Social Interactions and Managerial Attention to Climate Change Exposure

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December 3, 2023

[Job Market Paper]

Abstract

What makes a firm concern more about climate change than others? This paper examines the effect of social interactions on the amount of attention devoted to climate change exposure by firm management. I show that climate change topics are more discussed during earnings calls when local stakeholders have geographically distant friends who are exposed to disaster events. The exogenous shocks to far-away friends should not affect local firms except through a social channel. I provide evidence that the effect leads to a real outcome, a reduction in greenhouse gas emissions. My results imply that organizational efforts to heighten climate risk awareness can enhance corporate sustainable behaviors through a social network.

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1 Introduction

Over the past decade, the increasing toll of climate change has gained substantial attention from policymakers, the general public, investors, and businesses[1]. In response, firms have been reacting to rapidly evolving climate change exposures such as regulatory risk, physical risk, and new opportunities[2]. One factor that may play an important role in determining how firms respond to the climate change exposure is the allocation of managerial attention (Dessein and Santos (2021)). In other words, how managers perceive and pay attention to climate change may affect their responses. In this paper, I examine the role of social interactions as a determinant of firm-level attention to climate change exposure and find that it is essential in explaining firm responses and real outcomes such as reduction in greenhouse gas emissions.

Recent theoretical and empirical studies highlight the influence of social interactions on economic decisions (Hirshleifer (2020); Shiller (2017)). Building upon those studies, I explore how managerial attention changes in response to the shocks from climatic events transmitted through social interactions. The previous literature suggests different reasons behind companies incorporating sustainability factors into their corporate management. One prevailing explanation posits that such integration enhances profitability and firm value, often referred to as the "doing well by doing good" relationship[3]. Other studies consider the opposite perspective, that is, "doing good by doing well", by examining whether only well-performing firms can afford to invest in environmental, social, and governance (ESG) practices (Hong et al. (2012)). However, neither of the arguments alone may fully explain

[1]On November 16, 2022, the New York Times reported that, from 2011 to the end of 2021, 90 percent of US counties experienced floods, hurricanes, wildfires, or other significant calamities resulting in federal disaster declarations. More than 700 counties faced five or more such disasters during this period. For more details, see https://www.nytimes.com/2022/11/16/climate/climate-change-county-natural-disaster.html

[2]For instance, Governance & Accountability Institute reports that 96% of S&P 500 companies published sustainability reports in 2021 compared with 20% in 2011. For more details, see https://www.ga-institute.com/research/ga-research-directory/sustainability-reporting-trends/2022-sustainability-reporting-in-focus.html

[3]Albuquerque et al. (2019); Chava (2014); Deng et al. (2013); Dimson et al. (2015); Dowell et al. (2000); Flammer (2015); Konar and Cohen (2001); Krüger (2015); Lins et al. (2017); Orlitzky et al. (2003)

the variation observed across firms in their involvement with environmental, social, and governance (ESG) issues. Why do some companies engage more in ESG, whereas others do so to a lesser extent? Several studies in the literature have suggested that cross-country differences, such as economic development, culture, institutions (Cai et al. (2016)), legal origin (Liang and Renneboog (2017)), leadership characteristics (Cronqvist and Yu (2017); Di Giuli and Kostovetsky (2014)), and pressures from institutional investors (Chen et al. (2020); Dimson et al. (2015); Dyck et al. (2019)) serve as determinants of firms' engagement in ESG practices. My paper suggests social interactions as another determinant that can help explain this variation in firm practices regarding climate change exposure.

Identifying the causal effect of social interactions on firms' attention to climate change exposures faces several challenges. First, climate change exposures of firms are simultaneously affected by numerous factors such as regulation, opportunity, physical risk, financial conditions, and industry norms. Consequently, disentangling the effect of social interactions from these confounding factors is a complex task. Additionally, local stakeholders of the firms are endogenous and susceptible to the same common shocks as the firms (Manski (1993)). For example, the variation in the local economy can induce changes in the attention given to climate change exposure by both firms (Hong et al. (2012)) and the local stakeholders (Kahn and Kotchen (2010)). Establishing a clear causal relationship between social interactions and firms' attention to climate change exposures is challenging due to these interconnected complexities.

To overcome such concerns, I employ an identification strategy that utilizes the county-pairwise social network structure based on Facebook users and exploits disaster declarations as exogenous shocks experienced by friends within the network. Previous studies empirically document that friends' experiences are transmitted through social interactions and affect individuals' financial decisions. For instance, Bailey et al. (2018b) find that individuals are more inclined to transition from renting to owning homes when their distant friends experience significant increases in housing prices. Similarly, Hu (2022) shows that flood experiences among remote friends increase the uptake rates of flood insurance. Motivated by these findings, I use social network data to capture the transmission of distant shocks through social interactions and examine its effect on the level of managerial attention devoted to climate change exposure. Specifically, I utilize the county-pairwise Social Connectedness Index (Bailey et al. (2018a)), which is constructed based on anonymized information regarding friendship links between Facebook users. Given Facebook's extensive reach and pervasive presence in the market, this measure provides a realistic representation of the real-world social network in the United States.

To identify the causal impact of social interactions on firms' attention to climate change, my strategy leverages non-local disaster events as exogenous shocks to friends in distant locations. Declared disasters by nature are unlikely to be associated with other determinants of firms' climate change exposures due to their quasi-random nature. Using disaster declarations as exogenous shocks, I examine how the level of attention toward climate change exposure changes among firms located in geographically distant areas. Specifically, within each remote state, I compare the post-disaster change of firms located in counties that are more connected to the disaster area to that of firms in less connected counties. For example, for a disaster declared in Florida, I examine the firms in geographically distant states, such as Illinois. Within Illinois, I compare the changes in the attention of firms in counties that are more connected with Florida to those of firms in counties that are less connected with Florida, before and after the disaster strike in Florida. I preclude the direct influence of the disaster by only considering distant friendships in the network, isolating the effect of social interactions.

For the measurement of the attention level toward climate change exposure, I employ the climate change exposure measure from Sautner et al. (2020). This measure calculates the frequency of climate change-related bigrams within the transcripts of earnings calls and scales it by the total number of bigrams. I use this climate change exposure measure over other databases that provide ESG (Environmental, Social, and Governance) and CSR (Corporate Social Responsibility) scores for several reasons. First, the measure directly captures the revealed attention given to climate change-related topics, offering a more intuitive interpretation of the results. Second, it enables the timely assessment of changes in attention following a shock since it is derived from regular earnings calls without any delay. Third, it is worth noting that a change in attention toward climate change exposure may not always translate into specific ESG-related actions. Instead, it can manifest in various outcomes such as increased cash holdings (Heo (2021)) and lower leverage (Ginglinger and Moreau (2022)), which are not fully captured by conventional ESG scores.

Using a stacked difference-in-difference framework (Baker et al. (2022)) around declared disasters between 2010 and 2021, I find that firms located in counties that are more socially connected to the disaster area experience a significant increase in their attention towards climate change exposure compared to their counterparts in less connected counties within the same state. I also find that the magnitude of the effect varies across different specific topics covered by the climate change attention measure. The attention given to opportunity-related topics increases by 2.93%, while the attention on regulatory-related topics increases by 10.19%. On the other hand, the effect on attention toward physical risk is relatively small in both statistical significance and magnitude. Next, I find that this effect on attention is sharpest up to four quarters after the disaster before gradually reverting over subsequent quarters. I also show that there are no differential pre-disaster trends between more and less connected firms. Furthermore, I suggest additional evidence that is consistent with the idea that social interactions influence managerial attention to climate change exposure. First, I find that the effect is monotonic in the degree of social connection by using a sharper comparison between the top versus bottom quartile. Second, firm responses are more pronounced on average when they have high existing climate change exposure. I find stronger effects in the industries with high average climate change exposures.

I examine and address concerns about potential non-causal alternative interpretations for my findings. The empirical design of this paper rules out several potential non-causal alternative explanations. First, one can be concerned about the possibility of common shocks among counties. However, it is highly improbable that Illinois counties that are more closely connected to Florida would simultaneously experience a climatic event alongside Florida, while Illinois counties with weaker connections to Florida remain unaffected. Next, the research design rules out any potential influence from the local economy or local media because I am exclusively comparing counties within the same state, which is located far away from any area impacted by a disaster.

Another alternative interpretation is that social network data may reflect economic associations between counties and that firms are responding to the risk of climatic disasters. This explanation requires that economic links, such as supply chain relationships, between two locations are sufficiently reflected in social connection data. However, the survey evidence by Hampton et al. (2011) that only 10% of Facebook friendships are with co-workers, making it highly unlikely that the Facebook-based social connection measure sufficiently captures distant work-related connections. Additionally, I conduct an additional test on heterogeneous effects that align more consistently with the hypothesis that managerial attention on climate change exposure is attributable to social interactions rather than economic associations with the disaster area. Using the locations where firm managers received their education, I identify firms with more direct social connections to disaster areas. I show that, among firms in more connected counties, firms with managers who received their education in the state of the disaster strike respond stronger than their counterparts.

One potential concern with my empirical design is that some firms can be involved as either the treatment or control group in multiple events, leading to duplicate observations if the event windows overlap. I first address the issue of non-independent observations by clustering standard errors at the county level in all relevant regressions. Next, I address the concern by repeating the baseline test on a subsample of firm-quarter observations that belong exclusively to either the treatment or control group (without being in a treatment group for one event and a control group for another event). Last, I employ an alternative approach that uses the average disaster experience of each county within its social networks each period. This alternative approach results in only one observation per firm per time. In all cases, I find my findings to be consistent, suggesting that the observed effect is not confined to a particular empirical design. Furthermore, I perform robustness tests using different distance limits between disasters and firms, different regression models, and a placebo test. In these tests, I show that the results are consistent with my previous findings, implying that the findings are robust to alternative specifications and models.

