. These results are stronger at carbon-intensive "brown" firms, which are the predominant contributor to the sample of shareholder climate proposals. The results are also concentrated in periods of high public attention to climate change, but largely unrelated to investor type. Our findings are robust across various disaster exposure measures and after controlling for disasters at investors' headquarters locations, which, as shown by existing studies (Alok, Kumar, and Wermers, 2020; Fich and Xu, 2023), also influence portfolio allocation and voting decisions.

The sensitivity of investors' voting behavior to climate disasters in their portfolio is driven primarily by large and value-relevant disasters. When we partition our disaster exposure into anywhere from three to fifteen bins based on the ascending order of the distribution of investor portfolios' disaster exposure, the most extreme bin exhibits the largest marginal effect of disaster exposure on voting support for climate proposals. At the same time, the middle bins elicit weaker but still economically relevant effects. Separate analyses corroborate this idea, showing that disasters hitting portfolio firms' headquarters or those that have more significant valuation effects are more predictive of a shift toward voting support for climate proposals at other portfolio firms.

We next examine whether this post-disaster change in voting behavior is driven by investors paying more attention to climate-related proposals or less attention, perhaps due to them being distracted by concerns at disaster hit firms. To distinguish these alternatives, we test the extent to which our findings are driven by investors choosing to vote against the recommendations of proxy advisors, which significantly reduce the cost of information gathering and have substantial influence over voting behavior (McCahery, Sautner, and Starks, 2016; Malenko and Shen, 2016; Malenko and Malenko, 2019). Motivated by the idea that following proxy advisors' recommendations correlates with a low-cost and passive approach to voting (Iliev and Lowry, 2015; Gilje, Gormley, and Levit, 2020; Marsusaka and Shu, 2023), we study whether our findings are influenced by cases in which Institutional Shareholder Services (ISS) recommends against a proposal. We find that the increased likelihood of supporting climate proposals is concentrated in cases where ISS recommended against them, suggesting that disaster exposure makes investors more active voters.

Our investor-level findings so far suggest a post-disaster uptick in support for climate proposals across various types of investors, including those with significant impact. We next examine the connection between the aggregate climate disaster exposure of a firm's investor base and its climate policies. Our previous results make no clear predictions regarding this analysis. On the one hand, climate proposals often receive limited support. On the other hand, our voting results suggest shifts in investor interests and voting is one of several avenues through which more engaged institutional investors can shape corporate climate policies.

We find evidence of a significant relation between the extent of climate disaster exposure in a firm's investor base and changes in a variety of climate-related corporate outcomes, implying investor exposure is a mechanism encouraging firms to adopt ES policies. In the short-run, we find that investors' disaster exposure predicts more pessimistic climate sentiment in conference call discussions, as calculated in Sautner, Van Lent, Vilkov, and Zhang (2023). Over the longer-run, investors' disaster exposure is related to a decline in firm-level greenhouse gas (GHG) emissions and energy use as well as an increased adoption of governance mechanisms such as linking executive pay to emissions. As in our voting analyses, these firm-level adjustments concentrate in brown industries, echoing the insight of Hartzmark and Shue (2023) that climate-conscious policies should focus on impact by targeting firms with significant CO2 emissions.

Our study contributes to a large literature on how and when shareholders gather the information they use in their voting decisions. Specifically, we introduce portfolio exposure to climate disasters as a high-frequency, time-varying, investor-level determinant of active support for climate proposals. We add investors' portfolio experience with climate disasters to a list of several other personal experiences that affect managers' voting behavior on ESG issues. For instances, Foroughi, Marcus, and Nguyen (2023), Di Giuli et al. (2024) and Fich and Xu (2023) show that managers' personal exposure to pollution, extreme heat, or climate disasters affects their voting behavior. More generally, Iliev and Lowry (2015) discuss a long list of fund characteristics that predict active voting, such as fund (and fund family) size and ownership stake, Bolton et al. (2020) show that investor ideology plays a substantial role in their voting decisions, while Matvos and Ostrovsky (2010) emphasize peer effects. Ertimur, Ferri, and Oesch (2013) also show that firm characteristics, such as recent performance and the rationale behind the proposal, affect the probability of active voting. In terms of how investors gather their information, Calluzzo and Kedia (2019) highlight the importance of investor-manager connections in voting decisions, Iliev, Kalodimos, and Lowry (2021) show that investors engage in governance research via EDGAR filings, while Ellis, Gerken, and Jame (2021) document a complementary role between access to management and governance research.

Our paper further adds to ongoing debates on institutional investors' role in enhancing companies' ESG performance. While our voting analysis is tailored to identify voice effects, it is less suited to identify comparable investor exit effects since it is not obvious ex-ante exactly which portfolio firms investors would target with divestment.[3] Nevertheless, our study relates to the determinants of shareholders' propensity to discipline management. Divestitures and threats of exit can be one way that firms discipline managers to improve ES performance (Gantchev, Giannetti, and Li, 2022), but 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., Krueger, Sautner, and Starks, 2020; Naaraayanan, Sachdeva, and Sharma, 2021; Doidge, Dyck, Mahmudi, and Virani, 2019; Hoepner et al., 2024) and voting (e.g., Dikolli, Frank, Guo, and Lynch, 2022). Our work implies that, triggered by portfolio climate disaster shocks, institutional shareholders engage to impactfully improve the ESG performance of non-affected firms in the same portfolio.

Our study also contributes 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 (Krueger, Sautner, and Starks, 2020; Alok, Kumar, and Wermers, 2020), corporate loan yields (Correa, He, Herpfer, and Lel, 2023), and municipal bond yields (Painter, 2020; Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2021).[4] We propose a new economic mechanism to explain the adoption of corporate ES policies, adding a propagation channel through ownership networks to show the impact of climate change shocks on firms.

[3]Because we exploit investor-level shocks, there is no obvious way to compare our voting results with the propensity of investors to divest. The concentration of voting effects in brown firms raises the possibility that investors may exit brown firms, but we find no empirical support for this.

[4]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.

Lastly, our findings connect to the common ownership literature by presenting a new type of information that flows through 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 evidence, that the voice of investors changes following their portfolio exposure to climate events, builds on the idea in Edmans, Levit, and Reilly (2019) that, even across unrelated industries, there is a voice and exit channel to governance in a world with common ownership.

2 Empirical Measures and Sample Construction

In this section, we outline the data sources and methods used to study the effect of investors' portfolio exposure to climate disasters on their portfolio firms' voting decisions.

2.1 Climate Disaster Exposure through Institutional Ownership

We begin by describing how we construct the primary explanatory variable, which measures investors' indirect exposure to climate disasters within their portfolios. Appendix A.1 provides all variable definitions used in our study.

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 the present, and includes each hazard's type, location, timing, and direct losses (e.g., property and crop losses, injuries, and fatalities). This database is widely used in studies on the effects of natural disasters, including those on financial markets (e.g., Cortés and Strahan, 2017; Correa et al., 2023). To capture shocks created by relatively large disasters, we focus on disasters that led to Presidential Disaster Declarations by the 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 a large-scale disaster.

In accordance with the findings of the United Nations' Intergovernmental Panel on Climate Change (IPCC) reports (e.g., Seneviratne, Nicholls, Easterling, Goodess, Kanae, Kossin, Luo, Marengo, McInnes, Rahimi et al., 2017),[5] we focus our analysis on hurricanes/storms, floods, and wildfires, which are climate change-related severe disaster events. Recent studies attribute the increased severity of these disasters to climate change. Internet Appendix Section IA.1 supplies additional detailed discussions of this evidence. Panel A of Appendix Table IA.1 closely examines the big natural disasters in our sample period, showing that, conditional on entering our sample, disasters of all three types have average damages of over $1 billion. The most significant disasters on average are hurricanes or storms, which have average damages of almost $6 billion and hit 26 counties on average. Panel B 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, which have not crossed the $100 million damage threshold since before 2010.

Instead of only focusing on disaster exposure based on firms' headquarters, we construct a measure incorporating information based on firms' geographic footprints. To do so, we rely on the National Establishment Time-Series (NETS) dataset from Walls and Associates, which gives annual snapshots of detailed establishment-level information on geographic location and parent company ownership.[6] Following Kruttli, Roth Tran, and Watugala (2024), we calculate the share of firm i's establishments in a county c in year y as $Firm\ County\ Exposure_{i,c,y}$ and then define a firm's exposure to climate disasters in each year-quarter q as:

$$Disaster\ Exposure_{i,q} = \sum_{c} Firm\ County\ Exposure_{i,c,y-1} \times County\ Exposed_{c,q}, \tag{1}$$

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 comprehensively evaluates a company's exposure to climate disaster shocks.

As climate disasters disproportionately affect large geographically dispersed firms, $Disaster\ Exposure_{i,q}$ may be correlated with stable time and spatial characteristics. To guard against this as a driver of our results, we

[5]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.

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

construct a excess disaster exposures to interpret our main measure as an exogenous shock. Specifically, we start by constructing a quarterly disaster exposure benchmark for each firm in each year using the disaster map from the 1990s:

$$Expected\ Quarterly\ Exposure_{i,q} = \sum_{c} Firm\ County\ Exposure_{i,c,y-1} \times County\ Quarterly\ Exposed_{c,90s}, \qquad (2)$$

where $County\ Quarterly\ Exposed_{c,90s}$, ranging from 0 to 1, is the average fraction of the 40 quarters from the 1990s where county c experienced a climate disaster. This benchmark provides a hypothetical value for firms' quarterly disaster exposure based on the climate patterns from the 1990s by applying firms' current geographic footprints in year $y-1$ (relative to our dependent variable) but assuming the disaster map remains unchanged from the 1990s. Comparing Eqs. (1) and (2), we identify an unexpected climate disaster shock to firm i in year-quarter q if it suffers an excess disaster shock that is defined as:

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

$Excess\ Disaster\ Exposure_{i,q}$ 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 a typical quarter from 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 include many instances of when locations are spared from disasters compared with the 1990s. In our main analysis, we focus on an indicator-based measure, $I(Excess\ Disaster\ Exposure_{i,q} > 0)$, to interpret our measure as a percentage of portfolio value that is indirectly exposed to climate shocks as described in the next subsection. For robustness, we also report our main results using a measure constructed from $Excess\ Disaster\ Exposure_{i,q}$.

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. Figures of each disaster type are presented separately in Appendix Figures IA.1 to IA.3.

[Figure 1 here]

Panel A of Table 1 provides descriptive summaries of firms' disaster measures in the matched sample of NETS and Compustat. 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 the 1990s) to disasters in a given quarter. The mean of *Disaster Exposure* shows that an average U.S. firm has 3.5% of its establishments affected by a given climate disaster, while the average *Excess Disaster Exposure* is about 2.6 %, with 13.7% of firm-quarters recording a positive *Excess Disaster Exposure*.[7] 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 19% (i.e., 2.6/13.7) 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 Eq. (3) to identify disaster exposed focal firms. However, we also explore alternative benchmarks, considering factors like firms' size and geographic layout. These robustness checks, which we present in Section 3.5, 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

[7] These measures are comparable to the similar measure in Kruttli, Roth Tran, and Watugala (2024), which shows that the average U.S. firm has respectively 2.6% and 1% of its establishments in hurricane regions with 100-mile and 50-mile radii around a hurricane eye.

a 13F filer as an institutional investor or fund family as the disclosed positions are aggregated 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.[8]

Given firm i, institutional investor j, and year-quarter q, we aggregate the climate disaster shock to the institutional investor level and construct an 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 in quarter q. 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 value experiencing an excess 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 plots.

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

2.2 Voting Data and Climate-related Shareholder Proposals

The primary goal of this paper is to study the relationship between the aforementioned measures of investors' indirect portfolio exposure to climate events and investors' voting behavior.

Our first set of tests examines voting on shareholder-sponsored proposals.[9] For this analysis, we collect mutual fund voting records from 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 follow the approach of He, Huang, and Zhao (2019) in using a name-matching algorithm to merge this mutual fund-level data to our fund family-level 13F holdings data for most of our analyses.[10] At the end of Section 3.5, we investigate whether this aggregation masks economically relevant within-fund-family variation in voting behavior.

Similar to the procedure of He, Kahraman, and Lowry (2023), we adopt a rigorous multi-stage screening process to identify three 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 the 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 an initial sample of 428 climate, 537 other environmental, and 1,218 social shareholder-sponsored proposals. After requiring the data used in our main voting regression tests, our final sample includes 310 climate, 425 other environmental, and 936 social proposals. This sample of proposals tallies up to 1,671 proposals, which is almost the same count as the 1,658 ES proposals analyzed by He, Kahraman, and Lowry (2023) over the same 2004 to 2019 sample period.

[9]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).

[10]Another implication of funds always voting with their fund family is that our voting results are robust to an alternative clientele interpretation where fund-family voting is correlated with a subset of funds that target flows from climate-conscious investors. Moreover in later robustness tests, we show our portfolio exposure measure is a shock that is largely uncorrelated with stable investor characteristics such as clienteles.

In our voting regression tests, we construct support for a proposal with an indicator variable for when institutional investors do not vote against the proposal, which means they are not actively rejecting a given proposal. Therefore, our vote for a proposal variable is an upper bound on voting support. At the same time, we find nearly identical and significant estimates for our main results when defining voting support based on when investors affirmatively vote for a proposal.[11]

2.3 Describing the 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.[12] In contrast, the most popular other environmental proposals' item descriptions relate to preparing sustainability reports or adding sustainability as a metric for executive compensation.[13] Thus, the key distinction separating climate and environmental proposals pertains to actions affecting greenhouse gas emissions.[14] Lastly, the most popular social proposals are related to gender, sexual orientation, or diversity.

Panel B of Table 1 reports on the 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 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, Kahraman, and Lowry (2023) that ES proposals almost always fail.

