Toxic Emissions and Corporate Green Innovation

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Abstract

This paper examines the link between firms' toxic emissions and green innovation. We find that high-emission firms produce more high-quality, valuable green patents using explorative innovation strategies than do low-emission firms. We exploit the expansion of the Toxic Release Inventory (TRI) chemical list to address endogeneity concerns. We examine regulatory burdens and environmental awareness channels using President Trump's election and the BP Deepwater Horizon oil spill. Green patents produced by high-emission firms not only reduce their future toxic releases but also contribute to advancing the green knowledge frontier. Facing financial constraints, high-pollution firms cut non-green patenting, prioritizing green innovation efforts.

JEL Classification: G30, G38, K32, O30, Q50

Keywords: Corporate green innovation; Toxic emissions; Policy effect; Environmental awareness; ESG investments.

Data Availability: Data are available from the public sources cited in the text.

"We've been an innovator since the very beginning: on the diesel engine, natural gas engines, and on emissions controls. We see customer and environmental challenges as opportunities to demonstrate leadership and innovation. There's no question that our focus on environmental innovation and leadership has caused our company to grow, to become more profitable, and to increase our appeal with big companies that would like to partner with us because of our leading technologies."

--Tom Linebarger, Chairman and CEO of Cummins, Inc.

1. Introduction

One of the negative consequences of industrialization has been the generation and release of toxic chemicals that have detrimental effects on the environment, climate, and public health.[1] As the world grapples with environmental and climate change challenges, these byproducts are becoming an important issue drawing the attention of investors, scholars, and governments (Xu and Kim 2022, Chang and Dasgupta 2023, Dasgupta et al. 2023). For instance, toxic emissions are an important component of Environmental, Social and Governance (ESG) scores (e.g., MSCI & Sustainalytics) used by investors and other market participants worldwide. Prior research has also shown that investors demand a significantly higher rate of return and that banks charge a higher interest rate on loans for firms with higher toxic emissions (Chava 2014, Hsu et al. 2023). Recently, the U.S. Environmental Protection Agency (EPA) and the

[1] Toxic corporate emissions are the released pollutants and toxicants that are generated as byproducts of modern production processes (Xu and Kim 2022). Firms' toxic releases include various chemicals, such as ammonia, dichloromethane, toluene, carbon disulfide, carbonyl sulfide, ethylene oxide, boron trifluoride, zinc compounds, xylene (mixed isomers), hydrochloric acid, nickel, and methanol.

Department of Justice (DOJ) cooperated in federal environmental enforcement by establishing the Office of Environmental Justice (OEJ), which focuses on cases related to pollution, environmental crime, and climate change.[2]

In this study, we explore the link between firms' toxic releases and their investments in green innovation. Given that corporate green innovation helps firms address climate change and environmental concerns (Hong et al. 2020), our study aims to examine the extent to which high-pollution firms attempt to mitigate environmental and climate problems through green innovation. The main motivation of our research is the theoretical tension underpinning the relationship between corporate green innovation and toxic emissions. On the one hand, high-pollution firms should produce more green patents to reduce their regulatory burden and government investigations (e.g., EPA penalties). There is anecdotal evidence to suggest that firms invest in technology to address regulatory concerns. For instance, as part of their settlement with the DOJ and the EPA to resolve alleged violations of emissions, Cemex agreed to invest approximately $10 million to use state-of-the-art technology to reduce harmful pollution.[3] The consequences of environmental awareness provide additional support for this positive relationship between the level of firms' toxic releases and green innovation since environmental awareness is likely to increase investor activism (Akey and Appel 2019, Choi et al. 2021), the cost of capital (Hsu et al. 2023) and regulatory burdens.

On the other hand, impediments such as regulatory arbitrage (Dai et al. 2021,

[2] The news report is available at: https://www.complianceweek.com/regulatory-enforcement/new-doj-office-to-lead-environmental-justice-efforts/31647.article.

[3] Please see https://www.justice.gov/opa/pr/cement-manufacturer-cemex-reduce-harmful-air-pollution-five-plants-under-settlement-epa-and

Bartram et al. 2022) and managerial short-termism (He and Tian 2013) could mean that the green patenting efforts of high-emission firms are indistinguishable from those of low-emission firms. Thus, a priori, we do not have a clear expectation of the relationship between toxic emissions and green patenting.

In addition to the theoretical arguments, the debate surrounding the use of environmental, social, and governance (ESG) investments (also known as sustainable and responsible investments) provides yet another motivation for our research. By focusing on emissions and green patents, our study aims to provide insights into the role of ESG-focused investments, particularly environmentally minded investments, which exclude high-pollution firms, in addressing environmental risks.

The main data for our study come from two sources. We collect toxic release data from the Toxic Release Inventory (TRI) program administered by the EPA. We obtain data on corporate innovation (i.e., patents) from the innovation database constructed by Kogan et al. (2017). Our main independent variable is firm-level aggregate toxic emissions, while the primary dependent variables are two measures of green innovation, patent counts and citations. Our sample comprises 20,712 firm-year observations of 1,562 public firms over the sample period from 1987 to 2020.

Overall, our empirical results show a strong positive relationship between firms' toxic emissions and their green patents. Specifically, we find that firms with high toxic emissions produce more green patents that are of higher quality and value than those produced by firms with low toxic releases. Importantly, we find that emissions associated with human health impacts and onsite toxic releases are the main drivers of this relationship. Our findings also indicate that high-emission firms produce green innovation that is directly related to environmental risk management. Furthermore, we show that high-pollution firms utilize exploitative and explorative methods to generate green patents, indicating a desire to explore costly new technologies rather than merely developing expertise.

To mitigate the endogeneity concerns and establish causality, we utilize the expansions of the TRI chemical list to capture the exogenous increases in the corporate toxic emissions administered under the TRI program. The list of hazardous chemicals that are required to be reported has been expanded several times since the initiation of the TRI program. The additions of new chemicals to the reporting list are not due to any fundamental changes at the companies themselves, such as adopting new manufacturing processes or green technologies, but due to scientific research of chemicals' toxicity, public concerns, or legislative changes. Using a cohort-based difference-in-differences (DiD) approach, we show that relative to the firms that are not affected by the expansions of the TRI chemical list (i.e., firms that do not emit the newly added chemicals), the firms affected by such changes (i.e., firms that report releases of the newly added chemicals) significantly increase their green innovation after the new reporting requirements become effective. This finding supports a causal interpretation of the impact of firms' toxic emissions on their green innovation.

