Climate Risk and Corporate Green Innovation: Evidence from Nearby Climate Disasters*

Phong Truong
Pennsylvania State University

Scott Jinzhiyang Wang
Pennsylvania State University

September 2026

Abstract

We investigate whether heightened perceptions of climate risk induce firms to pursue green innovation. To isolate the effects of heightened climate risk perceptions, we compare firms located in counties near, but not directly hit by, climate disasters with those located farther away. Using a stacked difference-in-differences design, we find that nearby firms are more likely to file green patents following disasters, with increases in both patent quantity and quality. The response is stronger for firms with greater local media coverage, higher analyst engagement, headquarters in more Democratic-leaning counties, and stronger state green policy support. Executive risk-taking incentives, environment-linked compensation, and shareholder environmental proposals also increase, consistent with nearby disasters altering firms' governance environments in ways that encourage green innovation. The results remain robust after accounting for local economic spillovers and direct economic linkages to firms in disaster zones. Overall, our findings show that heightened climate risk perceptions can translate into substantive green innovation.

JEL Classification: G32, G34, M41, O31, O32, Q54

Keywords: climate risk perceptions, climate disasters, green innovation, green patents, stakeholder pressure, environmental governance

* We thank Jinhwan Kim, Trent Krupa, Ben Lourie, Henock Louis, Yifei Lu, Tendai Masaya, Rick Mergenthaler, Jed Neilson, Jing Pan, Jingwen Yang, and conference and workshop participants at AAA Global Connect and the Pennsylvania State University for their helpful comments and suggestions on this paper. We gratefully acknowledge the financial support provided by the Pennsylvania State University.

"Climate change has become a defining factor in companies' long-term prospects. […] *The evidence on climate risk is compelling investors to reassess core assumptions about modern finance.* […] *In the near future – and sooner than most anticipated – there will be a significant reallocation of capital."*

Larry Fink's 2020 Letter to CEOs

1. Introduction

Climate risk has become an increasingly important determinant of firms' long-term cash flows.[1] The escalating frequency and intensity of extreme climate events have increased scrutiny of how firms assess and manage exposure to both the physical risks of climate change and the transition risks associated with the shift toward a lower-carbon economy. The financial stakes are substantial: the U.S. Fourth National Climate Assessment (2018) estimates that climate change could cost the U.S. economy hundreds of billions of dollars annually by the end of the century, a projection reinforced by the U.S. Office of Management and Budget (2022). Against this backdrop, green innovation emerges as a potentially important tool for firms to mitigate climate risk exposure, improve operational resilience, and position themselves for business opportunities associated with emerging green markets (Fink, 2022). Yet, firms' responses to climate risk depend not only on the underlying risk they face, but also on how they perceive that risk. Despite growing attention to this topic in recent years, we still lack a clear understanding of whether and how heightened perceptions of climate risk induce firms to pursue green innovation.

Major climate disasters provide a natural setting in which to study this question. Their timing and location are difficult to predict and plausibly exogenous to firms' characteristics, while their prominence can heighten firms' perceptions of climate risk. However, firms in directly hit areas also suffer from physical damage, financial losses, and recovery demands that can constrain

[1] Climate risk refers to the potential negative effects of climate change on various aspects of the environment, businesses, society, and ecosystems (IPCC, 2020).

innovative activity. To address this empirical challenge, we exploit precise disaster-county geographic information to study the green innovation of firms located in counties near climate disasters but *not* directly hit by them. These nearby counties report no physical damage, financial losses, or human casualties from the disaster events, yet their proximity makes the disasters more salient and relevant to local firms than to those in more distant areas. Thus, this "near-miss" setting helps isolate changes in climate risk perceptions prompted by climate disasters from contemporaneous shocks that directly affect firm resources and managerial priorities.

There are compelling reasons why heightened climate risk perceptions may increase firms' propensity to pursue green innovation. First, greater perceived transition risk can raise the expected costs and benefits associated with changing stakeholder preferences. Managers may place greater weight on the revenue opportunities that climate-conscious demand creates for green technology, while also viewing failure to respond as carrying greater reputational costs, financing costs, and risks of losing market share (Aragón-Correa and Sharma, 2003; Howard-Grenville et al., 2014; Matsumura et al., 2014; Baldauf et al., 2020; Engle et al., 2020; Krueger et al., 2020; Bolton and Kacperczyk, 2021; Li et al., 2024). Second, greater perceived physical climate risks may heighten managers' expectations of the economic consequences associated with extreme weather events, strengthening the financial incentives for firms to invest in green technologies that reduce their long-term exposure to climate-related disruptions (Dell et al., 2012; Kruttli et al., 2025b).

However, heightened climate risk perceptions may not increase firms' propensity to pursue green innovation for two reasons. First, firms may remain uncertain about future operating conditions and the returns to green investment. Because green innovation is costly, long-horizon, and partly irreversible, investment theory suggests that greater uncertainty can raise the option value of waiting and reduce firms' incentives to invest in green technology (Arrow and Fisher, 1974; Bernanke, 1983; McDonald and Siegel, 1986; Bloom, 2009). Second, greater perceived climate risk may lead firms to adopt a more conservative approach and prioritize stability. As a result, they may favor established core business activities rather than diverting resources toward new initiatives like green innovation (Panousi and Papanikolaou, 2012; Julio and Yook, 2012; Gulen and Ion, 2016). Therefore, whether firms invest in green innovation in response to heightened climate risk perceptions remains an empirical question.

We obtain a list of major climate disasters in the U.S. and employ a stacked difference-in-differences design to study whether firms located in nearby counties (treated firms) are more likely to file a green patent than those located farther away (control firms) following disaster events. We define a county as near a climate disaster if the minimum distance between it and any directly hit county is within 100 miles (see Figure 1 for an illustration). We identify green patents using a combination of green patent codes developed by the Organisation for Economic Co-operation and Development (OECD), the World Intellectual Property Organization (WIPO), and the European Patent Office (EPO). We find that disaster-induced increases in climate risk perceptions have a positive impact on firms' propensity to invest in green innovation. Treated firms are about 1.5% more likely to produce green patents following a climate disaster event. Economically, the magnitude of this effect is about 16% of the unconditional mean, indicating a meaningful shift in green innovation behavior. Furthermore, we find no evidence of statistically significant pre-trends in green innovation, supporting the parallel trends assumption. These results suggest that nearby firms increase green innovation efforts following climate disasters.

The extent of green innovation responses is likely to vary with the local information environment in which firms operate. For a given disaster, greater media coverage can facilitate the dissemination of information about the event and its implications for firms. Thus, firms in areas with historically greater news coverage may update their perceptions of climate risk more strongly even when the underlying disaster is the same. Consistent with this prediction, the effect on green innovation is stronger among firms located in areas with greater pre-disaster media coverage.

The response to heightened climate risk perceptions may also depend on the external environment in which firms operate. For example, greater analyst engagement may reflect more intensive capital-market scrutiny, while firms in Democratic-leaning counties operate in communities where stakeholders place greater weight on environmental performance. These distinct external pressures can make inaction more consequential and encourage firms to respond through green innovation. Consistent with these predictions, the effect is stronger among firms with greater pre-period analyst engagement and those located in Democratic-leaning counties.

Whether heightened climate risk perceptions translate into green innovation should depend on the returns to undertaking it. State-level green incentives, such as subsidies and tax credits, can increase the expected returns to green technologies through policy support and creating more favorable market conditions for green investment. Firms operating in these states may therefore have stronger incentives to respond to heightened climate risk perceptions through green innovation. Consistent with this prediction, we find stronger effects among firms located in states with a higher number of green incentives.

We next examine whether these firms become more likely to discuss climate disasters in their annual reports following climate disasters, thereby providing supportive evidence consistent with heightened climate risk perceptions among nearby firms. We find that firms are indeed more likely to discuss disaster-related risks in their 10-K filings in the post-period. This finding supports the view that climate-related risks become more prominent in firms' assessments even though they do not experience direct physical disaster impacts.

Nearby disasters may alter firms' climate risk perceptions in part by changing the governance environment they face. Although the realization of a nearby disaster need not mechanically change firms' physical risk exposure (Dessaint and Matray, 2017; Huang et al. 2022), shareholders may respond by placing greater emphasis on environmental performance, strengthening managers' incentives to pursue green innovation. We examine this possibility in two steps. First, we find that managerial vega increases following nearby disasters, consistent with boards strengthening incentives for managerial risk taking. Second, both environment-specific incentives in executive compensation and shareholder-sponsored environmental proposals increase following nearby disasters, suggesting that these adjustments are environmentally oriented. Together, these findings suggest that nearby disasters alter firms' incentive structures more toward environmental objectives, encouraging investment in green innovation.

Climate disasters may generate spillover effects from directly impacted areas to nearby firms. Such spillovers may arise through changes to nearby counties' economic activity or firm's peer networks, affecting innovation independently of changes in climate risk perceptions. To address this concern, we first augment our baseline regression with a comprehensive set of county-level time-varying economic indicators (e.g., GDP, unemployment, job creation and destruction) to account for changes in nearby counties' economic conditions. The effect on green innovation remains positive and significant, suggesting that local economic spillovers are unlikely to explain our findings. We next examine whether disruptions via peer networks could explain our findings by excluding treated firms with supply-chain or product-market linkages to firms located in directly hit counties. If the effects are driven by disruption in peer networks, then the effects should be muted after excluding treated firms with peers located in directly hit counties. Instead, the effect remains positive and significant. Together, these findings suggest that the increase in green innovation is unlikely to be driven by local economic conditions, supply-chain disruptions, or competitive shocks associated with directly affected areas.

Finally, we examine whether the increase in firms' propensity to pursue green innovation extends to the quantity and quality of their output. Beyond the number of green patents filed, we consider two measures of quality: forward citations, which capture an invention's technological impact, and the patent value measure of Kogan et al. (2017), which captures its expected economic value to the firms. We find that nearby disasters increase all three measures. Firms therefore respond by producing green innovation with greater technological impact and economic value, not merely by increasing their likelihood of filing a green patent. This pattern is less consistent with symbolic green innovation or greenwashing (Duchin et al. 2025).

Our paper makes several contributions to the literature. First, we add to the literature on corporate innovation and green innovation in particular. Prior research shows that firms' innovative activities are shaped by financing conditions, ownership and governance structures, and managerial characteristics (Cohen and Klepper, 1996; Hall and Lerner, 2010; Brown et al., 2009; Aghion et al., 2013; Hirshleifer et al., 2013; Kim et al., 2025b). More recent studies also highlight the role of disclosure incentives in shaping innovation outcomes (e.g., Kim and Valentine, 2021, 2023; Dyer et al., 2024). We respond to calls for more research on when and how firms are incentivized to invest in green innovation by showing that heightened climate risk perceptions lead to stronger corporate green innovation responses (Glaeser and Lang, 2024; Acemoglu et al., 2012; Aghion et al., 2016; He and Qiu, 2025; Cheng et al., 2025; Skinner and Valentine, 2026).

Second, we contribute to the literature on firms' responses to climate risks. Accounting research shows that carbon disclosure mandates and benchmarking can induce reductions in emissions (Downar et al., 2021; Tomar, 2023), institutional ownership and ESG-linked compensation can shape firms' climate disclosure, environmental performance, and managerial incentives (Cohen et al., 2023a, 2023b), and government procurement opportunities can encourage corporate climate disclosure (Even-Tov et al., 2025). Recent work also documents that physical and transition climate risks affect operating performance, capital structure, supply-chain relationships, emissions abatement, investment, and employment (Ginglinger and Moreau, 2023; Pankratz and Schiller, 2024; Ramadorai and Zeni, 2024; Li et al., 2024). We complement this literature by using a near-miss disaster setting to examine how heightened climate risk perceptions shape green innovation among firms that avoid direct physical impacts and how changes in firms' governance environments reinforce this response.

Third, our paper also contributes to the literature on corporate and capital-market responses to natural disasters. Prior research shows that disasters affect analysts' risk assessments and capital-market uncertainty, financing conditions and production networks, and corporate policies such as cash holdings, inventory management, ESG disclosure, and shareholder voting (Barrot and Sauvagnat, 2016; Dessaint and Matray, 2017; Bourveau and Law, 2021; Huang et al., 2022; Kruttli et al., 2025b; Fich and Xu, 2025; Cho et al., 2026; Correa et al., 2026). We contribute by showing that disasters can prompt nearby firms to invest in green innovation.

Finally, a related strand of literature examines how disasters have heterogeneous effects on aggregate innovation in directly hit regions. These studies capture the combined influence of direct-hit consequences such as realized capital destruction, local disruptions, recovery dynamics, and policy responses that operate alongside changes in climate risk perceptions (Le et al., 2024; Zhao et al., 2022; Miao and Popp, 2014; Ahmed et al., 2023; Kruttli et al., 2025a; Ma et al., 2024; Keding and Ritterrath, 2024; Moscona, 2025). In contrast, by focusing on nearby firms, our near-miss design complements this literature by isolating the effect of disaster-induced climate-risk perceptions on corporate green innovation in the absence of direct-hit consequences.

