Natural Disasters and Green Innovation

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Abstract

Using natural disasters as quasi-natural experiments, we document that firms headquartered in disaster-zones during a natural disaster increase their investment in green innovation technologies following the incidents. We show that the positive effect originates from firms that are headquartered in the states with stricter environmental regulations, as well as those that are financially unconstrained, and that operate in high-polluting industries. Furthermore, firms whose majority shares are held by institutional investors with long-term horizons in the pre-disaster year increase their green innovation performance more. Yet, our results show that firms that are targeted by socially responsible investing (SRI) environment funds do not have better green innovation performance than firms that are not.

JEL Codes: G23, G31, G33

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1. Introduction

In the last decades climate change caused more frequent and severe incidents that resulted in catastrophic consequences for individuals, communities, businesses and governments. *2017 Climate Science Special Report* of U.S. Global Change Research Program (USGCRP) documents that since 1980, the extreme weather events in the United States have cost more than $1.1 trillion. Report suggests it is extremely likely that human influence has been the dominant cause of the observed global warming since the mid-20th century. In addition, the way companies deal with natural disasters is of interest to both policy makers and public. They have a major role in exacerbating climate change mainly via greenhouse gas emissions, which is considered the major cause of climate change (Karl & Trenberth, 2003; Meinshausen et al., 2009; Cadez et al., 2019). According to U.S. Environmental Protection Agency (EPA)'s 2021 Inventory of U.S. Greenhouse Gas Emissions and Sinks report[3] total U.S. emissions have increased by 1.8 percent from 1990 to 2019, down from a high of 15.6 percent above 1990 levels in 2007.

More businesses around the globe are adopting measures to mitigate the consequences of climate change, as the climate change causes more frequent extreme weather events (International Panel on Climate Change (2012), Environmental Defense Fund Fourth Wave Adoption Benchmark Survey (2019)). Indeed, EPA's above-mentioned report also documents that greenhouse gas emissions decreased from 2018 to 2019 by 1.7 percent, which was largely driven by the decrease in CO_2 emissions from fossil fuel combustion as a result of a 1 percent decrease in total energy use and reflects a continued shift from coal to less carbon intensive natural gas and renewables in the electric power sector. These environmental risk-mitigating technologies, mainly named as "green innovation", broadly refer to patents in categories related to reducing air or water pollution, hazardous waste prevention, disposal and control, recycling, and alternative energy (Carrion-Flores and Innes (2010)).

Previous studies document that green innovation leads to a competitive advantage for firms (Hart, 1995; Sharma and Vredenburg, 1998), and it is associated with higher growth rates and better quality of life for the society (Dangelico and Pujari, 2010), reduces toxic emissions (Carrion-Flores and Innes, 2010), leads to positive profitability effects (Rexhauser and Rammer, 2014; Ghisetti and Rennings, 2014), and significantly reduces corporate financing constraints (Zhang et

[3] https://www.epa.gov/sites/production/files/2021-04/documents/us-ghg-inventory-2021-main-text.pdf

al., 2020). Furthermore, green patents create firm-specific and aggregate path dependency, which is the propensity to innovate in clean technologies stimulated by exposure to past clean technologies (Aghion et al., 2016). This suggest that adopting such policies creates knowledge spillovers and social value at the aggregate level, by not only improving current innovation outcomes, but also making it more feasible for the public to adopt. Indeed, green patents have more citation than non-green patents (Dechezlepretre et al., 2013) and receive more citations from all areas of technological applications (Popp and Newell, 2012). This could be one of the reasons why green innovation is encouraged by institutions (Kock et al., 2012; Berrone et al., 2013).

As the threat from climate change is growing and leading to more natural disasters, there is an increased attention on how these natural events may be catalyst for technological innovation (Henderson and Newell, 2011; Aghion et al., 2016). Therefore, in this paper, we explore whether natural disasters influence firm behavior to innovate more in green innovation technologies. Natural disasters are random incidents that have devastating effects on the communities for a long period of time. Therefore, they serve as natural experiments to assess firms' green innovation incentives. Growing stakeholder and institutional pressure (Kock et al. (2012)) and increased engagement of investors to address environmental, social and governance (ESG) concerns (Dimson et al., 2015; Starks et al., 2018; Dyck et al., 2019; Ilhan et al., 2020; Krueger et al., 2020; Pastor et al., 2020) motivate firms towards adopting environmentally responsible practices. As Ballesteros et al. (2017) discusses, firms face social pressures to adopt responsibilities that have traditionally fallen to governments, aid agencies, and other types of organizations and disaster relief is one of those contexts where both internal and external stakeholders ask firms to play a larger role. Berrone et al. (2013) finds that these pressures have positive impacts on green innovation activities. However, the aftermath of natural disasters is a significant financial uncertainty period for firms located in disaster zones as they generate significant financial loss for individuals, firms, and investors (Henriksson, 2020). Dessaint and Matray (2017) find that after hurricanes, firms increase their cash holdings in the short run as the managers' perceived liquidity risk increases. Elnahas et al. (2018) find that lenders charge firms higher spread in more disaster-prone counties. They also have more conservative leverage policies and greater earnings volatility. Therefore, whether firms located in disaster areas will invest in green innovation technologies in the post-disaster years is an important empirical question that has not been explored yet.

In our analysis, to investigate firms' green innovation performance we estimate a difference-in-differences model by exploiting the randomness of natural disasters occurred in the United States between 1990 and 2015. To match treated and control firms, we use coarsened exact matching (CEM) model. We measure green innovation as the number of green patents and citations obtained by the firms. We define relative measures of green innovation performance by using the ratio of green patents (citations) to all patents (citations) as our main variables of interest. Therefore, our results allow us to compare green innovation performance to all innovation conducted by the firm. Accordingly, we find that firms that are headquartered in disaster zones, and experience a natural disaster, increase their green patent ratio by 2.3% within two years of the disaster[4] compared to firms that operate in the same industry and are headquartered in the same state, but are not exposed to the same disaster. We also find that this positive effect persists up to three years after the disaster and disappears thereafter. Moreover, we also document that green innovation quality – measured by green citations ratio – increase following the climate-related incidents. Yet, this effect is especially meaningful in the three-year analyses since it takes time to receive citations after the patent is granted.

Next, we test the impact of external governance mechanisms as outside pressures exerted to increase green innovation practices following natural disasters. Specifically, we analyze the heterogeneous effects of pre-disaster environmental regulatory pressures, stock analysts' coverage and institutional ownership on firms' green innovation performance in the post-disaster period. Following Seltzer et al. (2021) and Konisky (2007), we use EPA enforcement data provided in the Integrated Compliance Information System for Federal Civil Enforcement Case Data to measure firms' exposures to environmental regulation. Significant environmental legislation exists at both state and federal level in the United States and state governments generally hold the primary responsibility for enforcing these laws. However, while states are expected to handle enforcement at least as strictly as EPA standards, some states choose to impose additional environmental restrictions beyond those required by the EPA, creating variation in the enforcement practices across states. Exploiting this variation, we document that the increase in green innovation in the aftermath of natural disasters originates from those firms whose headquarters are located in states

[4] Timing of the positive effect of disasters on green patent ratio is consistent with the literature that finds that the time lag between R&D investment in innovation to patent application is two years (e.g., Acharya et al. 2014, Amore et al. 2013, Brunnermerier and Cohen 2003, Grilliches 1998, Hall et al. 1986, Pakes and Schankerman 1984).

with stricter environmental regulation, measured both by the number of enforced formal and informal actions, and average penalty amounts as a result of violation. These results are consistent with Berrone et al. (2013), who document that greater regulatory pressures from governments and normative pressures from non-governmental organizations make it more attractive for the firms to engage in environmental innovation.

Our results using stock analysts' coverage and institutional ownership as external governance mechanisms show that neither of these mechanisms have statistically significant impact on firms' green innovation performances in the post-disaster periods. Yet, following Bushee (1998), we construct investor horizons, and find that firms whose shares are held mostly by short-term (transient) investors reduce their green innovation performance in the post-disaster period compared to long-term (dedicated) investors and passive (quasi-indexers) investors. These findings confirm the findings of Bushee (2001) that shows that investors with longer horizons prefer long-term, stable dividend income and capital appreciation while those with short horizons focus on near-term earnings.

Further, to test whether socially responsible investing (SRI) further improves firms' green innovation performance in the aftermath of natural disasters, we analyze the impact of SRI on post-disaster green innovation performance of firms since there is evidence in the literature that sustainable investing produces positive social impact by making firms greener and by shifting real investment toward green firms (Pastor et al., 2020). For example, Krueger et al., (2020) finds that institutions with a higher fraction of holdings subject to ESG analysis engage in more climate risk management. Moreover, authors posit that investors choose engagement rather than divestment. Yet, Cohen et al. (2020) find evidence that the majority of green patenting is not driven by firms that are commonly favored by ESG funds, but instead by firms that mostly operate in the energy sector, which is explicitly excluded from ESG funds investment universe. Moreover, Heath et al. (2022) find that while SRI funds select companies with better environmental and social conduct, they do not improve the environmental or social behavior of their portfolio firms. Following Edmans (2011), we define SRI environment funds listed on Social Investment Forum which follow 'climate and clean tech', 'pollution and toxics' and 'environment and other' criteria out of 11 screening criteria. Our results do not show a statistically significant impact on the post-disaster green innovation performance of firms whose shares are held by SRI environment funds, confirming the discussions in Cohen et al. (2020) and Heath et al. (2022).

We further argue that if firms have low default risk prior to the disaster and in the post-disaster period, they will have more incentives and resources to invest in green innovation technologies. This is also consistent with the argument that credit constraints significantly increase pollution emissions (Anderson, 2017), and thereby less environmentally friendly practices. Accordingly, we find that the positive effect of natural disasters on green innovation originates from those firms that have low default risk, measured by Altman's z-score (Altman, 1968).