We then examine two channels through which toxic emissions affect green innovation: (i) regulatory burden using the 2016 election of U.S. President Trump and (ii) environmental awareness using the 2010 BP Deepwater Horizon oil spill. First, the unexpected election of Donald Trump as the U.S. president significantly reduced environment-related policy uncertainty and, with it, a potential reduction in regulatory liabilities (Ilhan et al. 2021, Ramelli et al. 2021, Hsu et al. 2023). If firms' green innovation is indeed driven by the regulatory burden associated with toxic releases, then we should observe a weaker relation between toxic emissions and green patenting in the years following Trump's election. We indeed find that firms with high levels of toxic releases, especially those headquartered in the U.S., substantially reduced their green patenting efforts following Trump's election. These results support our argument on the legal liabilities channel and show that (local) environmental and climate policy plays an important role in companies' green innovation decisions.

Second, the BP Deepwater Horizon oil spill that began on April 20, 2010, arguably served as a shock to the environmental awareness faced by high-emission firms in extractive industries, thereby strengthening these firms' emphasis on and attention to green innovation. If environmental awareness is a channel through which firms' toxic emission levels drive changes in corporate green patenting, we expect that extractive companies with higher toxic release levels at the time of the Deepwater Horizon event would subsequently do more to improve their green credentials. Our empirical results show that the positive relationship between toxic release levels and green innovation improved significantly for firms in extractive industries in the post-event period. This finding supports the environmental awareness induced channel of impact on green innovation.

In addition, we explore several implications of firms' green innovation. We find that green patents, particularly environmental-related patents, help mitigate toxic air releases.[4] This finding implies that the generation of environmental patents is not merely a form of greenwashing, but a genuine effort by high-emission firms to combat pollution. Additionally, we find that the green patents produced by high-pollution firms receive significant citations, both within and outside their industries. These findings suggest that the green innovation efforts of high-emission firms have both internal implications, by addressing their own pollution issues, and external implications, by contributing to the advancement of the green knowledge frontier for other firms. Despite these positive implications, we fail to find any enthusiasm among environmentally minded institutional investors towards green innovative high-emission firms, leading to continuous divestment from these companies.

Finally, we perform cross-sectional tests to explore whether financial constraints attenuate the positive relationship between firms' toxic emissions and corporate green innovation. We find that financial constraints do not impede high-emission firms' green patenting activities. Firms facing financial constraints reduce their nongreen patenting activities far more than their green patenting activities. This outcome can be attributed to the fact that financial constraints may simultaneously limit innovative activities (Amore et al. 2013, Moshirian et al. 2021) and increase environmental abatement costs (Xu and Kim 2022). Financially constrained high-emission firms are therefore likely to

[4] We focus on air emissions because air releases account for a major portion of the total toxic releases (Xu and Kim 2022) and the positive relationship between firms' toxic emissions and green patenting is mainly driven by air emissions (as shown in Panel B of IA Table 7). Moreover, air pollution imposes the most adverse impact on public health, such as affecting unborn babies' lungs and brains. The related news report is available at: https://www.theguardian.com/environment/2022/oct/05/toxic-air-pollution-particles-found-in-lungs-and-brains-of-unborn-babies#:~:text=Toxic%20air%20pollution%20particles%20have,vulnerable%20stage%20of%20human%20development

prioritize green innovation to achieve higher abatement efficiency and control potential legal liabilities, sacrificing nongreen innovation instead.

Our paper makes several contributions to the literature. First, to the best of our knowledge, this is the first study examining the impact of firms' toxic emissions on green innovation. We therefore contribute to a growing stream of literature that examines environmental pollution (Kim et al. 2019, Akey and Appel 2021, Xu and Kim 2022, Hsu et al. 2023) by showing that firms' high levels of toxic releases act as catalysts for pursuing green innovation. Our research extends the literature on firms' green innovation by going beyond the phenomenon (Cohen et al. 2023) and exploring its intrinsic nature and internal motivation (i.e., caused by the negative consequences related to toxic emissions).[5]

Importantly, our study also contributes to the debate on whether investors should *engage in* or *divest in* high-emission firms (Broccardo et al. 2020, Krueger et al. 2020, Atta-Darkua et al. 2023). Our findings suggest that environmentally minded institutional investors tend to adopt a blunt approach of divestment among high-pollution companies and overlook their productive green innovation efforts. Given the positive internal and external implications of green innovation, our evidence indicates that investors should move away from a blunt investment approach and instead conduct a thorough analysis of a company's sustainability practices (Heath et al. 2023). Investors should engage with high-emission firms that are implementing innovative

[5] While Cohen et al. (2023) make an important contribution to the literature by showing that the incremental green patent is more likely to come from energy firms (i.e., addressing the *who* question), our study focuses on the *why* question and provides economic explanations for the paradox observed by Cohen et al. (2023). Furthermore, we find the positive effect of firms' toxic emissions on corporate green innovation even after excluding energy-producing firms, indicating a broader implication of our findings (see Section 4.2).

solutions to reduce their environmental impact, which can further improve their environmental performance and help address climate change and other environmental issues.[6]

Second, we contribute to the studies focusing on the impacts of environmental and climate policies in financial areas. In particular, while most of the prior literature in this stream has examined the role of climate and environmental regulations in asset pricing (e.g., Barnett et al. 2020, Cao et al. 2021, Ilhan et al. 2021, Hsu et al. 2023), our paper explores the real effects of environmental and climate policies on corporate investment decisions (e.g., green innovations), which have received limited attention (e.g., Barnett 2019, Dai et al. 2021). Using Trump's 2016 election as an unexpected event shock, we show that less stringent (local) climate and environmental policies indeed reduce high-emission firms' green innovation.

Finally, prior studies show that financial constraints impede corporate innovation (Moshirian et al. 2021). Our paper extends the literature by showing that constrained firms make strategic *structural* decisions, prioritizing green innovation to address environmental concerns over other forms of innovation. Specifically, we show that financially constrained high-emission firms reduce nongreen innovation rather than green innovation, which is more relevant to their emission levels and abatement expenditures. Such cross-sectional results suggest that green innovation is of first-order importance to these high-polluting firms.

The remainder of this paper is organized as follows. Section 2 presents our

[6] Our findings are consistent with the engagement argument put forward by Mark Carney, an UN Special Envoy on Climate Action and Finance. Carney has suggested that responsible investment means going to where the emissions are and backing companies with credible transition plans to get emissions down.

hypothesis development. In Section 3, we describe the data and variable construction employed and provide the summary statistics. Sections 4, 5, 6, 7, and 8 present the empirical analyses. Section 9 concludes the paper.