[11] We report these results in Appendix Table IA.3

[12] The top five climate proposal item descriptions in the ISS data are 1) Adopt Quantitative GHG Goals for Products and Operations (27 proposals), 2) Report on Greenhouse Gas Emissions (16 proposals), 3) Report on Global Warming (13 proposals), 4) Report on Sustainability, Including GHG Goals (11 proposals), and 5) Report on Methane Emissions Management and Reduction Targets (11 proposals).

[13] The top five non-climate environmental proposal item descriptions in the ISS data are 1) Prepare Sustainability Report (48 proposals), 2) Report on Sustainability (43 proposals), 3) Require Director Nominee Qualifications (16 proposals), 4) Prepare a Sustainability Report (15 proposals), and 5) Include Sustainability as a Performance Measure for Senior Executive Compensation (10 proposals).

[14] The distinctive focus on greenhouse gas emissions is consistent with the notion of climate proposals within the popular press, e.g., https://www.cnbc.com/2024/01/22/oil-exxon-mobil-sues-activist-investors-to-stop-shareholder-proposals.html

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%.[15] Among fund families that vote on climate-related shareholder proposals, the average $Portfolio\ Exposed_{j,t}$ is 2.95%, namely the total portfolio weight of firms suffering excess climate shocks is on average 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 ($Portfolio\ Exposed^{cont.}$) becomes 0.18%. We also compute a generic measure of the voting influence of an investor in a firm by a specific investor's institutional ownership in that firm (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 Voting Impact of Investors' Climate Disaster Exposure

Our central research question is the extent to which investors' portfolio-level climate disaster exposure affects their voting behavior. As discussed above, our regression sample includes voting outcomes on shareholder-sponsored proposals for which we observe investors' portfolio exposure to climate disasters. After excluding firms with contemporaneous disaster exposure to focus on the spillover effect, we estimate the following regression,

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

[15]We note that this average computed at the investor-proposal level differs from the "Vote Not Against" average reported in Panel B of Table 1 because the number in the latter 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.

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. $Portfolio\ Exposed_{j,t-1}$ and $Portfolio\ Exposed^{cont.}_{j,t-1}$ are the four-quarter moving averages of the two fund family level portfolio exposure measures to climate disasters based on Eqs. (4) and (5), respectively, 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.[16]

The unit of observation in Eq. (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 estimate our coefficient of interest based 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 for unaffected firms 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 ($Log(Portfolio\ Value)$) and past performance ($Portfolio\ Return$). In particular, $IFO_{i,j,t-1}$ accounts for the effect of large shareholders' differential monitoring role in firms (see e.g., Alchian and Demsetz, 1972; Shleifer and Vishny, 1986).

Column (1) of Table 2 Panel A indicates a positive relation between portfolio exposure to climate disasters among other portfolio firms and the propensity to support climate shareholder proposals of unaffected firms (i.e., a positive γ_1 in Eq. (6). Column (2) restricts 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 $Portfolio\ Exposed_{j,t-1}$ is associated with a 3.49 unit increase in voting for climate proposals. Relative to the mean support, this corresponds to an approximate 8% to 9% increase in the likelihood that an investors does not vote against a climate proposal.

[16]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 $Portfolio\ Exposed_{j,t-1}$ are zero when there is a gap in the data.

[Table 2 here]

Columns (3) and (4) show that this result is specific to climate-related shareholder proposals. We do not find comparable spillover voting effects of investors' climate disaster exposure with respect to votes on other ES shareholder proposals. Although the estimated effect on other ES proposals is positive, the coefficients corresponding to the effect of investors' disaster exposure on other ES proposals are statistically insignificant with t-statistics that are less than 1 in magnitude.[17]

In Panel B of Table 2 we replicate the analysis in Panel A using $Portfolio\ Exposed^{cont}_{j,t-1}$ as our explanatory variable of interest. Unlike our primary measure, which defines a firm-year as disaster exposed if its geographic footprint experiences abnormal disaster activity, this measure also accounts for the extent of abnormal disaster exposure. Comparing the coefficients across the two panels shows that this additional granularity in our disaster measurement has little effect on our estimates.

3.1 Do Disasters Make Voters More Active?

We next study whether the climate disaster-induced changes in voting behavior that we observe are likely due to an increased level of investor attention to climate-related issues at other portfolio firms. *Ex-ante* whether the documented relation is driven by investors becoming more or less active voters is uncertain. On the one hand, climate disasters may trigger more attention and therefore more active voters if, for example, investors update their beliefs regarding future climate policy actions or the potential risks of future climate events. On the other hand, investors may pay less attention to climate-related issues at their other portfolio firms if they are distracted by the events transpiring at the disaster hit firms in their portfolio or come to believe that disasters pose lower risk going forward.

In Table 3, we test whether climate disasters lead to investors paying more attention to the climate-related shareholder proposals at their other portfolio firms by partitioning the effect of climate disasters on proposal votes based on whether or not the ISS proxy advisor recommends voting for or against the shareholder proposal. ISS

[17] We also find 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. This is consistent with the large literature suggesting a negative relation between institutional ownership and ESG proposal voting outcomes. According to He, Kahraman, and Lowry (2023), environmental and social (ES) proposals have limited voting support. Consistent with this finding, in our sample, the levels of support among investors on ES proposals remain lower than 30%.

recommendations are designed to reduce investors' information gathering costs and existing literature uses the propensity to go against ISS recommendations as a proxy for active voting (Iliev and Lowry, 2015; Gilje, Gormley, and Levit, 2020).

[Table 3 here]

Comparing the estimates in the first and second row of Table 3 suggests that the positive relation between investors' portfolio-level disaster exposure and their voting activity concentrates in an increased propensity to vote for climate proposals in the approximately 40% of cases in our sample in which ISS recommends against doing so. The coefficients in the first row of Columns (1) and (2) are 2 to 4 times larger than those in the second row. Unlike the results in Table 2, these findings extend to non-climate ES proposals as well. The coefficients on E (S) proposals are approximately 66% (35%) of the size of the estimated effect on climate proposals. Taken together these findings suggest that more active engagement on climate proposal voting is the primary channel through which climate disasters drive more support for climate proposals.

3.2 Disproportionate Effect of Large Disasters

We next study what types of disaster exposures drive the observed shift in voting behavior. We first consider whether the marginal effect of climate disaster exposure on voting rises as exposure levels become more extreme. This exercise is motivated in part by the significant skew in portfolio disaster exposure. Panel C of Table 1 shows that the median percentage of an investor's holdings that are in disaster-exposed firms (0.16%) is quite small relative to assets under management, while the average (2.95%) and 90th percentile (10.12%) are economically relevant.

To study the extent to which extreme disaster exposure levels drive our results we conduct a series of tests in which we decompose the explanatory variable of interest into between 3 to 15 bins.[18] We then regress vote for climate proposals on the collection of decomposed variables as in our main voting tests. Figure 2 plots the predicted effect for the top (Nth) or next ($N-1$th) bin, where the predicted effect for a 1 SD bin-specific shock

[18] Specifically, For a given bin size N, we decompose $Portfolio\ Exposed_{j,t-1}$ into N bins based on the ascending order of its values in each quarter. A decomposed variable $b \in N$ is equal to the values of $Portfolio\ Exposed_{j,t-1}$ in bin b, and 0 otherwise so that the sum of the N decomposed variables equals the original measure.

is the coefficient on the top or next bin variable times the standard deviation (SD) of the bin variable (when it is greater then 0).

[Figure 2 here]

Figure 2 shows that across bin sizes ranging from 3 to 15, we consistently observe that the tail (i.e., top bin) of our measure has an economically large voting effect of around a 6 to 8 unit increase in voting support (relative to the 2.38 average effect). However, we also see that, outside of the tail, the next bin has large voting effects. On the left side of the plot, based on a tercile decomposition, the middle third of the portfolio disaster distribution is associated with a comparable voting effect as that of the overall distribution. On the right side, as we increase the number of bins, the effects of the left tail and the next bin converge and have comparable magnitudes once we reach 15 bins. These results suggest even typically small portfolio exposures to climate disasters can shift investors' voting behavior for climate proposals, but in general we observe larger marginal effects for larger levels of disaster exposure.

We next decompose our $Portfolio\ Exposed_{j,t-1}$ measure based on its two building blocks: portfolio weight in the disaster firm and the climate disaster exposure. Building on Eq. (4), our general decomposition procedure is

$$Portfolio\ Exposed_{j,t-1} = \sum_b (Portfolio\ Exposed \mid \text{Condition } b)_{j,t-1} \tag{7}$$

$$= \sum_b \sum_i I(Excess\ Disaster\ Exposure_{i,q} > 0) \times w_{i,j,t-1} \times I(b), \tag{8}$$

where b is a condition on either the portfolio weight or a characteristic of the climate disaster. We then regress voting support for climate proposals on all of the decomposed variables, $(Portfolio\ Exposed \mid \text{Condition } b)_{j,t-1}$. To interpret economic magnitude relative to our main voting tests, we divide the decomposed variables by the standard deviation of the original $Portfolio\ Exposed_{j,t-1}$ variable.

Table 4 reports the results. In Column (1), we first replicate the tercile decomposition of $Portfolio\ Exposed_{j,t-1}$ depicted in Figure 2. In regression format, we again see that the voting effect is most positive and significant for the top tercile of the distribution of climate disaster portfolio exposure. Column (2) shows that large portfolio holdings helps to achieve this tail effect. Conditioning on whether disaster firm portfolio weights in each quarter are high, medium, or low, we find that only the measure conditioned on high portfolio weights is positive and significant. This is consistent with prior work that finds higher portfolio weights result in more investor attention (e.g., Fich, Harford, and Tran, 2015; Gilje, Gormley, and Levit, 2020).

[Table 4 here]

Next, we investigate whether the characteristics of the climate disaster affect investors' voting response. We posit that significant events, such as firm headquarter hits or declines in stock prices associated with climate shocks, may attract investor attention and thus drive the observed changes in voting behavior.[19] In Column (3) of Table 4, we decompose investors' portfolio exposure based on whether or not focal disaster firms suffer headquarter hits. In Column (4), disasters are classified as ones with severe or mild stock market responses based on 30-day cumulative abnormal returns (CARs) after disaster hits.[20] We find that when disaster firms experience headquarter hit by a disaster or when the disaster significantly negatively impacts stock prices, portfolio-exposed investors vote more for climate proposals at their other portfolio firms.

Altogether, these results suggest that even if portfolio exposures are small, climate disasters appear to be grabbing investors' attention and shifting their voting behavior. Higher exposures via portfolio weights and more value-relevant climate disasters further magnify investors' voting responses.

3.3 Dynamic Impact of Climate Disasters on Voting

We next delve into the timing over which disasters relate to voting behavior. This has two important benefits. First, it offers insights into the longevity of the effect. Second, climate disasters in future periods serve as placebo tests that inform on the plausibility of our identifying assumptions.

In Panel A of Table 5, we split our disaster exposure measure into recent and more distant disasters over the past year (i.e., quarters $q-4$ to $q-1$). 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. In

[19] Investors are also more likely to pay attention to climate shocks with big damages. However, as stated in section 2.1.1, all natural disasters included in our analyses trigger FEMA Presidential Disaster Declarations and are therefore severe by damage. Consistent with this fact, in untabulated tests, we find no evidence that the marginal effect of portfolio exposure on voting rises with disaster size. Of course, larger disasters have a larger effect on voting since they generate larger changes in the explanatory variable of interest, but the marginal effect of this exposure is similar across disaster size terciles in our test sample.

[20] See the Internet Appendix Section IA.2 for the detailed steps of testing stock market responses to each climate disaster.

Panel B, we conduct a placebo test by repeating the decomposition using the future shocks from quarters $q+1$ to $q+4$ after the shareholder meeting. Consistent with our identifying assumptions and benchmarking approach, we observe no impact on voting from future shocks. Importantly, the former result is consistent with either investor attention contributing to 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 5 here]

To study these alternatives more closely, Panels A and B of Figure 3 provide a graphical representation of Tables 2 and 5, 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. In our voting sample, 84% of proposals occur at firms that have a December 31st fiscal year end. Therefore, since shareholder votes are usually scheduled around one quarter after fiscal year end, time -1 is the final quarter that determines the annual fiscal results (i.e., October 1st - December 31st of the previous year). Times -2 through -6 reflect earlier periods, while times 0 through 4 reflect the five quarters after the current fiscal year.

[Figure 3 here]

The results in Panel A of Figure 3 are consistent with climate disasters temporarily impacting institutional investors' propensity to support shareholder climate proposals. Disasters occurring in the two most recent quarters before the vote have the most impact and correspond to the only statistically significant estimates across the eleven quarters examined. The next most positive coefficients are around half the magnitude of the time -1 estimate. Importantly, we find no significant effects in the quarters after the vote, suggesting that our findings are not primarily due to an unobserved correlation between our disaster and stable investor characteristics.

Figure 3 thus helps to clarify the timing of climate disaster events and how it propagates via ownership to impact subsequent shareholder voting. 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 during this period 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 that our disaster portfolio exposure shock is merged according to the quarter of the record date, then the significant effects at time -1 and -2 occurs about 1.5 to 2.5 quarters before the vote in calendar quarter Q2. In our disaster data, we unsurprisingly find that 69% of excess disaster shocks occur in Q3 and Q4. Panel B of Figure 3 highlights this point as it shows that once we account for the magnitude of the disaster exposure, the time -1 and -2 effects dominate, with both being positive and higher in magnitude than all other times. The time -2 effect is particularly statistically significant as it coincides with when the most severe climate disasters such as hurricanes and wildfires hit. 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.

3.4 Heterogeneity in Climate Disasters' Voting Impact

We next study the potential role of heterogeneity in how disaster exposure influences voting behavior. This analysis considers variation over time and across different firm and investor types.