I investigate whether increased attention to climate change exposure translates into any real effect. Using greenhouse gas emission data, I show that firms located in counties that are more socially connected to disaster areas tend to reduce their emissions more on average in the years following disasters. Moreover, I examine the specific categories or scopes of emissions to understand how social interactions affect firms' emission reduction efforts. The findings indicate that overall reduction is driven by both Scope 1 and Scope 2 emissions. Scope 1 emissions are direct emissions from operations owned or controlled by the reporting firm, while Scope 2 emissions are indirect emissions associated with the generation of purchased energy. However, the effect on the reduction of indirect emissions is much more significant, which is often an easier option for firms. Specifically, there is a significant reduction of up to 5.65% in Scope 2 emissions during post-disaster periods. These results support the hypothesis that social interactions are one of the driving factors behind firms' efforts to actively mitigate their environmental impact.

This study makes a contribution to the field of social finance, which investigates the role of social networks in shaping economic and financial decision-making. Previous studies, such as Bailey et al. (2018b) and Allen et al. (2022), have demonstrated how social networks impact individuals' investment decisions in housing and consumer loans, respectively. Furthermore, Kuchler et al. (2022) has shown the influence of social networks on institutional investors, indicating that stronger social ties to specific regions lead to increased investments in firms from those regions, resulting in higher liquidity and valuations. To the best of my knowledge, this research provides the first empirical evidence highlighting the influence of social networks on firms' attention to their climate change exposure.

This study also contributes to the literature on the determinants of ESG engagement. This research introduces social interactions as an additional determinant that not only encourages firms to pay more attention to climate change exposures but also drives them to make sustainable investments. By building upon previous research on the factors influencing corporate policies regarding climate change exposure, this study expands our understanding of the various drivers behind firms' engagement in climate-related issues. In addition, this study has extensive implications for organizations that promote the implementation of sustainable practices among firms. My results imply that organizational efforts to heighten climate risk awareness can enhance corporate sustainable behaviors through a social network.

2 Data

2.1 Social Connectedness Index

I capture the social network among counties using the Social Connectedness Index (SCI)[4] developed by Bailey et al. (2018a). Social Connectedness Index (SCI) uses aggregated de-identified snapshot of Facebook users and their friendship networks as of October 2021 to measure the level of social connectedness between locations. Bailey et al. (2018) calculate the Social Connectedness Index (SCI) between two counties using the number of Facebook friendship links between individuals in the two counties divided by the product of the number of Facebook users in the two counties. The resulting numbers are scaled to have a maximum value of 1,000,000,000 and a minimum value of 1. Consequently, the Social Connectedness Index for a given pair of counties measures the relative probability of a Facebook friendship link between a given Facebook user in one county and another user in another county.

[4] The data is publicly available from https://dataforgood.facebook.com/dfg/tools/social-connectedness-index.

The validity and applicability of the Social Connectedness Index (SCI) as a representation of real-world U.S. social networks have been established in prior research (Bailey et al. (2018b), Bailey et al. (2019), Bailey et al. (2022), Allen et al. (2022), Kuchler et al. (2022), Hu (2022)). It is arguably a realistic representation of real-world social networks in the United States because of Facebook's extensive user base, with 234 million active users in the United States and Canada. Furthermore, survey evidence indicates that individuals primarily utilize Facebook to interact with their existing social circles, reflecting the integration of the platform into real-world social interactions (Hampton et al. (2011), Jones et al. (2013)). Considering these factors, the SCI offers a reliable and robust measure of social networks, enhancing the validity and applicability of its use in this study.

2.2 Attention to Climate Change Exposure

I use the climate change exposure measure constructed by Sautner et al. (2020) to capture the firm-level attention devoted to climate change exposure. Building on recent work that uses quarterly earnings calls as a source to identify firms' risks and opportunities (Hassan et al. (2019, 2022, 2021a,b); Jamilov et al. (2021)), Sautner et al. (2020) use the proportion of earnings calls that pertain to climate change topics to capture the firm's attention devoted to climate change exposures at a given point in time. More specifically, the measure counts the frequency of climate change related bigrams in the transcript, scaled by the total number of bigrams in the transcript. Four related sets of climate change bigrams are constructed using the method that adapts the keyword discovery algorithm proposed in King et al. (2017). The first captures broadly defined aspects of climate change. The remaining three measures cover specific climate change topics: opportunities (e.g., renewable energy, new energy), physical shocks (e.g., sea level rise), and regulatory shocks (e.g., carbon taxes, cap and trade markets). Table A1 provides examples of bigrams used to measure the attention to general climate change topics.

Panel A of Table 1 presents firm-quarter level summary statistics for the attention measures. For the purpose of exposition, the measures are multiplied by 1,000. The measures for the attention to climate change exposure have a large mass of values at 0 since firms discuss climate-related topics during their earnings call only when they are relevant to their current business conditions. To account for such distributional characteristics, I show that my results are robust in the estimations using Poisson regressions and negative binomial regressions, which provide unbiased estimates for non-negative dependent variables with high dispersion.

2.3 Declared Disasters

I obtain data about disasters from the official FEMA Disaster Declaration database, which is raw data from FEMA's National Emergency Management Information System (NEMIS). The database provides unique disaster ID numbers, declaration dates, incident start and end dates, FIPS codes for declared states and counties, and incident types. I focus on the disasters with incident types that are commonly perceived to be related to climate change: coastal storms, fires, floods, hurricanes, Severe Storms, and Tsunamis. This leaves 1,338 declared disasters in my sample, with each declaration typically affecting multiple counties. Figure 2 presents the frequency of such declarations per county, with darker shades of blue indicating higher frequency. The heat map highlights that the declarations were not concentrated in specific areas, but rather spread out with some variations.

2.4 Other Data

I complete the sample using data from multiple sources. Financial data for firms are obtained from Compustat. Institutional ownership data is from Thomson Reuter 13F data and SEC 13F filings. Firm locations are identified using Augmented 10-X header data[5] from the University of Notre Dame. I obtain greenhouse gas emission data from Refinitiv Asset4 dataset and managers' education information from Boardex.

[5]https://sraf.nd.edu/data/augmented-10-x-header-data/

3 Identification Strategy

In this section, I outline the empirical strategy used to assess the effect of social interactions on managerial attention toward climate change exposure. My empirical design leverages exogenous shocks that occur in distant locations, which should influence attention levels primarily through peer effects with friends affected by the shock. Using those distant shocks, I employ a difference-in-difference approach to address concerns about common shocks. Specifically, I compare firms within the same state but located considerably far from the shock. This strategy enables me to isolate the causal impact of social interactions on firms' attention while controlling for potential confounding factors that may affect firms in the same state.

Non-local disaster events, as random shocks to geographically distant regions, should be orthogonal to the climate change exposure of firms. Thus, any change, stemming from those events, in the attention level devoted to climate change topics by management should reflect the aggregation of peer effects across individuals surrounding the firms. Specifically, for a given disaster d, I first identify the set of counties $\{a\}_d$ affected by the disaster d, and the set of counties $\{b\}_d$ in geographically distant states that are at least 750 miles away from the disaster d. Since disasters often affect multiple counties, I calculate the county b 's social connection to the disaster-affected area $\{a\}_d$ using the population- or equal-weighted average of the county-by-county SCI measure, which reflects the relative probability of friendship links between counties. Then, within each state, I define the treatment (control) group as the counties with the above (below) state-median social connection to the disaster area. Figure 1 illustrates an example of social connections in the context of one specific disaster, Hurricane Hermine, that impacted parts of Florida in September 2016. The figure shows a heat map indicating the levels of social connections (depicted in shades of blue) across the affected region (depicted in shades of brown). Counties within a 750-mile distance threshold are uncolored as they are excluded from the analysis pertaining to this specific disaster.

I employ a stacked difference-in-difference design (Baker et al. (2022)) by stacking individual event studies for every disaster event d and clustering the standard errors at the county level. Each event study is structured using the following difference-in-difference regression:

$$Y_{i,t} = \beta_0 + \beta_1 Connect_i + \beta_2 Post_t + \beta_3 Connect_i \times Post_t + X_{i,t} + \epsilon_{i,t} \tag{1}$$

where $Connect_i$ is an indicator variable for firm i located in the county b that has above state-median social connection to disaster area $\{a\}_d$. $Post_t$ is an indicator variable that equals 1 if quarter t is within subsequent k quarters after the disaster d. The outcome variable $Y_{i,t}$ measures the frequency of the specified climate change related bigrams in an earnings call transcript of firm i in quarter t. Control variables $X_{i,t}$ include $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. The interaction term $Connect_i \times Post_t$ is the key variable of interest which captures the effect of social interactions on the management's attention devoted to climate change exposure.

This empirical design leverages distant shocks that mainly propagate through social networks, thereby mitigating the endogeneity issue associated with common shocks that simultaneously affect both firms and local stakeholders. Moreover, I conduct comparisons among firms within the same state by defining treated and controlled firms conditional on being in the same state. Consequently, the firms in comparison are subjected to comparable climate and economic conditions. While variations in climate conditions within a state are plausible, the difference-in-difference framework effectively isolates the fixed disparities.

4 Empirical Results

In this section, I test the hypothesis that management devotes more attention to climate change related topics due to social interactions around the firm. I present the results of my empirical analysis, which exploit non-local disasters that occur to geographically distant friends. I also provide additional tests that exploit heterogeneity in the effect on attention.

4.1 Main Result

Applying the empirical design outlined in Section 3, I examine the change in the attention toward climate change among firms located within the same state but in the counties with different levels of social connection to a geographically distant disaster-affected area. Specifically, I define firms located in the counties with above state-median social connection to the disaster area as the treated firms.

Table 2 reports the coefficient estimates of regression 1. Under the hypothesis that social interactions affect firm management's attention toward climate change exposure, I expect a positive and significant coefficient on the interaction term $Connect_i \times Post_t$. In column 1 of Panel A, the estimate of 0.0282 represents a 2.54 percent increase over the average attention measure (1.11) at event time zero. This suggests that firm management devotes more attention to general climate change related topics when its local stakeholders have geographically distant friends who experience a disaster. Columns 2, 3, and 4 focus on the effect on the attention toward more specific topics: opportunity (OP), regulatory (RG), and physical risk (PH). Positively significant coefficients imply that the effect remains significant even when we limit our focus to each specific topic. The attention devoted to opportunity (column 2) and regulatory (column 3) topics also increases when distant friends of the local stakeholders experience a disaster. However, the coefficient on the key interaction term for physical risk (column 4) has a smaller magnitude with weaker statistical significance. This is consistent with the expectation because an exogenous shock transmitted from geographically distant areas is less likely to affect the attention on physical risk, which is closely related to the location of firms' assets. These results remain robust even when $Connect_i$ is defined using equal-weighted social connections to the disaster area in columns 5 through 8.