Following Flammer and Kacperczyk (2016), we also analyze the green innovation behavior of firms that operate in high-polluting industries, identified by EPA in Toxic Release Inventory (TRI) National Analysis Complete Report (EPA 2014, p. 9). Our results show that the positive effect of natural disasters on green innovation originates from those firms that operate in high-polluting industries.

To our best knowledge, this is the first study that tests firms' green innovation performance in the aftermath of natural disasters. Our paper contributes to the literature by documenting the occurrence of natural disasters as incentives for the firms to engage in innovative projects in green technologies. We show that our results originate from those firms that are exposed to stricter environmental regulations, that have low default risk prior to the disaster, and that operate in polluting industries. Moreover, our results also contribute to the literature on investor horizons that firms whose majority of institutional holdings are held by longer term institutional investors are the ones that increase their green innovation performance the most. Lastly, our findings contribute to the SRI literature that existence of SRI environment funds do not improve firms' green innovation performance in the post-disaster periods.

This paper is organized as follows. Section 2 discusses the theoretical motivation for hypothesizing a link between natural disasters and green innovation. Section 3 discusses the data and methodology, and Section 4 presents the results and Section 5 concludes.

2. Literature Review

2.1. Green innovation in the aftermath of natural disasters

The negative impact of natural disasters and other weather-related incidents on economic growth is documented by previous researchers. For example, Crespo et al. (2008) finds that disasters have negative impact on knowledge spillovers. This is also supported by Yang (2008a), who documents the impact of extreme weather events on financial flows and foreign aid to the affected countries. Similarly, the effect of natural disasters on human migration (Paxson and

Rouse, 2008; Yang, 2008b; Boustan et al., 2012), and other behaviors are examined by Baez et al., 2010; Finlay, 2009; Cassar et al., 2017; Cameron and Shah, 2015). Natural disasters can also change the investor behavior of "short-termism" based on the length of the climate-related events (Henriksson, 2020), as well as CEO risk-taking behavior, corporate policies and acquisition activities (Bernile et al., 2017). Disasters can change mutual fund manager behaviors, such as including or excluding disaster zone firms in their portfolios (Alok and Kumar, 2016). In addition, disasters also affect corporate policies, such as increased levels of cash holdings due to sudden shock to the perceived liquidity (Dessaint and Matray, 2017). Following the climate-related incidents, abrupt changes in consumer demands and difficulties in supply chains lower the sales (Barrot and Sauvagnat, 2016). These unexpected events also lead to lower leverage at firm level based on elevated operating disruptions (Elnahas et al., 2018). The disasters also influence physical assets and local economies (Ellson et al., 1984; Xiao, 2011), workers' earnings (Belasen and Polachek, 2008), and housing prices negatively (Bernstein et al., 2019).

While previous studies mainly document negative firm-level consequences of natural disasters, we argue in this paper that natural disasters spur firms to invest in green innovation technologies that can alleviate future catastrophic consequences. Benson and Clay (2004) suggest that while negative short-term impacts are inevitable, disasters are followed by long-term development and economic transformation in many regions around the globe. Skidmore and Toya (2002) documents that climate disasters are positively correlated with economic growth and factor productivity. This may be due to the fact that even though disasters reduce expected return of physical capital, there is also a substitution effect of more investment need - including new adoptive technologies - following the incidents. Environmental breakthroughs can lead to a competitive advantage for firms and is valuable for all stakeholders (Hart, 1995; Sharma and Vredenburg, 1998). Green innovation is associated with higher growth rates for responsible firms and encourage a better quality of life for society (Dangelico and Pujari, 2010). Bossle et al., (2016) find that there is a growing interest in adopting green innovation among firms. Moreover, Rexhauser and Rammer (2014) and Ghisetti and Rennings (2014) find that energy and resource efficient innovations increase profitability. There is also evidence in the literature that green innovation can significantly reduce corporate financing constraints (Zhang et al., 2020). However, Ahuja et al., (2008) document that compared to other environmental practices, green innovation is riskier, requires more financial investment, and has return on investment in the longer-term.

2.2. The Effect of External Monitoring on Green Innovation

2.2.1. Environmental Regulation

Regulatory pressures are typically oriented toward environmental improvements in terms of pollution emissions. Green innovation is geared toward this goal, thereby aligning this type of investment with external demands (Berrone et al., 2013). However, there are mixed findings in the literature as to whether environmental regulations improve innovative performance. Conducting industry-level analysis, Jaffe and Palmer (1997) document that environmental compliance expenditures have a significant positive effect on R&D expenditures but not on industries' inventive output. Similarly, Brunnermeier and Cohen (2003) find that environmental innovation responded to increases in pollution abatement expenditures in the U.S. manufacturing industries, however, increased monitoring and enforcement activities related to existing regulations did not provide any additional incentive to innovate. On the other hand, firm-level analyses document positive impact of environmental regulation and environmental management tools on environmental innovation in Germany (Horbach, 2008), positive but heterogenous effects on ex-ante less innovative firms compared to more innovative firms in the UK (Kesidou and Demirel, 2012), positive effects on firms' eco-innovation as well as eco-investment and eco-planning innovation in China in the absence of influences from the fiscal system and political promotion system (You et al., 2019), and positive effects on environmental innovation in the US (Berrone et al., 2013).

2.2.2. Stock Analysts and Institutional Blockholders

We also analyze whether stock analysts' coverage and institutional block-holder ownership serve as external governance mechanisms to impact firms' green innovation incentives. In a survey of 401 U.S. CFOs Graham et al. (2005) document that managers perceive analysts as one of the most important groups affecting the share price of their corporations. Yet, it is unclear what effect analyst coverage exerts on managers' incentives to engage in innovation. On the one hand, analysts can be deemed to be external monitors of managers (Jensen and Meckling, 1976; Healy and Palepu, 2001; Yu, 2008) such that if analysts accurately convey the information of a firm's innovative activities to other financial market participants (especially its investors) and help them understand the real value of these long-term investments, then the management of the firm would engage in value-enhancing innovation activities. On the other hand, analysts may exacerbate

managerial myopia and impede firm innovation by imposing short-term pressure on managers (He and Tian, 2013). Analysts' intolerance to short term failures translates into revising their forecasts downward and making unfavorable recommendations, leading to negative market reactions, and disciplining the managers. In addition, Graham et al. (2005) also show that a majority of CFOs declared that they are willing to sacrifice long-term firm value to meet the desired short-term earnings targets due to their own wealth, career, and external reputation concerns (Hong et al., 2000).

On the impact of institutional blockholder ownership on firm innovation, Aghion et al. (2013) find that by owning a large share of a firm, institutional owners have better incentives to monitor. In addition, their abilities to monitor are better as they typically own stocks in many firms, so they benefit from economies of scope in monitoring. This more effective monitoring encourages innovation. Consistent with this discussion, Edmans (2009) argues that block-holders have strong incentives to monitor the firm's fundamental value because they can sell their stakes upon negative information. By trading on private information, they cause prices to reflect fundamental value rather than current earnings. In doing so, they also improve the incentives of the managers to innovate. Furthermore, Sapra et al. (2014) finds that an unhindered market for corporate control fosters innovation through the incentives provided by takeover premia that increase with the degree of innovation. Yet not all investors' preferences are concentrated in long-term value creation generated by innovative practices. Bushee (1998) argues that short-term oriented behavior by institutions creates pressures for managers to sacrifice R&D for the sake of higher current earnings. Bushee (2001) finds that high levels of short-term investors (transient ownership) are associated with an over- (under-) weighting of near-term (long-term) expected earnings, and a trading strategy based on this finding generates significant abnormal returns.

2.2.3. SRI funds

We measure investors' preferences for ESG investments by analyzing a more dedicated investor group, SRI funds, which monitors firms' environmental responsibilities and responsiveness. The "ethical investment" by SRI funds includes green investing, which is providing capital for those who are investing in sustainable projects and being aware of climate risks. SRI investors are looking not only a return on their investment, but also a positive impact of the fund in social issues (Silva and Cortez, 2016) by constant screening and monitoring to evaluate their credentials (Brooks and Oikonomou, 2018). This suggests SRI funds are targeting not only

financial objectives, but also non-financial objectives – such as green innovation – and SRI is genuinely contributing to shareholder wealth (Leite and Cortez, 2015; Pastor et al., 2020). Furthermore, Krueger et al., (2020) finds that institutions with a higher fraction of holdings subject to ESG analysis engage in more climate risk management by choosing investor engagement rather than divestment. SRI-financed green projects can have a higher value (Eichholtz et al., 2010), and provide "good" for the community (Jackson, 2009). Since credit worthiness of the firm is also related to its' pollution levels (Seltzer et al., 2021), corporations enjoy lower cost of capital by improving their SRI policies (Sharfman and Fernando 2008; Chava 2014; El Ghoul et al. 2018) and investors experience lower portfolio risk by adding SRI-related climate criteria in their holdings (Hoepner et al. 2018; Gibson et al., 2018; Jagannathan et al., 2019; Rameli et al. 2019).

Yet, there is contradicting evidence as to whether SRI funds have the means and incentive to affect the investment decisions of their portfolio firms. For instance, Berk and van Binsbergen (2021) argue that the impact of SRI funds on the cost of capital is too small to meaningfully affect real investment decisions. Further, funds may lack the incentive to engage as the cost of engaging with portfolio firms and changing their behavior is likely higher than the cost of pure portfolio selection based on observable environmental and social performance (Davies and VanWesep, 2018). Moreover, SRI funds might lack the expertise, resources, or stewardship personnel to effectively engage with their portfolio firms (Bebchuk and Tallarita, 2020). Lastly, by examining 18 different environmental and social outcomes, Heath et al. (2022) find evidence of a selection effect, but not a treatment effect such that; SRI funds do select companies that behave in a relatively more environmentally and socially responsible manner, but they do not improve the environmental or social conduct of their portfolio firms.