3.4.1 Aggregate attention to climate change

We first study how aggregate climate attention interacts with portfolio-level climate-disaster exposure in determining shareholder voting outcomes. On the one hand, high aggregate attention to climate issues may complement the voting impact of climate disasters if it leads investors to interpret climate disasters as more predictive of future disasters (i.e., if managers put a larger probability of climate change causing the disaster as opposed to just bad luck with the weather). On the other hand, when aggregate attention is high investors may already be actively voting on climate issues, leaving little room for climate disasters to further increase their engagement.

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 *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 6 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 average levels of climate change attention there is a significant relation between investors' disaster exposure and their voting behavior on climate-related proposals.

[Table 6 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 positive but marginal in terms of statistical significance. Overall, these findings suggest that aggregate climate attention complements portfolio-level climate shocks in driving more supporting voting behavior on climate-related shareholder proposals.

3.4.2 Brown versus green firms

An interesting feature of climate proposals in our dataset is their frequent targeting of oil and energy companies, 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 firms with high GHG emissions. A natural question that follows is whether the climate voting effect we document concentrates in green or brown firms. The answer is not straightforward, as the academic debate continues over which type of firms should be the primary targets of climate activism. On one hand, green firms may more readily adopt green policies, while on the other, brown firms may experience the most significant impact from such policies.

The primary way we test this is by interacting the explanatory variable of interest with the extent of emissions produced by the firm. We consider two emissions measures: the natural log of CO2 emissions and CO2 scaled by sales.[21] Table 7 reproduces our voting analyses including this additional interaction term within the sample of emitting firms. The results suggest that the impact of investors' portfolio disaster exposure on their voting behavior is more pronounced when addressing climate proposals at brown firms.[22]

[Table 7 here]

In Appendix Table IA.5 we consider an industry-level measure of green and brown firms. Following Choi, Gao, and Jiang (2020), we label industries as brown based on the five major emitting industries identified by the IPCC: energy, transport, buildings, chemicals & metals, and AFOLU (agriculture, forestry, and other land use); all other industries are classified as green. 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. 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 byproduct of the fact that our results concentrate in brown firms is that it allows us to compare our voting results with corresponding investor exit results. While our previous tests are well suited to identify the voting or voice channel, it is hard to compare it with the relative importance of exit because it is not ex-ante clear what types of firms investors would target with their exit strategy. To the extent that brown firms are targeted by adjustments in voting behavior, an analysis of the relation between climate disaster exposure and brown firm divestment offers a comparison between investors' use of voice and exit.

We analyze investor exits in Appendix Table IA.6 using the same brown versus green industry classifications as above. Our analysis reveals that investors' exposure to climate disasters does not predict their portfolio weight

[21] 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.

[22] Requiring CO2 emissions data reduces the sample size by around half. Untabulated results show that our main results hold in the voting sample that lacks emissions data.

in brown industries, nor does it influence their rebalancing out of brown industries or high CO2 emitters within those industries. Moreover, 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. These findings underscore the importance of engagement over exit in our setting (e.g., Azar, Duro, Kadach, and Ormazabal, 2021; Krueger, Sautner, and Starks, 2020) and support a model where social responsibility is the majority preference among investors (Broccardo, Hart, and Zingales, 2022).

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 effect on 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 consistently support climate proposals and thus show a limited reaction to disaster shocks across their portfolio.

[Table 8 here]

Given our broad expectations, we consider a wide range of investor characteristics. In Panel A of Table 8, we interact an investor's disaster exposure with indicators for: the Big 3 indexers (i.e., Blackrock, State Street, and Vanguard), the Top 10 investors by portfolio value in a quarter, large mutual funds (banks) above the 75th percentile in portfolio value, and signatories of 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. Taken together, these findings suggest that that disaster exposure affects the most impactful voters, as well as smaller shareholders.

In Panel B of Table 8, we consider the potential role of investor size and activeness. While we continue to have no specific prior on investor preferences related to these two characteristics, we may infer that climate disasters portfolio exposure tend to mechanically affect larger and more passive investors holding stakes across many firms. In the data, we find a positive correlation between climate disaster portfolio exposure and an indicator for above median portfolio size by quarter. To examine whether this mechanical effect drives our results, we study an interaction of climate portfolio exposure with investor type defined by 2 by 2 independent sorts of investors by median portfolio size and activeness each quarter. Following standard practice (e.g., Agarwal, Jiang, Tang, and Yang, 2013), we measure activeness based on portfolio turnover.

In Column (1), we indeed observe that the voting effect is stronger for small investors with below-median portfolio size. Moreover, in Column (2), the effect is even stronger when the small investor is passive. In the remaining columns, we do not find statistical differences for active or large investors. Importantly, across all columns, we continue to find that the documented voting effect is robustly positive and significant if we exclude investors based on size and activeness.

3.5 Robustness and Interpretation

The dynamic illustration in Figure 3 is consistent with a causal interpretation whereby investors vote differently when their portfolio is more significantly affected by disasters in the preceding two quarters. Here, we provide several additional tests to support this causal interpretation and shed additional light on the type of disaster exposure that drives our results.

3.5.1 Alternative Benchmarks and Constructions of the Spillover

Our baseline disaster exposure measure following Eq. (3) 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 geographically dispersed firms will still be predisposed to take on higher disaster measures to the extent that 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 Panel A of Table 9, we first show that the use of the 1990s benchmark does not drive our main results.

Column (1) indicates qualitatively similar effects to those in Table 5 with somewhat larger magnitudes using the non-benchmarked disaster exposure measure, *Disaster Exposure*, defined in Eq. (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 9 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 $Expected\ Quarterly\ Exposure_{i,q}$ 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 estimates in Columns (2) through (4) of Table 9 exhibit similar magnitudes to that of the unbenchmarked estimates in Column (1) and the 1990s benchmarked estimates in Columns (3) and (4) of Table 5. To the extent that these tests appropriately account for size and footprint effects, these results suggest that our main results are predominantly driven by abnormal or unexpected disaster exposure.

Appendix Table IA.7 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. More specifically, we find 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, we reach similar conclusions.[23] These findings are consistent with investors adjusting their voting behavior on climate proposals

[23] In untabulated results, we also find 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.

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.

3.5.2 A Simulated Placebo Test

The relation between disaster-related portfolio exposure and the predisposition of large or geographically dispersed firms to be portfolio exposed may also raise 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 $County\ exposed_{c,q}$ 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 i.i.d. over time. We repeat this randomization 1000 times in order to generate a simulated distribution of t-statistics under the null hypothesis.

Panel B of Table 9 reports on the results of our placebo simulation. For the coefficients of interest in Tables 2 and 5, we compute the proportion of its respective simulated p-values that are below the nominal $\alpha = 5\%$ level. This proportion 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 "All" 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 at 7.3%. In the "IFO>0" sample, the main measure is slightly oversized, but the measure focusing on the two most recent quarters is properly sized at 5.1%. To account for these effects, 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 5 are above these adjusted critical values. Therefore, we again can reject the null of placebo disasters, and conclude that there is a robust effect related to the actual excess disaster shock.

3.5.3 Comparison with Direct Investor Exposure

We next consider the possibility that the location and disaster exposure of investors' headquarters may affect our findings. Alok, Kumar, and Wermers (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 show that hurricanes around investors' headquarters lead to changes in voting behavior. The intuition underlying our findings is distinct in that it relies on ownership network 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, 2024). 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 climate disaster. Across the four columns of Appendix Table IA.8, we find indeed evidence that investors' home location direct climate disaster exposure affects their votes on climate proposals. However, Columns (2) and (4) show that the inclusion of this control also has little effect on the main results in our paper.

3.5.4 Fund-level Results

Finally, we explore whether there is any meaningful residual variation in voting behavior at the fund level, as opposed to the fund family level that we aggregate to throughout the rest of our tests. As mentioned previously, earlier voting literature report that while funds almost exclusively vote with their fund-family, around 4% of funds do not, leaving them room to deviate from fund-family directives. Moreover, in our setting, recent work by Michaely, Ordonez-Calafi, and Rubio (2024) show ES funds, particularly in non-ES fund-families, strategically vote on ES issues by supporting improbable proposals (consistent with their fiduciary duties) while opposing contested proposals (i.e., accommodating family preferences).

Following Gao and Huang (Forthcoming), we start by developing a fund name-matching algorithm to merge NPX voting data and s12 mutual fund holdings data. Using a combination of hand-checking and strict name-matching criteria, we are able to identify 10,532 funds in both databases that account for 64.9% of the votes in the NPX database.[24] We then construct for fund f belonging to fund-family j an equivalent fund-level indirect exposure measure as in Eqs. (4) and (5).

We first check summary statistics for if funds deviate from their fund-family. For funds voting on climate proposals, the average voting support is 38.9% with a full-sample standard deviation of 48.7%.[25] Given this benchmark, we then compute standard deviations of voting support for funds in the same fund-family voting on a given proposal. The resulting average (median) within-family standard deviation is only 5.9% (0.0%). In fact, 89% of these standard deviations are 0, indicating the vast majority of funds never deviate from their fund family.

Appendix Table IA.9 reports on our fund-level voting results, which include Fund Family x Proposal fixed effects to isolate within fund-family voting variation on a given climate proposal. Across all four columns, we observe insignificant coefficients, regardless of whether we use an indicator or the continuous value of excess disaster exposure, or when we decompose the effect by recency. Thus, these fund-level tests indicate either no fund-level differences in our investor-level voting effect, or at the very least, no power to detect any potential effects. In unreported tests, we also observe similar insignificant results when studying other (non-climate) types of proposals.

[24]Relaxing the name-matching criteria can push this number to around 90% of the votes, but doing so introduces many false-positive matches. Upon manual examination, we find that the false-positives are driven by the fundamental fact that the N-PX voting data and mutual fund holdings data do not cover the same set of funds.

[25]For comparison, in the Panel C of Table 1, we find very similar fund-family support of 37.7% with a standard deviation of 46.2%.

4 Firm-level Effects

Our investor-level findings suggest an uptick in support for climate proposals in the post-disaster period, and this effect is observed across various types of investors, including those with significant impact. However, the connection between the aggregate climate disaster exposure of a firm's investor base and its climate policies remains unclear. Despite limited support for many climate proposals, managers and directors may respond to investor concerns to avoid losing voting support in elections. Prior studies suggest that even minimal dissent signals important impacts on corporate outcomes in other settings. For instance, although most directors receive over 90% of the votes cast, an increase in votes against directors is associated with lower CEO compensation, a higher likelihood of CEO turnover and poison pill removal (Cai, Garner, and Walkling, 2009), and increased director turnover with fewer future opportunities (Aggarwal, Dahiya, and Prabhala, 2019). In addition, voting is correlated with other avenues through which institutional investors can shape corporate climate policies, such as through public statements and promoting governance structures that enhance firms' responsiveness to investor demands on climate risks (Appel, Gormley, and Keim, 2016). Climate proposals can foster enhanced dialogue and awareness of climate change between the board of directors and shareholders (Flammer, Toffel, and Viswanathan, 2021), and a significant number of environmental shareholder proposals are settled and withdrawn before a vote (Fisch and Robertson, 2023). Even failures in proposal acceptance often pave the way for shareholder engagement, which can result in improvements in financial performance and corporate policies (Dimson, Karakaş, and Li, 2015).

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 climate outcomes. 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,

$$VW(Portfolio\ Exposed)_{i,q} = \sum_{j \in S_{i,q}} IFO_{i,j,q} \times Portfolio\ Exposed_{j,q}, \tag{9}$$

where $j \in S_{i,q}$ is the set of firm i's institutional investors, and $IFO_{i,j,q}$ is an investor j's ownership in this firm in quarter q. To focus on the portfolio spillover interpretation, we compute this measure for firms without direct contemporaneous climate disaster exposure. From Eq. (9), we see that the firm-level effect is the sum of interacted extensive and intensive margins. For the former, to affect firms, the investor must have non-zero positive ownership (and therefore influence) in the firm. Thus, we value-weight using $IFO_{i,j,q}$ since theoretical and empirical models of 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). For the latter, even if an investor has ownership, they must also experience a disaster shock in their portfolios. Eq. (9) also highlights the economic importance of common ownership links propagating climate disaster shocks. On average, when a firm is indirectly affected by an investor-level climate disaster shock, we find 42.1% of its institutional investor ownership – about two-thirds of the 70.4% average institutional ownership in our sample – experiences a portfolio climate disaster shock. Consequently, a substantial portion of shareholder influence is affected, which could potentially alter the way these investors interact with firms and influence their policies. 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 the disaster exposure of an investor base affects firms' quarterly conference call discussion of climate change. Our dependent variable is based on time-varying text-based measures of firm-level discussion of 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.[26] 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 components of $CC\ Sentiment_{i,q}$ and assess the impact on brown versus green industries. Our regression specification for detecting firm-level spillover effects is,

$$CC\ Sentiment_{i,q} = \beta_1 VW(Portfolio\ Exposed)_{i,q-1} + \beta_2 Disaster\ Exposure_{i,q-1} + \beta_3 X_{i,q-1} + FEs + \epsilon_{i,q}. \tag{10}$$

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

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 in the current quarter q. $Disaster\ Exposure_{i,q-1}$ controls for the effect of firms being directly hit by disasters in the previous quarter. 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 firms' headquarter states (e.g., disasters often cause spatial clustering by affecting geographic areas differently over time), while Industry × year fixed effects control for potential product market trends over time (e.g., several studies find common ownership is often associated with product market competition). $X_{i,q-1}$ further controls for time-varying firm characteristics.[27] For inference, we use robust standard errors double-clustered by firm and year-quarter.

Table 10 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. Since all the coefficients of interest are normalized by their full-sample standard deviations, the coefficient estimate of −0.39 suggests that a one standard deviation increase in portfolio disaster exposure leads to an approximate 0.39 percentage reduction in net climate change sentiment.[28] The next two columns show that the effect manifests primarily through increases in negative sentiment, while Column (4) shows that these findings hold across both brown and green industries although the coefficient is 78% larger in brown industries. Lastly, similar to that of our voting results, Panel A of Appendix Table IA.12 shows that these results are robust to using an alternative benchmark based on firm's expected disaster exposure based on size, geographic footprint, and historical exposure in the 1990s.