2. Hypothesis Development

2.1. Positive impact of firms' toxic emissions on corporate green innovation

We argue for a positive relationship between toxic releases and green patenting through the lenses of (i) regulatory burden and (ii) environmental awareness.

Firms with high toxic emissions face increased regulatory burdens and government investigations. In this context, Hsu et al. (2023) and Xu and Kim (2022) find high emissions are a significant predictor of environment-related lawsuits. Xu and Kim (2022) find similar evidence and show that firms with high toxic emissions have lower firm value relative to firms with low emissions. This lower firm value also reflects the environmental policy uncertainty risk (Hsu et al. 2023) these firms face, with an expectation of more stringent future environmental regulatory burdens. Hence, the regulatory burden and associated costs should influence the environmental decisions of high toxic-emission firms. Given the negative consequences of regulatory enforcement and the requirement that U.S. firms partially internalize their environmental costs by allocating resources for environmental protection (Xu and Kim 2022), we argue that firms with high toxic emissions should exhibit greater demand for green patents than should firms with low toxic emissions.

Another component of the positive relationship between toxic emissions and green patenting is related to environmental awareness. As the general public, investors, governments, and media become more cognizant of environmental issues (e.g., due to environmental disasters), the likelihood of increased investor activism (Akey and Appel 2019, Choi et al. 2021), reduced institutional ownership for firms with environmental concerns (Chava 2014), and the development and adoption of stricter environment-related policies (Ilhan et al. 2021) significantly escalates. This heightened awareness has the potential to increase regulatory burdens, undermine firm profitability, and subject firms to a higher cost of capital (Hsu et al. 2023). More importantly, because of the nature of their operations, high-emission firms are more susceptible to the adverse effects of environmental awareness than low-emission firms. We argue that high-emission firms could manage the risk of environmental awareness through increased green patenting efforts.

Thus, based on the above discussion, we formulate the following hypothesis:

Hypothesis 1a. Firms with high toxic release levels produce more green patents than those with low toxic release levels.

2.2. Impediments to generating green innovation for high-emission firms

We develop a null hypothesis on the relationship between toxic emissions and green patenting by exploring the following impediments to green innovation: (i) regulatory arbitrage and (ii) managerial short-termism.

High-emission firms can manage their chemical emissions via the regulatory arbitrage approach instead of investing in green patents. For instance, Bartram et al. (2022) show that financially constrained firms transfer their emissions activities from regulated to unregulated states to cope with environmental and climate-related policies without pursuing costly green innovation. Relatedly, Dai et al. (2021) show that firms with low relocation costs facing high local regulatory pressures relocate their plants and facilities to regions with less stringent environmental policies.

While managerial short-termism generally hinders firms from adopting long-term initiatives, it poses a significant roadblock for high-emission firms in pursuing green patenting. He and Tian (2013) show that analyst pressure to meet short-term goals impedes firm investments in long-term innovative projects. Corporate green innovations, particularly those exploratory in nature, are inherently risky and thus are likely to be avoided by managers interested in meeting short-term goals. Therefore, managerial short-termism, whether caused by external pressures and agency problems or generated by managers' personal styles, beliefs, or motivations (He and Tian 2013, Ladika and Sautner 2019), can lead firm managers to ignore or downplay corporate green innovation, thereby reducing firms' investment in green innovation.

Based on the above discussion, we postulate the following hypothesis on the relationship between emissions and green patenting.

Hypothesis 1b. The green patenting efforts of firms with high toxic release levels are indistinguishable from those with low toxic release levels.

3. Data, Variable Construction, and Summary Statistics

Our study relies mainly on the following two databases: (i) the Toxic Release Inventory (TRI) program database administered by the EPA and (ii) the patent database constructed by Kogan et al. (2017) containing utility patent and citation data for all patents filed (and eventually granted) with the United States Patents and Trademark Office (USPTO). We focus on publicly traded firms, as they have rich and publicly available information about their characteristics, profitability, and patent holdings.

First, we use TRI microdata from the EPA. The TRI database is widely used by economists and researchers in the areas of public health, public policy, and the environment (Akey and Appel 2021, Dasgupta et al. 2023).[7] The EPA has reported chemical-level release data in the TRI database since 1987. The database has comprehensive coverage, as any facility in the United States with ten or more employees that manufactures and processes TRI-listed chemicals above a certain threshold in a reportable industry sector is required to report its releases of hazardous pollutants to the EPA (Akey and Appel 2021, Li et al. 2021). Even though TRI data are self-reported, the EPA conducts an extensive quality analysis of TRI reporting data to identify anomalies, with misreporting by firms resulting in criminal or civil penalties (Xu and Kim 2022).

The EPA regulates emissions based on several acts. For example, the Clean Air Act concentrates on hazardous air pollutants, such as sulfur oxides and nitrogen oxides; the Clean Water Act (CWA) regulates pollutants discharged into water and those that affect the quality of surface waters, such as wastewater from production processes; and the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA), commonly known as Superfund, was implemented to use money collected via taxes to clean up abandoned or uncontrolled hazardous waste sites. In addition, the Occupational Safety and Health Administration (OSHA) aims to ensure that employers

[7] The U.S. EPA generally includes hazardous chemicals to the TRI list due to evidence or concerns about the chemicals' significant environmental or health impacts (EPA 2023), often based on scientific research or concerns from communities and stakeholders (EPA 1994). Legislative changes may also require the addition of certain chemicals. Therefore, our study using the TRI database focuses on firm-level regulated toxic emissions and those of public concern, rather than on other releases.

provide their workers with a safe and healthful workplace that is free of recognized hazards, such as toxic chemicals, unsanitary conditions, or excessive noise levels.

Additionally, we obtain chemical data from the EPA's Risk-Screening Environmental Indicators (RSEI). Specifically, the chemical table from the RSEI contains data regarding chemicals reported to the TRI, including toxicity and physicochemical properties. This information makes it feasible to further categorize firms' toxic emissions.

Following Li et al. (2019), we extract firm-level utility patent and citation data from Kogan et al. (2017). The data contain information on patent numbers, patent issue dates, patent application filing dates, the value of innovations, forward citations, and full Cooperative Patent Classification (CPC) classes. It also provides linking keys to connect with the Center for Research in Security Prices (CRSP) database. Initially constructed from 1926 to 2010, this database has recently been updated to 2020, rendering it suitable for our study. Typically, the patent application process takes 2-3 years from the filing date to the issue/grant date due to delays at the USPTO (Hall et al. 2005, Gao et al. 2017, Mukherjee et al. 2017). Therefore, we measure firms' green innovation at the firm-year level based on the patent filing date. This approach provides a more timely measure of firms' innovation activity than using the issue/grant date.