2.3. The Effect of Financial Constraints on Green Innovation

Climate risk that leads to frequent natural disasters has been widely accepted as an important risk component for the firms due to increased uncertainty about growth (Bansal et al., 2017; Hong et al., 2019), higher social costs (Bolton and Kacperczyk 2020; Hsu et al., 2019), increased regulatory risk (Daniel et al., 2016), increased geographic risks (Kruttli et al., 2020), increased screening costs (by institutional investors) (Krueger et al., 2020), and poor profit growth, which, in turn affect firm value, earnings, and overall operating performance (Kumar et al., 2019; Pankratz et al., 2019). Moreover, climate-related weather incidents influence firms' capital structure and borrowing habits such that increase in climate risk reduces both firms' demand for

borrowing and banks' lending to high-risk firms (Ginglinger and Moreau 2019). In fact, some financial institutions are now applying "carbon risk" to their loan rates following the Paris Agreement (Delis et al., 2019). Anderson (2017) finds that credit constraints distort the composition of assets towards over-investment in tangible assets, which can be pledged as collateral, thereby increasing the intensity of emissions.

3. Data and Model

We collect natural disaster data from Spatial Hazard Events and Losses Database for the United States (SHELDUS). It is a county-level hazard data set for the U.S. and covers natural hazards such thunderstorms, hurricanes, floods, wildfires, and tornados as well as perils such as flash floods, heavy rainfall, etc. We do not make a distinction between the disasters and consider a year with at least one of the above natural hazards as a disaster year in the county it occurs. This dataset also provides information on the amount of crop damages and property damages as a result of a natural disaster. In our analysis, we keep disasters that have only positive crop and/or property damages reported in the data. This allows us to focus on the incidents that cause a major impact on the communities in the disaster zones. We merge this data with firm headquarters using county FIPS (Federal Information Processing Standard Publication). We collect data on annual financial statements of U.S. public firms from Compustat database. We exclude companies that are incorporated outside the U.S. The period of analysis is 1990–2015. The sample consists of all firms with non-missing values of sales and total assets higher than $5 million. All the financial ratios are winsorized by 1% at both ends. Our final sample includes 122,166 firm-year observations of 10,489 firms.

The patent data comes from Bena et al. (2017). The authors collect the data for patent applications filed until mid 2017. In order to avoid truncation problem, we restrict our sample period to patents applications filed until the end of 2015. We measure firms' green innovation in terms of successful patent applications in environment-related technologies. Our main classification of green patents is based on the International Patent Classification system as in Johnstone et al. (2010). The main technological categories considered are broadly related to air or water pollution, hazardous waste prevention, disposal and control, recycling and alternative energy.

We measure green innovation as the number of green patents and citations obtained by firms in each year. We follow Amore and Bennedson (2016) and using the year of grant

application, we define our first variable of interest, *gr_pt_ratio,* as the ratio of green patents to all patents granted to the firms. Our second variable of interest, *gr_ct_ratio,* measures the quality of the green patents. We define this variable as the ratio of citations received by green patents to all citations received by all patents of a firm. We also define natural logarithm of one plus number of green patents (*ln_gr_pt*), natural logarithm of one plus number of green citations (*ln_gr_ct*) and natural logarithm of one plus the ratio of green citations to green patents (*ln_grct_grpt*) as alternative measures of green innovation performance. We provide the sample statistics in Table 1. According to these, an average firm in the sample has 4.6% of its patents in the green technology areas. Similarly, green citation ratio is 4.2% of all citations an average firm receives throughout the sample period. Average *ln_gr_pt* and *ln_gr_ct* are 19.3% and 39.5%, respectively. Average *ln_grct_grpt* is 26.4%.

Besides the green innovation performance measures, we control for firms' financial performance in our matching procedure and regression analysis. Specifically, we control for *firm size, ROA, cash holdings, leverage, tangibility, R&D ratio, R&D indicator dummy, capital expenditures ratio, Altman's z-score, HHI* and *high-polluting industry dummy*. An average firm size, defined as the natural logarithm of total assets, is 5.51 in the sample. We define profitability using return on assets (ROA) as the ratio of earnings before interests, taxes, depreciation and amortization scaled by the total assets. An average firm has 5.6% profitability. Cash holdings, defined as cash and equivalents scaled by total assets, have a mean of 17.5% in the sample. We define leverage as the ratio of book value of debt to the total of market value of equity and book value of debt. An average firm has a leverage ratio of 25.7% in the sample. Tangibility variable has a mean of 25.3. We define it as the ratio of net property, plant and equipment to total assets. An average firm has 4.5% R&D to total assets ratio and 51.3% of the firms in the sample have R&D expenditures. Capital expenditures to total assets ratio has a mean of 5.3% in the sample. We use Altman (1968)'s z-score to measure default risk, which has a sample mean of 1.04. We also define Herfindahl-Hirshman index (HHI) using sales to measure market concentration of the industry. The average HHI value in the sample is 4.1%. High-polluting industry definition is from EPA's 2014 Toxic Release Inventory (TRI) National Analysis Complete Report. According to this report, 92% of TRI chemicals disposed of or otherwise released originated from seven of the twenty-seven TRI industry sectors. These seven industries are metal mining, electric utilities, chemicals, primary metals, paper, food/beverages/tobacco and hazardous waste management. Our

high-polluting industry dummy variable takes value 1 for these seven industries using Fama and French (1985) 12-industry classification. In our sample, on average about 75% of firms operate in these seven industries.

In addition to firms' financial performance, we control for external governance in our analysis. We measure external governance using state-level environmental regulation, stock analyst coverage and institutional ownership. To measure the strictness of state-level environmental regulation, we use EPA enforcement data provided in the Integrated Compliance Information System for Federal Civil Enforcement Case Data to measure firms' exposures to environmental regulation, following Seltzer et al. (2021) and Konisky (2007). This measure of regulatory strictness captures compliance and enforcement actions for the Clean Water Act (CWA), Clean Air Act (CAA) and Resource Conservation and Recovery Act (RCRA) in a given state in a given year. Specifically, we define the ratio of total enforcement actions, which include both informal enforcement actions (notifications of violation) and formal actions (fines and administrative orders) by the state to the total number of facilities that are subject to EPA regulations in that state. Similar to Seltzer et al. (2021), to capture state-level enforcement we exclude all enforcement actions in the states in which the EPA is responsible for enforcement. In addition, we define penalty ratio as the total penalty amount charged in a state in a year scaled by the total number of facilities that are subject to EPA regulations in that state. According to the summary statistics, the average regulatory strictness ratio is 56% and average penalty ratio is $11,801.35 in our sample. We identify quartiles of regulatory strictness ratio and define *regulatory strictness* dummy variable that takes value one for the states in the highest quartile of the distribution of regulatory strictness ratio in the pre-disaster year and zero in the pre-disaster year for the states that are in the lowest quartile of the distribution of regulatory strictness ratio. Similarly, we define *high penalty* dummy variable that takes value one for the states in the highest quartile of the distribution of penalty ratio in the pre-disaster year and zero in the pre-disaster year for the states that are in the lowest quartile of the distribution of penalty ratio.

Analyst coverage data is from I-B-E-S. We calculate the natural logarithm of one plus the number of analysts that cover the firm each year. Then we define *coverage* dummy variable that takes value one for the firms that have below median analyst coverage in the sample in the pre-disaster year and zero for the firms that have above median analyst coverage in the sample in the pre-disaster year. We collect institutional ownership data from SEC 13-F filings on

Thomson/Refinitiv. We calculate the ratio of blockholders' ownership to common shares outstanding. The average firm in the sample has 30.6% institutional ownership. Then we define *institutional ownership* dummy variable that takes value one for the firms that have below median institutional ownership in the sample in the pre-disaster year and zero for the firms that have above median institutional ownership in the sample in the pre-disaster year. Among these institutional investors, Bushee (1998) defines dedicated institutional owners as long-term institutional investors, quasi-indexers as passive institutional investors and transient institutional owners as short-term institutional investors. We define the percentage of holdings by each group as the ratio to all institutional investors' holdings. Then, for each firm-year, we define the group that holds maximum percentage of shares and assign that group to that firm-year. Then, using below and above median of the distribution, we define *dedicated ownership, quasi-indexer ownership* and *transient ownership* dummy variables that characterize each firm's major institutional investor horizon in the pre-disaster year. According to these variables, in our sample on average 3.8% of the shares are held by dedicated owners, 48.5% of the shares are held by quasi-indexers and 18.6% of shares are held by transient owners.

We measure SRI environment funds' holdings from SEC S12 filings on Thomson/Refinitiv. Following Edmans (2011), we define SRI environment fund from Social Investment Forum and include those that follow 'climate and clean tech', 'pollution and toxics' and 'environment and other' criteria out of 11 screening criteria in our definition. Particularly, we identify those funds that have 'positive investment', which denotes that the fund seeks investments with positive impact in this area, 'restricted/exclusionary investment, which denotes that the fund seeks to avoid poorer performers in this area and combination of positive and restricted/exclusionary strategies. We calculate SRI fund ownership as the percent of common shares outstanding held by SRI environment funds. In our sample, average SRI environment fund holdings are 0.5%. Finally, we define *SRI_fund* dummy variable as one if a firm's shares were held by an SRI environment fund in the pre-disaster year and zero otherwise.

