# Propagation of climate disasters through ownership networks and its impact on corporate ESG policies \*

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#### Abstract

Climate disasters propagate through common ownership networks, impacting voting and firm-level environmental, social, and governance (ESG) outcomes. We propose new measures of climate risk based on this spillover. Institutional investors in firms hit by climate-related disasters are more likely to vote in favor of ESG shareholder proposals at the other firms they own, relative either to themselves at other times or other investors on the same proposal. In the quarters following (but not preceding) their investor bases' climate disaster exposure, firms experience more positive changes in ESG ratings and exhibit worse climate change sentiment on conference calls. Longer-run, firm emissions and value decline.

#### Keywords: common ownership, climate change, corporate ESG, CO2 emissions

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## 1 Introduction

Climate risk is one of the greatest challenges facing the world today and is quickly becoming a concern for large firms. A 2019 CDP report suggests that the world's largest 215 companies have \$250 billion in potential losses to write-offs of assets from climate impacts, with many likely to hit within the next 5 years.<sup>1</sup> The risk that these externalities have yet to be fully reflected in asset prices together with the regulatory risk in the transition to a low-carbon economy pose a long-term financial risk to institutional investors (Kruger, Sautner, and Starks, 2020; Bansal, Ochoa, and Kiku, 2017; Bolton and Kacperczy, 2021; Hoepner, Oikonomou, Sautner, Starks, and Zhou, 2020; Seltzer, Starks, and Zhu, 2020). Large investors are taking notice of these risks and exerting their influence over environmental, social, and governance (ESG) policies (see e.g., Dyck, Lins, Roth, and Wagner, 2019; Krueger, Sautner, and Starks, 2020; Jouvenot and Kruger, 2021).

In this paper, we study climate disasters' propagation through common ownership networks as a particular mechanism through which investors may impact corporate ESG policies. The idea lies at the intersection of studies on salience as a driver of asset prices (e.g., Cosemans and Frehen, 2021; Frydman and Wang, 2020; Bose, Cordes, Nolte, Schneider, and Camerer, 2022; Rehse, Riordan, Rottke, and Zietz, 2019), studies on information transmission through common ownership networks (e.g., Azar, Schmalz, and Tecu, 2018; Edmans, Levit, and Reilly, 2019), and those on investors engagement in corporate ESG performance management (e.g., Kruger et al., 2020; Naaraayanan, Sachdeva, and Sharma, 2021; Doidge, Dyck, Mahmudi, and Virani, 2019; Hoepner, Oikonomou, Sautner, Starks, and Zhou, 2018). Natural disasters are one salient event that impacts corporate managers and asset prices alike (e.g., Kruttli, Roth Tran, and Watugala, 2021; Dessaint and Matray, 2017; Bernile, Bhagwat, and Rau, 2017). In particular, Huang, Jiang, Xuan, and Zhou (2021) and Alok, Kumar, and Wermers (2020) show that directors and fund managers exhibit salience bias with respect to natural disasters. In this study, we conjecture that, investors' exposure to climate disasters impacts their ESG-related voting behavior, and in turn ESG performance, at firms in their portfolio, even when these firms are not directly hit by climate disasters themselves. This idea is supported by anecdotal evidence. For example, in the second quarter of 2017, after nearly 10% of its portfolio holdings affected by climate disaster shocks, GMO LLC. supported voting on

<sup>&</sup>lt;sup>1</sup>CDP is an international environmental NGO. See the report here: https://www.cdp.net/en/articles/media/ worlds-biggest-companies-face-1-trillion-in-climate-change-risks.

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

We begin by examining how investors' exposure to climate disasters across their portfolios impacts their ESG voting behavior at their other portfolio firms. In our first set of tests, we exploit within firm-time variation in investors' climate disaster exposure and examine how this exposure impacts the propensity of investors to support shareholder ESG proposals. The inclusion of proposal fixed effects and voter-industry fixed effects absorbs the average voting behavior on a given proposal and the typical voting patterns of specific funds within an industry.

We find that climate disaster shocks result in investors being more likely to vote in favor of shareholder ESG proposals at other firms they own, but only to the extent that the investor holds a large stake in the firm at which the vote occurs. Consistent with the uniquely documented fact that ESG proposals nearly always fail with the shareholder support almost never crossing the 50% threshold (He, Kahraman, and Lowry, 2023), we show that, in the absence of a climate disaster, investors with large stakes are significantly less likely to support shareholder ESG proposals. However, a 1.5 standard deviation shock to an investor's climate disaster exposure offsets this baseline effect. Institutional investors in firms hit by climate-related disasters have the propensity to support ESG proposals at other portfolio firms they own as large shareholders. The dynamics of this effect support a causal interpretation of our results, as the effect is concentrated in disasters occurring within two quarters of the vote and there is no evidence of a significant relationship between voting behavior and future exposure to climate disasters. Our evidence suggesting that exposure to climate disasters impacts voting through an ownership stake channel is consistent with literature suggesting that institutional investor attention is necessary but not sufficient to motivate a change in voting or the general idea that large shareholders take on a monitoring role (see e.g., Alchian and Demsetz, 1972; Shleifer and Vishny, 1986; Fich, Harford, and Tran, 2015).

Next, we examine whether these investor-level changes in voting are accompanied by changes in firm-level ESG outcomes. After showing that the investor-level voting changes culminate in a corresponding firm-level effect, we examine whether firm officials begin to discuss climate issues differently on earnings call conferences after firms' investor base has been subject to more extensive climate disasters elsewhere. We find that climate change sentiment in these conversations becomes more pessimistic, especially as it relates to physical climate risks.

Our primary firm-level outcome of interest is ESG ratings. For this set of tests, we examine how ESG changes

relate to investor ownership-weighted climate disaster exposure. We arrange the data so that the four-quarter period over which the disaster exposure is measured ends during the quarter in which the firm's 10-K is released, since that is often the trigger event for an updated ESG or emissions rating. We find consistent evidence of a significant positive relation between investors' exposure to climate disasters at their other portfolio firms and the change in these firms' ESG, or emissions, rating.

Several additional tests support our interpretation as a causal effect of investors' portfolio disaster exposure and mitigate alternative stories such as a spurious correlation between investors' disaster exposure and firm characteristics. In particular, the relationship between institutional holders' portfolio exposure to climate disasters significantly predicts changes in ESG ratings, but only when the disaster occurs in the three quarters prior to the end of the firm's fiscal year. This is consistent with the proclivity of ESG ratings to be updated only after a 10-K release. We find no significant effects when measuring disasters as of future dates suggesting that our findings are not primarily due to a correlation between our disaster and stable firm characteristics, such as size or institutional holdings. Moreover, in placebo tests considering non-climate disasters, we do not find similar impact of investors' portfolio disaster exposure on other portfolio firms' ESG or emission rating. This strengthens our conjecture that the salience is driven by climate risk perception.

Lastly, we investigate the implications for long-run emissions or firm value. We find that firm-level greenhouse gas emissions and environmental protection violations cumulatively decline in the three years responding to climate shocks through institutional investors. During the same period, we also find a decline in Tobin's Q of these firms, which echoes the existing studies that there are financial trade-offs to responsible investment(Pedersen, Fitzgibbons, and Pomorski, 2021; Pástor, Stambaugh, and Taylor, 2022; Avramov, Cheng, Lioui, and Tarelli, 2022).

Our paper is related to recent discussions about whether and how institutional investors improve companies' ESG performance. While divestitures and threats of exit could discipline managers to improve ES performance (Gantchev, Giannetti, and Li, 2022), some theoretical works argue that, to make social investing impactful, divestment is not as effective as engagement or holding a brown stock if the firm has taken a corrective action (Berk and van Binsbergen, 2021; Edmans, Levit, and Schneemeier, 2022). Existing work highlights that socially responsible funds could make them effective at influencing firm behavior through engagement (e.g., Kruger et al.,

2020; Naaraayanan et al., 2021; Doidge et al., 2019; Hoepner et al., 2018), and voting (e.g., Dikolli, Frank, Guo, and Lynch, 2022; He et al., 2023). Our work implies that, triggered by portfolio climate disaster shocks, institutional shareholders make impactful differences to improve the ESG performance of non-affected firms in the same portfolio.

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

Our study also 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 (Kruger et al., 2020; Alok et al., 2020), corporate loan yields (Correa, He, Herpfer, and Lel, 2022), and municipal bond yields (Painter, 2020; Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2021).<sup>2</sup> We add a propagation channel through common ownership to show the impact of climate change shocks on firms.

Finally, our findings connect to the common ownership literature by presenting a new type of information that flows through common ownership networks. There is some debate in this literature regarding what policies pass through common ownership networks (see e.g., Azar, Schmalz, and Tecu, 2018; Lewellen and Lowry, 2021;

<sup>&</sup>lt;sup>2</sup>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.

Koch, Panayides, and Thomas, 2021). Our voting results build on the idea in Edmans et al. (2019) that there is a voice and exit channel to governance in a world with common ownership with evidence that the voice of investors changes following their exposure to climate events.

## 2 Empirical Measures and Sample Construction

In this section, we describe the data used to construct our sample and the primary variables of interest. We first describe the data we use for each variable of interest, and then we conclude the section by presenting descriptive statistics for all variables used throughout our analyses.

#### 2.1 Measuring Investor-level Climate Disaster Exposure

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

#### 2.1.1 Disaster and ownership data

We first obtain data on natural disasters from SHELDUS, which is a county-level natural hazard dataset for the United States. It encompasses information from 1960 to the present. This database provides information on the type of hazard, affected location (county and state), year and month, and the direct losses caused by the hazard (e.g., property and crop losses, injuries, and fatalities). These data are widely used in studies on the effect of natural disasters, including studies on financial markets (e.g., Cortés and Strahan, 2017; Correa et al., 2022). To capture shocks created by relatively large disasters, we include disasters with total damage exceeding 100 million 2019 U.S. dollars. Based on reports produced by the IPCC (Seneviratne, Nicholls, Easterling, Goodess, Kanae, Kossin, Luo, Marengo, McInnes, Rahimi, et al., 2017), we classify hurricanes, floods, wildfires, coastal-related disasters, and storms as climate change related severe weather events, and the rest as non-climate change related.<sup>3</sup>

<sup>&</sup>lt;sup>3</sup>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. These 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.

