Climate Disasters and Corporate Innovation

Li Ai
Winthrop University
Email: ail@winthrop.edu

Lucia Gao
University of Massachusetts Boston
Email: lucia.silva-gao@umb.edu

Mine Ertugrul
University of Massachusetts Boston
Email: mine.ertugrul@umb.edu

Prianka Musa
Springfield College
Email: pmusa@springfield.edu

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ABSTRACT

This paper investigates whether catastrophic climate events spur environmental innovation in companies. Building upon prior evidence, we presume that managers estimate probabilities based on available information and use heuristics for assessing these probabilities, and climate disasters are random events whose occurrence may influence managers' risk perception. Using a novel approach to classify environmental patents under the updated U.S. patent classification system and a difference-in-differences design, we find that companies exposed to climate disasters experience a significant increase in environmental patent applications over the following three years. Moreover, the market value of these patents rises post-exposure. The effects are more pronounced for companies in industries with higher environmental materiality, located in states with stringent environmental regulations, and are weaker for financially distressed firms. Our findings also indicate an increase in cash flow volatility after climate disasters, partially mitigated for firms undertaking more environmental innovation. This suggests that corporate innovation could mitigate the impact of climate change on companies.

1. Introduction

The increase in the frequency and intensity of extreme weather events has been associated to climate change (Francis & Vavrus, 2012; Rahmstorf & Coumou, 2011) and poses significant impacts on businesses. Exposure to the effects of climate change can affect a firm's financial performance directly through asset damages and indirectly disrupt operations and supply chains, thus affecting overall operating performance (Hsu et al., 2018; Barrot and Sauvagnat, 2016; Huynh and Xia, 2021). In addition to the tangible physical risks, firms are exposed to transition risks associated with the responses required to tackle climate change, entailing both financial and reputational implications. These responses require policy, technology, and market changes to address the mitigation and adaptation to climate change. Within this framework, innovation could enable companies to proactively develop solutions for mitigating and adapting to the impacts and risks associated with climate change. [1]

Firm’s innovation policies, on the other hand, significantly rely on the behavior, preferences, and experiences of managers (Chemmanur et al., 2019; Duong et al., 2021, Sunder et al., 2017, Galasso and Simcoe, 2011; Hirshleifer et al., 2012). Even though innovation is vital for a firm’s competitive advantage and even survival, CEOs may not always engage in unplanned innovation (Hellmann and Thiele, 2011). Therefore, environmental innovation could depend on various factors, including managers’ preferences and perceptions.

The primary objective of this study is to investigate how climate disasters influence firms' innovation choices. Specifically, we investigate whether firms that have been exposed to climate disasters are more likely to pursue environmental innovation. Our conjecture is motivated by the predictions of behavioral theories that postulate that people estimate the probability of an event based on personal experience and this information plays an important role in decision-making (Tversky and Kahneman, 1973, 1974). Hanlon et al. (2022) consider that individuals who experience natural disasters assign a higher subjective probability to future disasters compared to individuals who read about these events in the news. CEOs’ innovation behavior can also be explained by the salience theory, which predicts that availability leads people to overweight a tail event thereby affecting how they assess risk (Bordalo et al., 2012). Moreover, prior empirical works show that natural disaster experiences affect risk perceptions and CEOs’ behavior (Gallagher, 2014; Bernile et al., 2017; Dessaint and Matray, 2017). We hypothesize that

[1] The U.S. Environmental Protection Agency states that “Technological improvements or innovations that support the transition to a lower-carbon, energy efficient economic system can have a significant impact on organizations. (…) The timing of technology development and deployment, however, is a key uncertainty in assessing technology risk.” In Climate Risks and Opportunities Defined, https://www.epa.gov/climateleadership/climate-risks-and-opportunities-defined

managers' risk perception, and consequently firm policies, are significantly influenced by the occurrence of extreme climate events.

Additionally, current physical and economic models do not provide sufficient information to address the uncertainty and the heterogeneity of the effects of climate change and there is a larger degree of uncertainty about the likelihood of occurrence and timing of climate disasters and the associated costs (e.g., Heal and Millner, 2014). Therefore, the occurrence of climate disasters can be considered an unexpected external event that affects firms exposed to the disaster differently when compared with firms that were not exposed. More specifically, climate disasters may serve as shocks that influence managers' risk perceptions of climate change.

To measure environmental innovations, we introduce a new approach based on the updated U.S. patent classification system and on a study by Haščič and Migotto (2015). While this study is based on the International Patent Classification (IPC) system, we use a similar approach but applied to the Cooperative Patent Classification (CPC) scheme in the U.S.

Using a staggered difference-in-differences design, we show that when the headquarters of a company is exposed to climate disasters, the number of environmental patent applications increases over the following three years. We use the list of billion-dollar disasters provided by the National Centers for Environmental Information (NOAA) to identify major climate disasters. The trend analysis corroborates these results and shows a significant increase in environmental patents activity after the company was exposed to climate disaster when compared with the previous three years. We also find that this effect is more pronounced in industries with higher environmental materiality, indicating that some industries are more vulnerable to the risks associated with climate change and may require more innovation to adapt to and mitigate climate risks. Furthermore, the results are consistent if we exclude companies in polluting industries and that have the worst environmental reputation. Consistent with previous studies that show that innovation is determined by funding availability, we find that the effect of climate disasters on environmental innovation is mitigated for firms with financial constraints. We also show that the effect is stronger if the company is headquartered in a state higher environmental risk, measured based on the number of enforcement actions that result in penalties.

Finally, we investigate whether environmental innovation spurred by climate disasters benefits companies that have engaged in this innovation. Prior research provides evidence of impacts on operating performance (Hsu et al., 2018; Barrot and Sauvagnat, 2016; Huynh and Xia, 2021) and firm risk (Ai and Gao, 2023) following climate disasters. Using mediation analysis, we find that innovation spurred by climate disasters is associated with lower cash flow volatility over the following five years. However, the results are significant only for firms in the upper quartile of innovation, suggesting that only the highest innovators realize the benefits from these investments.

Our study contributes to the literature on climate risk and firm decisions and outcomes (e.g., Dessaint and Matray, 2017; Huynh et al., 2020; Huynh and Xia, 2021; Flammer, 2021). We also contribute to the literature on innovation policies and factors that impact these policies (e.g., Chemmanur et al., 2019; Duong et al., 2021, Sunder et al., 2017, Galasso and Simcoe, 2011; Hirshleifer et al., 2012; Hellmann and Thiele, 2011). More specifically, we find that CEOs' personal perceptions and experiences influence innovation policies toward climate change. Finally, we add to the growing number of studies on environmental innovation (e.g., Cohen et at., 2020; Fabrizi et al., 2018; Miao and Popp, 2014).

2. Literature and hypotheses development

2.1. Risk assessment for climate disasters

Behavior theory predicts that people estimate the probability of an event based on their knowledge of similar events and, therefore, personal experience plays an important role in decision-making (Tversky and Kahneman, 1973, 1974). In the finance literature, research shows that experiences with macroeconomic events such as market bubbles, economic downturns, and inflation periods change investors' and managers' behavior (Greenwood and Nagel, 2009; Malmendier and Nagel, 2011, 2016; Knüpfer et al., 2017).

The salience theory suggests that people overweigh salient information in their decision-making (Bordalo et al., 2012, 2013, 2020). The empirical literature provides evidence of this effect. Bernile et al. (2017) show that CEOs who experience negative disaster experiences in their early years behave more conservatively across various corporate policies. Alok et al. (2020) find that fund managers reduce their holdings in companies located in disaster areas after catastrophe events.