We employ a difference-in-differences setting in order to analyze the impact of natural disasters on firms' green innovation performance. In order to satisfy the identifying assumption and exogeneity of the event, we select our treated sample from the disasters that happened only once in the last four years and next three years. Without imposing this restriction, it is not possible to identify the source and magnitude of the effect of an unexpected incident once we include

subsequent disasters that occurred in the disaster-prone zones. Our treated sample includes firms that are headquartered in the disaster zones at the time of the disaster, and we match them with our control sample firms who operate in the same industry, defined using Fama and French (1985) 12-industry classification, and who are headquartered in the same state but not in the declared disaster zones for the same disaster. Following Iacus et al. (2012), we employ a coarsened exact matching method, which does not impose any distributional assumptions in the matching process. We match treated and control group firms within each state-year and industry in the year prior to the disaster. We also include above-defined time-variant firm-level control variables and trends in dependent variables to satisfy the parallel trends assumption. We provide the pre-matching summary statistics of the variables in Table 2 and post-matching summary statistics of the variables in Table 3. According to these, although parallel trends assumption holds in the pre-matching sample, treated and control group firms have different characteristics in the pre-matching sample. Our matching methodology addresses that problem. As a result of one-to-one matching, our sample has 247 firms that are affected by a disaster in the treated group and 247 firms that are not affected by a disaster in the control group. Accordingly, within each industry and state our *Treated* dummy variable takes value 1 for treated group and 0 for the control group. *Disaster* dummy variable takes value of 1 for post-disaster years including the year of disaster and 0 for pre-disaster years. We focus on two years before versus after the natural disaster in our benchmark analysis as the time lag between R&D investment in innovation to patent application is two years (e.g., Acharya et al. 2014, Amore et al. 2013, Brunnermerier and Cohen 2003, Grilliches 1998, Hall et al. 1986, Pakes and Schankerman 1984). We also evaluate the persistence of the impact of disasters on green innovation by following the same treated and control samples in three-year and four-year pre- vs. post-disaster periods. Figure 1 in the Appendix provides a timeline of our difference-in-differences model.

4. Results

4.1. Effects of natural disasters on firms' green innovation performance

We present our two-year difference in differences results in Panel A of Table 4. The coefficient of *Disaster*Treated* interaction variable provides the difference between post- and pre-disaster effect of natural disasters on treated firms' green innovation performance, compared to that of control firms. In addition to firm, and year fixed effects, we control for state and year fixed

effects, which tighten our identification since they account for any local shocks that may affect green innovation and, at the same time, coincide with the treatment. We find that firms that are headquartered in disaster zones during a disaster year experience increases in their green innovation performance, measured by green patent ratio in column 1, by 2.3% at 5% statistical significance level in the year and one year after the disaster, compared to the control firms operating in the same industry and headquartered in a non-disaster county within the same state in the disaster year[5]. In column 2 we report the results using green citation ratio. According to these, in the year and one year after the disaster, green citation ratio of treated firms increases 1.7% higher than the control firms compared to two years prior to the disaster. However, this effect is only significant at 10% level since it takes time for granted patents to receive citations. We also measure firms' green innovation performance using natural log of total green patents, green citations, and ratio of green citations to green patents received by a firm each year. Column 3 shows that treated firms have 0.033 percentage points more green patents statistically significant at 10% level. The significance of the effect disappears in the results using natural logarithm of green citations and ratio of green citations to green patents as dependent variables in columns 4 and 5. These are consistent with delayed effect of citations received by granted patents. These results are consistent with our argument that firms that are headquartered in disaster-zones during a natural disaster increase their green patents in the post-disaster period.

Our matched sample consists of all Compustat firms, including those firms that do not produce patents throughout the sample period. Therefore, one potential concern is that our results may be affected by these nonpatenting firms. Although inclusion of firm fixed effects helps mitigate this concern by controlling for the "nonpatenting" attribute (Flammer and Kacperczyk, 2016), we verify in Table A1 of Online Appendix that our results are robust when we exclude nonpatenting firms.

4.2. Persistence of the effects of natural disasters on firms' green innovation performance

In addition to the short-term effects of natural disasters on firms' green innovation performance, we test longer-term effects to observe if the positive effect persists. To that end, we change our difference in differences estimate period to three years before and after the disaster in Panel B of Table 4, and four years before and after the disaster in Panel C of Table 4. According

[5] Our results are robust to including county level time-variant controls such as unemployment rate and population.

to these, compared to control firms operating in the same industry and headquartered in a non-disaster county within the same state in the disaster year, green innovation performance increase in firms that are headquartered in disaster zones during a disaster year experience persists in the three-year post disaster period. In column 1 of Panel B, we report results using green patent ratio as the dependent variable. The magnitude of the coefficient on interaction variable, *Disaster*Treated*, is 2.2% at 1% statistical significance level, while in green citation ratio results, the effect is 2.1% at 5% significance level. This is consistent with our previous discussion that there is a delay in citations after the patent is granted. We also find positive and significant results using natural log of total green patents in column 3 and green citations in column 4, both statistically significant at 5% level. The increase in the ratio of green citations to green patents in column 5 is also significant but at 10% level. Taken together, these results suggest that post-disaster green innovation performance of firms that are headquartered in disaster-zones during a natural disaster persists for three years after the disaster happens. Furthermore, these results also document evidence that the recognition and quality of the green patents, proxied by green citations, improve in the three-year post-disaster period.

Next, we analyze the four-year pre vs. post disaster effects on the same matched firms in the treated and control groups. Although smaller in magnitude in green patents ratio (2%) and green citations ratio regressions (1.8%) in columns 1 and 2 of Panel C, respectively, in Table 4, the coefficients of interaction variables are still statistically significance at 1% level. We also find positive and significant results using natural log of total green patents in column 3 and green citations in column 4, both statistically significant at 5% level. The increase in the ratio of green citations to green patents is also statistically significant at 5% level in the four-year pre vs. post disaster period analysis. These results confirm our previous findings that the effect of natural disasters on treated firms' green innovation performance persists in the longer-term.

4.3. Dynamics of the treatment effect of natural disasters on green innovation

In Table 5 we assess the dynamics of the treatment effect. To do so, we replace the treatment dummy with a set of seven dummy variables indicating the two years prior to the treatment (*Disaster (-2)* and *Disaster (-1)*); the year of the treatment (*Disaster (0)*); the first, second, and third year after the treatment (*Disaster (1), Disaster (2)* and *Disaster (3),* respectively); and four or more years after the treatment (*Disaster (4+)*). As shown, for both measures of innovation, the coefficients of all pretreatment dummies are small and statistically insignificant.

This finding is reassuring because it shows that there is no preexisting trend in the data. In the year of (*Disaster (0)*) and following the disaster (*Disaster (1)*) green patent ratio increases by 2.2% and 3%, respectively, significant at 5% level. The significant effect on green patents ratio disappears thereafter.

Consistent with the innovation lag found in previous studies (e.g., Acharya et al., 2014; Amore et al., 2013; Pakes and Schankerman, 1984), we find no effect in the year of the treatment on green citation ratio. In fact, as shown by the positive and statistically significant coefficient of *Disaster (1)*, it is only one year after the disaster year that the effect becomes statistically significant. The coefficients of *Disaster (2)* and *Disaster (3)* in green citation ratio regressions remain statistically significant at 10% level but *Disaster (4+)* becomes insignificant. Taken together, results in these analyses indicate that natural disasters do not have a long-lasting effect on firms' green innovation performance.

4.4. Possible explanations to the positive effect of natural disasters on green innovation

In this section, we analyze the possible channels that motivate and incentivize the firms to invest in green innovation technologies in the post-disaster period. Specifically, we analyze external governance mechanisms, namely, environmental regulation, stock analysts' coverage and institutional ownership, as well as investor horizon, SRI environment funds' holdings, default risk, and high-polluting industries as possible channels that affect firms' behavior.

4.4.1. The effect of external governance on firms' green innovation performance in the post-disaster period

In this section we analyze the effect of external governance mechanisms, namely, environmental regulation, stock analyst coverage and institutional ownership, on firms' green innovation performance in the post-disaster period.

In Table 6 Panel A we present the results of triple difference in differences estimation using *Disaster*Treated*Regulatory strictness* interaction variable. According to the results, the increase in both green patents ratio and green citations ratio in the two-year post-disaster period originates from those firms that operate in the states with stricter regulatory enforcements. This effect persists for green patents ratio estimation in the three-year and four-year analyses. However, the effect of regulatory strictness on green citation ratio disappears in three-year analysis. These results provide evidence that increase green innovation performance in the aftermath of a natural disaster originates from firms that are headquartered in the states with stricter regulatory enforcements

prior to a natural disaster. Alternatively, in Panel B we use penalty ratio as a proxy for regulatory strictness. The results of triple difference in differences estimation using *Disaster*Treated*High penalty* interaction variable are qualitatively and quantitatively similar to the results in Panel A and provide additional support for our above interpretation.

In Table 7 Panel A we show the results using stock analyst coverage as our second external monitoring mechanism. Triple difference in differences estimation results using *Disaster*Treated*Ln_coverage* interaction variable show that firms with high (above median) number of analyst coverage in the pre-disaster year do not have statistically significantly different post-disaster green innovation performance than those with low (below median) number of analyst coverage in the pre-disaster year. As a third external governance mechanism, we estimate the effect of institutional ownership on treated firms' green innovation performance in the post-disaster period. In Panel B, we report the estimation results using *Disaster*Treated*Inst. ownership* interaction. According to these, firms with higher levels of institutional ownership in the pre-disaster year do not have statistically significantly different post-disaster green innovation performance than those with low institutional ownership in the pre-disaster year.

4.4.2. *Investor horizons and firm's green innovation performance in the post-disaster period*

Although institutional ownership on average does not have an impact on firms' green innovation performance, institutional investor horizons can have varying effects on firms' outcomes. Therefore, in this section, we analyze how investor horizons affect our results. To do so, we employ a triple difference in differences model using interactions of three investor types – *dedicated ownership, quasi-indexer ownership* and *transient ownership* - defined by their holding preferences. We present our results in Table 8. According to these, *Disaster*Treated*Transient ownership* interaction variable is negative and statistically significant at 10% statistical significance level in both green patents ratio and green citations ratio regressions for two-year analyses. The effect disappears in three-year and four-year green patents ratio analyses. In the three-year and four-year analyses, however, the effect is still statistically significant at 10% level in green citations ratio regression. Moreover, the magnitude of this negative effect is larger than the main effect of the disaster (*Disaster*Treated),* suggesting that consistent with the expectations from their investors, firms whose shares are held mostly by transient owners reduce their green innovation performance. On the other hand, *Disaster*Treated*Dedicated ownership* and

*Disaster*Treated*Quasi-indexer ownership* interaction variables do not have significant coefficients different than the main interaction variable. Taken together, these results suggest that firms whose shares are held by short-term institutional investors in the pre-disaster year do not increase their green innovation performance in the post-disaster period. These findings are consistent with our arguments and contribute to existing discussions in the literature on how investor horizon affects ESG investing performance of firms.