[Table 10 here]

[27] The 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). Results remain consistent when excluding firms that are substantially hit by disasters or when including an interaction between a firm's own disaster exposure and that of their investor base.

[28] Appendix Tables IA.10 and IA.11 also report 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.

Figure 4 dynamically illustrates the relation between the disaster exposure of firms' investor base and their climate sentiment during conference calls. We observe that the significant negative relation is primarily concentrated in the quarter of the disaster and the preceding quarter. The estimated effect for the quarter before the disaster is larger than any other coefficient in the surrounding eleven quarters. Importantly, we again find no evidence of pre-trends, supporting a causal interpretation of our results. Thus, the aggregate exposure of a firm's investor base to climate disasters appears to be a significant factor influencing the firm's dialogue with investors.

[Figure 4 here]

4.2 Long-run Environmental Outcomes

We next examine if firms respond to indirect exposure to disasters via the ownership network in the long-run by adjusting their climate policies, namely physical outcomes and climate-related governance initiatives.

For our analysis of physical outcomes, we focus on GHG emissions and total energy use with data obtained from the Refinitiv ESG (Asset4) database. Carbon emissions are at the center of the United Nations' IPCC reports, 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, 2022; Ivanov, Kruttli, and Watugala, 2024).

Results from this analysis are reported in Table 11, where each row corresponds to a separate outcome variable. To capture the long-run effects, we modify Eq. (10) to the annual level with similar control variables and the same fixed effects. We respectively test 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. 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.[29]

[Table 11 here]

The first row of Panel A in Table 11 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). 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, or about $\frac{0.908/2}{5.639} = 8.1\%$ per year for an average firm (see Panle B of Appendix Table IA.2 for the summary statistics of firm-level outcome variables), over the next two years. This result is robust to scaling CO2 emissions by sales as shown in the next row, suggesting that the previous finding is not attributable to changes in business scale (Zhang, 2024). The coefficient (more precisely $-0.05591 \approx -0.06$) implies that a one standard deviation increase in indirect portfolio exposure in the firms' investor base drops CO2 emissions relative to sales by approximately $\frac{0.05591/2}{50.80/100} = 5.6\%$ per year over the next two years. In comparison, Azar et al. (2021) document a 2% decrease in CO2 emissions for a standard deviation increase in Big 3 ownership and Cohen, Kadach, Ormazabal, and Reichelstein (2023) show a 0.8% decrease in CO2 emissions for firms linking emission-specific metrics to executive compensation contracts.[30]

In the third row, we also show that firms reduce their total energy use, a key climate factor, within two years following indirect exposure to climate disasters through ownership networks. This reduction amounts to about $\frac{19.58/2}{44.48} = 22.0\%$ of the average yearly energy use. As energy usage is a significant driver of CO2 emissions, this evidence complements the earlier findings on CO2 emissions. Taken together, these results suggest that the indirectly exposed firms take drastic actions to mitigate their carbon footprint in the form of lower carbon emissions and energy usage compared to themselves prior to the indirect climate-change shocks and to other firms.

We next examine whether firms adjust their climate-related governance practices after indirect exposure to

[29] Panel B of Appendix Table IA.12 further shows that our following long-run results are robust to using an alternative benchmark based on firm's expected disaster exposure based on size, geographic footprint, and historical exposure in the 1990s.

[30] 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). 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.

climate disasters. Using data from the Carbon Disclosure Project, we focus on firms that incentivize executives to manage climate policies and assign the board responsibility for climate change.[31]

Linking executive pay to GHG emissions is one governance mechanism that can drive environmental action. For example, Cohen et al. (2023) show that ESG-based pay is accompanied by reductions in meaningful GHG emissions. Row 4 of Table 11 shows that a one standard deviation effect is associated with a 3.4% increase in the likelihood of firms adopting GHG-based executive pay policies within two years of exposure to climate disasters.[32] Another crucial governance mechanism is the board of directors (Adams, Hermalin, and Weisbach, 2010). The final row shows that boards are increasingly tasked with the explicit responsibility for climate change, with a 1 SD effect being a significant 5.6% rise in the likelihood of board accountability within two years. These findings suggest that greater investor support for climate proposals contributes to lasting governance changes, promoting reductions in CO2 emissions and energy use.

Lastly, we assess whether brown industries experience the greatest impact on their environmental policies. The results in Appendix Tables IA.13 to IA.15 show that the effects are indeed concentrated in brown industries, with minimal impact on green industries. For example, Panel C of Table IA.13 shows a significant decline in CO2 emissions for firms in brown industries, while no such effect is observed for green industries, as indicated by an insignificant interaction between indirect climate disaster exposure and the green industry indicator. Similar patterns are found for CO2 per unit of sales, energy use, and governance measures like pay incentives and board responsibility for climate management. These findings, along with the stronger climate proposal support in brown firms reported in Table 7, suggesting that institutional investors target high-emission firms after these shocks, prompting significant reductions in emissions and energy use. Taken together, these resutls echo the insight of Hartzmark and Shue (2023) that green policies targeting brown industries have the greatest effect, while green industries have less room for improvement in sustainability.

[31] 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. 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.

[32] In an untabulated test, 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 footprints.

5 Conclusion

We provide the first evidence that climate disasters in an investor's portfolio trigger increased attention to climate issues at other firms the investor owns. Following climate disaster exposure in their portfolios, investors become more active voters and engage more with the non-disaster hit firms in their portfolios to influence corporate climate policies. Specifically, large value-relevant disasters lead investors to adjust their voting activity on climate-related shareholder proposals at other non-affected firms for the next six months. This relation is most significant when aggregate attention to climate issues is high and when the votes occur at high-emission firms.

Aggregating to firm-level exposure, we find that firms whose investor bases are more affected by climate disasters adjust their climate policies. In the short-run, we see evidence of this in the form of more negative climate change sentiment on conference calls. In the longer-run, we find that investor-base climate disaster exposure leads to lower emissions and more climate-related governance provisions at the firm.

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 footprint, likely in tandem with coordinated regulatory actions.

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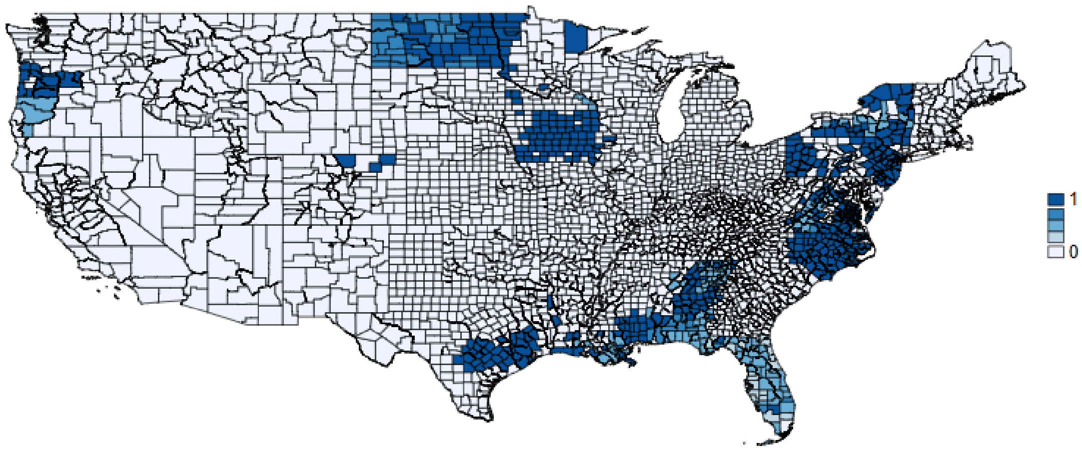
Figures

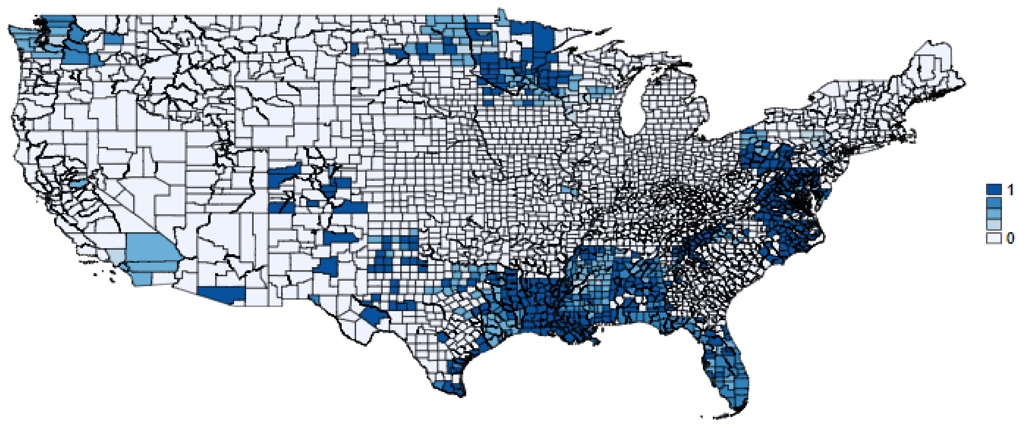
Figure 1: Climate disasters maps: from 1990 to 2019

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

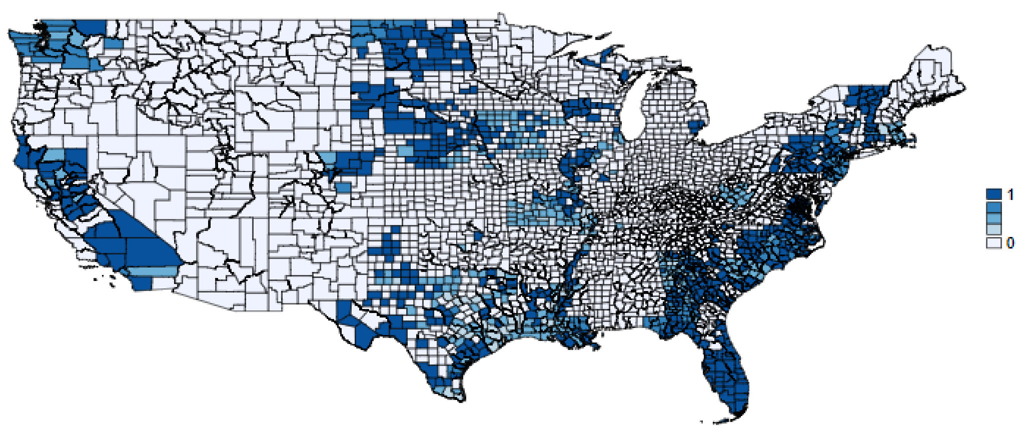


Figure 2: Climate voting magnitudes at the tails of the exposure distribution

This figure plots the predicted climate voting effect at the tails of the distribution of investors' indirect exposure to climate disasters. For a given bin size $b \in N$ (N=3, 4, 5,..., 15), we decompose our investor-quarter level overall measure for indirect portfolio exposure to climate disasters into N parts by partitioning the distribution of its values from smallest to largest into N ascending groups. Breakpoints are determined by quarter. The decomposed variable for bin b is equal to the original value within its bin group, and 0 otherwise. We then regress vote for climate proposals on the collection of decomposed variables as in our main voting tests. We plot the predicted effect for the top (Nth) or the next ($N-1$th) bin. The predicted effect for a 1 SD bin-specific shock is the coefficient on the top (Nth) or the next ($N-1$th) bin variable times the standard deviation (SD) of the bin variable (when it is greater then 0).