2. Hypothesis Development

Corporate responses to climate risk depend not only on firms' underlying exposure, but also on how managers perceive the economic consequences of that exposure. Because the economic consequences of climate risk are forward-looking and uncertain, managers must assess not only the potential operational consequences of physical climate events, but also how evolving environmental preferences among stakeholders may affect their firms. Prior research shows that managers' perceptions of climate-related risk influence firm disclosures, operational decisions, and other corporate policies (Li et al., 2024; Dessaint and Matray, 2017; Huang et al., 2022). However, one important yet relatively underexplored corporate response is green innovation—the development of technologies, processes, and products that reduce environmental impact, lower carbon footprints, or enhance resilience to climate-related shocks. Understanding whether and how firms invest in green innovation in response to heightened perceptions of climate risk is particularly relevant given its potential to address both the physical risks of climate change and the transition risks associated with the shift to a lower-carbon economy.

There are several reasons to expect heightened climate risk perceptions to increase corporate green innovation. First, greater perceived transition risk can increase the importance managers attach to changing stakeholder preferences. They may place greater weight on the revenue opportunities that climate-conscious demand creates for green technologies, while also viewing failure to respond as carrying greater reputational costs, financing costs, and risks of losing market share (Aragón-Correa and Sharma, 2003; Howard-Grenville et al., 2014; Matsumura et al., 2014; Engle et al., 2020; Krueger et al., 2020; Bolton and Kacperczyk, 2021; Baldauf et al., 2020; Li et al., 2024). Second, greater perceived physical climate risk may lead managers to anticipate more severe economic consequences from future extreme weather events. Because such events can damage physical assets, disrupt production, and increase operating costs (Dell et al., 2012; Kruttli et al., 2025b), managers may have stronger incentives to invest in technologies that increase the resilience of infrastructure, improve energy and resource efficiency, and reduce exposure to future climate-related disruptions.

In our setting, nearby climate disasters play a specific and important role by altering these perceptions without directly imposing the physical and financial consequences that come with being hit. Extreme climate events make the potential consequences of climate risk more vivid and locally relevant. They may also make the transition-related consequences of climate risk more prominent by drawing attention to how investors, customers, regulators, and other stakeholders respond to climate events. These considerations can increase the weight managers place on the potential costs and benefits associated with climate risk when evaluating green investment.

While climate disasters are publicly observable, the extent to which a disaster affects firms' climate-risk perceptions is likely to depend on geographic proximity. Firms located near disaster zones are more directly exposed to local discussion and media coverage of the event than firms located farther away. The same disaster may therefore have greater relevance for nearby firms' assessments of climate risk, even when they are not directly affected by the event. Accordingly, we expect firms located near, but not directly hit by, climate disasters to exhibit a stronger green innovation response:

H1: Firms exposed to nearby climate disasters are more likely to engage in green innovation activity.

This predicted effect is not unambiguous, however. Heightened climate risk perceptions may also increase uncertainty about future operating conditions and the returns to green investment. Because green innovation is costly, long-horizon, and partly irreversible, investment theory suggests that greater uncertainty can raise the option value of waiting and reduce firms' incentives to undertake such investments (Arrow and Fisher, 1974; Bernanke, 1983; McDonald and Siegel, 1986; Bloom, 2009; Wang et al., 2026). In addition, firms facing greater perceived risk may respond by adopting a more conservative approach to avoid risk and focus on existing core business activities rather than undertaking new, risky green innovation projects. These competing forces make the effect of heightened climate risk perceptions on green innovation ultimately an empirical question.

3. Data and Descriptive Statistics

3.1. Data

3.1.1. Green Patent Data

We obtain patent data from Kogan et al. (2017), a comprehensive dataset that provides detailed information on patents granted by the United States Patent and Trademark Office since 1926. The dataset links patents to publicly listed firms and includes patent-level characteristics such as filing dates, grant dates, technological classifications (patent codes), and patent economic values derived from market reactions to patent grants.

To identify green patents, we first follow the recommendation of Favot et al. (2023) and combine three institutional taxonomies of environment-related technologies to determine whether a patent code is considered "green." These include the ENV-TECH list of green patent codes created by the Organisation for Economic Co-operation and Development (OECD), the International Patent Classification (IPC) Green Inventory list of green patent codes from the World

Intellectual Property Organization (WIPO), and the Y02/Y04S tagging scheme developed by the European Patent Office (EPO). Although these schemes have been used individually in prior research (e.g., Cohen et al., 2026; Brown et al., 2022; Skinner and Valentine, 2026), Favot et al. (2023) show that combining all three sources to identify green patents substantially expands coverage and mitigates classification errors. Accordingly, we designate a patent code as "green" if it appears in any of the three lists. Next, we note that each patent often carries multiple patent codes in order to capture the full technological scope of an invention, which almost always spans more than one technical area. Therefore, we classify a patent as green if at least half of its codes are designated as green codes, ensuring that the patent's primary technological focus is environmentally oriented.

3.1.2. Climate Disaster Data

We obtain a list of major climate disasters in the United States from 1980 to 2019 from the National Centers for Environmental Information (NCEI).[2] According to NCEI (2025), these major climate disasters account for over 80% of the damage from all weather and climate events documented in the United States. Next, we match these disasters to county-level hazard data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to identify the counties that suffer from any damages, casualties, or costs caused by a given disaster.[3]

To identify the counties near, but not directly hit by, the climate disasters identified above, we use the County Disaster Database provided by the National Bureau of Economic Research (NBER) to classify a county into one of three categories: (i) directly hit counties, which include

[2] A climate disaster is defined as a major disaster if overall damages/costs reached or exceeded $1 billion (including CPI adjustment to 2019). This restriction follows prior literature on climate disasters (e.g., Alok et al., 2020; Ludvigson et al., 2021; Kim et al., 2025a)

[3] SHELDUS collects data on damages, casualties, and costs data from various sources and aggregates them at the disaster-county level.

all the counties experiencing any damages, casualties, or costs, (ii) nearby counties, which include those whose minimum distance between their geographical center and the center of any directly hit county is within 100 miles,[4] and (iii) other counties, which include all counties that are neither directly hit nor nearby. Figure 1 provides an illustration of how counties are classified using Hurricane Michael in 2018 as an example.

Our final sample includes 129 major climate disasters, spanning six categories: tropical cyclones, winter storms, freezes, floods, severe storms, and wildfires. Appendix B reports the yearly distribution of disasters. The distribution indicates an increasing number of major climate disasters over the years, consistent with the documented global rise in extreme climate events (IPCC, 2021).

3.1.3. Other Data

We obtain firm accounting data from the CRSP/Compustat Merged database and institutional ownership data from the Thomson Reuters 13F database. For supplementary analyses, we combine several additional data sources: textual content from firms' 10-K filings from EDGAR, conference call transcripts from Capital IQ, supply chain data from Compustat Segments, and product market peer data from the Hoberg-Phillips Data Library, news coverage data from RavenPack, environment-specific incentives in executive compensation and shareholder proposals from Institutional Shareholder Services (ISS), presidential election results from the Federal Election Commission (FEC), and state-level green incentives from the DSIRE database. Local economic data at the county level (such as GDP and unemployment) are obtained from various

[4] The distance is calculated using the Haversine formula based on center points in the geographic area. In Section 4.7, we assess the robustness of the main results using alternative definitions of nearby counties: those within 50 or 150 miles of directly hit counties, those that are bordering counties (i.e., share the same border with directly hit counties), and those that are among the top 10 nearest counties to the directly hit counties.

government agencies, namely the Bureau of Economic Analysis (BEA), the Bureau of Labor Statistics (BLS), and the U.S. Census Business Dynamics Statistics (BDS).

3.2. Sample Selection and Descriptive Statistics

Because different climate disasters occur in different years throughout the sample period, we use a stacked difference-in-differences (DiD) event-study design. For each disaster, we consider an event window spanning five years before and after the disaster, denoted as [-5, +5], with the disaster year designated as year 0. We consider firms located in the nearby counties as treated firms, and the firms located in the other counties as control firms.[5] To illustrate, the map in Figure 1 distinguishes among directly hit counties (red), nearby unimpacted counties (gray), and other control counties (unshaded). Firms in the gray counties are treated firms, whereas firms in the unshaded counties are control firms. Following the literature on the treatment effect of repeated non-absorbing shocks (Cengiz et al., 2019; Dube et al., 2025; de Chaisemartin and D'Haultfœuille, 2026), we require that control firms have never been treated at any time during the [-5,+5] window.[6] Each cohort (i.e., stack) corresponds to a disaster, consisting of treated and control firms associated with said disaster.

We then append the stacks together to obtain the initial sample. Because our analyses focus on firms with the capacity to generate innovation, we restrict the sample to firms that have filed at least one patent in their corporate history. Our main variable of interest is *GreenPatent*, an indicator equal to one if the firm files at least one green patent in a given year, and zero otherwise. We drop observations with missing values of variables used in the main analysis. All continuous

[5] Firm location information is obtained from historical 10-K filings.

[6] Recent developments in econometrics (e.g., Dube et al., 2025; de Chaisemartin and D'Haultfœuille 2026) show that when treatment shocks, such as climate disasters, are frequently repeated and non-absorbing (i.e., treatment can occur multiple times and does not permanently switch a unit into a treated state), imposing the conventional not-yet-treated requirement often used in stacked DiD would significantly shrink and distort the control pool, mis-specify treatment histories, and require unnecessarily strong identifying assumptions. Instead, firms treated outside of a given event window can still serve as valid controls, provided that the parallel trends assumption holds locally within that window.

variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. The resulting main (stacked) sample consists of 461,153 disaster-firm-year observations from 1979 to 2021.

Table 1 reports the descriptive statistics for the variables used in our main sample. Appendix A provides definitions of all variables. The mean of the *Treat* variable is 0.309, indicating that approximately 30.9% of the observations in our sample correspond to firms in the counties near directly hit areas. The mean of the *Post* variable is 0.547, consistent with our defined event window. The mean of our dependent variable of interest, *GreenPatent*, is 0.092, indicating that firms file at least one green patent in approximately 9.2% of firm-year observations. The standard deviation of *GreenPatent* is 0.289. The skewness of *GreenPatent* is consistent with prior evidence in the innovation literature (e.g., Cheng et al., 2025; Kim and Valentine, 2026).

Turning to firm characteristics, the mean and median of firm size (the natural logarithm of total assets) are 5.645 and 5.457, respectively. The leverage ratio has a mean and median of 0.173 and 0.111, respectively. The average (median) firm has a return on assets of -0.081 (0.021) and a book-to-market ratio of 0.504 (0.395). The mean of log-transformed firm age is 2.567, suggesting that the average age of the firms in our sample is approximately 12 years. These characteristics, along with other controls, are generally comparable to those found in recent studies on corporate innovation (e.g., Huang et al., 2021; Cheng et al., 2025; Valentine et al., 2025).

4. Main Analyses

4.1. Main Results: The Effects of Heightened Climate Risk Perception on Green Innovation

We begin our analyses by examining hypothesis H1, which tests whether disaster-induced increases in climate risk perception influence the propensity to engage in green innovation for firms located in nearby counties. To test this hypothesis, we use a stacked DiD regression model:

$$GreenPatent_{i,t} = \alpha_1 + \beta_1\ Treat_i \times Post_{i,t} + Controls_{i,t} + Cohort\text{-}Firm\ FE$$
$$+ Cohort\text{-}Year\ FE + \varepsilon_{i,t}, \quad (1)$$

where subscripts *i* and *t* denote firm *i* and year *t*, respectively. The dependent variable of interest is *GreenPatent*, an indicator equal to one if the firm files at least one green patent in a given year, and zero otherwise. *Treat* is an indicator equal to one for treated firms located in nearby counties, and zero for control firms located in other counties neither near nor directly hit by natural disasters (see Section 3.2 for additional details). The primary coefficient of interest is β_1 on the interaction term *Treat* × *Post*, which estimates the differential change in green innovation for treated firms relative to control firms following a disaster. A positive coefficient β_1 would support the hypothesis that heightened climate risk perception has a positive impact on firms' propensity to invest in green innovation.

We include a set of control variables to account for time-varying firm characteristics that may influence corporate innovation. For example, *Size* and *Age* capture scale and life-cycle effects that systematically relate to firms' R&D and innovation activity (Cohen and Klepper, 1996; Hirshleifer et al., 2013). *ROA* and *Cash* proxy for internal financing capacity, while *Leverage* and *Financial Constraint* capture financing frictions that can restrict innovation (Hall and Lerner, 2010; Brown et al., 2009). We also include the book-to-market ratio (*BTM*) to capture variation in growth opportunities. We control for industry competition using the Herfindahl-Hirschman Index (*HHI*) and institutional investors' influence on firm investment policy (*Institutional Holding*) (Aghion et al., 2013). Finally, we include capital expenditure (*CAPX*) to control for overall capital investment patterns that may complement or crowd out innovation investments.