4.4.3. *The effect of SRI environment fund holdings on firms' green innovation performance in the post-disaster period*

Next, we analyze whether SRI environment funds exert pressure on firms to invest in green innovation technologies especially in the aftermath of a natural disaster. We employ triple difference in differences methodology using *Disaster*Treated*SRI_fund* interaction variable. The results in Table 9 show that firms whose shares are held by SRI environment funds in the pre-disaster period do not have statistically significantly different green innovation performance in two-year, three-year and four-year analyses. These results suggest that existence of SRI environment funds do not increase firms' green innovation performance in the aftermath of natural disasters.

4.4.4. The effect of default risk on firms' green innovation performance in the post-disaster period

As a possible mechanism that might affect firms' green innovation performance in the post disaster period, we first analyze the effect of default risk. We measure default risk using Altman's z-score (Altman, 1968). We define *Default* variable that takes value 1 for above median and 0 for below median z-score distribution at the end of the previous fiscal year. By construction of z-score variable, above median z-score firms are low default risk firms. We estimate triple difference in differences using *Disaster*Treated*Default.* We provide the results of this estimation in Table 10. According to these, the positive and significant effect on green patents ratio emanate from low default risk firms in two-year analyses. That is, the coefficient of *Disaster*Treated* interaction variable becomes insignificant in the two-year analyses when we include the triple interaction variable, *Disaster*Treated*Default.* In the two-year before and after the disaster results in columns 1, compared to the pre-disaster period, in the post-disaster period treated firms with low default risk issue 2.9% higher green patents compared to all patents, statistically significant at 5% level. In the three-year estimations of green patents ratio in column 3, the magnitude of the coefficient

of *Disaster*Treated*Default* interaction variable becomes 2%, statistically significant at 10% level. The results in column 2 show that green citations ratio of treated firms with low default risk does not change in the two-year post-disaster period at a statistically significant level. In three-year estimations *Disaster*Treated* interaction variable becomes statistically significant at 10% level and indicates a 1.1% increase, whereas the coefficient of *Disaster*Treated*Default* interaction variable is statistically insignificant. In the four-year analyses, the coefficient of the triple interaction variable becomes statistically insignificant in both green patents ratio and green citations ratio regressions in columns 5 and 6, respectively. These results provide evidence that the increase in green innovation performance in the two-year post-disaster period originates from those firms that have low default risk at the end of the previous fiscal year.

4.4.5. High-polluting industries' green innovation performance in the post-disaster period

In this section we analyze whether green innovation performances of firms that operate in high polluting industries are different. To test this, we estimate triple difference in differences regressions using high-polluting industry dummy to identify those firms that operate in high polluting industries. Our results in Table 11 show that the coefficient of *Disaster*Treated*High-pollution* interaction variable in two-year analyses is positive and statistically significant at 1% significance level in both green patent ratio and green citations ratio regressions. The magnitude of the coefficient is 3.9% for green patent ratio and 3.4% for green citations ratio regressions in columns 1 and 2, respectively. In three-year analyses it increases to 4.3% at 1% statistical significance level for green patent ratio regressions in column 3, and 3.8% at 1% statistical significance level for green citation ratio regressions in column 4. In four-year analyses the significance of triple interaction variable becomes 3.4% at 1% statistical significance level in green patent ratio regressions in column 5. In green citations ratio regression column 6 the magnitude of the triple interaction variable becomes 2.7% at 1% statistical significance level. These results suggest that the increase in green innovation performance in the aftermath of natural disasters originates exclusively from the firms that operate in high-polluting industries in two-year, three-year and four-year analyses.

5. Conclusion

In this paper we explore the impact of natural disasters on the green innovation performance of firms that are headquartered in disaster-zones during a natural disaster. Our benchmark results suggest that firms, whose headquarters are located in disaster zones and experience a natural disaster increase their green patent ratio by 2.3% within two years of the disaster compared to firms that operate in the same industry and are located in the same state but are not affected by the disaster. We also provide evidence that these effects persist in three-year and four-year difference in differences estimations of the same treated and control firms.

We test the impact of external governance mechanisms as possible outside pressures exerted to increase green innovation in the aftermath of natural disasters. We use state-level environmental regulations, stock analyst coverage and institutional ownership as major external governance mechanisms. We present evidence that the increase in green innovation performance in the aftermath of natural disasters originate from those firm that are headquartered in the states with stricter environmental regulations in the pre-disaster year. We do not find statistically significant evidence that stock analyst coverage and institutional ownership impact firms' green innovation performance in the post-disaster period. However, when we define institutional investor groups by investor horizons, we find that our results are more pronounced for firms whose majority shares are held by long-term and passive institutional investors whereas, firms whose majority shares are held by short-term investors decrease their green innovation performance as short-term institutional investors prefer short-term earnings to long-term firm value and returns. These results are consistent with existing literature and provide further evidence that investor horizons matter for long-term ESG practices.

Lastly, we show that existence of SRI environment fund holdings in the pre-disaster year does not have statistically significant impact on firms' green innovation performance in the post-disaster period. This is consistent with the literature that SRI funds might not have the means and incentives to affect the investment decisions of their portfolio firms such that they select companies that behave in a relatively more environmentally and socially responsible manner, but they do not improve the environmental or social conduct of their portfolio firms.

Finally, consistent with previous findings in the literature, we provide evidence that our results are driven by firms that have low default risk during the period prior to the disaster and in the post-disaster since financially unconstrained firms will have more resources to invest in green

innovation technologies. Our results also show that the increase in green innovation performance in the two-year, three-year and four-year post-disaster periods originates exclusively from firms that operate in high-polluting industries.

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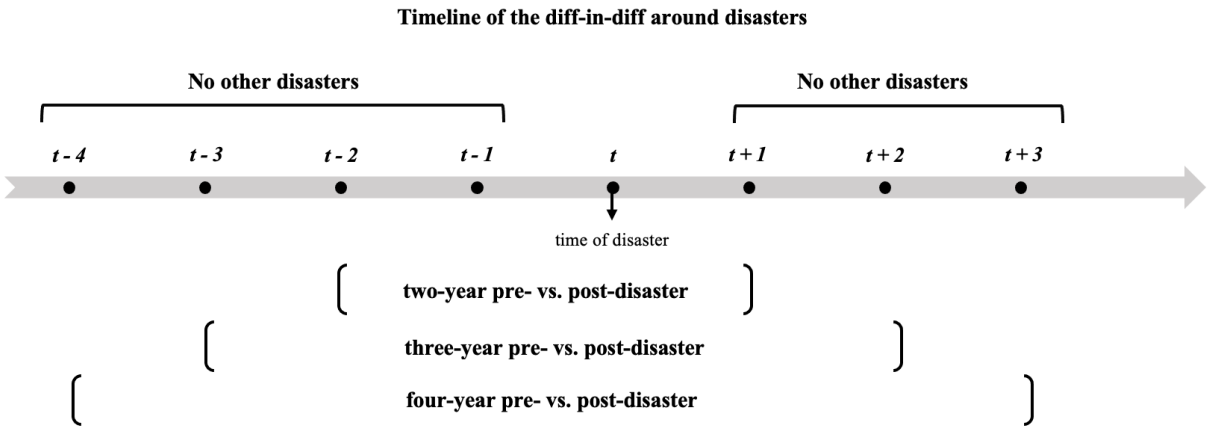
Appendix:

Figure 1



Variable definitions:

Gr_pt_ratio:	The ratio of green patents to total patents of a firm each year.
Gr_ct_ratio:	The ratio of citations for green patents to citations for total patents of a firm each year.
Ln_gr_pt:	Natural logarithm of one plus number of green patents of a firm each year.
Ln_gr_ct:	Natural logarithm of one plus sum of citations to all green patents of a firm each year.
Ln_grct_grpt:	The ratio of sum of green citations to number of green patents of a firm each year.
Disaster dummy:	Takes value of 1 for post-disaster years including the year of disaster and 0 for pre-disaster years.
Treated dummy:	Takes value 1 for treated group and 0 for the control group.
Size:	Natural logarithm of total assets.
ROA:	The ratio of earnings before interests, taxes, depreciation and amortization to total assets.
Cash holdings:	The ratio of cash and equivalents to total assets.
Leverage:	The ratio of book value of debt to market value of equity and book value of debt.
Tangibility:	The ratio of net property, plant and equipment to total assets.
R&D ratio:	The ratio of research and development expenses to total assets.
R&D dummy:	Takes value 1 if a firm has research and development expenses each year, 0 otherwise.
Capital expenditures ratio:	The ratio of capital expenditures to total assets.
HHI:	Herfindahl-Hershman index calculated using total revenue each year in each industry, defined using Fama-French (1985) 12 industry classification.
High-polluting industry:	Takes value 1 for firms that operate in seven TRI industries defined by EPA.
Coverage:	Takes value 1 for firms with above median number of analysts in the pre-disaster year and 0 otherwise.
Institutional ownership:	Takes value 1 for firms with above median ratio of blockowner shares in the pre-disaster year and 0 otherwise
Dedicated ownership:	Takes value 1 for firms whose majority shares are owned by long-term institutional investors in the pre-disaster year, defined by Bushee (1998).
Quasi-indexer ownership:	Takes value 1 for firms whose majority shares are owned by passive institutional investors in the pre-disaster year defined by Bushee (1998).
Transient ownership:	Takes value 1 for firms whose majority shares are owned by short-term institutional investors in the pre-disaster year defined by Bushee (1998).
SRI_fund:	Takes value 1 for firms whose shares are held with SRI environment funds in the pre-disaster year and 0 otherwise
Default	Takes value 1 for above median Altman's z_score distribution in the pre-disaster year, and 0 for below median distribution in the pre-disaster year.
Regulatory strictness	Takes value 1 for the states in the highest quartile of the distribution of regulatory strictness in the pre-disaster year and 0 for the states in the lowest quartile of the distribution of regulatory strictness in the pre-disaster year.
High Penalty	Takes value 1 for the states in the highest quartile of the distribution of average penalty amount in the pre-disaster year and 0 for the states in the lowest quartile of the distribution of average penalty amount in the pre-disaster year.