Furthermore, we identify the patents that may contribute to solving environmental and climate problems, referred to as "green patents" based on the guidelines provided by the Organisation for Economic Co-operation and Development (OECD) (Haščič and Migotto 2015). This classification organizes patents related to environmental/green technologies (i.e., green patents) into several broad environmental and CCM technology categories, including environmental management, water-related adaptation, biodiversity protection and ecosystem health, and CCM technologies.[8] One large category is represented by CCM technologies, which further include green patents focusing on CCM-related (i) energy generation, transmission or distribution, (ii) the capture, storage, sequestration, or disposal of greenhouse gases, (iii) transportation, (iv) buildings, (v) waste water treatment or waste management, and (vi) the production or processing of goods.

Finally, all financial and accounting data are obtained from Compustat and CRSP. The patent data from Kogan et al. (2017) already include company-level identifiers, which are used to match the patenting information with the Compustat/CRSP databases (Bena and Garlappi 2020). However, given the absence of consistent linking keys to connect the EPA TRI and Compustat/CRSP databases and that the TRI data provide the historical names of the included facilities' parent companies, we employ a string-matching process based on historical company names to match these datasets (i.e., the TRI and Compustat/CRSP). Details regarding this historical name matching process are provided in Section I of the Internet Appendix.

3.1. Measuring firm-level toxic emissions

As in Akey and Appel (2021), we use the natural logarithm of one plus the number of pounds of firm-level aggregate toxic emissions as the main measure of our dependent variable. Furthermore, following Xu and Kim (2022), we construct measures of emissions administered under various regulations, including CAA, CWA, CERCLA, and OSHA. We also categorize firms' releases as onsite or offsite emissions.

[8] There is currently no identification strategy for patents related to biodiversity protection and ecosystem health in the guidelines from OECD.

Specifically, onsite releases refer to emissions to air, water, and land onsite at a facility, whereas offsite releases are those reported as releases transferred to offsite locations for release or disposal. Furthermore, as the corresponding release channels are identifiable, we categorize overall onsite emissions into categories of releases emitted through various channels (including air, water, and ground) according to their physical properties. Moreover, based on whether each released chemical is associated with human health impacts, total emissions are classified as those with or without health effects. Overall, these subgroups of emissions can help us further investigate which kinds of toxic releases drive our empirical results.

3.2. Measuring corporate green innovation

Following previous studies (e.g., Cohen et al. 2023), we use listed firms' green patents to measure their green innovation efforts. We do not use research and development (R&D) expenses related to green innovation to measure green innovation inputs because it is not compulsory for firms to disclose their expenses related to green patenting. Therefore, we utilize total R&D expenses scaled by total assets to measure general innovation inputs and assign firm-year observations with missing R&D information a zero R&D value.

Our analysis focuses mainly on green patent counts and patent citations as measures of green innovation outputs. The first variable we use is *Ln(Green Pat)*, namely, the natural logarithm of one plus the total number of green patents the company filed (and was eventually granted) in a given year. To identify the innovativeness of high-emission firms at a granular level, we measure firms' green innovation based on eight subclassifications of green patents and further separate them into two main groups:

environmental technologies and CCM technologies.[9] Moreover, based on the corresponding innovation strategy, each green patent is categorized into one of two types: explorative or exploitative.

As simple patent counts cannot perfectly capture the success or importance of innovations (Griliches et al. 1987), we also use the total number of citations received by green patents during the given years (Trajtenberg 1990). To address time truncation bias for patents created toward the end of the sample period (Dass et al. 2017, Brav et al. 2018, He et al. 2023), we scale each patent's citation count by the average number of citations received by all patents in the same industry and year as the focal firm (Mudambi and Swift 2014, Duong et al. 2022). Thus, we construct *Tot GPat Cites* as the sum of the adjusted citation counts of green patents applied for by a firm during the year. We use the natural logarithm of this variable, *Ln(Tot GPat Cites)*, in our estimations.

We also measure the value of green innovations using the natural logarithm of the total value of green patents. Each patent's value is calculated as the product of the estimated stock return due to the value of the patent and the firm's market capitalization divided by the number of patents granted on the same day and multiplied by 2.27 (=1/(1-0.56)), where 0.56 is the unconditional probability of a successful patent application (Kogan et al. 2017).

Finally, following the previous literature on innovation (Custódio et al. 2019,

[9] The eight subclassifications comprise (i) environmental management; (ii) water-related adaptation; (iii) CCM-related energy generation, transmission or distribution; (iv) capture, storage, sequestration, or disposal of greenhouse gases; (v) CCM-related transportation; (vi) CCM-related buildings; (vii) CCM-related waste-water treatment or waste management; and (viii) CCM-related production or processing of goods. Categories (i) and (ii) belong to environmental technologies, and categories (iii) to (viii) are CCM technologies.

Almeida et al. 2020, Chu et al. 2021), we categorize green patents as either explorative or exploitative to identify the innovation strategy adopted by high-emission companies. A green patent is classified as exploitative if at least 60% of its citations are based on the corresponding firm's existing knowledge, while a green patent is categorized as explorative if at least 60% of its citations are based on new knowledge. A firm's existing knowledge includes all the patents that the firm has invented and all those that have been cited by the firm's patents filed over the past five years; all others are classified as new knowledge.

3.3. Control variables

We collect all our financial and accounting data from Compustat and CRSP. Following the previous literature, we include control variables associated with patenting activities. These variables include firm size measured as the natural logarithm of market equity (*Ln(Market Equity)*), leverage ratio proxied by the sum of long-term and short-term debt divided by total assets (*Leverage*), return-on-assets ratio (*ROA*), market-to-book ratio (*Tobin's q*), the ratio of fixed assets to total assets (*PPE/Assets*), the ratio of operating income after depreciation to total sales (*Profit Margin*), and cash holdings (*Cash*). In addition, we control for the investment intensity of a firm by using total capital expenditures scaled by total assets (*Capex/Assets*). Finally, we use R&D scaled by total assets to account for differences in R&D expenditures across firms to control the total inputs of corporate innovative activities (*R&D/Assets*), which are closely associated with innovation outputs (Islam and Zein 2020).

Table A.1 of the appendix provides detailed definitions of all the variables used in this study.