Unlike prior studies that only focus on firms' headquarters, when measuring firm-level disaster exposure, we construct detailed geographic footprints of corporations using the NETS dataset from Walls and Associates, which is constructed using annual snapshots of establishments with detailed information of geographic location, parent company ownership, employment, and sales. We use the county-level information that captures the number of establishments that a firm has in a given location to create a time-varying location-weighted measure of a company's exposure to each disaster type. To do so, in each quarter, for each type of natural disaster, we sum up each firm's fraction of establishments in counties hit by these disaster in the same quarter, thus we arrive at an time-varying operation-weighted measure of a firm's exposure for each type of disasters.

To translate this firm-level disaster exposure into an investor level measure, we collect information on institutional investors' quarterly equity holdings from 13F filings as compiled by Thomson/Refinitiv. The Securities and Exchange Commission requires financial institution that manages investment portfolios of over \$100 million in qualified securities to disclose their long-side quarterly holdings in Form 13F. Hereafter, we importantly refer to a 13F filer as a fund family as the disclosed positions are not individual portfolios but an aggregated one across funds. 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. We remove observations when the total portfolio weight is above 100% due to rare cases of when shares are double counted.

#### 2.1.2 Measuring indirect natural disaster shocks via common ownership

The firm-level disaster and investor-level holdings data combined allow us to measure an investor's overall exposure to climate disasters in a period. Considering firm i, institutional investor j, and year-quarter t, we calculate the proportion of a firm's footprints in counties hit by climate disasters during year-quarter t:  $Disaste exposure_{i,t}^{C}$ , which measures the firm-level direct climate disaster shock.

We then aggregate the climate disaster shock to the institutional investor level and construct the investor

indirect disaster exposure  $Ins \ Dis_{j,t}$  in three ways:

$$Indicator_{j,t} = I[\sum_{i} I(Disaster \ exposure_{i,t}^{C} > 0)], \tag{1}$$

$$Weight_{j,t} = \sum_{i} I(Disaster \ exposure_{i,t}^{C} > 0) \times w_{i,j,t},$$
(2)

$$(Weight \times \text{MCAP})_{j,t} = \sum_{i} I(Disaster \ exposure_{i,t}^C > 0) \times w_{i,j,t} \times \log(\text{Mcap})_{i,t},$$
(3)

where I(.) is the indicator function,  $w_{i,j,t} = \frac{Value_{i,j,t}}{\sum_i Value_{i,j,t}}$  is the weight of a holding in an institutional investor's portfolio with  $Value_{i,j,t}$  being the value of a portfolio holding, and  $Mcap_{i,t} = Shares Outstanding_{i,t} \times P_{i,t}$  is the market capitalization. The three measures are constructed based on the intuition that common ownership shifts managers' incentives depending on not only overlapping ownership but also investor attention (Gilje, Gormley, and Levit, 2020). The variety of measures helps account for different mappings between firm-level climate disaster shocks and the attention to those shocks from institutional shareholders. Our direct starting point is  $Indicator_{j,t}$ which indicates if an institutional investor owns a firm that is affected by a disaster. Next, in  $Weight_{j,t}$ , we allow for the possibility that institutional investors are more attentive to disaster-hit firms that take larger proportions in their portfolios (e.g., Van Nieuwerburgh and Veldkamp, 2010; Fich et al., 2015). In  $(Weight \times MCAP)_{j,t}$ , we account for the higher attention paid to larger firms (Da, Engelberg, and Gao, 2011).

Lastly, to analyze the spillover effect of climate disaster shocks on other firms in the same investor's portfolio, we aggregate the above investors' climate disaster exposures across all investors in a firm at a given time. Our firm-level indirect climate shock measure is then computed by value-weighting across institutional investors among indirectly affected firms:

$$VW(Indicator)_{i,t} = \sum_{j \in S} IO_{i,j,t} \times Indicator_{j,t},$$
(4)

$$VW(Weight)_{i,t} = \sum_{j \in S} IO_{i,j,t} \times Weight_{j,t},$$
(5)

$$VW(Weight \times MCAP)_{i,t} = \sum_{j \in S} IO_{i,j,t} \times (Weight \times MCAP)_{j,t},$$
(6)

where S is the set of a firm's institutional investors, and  $IO_{i,j,t} = \frac{Shares_{i,j,t}}{Shares Outstanding_{i,t}}$  is an institution's ownership

proportion of this firm. We value-weight using  $IO_{i,j,t}$  since theoretical and empirical models of common ownership typically assume that institutional ownership in a specific firm captures the influence of investors voting for their preferred managerial policies.

Plus, since all measures above are at the quarterly frequency, in all following tests, we apply four-quarter moving averages of these measures to account for the seasonality of disasters and to match the frequency of the yearly outcomes that we examine.

#### 2.2 Data on firms' voting, ESG, and climate-related outcomes

We examine the relation between the aforementioned measures of investors' exposure to climate events on a variety of investor and firm outcomes. Here, we discuss the data we use to define the outcomes of interest in our study.

#### 2.2.1 Votes for shareholder proposals

Our first set of tests examines shareholder proposal vote outcomes. For this analysis, we collect mutual fund voting records from Institutional Shareholder Services (ISS) Voting Analytics. ISS in turn compiles the voting results of mutual funds families from form N-PX that is filed to the SEC. Because Iliev and Lowry (2015) find funds vote in the same direction over 96% of the time as that of the fund family, we proceed to merge this mutual fund-level data to our fund family-level 13F holdings data. We follow He, Huang, and Zhao (2019) in adopting a name-matching algorithm for doing so and then aggregating voting records across funds by fund family for the same proposal.

Within the voting records, we use a keyword search of the proposal's item description to identify ESG- or climate-related shareholder-sponsored proposals. We focus on shareholder-sponsored as opposed to managementsponsored proposals as the literature has found that the former is more likely to need institutional investor's climate activism (Cvijanović, Dasgupta, and Zachariadis, 2016). The top 5 most frequent ESG-related proposal topics are political contribution disclosures, reports on sustainability, improvements to human rights policies and standards, community environmental impacts, and linking executive pay to social criteria. The top 5 most frequent climate-related proposal topics include greenhouse gas emissions, reports on climate change, renewable energy, anti-social proposals, and reports on environmental policies. We view a vote for these proposals as when a fund does not vote as "against", where against includes "against, abstain, do not vote, withhold" in the data. Fund-level voting as aggregated to the fund family-level similar to Eq. (1) of He et al. (2019).

#### 2.2.2 Attention to climate change issues in firms' earnings calls

We next study conference call outcomes. We obtain time-varying text-based measures of firm-level attention to climate change issues based on Sautner, van Lent, Vilkov, and Zhang (Forthcoming) (SLVZ). SLVZ extracted words related to climate change from transcripts of quarterly earnings conference calls of publicly-listed firms.<sup>4</sup> Adapting a machine learning keyword discovery algorithm, they first produce climate change bigrams and then construct an aggregate firm-level measure of climate change sentiment by counting the number of climate change bigrams after conditioning on the presence of the positive and negative tone words. Based on topics covered by the bigrams, there can also be sentiment measures of three separate climate change topics: opportunity (OP), physical (PH), and regulatory (RG). In our tests, we apply both the general climate change sentiment and the three topic-based ones.

#### 2.2.3 ESG and emission scores

We obtain firm-level ESG and emission scores from Refinitiv, which captures and calculates over 630 companylevel ESG measures. These measures are grouped into 10 categories that reformulate the three pillar scores and the final ESG score, which is a reflection of the company's ESG performance, commitment and effectiveness based on publicly-reported information. The category scores are rolled up into three pillar scores – environmental, social, and corporate governance. The ESG pillar score is a relative sum of the category weights, which vary per industry for the environmental and social categories. For governance, the weights remain the same across all industries. The pillar weights are normalized to percentages ranging between 0 and 100.

<sup>&</sup>lt;sup>4</sup>SLVZ measures are available on https://osf.io/fd6jq/.

#### 2.2.4 Greenhouse gas emission and environment violations

We obtain greenhouse gas emission from the Greenhouse Gas Reporting Program (GHGRP) of the United States Environmental Protection Agency (EPA). Starting from 2010, GHGRP publicize the facility-level greenhouse gas emissions of large emitters, including facilities that inject CO2 underground, and suppliers of products that result in greenhouse gas emissions when used in the United States. The data are made publicly available through the Facility Level Information on GHGs Tool (FLIGHT), providing plant-level information on the identity, geographic location, parent company ownership, and the quantity of greenhouse gas emissions are measured in metric tons of carbon dioxide equivalent (MTCO2e) of the plant on an annual basis. We manually match this dataset with annual financial accounting data from Compustat based on the names of parent companies.

We also collect EPA civil, judicial, and administrative enforcement cases from the EPA's enforcement division.<sup>5</sup> The data detailed here are related to violations of the Clean Air Act (CAA), Clean Water Act (CWA), Resource Conservation and Recovery Act (RCRA), and Safe Drinking Water Act (SDWA). We indicate each firm-year with 1 if there is at least one EPA violation, and 0 otherwise. We follow Lel (2022) when linking enforcement actions to the parent company level, and which we then merge to Compustat.

#### 2.3 Descriptive statistics

Table 1 displays summary statistics of firms, funds, and shareholder proposals. Our full sample period is from 2003 to 2019. All our tests is within the sample of firms with available ESG score and our firm-level indirect exposure measures. All variables are calculated as defined in Appendix A.1.

#### [Table 1 here]

Panel A covers all firm-year in our main test sample. When measured by VW(Indicator), the average indirect exposure to climate disasters through common ownership is 0.43, which means 43% of an average firm's institutional ownership belongs to institutional shareholders with some portfolio firms suffering climate-related disasters. The ownership is 24% when it comes to non-climate-related disasters. When the indirect exposure is measured

<sup>&</sup>lt;sup>5</sup>See, https://echo.epa.gov for historical enforcement actions in the EPA's Integrated Compliance Information System (ICIS) within ECHO.

by VW(Weight), which weights disasters at other portfolio firms based on the size of those firms in investors' portfolios, the average value is 0.16. When the indirect exposure is measured by VW(Weight  $\times$  MCAP), which accounts for the possibility that institutional investors pay more attention to disasters hitting large firms they own, the average value is 2.75. The corresponding indirect exposure to non-climate disasters are much smaller. Hereafter, to facilitate economic interpretation, in all tests, we divide these measures by their full sample standard deviations.