Following the recent literature on stacked DiD (Cengiz et al., 2019; Baker et al., 2022), we include cohort-firm fixed effects and cohort-year fixed effects, where each cohort corresponds to a climate disaster, to absorb time-invariant firm heterogeneity and aggregate time trends within each disaster. These fixed effects fully absorb the main effects of *Treat* and *Post*, rendering their explicit inclusion redundant. Standard errors are clustered at the firm level.

Table 2 presents the results of our baseline estimation of Equation (1). Column (1) reports the regression without controls, where the coefficient on the interaction term *Treat* × *Post* is positive and statistically significant at 0.0133 (t-stat = 3.29). In Column (2), we include the full set of firm-level controls. The coefficient of interest continues to be positive at 0.0148 and statistically significant at the one percent level (t-stat = 3.63). The results suggest that heightened climate risk perceptions induced by climate disasters increase firms' likelihood of engaging in green innovation. In terms of economic magnitude, the coefficient of 0.0148 suggests that, relative to control firms, treated firms increase their probability of filing a green patent by approximately 1.48% in the post-disaster period. This magnitude is roughly equal to 16% of the unconditional mean of *GreenPatent*, indicating a meaningful increase in green innovation.

Next, we assess the parallel trends assumption underlying the difference-in-differences estimation. To do so, we estimate a dynamic version of Equation (1) by replacing the *Post* variable with separate event-time indicators for each year in the [-5, +5] window relative to the disaster, omitting t-5 as the benchmark. Figure 2 plots the point estimates and 95% confidence intervals. As shown in the figure, the coefficients in the pre-period are small in magnitude and statistically indistinguishable from zero, consistent with the parallel trends assumption. Overall, the results support the notion that firms located near climate disasters are more likely to engage in green innovation activities.

4.2. Cross-Sectional Analysis

We next conduct a series of cross-sectional analyses to examine the underlying mechanisms through which heightened climate risk perceptions are more likely to translate into green innovation. We focus on three dimensions that should shape firms' responses to nearby climate disasters: variation in firms' local media environments, external stakeholder environments, and state-level policy support for green innovation.

4.2.1. News Coverage

We first examine whether the local media environment shapes firms' responses to nearby climate disasters. The accounting and finance literature documents an important role for the media in disseminating information and directing attention to economically relevant events (Bushee et al., 2010; Fang and Peress, 2009; Fritsch et al., 2025). A more active local media environment can increase the visibility and prominence of a nearby disaster, making its climate-related implications more relevant in managers' decision making (Huberman and Regev, 2001). Accordingly, if nearby disasters heighten firms' perceptions of climate risk, we expect the resulting green innovation response to be stronger in areas with greater media coverage.

We measure local news coverage using RavenPack data. We identify all news articles in the firm's state in a given year. To avoid endogeneity concerns in which contemporaneous coverage is related to the disaster in question, we use a firm's pre-treatment exposure to news coverage in the firm's headquarters state.[7] Specifically, we augment Equation (1) by adding the interaction between *Treat* × *Post* and *DecilePreNewsCoverage*, which is the decile rank of a firm's pre-treatment average exposure to news coverage, calculated as the average annual count of news articles in the firm's location state in the pre-period. We mean-center all decile-ranked variables

[7] We measure news coverage at the state level because RavenPack does not provide data at the county level.

so that the baseline effects correspond to firms at the average level of the respective cross-sectional variable. The results are reported in Table 3.

Because the news coverage data from RavenPack start in 2000 and we also require at least three years of pre-treatment data to calculate the average news coverage, the sample size in this analysis decreases to 281,477.[8] Therefore, we first replicate the main result and report the estimates in Column (1). The coefficient of interest, *Treat* × *Post*, is positive and statistically significant. More importantly, in Column (2), the coefficient of interest, *Treat* × *Post* × *DecilePreNewsCoverage*, is positive and statistically significant at the one percent level, suggesting that the main effect is more pronounced for firms located in states where there is a high level of news coverage.

To ensure this result is not an artifact of the state size or economic activity, we employ two alternative measures of pre-period news coverage. The first is *DecilePreNewsCoveragePerCapita*, which is the decile rank of the average annual count of news articles scaled by the population of the firm's state in the pre-period (Column (3)). The second is *DecilePreNewsCoveragePerGDP*, defined as the decile rank of the average annual count of news articles scaled by the GDP of the firm's state in the pre-period (Column (4)). Across both specifications, the coefficients on the triple interaction terms remain positive and statistically significant. Overall, these findings are consistent with greater news coverage strengthening the effects of nearby disasters on firms' climate risk perceptions and, in turn, their green innovation response.

4.2.2. External Stakeholder Environment

We next examine whether firms' responses to nearby climate disasters vary with the external environment in which they make strategic decisions. Corporate environmental policies

[8] We impose this restriction to mitigate measurement errors and ensure that our measurements capture the persistent, ex-ante information environment rather than transitory fluctuations. Our results are robust to removing this restriction.

can be shaped by the monitoring and pressure firms face from external stakeholders (Christensen et al., 2021). When external scrutiny is greater or stakeholders place greater weight on environmental performance, failing to respond to heightened climate risk perceptions may be more consequential for managers. We therefore examine two characteristics of firms' external stakeholder environments: the extent of analyst engagement and the political orientation of the local community.

We first consider analyst engagement. Financial analysts play an important monitoring role by questioning managers and directing capital-market attention toward issues relevant to firm value (Yezegel, 2023; Ashraf et al., 2024). Greater analyst engagement exposes firms to more intensive capital-market monitoring and scrutiny, which can better incentivize managers to respond to emerging climate-related concerns. We obtain conference call transcripts from Capital IQ starting in 2006, and require three years of pre-treatment analyst data to calculate the number of analysts asking questions during the Q&A sessions. Accordingly, the resulting sample contains 125,796 observations. We measure *DecilePreAnalystEngagement* as the decile rank of the firm's average number of analysts asking questions during conference calls in the pre-period. Panel A of Table 4 reports the results. Column (1) first replicates the baseline analysis using this reduced sample. In Column (2), the coefficient on *Treat* × *Post* × *DecilePreAnalystEngagement* is positive and statistically significant, indicating that the increase in green patenting following nearby disasters is stronger among firms subject to greater pre-period analyst engagement.

We next examine the environmental orientation of firms' local stakeholders. Firms headquartered in Democratic-leaning counties operate in communities that are more likely to have stronger pro-environmental preferences and expectations regarding corporate environmental performance. These local stakeholder preferences can make environmental inaction more consequential and strengthen firms' incentives to respond when climate risk becomes more prominent. We measure *DemocraticLeaningCounty* using the Democratic presidential nominee's vote share in the firm's headquarters county, carrying forward the most recent presidential-election result in non-election years. Panel B of Table 4 reports the results. Column (1) replicates the baseline analysis using the sample with available county-level election data. In Column (2), the coefficient on *Treat* × *Post* × *DemocraticLeaningCounty* is positive and statistically significant. Thus, the results indicate that the green innovation response to nearby disasters is stronger for firms located in more Democratic-leaning counties.

Overall, these findings suggest that the external stakeholder environment shapes how firms respond to heightened climate risk perceptions. Firms facing greater capital-market scrutiny and stronger local environmental preferences exhibit more pronounced increases in green innovation following nearby climate disasters.

4.2.3. State-level Green Incentives

The third dimension concerns the state policy environment in which firms make green innovation decisions. Green innovation is costly and uncertain, and state-level incentives for renewable energy and other green technologies can improve the economics of such investments by reducing effective costs or increasing expected returns. Firms operating in states with greater policy support for green technologies may therefore have stronger incentives to respond to heightened climate risk perceptions through green innovation.

We obtain information on state-level green incentive programs from the Database of State Incentives for Renewables & Efficiency (DSIRE) starting from 2000. We retain incentive programs implemented at the state level for which commercial or industrial entities are eligible and count the number of programs available in each state-year. We define

DecileStateGreenIncentives as the decile rank of the number of available green incentive programs in the firm's headquarters state in a given year.

Table 5 reports the results. Column (1) replicates the baseline analysis using the sample with available state-level green incentive data. In Column (2), the coefficient on the triple interaction term, *Treat* × *Post* × *DecileStateGreenIncentives*, is positive and statistically significant at the 1% level. Thus, the increase in the likelihood of filing a green patent following nearby climate disasters is more pronounced for firms located in states with greater contemporaneous green policy support.

Overall, these findings suggest that the state policy environment complements firms' responses to heightened climate risk perceptions. When existing state policies make green investment more attractive or feasible, firms exhibit a stronger green innovation response following nearby disasters.

4.3. Disaster Disclosure

Our interpretation of the main results is based on the premise that nearby climate disasters can heighten firms' perceptions of climate risk even when they do not experience direct physical impacts. Because these perceptions are not directly observable, we examine whether nearby firms become more likely to discuss climate disasters in their annual reports following disaster events. Corporate disclosures, in particular mandatory 10-K filings, provide a natural venue through which managers communicate their assessment of material risks (Graham et al., 2005; Loughran and McDonald, 2016; Matsumura et al., 2024), including those related to climate and extreme weather events. An increase in disaster-related discussion in 10-K filings therefore provides supportive evidence that climate-related risks become more prominent in firms' assessments following nearby climate disasters.

We measure disaster-related disclosure using *HasDisasterDisclosure*, an indicator equal to one if the firm's 10-K filing in a given year contains at least one disaster-related keyword in Appendix C, and zero otherwise. We then re-estimate Equation (1) using *HasDisasterDisclosure* as the dependent variable.

Table 6 reports the results. The coefficient on *Treat* × *Post* is positive and statistically significant at the one percent level both without and with firm-level controls. In Column (2), the coefficient of 0.0409 indicates that treated firms are approximately 4.09% more likely to discuss climate disasters in their annual reports following nearby disaster events. Overall, these findings are consistent with nearby disasters heightening firms' perceptions of climate risk and suggest that climate-related risks become more prominent in firms' formal risk assessments even in the absence of direct physical disaster impacts. These results are also consistent with prior findings showing that firms increase their environmental disclosures following nearby natural disasters (Dessaint and Matray, 2017; Huang et al., 2022).

4.4. Governance Responses to Nearby Climate Disasters

We next examine whether nearby climate disasters are followed by changes in firms' governance environments that can strengthen managers' incentives to pursue green innovation. Although a nearby disaster need not mechanically alter the firm's underlying physical risk exposure (Dessaint and Matray, 2017; Huang et al., 2022), it may prompt shareholders and boards to place greater emphasis on how managers respond to climate-related concerns, strengthening managers' incentives to invest in green innovation. We examine three governance outcomes: risk-taking incentives in executive compensation, environmental performance objectives in executive compensation contracts, and shareholder-sponsored environmental proposals.

We first examine executive risk-taking incentives. Green innovation is inherently costly and uncertain, requiring managers to commit resources to long-horizon projects whose outcomes are difficult to predict. Prior research shows that compensation convexity, commonly measured using executive Vega, provides managers with stronger incentives to undertake risky investments (Core and Guay, 2002; Coles et al., 2006). We obtain executive compensation data from the Coles, Daniel, and Naveen dataset and measure *ExecutiveVega* as the average sensitivity of executives' compensation to stock-return volatility in a given firm-year. We re-estimate Equation (1) using *ExecutiveVega* as the dependent variable.

Column (1) of Table 7 reports the results. The coefficient on *Treat* × *Post* is positive and statistically significant, suggesting that firms near climate disasters increase the risk-taking incentives embedded in executive compensation relative to control firms. This evidence is therefore consistent with boards altering the incentive structure to increase managers' willingness to undertake uncertain investments.

Because Vega captures general risk-taking incentives rather than incentives directed specifically toward environmental objectives, we next examine whether executive compensation becomes more explicitly tied to environmental performance. We define *EnvironmentalPay* as an indicator equal to one if the firm has at least one executive compensation performance objective classified under the "Environment" performance-metric category in a given year, and zero otherwise. As shown in Column (2), when *EnvironmentalPay* is the dependent variable, the coefficient on *Treat* × *Post* is positive and statistically significant. Thus, nearby firms become more likely to incorporate environmental performance objectives into executive compensation following climate disasters. This finding provides more direct evidence that changes in managerial incentives are oriented towards environmental outcomes.