Similarly, studies on climate risk and firm behavior reveal that personal experience and the salient nature of information play a significant role in risk assessments. For instance, using surveys, Konisky et al. (2016) find that people's concerns about climate change increase after experiencing extreme weather events, including excessive heat, droughts, flooding, and hurricanes, but this effect is significant only for recent events, as people tend to consider only their most recent experiences. Choi et al. (2020) observe that the public sentiment towards climate change, proxied by Google search volume, increases when temperatures are warmer than usual. This sentiment is also manifested in financial markets, as stocks of more carbon intensive companies underperform during these periods. Zaval et al. (2014), Akerlof et al. (2013), and

Myers et al. (2012) also show that personal experience with global warming, as reported in surveys, leads to an increased perception of climate risk. Additionally, Borick and Rabe (2014) find that actual weather conditions, and specifically seasonal snowfall, shape the process by which individuals arrive at their conclusions regarding the existence of global warming. Specifically, Akerlof et al. (2013) argue that the perceived personal experience of global warming reflects people's perception of the risks and is influenced by direct experience and/or perceptions from media and social constructs. Bansal et al. (2017) argue that market prices reflect long-run climate risks, as proxied by temperature fluctuations, but climate disasters are exogenous shocks and are not likely to be priced by investors. Additionally, Hong et al. (2020) defend that beliefs play a role in the financing of new technologies for climate adaptation and mitigation and in determining prices of assets in companies that are sensitive to climate change.

We argue that the occurrence of climate disasters is likely to change managers' perceptions of the risks associated with climate change, and therefore will influence their actions toward addressing these risks. More specifically, we test whether the experience of climate disaster events in the location of the headquarters of the firm leads managers to invest in environmental innovation. We test the following:

H1: Climate-related disasters that affect a firm's headquarters location are followed by an increase in environmental innovation.

2.2. Environmental Materiality

The impact of climate change and climate disasters on firms is likely to vary across industries. The literature documents an industry effect on environmental impacts on companies. Industries vary in their environmental practices and stakeholders may subject some industries to a higher level of scrutiny (e.g., Margolis et al., 2009; Malik et al., 2015). The Sustainability Accounting Standards Board (SASB) has recognized this industry effect and developed industry-specific standards for corporate environmental and social disclosures. Using the SASB materiality industry classification, Khan et al. (2016) find that firms with good ratings environmental and social ratings outperform firms with bad ratings, but only for material environmental and social issues. Also using the SASB materiality definition, Flammer (2021) finds that firms in industries where environmental issues are financially material are more likely to issue corporate green bonds.

This evidence suggests that companies in certain industries may be impacted to a larger degree by climate disaster events. We expect that companies in industries where environmental issues are material are more likely to innovate following climate disasters. Therefore, we test the following hypothesis:

H2: The increase in environmental innovation following climate-related disasters is more pronounced for firms in industries with higher environmental materiality.

2.3. Financial Constraints

Corporate innovation is highly dependent on the economic cycle and the availability of funding in the company (Brown et al., 2009; Hall and Lerner, 2010; Czarnitzki and Hottenrott, 2011). The resource dependency view predicts that financial constraints negatively impact innovation in the firm, as fewer financial resources are available for corporate investment. Therefore, we expect a lower impact of environmental disasters on firm innovation and test the following hypothesis:

H3: The increase in environmental innovation following climate-related disasters is less pronounced for firms experiencing financial constraints.

2.4. Environmental Regulatory Risk

Among the different risk associated with climate (physical, technological, and regulatory), regulatory risk is perceived as having the most immediate significance (Kruger et al., 2020; Stroebel and Wurgler, 2021). Specifically, the costs associated with environmental regulations can exert substantial impacts on firms' operating costs and cash flows (Karpoft et al., 2005). Additionally, the uncertainty surrounding future regulations imposes costs on both firms and their investors (Pindyck, 1993).

Therefore, we expect that firms located in areas with more stringent environmental regulatory risks are more likely to address the impacts of climate change. More specifically, we predict that firms located in areas with higher regulatory risk are more likely to reassess the risks associated with climate change when affected by climate disasters, and therefore more likely to engage in environmental innovation. We test the following hypothesis:

H4: The increase in environmental innovation following climate-related disasters is more pronounced for firms located in states with higher regulatory risk.

3. Empirical Design

3.1. Identifying Climate Disasters

We obtain information a list of major climate disasters from the Billion-Dollar Weather and Climate Disasters database[2] maintained by the National Centers for Environmental Information (NCEI) at the National Oceanic and Atmospheric Administration (NOAA) for the years from 1980 to 2014. The database lists climate disasters that resulted in overall damages and costs exceeded $1 billion dollars. NOAA provides the location of these climate disasters at the state

[2] The list is available at https://www.ncei.noaa.gov/access/billions.

level. We obtain county-level information on the location of these events from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). To conduct the empirical analysis, we aggregate the disaster data by county and year. We restrict our data to hazard events that occurred between 1980 and 2014 because 1980 is the first year NOAA provides historical data on climate disasters and because our treatment sample ends in 2018 and our treatment period is three years post-event. According to NOAA, there are 23 Droughts, 87 Severe storms, 23 Floods, 16 Winter Storms, 13 Wildfires, 38 Tropical Cyclones, and 8 Freezing billion-dollar disaster events that affected the U.S. between 1980 and 2014.

3.2. Environmental innovation

To measure environmental innovation at the firm level, we use patent data from the Kogan, Papanikolaou, Seru, and Stoffman (2017) (KPSS) patent database. The dataset provides information on the number of patents, the estimated market value of patents, and the number of citations received by all patents filed with the US Patent and Trademark Office (USPTO) that were eventually granted. The National Bureau of Economic Research (NBER) also provides a patent database containing comprehensive information for patents granted by the USPTO. We use the KPSS patent data rather than the NBER patent data for two reasons. First, KPSS has more recent data, allowing us to study the impact of climate disasters on innovation in more recent years, which increases our sample size significantly. Second, our identification of environmental performance is based on the latest Cooperative Patent Classification (CPC) system, which we can obtain from KPSS.

Prior studies classify green patents following Carrion-Flores and Innes (2010). This classification considers environmental patent categories based on the primary 3-digit US Patent Classification (USPC) system and is determined by association with air or water pollution, hazardous waste prevention, disposal and control, recycling, and alternative energy. However, the USPTO discontinued the USPC system and transitioned to the CPC system in 2011.[3] In addition, the relation between both systems is not clear. Most of the USPC codes can be matched with multiple CPC codes and there is no clear correlation between the classification in the two systems.

In our paper, we identify environmental patents using the CPC system and the classification strategy from the OECD EnvTech, as described in Haščič and Migotto (2015). In this paper, the authors provide patent search strategies for the identification of selected environment-related technologies (EnvTech) within the International Patent Classification (IPC)/CPC classification systems. The CPC system was developed based on the IPC system, but provides a more detailed level of categories. To identify environmental-related patents, we match CPC codes with environmental-related IPC codes. We use two ways to identify environmental innovations based according to the technological class of the CPC classification system. First, we use environmental-related classes in Haščič and Migotto (2015) and search the same descriptions in the CPC Scheme. We identify the CPC code with identical descriptions as environmental-related CPC. Second, the USPTO provides the CPC- IPC equivalence, allowing us to identify the CPC code corresponding to the IPC code. We identify 9 subclasses, 79 groups, and 309 subgroups in the CPC classification system that can be classified as environmental-related. In addition, the "Y02" class of CPC indicates technologies or applications for mitigation or adaptation against climate change. In addition to the environmental patents we identify using OECD EnvTech, we also consider the patents classified as Y02 in the CPC system.

[3] The United States Patent Classification was mostly replaced by the Cooperative Patent Classification on January 1, 2013. Only Plant and design patents are still classified solely within USPC at the USPTO.