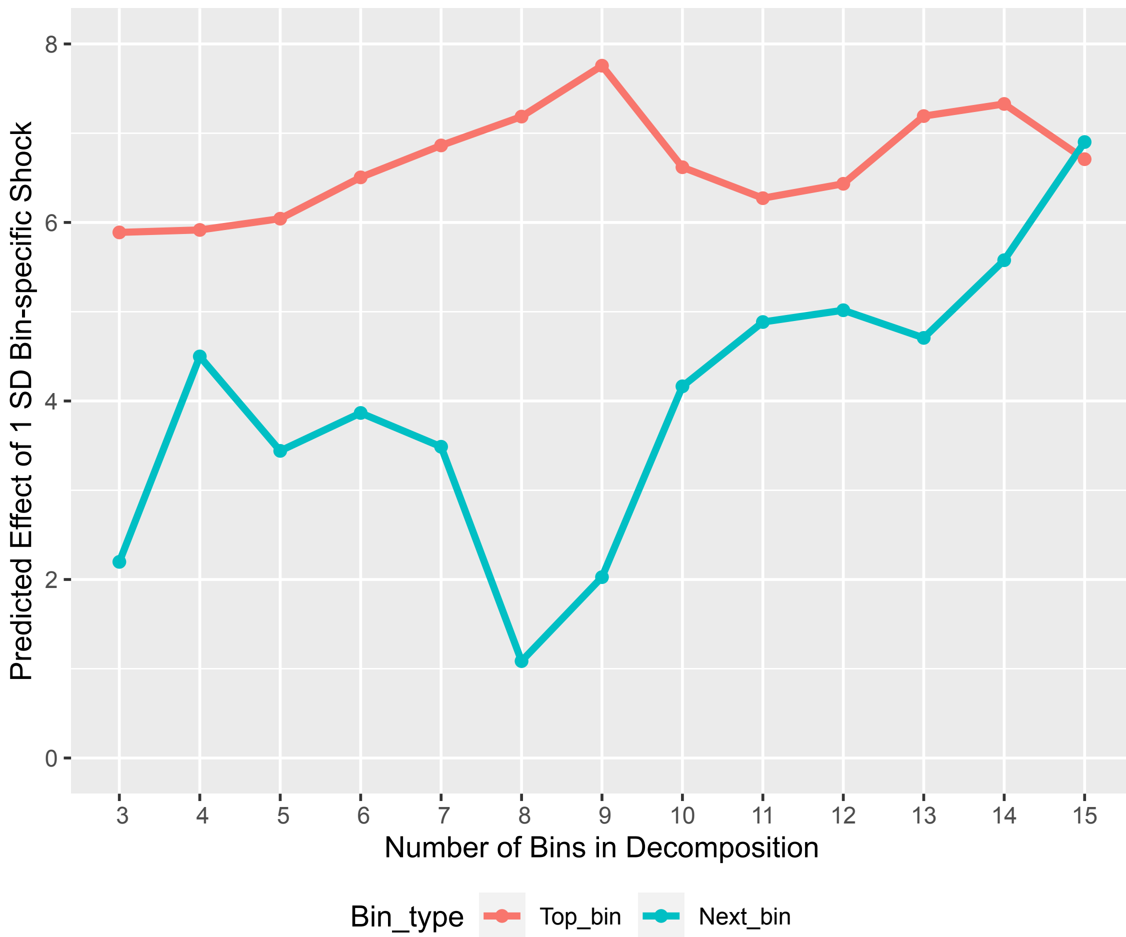
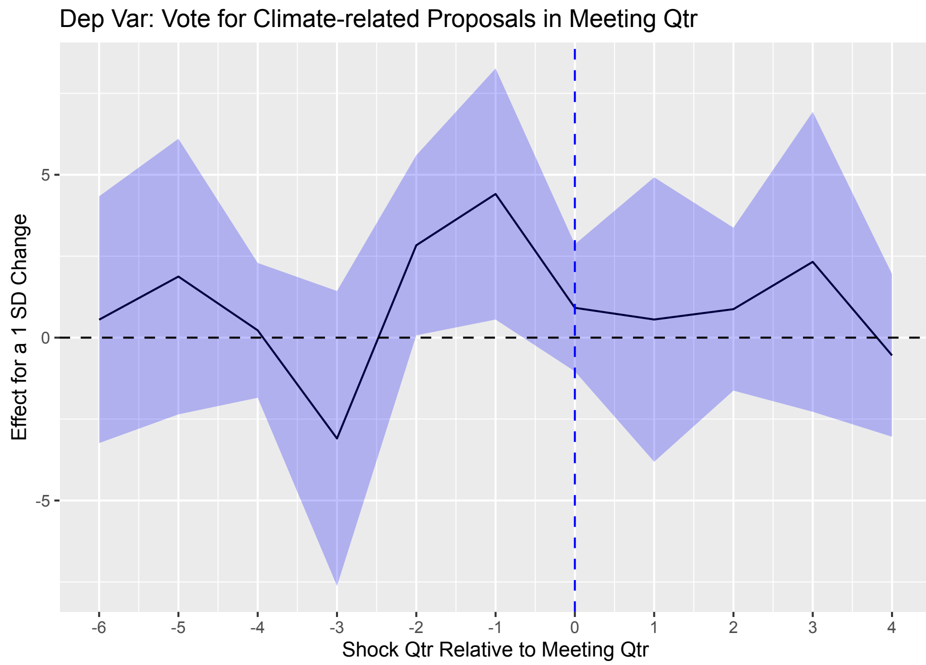


Figure 3: Dynamics of the voting effect

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 Eq. (6) in the main text, except we use the quarterly (instead of the four-quarter moving average) explanatory variable and we progressively construct the lag (or lead) of it by up to six (or four) quarters around the meeting quarter. In Panel A, 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 B, we focus on Portfolio Exposure$^{cont}_{j,t-1}$. The shaded areas are 95% confidence intervals based on robust standard errors clustered by institutional investor and year.

Panel A: Portfolio Exposed from I(Excess Disaster Exposure)



Panel B: Portfolio Exposed from Excess Disaster Exposure

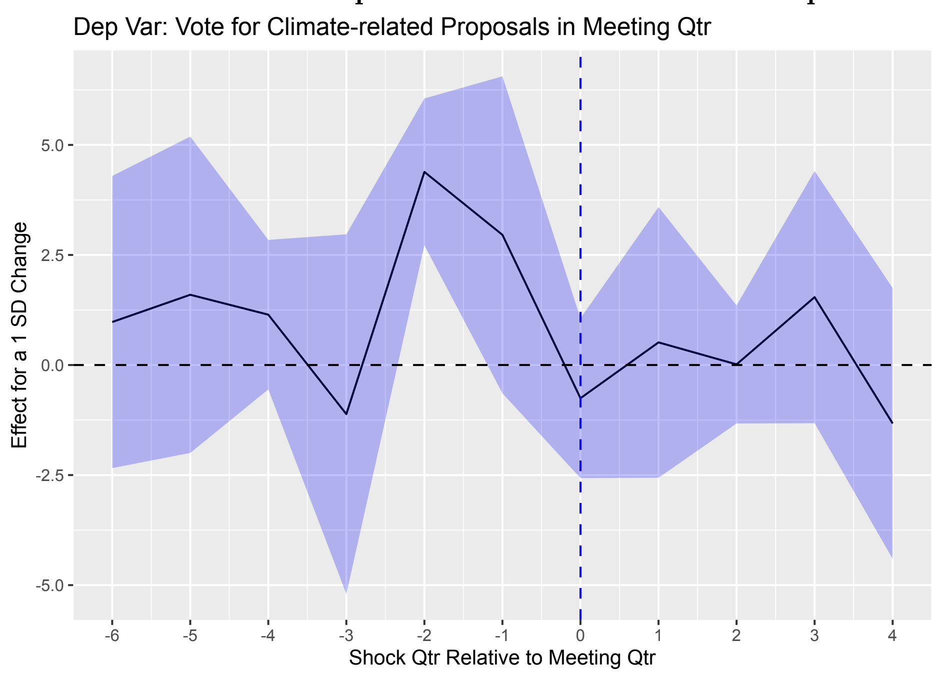
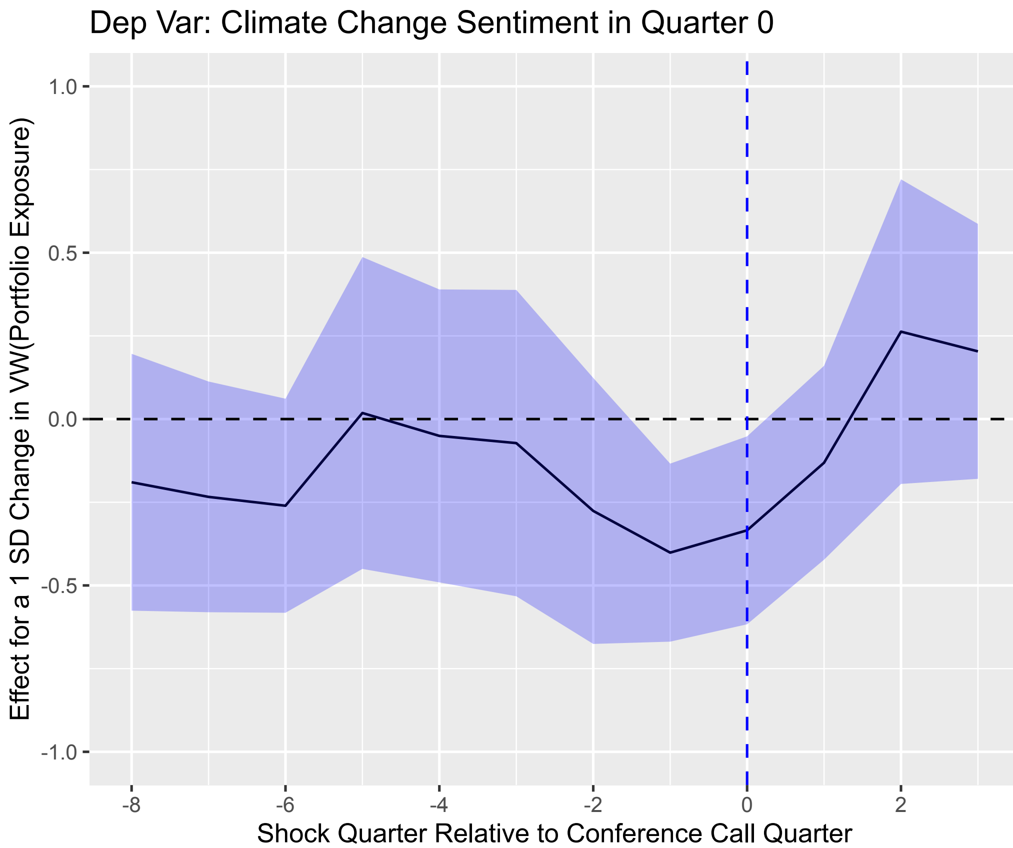


Figure 4: Dynamics of the effect on earnings call climate change sentiment

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 Eq. (10) 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 firms' disaster exposures 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, 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: Matched sample of NETS and Compustat in Disaster Quarters

Variable	Mean	SD	Median	Q0.10	Q0.25	Q0.75	Q0.90
Disaster Exposure$_{i,q}$	0.035	0.127	0.00	0.00	0.00	0.00	0.91
I(Excess Disaster Exposure$_{i,q}$>0)	0.137	0.344	0.00	0.00	0.00	0.00	1
Excess Disaster Exposure$_{i,q}$	0.026	0.116	0.00	0.00	0.00	0.000	0.82

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 (× 100)	15,842	2.95	6.03	0.16	0.00	0.00	2.85	10.12
Portfolio Exposed$^{cont.}$ (× 100)	15,842	0.18	0.50	0.00	0.00	0.00	0.11	0.47
IFO (× 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
ISS Recommend Vote "For" (%)	15,842	61.31	48.71	100.00	0.00	0.00	100.00	100.00

Table 2: Effect on shareholder voting for proposals

This table reports results from regressions of institutional investors' voting on shareholder proposals on their indirect portfolio exposure to climate disasters as in Eq. (6). The unit of observation is at the investor-proposal level, i.e., firm i's proposal k at time t 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), and (4) focus on the mutually exclusive sets of climate-related, environmental-related, and social-related shareholder proposals, respectively. At time $t-1$, indirect portfolio exposure to disasters is measured by $Portfolio\ Exposed_{j,t-1}$ in Panel A or $Portfolio\ Exposed^{cont.}_{j,t-1}$ in Panel B, which are four-quarter moving averages of the quarterly measures ending in the quarter of the record date before the shareholder meeting and then standardized by its 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)
Panel A: Indirect climate disaster exposure: $Portfolio\ Exposed_{j,t-1}$				
Portfolio Exposed$_{j,t-1}$	2.38**	3.49**	0.67	0.46
	(2.38)	(2.72)	(0.64)	(0.76)
IFO$_{i,j,t-1}$	−2.75***	−2.40**	−2.61***	−1.11**
	(−2.89)	(−2.25)	(−3.34)	(−2.31)
Log(Portfolio Value)$_{j,t-1}$	−3.57*	−4.02*	−2.62*	−0.93
	(−1.88)	(−1.80)	(−1.97)	(−0.93)
Portfolio Ret$_{j,t-1}$	−24.77	−65.81***	−11.03	−3.32
	(−1.37)	(−5.29)	(−0.88)	(−0.30)
Proposal FE	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes
N	15,842	8,594	20,764	46,316
Adjusted R^2	0.54	0.56	0.51	0.44
Panel B: Indirect climate disaster exposure: $Portfolio\ Exposed^{cont.}_{j,t-1}$				
Portfolio Exposed$^{cont.}_{j,t-1}$	2.32***	2.98**	0.97	0.48
	(3.54)	(2.64)	(1.00)	(0.97)
IFO$_{i,j,t-1}$	−2.71***	−2.38**	−2.60***	−1.11**
	(−2.87)	(−2.25)	(−3.39)	(−2.33)
Log(Portfolio Value)$_{j,t-1}$	−3.55*	−3.91*	−2.61*	−0.92
	(−1.87)	(−1.77)	(−1.97)	(−0.93)
Portfolio Ret$_{j,t-1}$	−23.68	−62.87***	−10.78	−3.27
	(−1.31)	(−4.72)	(−0.85)	(−0.29)
Proposal FE	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes
N	15,842	8,593	20,764	46,316
Adjusted R^2	0.54	0.56	0.51	0.44

Table 3: The influence of ISS recommendations on shareholder voting

This table tests how ISS recommendations influence shareholder voting when investors have indirect exposure to climate disasters. The test is similar to the one in Table 2, except the variables of interest are decompositions of $Portfolio\ Exposed_{j,t-1}$ into two parts based on if ISS recommends voting "For" or "Against" a proposal. For interpretation, the decomposed variables are scaled by the standard deviation of the original non-decomposed variable. 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)
(Portfolio Exposed | ISS Against)$_{j,t-1}$	4.62**	6.91***	3.09*	1.64**
	(2.21)	(3.11)	(1.95)	(2.12)
(Portfolio Exposed | ISS For)$_{j,t-1}$	1.38	1.46	−0.71	−0.93
	(0.93)	(0.99)	(−0.52)	(−0.78)
IFO$_{i,j,t-1}$	−2.73***	−2.39**	−2.60***	−1.10**
	(−2.89)	(−2.26)	(−3.35)	(−2.30)
Log(Portfolio Value)$_{j,t-1}$	−3.62*	−4.12*	−2.62*	−0.92
	(−1.90)	(−1.84)	(−1.97)	(−0.93)
Portfolio Ret$_{j,t-1}$	−24.57	−64.05***	−11.89	−3.18
	(−1.38)	(−4.96)	(−0.95)	(−0.29)
Proposal FE	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes
N	15,842	8,594	20,764	46,316
Adjusted R^2	0.54	0.56	0.51	0.44