3.4. Summary statistics

After deleting the firm-year observations with missing data for the dependent, independent, and control variables, our final sample includes 20,712 firm-year observations of 1,562 unique public firms over the period from 1987 to 2020.[10] We report summary statistics in Table 1, where Panels A, B, and C report the descriptive statistics for corporate green innovation, toxic emissions, and firm characteristics, respectively. The mean of *Green Pat* indicates that a typical public firm applies for 1.94 green patents per year. Most of the green patents produced by emitting firms are categorized as CCM technologies, as the mean of *Ln(GPat(Tot CCM))* is 0.30. However, polluting firms also produce environmental green patents, and the mean of *Ln(GPat(Tot Env))* is 0.17; more importantly, as a subclassification of environmental-related innovation, environmental management technologies *Ln(GPat(Env Mgt))* are the top green patent category, with a mean of 0.16.[11] It is worth mentioning that the means of *Ln(Explorative GPat)* and *Ln(Exploitative GPat)* are 0.21 and 0.15, respectively, indicating that a typical public firm that reports toxic releases to the TRI program of

[10] We begin our sample period in 1987 to coincide with the reliable availability of toxic emissions data from the TRI program (Akey and Appel 2021). Although Hsu et al. (2023) argue that the coverage of the TRI database is fairly limited and contains data errors until 1990, our results remain robust when we start the sample period in 1991. Additionally, some prior studies (Hall et al. 2001, Chemmanur and Tian 2018) have argued that truncation bias may affect the accuracy of patent counts because a 2-3 year lag exists between application and grant dates for a typical patent. Therefore, we examine our main empirical results using a sample covering from 1987 to 2017 (i.e., deleting the final three years) and find that our results are robust. The results of addressing the concern about truncation bias are shown in IA Table 1 of the Internet Appendix.

[11] The summary statistics on subcategories of corporate green innovation are shown in IA Table 2 of the Internet Appendix.

the EPA has more explorative than exploitative green patents.[12]

[Insert Table 1 about here]

Figure 1 presents the time series of the aggregate toxic releases by year (i.e., the total volume in each year) of the public firms in our sample for the period between 1987 and 2020.[13] Panel A presents total toxic release volumes and toxic emissions under various EPA regulations (including the CAA, CWA, CERCLA, and CERCLA); Panel B shows toxic releases with and without health effects; Panel C shows toxic emissions that are released onsite and offsite; and Panel D shows toxic releases grouped by physical properties. Overall, we find that the total volume of toxic releases declines over time, with the releases regulated under CERCLA and CAA, onsite emissions, air releases, and those associated with health effects being the main drivers of this pattern. These results are consistent with Xu and Kim (2022), who show that total toxic releases decreased gradually from 1990 to 2014.

[Insert Figure 1 about here]

Panel B of Table 1 shows the raw release levels in thousands of pounds (labeled "(1000s)"). We find that an average emitting firm in our sample releases approximately

[12] Given that the 25, 50 (median), and 75 percentiles of green-innovation-related variables are zero, we employ Poisson estimation, and the results are shown in IA Table 3 of the Internet Appendix and the discussion in Section 4.1. Our baseline results are robust to the use of Poisson regression.

[13] In 1998, the number of industries obliged to report toxic releases significantly increased. TRI required reports from seven new industries: coal mining, metal mining, chemical wholesale distributors, petroleum bulk storage and terminals, electric utilities, solvent recovery facilities, and hazardous waste management facilities. To keep the number of sectors constant over time, following Xu and Kim (2022), in Figure 1, we remove the industry sectors that were added to the TRI program in 1998. These sectors are, however, included in the following empirical analyses.

1.53 million pounds of toxic chemicals per year. We also find that the chemicals regulated under CERCLA and CAA are emitted in greater quantities than those regulated under CWA and OSHA. Most releases are associated with health effects. We find that onsite releases (mean of 1.23 million pounds) are much higher than offsite releases (mean of 0.15 million pounds), suggesting that firms mainly emit to the air, water, and land onsite at their plants. Emissions released into the air (mean of 0.55 million pounds) are significantly higher than those released through other channels, including water (mean of 0.05 million pounds).

Panel C of Table 1 shows that the average firm in our sample has an *Ln(Market Equity)* of 6.95, capital expenditures scaled by total assets of 0.05, return on assets of 0.09, fixed assets scaled by total assets of 0.32, profit margin of 0.08, Tobin's q of 1.69, leverage of 0.46, and cash ratio of 0.07. Moreover, the ratio of R&D to assets (R&D expenses scaled by total assets) has a mean and median of 0.02 and 0.01, respectively.

4. Baseline Results

In this section, we present our baseline empirical regression model, which investigates the impacts of firms' toxic releases on green innovation outputs. As discussed previously, the two measures of green innovation are (i) the natural logarithm of the number of patents each company filed (and was eventually granted) in a given year (*Ln(Green Pat)*) and (ii) the natural logarithm of one plus the total number of forward adjusted citations received by the firm's green patents (*Ln(Tot GPat Cites)*). We examine the relationship between toxic emissions and corporate green innovation by estimating the following ordinary least squares (OLS) model:

$$\begin{aligned} &Green\ Innovation_{i,t+1,2} \\ &\qquad = \alpha + \beta Toxic\ Emissions_{i,t} + \gamma Controls_{i,t} + FEs + \epsilon_{i,t} \end{aligned} \tag{1}$$

where *i* denotes a public firm and *t* denotes a year. The dependent variables are the green innovation proxies for years *t+1* and *t+2*.[14] We multiply all dependent variables (i.e., the innovation variables) by 1,000 in the regression analysis to enhance the readability of the coefficients. The variable of interest in these regressions is *Toxic Emissions*, which is measured as the natural logarithm of one plus the number of pounds of firm-level total toxic releases administered under the TRI program in year *t*.[15] $Controls_{i,t}$ is a set of control variables, including *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*.[16] Additionally, we include firm fixed effects and industry-year fixed effects simultaneously in all the regressions. Firm fixed effects absorb all time-invariant variations that could affect corporate innovative activities, and industry-year fixed effects control for all time-varying characteristics at the two-digit Standard Industrial

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[14] We follow the prior studies to measure dependent variables (innovation-related variables) in years *t+1* and *t+2*, so that the results are comparable (e.g., Fang et al. 2014). Our main results are robust when the dependent variables are measured in year *t*.