In Panel B, C, and D of Table 2, I check the persistence of the effect by examining extended time horizons after each disaster. According to the limited attention literature, it is expected that the initial surge in topical attention will gradually wane over time. Given the emergence of other pressing issues in subsequent quarters, it is difficult to sustain the same level of attention dedicated to climate change exposure. Panel B and C examine the effect on 6 and 8 subsequent quarters, respectively. The results still show positive and significant estimates but with monotonically decreasing magnitudes. In Panel D, I compare all post-disaster quarters to pre-disaster quarters. In this case, I find no significance in the estimates, which implies that the level of attention devoted to climate change topics reverts back to the long-run average in several years.

I show such dynamic effects through a more formal test. In Figure 3, I plot the coefficients on the interaction terms in the following equation:

$$Y_{i,t} = \beta_0 + \beta_1 Connect_i + \sum_k \beta_2^k \mathbf{1}(t = t^* + k) + \sum_k \beta_3^k Connect_i \times \mathbf{1}(t = t^* + k) + X_{i,t} + \epsilon_{i,t} \quad (2)$$

where t^* is the quarter when disaster d occurs. The coefficients are measured relative to the coefficient at $k = -1$. The dependent variable $Y_{i,t}$ measures the level of attention devoted to general climate change exposures (CC). First, I find the result that is consistent with the identifying assumption that there is no evidence of differential pre-trend. Prior to the event, the effect is not statistically different from zero, implying that the managerial attention of firms in the more and less connected counties has, on average, evolved in parallel. Second, the figure shows that the increased attention progressively reverts to the long-run average level. For instance, the magnitude of the effect peaks in the fourth quarter after a disaster, with a coefficient value of 0.034 on the corresponding interaction term. A coefficient decreases to statistically insignificant -.0002 in the eighth quarter, indicating that the effect of social interactions on managerial attention on climate change exposure diminishes as time passes.

4.2 Heterogeneous Effects

4.2.1 Social Connections

My identification strategy is based on the assumption that social connection levels capture the varying degrees of social interactions. Hence, the effect of social interactions is expected to be monotonic to the strength of the social connection. Management in most (least) connected counties should show the largest (smallest) increase in attention toward climate change exposure.

To test this heterogeneous effect in social connections, I use sharper definitions for the treatment and control group than those used in the baseline analysis. In Panel A of Table 3, I compare the top versus bottom quartiles of social connection within the same state. The estimate in column 1 is approximately 45% larger in raw magnitude than the baseline results. The estimate of 0.0411 is a 3.81-percent increase over the mean attention measure (1.077) at event time zero. Even when the analysis focuses on specific topical attentions in columns 2 and 3, the estimates are similarly larger in magnitude than the baseline results. I do not find a stronger effect on the attention towards physical risk, which should be less subject to the effect of geographically distant shocks.

4.2.2 Industries with High Climate Change Exposures

My hypothesis also implies that the effect of social interactions would be stronger on the firms with high existing climate change exposure than those without much exposure to pay attention to. That is, firms with interests at stake should be those more affected by social influences. In Panel B of Table 3, I use the subsample that only includes the top 10 SIC2 industries[6] based on the average climate change exposure measures. Across all dependent variables, I find the coefficient on the key interaction term to be much larger in magnitude than those from the baseline results in Table 2. For example, the coefficient on the key interaction term in column 1 is 0.0958, which is more than three times greater than the magnitude of the analogous baseline estimate. Consistent with previous results, the effect on the attention towards physical risk remains insignificant.

[6] Electric, Gas, & Sanitary Services, Heavy Construction, Construction, Transportation Equipment, Electronic & Other Electric Equipment, Coal Mining, Petroleum Refining, Local & Suburban Transit, Automative Dealers & Service Stations, Primary Metal

5 Alternative Interpretations

In this section, I examine possible alternative interpretations of the results and provide further evidence to rule out such explanations. First, several features of the empirical design used in this study make the influence of any common shocks among firms or counties highly unlikely to be the cause of the effect: 1) disasters used in the study are exogenous due to their quasi-random nature, 2) I only focus on disasters experienced by geographically distant friends, which are unlikely to be simultaneous with other local shocks in a systematic way, 3) the difference-in-difference framework that makes comparison within the same state further mitigates the concern about common shocks because possible common components, such as the local economy, are extracted out of the analysis. In order for the findings to be caused by common shocks, local counties that are more closely connected to a disaster area need to simultaneously experience a climatic event with the disaster area, while other local counties in the same state but with weaker connections to the disaster area remain unaffected. In addition, the difference-in-difference framework accounts for any inherent fixed differences (e.g., political inclinations) between counties in the same state.

5.1 Economic Association

Another alternative interpretation is that economic associations between areas make firms respond to climatic disasters. That is, firms pay more attention to their climate change exposure because the disaster-affected area is economically related to their business. First, this explanation requires social connections measured using Facebook data to capture economic links between counties. The survey evidence by Hampton et al. (2011) suggests that only 10% of Facebook friendships are with co-workers, making it highly unlikely that the Facebook-based social connection measure sufficiently captures distant work-related relationships. Therefore, it is unlikely that treatment and control groups defined using social connections measures are systematically associated with the economic links with disaster-affected areas. In addition, I conduct a test controlling for absolute values of cumulative abnormal returns after each disaster. Firms may be directly exposed to disasters through economic channels either because they have facilities or operations in the disaster area or because their suppliers or customers do. If such economic influences exist in the sample, they would be captured by abnormal returns after disaster occurrences in either positive or negative directions. In Panel A of Table 4, I show the estimates of the baseline regression 1 with the absolute value of the firm's abnormal returns around the disaster as an additional control variable. I calculate the abnormal returns following the procedure in Campbell et al. (1998). Cumulative abnormal returns are calculated using the market model $CAR[0,10]_i = \sum_{t=10}^{10} AR_{i,t}$ where $AR_{i,t} = R_{i,t} - [\hat{\alpha}_i + \hat{\beta}_i R_{m,t}]$. The parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$ are estimated from the equation $R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t}$ on a pre-event period of 250 trading days ending 30 days prior to event date.

Across all dependent variables, I find the effect to be robust to this additional control for economic channel. The coefficients on the key interaction term are not only positive and significant, but also greater in magnitude compared to the baseline result, supporting the hypothesis that the effect is arising from social channel, but not from the economic associations with the disaster area.

5.2 Information Gap

Another possible alternative interpretation is the information gaps between urban and rural areas. Urban areas generally have greater probability of having higher social centrality. If urban areas have easier access to more climate change information including disaster news, one may posit that the increase in managerial attention to climate change exposure is stemming from this information gap. To account for this information channel, I run the baseline test using the subsample with only the firms located in the Metropolitan Statistical Areas (MSAs)[7]. By defining the treatment and control groups only using the MSA subsample, I

[7]MSA is a geographic entity based on a county or a group of counties with at least one urbanized area with a population of at least 50,000 and adjacent counties with economic ties to the central area.

limit the analysis to only the urban areas.

Panel B of Table 4 reports the estimates from this MSAs subsample analysis. I find the effect to be robust in the subsample across all dependent variables. The magnitude and statistical significance of the key interaction term is also qualitatively similar to the baseline results, implying that the effect is not stemming from the information gap between urban and rural areas. This result also further addresses any concern about fixed differences between counties such as different political inclination within the same state, especially between urban and rural areas.

5.2.1 Education Location of Managers

To support the argument that the effect primarily results from social interactions rather than other firm-level economic relationships or information gaps, I examine the magnitude of the effect on firms where one or more chief officers (CEO, CFO, or COO) have a direct social relationship with the disaster-affected area. Specifically, I assume that firms whose chief officers received their undergraduate or graduate education in the state that was struck by the disaster have stronger social connections with the disaster-affected area. The underlying assumption is that a manager's educational experience would capture the social interactions that are less likely related to firm-level economic associations. If the increase in managerial attention on climate change exposure is a result of social interactions, the magnitude of the effect is expected to be greater in firms with managers with such social connections.

In Panel A of Table 5, I split the sample into firms with and without managers who have social connections to the disaster area through their educational experiences to compare the magnitude of the effect. I repeat the baseline regression on each subsample and find that the effect is indeed stronger in the subsample with only the firms whose managers have direct social connections to the disaster-affected area. For example, the coefficient estimate in column 2 is more than two-fold greater in magnitude than the estimate in column 1.

To formally test whether the increase in the managerial attention on climate change exposure is different for firms with versus without managers who have direct social connections to the disaster area, I perform the following triple difference regression:

$$\begin{aligned} Y_{i,t} =& \beta_0 + \beta_1 Connect_i + \beta_2 Post_t + \beta_3 Connect_i \times Post_t \\ &+ \beta_4 Connect_i \times Post_t \times Education_i + \beta_5 Connect_i^d \times Education_i \\ &+ \beta_6 Education_i \times Post_t + \beta_7 Education_i + X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $Education_i$ is an indicator variable that equals 1 if firm i has one or more chief officers who received their education in the state of disaster strike. As per the baseline regression 1, $Connect_i$ is an indicator variable for firm i located in the county b that has an above state-median social connection to $\{a\}_d$ and $Post_t$ is an indicator variable that equals 1 if quarter t is within subsequent 4 quarters after the disaster d. The outcome variable $Y_{i,t}$ measures the attention toward general climate change exposure (CC) of firm i in quarter t. The key variable of interest for this test is the triple interaction term $Connect_i \times Post_t \times Education_i$, which captures the incremental effect of social interactions when a firm's manager has a personal social connection to the disaster area. Panel B of Table 5 reports the coefficient estimates from the regression 3. In column 3, the coefficient estimate on the key interaction term is positive and significant, implying that direct social connection results in a stronger effect on managerial attention toward climate change exposure. In column 4, the finding remains consistently positive and significant when I use a negative binomial regression model. Overall, both the survey evidence and the regression results align consistently with the hypothesis that social interactions influence firm-level attention toward climate change exposure.