Table 4: Drivers of the voting effect

This table reports on the drivers of investors' indirect exposure to climate disasters via common ownership. Column (1) decomposes the indirect exposure measure into terciles (high, middle, or bottom) based on its ascending values, Column (2) by whether the portfolio weight in the disaster exposed firm is high, medium or low within a quarter, Column (3) by whether the disaster exposed firm is headquarter or other location hit, and Column (4) by whether the exposure to a disaster is followed by significant (severe vs. mild) drops in stock returns. For interpretation, all decomposed variables are scaled by the standard deviation of the original non-decomposed variable. 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$_{i,j,k,t}$			
	(1)	(2)	(3)	(4)
(Portfolio Exposed | Top Tercile)$_{j,t-1}$	2.32**			
	(2.23)			
(Portfolio Exposed | Middle Tercile)$_{j,t-1}$	1.66			
	(1.29)			
(Portfolio Exposed | Bottom Tercile)$_{j,t-1}$	1.75			
	(0.52)			
(Portfolio Exposed | High Portfolio Weight)$_{j,t-1}$		2.69**		
		(2.27)		
(Portfolio Exposed | Medium Portfolio Weight)$_{j,t-1}$		−4.15		
		(−1.35)		
(Portfolio Exposed | Low Portfolio Weight)$_{j,t-1}$		52.68		
		(1.52)		
(Portfolio Exposed | Headquarter Exposed)$_{j,t-1}$			9.23*	
			(1.80)	
(Portfolio Exposed | Other Location Exposed)$_{j,t-1}$			1.33	
			(0.98)	
(Portfolio Exposed | Severe Stock Market Response)$_{j,t-1}$				4.36**
				(2.36)
(Portfolio Exposed | Mild Stock Market Response)$_{j,t-1}$				1.85
				(1.39)
Proposal FE	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	15,842	15,842	15,842	15,842
Adjusted R^2	0.54	0.54	0.54	0.54

Table 5: Dynamics of voting effect

This table reports on the dynamics of the voting effect when we decompose the investor spillover measure based on recency to the vote. In Panel A, because Portfolio Exposed$_{j,t-1}$ is a four-quarter moving average, we decompose it into the part driven by the recent two quarters (Portfolio Exposed$_{j,t-1,q-1:q-2}$) and the latter two quarters (Portfolio Exposed$_{j,t-1,q-3:q-4}$). We then repeat our voting tests using the decomposed measures. Columns (1)–(2) report the results for the full sample, while Columns (3)–(4) focus on the IFO>0 sample. In Panel B, instead of the four most recent quarters, we present the same decomposition for future shocks from $q+1$ to $q+4$ (Portfolio Exposed$_{j,t,q+1:q+2}$ and Portfolio Exposed$_{j,t,q+3:q+4}$). 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.

Panel A: Decomposition of past shocks

	Dep Var: Vote for Climate Proposals$_{i,j,k,t}$			
	All		IFO>0	
	(1)	(2)	(3)	(4)
Portfolio Exposed$_{j,t-1,q-1:q-2}$	4.12***		6.21**	
	(2.78)		(2.71)	
Portfolio Exposed$_{j,t-1,q-3:q-4}$	0.46		0.22	
	(0.31)		(0.15)	
Portfolio Exposed$^{cont.}_{j,t-1,q-1:q-2}$		2.55**		4.62***
		(2.56)		(3.06)
Portfolio Exposed$^{cont.}_{j,t-1,q-3:q-4}$		2.02*		1.29
		(1.75)		(1.22)
IFO$_{i,j,t-1}$	−2.18***	−2.71***	−1.90***	−2.39**
	(−5.92)	(−2.87)	(−4.89)	(−2.25)
Log(Portfolio Value)$_{j,t-1}$	−2.69	−3.54*	−3.04	−3.88*
	(−1.61)	(−1.87)	(−1.44)	(−1.75)
Portfolio 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

Panel B: Decomposition of future shocks

	Dep Var: Vote for Climate Proposals$_{i,j,k,t}$			
	All		IFO>0	
	(1)	(2)	(3)	(4)
Portfolio Exposed$_{j,t,q+1:q+2}$	0.65		1.11	
	(0.53)		(0.84)	
Portfolio Exposed$_{j,t,q+3:q+4}$	2.26		0.51	
	(1.24)		(0.33)	
Portfolio Exposed$^{cont.}_{j,t,q+1:q+2}$		1.51		1.45
		(1.47)		(1.47)
Portfolio Exposed$^{cont.}_{j,t,q+3:q+4}$		2.00		0.76
		(1.42)		(0.56)
IFO$_{i,j,t-1}$	-2.11^{***}	-2.11^{***}	-1.83^{***}	-1.83^{***}
	(-5.70)	(-5.61)	(-4.81)	(-4.80)
Log(Portfolio Value)$_{j,t-1}$	-2.75	-2.72	-2.99	-2.96
	(-1.64)	(-1.63)	(-1.43)	(-1.43)
Portfolio Ret$_{j,t-1}$	-31.52^{**}	-32.14^{**}	-58.48^{***}	-59.46^{***}
	(-2.21)	(-2.25)	(-4.70)	(-4.77)
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	0.57	0.59	0.59

Table 6: Voting effect and aggregate attention to climate change

This table examines how the public attention to climate change affects the voting tests in Eq. (6). WSJ CC and Neg. CC are standardized attention indices constructed through textual analysis of newspapers and social media by Engle et al. (2020). WSJ CC is based on climate news coverage in *The Wall Street Journal* 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 7: Heterogeneity of spillover firms: Green versus brown firms

This table examines how firms' greenness affects the voting tests in Eq. (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$_{i,j,t}$	
	(1)	(2)
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
	(−2.74)	(−0.60)
IFO$_{i,j,t-1}$	−4.14*	−4.20*
	(−1.80)	(−1.81)
Log(Portfolio Value)$_{j,t-1}$	−2.57	−2.50
	(−1.15)	(−1.12)
Portfolio Ret$_{j,t-1}$	−54.47**	−55.81**
	(−2.70)	(−2.73)
Proposal FE	Yes	Yes
Fund Family × Industry FE	Yes	Yes
N	4,583	4,583
Adjusted R^2	0.57	0.57

Table 8: Heterogeneity of investors
This table examines how different types of investors affect the voting tests in Eq. (6). In Panel A, Big 3 indexers are Vanguard, State Street, and Blackrock, Top 10 Investors are the top 10 investors each quarter by portfolio size, Large MFs (Banks) are mutual funds (banks) above the 75th percentile of the portfolio size distribution each quarter, and UN PRI Signees are the investors that have signed the United Nation's Principles for Responsible Investment. In Panel B, we independently sort investors based on the prior quarter's median portfolio size (Small vs. Large), and portfolio turnover (Passive vs. Active). In the last row, we report the estimate and associated F-statistic for the total investor type effect from summing the coefficients on Portfolio Exposed$_{j,t-1}$ 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.

Panel A: Effect by Investor Type

	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)

Panel B: Small vs. Large and Passive vs. Active Investors

	Dep Var: Vote for Climate Proposals$_{i,j,t}$				
	Small Inv.	Small Passive	Small Active	Large Passive	Large Active
	(1)	(2)	(3)	(4)	(5)
Portfolio Exposed$_{j,t-1}$	3.27**	3.59***	3.66***	2.94*	4.37***
	(2.63)	(2.82)	(2.87)	(1.92)	(3.46)
Portfolio Exposed$_{j,t-1}$ × Investor Type$_{j,t}$	3.54*	4.62**	1.36	1.34	−1.78
	(1.94)	(2.11)	(1.44)	(1.44)	(−1.51)
Investor Type$_{j,t}$	−1.37	−2.65	1.22	−2.79	2.82
	(−0.22)	(−0.59)	(0.27)	(−0.93)	(0.93)
IFO$_{i,j,t-1}$	−2.39**	−2.38**	−2.39**	−2.42**	−2.41**
	(−2.24)	(−2.22)	(−2.24)	(−2.24)	(−2.23)
Log(Portfolio Value)$_{j,t-1}$	−4.04	−4.31*	−4.15	−3.91	−4.15*
	(−1.55)	(−1.85)	(−1.68)	(−1.68)	(−1.81)
Portfolio Ret$_{j,t-1}$	−66.46***	−63.48***	−64.90***	−61.72***	−62.28***
	(−5.52)	(−4.91)	(−5.35)	(−4.75)	(−4.77)
Proposal FE	Yes	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes	Yes
N	8,594	8,567	8,567	8,521	8,521
Adjusted R^2	0.56	0.56	0.56	0.56	0.56
Total Investor Type Effect	6.81***	8.21***	5.02***	4.28***	2.59
$F-$stat	(8.55)	(8.73)	(8.07)	(12.53)	(2.54)

Table 9: Robustness tests of the climate voting effect

This table reports on two sets of robustness tests of the voting effect after portfolio exposure to climate disasters. In the "IFO>0" sample, Panel A reports on the voting results from using the unadjusted and alternatively adjusted indirect disaster exposure measures. For brevity, we report coefficients only on the variables of interest. 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. Panel B reports on results from a placebo test, focusing on Portfolio Exposure$_{j,t}$. Under the null hypothesis that placebo disasters have no effect on climate voting, we simulate 1000 iterations of the tests in Tables 2 and 5. Test size is the proportion of simulated p-values below $\alpha = 0.05$. $t^{adj}_{0.025}$ and $t^{adj}_{0.975}$ are the 2.5 and 97.5 percentiles of the simulated distribution of t-statistics, respectively.

Panel A: Alternative adjustments and measures

	Dep Var: Vote for Climate Proposals$_{i,j,t}$			
Alternative Measure:	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)
Proposal FE	Yes	Yes	Yes	Yes
Fund Family × Industry FE	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
N	8,594	8,594	8,594	8,594
Adjusted R^2	0.56	0.56	0.56	0.56

Panel B: Placebo simulation tests

Sample	Independent Variable	Test Size at $\alpha = 5\%$	$t^{adj}_{0.025}$	$t^{adj}_{0.975}$
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 10: Short-run firm-level 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. We label SIC2 industries as Brown based on the five major industries identified by the IPCC, and Green otherwise, following Choi, Gao, and Jiang (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)$_{i,q-1}$ 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-quarter. *, **, 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$_{i,q-1}$	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 11: Long-run firm-level 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 independent variable is firm i's indirect exposure, VW(Portfolio Exposed)$_{i,t-1}$, 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 year $t-1$. The dependent variables of firm i are measured in year $t-1$ in Column (1), in year t in Column (2), and over years $t+1$ to $t+2$ in Column (3), respectively. This table summarizes the coefficients of VW(Portfolio Exposed), while the detailed reports of each regression are reported in Appendix Tables IA.13 to IA.15. t-statistics in parentheses and F-statistics 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.

	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

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.
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.
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$_{i,q}$.
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 Expected Quarterly Exposure$_{i,q}$. $I(.)$ 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. (9). 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.
ISS Recommends Vote "For"$_{i,j,k,t}$ (%)	An indicator in percentage points for when ISS recommends vote "For" for fund family j on proposal k as of the shareholder meeting held by firm i in year t.
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 database taking on the 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 Internet Appendix Table IA.3.
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$_{i,t}$	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, Gao, and Jiang (2020).

$\text{Industry}_{i,t}$	The 2 digit standard industry classification (SIC2) of the firm from Compustat.
$\text{InstOwn}_{i,q}$	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.
$\text{NBlocks}_{i,q}$	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 by 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.

Internet Appendix for
"Propagation of climate disasters through ownership networks"

Matthew Gustafson, Ai He, Ugur Lel, and Zhongling (Danny) Qin

IA.1 Evidence on Natural Disasters and Climate Change

This appendix provides a detailed discussion about why we classify hurricanes/storms, floods, and wildfires as climate-related. The scientific view on natural disasters and their connection to climate change has changed drastically in recent decades. The recent National Oceanic and Atmospheric Administration's (NOAA) climate special report (Wuebbles, Fahey, Hibbard, Arnold, DeAngelo, Doherty, Easterling, Edmonds, Edmonds, Hall et al., 2017) surveys the vast literature on climate change and natural disasters in the United States and presents an aggregation of related evidence (also see, e.g., Bender, Knutson, Tuleya, Sirutis, Vecchi, Garner, and Held, 2010; Grinsted, Ditlevsen, and Christensen, 2019; Smith and Katz, 2013). The report summarizes the state of the literature on hurricanes/storms, floods, and wildfires, as such:

For hurricanes/storms:

"**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.

IA.2 The Test of Stock Response to Each Climate Disasters

The test follows the following steps:

(1) We first estimate the CAPM model for each stock and climate disaster in our sample, based on 120 trading days before the disaster start date.

(2)For each climate disaster, we identify the test window from the disaster start date to 30 trading days afterward and use coefficient estimates from step (1) to compute each stock's CAPM CAR during this window.

(3) We then test the following regression for each climate disaster d:

$$CAR_{i,d}^{30} = \beta_d Disaster\ Exposure_{i,d} + \pi_{Ind} + \epsilon_{i,d},$$

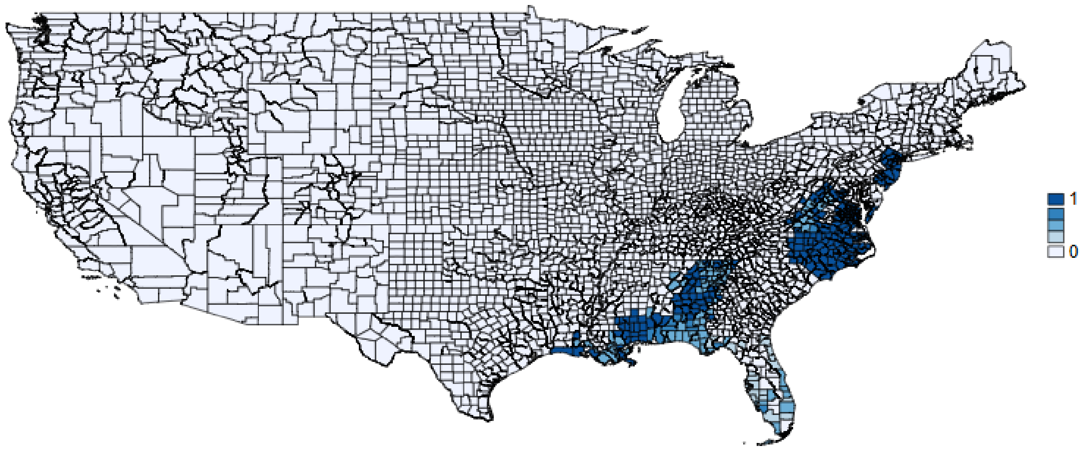
where $CAR_{i,d}^{30}$ is the 30-day CAR from step (2) for each firm i after disaster d; $Disaster\ Exposure_{i,d}$ is firm i's exposure to disaster d following the definition in Eq. (1), which is positive for disaster firms and zero for other firms; π_{Ind} controls for the industry fixed effect. Disaster d is identified as causing sever negative response in the stock market if β_d is negative with a $p-$value less than 10%.