[15] We primarily use the total amount of toxic emissions rather than emission intensities (i.e., scaled toxic releases) in our analyses because governments and the public mainly focus on the emission levels, which generate the real environmental externalities, instead of pollution intensities (Atta-Darkua et al. 2023). Some small firms can have high emission intensities due to less-efficient production processes. However, since their total emission levels are still relatively low, these firms do not face plenty of external pressures (e.g., regulatory burden and environmental awareness). For example, in our sample, DTI Medical Corp has a relatively low total emission levels but it has very high pollution intensities (measured by total emissions scaled by total assets). Specifically, its *Ln(Total Release)* ranges from 9.92 to 10.43, while its emission intensities ranges from 0.0040 to 0.0094, which are much higher than the sample mean of 0.0016. Nevertheless, our main results remain robust when we use emission intensities as the key independent variables. The results are presented in IA Table 4 of the Internet Appendix.

[16] The results in Table 2 are robust to replacing the proxy for firm size (the market equity) with either the book value of total assets or firm sales.

Classification (SIC) industry level. Moreover, standard errors are clustered at the firm level. We first hypothesize that the coefficient β in Model (1) is significantly positive, suggesting that firms with high toxic emission levels produce more (high-quality) green patents than their counterparts with low toxic release levels. Alternatively, the coefficient β is postulated to be insignificant, indicating that the green patenting efforts of high-emission firms are no different than those of their low-emission counterparts.

4.1. Firms' toxic emissions and corporate green innovation

Table 2 presents the baseline results, where the main variable of interest is the logarithm of the total number of pounds of toxic releases (Akey and Appel 2021).[17] In Columns (1), (3), and (5), the dependent variables are calculated for year *t+1*, while Columns (2), (4), and (6) show the results when they are measured for year *t+2*. Columns (1) and (2) show that the relationship between total toxic releases and firms' total R&D expenses is positive but not significant. This result is consistent with our expectation, as total R&D expenses may not accurately capture green patenting inputs.[18] Columns (3) to (6) also provide evidence showing that total R&D expenditures have no bearing on corporate green innovation outputs.

[Insert Table 2 about here]

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[17] Our results do not suffer from the criticism from (Cohn et al. 2022). The regression estimates based on Poisson estimation are shown in IA Table 3 of the Internet Appendix. For example, Column (1) shows that the incidence rate ratio of *Ln(Total Release)* is significantly greater than one, indicating that if a polluting firm were to increase its log pounds of total toxic emissions by one point, its rate ratio for the number of green patents would be expected to increase by a factor 1.049, while holding all other variables in the model constant. We report the results from estimating linear regressions of the log of one plus the outcome ("log1plus" regressions) so that we can compare our results with the existing literature.

[18] Due to data availability constraints, we cannot obtain firms' exact R&D expenditures related to green innovation.

More importantly, across all the specifications in Columns (3) to (6), firms' toxic releases show a significantly positive effect on the quantity and quality of corporate green innovation. The coefficient of 8.635 (Column (3)) indicates that, economically, a one-standard-deviation (4.05) increase in the natural logarithm of total toxic releases is associated with a 9.67% (4.05*8.635/361.71) increase in *Ln(Green Pat)* from the mean level of 361.71.[19] Moreover, the result shown in Column (5) implies that a one-standard-deviation (4.05) increase in *Ln(Total Release)* is also associated with an approximately 8.97% (4.05*6.400/288.87) increase in *Ln(Tot GPat Cites)* from the mean level of 288.87. The results are consistent when green patenting is measured for year *t+2*. Overall, the evidence in Table 2 supports Hypothesis 1a and rejects Hypothesis 1b. That is, firms with high toxic release levels produce more and higher-quality green patents than their counterparts with low toxic release levels.[20]

IA Table 5 of the Internet Appendix shows the regression estimates (Panel A) and correlation matrix (Panel B) of corporate green innovation on the toxic releases administered under various EPA regulations. Following Xu and Kim (2022), our study includes releases regulated under the CAA, the CWA, and the CERCLA, which are categorized based on disposal methods; moreover, we examine the results pertaining to

[19] All dependent variables are multiplied by 1,000 in the regression analysis to enhance the readability of the coefficients. The economic significance of *Ln(Total Release)* ranks second out of ten variables, second only to *Ln(Market Equity)*.

[20] A survey evidence of industry practitioners in Australia conducted by one of the authors of the paper also supports our Hypothesis 1a. In collaboration with a professional organization, the survey asked a group of treasurers, chief financial officers (CFOs), and directors to rank the important determinants of firms' green patenting efforts. Section II of the Internet Appendix presents a brief discussion of the survey and the result. Overall, the survey results show that a significant proportion of the respondents (24.14 percent) strongly agree that the level of toxic emissions is a crucial factor determining firms' green innovation efforts, which is second only to shareholder and stakeholder pressure (27.59 percent). The full survey report can be obtained from the authors.

emissions under OSHA to examine whether our results are still robust for firms with high toxic emissions that represent the greatest threats to workplace safety. The coefficients of the log pounds of various releases across all specifications are significantly positive, indicating that the disposal methods and workplace safety threats of emissions do not affect our baseline results. Economically, one-standard-deviation increases in the logarithms of CAA, CWA, CERCLA, and OSHA releases are associated with 7.54%, 8.72%, 9.22%, and 9.04% increases in *Ln(Green Pat)* from the mean level of 361.71, respectively. We do not include all types of toxic emissions in a single regression model, as the releases under different acts are highly correlated (Panel B), which is consistent with the findings of Xu and Kim (2022).

Next, we group toxic emissions based on their health effects and report the results in IA Table 6 of the Internet Appendix. The independent variables in Columns (1) and (2) are total releases associated with health effects (*Ln(Health Effects Release)*) and toxic emissions weighted by the RSEI hazard score (*Ln(RSEI Hazard)*), respectively. Column (3) presents the results for chemicals that are not associated with human health impacts (*Ln(No Health Effects Release)*). In addition, we include *Ln(Health Effects Release)* and *Ln(No Health Effects Release)* in Column (4) and similarly include *Ln(RSEI Hazard)* and *Ln(No Health Effects Release)* in Column (5). We find that harmful toxic emissions are the main drivers of our results, whereas releases without health effects exert no significant impacts. We observe that TRI chemicals with adverse health effects comprise approximately 94.62% (1,449.57/1,532.05 thousand pounds) of the total release volume. Moreover, 46.99% (734/1,562) of the sample firms emit chemicals associated with no health effects.

Finally, in IA Table 7 of the Internet Appendix, we group the toxic emissions based on their release sites and physical properties. Column (1) of Panel A shows that the coefficient of *Ln(Onsite Release)* is positive and statistically significant; economically, a one-standard-deviation increase in the logarithm of onsite releases is associated with an 11.34% increase in green patenting; in contrast, Column (2) shows that the effect of *Ln(Offsite Release)* is insignificant. We observe similar results when the measures of onsite and offsite toxic releases are included in a single regression. This evidence implies that our main results are driven by onsite releases. This result is intuitive because firms prefer to emit locally, as transferring toxic chemicals to offsite locations for release or disposal is more costly. In Panel B, we further separate onsite emissions into air, water, and ground releases according to their physical properties. We find that while *Ln(Air Release)* has a significant effect (in Columns (1) and (4)), the results for *Ln(Water Release)* and *Ln(Ground Release)* are insignificant.