The actual timing of innovation is more accurately captured by the patent application year than by the award year. As a result, we measure the company's environmental innovation as the number of environmental patent applications filed by a firm in a year that are eventually granted. Since innovation is a long-term process, to better capture the long-term impact, we calculate the total number of environmental patents and total market value of environmental patents using a 3-year window [t, t+3] following the disaster event. We use three different categories of measurements for environmental patents: environmental patents identified by OECD EnvTech (ENV_OECD), environmental patents identified by Y02 class (ENV_Y02), and environmental patents identified by either OECD EnvTech or Y02 class (ENV_OECDY02). We also calculate the market value for environmental patents using OECD (MV_ ENV_OECD), Y02(MV_ ENV_Y02), and OECDY02 (MV_ ENV_OECDY02) categories. The patent truncation bias has been acknowledged by researchers using patents to measure innovation. This bias occurs because the number of patent applications will be biased downward since it may take years between the time of the patent application and the time when it is granted. Although the KPSS dataset has data for patents filed until 2020, in our analyses we only include patents with application data until 2017 to partially address the truncation problem. There are also truncation biases associated with using measures of patent citations that have been addressed in prior studies by using the "weight factors" developed by Hall, Jaffe, and Trajtenberg (2001) However, because these factors are not available for more recent years, we do not use patent citations as a variable in our analyses. When there is no patent information for a firm in the KPSS dataset for a certain year, we assume that the firm did not file and patent in that year and set the value to 0. We exclude all firms that did not file any patent during our sample period and therefore do not pursue innovation.

3.3 Environmental Materiality

To investigate whether the impact of climate disasters is more pronounced in industries with larger materiality on environmental issues, we use the materiality scores from the Sustainability Accounting Standards Board (SASB). SASB is an independent organization that promotes the uniform disclosure of material sustainability information. Because the materiality of sustainability issues varies across industries, SASB developed industry-specific standards. For each industry, SASB assesses the materiality of environmental issues or "disclosure topics". The mapping of SASB industries to companies was graciously provided to us by the Value Reporting Foundation. Following Flammer (2021), we construct a materiality index by adding the number of environmental issues that are considered financially material for the company. The High Environmental Materiality (HEM) variable is then created as an indicator variable with a value of one if the company's materiality index value is greater than the median.

3.4 Control variables

To construct the set of control variables in our models, we obtain data from Compustat. We control for firm-level characteristics that might impact firm innovation, as documented in existing studies. *Size* is constructed as the natural logarithm of a firm's total assets. *ROA* is net income scaled by total assets. *Cash holding is* the cash and short-term investments divided by total assets. *Leverage* is the total Liabilities divided by total assets. *Tangibility* is Property, Plant, and Equipment scaled by average total assets; MTB is the market value to the book value. Because some firms may have already been innovating more than others independently of being impacted by natural disasters, we also control for prior innovation with the number of patents in year t-1. We winsorize all continuous variables in our sample at 1% and 99%. Appendix contains a detailed definition of all variables.

3.5 Empirical Design

To test our main hypothesis, we follow the DID design from Dessaint and Matray (2017) to capture the effect of billion-dollar disasters occurring at different times. We match each county hit by a billion-dollar disaster in NOAA/SHELDUS with the county locations of companies' headquarters. We use the historical county location for headquarters from the Loughran-McDonald database,[4] which captures information in the header section of 10-K forms available on the SEC's EDGAR website. Following Huynh et al. (2020), we also place a number of strict requirements for data to be included in this DID design to elicit the clearest effect of billion-dollar events on the environmental innovation of the company. First, we require that there are no billion-dollar disasters in the county of the company's headquarters in the 3 years before a billion-dollar disaster. This is to avoid any confounding effects from other previous disaster periods. Second, if a billion-dollar disaster hits the county where the headquarters are located within the past three years, we classify the headquarters as affected and exclude it from both the treatment and control samples for that disaster. Third, since unaffected firms located in the neighborhood of the disaster area may also change their innovation policies, we exclude these firms from the control sample if their headquarters are located within 50 miles of the county that was hit by the billion-dollar disaster. Therefore, we keep in the control sample only firms that were never exposed to any billion-dollar disaster or are located in the neighborhood area of a county hit by billion-dollar disasters.

Following the DID specification, we estimate the following model:

$$Environmental\ Innovation_{iy} = \alpha_i + \delta_y + \gamma X_{iy} + \beta Impacted_{yc} + \varepsilon_{iyc} \quad (1)$$

[4] The data is available here https://sraf.nd.edu/data/augmented-10-x-header-data/

where the subscripts i, y, and c denote firm, year, and county location, respectively. *Environmental Innovation* is the measure of environmental innovation for the three-year window following the event for firm i. We include firm fixed-effects (αi), year fixed-effects (δy), and a set of control variables (Xiy). Standard errors are clustered at the county level. *Impacted* is our main variable of interest, constructed as an indicator variable that takes the value of 1 if a billion-dollar disaster hit the county where the headquarters of the firm within the past three years, and 0 otherwise. Our choice of the event window size follows recent studies. Dessaint and Matray (2017) find that corporate managers not directly affected by hurricanes respond to the events by increasing cash holdings in the two years following the event. Since innovation decisions are likely to take a longer time to materialize, we extend the window by one more year and use a three-year event window. A positive value of the coefficient β indicates that companies affected by billion-dollar disasters generate more environmental patents than non-affected companies over the following three years.

In order to verify the parallel trend assumption in the DID design, we investigate the dynamic effects by replacing the variable *Impacted* with several time indicator variables.

Following the DID model specification, we estimate the following model:

$$Environmental\ Innovation_{iy} = \alpha_i + \delta_y + \gamma X_{iy} + \beta_1 Impacted\_year^{-2}_{yc} + \beta_2 Impacted\_year^{-1}_{yc}$$
$$+ \beta_3 Impacted\_year^{0}_{yc} + \beta_4 Impacted\_year^{+1}_{yc} + \beta_5 Impacted\_year^{+2}_{yc}$$
$$+ \beta_6 Impacted\_year^{+3}_{yc} + \varepsilon_{iyc} \quad (2)$$

where the subscripts i, y, and c denote firm, year, and county location, respectively. $Impacted\_year^{-n}_{yc}$ is an indicator equal to 1 if the year is n years before the billion-dollar disaster occurred and 0 otherwise. $\text{Impacted\_year}^{0}_{yc}$ is a dummy variable equal to 1 if the current year is the year when the billion-dollar disasters occur in companies' headquarters and 0 otherwise. $Impacted\_year^{+n}{}_{yc}$ is an indicator variable equal to 1 if the year is n years after the billion-dollar disaster occurred and 0 otherwise. We expect to observe positive and significant coefficients for the indicator variables that represent the years after exposure to disasters.

4. Results

4.1 Summary Statistics

Table 1 presents summary statistics for the variables of interest at the firm level. On average, a firm in our sample applied for 14.628 patents over the sample period of 1980-2017. In particular, on average companies file annually 0.348 OECD environmental patents, 0.404 Y02 environmental patents, and 0.510 patents under either the OECD or Y02 environmental categories. In addition, a company files 2.563 environmental patents with a market value of 70.399 million nominal dollars every 3 years. About 39% of the companies in our sample operate in industries with higher environmental materiality, and 62% have headquarters located in a democratic county, measured based on election results. The average value of 0.37 indicates that 37% of the companies in our sample are facing high financial constraints according to the WW index.

4.2 Climate Disasters and Environmental patents

Table 2 presents the effects of billion-dollar disasters on corporate environmental innovation based on the estimation of the model depicted in Equation 1. Columns (1) to (3) report the results of the estimation of the impact of climate disasters on corporate environmental patents under the three categorizations. All regressions include firm and year fixed effects and are estimated with standard errors clustered at the county level. The positive and significant (at the 5% level) coefficients of *Impacted* indicate that compared with companies that are not exposed to disasters, affected companies engage in environmental-related innovations and file more environmental patents. The magnitude of the coefficient is economically significant. For example, in the model represented in Column (3), changing *Impacted* from 0 to 1 is associated with a 3.02 percent (0.498/16.509) increase in the number of environmental patents filed over the following three years.