6 Alternative Methodology

In this section, I address a possible concern in my empirical design that associates social connections with attention to climate change by showing that my findings are robust to alternative specifications and empirical approaches. My empirical strategy employs a difference-in-difference framework that allows straightforward comparison between firms in more versus less connected counties without an endogeneity concern. On the other hand, stacked event studies imply that some firms can be involved in more than one event as either treated or controlled if the event windows overlap. In other words, there is a unique observation per firm per quarter per event, instead of a unique observation per firm per quarter.

To address the issue of non-independent observations, I first cluster the standard errors at the county level in all relevant regressions. Next, I address the concern by repeating the baseline test on the subsample with observations that are exclusively in the treatment or control group at a firm-date level. This subsample analysis precludes any possible bias from the observations that are in the treatment group for one event and in the control group for another event. I also focus on the event window between 4 quarters before and after each disaster to further mitigate any possible bias from the heterogeneous treatment effect. In Table 6, the coefficient estimates for the interaction term are positive and significant across all dependent variables, implying that the findings are not driven by such duplicating observations.

Furthermore, I employ an alternative empirical approach that is free from similar concerns. I construct a new variable $NetworkDisaster^N_{a,t_1,t_2}$ that measures the average disaster experience of county a's social network N between time t_1 and t_2. With the social network N being county a's network that only includes geographically distant counties, I define $\theta^N_{a,b}$ to be the share of county a's friends in network N who lives in county b and $Disaster_{b,t_1,t_2}$ to be the number of declared disasters in county b between t_1 and t_2. Then, I construct the key variable as:

$$NetworkDisaster^N_{a,t_1,t_2} = \sum_b \theta^N_{a,b} \times Disaster_{b,t_1,t_2} \tag{4}$$

With the key variable reflecting the weighted experience surrounding each firm in a social network, I estimate the following regression to capture the average effect of geographically distant friends' experience on the attention paid to climate change exposure:

$$Y_{i,t} = \beta_0 + \beta_1 NetworkDisaster^N_{a,t-4,t} + X_{i,t} + FE_{state\times time} + FE_{industry} + \epsilon_{i,t} \tag{5}$$

This regression model ensures that each firm has only one observation per time period, thereby eliminating any concern regarding duplicate observations. I isolate the effect of the disaster experience of friends in the network in the same state at the same time by controlling for the state-by-time fixed effects. In addition, I tease out any fixed difference across industries, such as exposure to regulations (e.g. carbon tax) and business opportunities (e.g. renewable energy), using industry fixed effects. Table 7 shows results from regression 5. The coefficients on the key variable $NetworkDisaster^N_{a,t-4,t}$ are positive and significant across all dependent variables. The relative order of magnitudes among estimates also follows the pattern from baseline results with column 1 being the largest and column 4 being the smallest. Overall, it is evident that the findings are robust to multiple approaches to mitigate the possible concern about the empirical design.

6.1 Robustness Test

As reported in Table 1, the measures for the attention to climate change exposure have a large mass of values at 0 since firms discuss climate-related topics during their earnings call only when they are relevant to their current business conditions. One might be concerned that these distributional characteristics may cause bias in the results. To account for these distributional characteristics of outcome variables, I estimate using a Poisson regression model, which provides unbiased estimates for non-negative dependent variables, and a negative binomial regression model, which is similar to the Poisson model but further accounts for excess variance.

The estimated results are reported in columns 1 through 4 of Table 8. In Panel A, consistent with the baseline result in Table 2, the coefficients on the key variable $Connect_i \times$

$Post_t$ estimated using a Poisson regression are positive and significant across all dependent variables. The magnitudes of effect on the attention to opportunity- and regulatory-related topics in columns 2 and 3, respectively, are significantly greater than the baseline results.[8] In Panel B, I find the estimated results using negative binomial regressions to be similar to those in Panel A. These robustness tests support that the baseline results do not stem from the distributional characteristics of variables but from the effect of social interactions.

In Table 9, I also show that my results are robust to a variety of distance limits between firms and a disaster. I vary my distance limit between a firm and a disaster from 750 miles to 250, 500, and 1000 miles to be included in the sample. Across all dependent variables, I find that estimates are robust to these alternative specifications and similar to my main findings presented in Table 2.

6.2 Falsification Test

I conduct a falsification test using the same baseline specification but with different dependent variables. I use the firm-level political risk measures constructed by Hassan et al. (2019) as the dependent variables in Table 10. Hassan et al. (2019) also use the frequency of bigrams in earnings calls to construct the measures. Therefore, the firm-level political risk measures are similar in nature to the attention toward climate change exposure measures used in this paper. Similar to the baseline result, the estimates reported in columns 1, 2, and 3 of Table 10 would capture the effect of social interactions on the attention toward political risk, non-political risk, and overall risk, respectively. They are insignificant across all dependent variables, implying that exogenous climatic disaster shocks transmitted through social interactions only affect the attention on climate change exposure, but not the attention on less-related topics.

I conduct another falsification test using the same baseline specification but with disaster

[8] In a Poisson model with a regression coefficient β, the magnitude of effect from a unit change in the independent variable is calculated as $e^{\beta}-1$. This effect size represents the percentage change in the dependent variable.

shocks that are not related to the climate change. Earthquakes are common and costly disaster in the U.S., but not generally not perceived as climate change related disaster because of its nature. Therefore, if the increase in managerial attention to climate change exposure is arising from the social interactions regarding climatic disasters, we do not expect to see similar effect when the shocks are less relevant to the climate change. Table 11 reports the estimates from this falsification test using the earthquakes as exogenous shocks. Consistent with the expectation, I do not find any significant effect on managerial attention to climate change exposures in this case. This result implies that the baseline results are indeed arising from the social interaction channels.

7 Do Social Interactions Result in Real Effect?

My hypothesis and regressions examine the effect of social interactions on managerial attention paid to climate change exposures. Since the attention level is measured using the discussion during the earnings calls, it is worth examining whether this increased attention leads to any real effect. Specifically, I investigate whether the effect of social interactions also leads to a reduction in greenhouse gas emissions.

I first examine if the effect of social interactions reduces aggregate greenhouse gas emissions scaled by revenue. Then, I use the greenhouse gas emission data that decomposes the total emission into three different categories: Scope 1, Scope 2, and Scope 3 emission. Scope 1 emissions are direct emissions from sources owned or controlled by the firm, such as those associated with fuel combustions in boilers, furnaces, vehicles, and so on. Scope 2 emissions are indirect emissions that stem from the purchase of electricity, steam, heat, or cooling. Scope 3 emissions are all other indirect emissions by suppliers and customers.

I estimate the following regression, which is slightly modified from the specification of regression 1 to conduct a real effect test:

$$Y_{i,t} = \beta_0 + \beta_1 Connect_i + \beta_2 Post_t + \beta_3 Connect_i \times Post_t + X_{i,t} + \epsilon_{i,t} \tag{6}$$

where all explanatory variables are defined the same as in regression 1. The outcome variables $Y_{i,t}$ measure the CO2/Revenue, Scope 1, 2, and 3 emissions of firm i in year t. I use annual-level observations since corporate greenhouse gas emission data is only available annually.

Table 12 reports the estimates of Regression 6. In column 1 of Panel A, I find a significant and negative estimate for the key interaction variable $Connect_i \times Post_t$, implying that firms reduce their aggregate emissions after their distant counties experience disaster events. In Panel B and C, I find that the effect is persistent for two and three years after disasters. The estimate of -16.83 is a 3.72-percent decrease over the mean overall emission level (452.85) at event time zero.

To understand how firms reduce their emissions – either directly or indirectly, I estimate the same regression using emissions of different scopes in columns 2, 3, and 4. I find that overall reduction is driven both by the change in Scope 1 and 2 emissions. In column 2 of Panel B and C, the estimate is significantly negative, implying a reduction in direct emissions. The estimate of -112,604.7 is a 2.62-percent decrease over the mean Scope 1 emission level (4,294,036) at event time zero. The magnitude of the effect is even larger for the reduction in Scope 2 emission. In column (3) of all three panels, I find a significant reduction of Scope 2 emissions that stems from the effect of social interactions. The estimate of -44134.1 is a 5.65-percent decrease over the mean Scope 2 emission level (781,600) at event time zero. For most companies, Scope 2 emissions can be one of the easier options to reduce emissions since the reduction can be done by simply finding more sustainable suppliers or renewable sources. Hence, the estimated result is within the boundary of our expectations.

I do not find a significant reduction in Scope 3 emissions. This is consistent with our expectation since Scope 3 emissions cover the emissions produced by customers using the company's products or those produced by suppliers making products that the company uses. In other words, Scope 3 emissions are under the control of suppliers or customers, so they are affected by decisions made outside of the company. Taken together, I find that the effect of social interactions on the attention toward climate change exposure leads to the real effect of reduction in greenhouse gas emissions.

8 Conclusion

This paper investigates the influence of a social channel on managerial attention towards climate change exposure. To measure the attention devoted to climate change exposure, I employ a measure that counts the frequency of climate change related bigrams in quarterly earnings calls (Sautner et al. (2020)), which provides an intuitive assessment of managerial attention. By leveraging declared disasters as quasi-random shocks to geographically distant friends and utilizing the Social Connectedness Index to capture the social network that can transmit these shocks, I identify the causal effect of social interactions on firms' attention to climate change exposure. The findings indicate that the level of attention towards climate change exposure increases by two to ten percent after their geographically distant but socially connected areas experience a disaster event. These findings have implications for organizations that promote the implementation of sustainable practices among firms and provide a rationale for ongoing efforts to raise awareness about climate change among stakeholders.