We also show other related firm characteristics. With 78% total institutional ownership and 2.79 institutional blockholders, the average firm owns \$18.52 billion in total assets, earns an annual stock return of 16%, and has firm valuations that are 1.76 times that of their total assets based upon Tobin's Q. Each year, 2% of an average firm's operational footprints are directly hit by natural disasters; it is graded with ESG score of 40.38 out of 100 and emission score of 27.29, and produces 6.36 billion metric tons of carbon dioxide equivalent. 14% of firm-year observations in our sample are flagged with EPA environment violations. The distribution of climate change sentiment abstracted from earnings call conferences is highly skewed, with the value being zero for at least 75% of firm-year observations.

Panel B summarizes characteristics at the fund family proposal level. 27.85% of ESG-related shareholder proposals get institutional shareholders' support in voting, with an average institutional ownership in a specific firm being of 0.20%. 29% of these shareholders suffer climate-related disaster hits in their portfolio, and the average total portfolio weight of all exposed holdings in portfolio is 10%. When considering the market caps of firms being hit with Weight  $\times$  MCAP, then the average portfolio-weighted market cap of disaster-exposed firms in a portfolio is 1.7. These proposal-variable and disaster-exposures are quite similar in the sub sample of climate-related shareholder proposals.

Panel C shows fund family characteristics of funds with and without environmental activism, respectively. Taking funds voting in ESG-related proposals as an example, an average high portfolio ESG score fund family has a total portfolio value of \$64.93 billion, with an average portfolio weight being 0.55%, an average ownership being 0.65%, and an weighted average market cap being \$477.15 billion in each holding; the portfolio's Herfindahl–Hirschman index is 156.11. In comparison, an average low portfolio ESG score fund family has much smaller total portfolio value of \$12.82 billion, its portfolio holdings are more concentrated with a higher Herfindahl-Hirschman index, and its average holding has a much smaller market cap. In a word, comparing with low portfolio ESG score funds, high portfolio ESG score funds are larger in size, more diversified in portfolio holdings, and invest in bigger firms. The fund family characteristics in high and low portfolio emission score funds and the differences between the two groups are similar. We find similar patterns switching to the sub sample of funds voting in climate-related proposals, except that total portfolio value is larger.

## 3 Empirical methodology and results

Our central research question is the extent to which climate events propagate through common ownership networks to impact corporate ESG outcomes. We test this in two stages. First, we conduct voter-level tests to understand how climate events impact voting behavior. Then, we examine the effects on firm-level outcomes.

#### 3.1 Voting analyses

Before turning to firm-level outcomes, we first analyze how climate disasters may propagate through the common ownership network in the form of institutional investors' voting on shareholder ESG proposals. We estimate the following regression,

$$Vote \ Proposal_{i,j,k,t} = \gamma_1 Ins \ Dis_{j,t-1} \times IO_{i,j,t-1} + \gamma_2 Ins \ Dis_{j,t-1} + \gamma_3 IO_{i,j,t-1} + FEs + \epsilon_{i,j,k,t},$$
(7)

where *Vote*  $Proposal_{i,j,k,t}$  is the voting percentage points by fund family j for proposal k as of the shareholder meeting held by firm i in year t. Ins  $Dis_{j,t-1}$  is the four-quarter moving average of the fund family level indirect measures based on Equations (1)–(3), while  $IO_{i,j,t-1}$  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.

From institutional investors' perspective, when making voting decisions in ESG proposals, they may consider both their ownership stake in a spillover firm (measured in  $IO_{i,j,t}$ ) and climate disaster shocks in their portfolio (measured in *Ins Dis*<sub>j,t</sub>). In other words, when institutional investor ownership (and thereby attention) in a spillover firm is 0 or the institution investor's indirect climate disaster exposure is 0, then  $IO_{i,j,t}$  or *Ins Dis*<sub>j,t</sub>, respectively, are potentially separate drivers of investors' voting behavior. Thus, our variables of interest are  $\gamma_1$ ,  $\gamma_2$ , and  $\gamma_3$ .

Our specification in Equation (7) has several advantages from an identification perspective. First, the unit of observation is at the fund family-proposal-year-level as a proposal can only be filed by one firm as of its shareholder meeting date. Thus, we can include proposal fixed effects that absorb all time-specific firm-level attributes and focuses our coefficient estimates on how different investors vote on the same proposal. As in our subsequent firm-level tests, we also add state  $\times$  year and industry  $\times$  year fixed effects. We also add fund family  $\times$ industry fixed effects to control for the typical voting patterns of each investor. Thus, the coefficients of interest collectively identify how fund families vote differently in periods when they experience a climate disaster at their other portfolio firms, relative to both their own typical voting patterns and the voting patterns of other, untreated, investors at the same time.

A key difference between our voting level analyses and any firm level tests is that we observe variation in the indirect climate-related disaster exposure across investors in the same firm at the same time. This allows us to hypothesize separately and then identify the effects of ownership stake, experiencing a disaster, and their interaction. When investors have large ownership stakes but no exposure to a disaster, existing literature suggests a negative relation between institutional ownership and ESG proposal voting outcome. According to He et al. (2023), environmental and social (ES) proposals nearly always fail with shareholder support almost never crossing the 50% threshold. Consistent with this finding, in our sample, the levels of support among mutual funds on ESG proposals remain lower than 30%.

With respect to the effect of climate disasters at other portfolio firms on support for ESG proposals, investors may update their beliefs on (or pay more attention to) ESG issues following a climate disaster shocks. This may change their voting patterns across all of the other firms in the portfolio. This would manifest as a significant main effect of disaster exposure. To the extent the effect is uniform across all firms in their portfolio it would produce insignificant estimates on the interaction effects. Alternatively, institutional investors may only adjust their voting behavior in response to a climate disaster when they are motivated by owning a large stake, leading to a significant interaction effect. This idea is consistent with the story in Fich et al. (2015) in which institutional investor attention is necessary but not sufficient to motivate a change in voting or the general idea that large shareholders take on monitoring roles in firms (see e.g., Alchian and Demsetz, 1972; Shleifer and Vishny, 1986).

#### [Table 2 here]

Consistent with the latter hypothesis, Table 2 indicates a positive relation between climate disasters among other portfolio firms and the propensity to support ESG shareholder proposals of firms only when an investor has a large ownership stake, whether the proposal is broadly related to ESG (Columns 1-3) or the 23% of these that are specifically related to climate initiatives (Columns 4-6). In both cases, the main effect of a climate disaster at other portfolio firms is positive, but statistically insignificant, while the interaction between an investor's climate disaster exposure and their stake in the firm is positive and statistically significant in all six columns. Thus, investors' exposure to climate disasters does affect their support for shareholder ESG proposals, but only to the extent that the investor is a large shareholder. We also document a significant negative relationship between the level of institutional ownership by a specific investor and the probability of them supporting ESG-related or climate-related shareholder proposals. For example, a one standard deviation increase in  $IO_{i,j,t}$  results in a 2.60 to 3.26 (4.11 to 5.04) percentage points lower support for ESG-related (climate-related) shareholder proposals. Thus, one way to think about the magnitude of the interaction coefficient is how big of a standard deviation shift in climate disaster exposure it takes to offset the negative baseline effect of institutional ownership on the propensity to support such shareholder proposals. Put this way, the magnitudes are very consistent across the 6 columns as it requires between a very plausible 1.49 to 1.68 standard deviation shock to climate disasters among investors with large ownership stakes to offset the baseline negative relation between institutional holdings and support for shareholder ESG proposals. Consistent with He et al. (2023), since the average fund family support for these proposals are lower than 30% in Table 1, it would take an implausibly rare 4-5+ standard deviation increase in the interaction term to overall pass such proposals.

We next explore the dynamics with which the effect of climate disasters on voting behavior emerges. If the estimates are indeed reflective of a causal effect of climate disaster exposures then we expect the relation to emerge at precisely the time at which the disaster occurs. We examine this in Figure 1, which provides a graphical representation of Table 2 that lags or leads the disaster shock by up to 4 quarters. Thus, Panels (A) through (C) of the figure plot a dynamic representation of Columns (1)–(3) of Table 2, respectively.

#### [Figure 1 here]

The results in Figure 1 are consistent with climate disasters temporarily impacting institutional investors' propensity to support shareholder ESG proposals. Disaster occurring one quarter before the vote have the most impact, while disasters occurring two quarters before have the next largest impact. There is little evidence of longer-run effects, although the point estimate remains qualitatively similar with approximately half the magnitude in other periods. Importantly, we find no significant effects in the quarters after the vote, suggesting that our findings are not primarily due to a correlation between our disaster and stable investor characteristics.

#### 3.2 Firm-level outcomes

We first outline the type of specification we estimate for our firm level outcomes. We regress a number of firm level outcomes, such as changes in firms' ESG and Emissions scores, on measures of the ownership base's recent exposure to climate-related events in their other portfolio firms. We arrange the firm-level outcome data so that the four-quarter period over which the disaster exposure is measured ends during the quarter in which the firm's 10-K is released, denoted quarter t, since that is often the trigger event for an updated ESG or emissions rating. To the extent that there are special updates to ESG or Emissions scores at other times, we expect the estimated relation to understate the true relation.

Following Equation (7) of Boehmer, Jones, and Zhang (2020) and Equations (4.1)–(4.4) of Dou, Johnson, Shao, and Wu (2022), our regression specification for detecting spillover effects is,

$$Y_{i,t} = \beta_1 MA \ exposure_{i,t-1} + \beta_2 \ exposure_{i,t} + \beta_3 MA \ exposure_{i,t-1} \times Disaster \ exposure_{i,t} + Controls_{i,t-1} + \epsilon_{i,t},$$

$$(8)$$

where  $MA \ exposure_{i,t-1}$  is the four-quarter moving average of the firm level spillover measures based on Equations (4)–(6), and  $Disaster \ exposure_{i,t}$  controls for the effect of firms being directly hit by disasters. The coefficient of interest,  $\beta_1$  on  $MA \ exposure_{i,t-1}$ , measures the spillover effect of climate disasters that institutional investors face at their other portfolio firms on changes in ESG outcomes, while the  $MA \ exposure_{i,t-1} \times Disaster \ exposure_{i,t}$  interaction controls for when a firm's own disaster damages impact the relevance of investors' disaster experiences

at other portfolio firms. The other controls include the previous year's log assets (to account for firm size), the overall institutional ownership, and the number of institutional blockholders (to account for underlying ownership structure at the firm level).