Finally, we examine whether nearby disasters are accompanied by greater environmental pressure from shareholders. Shareholder-sponsored environmental proposals provide a direct mechanism through which investors can raise environmental issues for managerial and board attention. We define *EnvironmentalProposal* as an indicator equal to one if the firm receives at least one environmental shareholder proposal in a given year, and zero otherwise. In this analysis, we additionally control for the log-transformed number of shareholder meetings and number of shareholder proposals to account for differences in opportunities for environmental proposals to arise. Column (3) shows that the coefficient on *Treat* × *Post* is positive and statistically significant, indicating that nearby firms are more likely to receive environmental shareholder proposals following nearby climate disasters.

Taken together, the results in Table 7 indicate that nearby climate disasters are followed by changes in both internal managerial incentives and external shareholder pressure. The increase in executive Vega suggests stronger incentives for managerial risk taking, while the increases in environmental performance-based compensation and environmental shareholder proposals indicate that these governance responses are also oriented toward environmental objectives. Thus, the findings are consistent with nearby disasters shifting firms' governance environments in ways that encourage investment in green innovation.

4.5. Spillover Effects of Climate Disasters on Nearby Counties

A potential alternative explanation for our findings is the possibility of economic spillovers. Climate disasters can generate significant local economic disruptions in the directly hit counties and potentially spill over to nearby counties. If nearby counties experience an economic recession (or expansion) relative to control counties, our results could be driven by general economic changes rather than by changes in climate risk perceptions. Additionally, firms in the nearby counties may share supply chains or product markets with geographically nearby firms in the disaster zones. If the disaster disrupts the suppliers, customers, or competitors in the directly hit areas, treated firms might innovate in response to these supply-chain or competitive shocks rather than to heightened climate risk perceptions.

To mitigate these concerns, we conduct two sets of tests. First, we augment our baseline model (Equation (1)) with a comprehensive set of county-level economic indices to capture local economic conditions. We report the regression results in Panel A of Table 8. In Column (1), we include controls for the level of new business entry (*BusinessEntry*) and exit (*BusinessExit*) in the firm's county in a given year, the number of jobs created (*EmploymentCreation*) and destroyed (*EmploymentDestruction*), as well as the unemployment level (*Unemployment*) to capture the intensity of reallocation and creative destruction within the local economy (Davis and Haltiwanger, 1992; Decker et al., 2014). Additionally, we control for GDP (*GDP*) and total personal income in the firm's county (*PersonalIncome*) to further account for aggregate local economic conditions and demand. In Column (2), we replace these controls with their respective rates (*BusinessEntryRate*, *BusinessExitRate*, *EmploymentCreationRate*, *EmploymentDestructionRate*, *GDPRate*, *PersonalIncomeRate,* and *UnemploymentRate*) as an alternative set of controls. Across both specifications, the coefficient on the interaction term remains positive and statistically significant. The effects are also quantitatively similar to those documented in Table 2. These results are consistent with the notion that potential spillover effects from directly hit counties on nearby counties' economic conditions are unlikely to explain the observed increase in green innovation activities.[9]

[9] In untabulated analyses, we find that nearby disasters have a weakly negative, rather than positive, impact on nearby counties' economic conditions. Such adverse effects would generally hinder, rather than stimulate, innovative investment among treated firms, implying that any spillover effects would work against our results.

In the second set of tests, we examine whether the main results are driven by direct economic linkages to peer firms located in disaster zones. We separately exclude treated firms with supply-chain peers and product-market peers that are directly affected by the disaster, using supply-chain relationships from Compustat and product-market relationships from Hoberg and Phillips (2016). The results are reported in Panel B of Table 8. The coefficient on *Treat* × *Post* remains positive and statistically significant in both restricted samples, with magnitudes similar to the baseline estimate. These findings indicate that direct supply-chain disruptions or competitive shocks transmitted from firms in disaster zones are unlikely to explain the green innovation response of treated firms.

4.6. Quantity and Quality of Green Patents

To assess whether the green innovation response extends beyond firms' propensity to file a green patent, we examine the quantity and quality of the green patents they produce. The innovation literature notes that the economic significance of innovation depends not only on whether firms innovate, but also on the amount and technological impact of their inventive output (e.g., Hall et al., 2005; Kogan et al., 2017). Moreover, a potential concern is that the observed increase in green patenting may reflect greenwashing, whereby firms produce filings intended to signal environmental commitment rather than substantive technological advancement (Duchin et al., 2025). If the observed response is primarily symbolic, we would not expect nearby disasters to lead firms to produce a greater number of economically and technologically valuable green patents. We therefore extend our analysis to examine both the quantity and quality of green patents produced following nearby climate disasters.

We first examine the quantity of green patents. We define *NumGreenPatent* as the number of green patents filed by a firm in a given year and re-estimate Equation (1) using a Poisson regression. Column (1) of Table 9 reports the results. The coefficient on *Treat* × *Post* is positive and statistically significant, indicating that treated firms file more green patents following nearby climate disasters. Therefore, the increase in firms' propensity to engage in green patenting documented in our baseline analysis is accompanied by an increase in the quantity of green innovation output.

We next examine the quality of these green patents along two dimensions: technological impact and economic value. To capture technological impact, we use a patent's forward citations, which measure the extent to which an invention contributes to subsequent technological developments. We define *GreenCitation* as the average number of forward citations received by green patents filed by the firm in a given year. To measure economic value, we use the measure developed by Kogan et al. (2017), which estimates a patent's economic value based on the stock-market reaction around its grant date. We define *EconomicValueGreenPatent* as the average economic value of the green patents filed by a firm in a given year. As shown in Columns (2) and (3), the coefficient on *Treat* × *Post* is positive and statistically significant, indicating an increase in patent quality.

Overall, the results in Table 9 suggest that nearby firms not only become more likely to engage in green patenting, but also produce a greater quantity of green patents with higher technological impact and economic value. These findings suggest that the documented increase in green innovation is unlikely to reflect merely symbolic patenting or greenwashing, but instead represents a substantive increase in green innovation activity.

4.7. Robustness

To assess the robustness of our findings, we examine whether the results are sensitive to alternative definitions of geographic proximity to disaster zones. In our baseline analysis, we define treated firms as those headquartered in unaffected counties located within 100 miles of a directly hit county. In this Section, we consider several alternative definitions that vary the geographic scope and the way proximity to directly hit counties is measured.

The results are reported in Table 10. In Column (1), a firm is treated if its headquarters is in an unaffected county within 50 miles of a directly hit county. In Column (2), a firm is treated if its headquarters is in an unaffected county within 150 miles of a directly hit county. In Column (3), a firm is treated if its headquarters is in an unaffected county that borders a directly hit county. In Column (4), a firm is treated if its headquarters is in one of the ten unaffected counties closest to any county directly hit by a disaster. Consistent with our main analysis, the *Treat* × *Post* coefficient is positive and statistically significant across all specifications. These findings indicate that the increase in firms' likelihood of filing a green patent is robust to alternative ways of defining proximity to climate disasters.

5. Conclusion

Given the growing economic importance of climate risk, understanding how firms respond to heightened perceptions of that risk is an important question. In this study, we leverage nearby climate disasters to examine whether green innovation is one avenue through which firms respond to climate risk in the absence of direct physical disaster impacts. We posit that heightened climate risk perceptions can increase the importance managers attach to both the physical consequences of climate-related disruptions and the transition-related costs and opportunities associated with evolving stakeholder preferences. Using a stacked difference-in-differences design, we find that firms located near, but not directly hit by, climate disasters become more likely to file green patents following these events. The response is substantive: nearby firms also produce more green patents, and these patents exhibit greater technological impact and economic value.

Our cross-sectional analyses further show that the green innovation response is stronger for firms with greater local media coverage, higher analyst engagement, headquarters in more Democratic-leaning counties, and stronger state green policy support. These patterns are consistent with heightened climate risk perceptions translating more strongly into green innovation when climate-related information is more widely disseminated, external stakeholder pressures are stronger, and the policy environment is more supportive of green investment. Additionally, executive risk-taking incentives, environment-linked compensation, and environmental shareholder proposals increase following nearby disasters, consistent with changes in firms' governance environments that encourage green investment. We also provide evidence suggesting that economic spillovers from disaster zones and disruptions in peer networks are unlikely to be the main drivers of the results. Overall, our findings extend our understanding of when heightened climate risk perceptions translate into substantive corporate action and highlight green innovation as an important response through which firms manage climate-related risk.

References

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The Environment and Directed Technical Change. *American Economic Review*, *102*(1), 131–166.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, *124*(1), 1–51.

Aghion, P., Van Reenen, J., & Zingales, L. (2013). Innovation and institutional ownership. *American Economic Review*, 103(1), 277–304.

Ahmed, N., Ore Areche, F., Saenz Arenas, E. R., Cosio Borda, R. F., Javier-Vidalón, J. L., Silvera-Arcos, S., Ober, J., & Kochmańska, A. (2023). Natural disasters and energy innovation: Unveiling the linkage from an environmental sustainability perspective. *Frontiers in Energy Research, 11*.

Alok, S., Kumar, N., & Wermers, R. (2020). Do fund managers misestimate climatic disaster risk. *Review of Financial Studies*, *33*(3), 1146–1183.

Aragón-Correa, J. A., & Sharma, S. (2003). A contingent resource-based view of proactive corporate environmental strategy. *Academy of Management Review*, *28*(1), 71–88.

Arrow, K. J., & Fisher, A. C. (1974). Environmental Preservation, Uncertainty, and Irreversibility. *The Quarterly Journal of Economics*, *88*(2), 312–319.

Ashraf, M., de Franco, G., Small, R. C., & Young, S. (2024). Users' Solicitation of Disclosure When Accounting Standards Restrict Managers' Discretion Over Financial Reporting: Evidence from Conference Calls. *Working paper*.

Baker, A. C., Larcker, D. F., & Wang, C. C. Y. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, *144*(2), 370–395.

Baldauf, M., Garlappi, L., & Yannelis, C. (2020). Does Climate Change Affect Real Estate Prices? Only If You Believe in It. *Review of Financial Studies*, *33*(3), 1256–1295.

Barrot, J. N., & Sauvagnat, J. (2016). Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks. *The Quarterly Journal of Economics*, *131*(3), 1543–1592.

Bernanke, B. S. (1983). Irreversibility, Uncertainty, and Cyclical Investment. *The Quarterly Journal of Economics*, *98*(1), 85–106.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica*, *77*(3), 623–685.

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517–549.

Bourveau, T., & Law, K. K. F. (2021). Do Disruptive Life Events Affect How Analysts Assess Risk? Evidence from Deadly Hurricanes. *The Accounting Review, 96*(3), 121–140.

Brown, J. R., Fazzari, S. M., & Petersen, B. C. (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *Journal of Finance*, 64(1), 151–185.

Brown, J. R., Martinsson, G., & Thomann, C. (2022). Can Environmental Policy Encourage Technical Change? Emissions Taxes and R&D Investment in Polluting Firms. *Review of Financial Studies*, *35*(10), 4518–4560.

Bushee, B. J., Core, J. E., Guay, W., & Hamm, S. J. W. (2010). The role of the business press as an information intermediary. *Journal of Accounting Research*, *48*(1), 1–19.

Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The Effect of Minimum Wages on Low-Wage Jobs. *Quarterly Journal of Economics*, *134*(3).

Cheng, Q., Lin, A. P., & Yang, M. (2025). Green Innovation and Firms' Financial and Environmental Performance: The Roles of Pollution Prevention Versus Control. *Journal of Accounting and Economics*, *79*(1), 101706.

Cho, S., Jung, B. C., Silva, F. B. G., & Yoo, C. Y. (2026). Managers' Inventory Holding Decisions in Response to Natural Disasters. *The Accounting Review*, *101*(2), 89–119.

Christensen, H. B., Hail, L., & Leuz, C. (2021). Mandatory CSR and Sustainability Reporting: Economic Analysis and Literature Review. *Review of Accounting Studies*, *26*, 1176–1248.

Cohen, L., Gurun, U. G., & Nguyen, Q. H. (2024). The ESG-Innovation Disconnect: Evidence from Green Patenting. *Working paper*.

Cohen, S., Kadach, I., & Ormazabal, G. (2023a). Institutional Investors, Climate Disclosure, and Carbon Emissions. *Journal of Accounting and Economics*, *76*(2–3), 101640.

Cohen, S., Kadach, I., Ormazabal, G., & Reichelstein, S. (2023b). Executive Compensation Tied to ESG Performance: International Evidence. *Journal of Accounting Research, 61*(3), 805–853.

Cohen, W. M., & Klepper, S. (1996). A reprise of size and R&D. *Economic Journal*, 106(437), 925–951.

Coles, J. L., Daniel, N. D., & Naveen, L. (2006). Managerial Incentives and Risk-Taking. *Journal of Financial Economics, 79*, 431–468.

Core, J. E., & Guay, W. (2002). Estimating the Value of Employee Stock Option Portfolios and Their Sensitivities to Price and Volatility. *Journal of Accounting Research, 40*, 613–630.