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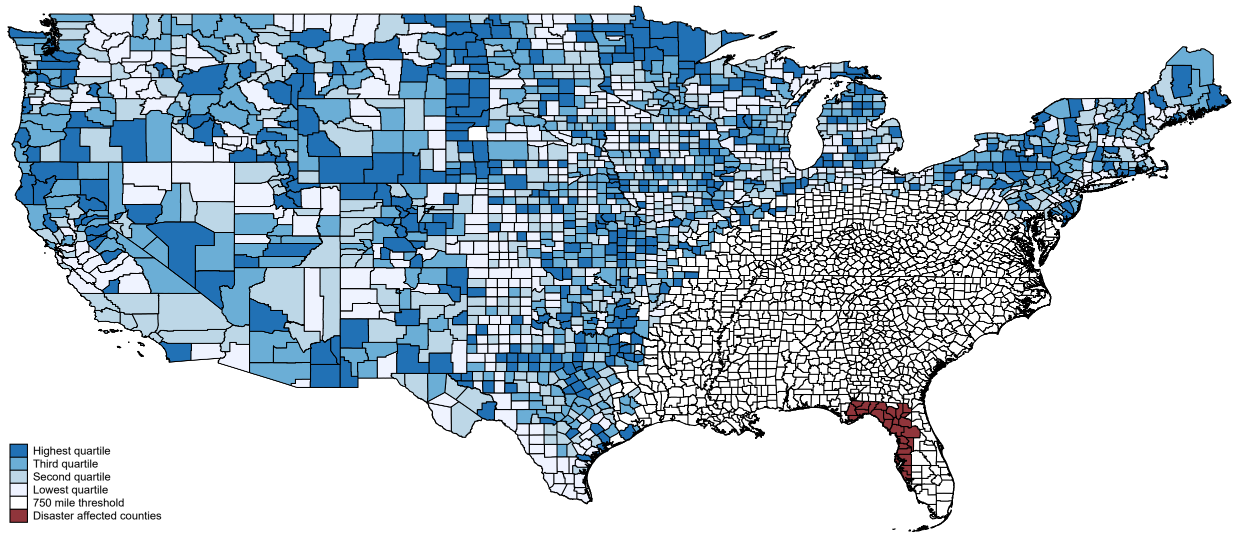

Figure 1: This figure provides an illustrative example that demonstrates the data and empirical design, focusing on a specific disaster: Hurricane Hermine in September 2016. The affected counties are colored brown, while the blue shades represent the heat map of social connectedness with the impacted area. Only counties located at least 750 miles away from the disaster affected area are colored in this figure and included in the analysis.

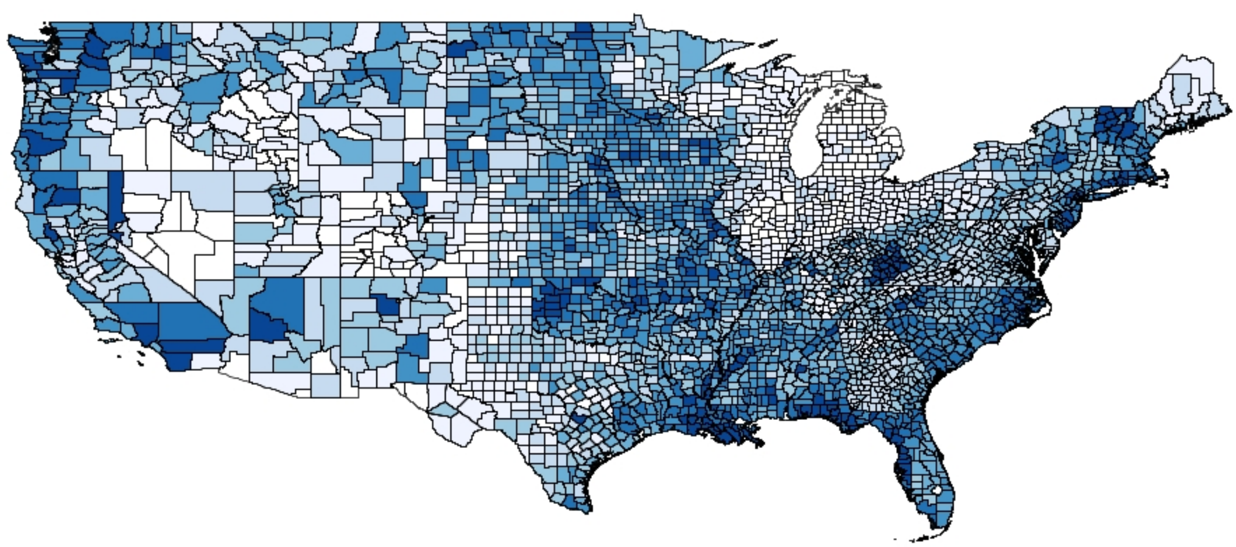

Figure 2: This figure displays the frequency of disaster declarations per county from 2010 to 2021. The heat map uses blue shades with darker colors indicating higher frequency.

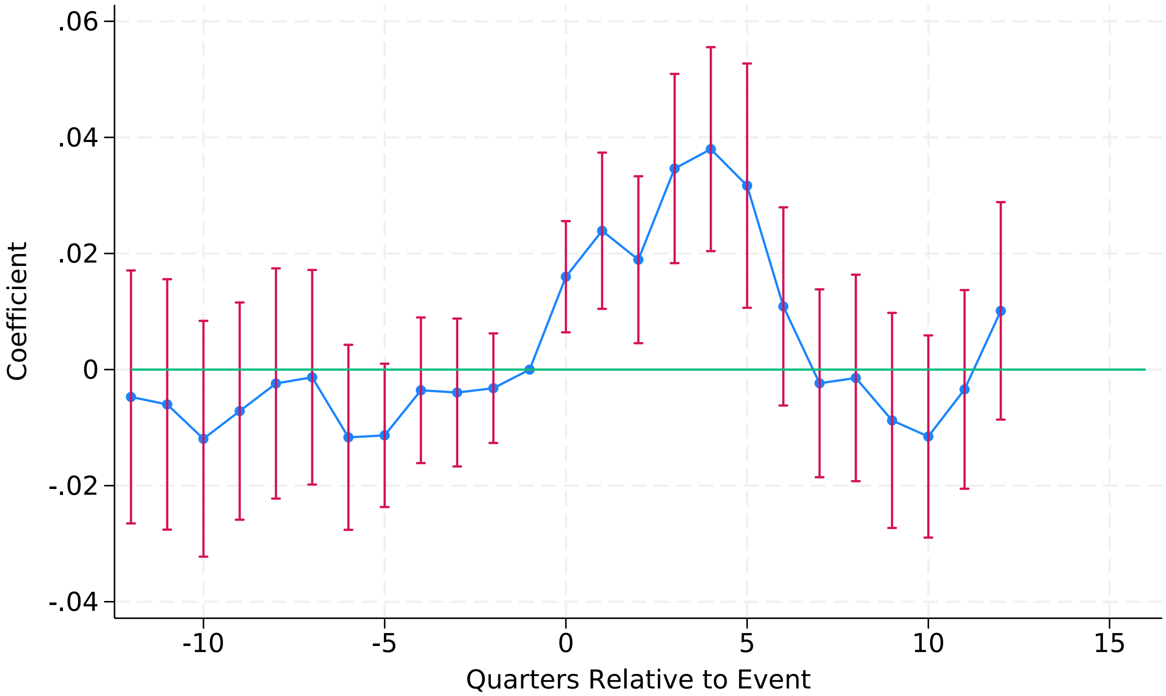

Figure 3: This figure shows the dynamic effects of social interactions on the attention towards climate change exposures. It plots the coefficient estimates of $\{\beta_3^k\}$ from the following regression: $Y_{i,t} = \beta_0 + \beta_1 Connect_i + \sum_k \beta_2^k \mathbf{1}(t = t^* + k) + \sum_k \beta_3^k Connect_i \times \mathbf{1}(t = t^* + k) + X_{i,t} + \epsilon_{i,t}$ for firm i, year-quarter t, and disaster d. $\{\beta_3^k\}$ are measured relative to $\beta_3^{k=-1}$ which is omitted. For a given disaster d and the affected counties $\{a\}^d$, social connectedness of county b to $\{a\}^d$ is measured using the population weighted average of the social connectedness index between county b and $\{a\}^d$, where social connectedness index is the relative probability of Facebook relationship on county pair level obtained from Bailey et al. (2018b). t^* is the quarter when disaster d occurs. The sample is only comprised of the firms located in the counties that are at least 750 miles apart from the disaster d. $Connect_i^d$ is an indicator variable for firm i located in the county b that has above state-median social connectedness to $\{a\}^d$. The dependent variable $Y_{i,t}^d$ measures the level of attention devoted to general climate change exposures (CC). The sample period is between January 2010 and December 2021. Control variables $X_{i,t}$ include $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

Table 1: Summary Statistics

This table reports firm-quarter level summary statistics for key variables in my sample from January 2010 and December 2021. Panel A shows the level of attention devoted to different types of climate change exposures: general climate change (CC), opportunity (OP), regulatory (RG), and physical risk (PH). Panel B reports the summary statistics for the control variables.