IA.3 Internet Appendix Figures

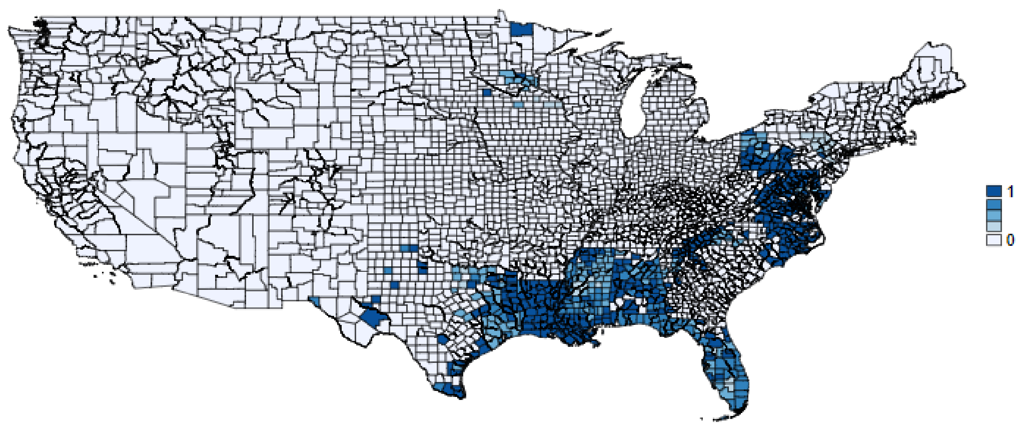
Figure IA.1: Hurricane/storm maps: from 1990 to 2019

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

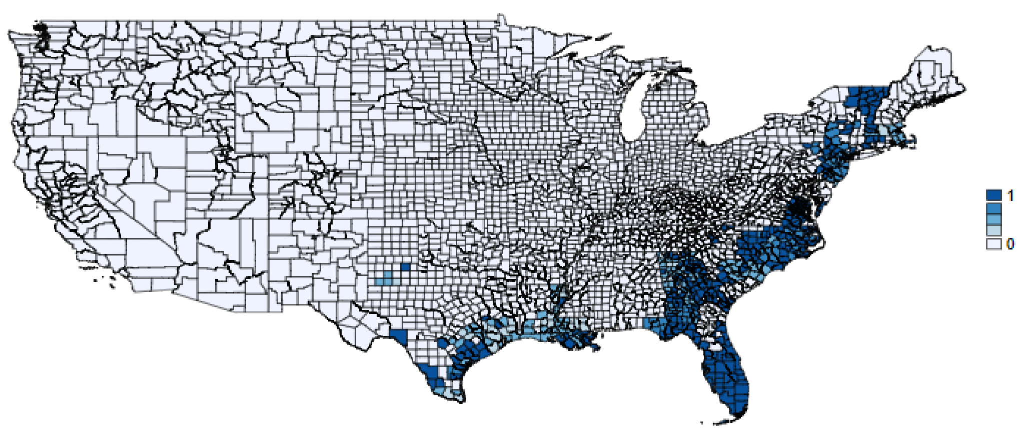
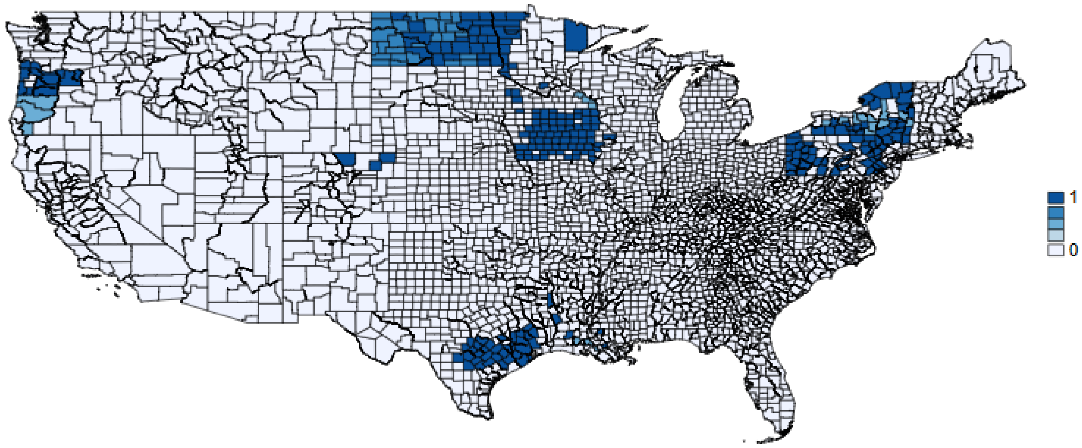


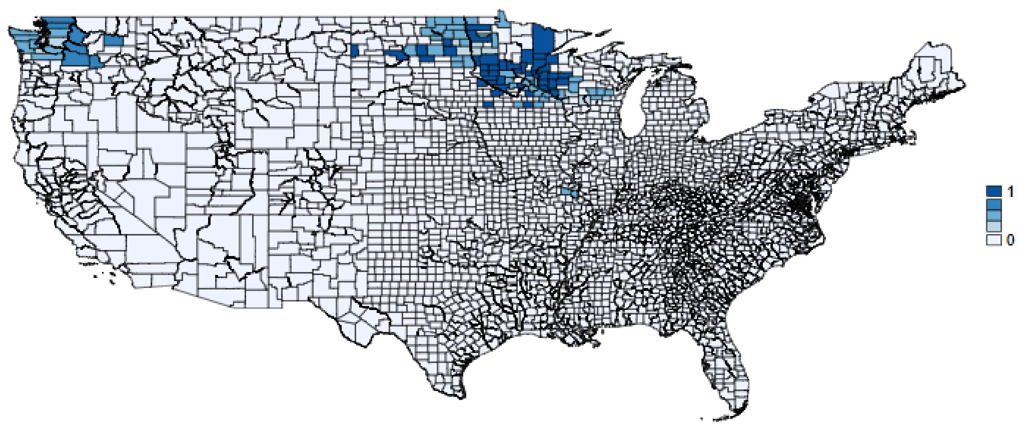
Figure IA.2: Flood maps: from 1990 to 2019

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

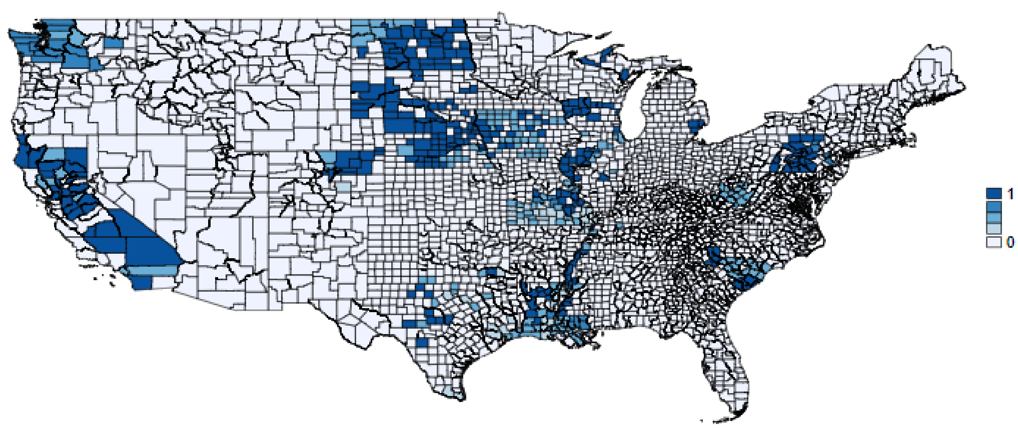
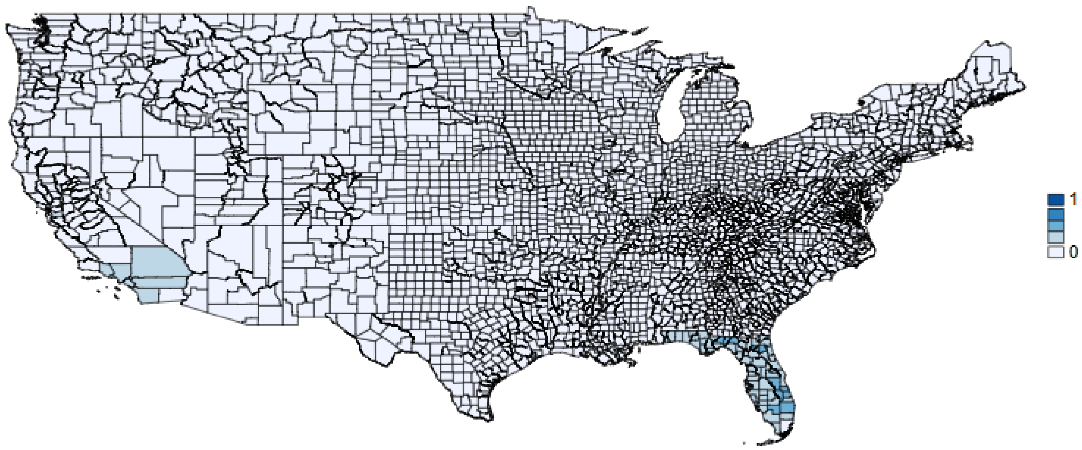


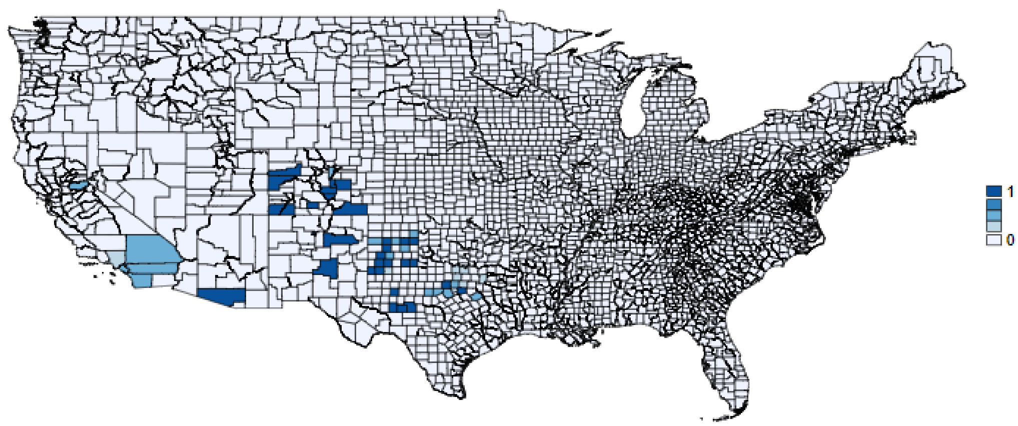
Figure IA.3: Wildfire maps: from 1990 to 2019

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 C: Counties hit by wildfires during the 2010s

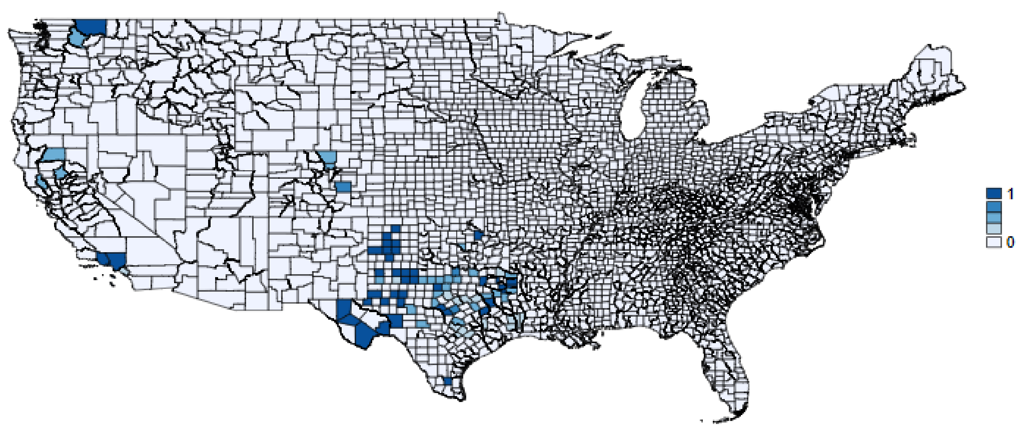
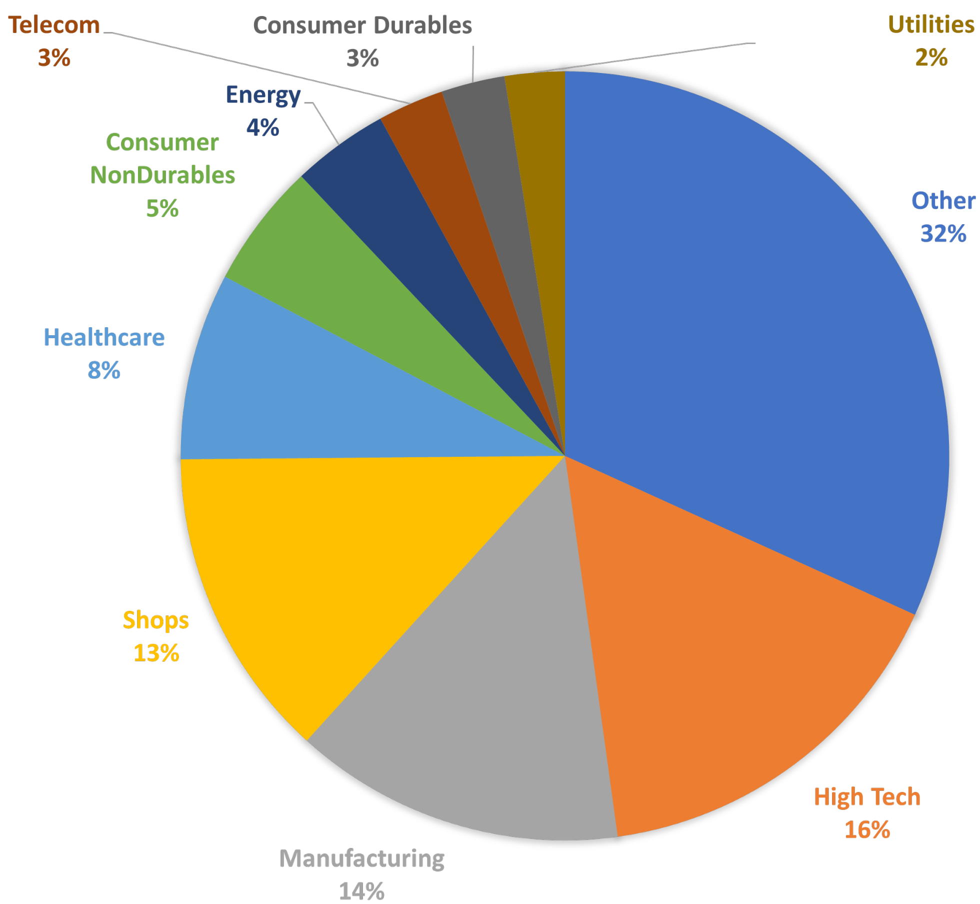