Columns (4) to (6) examine whether there is an increase in the nominal value of environmental patents after companies' headquarters faced disasters. The positive and significant (at the 10% level) coefficient of *Impacted* in columns (4) and (5) suggests that relative to non-exposed firms, firms with headquarters exposed to billion-dollar disasters experienced a significant increase in the market value of environmental patents. The results are also economically significant. The results in Column (4) indicate that changing *Impacted* from 0 to 1 is associated with a 2.06 percent (8.170/395.865) increase relative to the standard deviation of the three-year market value of environmental patents. Overall, the results presented in Table 10 confirm that companies engage in environmental patenting activities after being exposed to billion-dollar disasters and provide support to Hypothesis 1.

Table 3 presents the results of the dynamic treatment effect model, as depicted in Equation 2. As shown in Columns (1) to (3) in Table 11, the coefficients on $Impacted\_year^{-2}$ and $Impacted\_year^{-1}$ are both not statistically significant, indicating that the impacted companies did not engage in environmental innovation before the disaster event. The coefficients are positive and statistically significant on all post-disaster indicator variables, including from one year to three years post-event. These results suggest that the increase in firms' environmental patents happens during or after headquarters' exposure to disasters. Figure 1 confirms the trend of environment patents around the year of climate disaster: the number of patents filed is close to 0 in the years preceding the event, and visibly increases in the three years following the event. We find similar results for the market value of environmental patents measured from the Y02 category. The market value of environmental patents increases for two years after the company's headquarters is hit by billion-dollar disasters. Overall, the results presented in Table 11 support our assumption on parallel trends and that the occurrence of a disaster is more likely to be an external shock rather than a perceived response to other economic factors.

4.3. Environmental Materiality

When companies operate in industries where the market expects environmental risk to be material, the market expects firms to disclose environmental related risk. In addition, when environmental issues become financially material or when related regulations are enforced, companies are more likely to develop an innovation that addresses the issue. Therefore, we investigate the effect of exposure to billion-dollar disasters on environmental innovations when a company has more environmental issues that are financially material. High Environmental Materiality (HEM) is a dummy indicator variable with a value of one if the company's materiality index value is greater than the median and 0 otherwise. The positive and significant coefficient of Impacted in columns (1) to (4) suggests that relative to the firms operating in industries with low environmental materiality, the relationship between headquarters exposed to billion-dollar disasters and environmental innovation is stronger for firms in industries with high environmental materiality. The results in Table 4 demonstrate that the impact of exposure to billion-dollar disasters on environmental innovation is stronger when a company operates in an industry with more environmental issues which are financially material.

4.5 Financial constraints

We also investigate whether the effect of exposure to climate disasters on environmental innovation is mitigated for firms with financial constraints. Firms with financial constraints have limited funds devoted to innovation. If the relationship between climate disasters and environmental innovation is partially driven by the availability of funds in the company, we expect this relationship to be weaker.

We measure financial constraints with the WW index from Whited and Wu (2006). This index is constructed using six components: cash flow, a dividend dummy, leverage, total assets, industry sales growth, and firm sales growth. A higher WW index value indicates that a firm is more financially constrained. Our variable is an indicator equal to one if the WW index is above the median, and 0 otherwise. For our analysis, we split the sample into subgroups based on the median value of the WW index.

The results are reported in Table 5. Columns (1) to (3) provide the results for companies with high financial constraints, and Columns (4) to (6) provide the results for companies with low financial constraints. The results show that when a company's financial constraints are low, the positive effects of exposure to billion-dollar disasters on all three measures of environmental patents remain significant, suggesting that after the company's headquarters are hit by disasters, firms without financial constraints have more resources to devote to environmental innovation. In contrast, the coefficients of *Impacted* are not significant when firms are under financial constraints.

We exclude the company in pulp & paper (SIC 26), chemicals (SIC 28), oil & gas (SIC 29) and metals & mining (SIC 33).given the evidence in the literature that they are the most polluting sectors in the US (Clarkson et al., 2011), and the Table 6 report the results and remain the same.

4.6. Highly Polluting Industries

It could be that our results are driven by companies in highly polluting industries, for which the physical and reputational impacts of climate change are more significant. As a robustness test, we reestimate the model depicted in equation 1 for a sample excluding these companies. More specifically we exclude companies in pulp & paper (SIC 26), chemicals (SIC 28), oil & gas (SIC 29) and metals & mining (SIC 33), considered in the most polluting sectors (Clarkson et al., 2011). The results are reported in Table 6 and confirm that our results are consistent after excluding highly polluting industries.

4.7. Environmental Regulations

We also investigate whether the effect of exposure to climate disasters on environmental innovation is mitigated for firms in states with more stringent environmental regulations. To measure stringiness of environmental regulations, we acquired data from the EPA's Integrated Compliance Information System (ICIS) for Federal Civil Enforcement Case Data. Following previous studies (Konisky, 2007; Seltzer at el. 2022), we construct measures that encompass compliance and enforcement activities under the Clean Water Act (CWA), Clean Air Act (CAA), and Resource Conservation and Recovery Act (RCRA) within a specific state and year. We incorporate both informal and formal enforcement actions that result in penalties. To standardize the measures at the state level, we divide the number of enforcement actions by the total number of facilities subject to EPA regulations in the respective state (measured in thousands). The facility count is obtained from the Facility Registry Services (FRS). Our variable *High Enforcement* is an indicator variable equal to one if the EPA enforcement is above the median, and 0 otherwise. For our analysis, we split the sample into subgroups based on the median value of the EPA enforcement.

The results are reported in Table 7. The results show that when a is locate in a state with high EPA enforcement, the positive effects of exposure to billion-dollar disasters on all three measures of environmental patents remain significant, suggesting that after the company's headquarters are hit by disasters, firms in a state with high EPA enforcement are more likely to pursue environmental innovation.

4.8. Impact on the Volatility of Cash Flows

Climate disasters disrupt companies' operations and supply chains, and consequently impact operating performance (Hsu et al., 2018; Barrot and Sauvagnat, 2016; Huynh and Xia, 2021). Prior research also provides evidence of an impact of climate disasters on firm risk (Ai and Gao, 2023). We investigate whether companies that pursue environmental innovation benefit from their investments. More specifically, we test whether climate disasters increase cash flow volatility and if this increase in volatility is mitigated by investment in environmental innovation. We measure Cash Flow Volatility as the standard deviation of the ratio of cash flow scaled by total assets over the succeeding five years following the disaster. We conduct a mediation analysis following the methodology developed by Preacher and Hayes (2004) that is widely used in literature (for example, Bardos et al., 2020). This approach estimates environmental innovation spurred by the disaster and then its impact of cash flow volatility. We estimate the following model of simultaneous equations:

$$\widehat{Cash\ Flow\ Volatility} = i_1 + c * Impacted \qquad (3)$$

$$\widehat{Different\ Environmental\ Innovation\ level} = i_2 + a * Impacted \qquad (4)$$

$$\widehat{Cash\ Flow\ Volatility} = i_3 + c' * Impacted + b * Env\ Inno \qquad (5)$$

$$\widehat{Cash\ Flow\ Volatility} = i_4 + c' * Impacted + b * Mid\text{-}Env\ Inno \qquad (6)$$

$$\widehat{Cash\ Flow\ Volatility} = i_5 + c' * Impacted + b * High\text{-}Env\ Inno \qquad (7)$$

Env Inno is an indicator equal to 1 if a company generates any Environmental patent in a 3-year window [t, t+3] following the disaster event, and 0 otherwise. Mid-Env Inno is an indicator equal to 1 if company generates Environmental patents more than the median amount in a 3-year window, and 0 otherwise. High-Env Inno is an indicator equal to 1 if the number of Environmental patents the company generated is in the 4th quartile in a 3-year window, and 0 otherwise. In this set-up, X is the exposure to climate disaster in the past three years and Y is the cash flow volatility. The level of environmental innovation the company invented is the mediator.