	N	Mean	SD	25th	Median	75th
Panel A: Attention to Climate Change Exposure						
CC	111405	1.0985	2.9598	0.0000	0.2963	0.8453
OP	111405	0.4390	1.5754	0.0000	0.0000	0.2999
RG	111405	0.0635	0.3665	0.0000	0.0000	0.0000
PH	111405	0.0125	0.1237	0.0000	0.0000	0.0000
Panel B: Controls						
Log(Asset)	111405	7.2005	2.0424	5.7797	7.1975	8.5426
Debt/Asset	111405	0.2497	0.2524	0.0499	0.2052	0.3743
Cash/Asset	111405	0.2042	0.2262	0.0400	0.1161	0.2854
PPE/Asset	111405	0.2181	0.2347	0.0444	0.1251	0.3126
CAPEX/Asset	111405	0.0403	0.0544	0.0098	0.0239	0.0497
EBIT/Asset	111405	0.0136	0.2598	0.0080	0.0556	0.1051
R&D/Asset	111405	0.0546	0.1475	0.0000	0.0000	0.0546
Institutional Ownership	111405	1.5735	56.6137	0.3727	0.5354	0.7567

Table 2: Distant Disasters and Attention to Climate Change Exposure

This table shows results from the stacked difference-in-difference regression using the model: $Y_{i,t} = \beta_0 + \beta_1 Connect_i + \beta_2 Post_t + \beta_3 Connect_i \times Post_t + X_{i,t} + \epsilon_{i,t}$ for firm i, year-quarter t, and disaster d. For a given disaster d and the affected counties $\{a\}^d$, the social connection of county b to $\{a\}^d$ is measured using the population or equal-weighted average of the social connectedness index between county b and $\{a\}^d$, where social connectedness index is the relative probability of Facebook relationship on county pair level obtained from Bailey et al. (2018b). The sample is only comprised of the firms located in the counties that are at least 750 miles apart from the disaster d. $Connect_i$ is an indicator variable for firm i located in the county b that has above state-median social connection to $\{a\}^d$. $Post_t$ is an indicator variable that equals 1 if quarter t is within subsequent k quarters after the disaster d. Panel A, B, C, and D show the results with k = 4, 6, 8, and all post-disaster quarters, respectively. The dependent variable $Y_{i,t}$ measures the level of attention devoted to climate change exposures. Different dependent variables $Y_{i,t}$ are used based on the types of climate change exposures discussed during the earnings call: general climate change (CC), opportunity (OP), regulatory (RG), and physical risk (PH). The sample period is between January 2010 and December 2021. Control variables $X_{i,t}$ include $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	(1) CC	(2) OP	(3) RG	(4) PH	(5) CC	(6) OP	(7) RG	(8) PH
Panel A: $k = 4$ quarters								
Connect X Post	0.0282***	0.0131***	0.00648***	0.000295*	0.0279***	0.0136***	0.00626***	0.000329**
	(4.97)	(4.04)	(6.82)	(1.93)	(4.76)	(4.05)	(6.10)	(2.14)
Connect	-0.0302	-0.0228	-0.00115	0.000508	-0.0174	-0.0160	-0.00151	0.000686
	(-0.79)	(-1.11)	(-0.49)	(0.69)	(-0.41)	(-0.71)	(-0.60)	(0.88)
Post	-0.00172	0.000704	-0.000428	-0.000132	0.000329	0.00142	0.0000981	-0.000133
	(-0.46)	(0.34)	(-0.88)	(-1.13)	(0.10)	(0.74)	(0.21)	(-1.11)
R-squared	0.0753	0.0458	0.0457	0.00217	0.0753	0.0458	0.0457	0.00217

Table 2 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CC	OP	RG	PH	CC	OP	RG	PH
Panel B: $k = 6$ quarters								
Connect X Post	0.0254***	0.0120***	0.00596***	0.000171	0.0271***	0.0132***	0.00613***	0.000213*
	(4.55)	(4.00)	(6.48)	(1.38)	(4.63)	(4.20)	(5.98)	(1.69)
Connect	-0.0306	-0.0230	-0.00124	0.000509	-0.0179	-0.0163	-0.00163	0.000686
	(-0.80)	(-1.12)	(-0.54)	(0.69)	(-0.43)	(-0.73)	(-0.65)	(0.88)
Post	-0.00399	-0.000439	-0.000824*	-0.000169	-0.00299	-0.0000928	-0.000515	-0.000180
	(-1.12)	(-0.22)	(-1.76)	(-1.50)	(-0.90)	(-0.05)	(-1.11)	(-1.57)
R-squared	0.0753	0.0458	0.0457	0.00217	0.0753	0.0458	0.0457	0.00217
Panel C: $k = 8$ quarters								
Connect X Post	0.0204***	0.00946***	0.00493***	0.0000120	0.0217***	0.0102***	0.00509***	0.0000278
	(4.03)	(3.47)	(6.04)	(0.08)	(3.96)	(3.53)	(5.63)	(0.20)
Connect	-0.0307	-0.0231	-0.00128	0.000519	-0.0180	-0.0163	-0.00167	0.000697
	(-0.81)	(-1.12)	(-0.55)	(0.70)	(-0.43)	(-0.73)	(-0.66)	(0.90)
Post	-0.00803**	-0.00269	-0.00155***	-0.000138	-0.00714**	-0.00229	-0.00131***	-0.000147
	(-2.38)	(-1.36)	(-3.54)	(-1.23)	(-2.28)	(-1.27)	(-2.99)	(-1.36)
R-squared	0.0753	0.0458	0.0457	0.00217	0.0753	0.0458	0.0457	0.00217

Table 2 (Continued)

	(1) CC	(2) OP	(3) RG	(4) PH	(5) CC	(6) OP	(7) RG	(8) PH
Panel D: $k = T - t$ (all subsequent) quarters								
Connect X Post	-0.00150	0.00659	0.00132	-0.000225	0.000128	0.00839	0.000968	-0.000317
	(-0.13)	(0.91)	(0.90)	(-0.80)	(0.01)	(1.08)	(0.61)	(-1.09)
Connect	-0.0280	-0.0271	-0.00185	0.000685	-0.0159	-0.0214	-0.00187	0.000934
	(-0.69)	(-1.24)	(-0.75)	(1.02)	(-0.37)	(-0.92)	(-0.72)	(1.28)
Post	0.0558***	0.0284***	0.0119***	0.000397	0.0548***	0.0278***	0.0121***	0.000432
	(3.17)	(3.01)	(4.51)	(0.90)	(3.18)	(3.02)	(4.54)	(0.96)
R-squared	0.0753	0.0459	0.0459	0.00217	0.0753	0.0459	0.0459	0.00217
Observations	184,791,625	184,791,625	184,791,625	184,791,625	184,791,625	184,791,625	184,791,625	184,791,625
County clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Connect weight	PW	PW	PW	PW	EW	EW	EW	EW

Table 3: Heterogeneous Effect

This table shows estimates from the regression model $Y_{i,t} = \beta_0 + \beta_1 Connect_i + \beta_2 Post_t + \beta_3 Connect_i \times Post_t + X_{i,t} + \epsilon_{i,t}$ with subsample or specific changes in specification from the baseline analysis. In Panel A, $Connect_i$ is an indicator variable that equals 1 for firm i located in the county that has a social connection to the disaster-affected counties $\{a\}^d$ in the top quartile and equals 0 for firm i located in the county that has a social connection to $\{a\}^d$ in the bottom quartile. In Panel B, only the top 10 industries based on the average climate change exposure measure are included in the subsample. For all panels, $Post_t$ is an indicator variable for the following 4 quarters from the disaster d. All other variables are defined as per the description in Table 2. The sample period is between January 2010 and December 2021. Control variables include $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	(1) CC	(2) OP	(3) RG	(4) PH
Panel A: Top against Bottom Quartiles				
Connect X Post	0.0411***	0.0226***	0.00794***	0.000228
	(5.49)	(4.80)	(6.33)	(1.04)
Connect	-0.0384	-0.0310	-0.000861	0.00133
	(-0.67)	(-1.01)	(-0.24)	(1.19)
Post	-0.00670*	-0.00308	-0.000990*	-0.0000313
	(-1.72)	(-1.15)	(-1.91)	(-0.19)
R-squared	.0739	.0459	.0417	.00181
Observations	105,306,853	105,306,853	105,306,853	105,306,853
Panel B: High Climate Change Exposure Industries				
Connect X Post	0.0958***	0.0487***	0.0196***	0.000558
	(4.10)	(3.16)	(5.26)	(1.24)
Connect	0.0952	0.0317	0.00801	-0.00189
	(0.67)	(0.37)	(0.80)	(-1.19)
Post	-0.00796	0.0000827	-0.00109	-0.000136
	(-0.52)	(0.01)	(-0.68)	(-0.40)
R-squared	.172	.104	.102	.0139
Observations	31,554,494	31,554,494	31,554,494	31,554,494
County clustered SE	Yes	Yes	Yes	Yes
Connect weight	PW	PW	PW	PW

Table 4: Tests on Alternative Interpretations

This table shows estimates from the regression model $Y_{i,t} = \beta_0 + \beta_1 Connect_i + \beta_2 Post_t + \beta_3 Connect_i \times Post_t + X_{i,t} + \epsilon_{i,t}$ controlling for the absolute value of abnormal returns or using a subsample with only MSAs. In Panel A, I additionally control for the absolute value of cumulative abnormal returns after each disaster. Following the procedure in Campbell et al. (1998), cumulative abnormal returns are calculated using the market model $CAR[0,10]_i = \sum_{t=10}^{10} AR_{i,t}$ where $AR_{i,t} = R_{i,t} - [\hat{\alpha}_i + \hat{\beta}_i R_{m,t}]$. The parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$ are estimated from the equation $R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t}$ on a pre-event period of 250 trading days ending 30 days prior to event date. In Panel B, only the firms located in the Metropolitan Statistical Areas (MSAs) are included in the subsample. For all panels, $Post_t$ is an indicator variable for the following 4 quarters from the disaster d. All other variables are defined as per the description in Table 2. The sample period is between January 2010 and December 2021. Control variables include $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	(1) CC	(2) OP	(3) RG	(4) PH
Panel A: Controlling for Cumulative Abnormal Returns				
Connect X Post	0.0327***	0.0166***	0.00710***	0.000482***
	(5.75)	(4.96)	(6.99)	(2.72)
Connect	-0.0318	-0.0244	-0.00157	0.000389
	(-0.82)	(-1.16)	(-0.65)	(0.49)
Post	0.000925	0.000813	0.000230	-0.000189
	(0.25)	(0.41)	(0.52)	(-1.44)
R-squared	.0746	.0455	.0453	.00214
Observations	184,791,625	184,791,625	184,791,625	184,791,625
Panel B: Subsample with only MSAs				
Connect X Post	0.0208***	0.0105***	0.00479***	0.000148
	(4.00)	(3.39)	(6.10)	(0.86)
Connect	0.00545	-0.00214	-0.000220	0.000408
	(0.13)	(-0.09)	(-0.09)	(0.50)
Post	0.00392	0.00258	0.000612	-0.0000837
	(1.09)	(1.31)	(0.99)	(-0.66)
R-squared	.0774	.046	.0468	.00219
Observations	176,514,119	176,514,119	176,514,119	176,514,119