Correa, R., He, A., Herpfer, C., & Lel, U. (2026). The Rising Tide Lifts Some Interest Rates: Climate Change, Natural Disasters and Loan Pricing. *Journal of Finance, Forthcoming*.

Davis, S. J., & Haltiwanger, J. (1992). Gross Job Creation, Gross Job Destruction, and Employment Reallocation. *Quarterly Journal of Economics*, *107*(3), 819–863.

de Chaisemartin, C., & d'Haultfoeuille, X. (2026). Difference-in-Differences Estimators of Intertemporal Treatment Effects. *Review of Economics and Statistics, 108*(4), 863–880.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2014). The Role of Entrepreneurship in US Job Creation and Economic Dynamism. *Journal of Economic Perspectives*, *28*(3), 3–24.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95.

Dessaint, O., & Matray, A. (2017). Do managers overreact to salient risks? Evidence from hurricane strikes. *Journal of Financial Economics*, *126*(1), 97–121.

Downar, B., Ernstberger, J., Reichelstein, S., Schwenen, S., & Zaklan, A. (2021). The impact of carbon disclosure mandates on emissions and financial operating performance. *Review of Accounting Studies, 26*(3), 1137–1175.

Dube, A., Girardi, D., Jordà, Ò., & Taylor, A. M. (2025). A Local Projections Approach to Difference-in-Differences. *Journal of Applied Econometrics*, *40*(7), 741–758.

Duchin, R., Gao, J., & Xu, Q. (2025). Sustainability or Greenwashing: Evidence from the Asset Market for Industrial Pollution. *Journal of Finance*, 80(2), 699–754.

Dyer, T. A., Glaeser, S., Lang, M. H., & Sprecher, C. (2024). The Effect of Patent Disclosure Quality on Innovation. *Journal of Accounting and Economics*, *77*(2–3), 101647.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging Climate Change News. *Review of Financial Studies*, *33*(3), 1184–1216.

Even-Tov, O., She, G., Wang, L. L., & Yang, D. (2025). How Government Procurement Shapes Corporate Climate Disclosures, Commitments, and Actions. *Review of Accounting Studies, 30*(2), 1968–2014.

Fang, L., & Peress, J. (2009). Media Coverage and the Cross-Section of Stock Returns. *Journal of Finance*, *64*(5), 2023–2052.

Favot, M., Vesnic, L., Priore, R., Bincoletto, A., & Morea, F. (2023). Green patents and green codes: How different methodologies lead to different results. *Resources, Conservation & Recycling Advances*, *18*, 200132.

Fich, E. M., & Xu, G. (2025). Do salient climatic risks affect shareholder voting? *Review of Finance, 29*(2), 567–602.

Fink, L. (2020). A Fundamental Reshaping of Finance. BlackRock.

Fink, L. (2022). The Power of Capitalism. BlackRock.

Fritsch, F., Zhang, Q., & Zheng, X. (2025). Responding to Climate Change Crises: Firms' Trade-Offs. *Journal of Accounting Research*, *63*(5), 2137–2179.

Glaeser, S., & Lang, M. (2024). Measuring Innovation and Navigating Its Unique Information Issues: A Review of the Accounting Literature on Innovation. *Journal of Accounting and Economics*, *78*(2–3), 101720.

Ginglinger, E., & Moreau, Q. (2023). Climate Risk and Capital Structure. *Management Science, 69*(12), 7492–7516.

Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, *40*(1–3), 3–73.

Gulen, H., & Ion, M. (2016). Policy Uncertainty and Corporate Investment. *Review of Financial Studies*, *29*(3), 523–564.

Hall, B. H., & Lerner, J. (2010). The Financing of R&D and Innovation. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the Economics of Innovation* (Vol. 1, pp. 609–639). Elsevier.

Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market Value and Patent Citations. *RAND Journal of Economics*, *36*(1), 16–38.

He, Q., & Qiu, B. (2025). Environmental Enforcement Actions and Corporate Green Innovation. *Journal of Corporate Finance*, *91*, 102711.

Hirshleifer, D., Hsu, P.-H., & Li, D. (2013). Innovative Efficiency and Stock Returns. *Journal of Financial Economics*, 107(3), 632–654.

Hoberg, G., & Phillips, G. (2016). Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy, 124*(5), 1423–1465.

Howard-Grenville, J., Buckle, S. J., Hoskins, B. J., & George, G. (2014). Climate Change and Management. *Academy of Management Journal*, *57*(3), 615–623.

Huang, S., Ng, J., Ranasinghe, T., & Zhang, M. (2021). Do Innovative Firms Communicate More? Evidence from the Relation between Patenting and Management Guidance. *The Accounting Review*, 96(1), 273–297.

Huang, Q., Li, Y., Lin, M., & McBrayer, G. A. (2022). Natural Disasters, Risk Salience, and Corporate ESG Disclosure. *Journal of Corporate Finance*, 72, 102152.

Huberman, G., & Regev, T. (2001). Contagious speculation and a cure for cancer: A nonevent that made stock prices soar. *Journal of Finance*, *56*(1), 387–396.

Intergovernmental Panel on Climate Change (IPCC). (2020). The concept of risk in the IPCC Sixth Assessment Report: A summary of cross-Working Group discussions.

Intergovernmental Panel on Climate Change (IPCC). (2021). Climate Change 2021: The Physical Science Basis, the Working Group I.

Julio, B., & Yook, Y. (2012). Political Uncertainty and Corporate Investment Cycles. *Journal of Finance*, *67*(1), 45–83.

Keding, L., and Ritterrath, M. C. (2024). The Effects of Climate disasters on Green Innovation. *Academy of Management Proceedings*, 2024(1), 16159.

Kim, H. S., Matthes, C., & Phan, T. (2025a). Severe Weather and the Macroeconomy. *American Economic Journal: Macroeconomics*, *17*(2), 315–341.

Kim, J., & Valentine, K. (2021). The Innovation Consequences of Mandatory Patent Disclosures. *Journal of Accounting and Economics*, *71*(2–3), 101381.

Kim, J., & Valentine, K. (2023). Public Firm Disclosures and the Market for Innovation. *Journal of Accounting and Economics*, *76*(1), 101577.

Kim, J., & Valentine, K. (2026). Earnings Targets, Strategic Patent Sales, and Patent Trolls. *Journal of Accounting and Economics*, *81*(3), 101853.

Kim, J., Shi, T. T., & Verdi, R. S. (2025b). The Innovation Consequences of Judicial Efficiency. *Journal of Accounting and Economics*, *80*(2–3), 101813.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological Innovation, Resource Allocation, and Growth. *The Quarterly Journal of Economics*, *132*(2), 665–712.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The Importance of Climate Risks for Institutional Investors. *Review of Financial Studies*, *33*(3), 1067–1111.

Kruttli, M. S., Stoffman, N., & Watugala, S. W. (2025a). Two Centuries of U.S. Innovation and the Capital Channel: Evidence from Natural Disasters. *Working paper*.

Kruttli, M. S., Tran, B. R., & Watugala, S. W. (2025b). Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics. *Journal of Finance*, *80*(2), 783–832.

Le, H., Nguyen, T., Gregoriou, A., and Healy, J. (2024). Natural Disasters and Corporate Innovation. *European Journal of Finance*, 30(2), 144–172.

Li, Q., Shan, H., Tang, Y., & Yao, V. (2024). Corporate Climate Risk: Measurements and Responses. *Review of Financial Studies*, 37(6), 1778–1830.

Loughran, T., & McDonald, B. (2016). Textual Analysis in Accounting and Finance: A Survey. *Journal of Accounting Research*, *54*(4), 1187–1230.

Ludvigson, S. C., Ma, S., & Ng, S. (2021). COVID-19 and the Costs of Deadly Disasters. *AEA Papers and Proceedings*, *111*, 366–370.

Ma, Y., Feng, G. F., and Chang, C. P. (2024). From Traditional Innovation to Green Innovation: How an Occurrence of Natural Disasters Influences Sustainable Development? *Sustainable Development*, *32*(3), 2779-2796.

Matsumura, E. M., Prakash, R., & Vera-Muñoz, S. C. (2014). Firm-Value Effects of Carbon Emissions and Carbon Disclosures. *The Accounting Review*, *89*(2), 695–724.

Matsumura, E. M., Prakash, R., & Vera-Muñoz, S. C. (2024). Climate-Risk Materiality and Firm Risk. *Review of Accounting Studies, 29*(1), 33–74.

McDonald, R., & Siegel, D. (1986). The Value of Waiting to Invest. *The Quarterly Journal of Economics*, *101*(4), 707–727.

Miao, Q. and Popp, D. (2014). Necessity as the mother of invention: Innovative responses to natural disasters. *Journal of Environmental Economics and Management*, *68*(2), 280-295.

Moscona, J. (2025). Environmental Catastrophe and the Direction of Invention: Evidence from the American Dust Bowl. *Working paper*.

National Centers for Environmental Information (NCEI). (2025). U.S. Billion-Dollar Weather and Climate Disasters. National Oceanic and Atmospheric Administration.

Pankratz, N. M. C., & Schiller, C. M. (2024). Climate Change and Adaptation in Global Supply-Chain Networks. *Review of Financial Studies, 37*(6), 1729–1777.

Panousi, V., & Papanikolaou, D. (2012). Investment, Idiosyncratic Risk, and Ownership. *Journal of Finance*, *67*(3), 1113–1148.

Ramadorai, T., & Zeni, F. (2024). Climate Regulation and Emissions Abatement: Theory and Evidence from Firms' Disclosures. *Management Science, 70*(12), 8366–8385.

Skinner, A. N., & Valentine, K. (2026). Green Patenting and Voluntary Innovation Disclosure. *Review of Accounting Studies, forthcoming*.

Tomar, S. (2023). Greenhouse Gas Disclosure and Emissions Benchmarking. *Journal of Accounting Research, 61*(2), 451–492.

U.S. Global Change Research Program. (2018). Fourth National Climate Assessment, Volume II: Impacts, risks, and adaptation in the United States.

U.S. Office of Management and Budget. (2022). Climate Risk Exposure: An Assessment of the Federal Government's Financial Risks to Climate Change.

Valentine, K., Zhang, J. L., & Zheng, Y. (2025). Strategic Scientific Disclosure: Evidence from the Leahy–Smith America Invents Act. *Journal of Accounting Research*, 63(4), 1723–1755.

Wang, M., Wurgler, J., & Zhang, H. (2026). Policy Uncertainty Reduces Green Innovation. *Journal of Financial Economics*, 175, 104189.

Whited, T. M., & Wu, G. (2006). Financial Constraints Risk. Review of Financial Studies, 19(2), 531–559.

Yezegel, A. (2023). The Value of Eliciting Information: Evidence from Sell-Side Analysts. *The Accounting Review*, *98*(3), 459–486.

Zhao, X. X., Zheng, M., & Fu, Q. (2022). How Natural Disasters Affect Energy Innovation? The Perspective of Environmental Sustainability. *Energy Economics*, *109*, 105992.

Figure 1: Example – Identifying Treated and Control Firms

This figure provides an example of identifying treated and control firms using Hurricane Michael in 2018. The counties shaded in red are those directly hit by the disaster, as identified using SHELDUS data, which considers a county impacted if it reports any kind of damage caused by a disaster. The gray-shaded counties are those for which the minimum distance between their geographical center and the center of any directly hit county is less than or equal to 100 miles. These counties are considered nearby but not directly hit by the disaster. A firm is considered treated if its headquarters is located in a gray-shaded county and considered a control if its headquarters is in an unshaded county. Firms with headquarters in the disaster zone (red-shaded counties) are not considered in the analysis.