Table 1: Summary Statistics
Variable definitions are provided in the Appendix.

Variable	N	Mean	St. dev	Min	Q1	Median	Q3	Max
Gr_pt_ratio	122,166	0.046	0.163	0.000	0.000	0.000	0.000	1.000
Gr_ct_ratio	122,166	0.042	0.164	0.000	0.000	0.000	0.000	1.000
Ln_gr_pt	122,166	0.193	0.633	0.000	0.000	0.000	0.000	6.551
Ln_gr_ct	122,166	0.395	1.255	0.000	0.000	0.000	0.000	9.029
Ln_grct_grpt	122,166	0.264	0.826	0.000	0.000	0.000	0.000	6.544
Size	122,166	5.513	2.136	1.736	3.842	5.398	6.979	10.834
ROA	122,166	0.056	0.198	-0.946	0.018	0.093	0.155	0.413
Cash / Total assets	122,166	0.175	0.213	0.000	0.024	0.082	0.247	0.902
Leverage	122,166	0.257	0.260	0.000	0.020	0.178	0.421	0.955
Tangibility	122,166	0.253	0.243	0.000	0.056	0.169	0.383	0.902
R&D / Total assets	122,166	0.045	0.104	0.000	0.000	0.000	0.040	0.748
R&D dummy	122,166	0.513	0.500	0	0	1	1	1
Capital expenditures / Total assets	122,166	0.053	0.064	0.000	0.012	0.032	0.066	0.369
Altman's z-score	122,166	1.046	0.951	-1.417	0.400	0.885	1.435	41.883
HHI	122,166	0.041	0.036	0.012	0.026	0.031	0.040	0.250
High-polluting industry dummy	122,166	0.748	0.433	0	0	1	1	1
Ln (1+Analyst coverage)	122,166	0.827	1.112	0.000	0.000	0.000	1.791	4.220
Institutional ownership	122,166	0.306	0.311	0.000	0.000	0.210	0.563	1.000
Dedicated ownership	122,166	0.038	0.107	0.000	0.000	0.000	0.017	1.000
Quasi-indexer ownership	122,166	0.485	0.350	0.000	0.000	0.586	0.762	1.000
Transient ownership	122,166	0.186	0.204	0.000	0.000	0.145	0.303	1.000
SRI fund ownership	122,166	0.005	0.102	0.000	0.000	0.000	0.000	20.617
Regulatory strictness	122,166	0.559	0.197	0.000	0.461	0.580	0.695	0.973
Penalty ratio	122,166	11,801	43,369	0.000	1,915	4,423	10,927	1,043,181

Table 2: Unbalanced variables before matching
Variable definitions are provided in the Appendix.

	Treated (1)	Control (2)	Difference (2) - (1)	t-value
Trend in dependent variables				
ΔGr_pt_ratio$_{t-(t-1)}$	0.001	0.001	-0.001	-0.05
ΔGr_pt_ratio$_{(t-1)-(t-2)}$	0.001	0.001	0.000	0.00
ΔGr_pt_ratio$_{(t-2)-(t-3)}$	-0.002	0.002	-0.004	-0.50
ΔGr_pt_ratio$_{(t-3)-(t-4)}$	-0.002	0.002	-0.004	-0.50
ΔGr_ct_ratio$_{t-(t-1)}$	-0.005	0.002	-0.007	-0.90
ΔGr_ct_ratio$_{(t-1)-(t-2)}$	0.002	0.002	-0.001	-0.05
ΔGr_ct_ratio$_{(t-2)-(t-3)}$	-0.005	0.002	-0.007	-1.00
ΔGr_ct_ratio$_{(t-3)-(t-4)}$	-0.005	0.002	-0.007	-1.00
ΔLn_gr_pt$_{t-(t-1)}$	0.010	0.007	0.003	0.20
ΔLn_gr_pt$_{(t-1)-(t-2)}$	-0.002	0.007	-0.009	-0.75
ΔLn_gr_pt$_{(t-2)-(t-3)}$	-0.005	0.005	-0.011	-0.95
ΔLn_gr_pt$_{(t-3)-(t-4)}$	0.004	0.004	-0.001	-0.05
ΔLn_gr_ct$_{t-(t-1)}$	-0.012	-0.006	-0.006	-0.20
ΔLn_gr_ct$_{(t-1)-(t-2)}$	-0.017	0.018	-0.035	-1.00
ΔLn_gr_ct$_{(t-2)-(t-3)}$	-0.034	0.002	-0.036	-1.05
ΔLn_gr_ct$_{(t-3)-(t-4)}$	0.015	-0.014	0.029	0.85
Control variables				
Size	5.887	5.697	0.190	2.35**
ROA	0.101	0.074	0.026	4.05***
Cash / Total assets	0.147	0.171	-0.024	-3.10***
Leverage	0.251	0.251	0.000	0.00
Tangibility	0.279	0.263	0.017	1.75*
R&D / Total assets	0.036	0.045	-0.009	-2.35**
Capital expenditures / Total assets	0.054	0.052	0.002	0.85
Altman's z-score	1.171	1.053	0.118	3.35***
Ln_coverage	1.015	0.917	0.098	2.38**
Institutional ownership	0.348	0.308	0.040	3.55***
SRI fund ownership	0.004	0.003	0.001	1.14

Table 3: Balanced variables after matching
Variable definitions are provided in the Appendix.

	Treated (1)	Control (2)	Difference (1) - (2)	t-value
Trend in dependent variables				
ΔGr_pt_ratio$_{t-(t-1)}$	0.006	-0.010	0.016	1.40
ΔGr_pt_ratio$_{(t-1)-(t-2)}$	0.012	0.009	0.003	0.30
ΔGr_pt_ratio$_{(t-2)-(t-3)}$	-0.015	-0.004	-0.011	-1.50
ΔGr_pt_ratio$_{(t-3)-(t-4)}$	-0.015	-0.004	-0.011	-1.50
ΔGr_ct_ratio$_{t-(t-1)}$	0.011	-0.010	0.021	1.55
ΔGr_ct_ratio$_{(t-1)-(t-2)}$	0.009	0.013	-0.003	-0.40
ΔGr_ct_ratio$_{(t-2)-(t-3)}$	-0.015	-0.006	-0.009	-1.15
ΔGr_ct_ratio$_{(t-3)-(t-4)}$	-0.015	-0.006	-0.009	-1.15
ΔLn_gr_pt$_{t-(t-1)}$	0.017	0.005	0.011	0.45
ΔLn_gr_pt$_{(t-1)-(t-2)}$	0.031	0.011	0.021	0.95
ΔLn_gr_pt$_{(t-2)-(t-3)}$	-0.019	-0.010	-0.009	-0.55
ΔLn_gr_pt$_{(t-3)-(t-4)}$	-0.022	-0.015	-0.007	-0.40
ΔLn_gr_ct$_{t-(t-1)}$	0.055	-0.022	0.077	1.05
ΔLn_gr_ct$_{(t-1)-(t-2)}$	0.079	0.061	0.017	0.25
ΔLn_gr_ct$_{(t-2)-(t-3)}$	-0.057	-0.033	-0.024	-0.50
ΔLn_gr_ct$_{(t-3)-(t-4)}$	-0.060	-0.067	0.007	0.15
Control variables				
Size	5.389	5.476	-0.086	-0.50
ROA	0.091	0.077	0.014	1.05
Cash holdings	0.170	0.189	-0.019	-1.00
Leverage	0.247	0.246	0.001	0.05
Tangibility	0.216	0.212	0.004	0.20
R&D ratio	0.046	0.045	0.001	0.15
Capital expenditures ratio	0.043	0.049	-0.006	-1.35
Altman's z-score	1.230	1.182	0.048	0.62
Ln_coverage	0.830	0.883	-0.053	-0.53
Institutional ownership	0.302	0.303	-0.001	-0.02
SRI fund ownership	0.003	0.006	-0.003	-0.67

Table 4: Difference in Differences Regressions of Green Patents and Green Citations

This table presents the results of difference in differences analysis. *Gr_pt_ratio* is defined as the ratio of green patents to total patents of a firm each year. *Gr_ct_ratio* is defined as the ratio of citations received by green patents to citations received by all patents of a firm each year. *Ln_gr_pt* is defined as the natural logarithm of one plus number of green patents of a firm each year. *Ln_gr_ct* is defined as the natural logarithm of one plus sum of citations to all green patents of a firm each year. *Ln_grct_grpt* is defined as the ratio of sum of green citations to number of green patents of a firm each year. In Panel A *Disaster* dummy takes value of 1 for the year and the following year of the disaster years and 0 for two years before the disaster. In Panel B *Disaster* dummy takes value of 1 for the year and two years following year of the disaster years and 0 for three years before the disaster. In Panel C *Disaster* dummy takes value of 1 for the year and three years following year of the disaster years and 0 for four years before the disaster. *Treated* dummy takes value 1 for treated group and 0 for the control group. The period of analysis is 1990-2015. The definitions of the control variables are provided in the Appendix. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Two years before and after the disaster