Even though many of the dependent variables we examine are constructed in changes, we include firm fixed effects to control for unobserved constant differences across firms (e.g., some firms have rising ESG scores on average). We also include state × year fixed effects and industry × year fixed effects. State × year fixed effects control for unobserved time-varying trends across states (e.g., disasters often cause spatial clustering by affecting geographic areas differently over time). 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). For inference, we use robust standard errors double-clustered by firm and year.

#### 3.2.1 Voting and earnings conference calls

The evidence in Table 2 and Figure 1 suggests that voting is one avenue through which climate disasters impact firm behavior via common ownership. We interpret this evidence of an *observable* increase in voting for ESG- and climate-related policies, despite our similar finding with that of He et al. (2023) that nearly all such proposals tend to fail anyways, as the formal part of a broader environment of (possibly informal and less costly) intervention and communication by institutional investors supporting such policies (e.g., Appel, Gormley, and Keim, 2016; Levit, 2019). To the extent our conjecture holds, we naturally next examine whether such behavior aggregates to make a difference at the firm level.

#### [Table 3 here]

So, in Table 3, we first examine the *likelihood* of an ESG- or climate-related proposal. Specifically, we estimate Equation (8) with the dependent variable being an indicator equal to 1 if the firm has ESG- or climate-related proposals on its shareholder meeting agenda and zero otherwise. While Columns (1)-(3) indicate that the likelihood of an ESG-related proposal is unrelated, Columns (4)-(6) do indeed find that our indirect exposure measures have a positive and significant association with climate-related proposals. Economically, a one standard deviation increase in indirect exposure is associated with a 0.15 to 0.20 percentage point increase in the likelihood of

climate-related proposals. Thus, the relevance of investors' disaster experiences at other portfolio firms matters for pushing these kinds of shareholder proposals to a vote.

#### [Table 4 here]

As climate-related proposals appear to be more important and to explore a more informal investor intervention outcome, in Table 4, we turn to whether climate change conference call sentiment also reflects investors' climate disaster exposure at their other portfolio firms. As dependent variables, we utilize the Sautner et al. (Forthcoming) (SLVZ)'s climate change conference call sentiment measures, which are constructed at the firm-quarter level from earnings calls scripts. Higher sentiment indicates two effects: 1) a higher proportion of conference call scripts that discuss climate-change pairs of words (bigrams) that also contain 2) a higher imbalance between the number of positive and negative terms. To control for the former effect, we estimate Equation (8) adding in a control for SLVZ's overall climate change exposure measure. Our results start with Columns (1)-(3) that employ their full climate-change sentiment measure, while subsequent columns break this down into three sub-categories of discussion: opportunity (OP), regulation (RG) and physical (PH) "shocks".

Columns 1 to 3 suggest 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. Unreported tests that break the measure down by positive and negative sentiment indicate that this result is primarily due to less positive sentiment around climate issues. The component breakdown in Columns 4 through 12 suggests that the overall result is driven by climate sentiment involving physical risks (i.e., Columns 10-12), but the insignificant point estimates on the opportunity and regulation components in Columns 4 through 9 operate in the same direction. Consistent with the SLVZ climate-change sentiment being also driven by overall climate change discussion (in addition to the imbalance in sentiment that we are interested), we find a positive relation between climate change exposure and climate change sentiment that we control for throughout.

Overall, the evidence in this section provides several ways in which investors behavior toward ESG and specifically climate-related initiatives changes when they experience climate related disasters at their other portfolio firms. Investors begin to support more ESG-related shareholder proposals and exhibit more negative sentiment relating to climate change issues.

#### 3.2.2 ESG ratings

We next turn our attention to firm-level ESG outcomes to understand if investors' disaster exposure impacts firms' ESG behavior.

#### [Table 5 here]

In Columns 1 through 3 of Table 5 Panel A, we use annual changes in ESG ratings as the dependent variable of interest, adjusting our measurement of investors' exposure to climate disasters as in Equations (4)–(6). Specifically, we use a value-weighted indicator if any of their other portfolio firms are exposed in Column 1, the percentage of their portfolio that is exposed in Column 2, and lastly a portfolio-weighted market capitalization of disaster exposed firms in Column 3. Across all three columns, we observe a significant positive relation between investors' exposure to climate disasters at their other portfolio firms and changes in ESG rating.

Our estimates of the economic magnitude also remain quantitatively similar across the three climate disaster exposure measure we employ. The coefficient in Column 1 indicates that a one standard deviation increase in the value-weighted proportion of institutional investors that are indicated to be exposed to disasters results in a 0.39 increase in the change in ESG score. Accounting for investor attention in both the spillover firm and disaster firm, Column 3 says that a one standard deviation increase in indirect exposure is associated with a 0.24 increase in the change in ESG score. So economically, these estimates corresponds to around 20% to 40% of the 2.19 average change in ESG score in our sample. This effect attenuates, albeit insignificantly, for firms with disaster exposure, and the attenuation is small in most cases. For instance, at the average (median) disaster exposure of 0.02 (0.01), the Column 3 coefficient attenuates by 15.5% (7.8%) compared to a firm with zero exposure. With that said, there is also a significant positive direct effect of disaster exposure on changes in ESG score.

In Columns 4 through 6, we conduct a similar analysis using the change in emission score as the outcome of interest in order to narrow in on the climate-aspect of ESG policy. Again, we find a significant positive relation with investors' exposure to climate disasters at their other portfolio firms, but the implied economic magnitudes are around twice as large. Focusing on Column 6, the coefficient implies that a one standard deviation increase in indirect exposure, accounting for attention to both spillover and the disaster firms, is associated with a 0.56 increase in the change in emission score. This represents about one-fifth of the average change in emission score

(2.97) in our sample.

We next conduct several additional tests to bolster our interpretation of the estimates in Table 5. If the estimates are indeed reflective of climate disaster exposures propagating through common ownership networks, as opposed to a spurious result due to correlated firm characteristics,<sup>6</sup> then we expect the effect (1) to emerge at precisely the time at which the disaster occurs, and (2) not be present when considering non-climate disasters. We test these ideas respectively in Figure 2 and Table 5 Panel B, respectively.

#### [Figure 2 here]

Figure 2 provides a graphical representation of Table 5 Panel A, after shifting the timing of the disaster shock. Time 0 represents the relation between disasters occurring in the quarter in which a firms 10-K is released, which is the quarter after the fiscal year to which the report refers and the last quarter that comprises the annual disaster shocks in Table 5. Since the 10-K is filed 60-90 days after the quarter end, most disasters during this quarter will have happened, but will likely not have been reflected in the company filings. Thus, if the estimates are driven by our proposed mechanism, then we expect some effect in quarter 0, but larger effects in the three previous quarters. We do not expect effects when disasters are measured after the ESG rating change date (i.e., in quarters 1 through 8) and view the extent of longer-run effects (i.e., in quarters -4 through -7) as an empirical question.

The results in Figure 2 are consistent with our proposed mechanism. The relation between institutional holders' portfolio exposure to climate disasters significantly predicts changes in ESG ratings, but only when the disaster occurs in the three quarters prior to the end of the firm's fiscal year. This is consistent with the proclivity of ESG ratings to be updated only after a 10-K release. We find no evidence of longer-run effects, suggesting that ESG ratings quickly capture the effect that disaster-exposed institutions have on ESG policy. Importantly, we find no significant effects in quarters 1 through 8, suggesting that our findings are not primarily due to a correlation between our disaster and stable firm characteristics, such as size or institutional holdings.

<sup>&</sup>lt;sup>6</sup>The institutional investor exposure measures that we create are related to firm characteristics, such as institutional ownership. Although we control for these factors in our main specifications, our baseline analysis in Table 5 cannot entirely rule out a spurious relation to the extent that there are uncontrolled for or non-linear effects relating to these correlated firm characteristics. We allay these concerns to some extent with a matching robustness test by pairing treated firms (i.e., above median indirect exposure) on control firms (i.e., below median indirect exposure) outside of the same industry and state matched on our control variables. In untabulated results, we find that the ESG score-relation remains positive but insignificant, and the emission score-relation is positive and more statistically significant.

To further clarify the appropriate interpretation of our findings, we re-run the analysis in Table 5 Panel A using non-climate related disasters in Panel B. Non-climate disasters are less common and have smaller direct footpoints on firms' operations. They also reduce our test sample by approximately 28% because they end in Q4 of 2017 compared with our full sample period ending in Q4 of 2019. The weighted indirect exposure measures have averages that are approximately 20% of their climate disaster-related counterpart. We find no significant relation between investors' exposure to these non-climate disasters and changes in ESG metrics. Moreover, the possibility that a lack of power drives the insignificance is mitigated by the fact that the point estimates are in the opposite direction of those in Panel A relating to climate disasters.

Together, the findings in Table 5 and Figure 2 suggest that climate disasters experienced by institutional shareholders have effects on ESG policy that propagate through common ownership networks. This propagation occurs within a year and is specific to climate disasters.

#### 3.2.3 Long-run outcomes

In the final part of our analysis, we examine if real firm climate-change outcomes respond in the long-run to indirect exposure to disasters. Such an objective is important in light of our findings that formal voting mechanisms tend to fail despite garnering increased voting support while less formal conference call discussion increase. Thus, one interpretation of our documented increase in the change in ESG and Emission score is that firms are responding to institutional investor pressure by greenwashing and cheap talking their ESG policy (e.g., Yang, 2022). This is a particularly acute concern given that 1) ESG ratings are likely to rely on data sources that firms can influence such as their disclosure and communications (Douglas, Van Holt, and Whelan, 2017), and 2) firms may tangibly benefit from showcasing ESG criteria that drives an institutional investment industry valued at over \$35 trillion dollars in 2020.<sup>7</sup> On the other hand, a variety of studies do indeed find that firms' ESG commitments lead to tangible changes (see e.g., Edmans, 2011; Flammer, 2015; Ferrell, Liang, and Renneboog, 2016; Liang and Renneboog, 2017).

[Table 6 here]

<sup>&</sup>lt;sup>7</sup>See, the Global Sustainable Investment Review 2020 at http://www.gsi-alliance.org/.