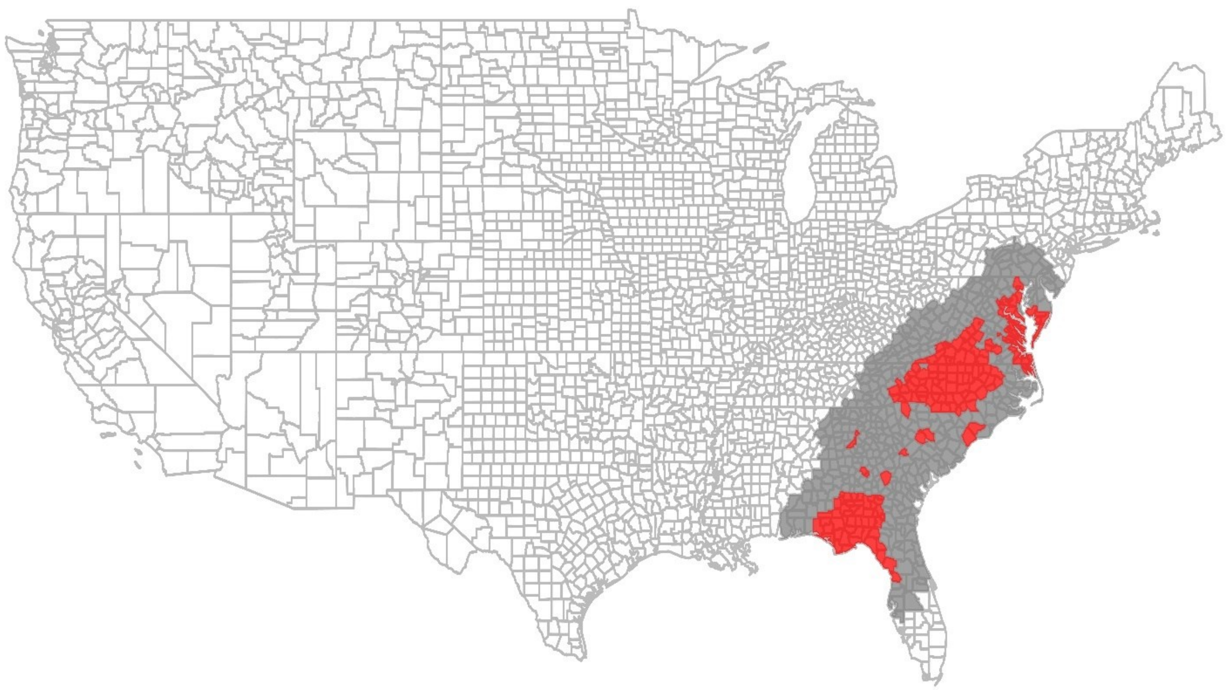


Figure 2: The Dynamic Effects of Heightened Climate Risk Perception on Green Innovation

This figure shows coefficient estimates and 95% confidence intervals from the stacked difference-in-differences regression, estimating the effect of heightened climate risk perception on green innovation in the period [-5, +5] years around a climate disaster. The disaster occurs at year $t = 0$, with year $t = -5$ serving as the benchmark.

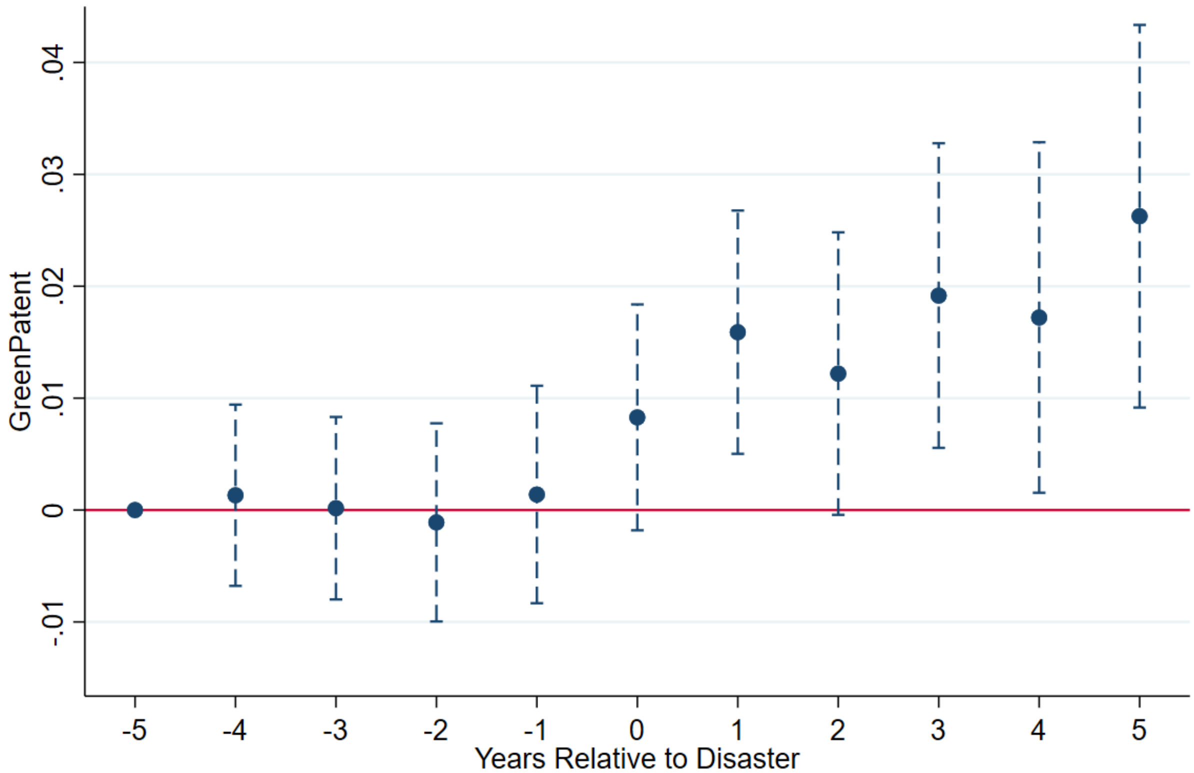


Table 1: Summary Statistics

This table reports summary statistics for variables used in the analysis. All variables are defined in Appendix A. Continuous variables are winsorized at the 1% and 99% levels.

Variable	N	Mean	P25	Median	P75	SD
GreenPatent	461,153	0.092	0.000	0.000	0.000	0.289
Treat	461,153	0.309	0.000	0.000	1.000	0.462
Post	461,153	0.547	0.000	1.000	1.000	0.498
Size	461,153	5.645	4.075	5.457	7.027	2.161
Leverage	461,153	0.173	0.001	0.111	0.276	0.201
ROA	461,153	-0.081	-0.123	0.021	0.077	0.301
Age	461,153	2.567	1.946	2.639	3.178	0.818
Cash	461,153	0.303	0.082	0.236	0.473	0.257
Book-to-Market	461,153	0.504	0.209	0.395	0.687	0.462
FinancialConstraint	461,153	-0.264	-0.341	-0.256	-0.177	0.124
HHI	461,153	0.259	0.127	0.191	0.335	0.198
InstitutionalHolding	461,153	0.500	0.058	0.536	0.883	0.385
CAPX	461,153	0.041	0.014	0.028	0.052	0.042
PreNewsCoverage	281,477	960.3	102.4	501.9	1,570	1,097
PreNewsCoveragePerCapita	281,477	37.85	5.568	26.02	60.58	50.69
PreNewsCoveragePerGDP	281,477	0.682	0.126	0.525	1.110	0.605
PreAnalystEngagement	125,796	5.928	3.849	5.436	7.543	2.881
DemocraticLeaningCounty	355,208	0.618	0.513	0.638	0.721	0.138
StateGreenIncentives	355,208	14.44	10	13	21	6.450
HasDisasterDisclosure	403,354	0.563	0.000	1.000	1.000	0.496
ExecutiveVega	187,204	58.25	7.762	22.97	63.62	107.3
EnvironmentalPay	170,237	0.001	0.000	0.000	0.000	0.028
EnvironmentalProposal	91,601	0.065	0.000	0.000	0.000	0.246
BusinessEntry	333,923	8.151	7.583	8.308	8.903	0.984
BusinessExit	333,923	8.080	7.493	8.283	8.806	0.978
EmploymentCreation	333,923	11.37	10.80	11.60	12.01	1.015
EmploymentDestruction	333,923	11.30	10.70	11.53	11.99	1.025
GDP	333,923	11.50	10.93	11.71	12.21	1.064
PersonalIncome	333,923	18.05	17.50	18.28	18.74	1.018
Unemployment	333,923	10.51	9.826	10.59	11.20	1.032
BusinessEntryRate (%)	317,695	11.35	10.41	11.27	12.18	1.635
BusinessExitRate (%)	317,695	10.55	9.706	10.36	11.39	1.358
EmploymentCreationRate (%)	317,695	14.67	13.34	14.75	16.06	2.169
EmploymentDestructionRate (%)	317,695	13.88	11.51	12.90	15.54	3.334
GDPRate (%)	317,695	3.458	1.360	3.371	6.007	3.943
PersonalIncomeRate (%)	317,695	4.714	2.548	5.172	7.627	4.071
UnemploymentRate (%)	317,695	5.950	4.223	5.300	7.492	2.291
NumGreenPatent	461,153	0.632	0.000	0.000	0.000	5.008
GreenCitation	461,153	0.966	0.000	0.000	0.000	6.355
EconomicValueGreenPatent	461,153	0.778	0.000	0.000	0.000	3.577

Table 2: Main Results – Heightened Climate Risk Perception and Green Innovation

This table reports coefficients from stacked difference-in-differences regressions estimating the effects of heightened climate risk perception on green innovation. The dependent variable is *GreenPatent*, an indicator equal to one if the firm files at least one green patent in a given year, and zero otherwise. The main independent variable of interest is *Treat* × *Post*, where *Treat* is an indicator for treated firms, and *Post* is an indicator for observations in the post-period. Control variables include *Size, Leverage, ROA, Age, Cash, Book-to-Market, Financial Constraint, HHI, Institutional Holding, and CAPX*. Appendix A contains all variable definitions. Cohort-Firm fixed effects and Cohort-Year fixed effects are included to absorb time-invariant firm-specific characteristics and time trends in green innovation, respectively. Each cohort corresponds to a disaster. Standard errors are clustered by firm, and *t*-stats are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	Dependent Variable: GreenPatent	
	(1)	(2)
Treat* × *Post	**0.0133*** **	**0.0148*** **
	(3.29)	**(3.63)**
Size		0.0158***
		(3.51)
Leverage		0.0118
		(0.87)
ROA		-0.0181**
		(-2.07)
Age		0.0040
		(0.48)
Cash		0.0113
		(0.69)
Book-to-Market		0.0003
		(0.07)
Financial Constraint		0.0436
		(1.50)
HHI		-0.0406
		(-1.32)
Institutional Holding		0.0231**
		(2.11)
CAPX		0.0878*
		(1.67)
Cohort-Firm FE	Yes	Yes
Cohort-Year FE	Yes	Yes
Obs.	461,153	461,153
Adj. R^2	0.537	0.538

Table 3: Cross-sectional Analyses – News Coverage

This table reports the results of the cross-sectional analyses based on news coverage. The dependent variable is *GreenPatent*, an indicator equal to one if the firm files at least one green patent in a given year, and zero otherwise. Column (1) replicates the main result in Table 2 using the reduced sample with news coverage data. The main independent variables of interest are the triple interaction terms: *Treat* × *Post* × *DecilePreNewsCoverage* (Column (2)), *Treat* × *Post* × *DecilePreNewsCoveragePerCapita* (Column (3)), and *Treat* × *Post* × *DecilePreNewsCoveragePerGDP* (Column (4)). *DecilePreNewsCoverage* is the decile rank of a firm's pre-treatment average exposure to news coverage, calculated as the average annual count of news articles in the firm's location state in the pre-period. *DecilePreNewsCoveragePerCapita* is the decile rank of a firm's pre-treatment average exposure to population-standardized news coverage, calculated as the average annual count of news articles scaled by the population (in 1,000) of the firm's state in the pre-period. *DecilePreNewsCoveragePerGDP* is the decile rank of a firm's pre-treatment average exposure to GDP-standardized news coverage, calculated as the average annual count of news articles scaled by GDP (in $1,000,000) of the firm's state in the pre-period. Control variables include *Size, Leverage, ROA, Age, Cash, Book-to-Market, Financial Constraint, HHI, Institutional Holding, and CAPX*. Appendix A contains all variable definitions. Cohort-Firm fixed effects and Cohort-Year fixed effects are included to absorb time-invariant firm-specific characteristics and time trends in green innovation, respectively. Each cohort corresponds to a disaster. Standard errors are clustered by firm, and *t*-stats are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	Dependent Variable: GreenPatent			
	(1)	(2)	(3)	(4)
Treat × *Post*	0.0177***	0.0197***	0.0190***	0.0190***
	(3.09)	(3.13)	(3.26)	(3.26)
Treat* × *Post* × *DecilePreNewsCoverage		**0.0096*** **		
		(3.96)		
Treat* × *Post* × *DecilePreNewsCoveragePerCapita			**0.0111*** **	
			(4.51)	
Treat* × *Post* × *DecilePreNewsCoveragePerGDP				**0.0112*** **
				(4.50)
Controls	Yes	Yes	Yes	Yes
Other Interaction Terms	No	Yes	Yes	Yes
Cohort-Firm FE	Yes	Yes	Yes	Yes
Cohort-Year FE	Yes	Yes	Yes	Yes
Obs.	281,477	281,477	281,477	281,477
Adj. R^2	0.546	0.546	0.547	0.546