Dependent variable:	Gr_pt_ratio	Gr_ct ratio	Ln_gr_pt	Ln_gr_ct	Ln_grct_grpt
Disaster*Treated	0.023	0.017	0.033	0.076	0.055
	(2.65)***	(1.96)*	(2.08)**	(1.65)*	(1.37)
Disaster	0.003	-0.012	-0.024	-0.099	-0.084
	(0.24)	(1.13)	(1.08)	(1.57)	(1.46)
Constant	-0.088	-0.075	-0.709	-0.309	0.635
	(3.27)***	(2.02)**	(4.61)***	(0.44)	(0.95)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES
N	1,976	1,976	1,976	1,976	1,976
Adjusted R^2	0.03	0.07	0.10	0.06	0.04

Panel B: Three years before and after the disaster

Dependent variable:	Gr_pt_ratio	Gr_ct ratio	Ln_gr_pt	Ln_gr_ct	Ln_grct_grpt
Disaster*Treated	0.022	0.021	0.036	0.097	0.075
	(2.94)***	(2.70)***	(2.22)**	(2.11)**	(1.93)*
Disaster	0.004	-0.006	-0.000	-0.028	-0.027
	(0.50)	(0.68)	(0.02)	(0.48)	(0.54)
Constant	-0.001	-0.024	-0.521	-0.475	0.221
	(0.01)	(0.47)	(2.91)***	(0.76)	(0.47)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES
N	2,964	2,964	2,964	2,964	2,964
Adjusted R^2	0.02	0.03	0.07	0.03	0.01

Panel C: Four years before and after the disaster

Dependent variable:	Gr_pt_ratio	Gr_ct ratio	Ln_gr_pt	Ln_gr_ct	Ln_grct_grpt
Disaster*Treated	0.019	0.017	0.033	0.093	0.075
	(2.80)***	(2.59)***	(2.11)**	(2.11)**	(1.98)**
Disaster	0.006	-0.001	0.012	0.007	-0.001
	(0.80)	(0.18)	(0.93)	(0.16)	(0.03)
Constant	-0.006	0.018	-0.546	-0.262	0.425
	(0.28)	(0.59)	(4.73)***	(0.67)	(1.14)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES
N	3,792	3,792	3,792	3,792	3,792
Adjusted R^2	0.02	0.02	0.08	0.04	0.03

Table 5: Dynamics of Treatment Effect on Green Patents and Green Citations

This table presents the results of difference in differences analysis. *Gr_pt_ratio* is defined as the ratio of green patents to total patents of a firm each year. *Gr_ct_ratio* is defined as the ratio of citations received by green patents to citations received by all patents of a firm each year. $Disaster_{(-2)}$dummy takes value of 1 for two years before the disaster and 0 otherwise. $Disaster_{(-1)}$dummy takes value of 1 for one years before the disaster and 0 otherwise. $Disaster_{(0)}$dummy takes value of 1 for the year of the disaster and 0 otherwise. $Disaster_{(1)}$dummy takes value of 1 for the year after the disaster and 0 otherwise. $Disaster_{(2)}$dummy takes value of 1 for two years after the disaster and 0 otherwise. $Disaster_{(3)}$dummy takes value of 1 for three years after the disaster and 0 otherwise. $Disaster_{(4+)}$dummy takes value of 1 for four years after the disaster and the following years and 0 otherwise. The period of analysis is 1990-2015. The definitions of the control variables are provided in the Appendix. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	Gr_pt_ratio		Gr_ct ratio	
	(1)	(2)	(3)	(4)
$Disaster_{(-2)}$	-0.001	-0.002	-0.004	-0.004
	(0.12)	(0.30)	(0.78)	(0.92)
$Disaster_{(-1)}$	0.005	0.004	0.008	0.008
	(0.59)	(0.46)	(0.95)	(0.90)
$Disaster_{(0)}$	0.023	0.022	0.013	0.012
	(2.04)**	(1.98)**	(1.53)	(1.45)
$Disaster_{(1)}$	0.031	0.030	0.028	0.028
	(2.59)***	(2.56)**	(2.32)**	(2.32)**
$Disaster_{(2)}$	0.011	0.010	0.022	0.022
	(1.02)	(0.95)	(1.85)*	(1.86)*
$Disaster_{(3)}$	0.015	0.015	0.016	0.017
	(1.47)	(1.44)	(1.71)*	(1.74)*
$Disaster_{(4+)}$	0.007	0.007	0.003	0.003
	(0.81)	(0.80)	(0.30)	(0.37)
Control Variables	NO	YES	NO	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES
N	9,014	9,012	9,014	9,012
Adjusted R^2	0.01	0.01	0.01	0.02

Table 6: Regressions of Green Innovation and State-level Environmental Regulation

In columns 1, 3 and 5 the dependent variable is *Gr_pt_ratio,* defined as the ratio of green patents to total patents of a firm each year. In columns 2, 4 and 6 the dependent variable is *Gr_ct_ratio,* defined as the ratio of citations received by green patents to citations received by all patents of a firm each year. *Disaster* dummy takes value of 1 for post-disaster years including the year of disaster and 0 for pre-disaster years. *Treated* dummy takes value 1 for treated group and 0 for the control group. *Regulatory Strictness* dummy takes value 1 for the states in the highest quartile of the distribution of regulatory strictness in the pre-disaster year and 0 for the states in the lowest quartile of the distribution of regulatory strictness in the pre-disaster year. *High Penalty* dummy takes value 1 for the states in the highest quartile of the distribution of average penalty amount in the pre-disaster year and 0 for the states in the lowest quartile of the distribution of average penalty amount in the pre-disaster year. The period of analysis is 1990-2015. The definitions of the control variables are provided in the Appendix. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Regulatory Strictness

	2 years before and after		3 years before and after		4 years before and after	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster*Treated	-0.008	-0.015	-0.003	-0.004	0.002	-0.001
	(0.62)	(1.10)	(0.23)	(0.36)	(0.17)	(0.11)
Disaster*Treated*Regulatory Strictness	0.078	0.066	0.056	0.050	0.039	0.033
	(2.49)**	(2.30)**	(2.26)**	(2.13)**	(1.74)*	(1.71)*
Disaster	-0.005	-0.031	0.008	-0.014	0.010	-0.004
	(0.11)	(1.04)	(0.44)	(1.01)	(0.65)	(0.33)
Constant	0.152	0.124	0.189	0.156	0.148	0.043
	(1.38)	(1.33)	(2.46)**	(1.35)	(2.54)**	(0.57)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES	YES
N	928	928	1,392	1,392	1,856	1,856
Adjusted R^2	0.05	0.09	0.00	0.01	0.01	0.01

Panel B: High Penalty

	2 years before and after		3 years before and after		4 years before and after	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster*Treated	-0.012	-0.005	-0.007	-0.003	-0.007	-0.005
	(0.99)	(0.45)	(0.84)	(0.33)	(0.87)	(0.56)
Disaster*Treated*High Penalty	0.073	0.046	0.059	0.045	0.047	0.035
	(2.53)**	(1.71)*	(2.55)**	(2.11)**	(2.01)**	(1.70)*
Disaster	-0.014	-0.037	-0.001	-0.005	0.003	0.001
	(0.45)	(1.58)	(0.11)	(0.42)	(0.23)	(0.05)
Constant	0.125	0.032	0.049	0.113	-0.012	-0.049
	(1.24)	(0.55)	(0.57)	(1.52)	(0.29)	(1.26)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES	YES
N	992	992	1,488	1,488	1,984	1,984
Adjusted R^2	0.07	0.09	0.05	0.06	0.05	0.04

Table 7: Regressions of Green Innovation and External Monitoring

In columns 1, 3 and 5 the dependent variable is *Gr_pt_ratio,* defined as the ratio of green patents to total patents of a firm each year. In columns 2, 4 and 6 the dependent variable is *Gr_ct_ratio,* defined as the ratio of citations received by green patents to citations received by all patents of a firm each year. *Disaster* dummy takes value of 1 for post-disaster years and 0 for pre-disaster years. *Treated* dummy takes value 1 for treated group and 0 for the control group. *Coverage* takes value one for firms with above median number of analysts in the pre-disaster year and zero otherwise. *Institutional ownership* takes value one for firms with above median ratio of blockowner shares in the pre-disaster year and zero otherwise. The period of analysis is 1990-2015. The definitions of the control variables are provided in the Appendix. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Interactions with Coverage

	2 years before and after		3 years before and after		4 years before and after	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster*Treated	0.029	0.025	0.025	0.025	0.025	0.022
	(2.30)**	(2.00)**	(2.34)**	(2.23)**	(2.51)**	(2.37)**
Disaster*Treated* Coverage	-0.013	-0.019	-0.008	-0.011	-0.013	-0.012
	(0.88)	(1.35)	(0.66)	(0.84)	(1.19)	(1.11)
Coverage	-0.012	-0.063	0.002	-0.056	0.012	-0.024
	(0.25)	(1.29)	(0.07)	(1.44)	(0.51)	(1.00)
Disaster	0.002	-0.016	0.004	-0.009	0.006	-0.002
	(0.14)	(1.38)	(0.45)	(0.91)	(0.80)	(0.30)
Constant	-0.077	-0.036	0.003	0.010	-0.005	0.035
	(1.38)	(1.33)	(2.46)**	(1.35)	(2.54)**	(0.57)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES	YES
N	1,976	1,976	2,964	2,964	3,952	3,952
Adjusted R^2	0.03	0.07	0.02	0.03	0.02	0.02