Table 5: Triple Difference Test using Education Location

This table shows estimates from regressions using the location of chief officers' education. Columns 1 and 2 report the coefficient estimates from the regression model $Y_{i,t} = \beta_0 + \beta_1 Connect_i + \beta_2 Post_t + \beta_3 Connect_i \times Post_t + X_{i,t} + \epsilon_{i,t}$ on the subsample of firms with or without chief officers who received their education in the state of disaster strike. Columns 3 and 4 report the coefficient estimates from the triple difference regression model $Y_{i,t} = \beta_0 + \beta_1 Connect_i + \beta_2 Post_t + \beta_3 Connect_i \times Post_t + \beta_4 Connect_i \times Post_t \times Education_i + \beta_5 Connect_i \times Education_i + \beta_6 Education_i \times Post_t + \beta_7 Education_i + X_{i,t} + \epsilon_{i,t}$, where $Education_i$ is an indicator variable that equals 1 if firm i has a chief officer who received their education in the state of disaster strike. As per Table 2, $Connect_i$ is an indicator variable that equals 1 for firm i located in the county that has an above state-median social connection to the disaster-affected counties, and $Post_t$ is an indicator variable for the following 4 quarters from the disaster d. The sample period is between January 2010 and December 2021. All regressions include control variables $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	A. With vs. Without Education Link		B. Triple Difference	
	(1) Without Link	(2) With Link	(3)	(4)
Connect X Post	0.0239***	0.0624***	0.0239***	0.0202***
	(4.13)	(2.94)	(4.13)	(3.96)
Connect	-0.0228	-0.121	-0.0230	-0.0144
	(-0.57)	(-1.31)	(-0.57)	(-0.49)
Post	0.00311	-0.0166	0.00313	0.00233
	(0.80)	(-0.87)	(0.81)	(0.68)
Connect X Post X Education			0.0382**	0.0412**
			(2.02)	(2.39)
Connect X Education			-0.0980	-0.104*
			(-1.12)	(-1.70)
Education X Post			-0.0194	-0.0165
			(-0.98)	(-1.00)
Education			0.0906	0.114*
			(0.96)	(1.78)
Model	OLS	OLS	OLS	Neg Binomial
ln(Alpha)				0.655***
R-sq. / pseudo R-sq.	.0719	.0832	.0724	0.044
Observations	177,033,937	7,757,688	184,791,625	184,791,625
County Clustered SE	Yes	Yes	Yes	Yes
Connect Weight	PW	PW	PW	PW
Post Period Length	4Q	4Q	4Q	4Q

Table 6: Clean Treatment versus Clean Control

This table reports estimates from the regression model in Table 2 on the subsample with observations that are exclusively in the treatment or control group at a firm-date level. The regressions focus on the event window between 4 quarters before and after each disaster. All variables are defined as per in Table 2. The sample period is between January 2010 and December 2021. Control variables $X_{i,t}$ include $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	(1) CC	(2) OP	(3) RG	(4) PH
Connect x Post	0.0668***	0.0104***	0.00660***	0.00133*
	(3.26)	(3.78)	(6.64)	(2.13)
Connect	0.541	0.201	-0.0372	-0.0025
	(1.75)	(1.73)	(-1.79)	(-1.69)
Post	-0.000983	-0.00554	-0.00125	-0.00108
	(-0.20)	(-0.39)	(-1.34)	(-1.73)
N	72,602	72,602	72,602	72,602
R-squared	.405	.354	.173	.0222
County Clustered SE	Yes	Yes	Yes	Yes
Connect Weight	PW	PW	PW	PW
Event Window	4Q	4Q	4Q	4Q

Table 7: Alternative Methodology to Estimate the Causal Effect of Social Interactions

This table shows estimates from the regression model $Y_{i,t} = \beta_0 + \beta_1 NetworkDisaster^N_{a,t-4,t} + X_{i,t} + FE_{state\times time} + FE_{industry} + \epsilon_{i,t}$ where $NetworkDisaster^N_{a,t-4,t}$ measures the average experience of county a's social network N between t_1 and t_2. $NetworkDisaster^N_{a,t-4,t}$ is defined as the weighted average $NetworkDisaster^N_{a,t_1,t_2} = \sum_b \theta^N_{a,b} \times Disaster_{b,t_1,t_2}$ where $\theta^N_{a,b}$ is the share of county a's friends in network N who lives in county b and $Disaster_{b,t_1,t_2}$ to be the number of declared disasters in county b between t_1 and t_2. The sample period is between January 2010 and December 2021. Control variables include $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	(1) CC	(2) OP	(3) RG	(4) PH
NetworkDisaster	0.0550***	0.0293***	0.00419**	0.00246***
	(5.00)	(4.05)	(2.15)	(2.65)
Log(Asset)	-0.0253	-0.00672	-0.00472	-0.000810
	(-0.88)	(-0.46)	(-1.50)	(-0.53)
Debt/Asset	-0.0980**	-0.0599**	-0.0103	0.00588
	(-1.98)	(-2.01)	(-1.64)	(1.47)
Cash/Asset	0.125	0.111**	0.0170**	-0.000
	(1.57)	(2.43)	(1.98)	(-0.01)
PPE/Asset	0.921***	0.464**	0.108***	0.0130
	(2.99)	(2.50)	(4.34)	(1.62)
CAPEX/Asset	0.0336	0.102	-0.0619	-0.0183
	(0.09)	(0.73)	(-1.10)	(-0.67)
EBIT/Asset	0.0832	0.0530	0.00196	-0.000484
	(1.39)	(1.63)	(0.21)	(-0.10)
R&D/Asset	0.0956	0.0816*	0.00624	0.00403
	(1.06)	(1.71)	(0.52)	(0.64)
Inst Ownership	0.00139***	0.000224**	0.000441***	0.000***
	(3.37)	(2.24)	(3.79)	(3.50)
Constant	0.909***	0.286**	0.0612***	0.0130
	(4.01)	(2.42)	(2.62)	(1.06)
R-squared	.71	.637	.395	.306
Observations	176,598	176,598	176,598	176,598
State X Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
County clustered SE	Yes	Yes	Yes	Yes

Table 8: Robustness Test - Alternative Regression Models

This table shows estimates from a Poisson regression in Panel A and a negative binomial regression in Panel B. As per Table 2, $Connect_i^d$ is an indicator variable that equals 1 for firm i located in the county with the above state-median social connection to the disaster-affected counties. $Post_t^d$ is an indicator variable for the following 4 quarters from the disaster d. The sample period is between January 2010 and December 2021. All regressions include control variables $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	(1) CC	(2) OP	(3) RG	(4) PH
Panel A: Poisson Regression				
Connect x Post	0.0248***	0.0287***	0.0931***	0.0232*
	(5.03)	(4.11)	(8.21)	(1.95)
Connect	-0.0279	-0.0524	-0.0191	0.0367
	(-0.80)	(-1.12)	(-0.47)	(0.61)
Post	-0.00160	0.00144	-0.00796	-0.0113
	(-0.45)	(0.30)	(-0.95)	(-1.16)
Pseudo R-sq	0.1094	0.0884	0.1187	0.0184
Panel B: Negative Binomial				
Connect x Post	0.0281***	0.0332***	0.0933***	0.0232*
	(5.62)	(4.67)	(8.24)	(1.95)
Connect	-0.0242	-0.0528	-0.0116	0.0369
	(-0.85)	(-1.32)	(-0.30)	(0.61)
Post	0.00144	0.00674	-0.00844	-0.0113
	(0.43)	(1.48)	(-1.04)	(-1.16)
N	184,791,625	184,791,625	184,791,625	184,791,625
Pseudo R-sq	0.0463	0.0462	0.1029	0.0184
ln(Alpha)	0.641***	1.102***	0.747***	-1.477
County clustered	Yes	Yes	Yes	Yes
Connect weight	PW	PW	PW	PW
Post Period Length	4Q	4Q	4Q	4Q

Table 9: Robustness Test - Different Distance Limits

This table reports estimates using the same regression model from Table 2, but with varying distance limits between firms and a disaster. For a given disaster d and the affected counties $\{a\}^d$, I require counties in $\{a\}^d$ to be at least 250, 500, and 1000 miles apart from a disaster d to be included in the sample. All other variables are defined as per in Table 2. The sample period is between January 2010 and December 2021. Control variables $X_{i,t}$ include $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	(1) CC	(2) OP	(3) RG	(4) PH	(5) CC	(6) OP	(7) RG	(8) PH	(9) CC	(10) OP	(11) RG	(12) PH
Connect x Post	0.0280***	0.0116***	0.00715***	0.0000935	0.0265***	0.0121***	0.00659***	0.000153	0.0316***	0.0153***	0.00626***	0.000389*
	(4.08)	(3.65)	(5.16)	(0.59)	(4.78)	(4.01)	(7.00)	(1.00)	(4.66)	(3.94)	(6.76)	(1.93)
Connect	-0.0175	-0.0142	-0.00126	0.000450	-0.0206	-0.0173	-0.000783	0.000635	-0.0444	-0.0316	-0.00114	0.000467
	(-0.51)	(-0.78)	(-0.58)	(0.72)	(-0.56)	(-0.88)	(-0.35)	(0.93)	(-1.08)	(-1.40)	(-0.45)	(0.59)
Post	-0.000695	0.000537	-0.000770**	-0.000106	0.000387	0.00140	-0.000425	-0.000107	-0.00460	-0.000734	-0.000550	-0.000115
	(-0.21)	(0.30)	(-1.98)	(-0.91)	(0.12)	(0.77)	(-1.11)	(-0.94)	(-1.02)	(-0.27)	(-0.95)	(-0.68)
N	238,541,745	238,541,745	238,541,745	238,541,745	209,236,172	209,236,172	209,236,172	209,236,172	142,612,512	142,612,512	142,612,512	142,612,512
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-sq / Pseudo R-sq	.0745	.0448	.0459	.00214	.075	.0453	.0459	.00213	.0769	.0476	.0434	.00223
Distance Limit	250	250	250	250	500	500	500	500	1000	1000	1000	1000
County clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Connect weight	PW	PW	PW	PW	PW	PW	PW	PW	PW	PW	PW	PW
Post Period Length	4Q	4Q	4Q	4Q	4Q	4Q	4Q	4Q	4Q	4Q	4Q	4Q