In Table 6, we examine how carbon emissions (CO2) up to three years into the future respond to indirect exposure to disasters. Specifically, we re-estimate Equation (8) except we include the one-, two-, and three- year lags of indirect exposure relative to the year of the carbon emission. As there is a secular declining trend in CO2 emissions in the United States, we again use changes in CO2 as the dependent variable. All other control variables and fixed effects remain the same. Across all three specifications of indirect exposure, we find that CO2 emissions cumulatively decline in the three years after a positive shock to indirect exposure, with the third year being statistically significant. In Column 3, for example, for a one standard deviation increase in indirect exposure accounting for both attention to spillover and disaster firms results in a drop in the change in CO2 of 0.49 millions of metric tons. Economically, this is very large compared with the average change in CO2 of 0.04 and represents about 7.7% of average CO2 emissions in our sample.

#### [Table 7 here]

In Table 7, we move to examining if environmental failures as measured by Environmental Protection Agency (EPA) violations decline after a positive indirect exposure shock. Violations of environmental laws result in civil or criminal enforcement by the EPA and imposes possible monetary penalties, injunctions to compel firms to correct violations, or even imprisonment.<sup>8</sup> Our key dependent variable is then the percentage point likelihood of an EPA violation up to three years after a positive shock to indirect exposure to disasters. We find across all three measures that the chances of EPA violations decline cumulatively in the next 3 years, with year two being negative and significant. In Column 3, the decline of 1.25 percentage points for a one standard deviation increase in indirect exposure accounts for around 9% of the unconditional 14 percentage point likelihood of EPA violations in our sample.

#### [Table 8 here]

Lastly, we study in Table 8 the valuation consequences to these climate-related changes because there is considerable theoretical and empirical debate on whether there are financial trade-offs to responsible investment (Pedersen et al., 2021; Pástor et al., 2022; Avramov et al., 2022). We measure firms' valuation using either annual

<sup>&</sup>lt;sup>8</sup>See, https://www.epa.gov/enforcement/basic-information-enforcement.

returns or the level of Tobin's Q up to three years after a shock to indirect exposure to disasters. We again observe a significant effect in year 3 across our three measures. Returns decline by around 1%, compared to the sample average of 16% per year, while Tobin's Q declines by 0.03 to 0.04 compared a sample average of 1.76. As a result, there appears to be a modest valuation trade-off for firms that improve on their ESG policy and outcomes.

### 4 Conclusion

We provide the first evidence that the salience effect of climate disasters on fund managers flows through to affect corporate ESG governance. We find that after a firm is hit by climate-change related disasters, the institutional investors that hold this firm arise the awareness of climate change issues and accordingly engage with the other firms in her portfolios to influence corporate environmental policies from proposal voting to long-term greenhouse gass emission. The findings suggest that market-based solutions can be effective in reaching national and global ESG targets like emission reduction. This can be an important mechanism for the financial markets to complement coordinated government-based interventions

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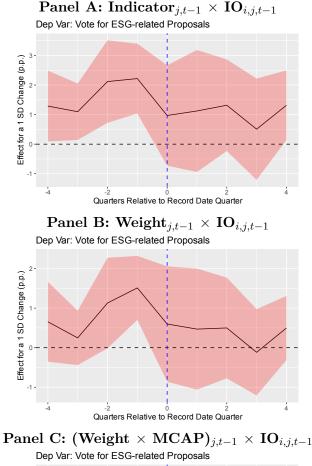
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## Figures

Figure 1: The voting response to indirect exposure to disasters

This figure presents the voting response for ESG-related proposals by institutional investors associated with indirect exposure to climate-related disasters via common ownership. The plot shows  $\hat{\gamma}_1$  from estimating Equation (7) in the main text, except we progressively lag or lead the explanatory variable by up to 4 quarters.  $\hat{\gamma}_1$  is interpreted as the percentage point increase in voting for a proposal associated with a one standard deviation increase in the interaction term that drives the variation in our indirect exposure measures. Panels A, B, and C report the estimate for the interaction term within V(Indicator), V(Weight), and V(weight × MCAP), respectively. The shaded areas are 95% confidence intervals based on robust standard errors clustered by institutional investor and year.



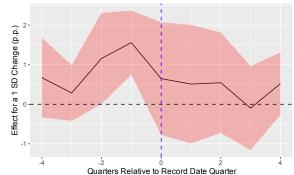
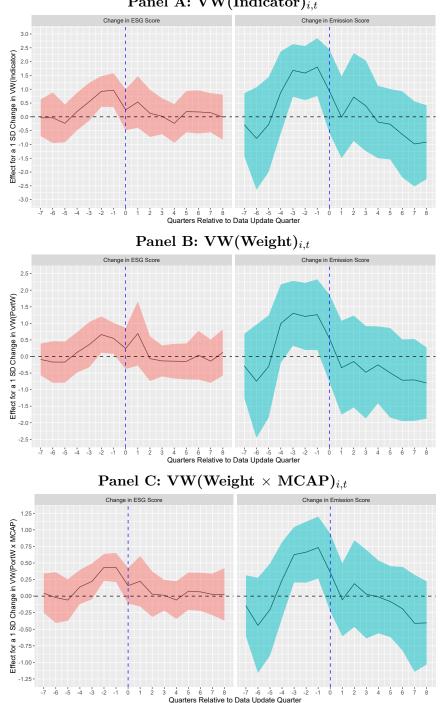


Figure 2: The ESG and emission score response to indirect exposure to disasters

This figure presents the change in ESG or Emission score associated with indirect exposure to climate-related disasters via common ownership. The plot shows  $\hat{\beta}_1$  from estimating Equation (8) in the main text, except we progressively lag or lead the explanatory variable by up to 8 quarters.  $\hat{\beta}_1$  is interpreted as the increase in the change in ESG or Emission scores associated with a one standard deviation increase in our indirect exposure measures. Panels A, B, and C report the estimate for V(Indicator), V(Weight), and  $V(weight \times MCAP)$ , respectively. 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 at the firm-year-level in Panel A, fund family-proposal level in Panel B, and fund family-year-level in Panel C. See Appendix A.1 for variable definitions. N is the number of observations used in our regression estimation, which requires available ESG score, the indirect exposure measure, and all controls. Mean, SD, Median, and IQR reports on the sample average, standard deviation, median, and difference between the 75th and 25th percentiles, respectively. Q0.10, Q0.25, Q0.75, and Q0.90 denotes the 10th, 25th, 75th, and 90th percentiles of the sample distribution. Finally, Skew is computed as classical skewness. The sample period is 2003 to 2019, except for the non-climate indirect exposure that ends in 2017.

	Pane	el A: Fin	m-Year	Sample						
Variable	N	Mean	SD	Median	IQR	Q0.10	Q0.25	Q0.75	Q0.90	Skew
Indirect H	Exposure	Measur	es of Cl	imate Dis	aster Sh	locks				
VW(Indicator)	15,394	0.43	0.30	0.42	0.48	0.00	0.20	0.68	0.87	0.26
VW(Weight)	$15,\!394$	0.16	0.13	0.14	0.19	0.00	0.05	0.24	0.34	0.63
$VW(Weight \times MCAP)$	$15,\!394$	2.75	2.21	2.50	3.34	0.00	0.94	4.28	5.88	0.59
	Oth	er Firm	Charac	teristics						
Institutional Ownership (InstOwn)	15,394	0.78	0.19	0.81	0.23	0.53	0.68	0.91	0.98	-0.72
Number of Institutional Blocks (NBlocks)	$15,\!394$	2.79	1.51	2.75	2.00	1.00	1.75	3.75	4.75	0.29
Assets (\$Bil)	15,394	18.52	38.47	4.96	13.42	0.74	1.92	15.33	44.51	3.82
Annual Return	15,394	0.16	0.56	0.12	0.41	-0.29	-0.08	0.33	0.57	21.52
Tobin's Q	15,394	1.76	2.26	1.29	1.31	0.41	0.80	2.12	3.50	41.30
Disaster Exposure $(0 \text{ to } 1)$	15,394	0.02	0.04	0.01	0.03	0.00	0.00	0.03	0.06	3.97
ESG Score	15,394	40.38	18.70	37.17	26.95	18.48	26.00	52.95	68.46	0.52
Emission Score	15,379	27.29	31.74	12.43	51.70	0.00	0.00	51.70	80.23	0.82
MTCO2e (Bil of Metric Tons)	1,711	6.36	16.88	0.57	3.33	0.03	0.09	3.43	17.60	4.70
EPA Violation	$14,\!665$	0.14	0.35	0.00	0.00	0.00	0.00	0.00	1.00	2.08
CC Sentiment (× $10^3$ )	16,031	2.08	10.21	0.00	0.00	0.00	0.00	0.00	7.38	7.84
CC Sentiment - Opportunities (OP, $\times 10^3$ )	16,031	0.93	5.88	0.00	0.00	0.00	0.00	0.00	3.08	9.63
CC Sentiment - Regulation (RG, $\times 10^3$ )	16,031	0.09	1.41	0.00	0.00	0.00	0.00	0.00	0.00	7.69
CC Sentiment - Physical (PH, $\times 10^3$ )	16,031	0.02	0.76	0.00	0.00	0.00	0.00	0.00	0.00	11.89

	Panel	B: Fund	l Famil	y-Proposa	l Sample					
Variable	N	Mean	SD	Median	IQR	Q0.10	Q0.25	Q0.75	Q0.90	Skew
				( = ( = - ) =		_				
E	SG-relate	ed Share	holder	(S/H) Pro	posal Sa	mple				
Vote for Proposals $(\%)$	38,001	27.85	43.15	0.00	87.50	0.00	0.00	87.50	100.00	1.00
Indicator	38,001	0.29	0.32	0.25	0.50	0.00	0.00	0.50	0.75	0.96
Weight	38,001	0.10	0.14	0.02	0.14	0.00	0.00	0.14	0.32	1.76
Weight $\times$ MCAP	38,001	1.70	2.51	0.41	2.41	0.00	0.00	2.41	5.60	1.78
Institutional Ownership (IO, $\times$ 100)	38,001	0.20	0.80	0.00	0.04	0.00	0.00	0.04	0.31	7.12
Clir	nate-rela	ited Sha	reholder	$r (S/H) P_{1}$	roposal S	ample				
Vote for Proposals (%)	8,832	29.50	43.91	0.00	100.00	0.00	0.00	100.00	100.00	0.91
Indicator	8,832	0.30	0.32	0.25	0.50	0.00	0.00	0.50	0.75	0.90
Weight	8,832	0.10	0.15	0.02	0.16	0.00	0.00	0.16	0.33	1.59
Weight $\times$ MCAP	8,832	1.79	2.55	0.37	2.78	0.00	0.00	2.78	5.82	1.60
Institutional Ownership (IO, $\times$ 100)	8,832	0.22	0.88	0.00	0.05	0.00	0.00	0.05	0.31	6.77