Table 4: Cross-sectional Analyses – External Stakeholder Environment

This table reports the results of the cross-sectional analyses based on two characteristics of the external stakeholder environment in which firms make strategic decisions: analyst engagement (Panel A) and county-level political leaning (Panel B). In both Panels, the dependent variable is *GreenPatent*, an indicator equal to one if the firm files at least one green patent in a given year, and zero otherwise. In Panel A, Column (1) replicates the main result in Table 2 using the reduced sample with conference call data. In Column (2), the main independent variable of interest is the triple interaction term: *Treat* × *Post* × *DecilePreAnalystEngagement*, where *DecilePreAnalystEngagement* is the decile rank of a firm's pre-period average exposure to analyst engagement, calculated as the average number of analysts asking questions during conference calls in the pre-period. In Panel B, Column (1) replicates the main result in Table 2 using the reduced sample with county-level election data. In Column (2), the main independent variable of interest is the triple interaction term: *Treat* × *Post* × *DemocraticLeaningCounty*, where *DemocraticLeaningCounty* is a firm-year measure based on the Democratic presidential nominee's vote share in the firm's county, with values in non-presidential-election years carried forward from the most recent presidential election. Control variables include *Size, Leverage, ROA, Age, Cash, Book-to-Market, Financial Constraint, HHI, Institutional Holding, and CAPX*. Appendix A contains all variable definitions. Cohort-Firm fixed effects and Cohort-Year fixed effects are included to absorb time-invariant firm-specific characteristics and time trends in green innovation, respectively. Each cohort corresponds to a disaster. Standard errors are clustered by firm, and *t*-stats are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A. Analyst Engagement

	Dependent Variable: GreenPatent	
	(1)	(2)
Treat × *Post*	0.0545***	0.0549***
	(4.46)	(4.62)
Treat* × *Post* × *DecilePreAnalystEngagement		**0.0083****
		(2.23)
Controls	Yes	Yes
Other Interaction Terms	No	Yes
Cohort-Firm FE	Yes	Yes
Cohort-Year FE	Yes	Yes
Obs.	125,796	125,796
Adj. R^2	0.570	0.572

Panel B. Democratic-leaning Counties

	Dependent Variable: GreenPatent	
	(1)	(2)
Treat × *Post*	0.0165***	0.0127**
	(3.03)	(2.38)
Treat* × *Post* × *DemocraticLeaningCounty		**0.0764****
		(2.10)
Controls	Yes	Yes
Other Interaction Terms	No	Yes
Cohort-Firm FE	Yes	Yes
Cohort-Year FE	Yes	Yes
Obs.	355,208	355,208
Adj. R^2	0.541	0.541

Table 5: Cross-sectional Analyses – State-level Green Incentives

This table reports the results of the cross-sectional analyses based on state-level green incentives. The dependent variable is *GreenPatent*, an indicator equal to one if the firm files at least one green patent in a given year, and zero otherwise. Column (1) replicates the main result in Table 2 using the reduced sample with state-level green incentive data. In Column (2), the main independent variable of interest is the triple interaction term: *Treat* × *Post* × *DecileStateGreenIncentives*, where *DecileStateGreenIncentives* is the decile rank of the number of available green incentives in the firm's state in a given year. Control variables include *Size, Leverage, ROA, Age, Cash, Book-to-Market, Financial Constraint, HHI, Institutional Holding, and CAPX*. Appendix A contains all variable definitions. Cohort-Firm fixed effects and Cohort-Year fixed effects are included to absorb time-invariant firm-specific characteristics and time trends in green innovation, respectively. Each cohort corresponds to a disaster. Standard errors are clustered by firm, and *t*-stats are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	Dependent Variable: GreenPatent	
	(1)	(2)
Treat × *Post*	0.0176***	0.0213***
	(2.73)	(2.96)
Treat* × *Post* × *DecileStateGreenIncentives		**0.0089*** **
		(4.13)
Controls	Yes	Yes
Other Interaction Terms	No	Yes
Cohort-Firm FE	Yes	Yes
Cohort-Year FE	Yes	Yes
Obs.	355,208	355,208
Adj. R^2	0.541	0.541

Table 6. Heightened Climate Risk Perception and Disaster Disclosure

This table reports coefficients from stacked difference-in-differences regressions estimating the effects of heightened climate risk perception on whether firms discuss climate disasters in their annual reports. The dependent variable is *HasDisasterDisclosure*, an indicator variable equal to 1 if the firm's 10-K filing mentions any disaster-related keyword and 0 otherwise. Control variables include *Size, Leverage, ROA, Age, Cash, Book-to-Market, Financial Constraint, HHI, Institutional Holding, and CAPX*. Appendix A contains all variable definitions. Cohort-Firm fixed effects and Cohort-Year fixed effects are included to absorb time-invariant firm-specific characteristics and time trends in disaster disclosure, respectively. Each cohort corresponds to a disaster. Standard errors are clustered by firm, and *t*-stats are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	Dependent Variable: HasDisasterDisclosure	
	(1)	(2)
Treat × Post	**0.0526*** **	**0.0409*** **
	(5.10)	**(4.04)**
Size		0.0377***
		(3.99)
Leverage		0.0111
		(0.39)
ROA		-0.0024
		(-0.13)
Age		-0.0866***
		(-4.54)
Cash		0.0538*
		(1.75)
Book-to-Market		0.0060
		(0.57)
Financial Constraint		0.0111
		(0.14)
HHI		0.0211
		(0.42)
Institutional Holding		-0.0011
		(-0.04)
CAPX		0.1258
		(1.02)
Cohort-Firm FE	Yes	Yes
Cohort-Year FE	Yes	Yes
Obs.	403,354	403,354
Adj. R^2	0.479	0.481

Table 7: Governance Responses to Nearby Climate Disasters

This table reports coefficients from stacked difference-in-differences regressions examining governance responses to nearby climate disasters. In Column (1), the dependent variable is *ExecutiveVega*, a measure of risk-taking incentives in executive compensation contracts, calculated as the average sensitivity of compensation to stock volatility of all executives of the firm in a given year. In Column (2), the dependent variable is *EnvironmentalPay*, an indicator equal to one if the firm has at least one executive compensation performance objective classified under the performance metric category "Environment" in a given year, and zero otherwise. In Column (3), the dependent variable is *EnvironmentalProposal,* an indicator equal to one if the firm receives at least one environmental shareholder proposal in a given year, and zero otherwise. The main independent variable of interest is *Treat* × *Post*, where *Treat* is an indicator for treated firms, and *Post* is an indicator for observations in the post-period. Control variables include *Size, Leverage, ROA, Age, Cash, Book-to-Market, Financial Constraint, HHI, Institutional Holding, and CAPX*. In Column (3), we also include *NumberOfMeeting* and *NumberOfProposals* as controls. Appendix A contains all variable definitions. Cohort-Firm fixed effects and Cohort-Year fixed effects are included to absorb time-invariant firm-specific characteristics and time trends, respectively. Each cohort corresponds to a disaster. Standard errors are clustered by firm, and *t*-stats are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	Dependent Variable:		
	ExecutiveVega	*EnvironmentalPay*	*EnvironmentalProposal*
	(1)	(2)	(3)
Treat* × *Post	**9.9024****	**0.0032***	**0.0191****
	(2.52)	**(1.83)**	**(2.23)**
Controls	Yes	Yes	Yes
Cohort-Firm FE	Yes	Yes	Yes
Cohort-Year FE	Yes	Yes	Yes
Obs.	187,204	170,237	91,601
Adj. R^2	0.787	0.053	0.453

Table 8: Potential Economic Spillovers from Disaster Zones

Panel A of this table reports the main results controlling for county-level economic indices. The dependent variable is *GreenPatent*, an indicator equal to one if the firm files at least one green patent in a given year, and zero otherwise. The main independent variable of interest is *Treat* × *Post*, where *Treat* is an indicator for treated firms, and *Post* is an indicator for observations in the post-period. In Column (1), the local economic indices include *BusinessEntry, BusinessExit, EmploymentCreation, EmploymentDestruction, GDP, PersonalIncome,* and *Unemployment*. In Column (2), the indices instead include *BusinessEntryRate, BusinessExitRate, EmploymentCreationRate, EmploymentDestructionRate, GDPRate, PersonalIncome Rate,* and *UnemploymentRate*. In both columns, *Size, Leverage, ROA, Age, Cash, Book-to-Market, Financial Constraint, HHI, Institutional Holding, and CAPX* are also included as controls. Panel B of this table reports the estimates of the main analysis excluding treated firms with at least one supply-chain peer (Column (1)) or product-market peer (Column (2)) directly hit by climate disasters. The dependent variable is *GreenPatent*. The main independent variable of interest is *Treat* × *Post*, where *Treat* is an indicator for treated firms, and *Post* is an indicator for observations in the post-period. Control variables include *Size, Leverage, ROA, Age, Cash, Book-to-Market, Financial Constraint, HHI, Institutional Holding, and CAPX*. Appendix A contains all variable definitions. Cohort-Firm fixed effects and Cohort-Year fixed effects are included in both Panels to absorb time-invariant firm-specific characteristics and time trends in green innovation, respectively. Each cohort corresponds to a disaster. Standard errors are clustered by firm, and *t*-stats are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A. Main Results Controlling for County-Level Economic Indices

	Dependent Variable: GreenPatent	
	(1)	(2)
Treat* × *Post	**0.0141***** **(2.64)**	**0.0198***** **(3.33)**
BusinessEntry	0.0784** (2.25)	
BusinessExit	-0.0528 (-1.36)	
EmploymentCreation	0.0342 (1.53)	
EmploymentDestruction	-0.0033 (-0.18)	
GDP	-0.0128 (-0.55)	
PersonalIncome	-0.0745** (-2.25)	
Unemployment	0.0175 (1.18)	
BusinessEntryRate		0.0022 (0.58)
BusinessExitRate		-0.0083* (-1.86)

EmploymentCreationRate		0.0018
		(0.91)
EmploymentDestructionRate		-0.0001
		(-0.06)
GDPRate		0.0721
		(0.86)
PersonalIncomeRate		-0.0346
		(-0.34)
UnemploymentRate		0.0049*
		(1.72)
Disaster-Year Fixed Effects	Yes	Yes
Disaster-Firm Fixed Effects	Yes	Yes
Observations	333,923	317,695
Adj. R^2	0.539	0.538

Panel B. Main Results and the Economic Links to Firms in Disaster Zones

	Dependent Variable: GreenPatent	
	(1)	(2)
Exclusion Criteria:	Supply-Chain Peers	Product-Market Peers
Treat × Post	**0.0147*** **	**0.0155*** **
	(3.73)	**(3.48)**
Controls	Yes	Yes
Cohort-Firm FE	Yes	Yes
Cohort-Year FE	Yes	Yes
Obs.	441,001	373,751
Adj. R^2	0.527	0.529

Table 9: Quantity and Quality of Green Patents

This table reports coefficients from stacked difference-in-differences regressions estimating the effects of heightened climate risk perception on green innovation quantity and quality. In Column (1), the dependent variable is *NumGreenPatent*, the number of green patents a firm files in a given year, and Poisson regression is used. In Column (2), the dependent variable is *GreenCitation*, the average forward citations of the green patents filed by the firm in a given year, and Poisson regression is used. In Column (3), the dependent variable is *EconomicValueGreenPatent*, the average economic value of the green patents filed by the firm in a given year, and OLS regression is used. Across all specifications, the main independent variable of interest is *Treat* × *Post*, where *Treat* is an indicator for treated firms, and *Post* is an indicator for observations in the post-period. Control variables include *Size, Leverage, ROA, Age, Cash, Book-to-Market, Financial Constraint, HHI, Institutional Holding, and CAPX*. Appendix A contains all variable definitions. Cohort-Firm fixed effects and Cohort-Year fixed effects are included to absorb time-invariant firm-specific characteristics and time trends, respectively. Each cohort corresponds to a disaster. Standard errors are clustered by firm, and *t*-stats are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	Dependent Variable:		
	NumGreenPatent	*GreenCitation*	*EconomicValueGreenPatent*
	Poisson	Poisson	OLS
	(1)	(2)	(3)
Treat* × *Post	**0.2042****	**0.2143*****	**0.1188****
	(2.15)	**(2.71)**	**(2.30)**
Controls	Yes	Yes	Yes
Cohort-Firm FE	Yes	Yes	Yes
Cohort-Year FE	Yes	Yes	Yes
Obs.	106,482	95,548	461,153
Pseudo/Adj. R^2	0.800	0.718	0.611