Table 10: Falsification Test using Political Risk Measure

This table shows results from the falsification tests using the same regression model from Table 2: $Y_{i,t} = \beta_0 + \beta_1 Connect_i + \beta_2 Post_t + \beta_3 Connect_i \times Post_t + X_{i,t} + \epsilon_{i,t}$. The dependent variable $Y_{i,t}$ measures political risk, non-political risk, and overall risk exposure, which are the measures constructed by Hassan et al. (2019) using bigrams in transcript data from quarterly earnings calls. All other variables are defined as per in Table 2. The sample period is between January 2010 and December 2021. Control variables $X_{i,t}$ include $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	(1) Political Risk	(2) Non-Political Risk	(3) Overall Risk
Connect X Post	0.149	-0.0900	0.0980
	(0.34)	(-0.03)	(0.72)
Post	3.031	16.43*	1.468**
	(1.61)	(1.75)	(2.32)
Connect	0.282	4.515	0.149
	(0.68)	(1.45)	(1.20)
R-squared	.0055	.00545	.0199
Observations	184,717,722	184,717,722	184,717,722
County clustered SE	Yes	Yes	Yes
Connect weight	PW	PW	PW

Table 11: Falsification Test using Non-Climate Change Disasters

This table shows results from the falsification tests using the same baseline regression model from Table 2 but using earthquakes as disaster events. As per Table 2, $Connect_i^d$ is an indicator variable that equals 1 for firm i located in the county with the above state-median social connection to the disaster-affected counties. $Post_t^d$ is an indicator variable for the following 4 quarters from the disaster d. The sample period is between January 2010 and December 2021. All regressions include control variables $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	(1) CC	(2) OP	(3) RG	(4) PH
Connect x Post	0.0621	0.0436*	0.00313	-0.000235
	(1.62)	(1.70)	(0.69)	(-0.12)
Connect	-0.0756*	-0.0519	-0.000208	-0.000520
	(-1.70)	(-1.63)	(-0.07)	(-0.61)
Post	0.0118	0.00421	0.0102**	-0.000141
	(0.38)	(0.26)	(2.20)	(-0.09)
R-squared	.0671	.0416	.0398	.00192
Observations	1,015,403	1,015,403	1,015,403	1,015,403
Connect weight	PW	PW	PW	PW
Post Period Length	4Q	4Q	4Q	4Q

Table 12: Real Effect on Greenhouse Gas Emissions

This table shows estimates from the regression model $Y_{i,t} = \beta_0 + \beta_1 Connect_i + \beta_2 Post_t + \beta_3 Connect_i \times Post_t + X_{i,t} + \epsilon_{i,t}$, where dependent variable $Y_{i,t}$ are aggregate greenhouse gas emission scaled by revenue and greenhouse gas emissions based on different scopes (Scope 1, Scope 2, and Scope 3). As per Table 2, $Connect_i$ is an indicator variable that equals 1 for firm i located in the county that has an above state-median social connection to the disaster-affected counties. $Post_t$ is an indicator variable for the following k years after disaster d. The sample period is between January 2010 and December 2021. Control variables $X_{i,t}$ include $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	(1) CO2/Revenue	(2) Scope 1	(3) Scope 2	(4) Scope 3
Panel A: $k = 1$ year				
Connect X Post	-14.14**	-98953.0	-28923.6**	-178999.7
	(-2.45)	(-1.32)	(-2.57)	(-0.49)
Connect	159.5***	1167892.4**	91178.4	-445278.3
	(3.48)	(2.00)	(1.48)	(-0.15)
Post	11.72***	129043.5*	17940.5*	67318.5
	(2.71)	(1.80)	(1.96)	(0.21)
R-squared	0.00405	0.00174	0.000483	0.0000135
Observations	5112784	4505625	4335991	2745684
Panel B: $k = 2$ year				
Connect X Post	-16.83***	-112604.7**	-44134.1***	-78841.3
	(-2.81)	(-2.22)	(-3.35)	(-0.23)
Connect	160.4***	1173176.5**	93620.9	-445966.7
	(3.50)	(2.01)	(1.53)	(-0.15)
Post	12.39***	109341.4***	23259.0***	77808.5
	(3.17)	(2.69)	(2.96)	(0.30)
R-squared	0.00406	0.00174	0.000490	0.0000135
Observations	5112784	4505625	4335991	2745684
Panel C: $k = 3$ year				
Connect X Post	-14.84***	-101184.7**	-40668.9***	-133197.8
	(-2.81)	(-2.21)	(-3.24)	(-0.36)
Connect	160.8***	1176866.0**	94989.9	-437199.6
	(3.52)	(2.02)	(1.55)	(-0.15)
Post	13.33***	161124.6***	27438.1***	-63643.4
	(3.05)	(3.96)	(3.33)	(-0.29)
R-squared	0.00406	0.00175	0.000493	0.0000141
Observations	5112784	4505625	4335991	2745684
County clustered SE	Yes	Yes	Yes	Yes
Connect weight	PW	PW	PW	PW

Table 13: Real Effect on Greenhouse Gas Emissions

This table shows estimates from the regression model $Y_{i,t}^d = \beta_0 + \beta_1 Connect_i^d + \beta_2 Post_t^d + \beta_3 Connect_i^d \times Post_t^d + X_{i,t} + \epsilon_{i,t}$, where dependent variable $Y_{i,t}^d$ are aggregate greenhouse gas emission scaled by revenue and greenhouse gas emissions based on different scopes (Scope 1, Scope 2, and Scope 3). As per Table 2, $Connect_i^d$ is an indicator variable that equals 1 for firm i located in the county that has above state-median social connectedness to the disaster-affected counties. $Post_t^d$ is an indicator variable for the following k years after disaster d. The sample period is between January 2010 and December 2021. Control variables $X_{i,t}$ include $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $CAPEX/Assets$, $PPE/Assets$, $EBIT/Assets$, $R\&D/Assets$ and institutional ownership. t-statistics, calculated using standard errors clustered by county, are shown in parentheses below the estimates. *, **, and *** denote statistical significance at the 10%, 5%, 1% level, respectively.

	(1) CO2/Revenue	(2) Scope 1	(3) Scope 2	(4) Scope 3
Panel A: $k = 1$ year				
Connect x Post	-9.480**	-58361.6	-28923.6**	-178999.7
	(-1.93)	(-1.16)	(-2.57)	(-0.49)
Post	-3.869	-22104.6	-2919.4	260312.9
	(-0.78)	(-0.42)	(-0.42)	(1.06)
Connect	59.75*	391586.3	16730.6	-1253637.0
	(1.68)	(0.99)	(0.35)	(-0.49)
N	2600434	2287934	2199324	1379372
R-squared	0.259	0.255	0.132	0.0781
Panel B: $k = 2$ year				
Connect x Post	-10.236**	-112604.7**	-44134.1***	-78841.3
	(-2.07)	(-2.22)	(-3.35)	(-0.23)
Post	-6.392	-39160.4	4712.3	458133.2
	(-0.97)	(-0.65)	(0.47)	(1.37)
Connect	60.21*	396646.8	19222.3	-1305249.9
	(1.69)	(1.00)	(0.40)	(-0.51)
N	2600434	2287934	2199324	1379372
R-squared	0.259	0.255	0.132	0.0781
Panel C: $k = 3$ year				
Connect x Post	-10.208**	-101184.7**	-40668.9***	-133197.8
	(-2.03)	(-2.21)	(-3.24)	(-0.36)
Post	-9.999	-28973.3	6845.7	458133.2
	(-1.19)	(-0.34)	(0.51)	(1.37)
Connect	60.69*	406251.3	19646.8	-1369209.8
	(1.70)	(1.02)	(0.41)	(-0.54)
N	2600434	2287934	2199324	1379372
R-squared	0.259	0.255	0.132	0.0781
County clustered SE	Yes	Yes	Yes	Yes
Connect weight	PW	PW	PW	PW

Table A1: Examples of Bigrams Captured by Climate Change Exposure

This table reports the 100 highest-frequency bigrams from Sautner et al. (2020) that are used to measure attention to broadly defined climate change (CC), which measures the relative frequency with which bigrams related to climate change occur in earnings call transcripts.

Bigrams associated with general climate change topic (CC)			
renewable energy	clean power	major design	source power
electric vehicle	carbon price	vehicle manufacturer	sustainability goal
clean energy	world population	future energy	energy reform
new energy	solar farm	motor control	plant power
climate change	energy regulatory	combine heat	compare conventional
wind power	obama administration	electric bus	gas vehicle
wind energy	heat power	distribute power	effort energy
energy efficient	carbon tax	environmental benefit	pass house
greenhouse gas	unite nation	eco friendly	carbon free
solar energy	onshore wind	electrical vehicle	driver assistance
air quality	electric motor	carbon neutral	electrical energy
clean air	provide energy	fast charge	solar installation
carbon emission	efficient solution	cell power	snow ice
gas emission	global warm	energy team	renewable natural
extreme weather	power generator	cycle gas	promote use
carbon dioxide	solar pv	coal gasification	farm project
water resource	scale solar	environmental concern	laser diode
autonomous vehicle	need clean	carbon intensity	deliver energy
energy environment	coastal area	energy application	protect environment
wind resource	energy star	produce electricity	sustainable energy
government india	environmental footprint	help state	manage energy
battery power	design use	environmental standard	invest energy
air pollution	area energy	power agreement	electric energy
battery electric	charge station	supply energy	forest land
integrate resource	clean water	electric hybrid	capacity energy