Par	nel C: F	und Fam	ily-Year Sample			
Variable	N	Mean	SD	N	Mean	SD
Fund Fa	amily V	Voting ES	G-related Propo	sals		
	Hig	h Portfol	io ESG Score	Lov	v Portfoli	o ESG Score
Total Portfolio Value (\$Bil)	3229	64.93	217.77	1526	12.82	29.82
Avg. Portfolio Weight (%)	3229	0.55	1.09	1526	0.62	1.35
Portfolio HHI	3229	156.11	174.79	1526	250.30	383.39
Avg. Institutional Ownership $(\%)$	3229	0.65	1.01	1526	0.81	1.03
VW MCAP (\$Bil)	3229	477.15	1702.88	1526	192.38	544.27
	High	Portfolio	Emission Score	Low I	Portfolio I	Emission Score
Total Portfolio Value (\$Bil)	3130	67.12	220.99	1613	12.82	29.30
Avg. Portfolio Weight (%)	3130	0.56	1.13	1613	0.61	1.28
Portfolio HHI	3130	160.32	188.03	1613	236.31	365.07
Avg. Institutional Ownership (%)	3130	0.64	1.01	1613	0.81	1.03
VW MCAP (\$Bil)	3130	482.23	1720.46	1613	199.26	582.53

Fund Family Voting Climate-related Proposals

miy vo	ting Chin	late-related FTOL	osais		
Hig	h Portfoli	io ESG Score	Lov	v Portfolic	ESG Score
2307	82.66	251.24	926	16.80	36.54
2307	0.43	0.99	926	0.50	1.29
2307	139.98	154.68	926	234.55	310.44
2307	0.71	1.09	926	0.77	0.85
2307	408.29	1957.57	926	146.97	331.37
High	Portfolio	Emission Score	Low 1	Portfolio E	Emission Score
2258	84.36	253.71	972	16.99	35.96
2258	0.44	1.04	972	0.49	1.18
2258	145 50	175.63	972	219.26	281.57
2200	110.00	110100	·		-01.01
2258	0.70	1.09	972	0.80	0.89
	Hig 2307 2307 2307 2307 2307 2307 High 2258 2258	High Portfol:           2307         82.66           2307         0.43           2307         139.98           2307         0.71           2307         408.29           High Portfolio         2258           2258         0.44	High Portfolio ESG Score           2307         82.66         251.24           2307         0.43         0.99           2307         139.98         154.68           2307         0.71         1.09           2307         408.29         1957.57           High Portfolio Emission Score         2258         84.36	2307       82.66       251.24       926         2307       0.43       0.99       926         2307       139.98       154.68       926         2307       0.71       1.09       926         2307       408.29       1957.57       926         High Portfolio Emission Score         Low I       2258       84.36       253.71       972         2258       0.44       1.04       972	High Portfolio ESG Score         Low Portfolio           2307         82.66         251.24         926         16.80           2307         0.43         0.99         926         0.50           2307         139.98         154.68         926         234.55           2307         0.71         1.09         926         0.77           2307         408.29         1957.57         926         146.97           High Portfolio Emission Score         Low Portfolio E         2258         84.36         253.71         972         16.99           2258         0.44         1.04         972         0.49

Table 2: Effect on voting for ESG- or climate-related shareholder proposals

This table reports results from regressions of institutional investors' voting on their indirect exposure to disasters. The unit of observation is at the proposal-fund family level, i.e., firm *i*'s proposal *k* is being voted on by an institutional investor *j*. The dependent variable at time *t* is the voting outcome measured as a fund family's percentage vote on a shareholder (S/H) proposal. Columns (1)–(3) and Columns (4)–(6) focus on climate-related and other ESG-related shareholder proposals, respectively. The variables of interest comprise the full interaction between one of the three proxies for the attention shock to the institutional investor and institutional ownership, which together aggregates to our firm-level indirect exposure measure. These variables at time t - 1 are computed as the four-quarter moving average ending in the quarter of the record date before the shareholder meeting, and then standardized by the full-sample standard deviation. Standard errors are double clustered by fund-family and year. \*, \*\* and \*\*\* indicate statistical significance at the ten, five and one percent level, respectively.

			Vote For P	roposal <sub>i, i,k,t</sub>		
	ESG-	related Prop			e-related P	roposals
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Indicator}_{j,t-1} \times \text{IO}_{i,j,t-1}$	$2.09^{**}$ (3.03)			$3.38^{**}$ (2.87)		
Weight <sub>j,t-1</sub> × IO <sub>i,j,t-1</sub>		$1.54^{***}$ (3.69)			$2.71^{**}$ (3.01)	
$(\text{Weight} \times \text{MCAP})_{j,t-1} \times \text{IO}_{i,j,t-1}$			$1.60^{***}$ (3.85)			$2.63^{**}$ (2.99)
$\operatorname{Indicator}_{j,t-1}$	1.19 (1.58)			$\begin{array}{c} 0.73 \\ (0.56) \end{array}$		
$\operatorname{Weight}_{j,t-1}$		$\begin{array}{c} 0.13 \\ (0.21) \end{array}$			$0.55 \\ (0.76)$	
(Weight $\times$ MCAP) <sub>j,t-1</sub>			0.14 (0.22)			0.47 (0.64)
$\mathrm{IO}_{i,j,t-1}$		$-2.60^{***}$ (-4.45)			$-4.20^{***}$ (-3.67)	
Proposal FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund Family $\times$ Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N D <sup>2</sup>	38,001	38,001	38,001	8,832	8,832	8,832
R <sup>2</sup>	0.55	0.55	0.55	0.58	0.58	0.58

#### Table 3: Firm-level relation with ESG- or climate-related shareholder proposals

This table reports results from regressions of the likelihood of a ESG- or climate-related proposal on firms' indirect exposure to disasters via common ownership as in Equation (8). The dependent variable is an indicator (in percentage points) for a ESG-related proposal in Columns (1)–(3), or a climate-related proposal in Columns (4)–(6). Firms' indirect exposure, using either VW(Indicator), VW(Weight), or VW(Weight × MCAP), is standardized by the full-sample standard deviation. These variables at time t - 1 are computed as the four-quarter moving average ending in the quarter before the fiscal year-end quarter. Standard errors are double clustered by firm and year. \*, \*\* and \*\*\* indicate statistical significance at the ten, five and one percent level, respectively.

	ESG-r	elated Proj	$\operatorname{posal}_{i,t}$	Climate	e-related Pr	$\operatorname{roposal}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$VW(Indicator)_{i,t-1}$	$0.38 \\ (0.93)$			$0.20^{*}$ (1.95)		
$VW(Weight)_{i,t-1}$		$0.32 \\ (0.86)$			$0.15^{**}$ (2.41)	
$VW(Weight \times MCAP)_{i,t-1}$			$\begin{array}{c} 0.33 \\ (0.89) \end{array}$			$0.15^{**}$ (2.36)
Disaster $\text{Exposure}_{i,t}$	0.77 (0.05)	-3.16 (-0.24)	-2.33 (-0.18)	$1.06 \\ (0.19)$	$0.89 \\ (0.21)$	0.86 (0.20)
$VW(Indicator)_{i,t-1} \times Disaster Exposure_{i,t}$	-2.50 (-0.37)			-0.21 (-0.08)		
$VW(Weight)_{i,t-1} \times Disaster Exposure_{i,t}$		-0.46 $(-0.08)$			-0.18 (-0.10)	
$VW(Weight \times MCAP)_{i,t-1} \times Disaster Exposure_{i,t}$			-0.98 (-0.17)			-0.16 $(-0.08)$
$Log(Assets)_{i,t-1}$	$2.56^{**}$ (2.83)	$2.56^{**}$ (2.84)	$2.56^{**}$ (2.84)	$0.09 \\ (0.60)$	$0.09 \\ (0.58)$	$0.09 \\ (0.57)$
$InstOwn_{i,t-1}$	-0.58 (-0.18)	-0.48 $(-0.15)$	-0.49 (-0.16)	$0.03 \\ (0.05)$	$0.09 \\ (0.17)$	$0.09 \\ (0.17)$
$\mathrm{NBlocks}_{i,t-1}$	-0.58 (-1.73)	-0.58 $(-1.73)$	-0.58 (-1.73)	-0.08 (-1.27)	-0.08 (-1.27)	-0.08 (-1.27)
Controls Firm FE State × Year FE Industry × Year FE	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes	Yes Yes Yes Yes
$\frac{N}{R^2}$	$     11,968 \\     0.61   $	11,968 0.61	$     11,968 \\     0.61   $	$     11,968 \\     0.65     $	11,968 0.65	11,968 0.65