Table 8 presents the results. Column (1) shows the estimation of equation (3) and finds a positive and significant coefficient on *Impacted*. We observe that exposure to climate disasters has a significant impact on cash volatility over the 5 years following the event. Column (2) estimates equation (5). The coefficient on *Env Inno* is negative but not statistically significant. Column (3) presents the results of the estimation of equation (6). Once again, the coefficient on the innovation variable, *Mid-Env Inno*, is negative but not statistically significant. Column (4) presents the results of the estimation of equation (7). In this model, the variable proxying for innovation considers only companies in the top quartile, and therefore, the highest innovators. The coefficient on *High-Env Inno* is negative and statistically significant. These results demonstrate that environmental innovation reduces the impact of climate disasters on firm risk.

5. Conclusion

In this paper, we study whether catastrophic climate events spur environmental innovation in companies. Using a new approach to classify environmental patents under the updated U.S. patent classification system and a staggered difference-in-differences design, we show that when the headquarters of a company are exposed to a climate disaster, the number of environmental patent applications and the market value of environmental patents increase over the following three years. This effect is stronger for companies operating in an industry with higher environmental materiality, when companies' headquarters are located in areas with more stringent environmental regulation enforcements, and is weaker for companies experiencing financial distress. We also find that companies with higher levels of innovation exhibit lower cash flow volatility following climate disasters. Overall, we find that CEOs' personal perceptions and experiences influence corporate innovation policies to address the risks associated with climate change.

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Table 1 - Summary statistics

This table presents summary statistics for the variables used in the analysis for the period 1980–2017. All continuous variables are winsorized at the 1 st and 99 th percentile.All variables are defined in Appendix A.

	Mean	Median	SD	N
Patent	14.628	0.000	92.953	11209
ENV_OECD	0.348	0.000	1.894	11209
ENV_Y02	0.404	0.000	2.211	11209
ENV_OECDY02	0.510	0.000	2.655	11209
MV_ ENV_OECD	7.400	0.000	49.968	11209
MV_ ENV_Y02	9.670	0.000	62.560	11209
MV_ ENV_OECDY02	12.067	0.000	74.792	11209
Patent [t, t+3]	49.756	0.000	252.682	11209
ENV_OECD[t, t+3]	1.755	0.000	11.779	11209
ENV_Y02[t, t+3]	2.142	0.000	14.487	11209
ENV_OECDY02[t, t+3]	2.563	0.000	16.509	11209
MV_ ENV_OECD [t, t+3]	50.150	0.000	395.865	11209
MV_ ENV_Y02 [t, t+3]	58.784	0.000	457.712	11209
MV_ ENV_OECDY02[t, t+3]	70.399	0.000	521.677	11209
Size	5.288	5.086	2.428	11209
Cash holding	0.228	0.135	0.243	11209
ROA	-0.118	0.021	0.496	11209
Leverage	0.515	0.464	0.468	11209
Tangibility	0.238	0.166	0.217	11209
MTB	3.066	2.034	5.864	11209
Materiality Index	1.624	1.000	1.776	7165
HEM	0.390	0.000	0.488	7165
Democrat	0.621	1.000	0.485	7717
High WWindex	0.370	0.000	0.483	7042

Table 2 - Billion dollar disasters and environmental innovations

This table presents difference-in-differences estimates of the effects of headquarters' exposure to billion-dollar disasters on the environmental innovations. Impacted is a dummy variable equal to one if the county of the firm headquarters is in an area hit by billion-dollar disasters over the past three years. Standard errors are corrected for clustering of the observations at the county level. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively. All continuous variables are winsorized at the 1 st and 99 th percentile. All variables are defined in Appendix A.

Year 1980-2017	Window [t, t+3]						
	Patent	ENV_OECD	ENV_Y02	ENV_OECDY02	MV_ ENV_OECD	MV_ ENV_Y02	MV_ ENV_OECDY02
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Impacted	1.009	0.437**	0.528**	0.498**	8.170*	12.156*	8.853
	[0.750]	[0.017]	[0.024]	[0.035]	[0.067]	[0.059]	[0.162]
Size	6.616*	0.234***	0.180	0.239**	5.544	4.507	5.924
	[0.080]	[0.009]	[0.121]	[0.037]	[0.204]	[0.152]	[0.188]
Cash holding	9.178	0.421	0.369	0.742	-4.637	-6.877	-5.764
	[0.267]	[0.311]	[0.467]	[0.233]	[0.747]	[0.545]	[0.691]
ROA	-3.224	-0.117	-0.006	-0.042	-2.908	1.266	-0.342
	[0.189]	[0.121]	[0.959]	[0.691]	[0.150]	[0.685]	[0.900]
Leverage	-4.270	-0.180	-0.162	-0.208	-3.024	0.085	-1.421
	[0.158]	[0.197]	[0.333]	[0.239]	[0.315]	[0.972]	[0.645]
Tangibility	24.207	0.418	0.320	0.639	-27.029	-25.735	-23.163
	[0.174]	[0.562]	[0.707]	[0.483]	[0.102]	[0.262]	[0.299]
MTB	0.025	0.004	0.007	0.003	0.226	0.392*	0.405*
	[0.802]	[0.474]	[0.467]	[0.749]	[0.175]	[0.058]	[0.074]
Num. of Patent$_{t-1}$	1.735***	0.046***	0.072***	0.084***	0.481	0.750*	0.719
	[0.000]	[0.003]	[0.002]	[0.000]	[0.309]	[0.055]	[0.104]
Constant	-16.932	-0.452	-0.152	-0.348	18.745	26.025	31.539
	[0.285]	[0.376]	[0.824]	[0.629]	[0.528]	[0.168]	[0.290]
Observations	11,209	11,209	11,209	11,209	11,209	11,209	11,209
year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.911	0.865	0.880	0.878	0.870	0.890	0.889

Table 3 - Billion dollar disasters and environmental innovations

Impacted_year +t is a dummy equal to one if the county of the firm headquarters at year +t is in an area hit by billion-dollar disasters (is in an area) hit by a billion dollar diasters during year0. Standard errors are corrected for clustering of the observations at the county level. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively. All continuous variables are winsorized at the 1 st and 99 th percentile. All variables are defined in Appendix A.