Table 10: Robustness – Alternative Definition of Treated Firms

This table reports the results using alternative definitions of treated firms. In Column (1), a firm is treated if its headquarters is in an unaffected county within 50 miles of a directly hit county. In Column (2), a firm is treated if its headquarters is in an unaffected county within 150 miles of a directly hit county. In Column (3), a firm is treated if its headquarters is in an unaffected county that borders a directly hit county. In Column (4), a firm is treated if its headquarters is in one of the ten unaffected counties closest to any county directly hit by a disaster. Across all specifications, the dependent variable is *GreenPatent*, an indicator equal to one if the firm files at least one green patent in a given year, and zero otherwise. Across all specifications, the independent variable of interest is *Treat* × *Post*, where *Treat* is an indicator for treated firms, and *Post* is an indicator for observations in the post-period. Control variables include *Size, Leverage, ROA, Age, Cash, Book-to-Market, Financial Constraint, HHI, Institutional Holding, and CAPX*. Appendix A contains all variable definitions. Cohort-Firm fixed effects and Cohort-Year fixed effects are included to absorb time-invariant firm-specific characteristics and time trends in green innovation, respectively. Each cohort corresponds to a disaster. Standard errors are clustered by firm, and *t*-stats are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	Dependent Variable: GreenPatent			
	50 Miles	*150 Miles*	*Border Counties*	*Top10Nearby*
	(1)	(2)	(3)	(4)
Treat* × *Post	**0.0100****	**0.0141*****	**0.0082***	**0.0094****
	(2.54)	**(3.17)**	**(1.95)**	**(2.30)**
Controls	Yes	Yes	Yes	Yes
Cohort-Firm FE	Yes	Yes	Yes	Yes
Cohort-Year FE	Yes	Yes	Yes	Yes
Obs.	479,410	458,114	464,835	452,005
Adj. R^2	0.542	0.544	0.542	0.540

Appendix A. Variable Definitions

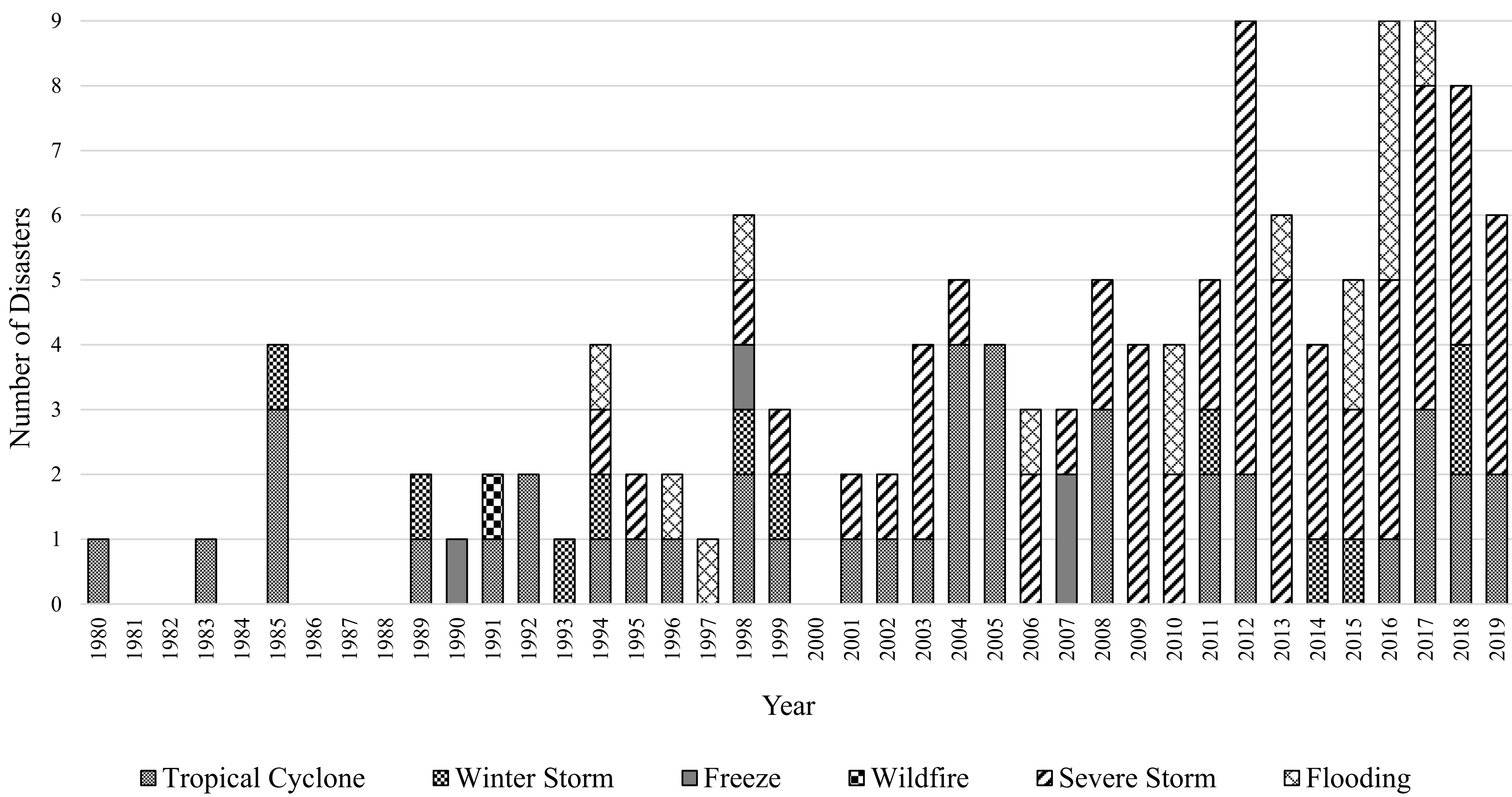
Variables	Definition
Age	The natural logarithm of one plus the age of the firm (in years) as of a given year.
Book-to-Market	The book-to-market ratio of the firm in a given year, defined as the book equity at the end of a fiscal year (CEQ+TXDB), divided by the market value of equity.
BusinessEntry	The business establishment entries in a county in a given year, calculated as the natural logarithm of one plus the establishment entry count.
BusinessEntryRate (%)	The business establishment entry rate, defined as the count of establishment entrants in year *t* divided by the average count of employment-active establishments in year *t* and year *t*-1.
BusinessExit	The business establishment exits in a county in a given year, calculated as the natural logarithm of one plus the establishment exit count.
BusinessExitRate (%)	The business establishment exit rate, defined as the count of establishment exits in year *t* divided by the average count of employment-active establishments in year *t* and year *t*-1.
CAPX	The amount of capital expenditure of a firm in a given year, divided by total assets.
Cash	Cash and short-term investments of a firm in a given year, divided by total assets.
DecilePreAnalystEngagement	The decile rank of *PreAnalystEngagement.*
DecilePreNewsCoverage	The decile rank of *PreNewsCoverage*.
DecilePreNewsCoveragePerCapita	The decile rank of *PreNewsCoveragePerCapita*.
DecilePreNewsCoveragePerGDP	The decile rank of *PreNewsCoveragePerGDP*.
DecileStateGreenIncentives	The decile rank of *StateGreenIncentives.*
DemocraticLeaningCounty	A firm-year measure based on the Democratic presidential nominee's vote share in the firm's county, with values in non-presidential-election years carried forward from the most recent presidential election.
EconomicValueGreenPatent	The average economic value of the green patents filed by the firm in a given year. The economic value of a patent is obtained from Kogan et al. (2017), which is calculated based on capital market reactions to the patent grant.
EmploymentCreation	The job creation in a county in a given year, calculated as the natural logarithm of one plus the absolute number of jobs created.
EmploymentCreationRate (%)	The job creation rate, defined as the absolute number of jobs created in year *t* divided by the average employment count in year *t* and year *t*-1.
EmploymentDestruction	The job destruction in a county in a given year, calculated as the natural logarithm of one plus the absolute number of job losses.
EmploymentDestructionRate (%)	The job destruction rate, defined as the absolute number of jobs destroyed in year *t* divided by the average employment count in year *t* and year *t*-1.
EnvironmentalPay	An indicator equal to one if the firm has at least one executive compensation performance objective classified under the performance metric category "Environment" in a given year, and zero otherwise.

EnvironmentalProposal	An indicator equal to one if the firm receives at least one environmental shareholder proposal in a given year, and zero otherwise.
ExecutiveVega	A measure of risk-taking incentives in executive compensation contracts, calculated as the average sensitivity of compensation to stock volatility of all executives of the firm in a given year, defined following Coles et al. (2006) and Core and Guay (2002).
FinancialConstraint	The Whited-Wu index of a firm in a given year.
GDP	The inflation-adjusted GDP of a county in a given year, calculated as the natural logarithm of one plus the inflation-adjusted real GDP.
GDPRate (%)	The growth rate of the inflation-adjusted GDP of a county in a given year.
GreenCitation	The average forward citations of the green patents filed by the firm in a given year.
GreenPatent	An indicator variable equal to 1 if the firm files a green patent in a given year, and 0 otherwise. A patent is considered a green patent if at least half of its patent codes are classified as green.
HasDisasterDisclosure	An indicator variable equal to 1 if the firm's 10-K filing mentions any disaster-related keyword and 0 otherwise.
HHI	The Herfindahl-Hirschman Index calculated within a firm's four-digit SIC industry in a given year, defined as the sum of an industry's squared market shares (in percentage).
InstitutionalHolding	The average institutional holding ownership of a firm in a given year, calculated using Form 13F holding data.
Leverage	The leverage of the firm in a given year, defined as total liabilities divided by total assets.
NumberOfMeeting	The natural logarithm of one plus the number of shareholder meetings for the firm in a given year.
NumberOfProposals	The natural logarithm of one plus the total number of shareholder proposals received by the firm in a given year.
NumGreenPatent	The number of green patents that the firm files in a given year. A patent is considered a green patent if at least half of its patent codes are classified as green.
PersonalIncome	The total personal income of a county in a given year, calculated as the natural logarithm of one plus the total personal income.
PersonalIncomeRate (%)	The growth rate of the total personal income of a county in a given year.
Post	Indicator variable equal to 1 for the years starting from the disaster occurrence, and 0 for the years before the disaster, within a [-5,+5] year window around the event.
PreAnalystEngagement	The firm's pre-period average exposure to analyst engagement, calculated as the average number of analysts asking questions during conference calls in the pre-period.
PreNewsCoverage	The pre-treatment average exposure to news coverage of a firm, calculated as the average annual count of news articles in the firm's location state in the pre-period.
PreNewsCoveragePerCapita	The pre-treatment average exposure to population-standardized news coverage of a firm, calculated as the average annual count of news articles scaled by the population (in 1,000) of the firm's state in the pre-period.

PreNewsCoveragePerGDP	The pre-treatment average exposure to GDP-standardized news coverage of a firm, calculated as the average annual count of news articles scaled by GDP (in $1,000,000) of the firm's state in the pre-period.
ROA	The return on assets of the firm in a given year, defined as net income divided by total assets.
Size	The natural logarithm of the firm's total assets in a given year.
StateGreenIncentives	The number of available green incentives in the firm's state in a given year.
Treat	An indicator variable equal to 1 if the firm's headquarters is located in a nearby county that is near, but not directly hit by, a climate disaster (treated firms), and 0 if the headquarters is located in a county that is neither near nor directly hit by the climate disaster. A county is considered nearby if its distance to the closest directly hit county is less than or equal to 100 miles. If this distance is more than 100 miles, the county is considered neither near nor directly hit.
Unemployment	The average number of unemployed people in a county in a given year, calculated as the natural logarithm of one plus the absolute average number of unemployed people reported.
UnemploymentRate (%)	The unemployment rate, defined as the absolute average number of unemployed people reported in year *t* divided by the average size of the total labor force.

Appendix B. Distribution of Climate Disasters

This appendix presents the yearly distribution of climate disasters with total monetary damages of at least 1 billion dollars (adjusted to 2019 dollars) used in the analysis.



Appendix C. List of Disaster-Related Keywords

acid rain
atmospheric drought
atmospheric river
avalanche
biological disaster
blizzard
bomb cyclone
bombogenesis
bushfire
category 1 storm
category 2 storm
category 3 storm
category 4 storm
category 5 storm
climate disaster
cloudburst
coastal erosion
coastal flooding
coastal inundation
coldwave
convective storm
cyclone
derecho
disast
disaster
disaster aid
disaster area
disaster finance
disaster management
disaster prepar
disaster recovery
disaster relief
disaster risk investment
disaster struck
downburst
drought
dust storm
earthquake
environmental disaster
extreme cold
extreme drought
extreme heat
extreme precipitation
extreme rainfall
extreme weather
firestorm
flash drought
flash flood
flood
flooding
forest fire
freeze
frost drought
geological disaster
glacier melt
hail
hailstorm
heat wave
high wind
hurricane
hydrological disaster
ice melt
ice storm
inland flooding
landslide
lightning
megafire
meteorological disaster
mudslide
natural disaster
natural hazard
nor'easter
polar vortex
precipitation extremes
raging fire
rainstorm
river flooding
rockslide
sandstorm
seasonal drought
severe storm
severe weather
snowstorm
soil erosion
storm
storm surge
stormwater
supercell storm
superstorm
thunderstorm
tidal flooding
tidal wave
tornado
torrential rain
tropical cyclone
tropical storm
tsunami
twister
typhoon
urban flooding
volcanic eruption
volcano
wildfire
wildland fire
winterstorm