Panel B: Interactions with Institutional ownership

	2 years before and after		3 years before and after		4 years before and after	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster*Treated	0.024	0.024	0.023	0.026	0.022	0.023
	(1.74)*	(1.79)*	(1.96)*	(2.18)**	(1.96)*	(2.28)**
Disaster*Treated* Inst. ownership	-0.001	-0.014	-0.003	-0.011	-0.005	-0.012
	(0.06)	(0.83)	(0.20)	(0.76)	(0.42)	(0.97)
Inst. ownership	-0.049	-0.108	0.012	-0.059	0.019	-0.018
	(0.49)	(1.28)	(0.32)	(1.30)	(0.75)	(0.72)
Disaster	-0.000	-0.020	0.005	-0.010	0.007	-0.003
	(0.01)	(1.46)	(0.49)	(0.99)	(0.85)	(0.33)
Constant	-0.060	-0.010	-0.007	0.016	-0.017	0.027
	(0.93)	(0.16)	(0.13)	(0.27)	(0.65)	(0.77)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES	YES
N	1,976	1,976	2,964	2,964	3,952	3,952
Adjusted R^2	0.03	0.07	0.02	0.03	0.02	0.02

Table 8: Regressions of Green Innovation and Investor Horizons

In columns 1, 3 and 5 the dependent variable is *Gr_pt_ratio,* defined as the ratio of green patents to total patents of a firm each year. In columns 2, 4 and 6 the dependent variable is *Gr_ct_ratio,* defined as the ratio of citations received by green patents to citations received by all patents of a firm each year. *Disaster* dummy takes value of 1 for post-disaster years including the year of disaster including the year of disaster and 0 for pre-disaster years. *Treated* dummy takes value 1 for treated group and 0 for the control group. *Dedicated ownership* dummy takes value 1 for firms whose majority shares are owned by long-term institutional investors in the pre-disaster year. *Quasi-indexer ownership* dummy *t*akes value 1 for firms whose majority shares are owned by passive institutional investors in the pre-disaster year. *Transient ownership* dummy takes value 1 for firms whose majority shares are owned by short-term institutional investors in the pre-disaster year. The period of analysis is 1990-2015. The definitions of the control variables are provided in the Appendix. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	2 years before and after		3 years before and after		4 years before and after	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster*Treated	0.029	0.031	0.028	0.031	0.025	0.026
	(2.11)**	(2.26)**	(2.28)**	(2.49)**	(2.25)**	(2.48)**
Disaster*Treated*Dedicated own.	0.016	0.020	0.001	0.003	-0.004	-0.002
	(0.30)	(0.38)	(0.02)	(0.09)	(0.17)	(0.09)
Disaster*Treated*Quasi-indexer own.	-0.008	-0.027	-0.010	-0.022	-0.011	-0.018
	(0.42)	(1.58)	(0.68)	(1.48)	(0.84)	(1.45)
Disaster*Treated*Transient own.	-0.058	-0.071	-0.035	-0.043	-0.026	-0.029
	(1.83)*	(1.91)*	(1.55)	(1.74)*	(1.42)	(1.72)*
Disaster	-0.000	-0.020	0.005	-0.011	0.007	-0.003
	(0.01)	(1.46)	(0.47)	(1.01)	(0.86)	(0.32)
Constant	-0.074	-0.026	-0.001	0.015	-0.010	0.032
	(1.28)	(0.46)	(0.02)	(0.27)	(0.40)	(0.93)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES	YES
N	1,976	1,976	2,964	2,964	3,952	3,952
Adjusted R^2	0.03	0.07	0.02	0.03	0.02	0.02

Table 9: Regressions of Green Innovation and SRI funds

In columns 1, 3 and 5 the dependent variable is *Gr_pt_ratio,* defined as the ratio of green patents to total patents of a firm each year. In columns 2, 4 and 6 the dependent variable is *Gr_ct_ratio,* defined as the ratio of citations received by green patents to citations received by all patents of a firm each year. *Disaster* dummy takes value of 1 for post-disaster years including the year of disaster and 0 for pre-disaster years. *Treated* dummy takes value 1 for treated group and 0 for the control group. *SRI_fund* takes value 1 for firms whose shares are held with SRI environment funds in the pre-disaster year and 0 otherwise. The period of analysis is 1990-2015. The definitions of the control variables are provided in the Appendix. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	2 years before and after		3 years before and after		4 years before and after	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster*Treated	0.023	0.016	0.022	0.020	0.020	0.017
	(2.52)**	(1.77)*	(2.83)***	(2.57)**	(2.81)***	(2.46)**
Disaster*Treated*SRI_fund	0.006	0.029	-0.001	0.009	-0.018	0.007
	(0.36)	(1.22)	(0.07)	(0.56)	(1.44)	(0.57)
SRI_fund	0.186	0.168	0.121	0.077	0.123	0.002
	(1.04)	(0.96)	(1.93)*	(0.97)	(2.97)***	(0.03)
Disaster	0.003	-0.012	0.004	-0.006	0.006	-0.001
	(0.24)	(1.12)	(0.50)	(0.68)	(0.80)	(0.18)
Constant	0.074	0.072	0.112	0.048	0.108	0.020
	(0.48)	(0.48)	(1.68)*	(0.64)	(2.29)**	(0.27)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES	YES
N	1,976	1,976	2,964	2,964	3,952	3,952
Adjusted R^2	0.03	0.07	0.02	0.03	0.02	0.02

Table 10: Regressions of Green Innovation and Default Risk

In columns 1, 3 and 5 the dependent variable is *Gr_pt_ratio,* defined as the ratio of green patents to total patents of a firm each year. In columns 2, 4 and 6 the dependent variable is *Gr_ct_ratio,* defined as the ratio of citations received by green patents to citations received by all patents of a firm each year. *Disaster* dummy takes value of 1 for post-disaster years including the year of disaster and 0 for pre-disaster years. *Treated* dummy takes value 1 for treated group and 0 for the control group. *Default* takes value 1 for above median Altman's z_score distribution in the pre-disaster year, indicating low default probability, and 0 for below median Altman's z_score distribution in the pre-disaster year, indicating high default probability. The period of analysis is 1990-2015. The definitions of the control variables are provided in the Appendix. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	2 years before and after		3 years before and after		4 years before and after	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster*Treated	0.005	0.005	0.010	0.011	0.013	0.014
	(0.77)	(0.82)	(1.73)*	(1.77)*	(1.82)*	(1.96)*
Disaster*Treated* Default	0.029	0.019	0.020	0.016	0.011	0.005
	(2.11)**	(1.49)	(1.73)*	(1.39)	(0.98)	(0.43)
Disaster	0.004	-0.012	0.005	-0.006	0.006	-0.001
	(0.28)	(1.10)	(0.54)	(0.65)	(0.81)	(0.18)
Constant	-0.091	-0.077	-0.004	-0.027	-0.008	0.017
	(3.50)***	(2.09)**	(0.09)	(0.53)	(0.38)	(0.55)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES	YES
N	1,976	1,976	2,964	2,964	3,952	3,952
Adjusted R^2	0.03	0.07	0.02	0.03	0.02	0.02

Table 11: Regressions of Green Innovation for High-Polluting Industries

In columns 1, 3 and 5 the dependent variable is *Gr_pt_ratio,* defined as the ratio of green patents to total patents of a firm each year. In columns 2, 4 and 6 the dependent variable is *Gr_ct_ratio,* defined as the ratio of citations received by green patents to citations received by all patents of a firm each year. *Disaster* dummy takes value of 1 for post-disaster years including the year of disaster and 0 for pre-disaster years. *Treated* dummy takes value 1 for treated group and 0 for the control group. *High-polluting industry* dummy variable takes value 1 for firms that operate in seven TRI industries defined by EPA. The period of analysis is 1990-2015. The definitions of the control variables are provided in the Appendix. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	2 years before and after		3 years before and after		4 years before and after	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster*Treated	-0.006	-0.008	-0.011	-0.008	-0.006	-0.003
	(0.99)	(1.12)	(1.79)*	(1.22)	(1.27)	(0.55)
Disaster*Treated* High_Polluting	0.039	0.034	0.043	0.038	0.034	0.027
	(3.23)***	(2.86)***	(3.67)***	(3.19)***	(3.37)***	(2.74)***
Disaster	0.002	-0.013	0.004	-0.007	0.005	-0.002
	(0.15)	(1.23)	(0.43)	(0.74)	(0.75)	(0.22)
Constant	-0.075	-0.063	0.009	-0.015	0.002	0.024
	(2.59)***	(1.66)*	(0.19)	(0.31)	(0.07)	(0.77)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES	YES
N	1,976	1,976	2,964	2,964	3,952	3,952
Adjusted R^2	0.03	0.07	0.03	0.04	0.02	0.03

Online Appendix:

Table A1: Regressions of Green Patents and Green Citations using Patenting Firms

This table presents the results of difference in differences analysis of subsample of firms that produce patents throughout the sample period. In columns 1, 3 and 5 the dependent variable is *Gr_pt_ratio,* defined as the ratio of green patents to total patents of a firm each year. In columns 2, 4 and 6 the dependent variable is *Gr_ct_ratio,* defined as the ratio of citations received by green patents to citations received by all patents of a firm each year. We match treated and control firms using coarsened exact matching the year before the disaster happens. *Disaster* dummy takes value of 1 for the year and the following year of the disaster years and 0 for two years before the disaster. *Treated* dummy takes value 1 for treated group and 0 for the control group. The period of analysis is 1990-2015. The definitions of the control variables are provided in the Appendix. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	2 years before and after		3 years before and after		4 years before and after	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster*Treated	0.033	0.016	0.048	0.037	0.042	0.036
	(1.46)	(0.71)	(2.59)**	(1.99)**	(2.44)**	(2.25)**
Disaster	-0.054	-0.054	0.010	0.019	-0.001	0.004
	(1.21)	(1.18)	(0.30)	(0.53)	(0.02)	(0.15)
Constant	-0.105	-0.112	0.163	0.134	0.008	0.047
	(0.89)	(0.94)	(2.09)**	(1.75)*	(0.13)	(0.88)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State x Year FE	YES	YES	YES	YES	YES	YES
N	792	792	1,188	1,188	1,584	1,584
Adjusted R^2	0.07	0.10	0.08	0.09	0.04	0.06