Year 1980-2017	Window [t, t+3]						
	Patent	ENV_OECD	ENV_Y02	ENV_OECDY02	MV_ ENV_OECD	MV_ ENV_Y02	MV_ ENV_OECDY02
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Impacted_year_2	-1.597	0.025	0.027	0.042	4.001	2.133	1.754
	[0.163]	[0.685]	[0.741]	[0.597]	[0.281]	[0.576]	[0.660]
Impacted_year _1	-3.747	0.085	0.071	0.046	7.000	7.063	4.919
	[0.161]	[0.506]	[0.552]	[0.742]	[0.280]	[0.162]	[0.417]
Impacted_year 0	-3.149	0.318*	0.288	0.210	13.609*	14.967**	10.930
	[0.382]	[0.073]	[0.130]	[0.314]	[0.086]	[0.010]	[0.141]
Impacted_year +1	-2.133	0.439**	0.513**	0.454*	12.937	17.897**	12.481
	[0.622]	[0.041]	[0.014]	[0.065]	[0.143]	[0.010]	[0.157]
Impacted_year +2	-0.129	0.660**	0.713**	0.771**	12.112	17.355*	12.708
	[0.980]	[0.017]	[0.011]	[0.011]	[0.264]	[0.059]	[0.261]
Impacted_year +3	-2.412	0.712**	0.842**	0.877**	15.662	18.277	13.374
	[0.688]	[0.034]	[0.011]	[0.013]	[0.181]	[0.119]	[0.304]
Size	12.781***	0.399***	0.414**	0.518***	7.970	7.249*	9.111
	[0.008]	[0.000]	[0.019]	[0.005]	[0.127]	[0.078]	[0.108]
Cash holding	20.947	0.753	0.831	1.272	3.111	0.895	1.427
	[0.101]	[0.155]	[0.234]	[0.118]	[0.849]	[0.950]	[0.932]
ROA	-6.626***	-0.251**	-0.207	-0.280**	-4.166	0.011	-1.813
	[0.005]	[0.012]	[0.104]	[0.035]	[0.128]	[0.997]	[0.616]
Leverage	-6.118	-0.293*	-0.318	-0.391	-4.454	-1.452	-3.025
	[0.117]	[0.094]	[0.144]	[0.105]	[0.164]	[0.610]	[0.386]
Tangibility	48.563*	0.896	1.309	1.731	-17.995	-12.904	-14.267
	[0.085]	[0.265]	[0.265]	[0.179]	[0.249]	[0.607]	[0.524]
MTB	0.093	0.004	-0.000	-0.005	0.397	0.598*	0.625
	[0.384]	[0.625]	[0.992]	[0.779]	[0.123]	[0.099]	[0.119]
Constant	-29.978	-0.819	-0.600	-0.877	6.641	16.294	20.792
	[0.285]	[0.255]	[0.612]	[0.468]	[0.815]	[0.488]	[0.512]
Observations	12,342	12,342	12,342	12,342	12,342	12,342	12,342
year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.871	0.843	0.853	0.846	0.838	0.858	0.859

Fig. 3. Trends in corporate environmental innovations.

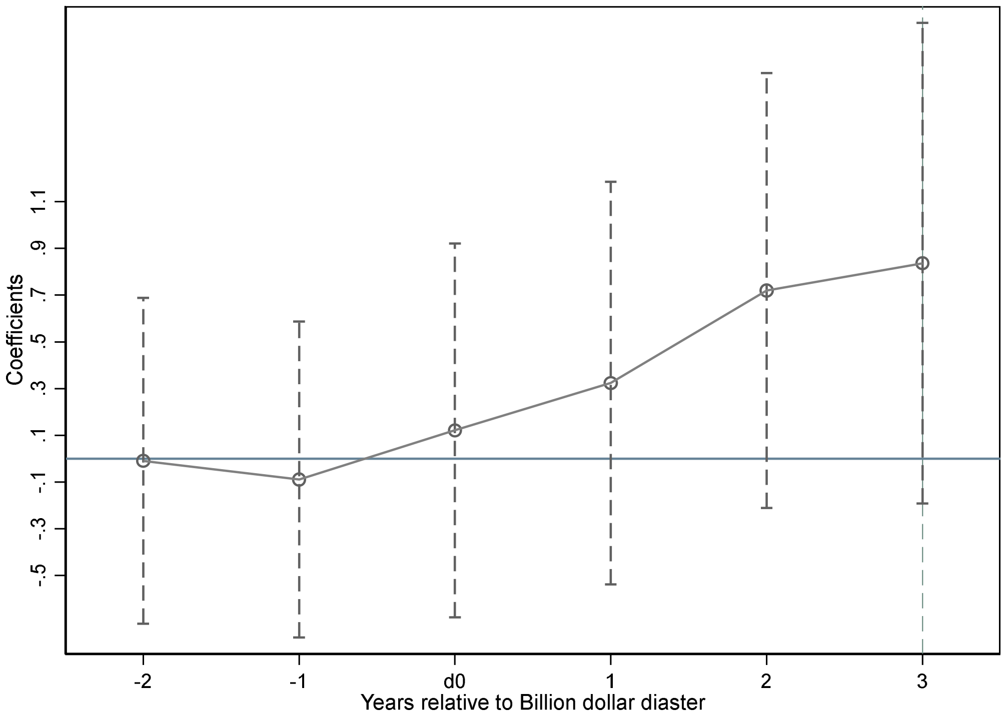

Table 4 - High Environmental Materiality

This table presents difference-in-differences estimates of the effects of headquarters' exposure to billion-dollar disasters on the environmental innovations condition on High Environmental Materiality. Impacted is a dummy variable equal to one if the county of the firm headquarters is in an area hit by billion-dollar disasters over the past three years. The High Environmental Materiality (HEM) is a dummy indicator variable with a value of one if the company's materiality index value is greater than the median and 0 otherwise. Standard errors are corrected for clustering of the observations at the county level. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively. All continuous variables are winsorized at the 1 st and 99 th percentile. All variables are defined in Appendix A.

Year 1980-2017	Window [t, t+3]						
	Patent	ENV_OECD	ENV_Y02	ENV_OECDY02	MV_ ENV_OECD	MV_ ENV_Y02	MV_ ENV_OECDY02
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Impacted*HEM	1.421	1.076*	1.029*	1.482**	31.543**	39.979	37.859
	[0.870]	[0.054]	[0.068]	[0.049]	[0.040]	[0.107]	[0.127]
Impacted	0.528	0.128	0.237	0.017	-0.676	-0.097	-2.997
	[0.906]	[0.581]	[0.462]	[0.961]	[0.903]	[0.992]	[0.755]
Size	10.239*	0.282*	0.227	0.278	6.892	4.671	6.717
	[0.093]	[0.069]	[0.264]	[0.181]	[0.225]	[0.239]	[0.232]
Cash holding	14.888	0.546	0.518	1.058	-13.610	-12.753	-10.394
	[0.181]	[0.403]	[0.470]	[0.249]	[0.473]	[0.310]	[0.549]
ROA	-4.160	-0.076	0.036	0.018	-2.059	3.538	1.426
	[0.199]	[0.456]	[0.812]	[0.899]	[0.508]	[0.431]	[0.734]
Leverage	-4.831	-0.223	-0.198	-0.253	-2.802	1.366	-0.332
	[0.228]	[0.212]	[0.319]	[0.241]	[0.264]	[0.608]	[0.911]
Tangibility	46.412*	1.049	0.595	1.179	-20.843	-24.555	-10.471
	[0.087]	[0.360]	[0.673]	[0.427]	[0.242]	[0.436]	[0.676]
MTB	-0.012	0.004	0.010	0.004	0.192	0.443	0.419
	[0.924]	[0.570]	[0.419]	[0.739]	[0.379]	[0.119]	[0.168]
Num. of Patent$_{t-1}$	1.789***	0.047***	0.074***	0.087***	0.350	0.629*	0.576
	[0.000]	[0.005]	[0.005]	[0.000]	[0.430]	[0.068]	[0.143]
Constant	-37.142	-0.655	-0.204	-0.419	28.917	46.009*	50.099
	[0.167]	[0.543]	[0.890]	[0.794]	[0.442]	[0.087]	[0.198]
Observations	7,165	7,165	7,165	7,165	7,165	7,165	7,165
year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.912	0.887	0.876	0.876	0.820	0.627	0.671

Table 5 - Financial Constraints

This table presents difference-in-differences estimates of the effects of headquarters' exposure to billion-dollar disasters on the environmental innovations condition on Financial Constrain. Impacted is a dummy variable equal to one if the county of the firm headquarters is in an area hit by billion-dollar disasters over the past three years. High WW index, an indicator equal to one if WW index in above the median and 0 otherwise. Standard errors are corrected for clustering of the observations at the county level. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively. All continuous variables are winsorized at the 1 st and 99 th percentile.