in the quarter before the fiscal year-end quarter. Standard errors are do statistical significance at the ten, five and one percent level, respectively.	Ŭ	CC Sentiment <sub>et</sub>	**	00	CC Sentiment <sup>OP</sup>	OP	CC	$CC Sentiment_{BG}^{RG}$	$_{BG}^{RG}$	00	CC Sentiment $_{L}^{PH}$	He
$\overline{VW}(\operatorname{Indicator})_{i,t-1}$	$ \begin{array}{c} (1) \\ -0.43^{**} \\ (-2.23) \end{array} $	(2)	<i>u</i> (3)	(4) (-1.10)	(5)	it (6)	(7) $(-0.04^*$ (-2.02)	(8)	<sup>it</sup> (9)	$\begin{array}{c} (10) \\ -0.02^{*} \\ (-2.01) \end{array}$	(11)	t (12)
$\mathrm{VW}(\mathrm{Weight})_{i,t-1}$		$-0.35^{*}$ (-2.10)			-0.09 (-0.94)			-0.03 (-1.52)			$-0.02^{*}$ (-1.75)	
$\rm VW(Weight \times MCAP)_{i,t-1}$			$-0.36^{*}$ (-2.10)			-0.09 (-0.92)			-0.03 (-1.52)			$-0.02^{*}$ (-1.81)
Disaster Exposure, t	-2.28 (-0.50)	-1.90 (-0.61)	-1.86 (-0.59)	0.19 (0.07)	0.33 (0.16)	0.40 (0.20)	-0.54 (-0.99)	-0.25 (-0.45)	-0.22 (-0.41)	0.46 (1.15)	0.27 (0.87)	0.29 (0.90)
VW(Indicator)_{i,t-1} × Disaster Exposure <sub>i,t</sub>	-0.06 (-0.03)			-1.16 (-1.04)			-0.03 (-0.10)			-0.44 (-1.70)		
VW(Weight)_{i,t-1} × Disaster Exposure <sub>i,t</sub>		-0.40 (-0.28)			-1.32 (-1.63)			-0.24 (-0.90)			-0.32 (-1.48)	
VW (Weight $\times$ MCAP)_{i,i-1} $\times$ Disaster Exposure, i,t			-0.43 (-0.30)			-1.37 (-1.64)			-0.26 (-0.96)			-0.33 (-1.51)
$CC Exposure_{i,t}$	$0.28^{***}$ (12.67)	$0.28^{***}$ (12.67)	$0.28^{***}$ (12.67)	$0.13^{***}$ (7.50)	$0.13^{***}$ (7.50)	$0.13^{***}$ (7.50)	$0.01^{***}$ (4.40)	$0.01^{***}$ (4.40)	$0.01^{***}$ (4.40)	$0.001^{*}$ (2.04)	$0.001^{*}$ (2.04)	$0.001^{*}$ (2.04)
$\operatorname{Log}(\operatorname{Assets})_{i,i-1}$	$-0.48^{**}$ (-2.19)	$-0.48^{**}$ (-2.15)	$-0.48^{**}$ (-2.14)	-0.17 (-1.65)	-0.17 (-1.63)	-0.17 (-1.63)	-0.06 (-1.40)	-0.06 (-1.40)	-0.06 (-1.39)	-0.01 (-0.49)	-0.01 (-0.51)	-0.01 (-0.51)
$\operatorname{InstOwn}_{i,i-1}$	$0.54 \\ (0.54)$	0.38 (0.39)	0.38 (0.39)	$0.11 \\ (0.25)$	0.06 (0.14)	0.06 (0.14)	$0.35^{*}$ (2.11)	$0.33^{*}$ (2.06)	$0.33^{*}$ (2.06)	-0.08 (-1.05)	-0.09 (-1.13)	-0.09 (-1.12)
$\operatorname{NBlocks}_{i,t-1}$	-0.04 (-0.42)	-0.04 (-0.42)	-0.04 (-0.42)	-0.01 (-0.31)	-0.02 (-0.32)	-0.02 (-0.32)	-0.03 (-1.38)	-0.03 $(-1.39)$	-0.03 (-1.39)	0.002 (0.26)	$0.002 \\ (0.25)$	0.002 (0.25)
Firm FE State $\times$ Year FE Industry $\times$ Year FE N	Yes Yes Yes 16,031	Yes Yes Yes 16,031	Yes Yes Yes 16.031	Yes Yes Yes 16,031	Yes Yes Yes 16,031	Yes Yes Yes 16.031	Yes Yes Yes 16.031	Yes Yes Yes 16.031	Yes Yes Yes 16 031	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes 16.031

#### Table 5: Relation with ESG and emission scores

This table reports results from regressions of ESG related score change on firms' indirect exposure to disasters via common ownership as in Eq. (8). Panels A and B focuses on the indirect exposure constructed from climateand non-climate-related disasters, respectively. The dependent variable is the change in a firm's ESG score in Columns (1)–(3), and the change in a firm's emission score in Columns (4)–(6). Firms' indirect exposure, using either VW(Indicator), VW(Weight), or VW(Weight × MCAP), is standardized by the full-sample standard deviation. These variables at time t - 1 are computed as the four-quarter moving average ending in the quarter before the fiscal year-end quarter. Standard errors are double clustered by firm and year. \*, \*\* and \*\*\* indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: 0	Climate-rela	ted Disaste	ers			
	Δ	ESG Score	$\Theta_{i,t}$	$\Delta$ E	mission Sco	$\text{ore}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$VW(Indicator)_{i,t-1}$	$\begin{array}{c} 0.39^{***} \\ (3.17) \end{array}$			$0.73^{***}$ (3.36)		
$\mathrm{VW}(\mathrm{Weight})_{i,t-1}$		$0.23^{**}$ (2.43)			$0.53^{**}$ (2.39)	
$VW(Weight \times MCAP)_{i,t-1}$			$0.24^{**}$ (2.47)			$0.56^{**}$ (2.45)
Disaster $\text{Exposure}_{i,t}$	$15.58^{***}$ (3.64)	$\begin{array}{c} 14.25^{***} \\ (3.94) \end{array}$	$\begin{array}{c} 14.30^{***} \\ (3.89) \end{array}$	10.74 $(1.44)$	7.04 $(1.04)$	7.37 (1.08)
$VW(Indicator)_{i,t-1} \times Disaster Exposure_{i,t}$	-3.49 (-1.72)			$-8.96^{*}$ (-2.09)		
$VW(Weight)_{i,t-1} \times Disaster Exposure_{i,t}$		-3.03 (-1.74)			-6.66 $(-1.60)$	
$VW(Weight \times MCAP)_{i,t-1} \times Disaster Exposure_{i,t}$			-3.03 (-1.72)			-6.82 (-1.64)
$\log(Assets)_{i,t-1}$	$0.80^{***}$ (4.70)	$0.78^{***}$ (4.60)	$\begin{array}{c} 0.78^{***} \\ (4.60) \end{array}$	$1.60^{***}$ (4.54)	$\frac{1.59^{***}}{(4.47)}$	$1.58^{***}$ (4.46)
InstOwn <sub><i>i</i>,<i>t</i>-1</sub>	$0.36 \\ (0.43)$	$0.54 \\ (0.61)$	$0.54 \\ (0.61)$	$0.78 \\ (0.44)$	$1.01 \\ (0.55)$	$0.99 \\ (0.54)$
$\mathrm{NBlocks}_{i,t-1}$	$-0.09 \\ (-0.89)$	$-0.09 \\ (-0.91)$	$-0.09 \\ (-0.91)$	$-0.29^{**}$ (-2.34)	$-0.30^{**}$ (-2.34)	$-0.30^{**}$ (-2.34)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	$15,\!394$	$15,\!394$	$15,\!394$	$15,\!575$	$15,\!575$	$15,\!575$
$\mathbb{R}^2$	0.28	0.28	0.28	0.28	0.28	0.28

Panel B: No	on-climate-r	elated Disa	asters			
	Δ	Second ESG Score	$e_{i,t}$	$\Delta$ E	Emission Sc	$\operatorname{ore}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$VW(Indicator)_{i,t-1}$	-0.09 (-0.45)			-0.03 (-0.09)		
$\mathrm{VW}(\mathrm{Weight})_{i,t-1}$		-0.002 (-0.01)			$0.09 \\ (0.40)$	
$VW(Weight \times MCAP)_{i,t-1}$			-0.001 (-0.005)			$0.09 \\ (0.39)$
Disaster $\text{Exposure}_{i,t}$	$9.67^{**}$ (2.41)	$\frac{11.64^{**}}{(2.83)}$	$11.63^{**}$ (2.80)	-0.67 (-0.09)	-3.74 (-0.59)	-3.78 (-0.60)
$VW(Indicator)_{i,t-1} \times Disaster Exposure_{i,t}$	-1.81 (-0.66)			-5.53 (-1.25)		
$VW(Weight)_{i,t-1} \times Disaster Exposure_{i,t}$		$-4.28^{*}$ (-2.03)			-2.43 (-0.52)	
$VW(Weight \times MCAP)_{i,t-1} \times Disaster Exposure_{i,t}$			$-4.20^{*}$ (-1.98)			-2.36 (-0.51)
$\log(Assets)_{i,t-1}$	$0.71^{**}$ (2.70)	$0.71^{**}$ (2.67)	$0.71^{**}$ (2.67)	$1.27^{**}$ (2.54)	$1.28^{**}$ (2.53)	$1.28^{**}$ (2.53)
$InstOwn_{i,t-1}$	-0.15 (-0.15)	-0.23 (-0.22)	-0.22 (-0.22)	-0.11 (-0.05)	-0.28 (-0.12)	-0.28 (-0.12)
$\mathrm{NBlocks}_{i,t-1}$	-0.14 (-1.27)	-0.14 (-1.29)	-0.14 $(-1.29)$	$-0.38^{**}$ (-2.51)	$-0.38^{**}$ (-2.50)	$-0.38^{**}$ (-2.50)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11,042	11,042	11,042	11,025	11,025	11,025
<u>R<sup>2</sup></u>	0.31	0.31	0.31	0.29	0.29	0.29

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Table 6: Long-run impact on greenhouse gas emissions

This table reports results from regressions of the change in greenhouse gas emissions on firms' indirect exposure to disasters via common ownership. Greenhouse gas emissions in year t are measured in millions of metric tons of carbon dioxide equivalent (CO2). Firms' indirect exposure, using either VW(Indicator), VW(Weight), or VW(Weight × MCAP), is standardized by the full-sample standard deviation. These variables at time t - k for year lags,  $k \in 1, 2, 3$ , are computed as the four-quarter moving average ending in the fiscal year-end quarter of that year. Standard errors are double clustered by firm and year. \*, \*\* and \*\*\* indicate statistical significance at the ten, five and one percent level, respectively.