Figure IA.4: Industries for firms with *Excess disaster exposure*>0

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



IA.4 Internet 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	Average 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	Average 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 Sample							
Vote for Proposals (%)	8,594	39.73	46.69	0.00	0.00	0.00	100.00	100.00
Portfolio exposed ($\times$ 100)	8,594	5.44	7.31	2.21	0.22	0.61	8.64	13.33
Portfolio exposed$^{cont.}$ ($\times$ 100)	8,594	0.32	0.64	0.08	0.01	0.02	0.36	0.76
IFO ($\times$ 10000)	8,594	38.21	115.30	2.26	0.06	0.30	16.55	88.38
Portfolio Value ($Bil)	8,594	121.88	297.23	16.53	0.51	2.82	75.73	313.43
Portfolio Return (%)	8,594	3.95	7.68	4.76	-4.64	1.88	8.34	11.46
ISS Recommend Vote "For" (%)	8,594	66.94	47.04	100.00	0.00	0.00	100.00	100.00
	Environmental Proposals							
Vote for Proposals (%)	20,764	32.05	44.28	0.00	0.00	0.00	100.00	100.00
Portfolio exposed ($\times$ 100)	20,764	3.11	7.02	0.07	0.00	0.00	2.60	10.40
Portfolio exposed$^{cont.}$ ($\times$ 100)	20,764	0.20	0.61	0.00	0.00	0.00	0.11	0.47
IFO ($\times$ 10000)	20764	19.09	80.01	0.04	0.00	0.00	3.05	27.80
Portfolio Value ($Bil)	20,764	94.61	248.33	12.92	0.35	1.71	59.08	226.50
Portfolio Return (%)	20,764	4.14	9.00	5.00	-7.34	1.35	9.66	14.05
ISS Recommend Vote "For" (%)	20,764	47.51	49.94	00.00	0.00	0.00	100.00	100.00
	Social Proposals							
Vote for Proposals (%)	46,316	32.70	44.57	0.00	0.00	0.00	100.00	100.00
Portfolio exposed ($\times$ 100)	46,316	2.53	6.37	0.00	0.00	0.00	1.33	8.93
Portfolio exposed$^{cont.}$ ($\times$ 100)	46,316	0.17	0.57	0.00	0.00	0.00	0.05	0.41
IFO ($\times$ 10000)	46,316	13.85	65.01	0.00	0.00	0.00	1.45	18.96
Portfolio Value ($Bil)	46,316	86.03	225.43	13.48	0.35	1.71	59.19	205.76
Portfolio Return (%)	46,316	2.60	11.55	4.19	-14.93	-2.12	10.17	14.85
ISS Recommend Vote "For" (%)	46,316	45.84	49.83	00.00	0.00	0.00	100.00	100.00

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 ($Bil)	139,532	8.75	26.73	1.36	0.12	0.36	4.86	17.77
Institutional Ownership (%)	139,532	70.36	127.75	75.08	30.50	53.50	89.23	97.79
Number of Blockholders	139,532	2.71	1.61	2.75	0.50	1.50	3.75	4.75
				Annual Long-run Outcomes Sample				
Total CO2 (per 1000 MTs)	5,084	5638.70	16738.32	462.28	31.85	98.35	2716.77	14407.00
Total CO2/Sales ($\times$ 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 approach to define voting support for a proposal. *, **, 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$_{j,t-1}$	2.23**		2.79**		−0.58		−0.22	
	(2.29)		(2.26)		(−0.74)		(−0.42)	
Portfolio Exposed$^{cont}_{j,t-1}$		2.48***		2.70**		−0.59		−0.15
		(3.17)		(2.46)		(−0.72)		(−0.30)
IFO$_{i,j,t-1}$	−2.16***	−2.13***	−1.86***	−1.85***	−1.72***	−1.73***	−0.73**	−0.74**
	(−5.95)	(−5.88)	(−4.93)	(−4.93)	(−4.56)	(−4.56)	(−2.43)	(−2.51)
Log(Portfolio Value)$_{j,t-1}$	−2.72	−2.69	−3.08	−2.99	−1.97*	−1.98*	−0.61	−0.61
	(−1.63)	(−1.62)	(−1.47)	(−1.45)	(−1.74)	(−1.74)	(−0.76)	(−0.76)
Portfolio Ret$_{j,t-1}$	−30.24**	−29.12**	−56.79***	−54.26***	−16.15	−16.34	−13.19**	−13.18**
	(−2.16)	(−2.08)	(−4.21)	(−3.93)	(−1.33)	(−1.34)	(−2.34)	(−2.33)
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	20,764	20,764	46,316	46,316
Adjusted R^2	0.57	0.57	0.59	0.59	0.54	0.54	0.51	0.51

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: Heterogeneity of Spillover Firms: Green versus Brown Industries
This table examines how firms' greenness affects the voting tests in Eq. (6). 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, Gao, and Jiang (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.6: 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 $\text{Exposed}_{j,t-1}$. We label SIC2 industries as Brown based on the five major industries identified by the IPCC, and Green otherwise, following Choi, Gao, and Jiang (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 $\text{Exposed}_{j,t-1}$	−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 $\text{Value})_{j,t-1}$	−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 $\text{Ret}_{j,t-1}$	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.7: 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. *, **, 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 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 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$_{j,q}$	0.96**	0.96**	0.65*	0.65*
	(2.53)	(2.53)	(1.95)	(1.90)
Portfolio Exposed$_{j,t-1}$		2.39**		3.50**
		(2.40)		(2.73)
IFO$_{i,j,t-1}$	−2.66***	−2.75***	−2.36**	−2.41**
	(−2.84)	(−2.88)	(−2.24)	(−2.25)
Log(Portfolio Value)$_{j,t-1}$	−3.61*	−3.63*	−3.86*	−4.05*
	(−1.90)	(−1.91)	(−1.76)	(−1.81)
Portfolio Ret$_{j,t-1}$	−24.91	−25.24	−64.70***	−65.99***
	(−1.40)	(−1.44)	(−5.35)	(−5.22)
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: Minimal Proposal Fund-level Variation within a Fund-Family

This table reports on within-fund-family results from regressions of fund-level (as opposed to fund-family level) voting on shareholder proposals on their indirect exposure to disasters as in Eq. (6). The unit of observation is at the fund-proposal level, i.e., firm i's proposal k at time t is being voted by fund f belonging to an institutional investor j. The dependent variable at time t is the voting outcome measured as an investor's percentage vote on a climate-related shareholder (S/H) proposal. At time $t-1$, a fund's indirect disaster exposure is measured by the Portfolio Exposed$_{j,f,t-1}$, which is a four-quarter moving average of the quarterly measure ending in the quarter of the record date before the shareholder meeting and then standardized by the full-sample standard deviation. Columns (1)–(2) use the measure constructed with an indicator for excess disaster exposure, while Columns (3)–(4) use the continuous excess disaster exposure. 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$_{i,j,k,f,t}$			
	Using I(Excess Disaster Exposure)		Using Excess Disaster Exposure	
	(1)	(2)	(3)	(4)
Portfolio Exposed$_{j,f,t-1}$	−0.14		−0.10	
	(−0.71)		(−0.68)	
Portfolio Exposed$_{j,f,t-1,q-1,q-2}$		0.20		0.08
		(0.54)		(0.65)
Portfolio Exposed$_{j,f,t-1,q-3,q-4}$		−0.53		−0.46
		(−1.46)		(−1.47)
IFO$_{i,j,f,t-1}$	0.15	0.15	0.15	0.15
	(1.46)	(1.48)	(1.48)	(1.50)
Log(Portfolio Value)$_{j,f,t-1}$	0.61	0.62	0.61	0.61
	(1.37)	(1.39)	(1.36)	(1.37)
Portfolio Ret$_{j,f,t-1}$	0.15	0.17	0.08	0.25
	(0.03)	(0.04)	(0.02)	(0.06)
Fund Family x Proposal FE	Yes	Yes	Yes	Yes
Fund x Industry FE	Yes	Yes	Yes	Yes
N	35,944	35,944	35,944	35,944
Adjusted R^2	0.96	0.96	0.96	0.96

Table IA.10: Conference Call Reaction by 13F Investor Type

This table examines how the conference call reaction varies by the investor type. The test is similar to Column (1) in Table 10. 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$_{i,q-1}$	−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.11: Conference Call Reaction by Big-3 and UN PRI Signatories
This table examines how the conference call reaction varies by the investor type. The test is similar to Column (1) in Table 10. 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$_{i,q-1}$	−0.01	0.01	−0.02	0.01
	(−0.05)	(0.05)	(−0.13)	(0.04)
Firm FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Industry × 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.12: Firm-level Robustness: Alternative Measures and Adjustment

This table reports on the firm-level conference call test in Panel A (the test is similar to Column (1) in Table 10) and long-run outcomes in Panel B (the tests are similar to the ones in Table 11) from using the "All-adjusted" indirect disaster exposure measure that measures firms excess disaster exposure above its expected exposure based on firm size, geographic footprint, and historical exposure in the 1990s, which are constructed in the similar way of Column (4) in Table 9. *, **, and *** indicate statistical significance at the ten-, five-, and one-percent level, respectively.

Panel A: Short-run Conference Call Discussion

	Dep Var: CC Sentiment$_{i,q}$			
	Pos. − Neg.	Positive	Negative	Pos. − Neg.
	(1)	(2)	(3)	(4)
VW(Portfolio Exposed)$_{i,q-1}$	−0.43***	−0.14	0.28**	−0.60**
	(−3.08)	(−0.92)	(2.48)	(−2.83)
Disaster Exposure$_{i,q-1}$	−0.70	0.09	0.57	−0.62
	(−0.48)	(0.07)	(0.62)	(−0.43)
Log(Assets)$_{i,t-1}$	0.30	0.70**	0.47**	−0.13
	(0.90)	(2.40)	(2.56)	(−0.39)
InstOwn$_{i,q-1}$	−0.08***	−0.05***	0.04***	−0.06***
	(−5.40)	(−5.46)	(3.61)	(−4.48)
NBlocks$_{i,q-1}$	0.003	0.11	0.12	0.04
	(0.02)	(0.92)	(1.09)	(0.26)
VW(Portfolio Exposed)$_{i,q-1}$ × Green Industry				0.27
				(1.05)
Green Industry				−0.27
				(−0.18)
Firm FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	No
N	139,483	139,483	139,483	139,483
Adjusted R^2	0.07	0.12	0.06	0.06
Total Green Industry Effect				−0.33**
F−stat				(4.87)

Panel B: Long-run Outcomes

	Independent Var: VW(Portfolio Exposed)$_{i,t-1}$		
	$k=-1$	$k=0$	$k \in [+1,+2]$
	(1)	(2)	(3)
Total CO2$_{i,t+k}$	-31.75	-167.29	-857.09^{**}
	(-0.26)	(-1.41)	(-2.61)
Total CO2/Sales$_{i,t+k}$	0.01	-0.01	-0.04^{*}
	(0.46)	(-1.02)	(-2.00)
Energy Use$_{i,t+k}$	0.15	7.88	-18.19^{**}
	(0.04)	(1.63)	(-2.38)
Pay Incentive$_{i,t+k}$	-0.004	-0.02	0.03^{*}
	(-0.26)	(-1.45)	(2.05)
Board Responsibility$_{i,t+k}$	0.001	-0.005	0.05^{*}
	(0.09)	(-0.30)	(1.85)
Firm Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes

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 IPCC, and Green otherwise, following Choi, Gao, and Jiang (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)$_{i,t-1}$ $\times$ 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 $\times$ Year FE	Yes	Yes	Yes
Industry $\times$ 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)$_{i,t-1}$ × 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 × Year FE	Yes	Yes	Yes
Industry × 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 IPCC, and Green otherwise, following Choi, Gao, and Jiang (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 × 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

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 IPCC, and Green otherwise, following Choi, Gao, and Jiang (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)$_{i,t-1}$ × 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 × Year FE	Yes	Yes	Yes
Industry × 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 - Board 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

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