Year 1980-2017	Window [t, t+3]						
	Patent	ENV_OECD	ENV_Y02	ENV_OECDY02	MV_ ENV_OECD	MV_ ENV_Y02	MV_ ENV_OECDY02
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
Impacted* High WW index	-0.767	-0.607	-0.955*	-1.069	-2.970	-3.945	-3.016
	[0.889]	[0.156]	[0.095]	[0.139]	[0.728]	[0.570]	[0.714]
Impacted	2.030	0.737**	0.815***	0.811***	4.864	5.434	-0.718
	[0.662]	[0.012]	[0.002]	[0.006]	[0.457]	[0.251]	[0.917]
High WW index	-4.007	0.187	0.327	0.317	1.934	2.032	1.734
	[0.341]	[0.475]	[0.280]	[0.408]	[0.705]	[0.646]	[0.767]
Size	21.761***	0.679***	0.782**	0.891***	13.238**	13.220*	16.934**
	[0.009]	[0.002]	[0.031]	[0.010]	[0.012]	[0.065]	[0.022]
Cash holding	11.809	0.624	0.798	1.251	-4.056	-9.105	-7.085
	[0.421]	[0.466]	[0.330]	[0.251]	[0.784]	[0.505]	[0.624]
ROA	-8.525**	-0.288**	-0.312*	-0.381**	-6.810**	-4.290	-7.438**
	[0.022]	[0.040]	[0.083]	[0.048]	[0.022]	[0.203]	[0.032]
Leverage	-3.496	-0.171	-0.165	-0.250	-2.034	0.915	-1.064
	[0.403]	[0.266]	[0.422]	[0.281]	[0.425]	[0.747]	[0.780]
MTB	0.035	0.000	-0.006	-0.015	0.106	0.366	0.309
	[0.806]	[0.973]	[0.796]	[0.564]	[0.756]	[0.450]	[0.577]
CAPX	74.283**	1.604	-0.111	0.436	-9.634	-56.561	-36.822
	[0.047]	[0.384]	[0.963]	[0.889]	[0.767]	[0.300]	[0.393]
Constant	-60.454	-2.092	-2.055	-2.276	-18.456	-3.435	-10.799
	[0.192]	[0.145]	[0.360]	[0.292]	[0.543]	[0.937]	[0.808]
Observation	7,621	7,621	7,621	7,621	7,621	7,621	7,621
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.882	0.871	0.882	0.867	0.906	0.906	0.913

Year 1980-2017	Window [t, t+3]						
	Patent	ENV_OECD	ENV_Y02	ENV_OECDY02	ENV_OECD	ENV_Y02	ENV_OECDY02
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B							
Impacted_year_2*	-						
High WW index	9.269**	-0.209	0.011	-0.128	-4.508	7.751	0.797
	[0.025]	[0.530]	[0.974]	[0.749]	[0.673]	[0.366]	[0.943]
Impacted_year _1*							
High WW index	0.921	-0.093	-0.292	-0.353	-8.836	-5.574	-5.695
	[0.863]	[0.647]	[0.401]	[0.304]	[0.290]	[0.379]	[0.556]
Impacted_year 0*							
High WW index	1.570	-0.456*	-0.503	-0.557	-10.996	-3.014	-1.400
	[0.780]	[0.058]	[0.147]	[0.135]	[0.186]	[0.735]	[0.858]
Impacted_year +1*							
High WW index	-4.992	-0.613	-0.721	-0.828	-0.609	-2.202	-1.425
	[0.300]	[0.123]	[0.112]	[0.119]	[0.956]	[0.837]	[0.899]
Impacted_year +2*							
High WW index	-2.352	-1.034*	-1.430*	-1.885*	-13.057	-15.807	-21.243
	[0.808]	[0.069]	[0.062]	[0.074]	[0.332]	[0.105]	[0.125]
Impacted_year +3*							
High WW index	-6.280	-0.765	-1.729*	-1.798	0.504	7.359	7.822
	[0.415]	[0.225]	[0.053]	[0.111]	[0.961]	[0.495]	[0.504]
Impacted_year_2	1.108	0.072	0.014	0.054	3.496	-3.381	-2.661
	[0.592]	[0.581]	[0.911]	[0.697]	[0.291]	[0.421]	[0.603]
Impacted_year _1	-2.903	0.165	0.192	0.147	5.367	4.555	-1.159
	[0.462]	[0.479]	[0.428]	[0.645]	[0.313]	[0.521]	[0.875]
Impacted_year 0	-1.810	0.522*	0.448**	0.336	10.534	7.034	-1.506
	[0.709]	[0.067]	[0.043]	[0.241]	[0.140]	[0.180]	[0.825]
Impacted_year +1	1.037	0.736**	0.760***	0.698*	6.693	7.133	-2.320
	[0.863]	[0.032]	[0.005]	[0.060]	[0.363]	[0.220]	[0.771]
Impacted_year +2	3.744	1.171**	1.286***	1.443***	7.696	9.389	1.845
	[0.649]	[0.011]	[0.001]	[0.004]	[0.424]	[0.114]	[0.813]
Impacted_year +3	2.088	1.179**	1.488***	1.537***	5.709	0.736	-8.332
	[0.837]	[0.034]	[0.001]	[0.007]	[0.511]	[0.928]	[0.361]
High WW index	-2.212	0.252	0.394	0.425	4.725	1.774	2.821
	[0.601]	[0.283]	[0.197]	[0.266]	[0.577]	[0.757]	[0.754]
Controls	YES	YES	YES	YES	YES	YES	YES
Constant	-59.676	-2.210	-2.138	-2.356	-21.079	-4.800	-9.625
	[0.205]	[0.128]	[0.344]	[0.281]	[0.497]	[0.913]	[0.832]
year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.882	0.871	0.882	0.867	0.906	0.906	0.913

Table 6 - Billion dollar disasters and environmental innovations exclude most polluting sectors

This table presents difference-in-differences estimates of the effects of headquarters' exposure to billion-dollar disasters on the environmental innovations. Impacted is a dummy variable equal to one if the county of the firm headquarters is in an area hit by billion-dollar disasters over the past three years. Standard errors are corrected for clustering of the observations at the county level. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively. All continuous variables are winsorized at the 1 st and 99 th percentile. All variables are defined in Appendix A.

Year 1980-2017	Window [t, t+3]						
	Patent	ENV_OECD	ENV_Y02	ENV_OECDY02	MV_ ENV_OECD	MV_ ENV_Y02	MV_ ENV_OECDY02
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Impacted	0.548	0.479**	0.616***	0.579**	7.890	11.884**	9.489
	[0.879]	[0.023]	[0.009]	[0.024]	[0.120]	[0.026]	[0.109]
Size	6.475	0.212**	0.148	0.194	8.701**	5.471*	8.512**
	[0.116]	[0.028]	[0.252]	[0.124]	[0.025]	[0.065]	[0.024]
Cash holding	11.899	0.504	0.526	0.889	-1.217	-2.729	0.211
	[0.236]	[0.268]	[0.253]	[0.123]	[0.928]	[0.816]	[0.988]
ROA	-2.862	-0.081	0.023	0.006	-3.938*	0.522	-1.537
	[0.359]	[0.377]	[0.882]	[0.967]	[0.073]	[0.881]	[0.621]
Leverage	-5.115	-0.194	-0.072	-0.125	-1.945	1.030	-0.009
	[0.194]	[0.253]	[0.704]	[0.518]	[0.509]	[0.667]	[0.998]
Tangibility	28.345	0.399	0.472	0.730	-27.984	-26.439	-26.711
	[0.175]	[0.664]	[0.573]	[0.487]	[0.153]	[0.253]	[0.291]
MTB	0.026	0.007	0.010	0.006	0.271	0.379	0.408
	[0.845]	[0.354]	[0.248]	[0.437]	[0.174]	[0.123]	[0.133]
Num. of Patent$_{t-1}$	1.722***	0.047***	0.069***	0.082***	0.648	0.760**	0.849**
	[0.000]	[0.008]	[0.002]	[0.000]	[0.141]	[0.044]	[0.035]
Constant	-16.442	-0.353	-0.197	-0.357	-6.077	14.463	6.656
	[0.338]	[0.529]	[0.775]	[0.632]	[0.791]	[0.404]	[0.770]
Observations	9,687	9,687	9,687	9,687	9,687	9,687	9,687
year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.909	0.865	0.892	0.885	0.876	0.889	0.894

Table 7 – EPA Enforcement

This table presents difference-in-differences estimates of the effects of headquarters' exposure to billion-dollar disasters on the environmental innovations conditioned on EPA Enforcement. Impacted is a dummy variable equal to one if the county of the firm headquarters is in an area hit by billion-dollar disasters over the past three years. High Enforcement, an indicator equal to one if EPA Enforcements is above the median and 0 otherwise. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively. All continuous variables are winsorized at the 1 st and 99 th percentile.