	Ĺ	A MTCO2e	it
	(1)	(2)	(3)
$VW(Indicator)_{i,t-1}$	-0.13 (-0.41)		
$VW(Indicator)_{i,t-2}$	-0.07 (-0.31)		
$VW(Indicator)_{i,t-3}$	$-0.63^{**}$ (-2.44)		
$VW(Weight)_{i,t-1}$		-0.18 (-0.69)	
$VW(Weight)_{i,t-2}$		0.04 (0.12)	
$VW(Weight)_{i,t-3}$		$-0.49^{**}$ (-2.36)	
$VW(Weight \times MCAP)_{i,t-1}$			-0.18 (-0.67)
$VW(Weight \times MCAP)_{i,t-2}$			0.03 (0.11)
$VW(Weight \times MCAP)_{i,t-3}$			$-0.49^{**}$ (-2.34)
Disaster $\text{Exposure}_{i,t}$	-9.10 (-1.13)	-7.45 (-1.48)	-7.47 (-1.49)
Controls Firm FE State $\times$ Year FE Industry $\times$ Year FE N	Yes Yes Yes 1,711	Yes Yes Yes 1,711	Yes Yes Yes 1 711
$\frac{1}{R^2}$	$1,711 \\ 0.43$	$1,711 \\ 0.43$	$1,711 \\ 0.43$

#### Table 7: Long-run impact on EPA violations

This table reports results from regressions of EPA violations on firms' indirect exposure to disasters via common ownership. The dependent variable in year t is an indicator equal to 1 if an EPA violations occurs in a firm-year and 0 otherwise. Firms' indirect exposure, using either VW(Indicator), VW(Weight), or VW(Weight × MCAP), is standardized by the full-sample standard deviation. These variables at time t - k for year lags,  $k \in 1, 2, 3$ , are computed as the four-quarter moving average ending in the fiscal year-end quarter of that year. Standard errors are double clustered by firm and year. \*, \*\* and \*\*\* indicate statistical significance at the ten, five and one percent level, respectively.

	EI	PA Violation	$\mathbf{n}_{i,t}$
	(1)	(2)	(3)
$\overline{\text{VW}(\text{Indicator})_{i,t-1}}$	$0.87^{**}$ (2.51)		
$VW(Indicator)_{i,t-2}$	$-1.32^{***}$ (-5.19)		
$VW(Indicator)_{i,t-3}$	$\begin{array}{c} 0.35 \\ (0.95) \end{array}$		
$VW(Weight)_{i,t-1}$		0.41 (1.09)	
$\mathrm{VW}(\mathrm{Weight})_{i,t-2}$		$-1.23^{***}$ (-5.31)	
$VW(Weight)_{i,t-3}$		$0.25 \\ (0.76)$	
$VW(Weight \times MCAP)_{i,t-1}$			0.45 (1.24)
$VW(Weight \times MCAP)_{i,t-2}$			$-1.25^{***}$ (-5.35)
$VW(Weight \times MCAP)_{i,t-3}$			$0.27 \\ (0.79)$
Disaster $\operatorname{Exposure}_{i,t}$	-15.93 (-0.90)	-10.17 (-0.69)	-10.92 (-0.75)
Controls Firm FE State $\times$ Year FE Industry $\times$ Year FE N $\mathbb{R}^2$	Yes Yes Yes 14,665 0.70	Yes Yes Yes 14,665 0.70	Yes Yes Yes 14,665 0.70

#### Table 8: Long-run impact on firms' valuations

This table reports results from regressions of firms' financial outcomes on firms' indirect exposure to disasters via common ownership. The dependent variable in year t is annual returns and Tobins' Q. Firms' indirect exposure, using either VW(Indicator), VW(Weight), or VW(Weight × MCAP), is standardized by the full-sample standard deviation. These variables at time t - k for year lags,  $k \in 1, 2, 3$ , are computed as the four-quarter moving average ending in the fiscal year-end quarter of that year. Standard errors are double clustered by firm and year. \*, \*\* and \*\*\* indicate statistical significance at the ten, five and one percent level, respectively.

	An	nual Retur	$\mathbf{n}_{i,t}$		Tobin's $\mathbf{Q}_{i,i}$	t
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{VW}(\text{Indicator})_{i,t-1}}$	-0.01 (-0.90)			0.03 (1.57)		
$VW(Indicator)_{i,t-2}$	$\begin{array}{c} 0.01 \\ (1.30) \end{array}$			$0.02 \\ (1.08)$		
$VW(Indicator)_{i,t-3}$	-0.01 (-1.49)			$-0.04^{**}$ $(-2.28)$		
$\mathrm{VW}(\mathrm{Weight})_{i,t-1}$		-0.01 (-0.95)			$0.02 \\ (0.97)$	
$VW(Weight)_{i,t-2}$		0.01 (1.48)			$0.02 \\ (1.26)$	
$\mathrm{VW}(\mathrm{Weight})_{i,t-3}$		$-0.01^{*}$ (-1.95)			$-0.03^{*}$ $(-1.92)$	
$VW(Weight \times MCAP)_{i,t-1}$			-0.01 (-1.09)			0.02 (1.00)
$VW(Weight \times MCAP)_{i,t-2}$			$0.01 \\ (1.54)$			0.02 (1.26)
$VW(Weight \times MCAP)_{i,t-3}1$			$-0.01^{*}$ $(-1.91)$			$-0.04^{*}$ $(-1.91)$
Disaster $\operatorname{Exposure}_{i,t}$	0.04 (0.16)	-0.09 (-0.38)	-0.08 (-0.35)	0.71 (0.78)	$0.30 \\ (0.43)$	0.31 (0.45)
Controls Firm FE State $\times$ Year FE Industry $\times$ Year FE N	Yes Yes Yes 16,875	Yes Yes Yes 16,875	Yes Yes Yes 16,875	Yes Yes Yes 16,801	Yes Yes Yes 16,801	Yes Yes Yes 16,801
$\underline{\mathbf{R}^2}$	0.52	0.52	0.52	0.76	0.76	0.76

## Appendix for

# "Propagation of climate disasters through ownership networks and its impact on corporate ESG policies "

Firm Variables	
$VW(Indicator \mid S)_{i,t}$	See, Eq.(4). When $S$ is all institutional investors in our main tests, we omit the notation conditioning on $S$ .
$VW(Weight \mid S)_{i,t}$	See, Eq.(5). When $S$ is all institutional investors in our main tests, we omit the notation conditioning on $S$ .
$VW(Weight \times MCAP \mid S)_{i,t}$	See, Eq.(6). When $S$ is all institutional investors in our main tests, we omit the notation conditioning on $S$ .
Disaster $\text{Exposure}_{i,t}$	This is the proportion from 0 to 1 of firm <i>i</i> 's foot- prints that suffer disaster hit(s) in year <i>t</i> , computed from averages of quarterly operations-weighted exposure to disasters. Disaster exposures are decomposed to be climate- and non-climate related ( <i>Disaster_exposure</i> <sup>C</sup> <sub><i>i</i>,<i>t</i></sub> and <i>Disaster_exposure</i> <sup>NC</sup> <sub><i>i</i>,<i>t</i></sub> , respectively). Climate- related disasters include flooding, hurricanes, wild fires, coastal-related, and storms. Non-climate related include earthquakes, tornadoes, and winter weather.
ESG Score <sub><math>i,t</math></sub>	The ESG score for firm $i$ in year $t$ . For year $t$ , we assume that a score is updated in the first quarter after the fiscal year end of a firm.
Emission $Score_{i,t}$	The ESG score for firm $i$ in year $t$ . For year $t$ , we assume that a score is updated in the first quarter after the fiscal year end of a firm.
$MTCO2e_{i,t}$	The firm-level greenhouse gas emission measured in mil- lions of metric tons of carbon dioxide equivalent (CO2).
EPA Violation <sub><math>i,t</math></sub>	An indicator equal to 1 for if a firm-year has an EPA violation, and 0 otherwise.
Annual $\operatorname{Returns}_{i,t}$	Yearly returns computed from the exponential of the sum of log gross monthly returns minus one.
Tobin's $Q_{i,t}$	Market value of equity (csho times prcc_f) plus the book value of preferred stock (pstkl, then pstkrv, then upstk), short term and long term debt (dltt+dlc) minus deferred taxes and investment tax credits (txditc) all over total assets (at), computed from Compustat.
$Assets_{i,t}$	Annual total assets (at) from Compustat. We winsorize at the $1\%$ tail each year in the full Compustat panel.

# A.1 Variable Definitions

$\mathrm{InstOwn}_{i,t}$	The yearly average of quarterly percentage institutional ownership from the WRDS 13F database.
$\mathrm{NBlocks}_{i,t}$	The yearly average of the number of 5% blockholders from the WRDS 13F database.
$\operatorname{CC} \operatorname{Exposure}_{i,t}$	The firm-level climate change measure extracted from conference call transcripts by Sautner et al. (Forthcoming).
$\operatorname{CC} \operatorname{Sentiment}_{i,t}$	The firm-level climate change sentiment extracted from conference call transcripts by Sautner et al. (Forthcom- ing). We also use the variations of this measure related to climate change opportunity (OP), regulation (RG), and physical "shocks" (PH).
$\mathrm{MCAP}_{i,t}$	The quarter-end market capitalization of the firm com- pustated as price times shares outstanding from CRSP.
$\mathrm{State}_{i,t}$	The state where the headquarter of the firm from Com- pustat.
$\operatorname{Industry}_{i,t}$	The 2 digit standard industry classification (SIC2) of the firm from Compustat.

## Institutional Investor/Fund-Family Variables

$\text{Indicator}_{j,t} \mid S$	See, Eq.(1). When $j \in S$ is all institutional investors in our main tests, we omit the notation of conditioning on $C$
Weight <sub><i>j</i>,<i>t</i></sub>   $S$	S. See, Eq.(2). When $j \in S$ is all institutional investors in our main tests, we omit the notation of conditioning on S.
$(\text{Weight} \times \text{MCAP})_{j,t} \mid S$	See, Eq.(3). When $j \in S$ is all institutional investors in our main tests, we omit the notation of conditioning on $S$ .
$\mathrm{IO}_{i,j,t}$	The quarterly institutional ownership computed as shares owned by institutional investor $j$ in firm $i$ divided by total shares outstanding. Shares are from the Refini- tiv 13F database and shares outstanding is from CRSP.
Vote for $\operatorname{Proposal}_{i,j,k,t}$	The percentage vote by a fund family $j$ for firm $i$ 's share- holder proposal $k$ . This voting outcome is as of the shareholder meeting in year $t$ . Because mutual funds comprising the fund family may vote differently, the re- sulting measure ranges from 0 to 100. The vast ma- jority of mutual funds vote the same way for the same fund family. We use keywords to classify proposals into climate-related and other ESG-related shareholder pro- posals. Voting records are from N-PX data.