4.2. Robustness check

To eliminate the possibility that the patenting efforts of energy firms are driving our results (Cohen et al. 2023), we rerun our baseline regression by excluding energy-producing firms.

Following Cohen et al. (2023), we exclude firms in the following two-digit SIC industries: 10 (Metal, Mining), 12 (Coal Mining), 13 (Oil & Gas Extraction), 14 (Nonmetallic Minerals, Except Fuels), 29 (Petroleum & Coal Products), and 49 (Electric, Gas, & Sanitary Services). As shown in IA Table 8 of the Internet Appendix, the effect of firms' toxic emissions on green innovation output (both quantity and quality) remains significantly positive even after excluding energy firms. This finding suggests that the positive relationship between firms' toxic releases and green patenting exists not only for the energy sector but also for the market as a whole.[21]

4.3. *The nature of high-emission firms' green innovation*

In this section, we further explore the specific activities and strategies adopted by high-emission firms in relation to green innovation. First, we examine whether green patents produced by high-emission firms are valuable. Second, we separately examine eight subcategories of green patents based on OECD guidelines to highlight high-emission firms' green patenting efforts. Finally, we discuss the innovation strategies of firms with high toxic emission levels.

In Panel A of Table 3, using the innovation measure by Kogan et al. (2017), we examine the value of green patents generated by high-emission firms. Columns (1) and (2) show the results when the total (real and nominal) value of firms' green innovation is the dependent variable, and Columns (3) and (4) present the results when the average (real and nominal) value is the dependent variable. Across all the specifications in Table 3 Panel A, firms' total toxic releases have a significantly positive effect on green patent values (at significance levels of 5% or 10%), suggesting that green patents produced by high-emission firms have higher total and higher average values. Moreover, taken together with the evidence shown in Table 2 that the quality (patent citations) of high-pollution firms' green innovation is also higher than that of low-emission firms, our findings indicate that the green patenting of high-pollution firms is unlikely to be just a

[21] IA Table 9 presents the average number of green patents and average total toxic releases (in thousands of pounds) for each two-digit SIC industry in our final sample. Although Metal, Mining industry (two-digit SIC = 10, one of the energy industries) has a high average toxic emission level, it exhibits a relatively low green innovation effort. In addition, several industries other than the energy industries also have relatively high toxic release levels and green patent outputs, such as Paper & Allied Products (two-digit SIC = 26) and Chemical & Allied Products (two-digit SIC = 28).

greenwashing activity.

[Insert Table 3 about here]

Then, we investigate the types of green patents emphasized by firms with high toxic emission levels and present the results in Panel B of Table 3. We explore environmental (Columns (1)-(2)) and CCM (Columns (3)-(8)) patent categories. We find that high-emission companies demonstrate better performance in both the environmental (Column (9)) and CCM (Column (10)) categories than low-emission firms. The production of these two types of green innovation may have different purposes. Environmental green patents are used in daily operations to control toxic emissions and abatement costs, while CCM technologies mainly address the risks and challenges caused by global climate change and related issues. Our findings suggest that high-emission companies make an effort to produce green patents for both purposes.

Consistent with the notion that high toxic-emission firms should be more concerned with environmental risk, we find that these firms produce significantly more green patents related to environmental issues (in Column (9)) than CCM technologies (in Column (10)). Economically, a one-standard-deviation increase in the natural logarithm of total toxic releases in Column (9) is associated with a 16.34% increase in *Ln(GPat(Tot Env))* from the mean level of 170.71. Furthermore, a one-standard-deviation increase in the natural logarithm of total toxic releases in Column (10) is associated with only an 8.99% increase in *Ln(GPat(Tot CCM))* from the mean level of 301.70. We also find a significant relationship between toxic releases and green patenting classified as CCM technologies related to (i) energy generation, transmission, or distribution (Du and Karolyi 2023); (ii) wastewater treatment or waste management; and (iii) the production or processing of goods. Interestingly, patents related to CCM greenhouse gases (GH) in Column (4) are only marginally significant. This result is not surprising, as toxic emissions do not include greenhouse gases.

Finally, we explore the strategic choice of high-emission firms when generating green innovation and present the results in Panel C of Table 3. Following Chu et al. (2021), we use the natural logarithm of one plus the number of explorative and exploitative green patents filed by (and eventually granted to) a firm to capture the strategy it adopts in relation to green patenting. Columns (1) and (2) of Table 3 Panel C show that firms with high toxic emission levels exhibit better performance in both explorative and exploitative green innovation. Economically, a one-standard-deviation increase in the natural logarithm of total toxic releases is associated with an 11.74% increase in explorative green patenting from the mean *Ln(Explorative GPat)* level of 209.89; additionally, a one-standard-deviation increase in the logarithm of total toxic releases is associated with a 12.50% increase in exploitative green patenting from the mean *Ln(Exploitative GPat)* level of 151.25. Overall, the evidence in Table 3 Panel C suggests that high-pollution companies use both explorative and exploitative strategies in green innovation. Thus, we find that high-emission firms push their boundaries and explore new technologies rather than relying only on developing expertise when producing green patents.

5. Identification

Although we demonstrate a positive correlation between firms' green patenting and toxic releases, we have yet to establish the causal effect of toxic emission levels on corporate green innovation. One of the potential concerns underlying our analysis is that of omitted variable bias. Specifically, firms' release levels and decision-making on green innovation may be simultaneously affected by unobservable factors, which may bias the coefficients of OLS regressions in either direction. To support a causal interpretation, we exploit the exogenous changes of the TRI chemical list, which can serve as a shock to firm-level toxic releases that are regulated by the U.S. EPA and are of concern to the public. Specifically, we capture the exogenous increases in toxic emissions administered under the TRI program due to the additions of new hazardous chemicals to the reporting list and examine whether such changes affect firms' green patenting efforts.[22]

The U.S. EPA revises the TRI chemical list through EPA-initiated assessments and the chemical petitions process. The list of toxic chemicals subject to reporting has undergone several expansions since the initiation of the TRI program.[23] The largest expansion happened in 1995 when the number of chemicals administered by the TRI program was almost doubled. The addition of hazardous chemicals can be driven by several reasons. First, if there is evidence or concerns about the significant adverse environmental or human health effects posed by a particular chemical, the EPA may add it to the TRI list (EPA 2023). The evidence can come from ongoing scientific

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[22] As explained in footnote 7 of Section 3 (*Data, Variable Construction, and Summary Statistics*), our study uses EPA's TRI dataset and therefore focuses on firm-level regulated toxic emissions and those of public concern, rather than on total releases. Even though firms may have the same amount of total releases before and after the expansions of the TRI chemical list, their firm-level toxic emissions regulated by the U.S. EPA and of public concern significantly increase after these expansions.