Year 1980-2017	Window [t, t+3]						
	Patent	ENV_OECD	ENV_Y02	ENV_OECDY02	MV_ ENV_OECD	MV_ ENV_Y02	MV_ ENV_OECDY02
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
Impacted* High Enforcement	3.374	0.575**	0.513*	0.703**	7.646	2.804	7.774
	[0.402]	[0.012]	[0.053]	[0.022]	[0.312]	[0.477]	[0.332]
Impacted	-1.609	-0.023	0.118	-0.063	1.829	0.758	5.946
	[0.668]	[0.914]	[0.633]	[0.825]	[0.795]	[0.837]	[0.426]
High Enforcement	-4.951**	-0.360***	-0.299*	-0.424**	-6.817	-3.614	-6.199
	[0.039]	[0.009]	[0.060]	[0.020]	[0.131]	[0.125]	[0.195]
Size	5.644***	0.178***	0.132*	0.178*	4.434**	2.073*	3.459
	[0.000]	[0.009]	[0.094]	[0.050]	[0.048]	[0.076]	[0.145]
Cash holding	3.948	0.339	0.310	0.580	0.950	-0.245	-1.298
	[0.456]	[0.261]	[0.374]	[0.149]	[0.924]	[0.962]	[0.902]
ROA	-3.253	-0.097	0.004	-0.032	-1.998	-0.823	1.474
	[0.137]	[0.434]	[0.981]	[0.849]	[0.627]	[0.701]	[0.735]
Leverage	-3.328	-0.143	-0.121	-0.162	-3.296	-1.056	-0.586
	[0.167]	[0.297]	[0.447]	[0.377]	[0.467]	[0.655]	[0.903]
MTB	0.017	0.003	0.006	0.002	0.166	0.076	0.298
	[0.886]	[0.641]	[0.467]	[0.799]	[0.462]	[0.518]	[0.213]
Num. of Patentt-1	1.728***	0.046***	0.071***	0.084***	0.463***	0.179***	0.728***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	-5.841	-0.005	0.171	0.174	13.269	8.456	19.502
	[0.394]	[0.989]	[0.705]	[0.738]	[0.303]	[0.208]	[0.153]
Observations	13,992	13,992	13,992	13,992	13,992	13,992	13,992
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.910	0.864	0.880	0.878	0.867	0.858	0.889

Table 8 – Mediation Analysis

This table presents the results of mediation analysis. Impacted is a dummy variable equal to one if the county of the firm headquarters is in an area hit by billion-dollar disasters over the past three years. Env Inno is an indicator equal to 1 if a company generate Environmental patent a 3-year window [t, t+3] following the disaster event. Mid-Env Inno is an indicator equal to 1 if company generate Environmental patent more than the median amount in a 3-year window. Mid-Env Inno is an indicator equal to 1 if the amount of Environmental patents company generated are in 4th quartile in a 3-year window, and 0 otherwise. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Year 1980-2017				
	Cash flow volatility			
VARIABLES	(1)	(2)	(3)	(4)
Env Inno		-9.740		
		[0.594]		
Mid-Env Inno			-18.971	
			[0.154]	
High-Env Inno				-45.369***
				[0.002]
Impacted	55.431***	55.400***	55.171***	55.098***
	[0.000]	[0.000]	[0.000]	[0.000]
Size	104.113***	104.648***	105.713***	108.033***
	[0.000]	[0.000]	[0.000]	[0.000]
Cash holding	-7.173	-5.800	-2.730	1.965
	[0.829]	[0.862]	[0.935]	[0.953]
ROA	-77.723***	-77.797***	-77.958***	-78.398***
	[0.000]	[0.000]	[0.000]	[0.000]
Leverage	9.105	8.831	7.122	5.771
	[0.621]	[0.632]	[0.700]	[0.755]
Tangibility	8.619	8.347	6.731	3.891
	[0.817]	[0.823]	[0.857]	[0.917]
R&D	139.354**	139.614**	142.613**	148.903***
	[0.013]	[0.013]	[0.011]	[0.008]
MTB	4.702***	4.706***	4.770***	4.831***
	[0.000]	[0.000]	[0.000]	[0.000]
Sales Growth	-0.005	-0.005	-0.007	-0.009
	[0.978]	[0.976]	[0.968]	[0.958]
Num. of Patent$_{t-1}$	1.211***	1.219***	1.219***	1.235***
	[0.000]	[0.000]	[0.000]	[0.000]
Constant	-472.651***	-474.815***	-474.304***	-483.182***
	[0.000]	[0.000]	[0.000]	[0.000]
Observations	13,230	13,230	13,230	13,230
Year dummies	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES
Adjusted R^2	0.175	0.175	0.175	0.175

Appendix A: Variable definitions

Variable	Description
ENV_OECD	The number of environmental patents filed and eventually granted categorized by OECD EnvTech.
ENV_Y02	The number of environmental patents filed and eventually granted categorized by Y02 class.
ENV_OECDY02	The number of environmental patents filed and eventually granted categorized by OECD EnvTech or Y02 class.
MV_ ENV_OECD	The nominal market value of environmental patents filed and eventually granted categorized by OECD EnvTech..
MV_ ENV_Y02	The nominal market value of environmental patents filed and eventually granted categorized by Y02 class.
MV_ ENV_OECDY02	The nominal market value of environmental patents filed and eventually granted categorized by OECD EnvTech or Y02 class.
Patent [t, t+3]	The environment concern score divided by the total maximum possible number of environmental concerns.
ENV_OECD[t, t+3]	The number of environmental patents filed and eventually granted categorized by OECD EnvTech in three years.
ENV_Y02[t, t+3]	The number of environmental patents filed and eventually granted categorized by Y02 class in three years.
ENV_OECDY02[t, t+3]	The number of environmental patents filed and eventually granted categorized by OECD EnvTech or Y02 class in three years.
MV_ ENV_OECD [t, t+3]	The nominal market value of environmental patents filed and eventually granted categorized by OECD EnvTech in three years.
MV_ ENV_Y02 [t, t+3]	The nominal market value of environmental patents filed and eventually granted categorized by Y02 class in three years.
MV_ ENV_OECDY02[t, t+3]	The nominal market value of environmental patents filed and eventually granted categorized by OECD EnvTech or Y02 class in three years.
Size	Natural logarithm of total assets.
Cash holding	The sum of value of debt and market value of equity divided by the book value of assets.
ROA	Net income divided by total assets.
Leverage	Total debt divided by the market value of the equity.
Tangibility	Tangible assets scaled by total assets.
MTB	The sum of value of debt and market value of equity divided by the book value of assets.
Materiality Index	The number of environmental issues that are considered financially material for the company
HEM	A dummy indicator variable with a value of one if the company's materiality index value is greater than the median and 0 otherwise.