[23] The U.S. EPA also removes chemicals from the reporting list. However, such changes rarely happened. Specifically, only approximately 30 chemicals are eliminated from the list, while approximately 500 chemicals are added to the TRI chemical list from 1987 to 2020. In the untabulated tests, we observe no significant effects when companies cease reporting the removed chemicals. More details about changes of TRI chemical list are available at: https://www.epa.gov/toxics-release-inventory-tri-program/tri-listed-chemicals.

research that reveals previously unknown toxicity of certain chemicals to humans and other organisms. The concerns raised by communities, environmental organizations, or industry stakeholders can also prompt the EPA to consider adding specific chemicals (EPA 1994). In addition, changes in legislation may require the EPA to add certain chemicals to the TRI list. For example, amendments to environmental laws (e.g., the Emergency Planning and Community Right-to-Know Act (EPCRA)) can necessitate the inclusion of additional chemicals. Most importantly, the expansions of the TRI chemical list are unlikely to be caused by any fundamental changes at the firms themselves, such as the adoption of new manufacturing processes or new (green) technologies. The mandatory reporting of additional chemicals captures the exogenous increases in toxic emissions that are regulated by the U.S. EPA and are of public concern.

Given that several expansions of the TRI chemical list occurred since the establishment of the TRI program, we follow Gormley and Matsa (2011) and adopt a cohort-based DiD approach. Specifically, for each year in which new chemicals are added to the TRI chemical list, we construct a cohort consisting of (i) treatment firms reporting emissions of the newly added chemicals after the expansion and (ii) control firms within the same 2-digit SIC industries of treatment firms that do not release any newly added chemicals. Each cohort comprises firm-year observations for the five years before and the five years after the implementation of the new regulation (i.e., expansion of the chemical list).[24] Within each cohort, we ensure that companies do not report new chemicals mandated by other TRI chemical list expansions. We then pool

[24] The results are similar if we instead use the three years before and the three years after each expansion.

all the data across cohorts to construct the final sample, encompassing major TRI list expansions occurring in 1990, 1991, 1994, 1995, 2000, 2011, 2012, 2014, 2015, 2016, 2017, and 2019. Specifically, we estimate the following regression:[25]

$$\begin{aligned} Green\ Innovation_{i,t} \\ &= \alpha + \beta_1 Treated_{i,t} \times Post_{i,t} + \beta_2 Treated_{i,t} + \beta_3 Post_{i,t} \\ &+ \gamma Controls_{i,t} + FEs + \epsilon_{i,t} \end{aligned} \tag{2}$$

where *i* indexes public firms, and *t* indexes years. *Treat* is an indicator variable that equals one for treatment firms and zero for control firms. *Post* is an indicator variable that equals one for the five years after the list expansions and zero for the five years before the expansions. The control variables are identical to those in Model (1). We also include firm and industry-year fixed effects.[26]

[Insert Table 4 about here]

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[25] Our results remain robust when we use an instrumented difference-in-differences (DiD-IV) approach. Specifically, in the first stage, we regress total toxic releases ($Toxic\ Emissions$) on the variables that capture the exogenous shocks of TRI list expansions (i.e., $Treated \times Post$, $Treated$, and $Post$), which allows us to ascertain whether the total emission levels of treatment firms indeed increased as expected. In the second stage, we regress $Green\ Innovation$ on the instrumented total toxic emissions ($Toxic\ \widehat{Emissions}$) predicted from the first-stage regressions. The two-stage regression models are specified as follows:

First-Stage Regression

$$\begin{aligned} Toxic\ Emissions_{i,t} \\ &= \alpha + \beta_1 Treated_{i,t} \times Post_{i,t} + \beta_2 Treated_{i,t} + \beta_3 Post_{i,t} + \gamma Controls_{i,t} \\ &+ FEs + \epsilon_{i,t} \end{aligned}$$

Second-Stage Regression

$$Green\ Innovation_{i,t} = \alpha + \beta Toxic\ \widehat{Emissions}_{i,t} + \gamma Controls_{i,t} + FEs + \epsilon_{i,t}$$

The results are reported in IA Table 10. In the first-stage regression (Column (1)), we confirm that the expansions of TRI chemical list indeed increase the toxic emission levels of the treatment firms. In the second-stage regressions (Columns (2) and (3)), the coefficients of the instrumented total toxic emissions ($Toxic\ \widehat{Emissions}$) are all positive and statistically significant.

[26] Our results are robust to replacing firm fixed effects and industry-year fixed effects by firm-cohort fixed effects and industry-year-cohort fixed effects.

We present the results in Table 4. Column (1) reports the results when the dependent variable is *Ln(Green Pat)*, while Column (2) reports the results when the dependent variable is *Ln(Tot GPat Cites)*. Across all specifications, the coefficient estimates of *Treated* × *Post* are positive and statistically significant, indicating that compared with control firms that are not affected by the expansions of the TRI chemical list, treatment firms are inclined to produce more green patents after the new reporting lists become effective. That is, the exogenous increases in the reported toxic emissions that are emphasized by the EPA and the public lead to an improvement in corporate green innovation.

Overall, our results based on the expansion of the TRI chemical list alleviate the concerns that the results in Table 2 might be driven by firm characteristics that affect both toxic emissions and green innovation, and therefore provide support for a causal interpretation of the relationship between firms' toxic releases and their green innovation.

6. Channels

6.1. Regulatory burdens: The 2016 election of President Trump

We follow previous studies (Cao et al. 2021) and exploit President Trump's election on November 9, 2016, as a shock that decreased regulatory liabilities and risks faced by high-emission companies. We take advantage of Trump's election to validate our argument related to the regulatory burden channel in Hypothesis 1a.

The unexpected election of Trump on November 9, 2016 exerted significant impact on companies and financial markets. First, this event reduced climate and environmental policy uncertainty in the short term as Trump signaled in his campaigns that he would preserve the prevailing climate policies and that the status quo of U.S. climate and environmental regulation would not become stricter (Ilhan et al. 2021). Second, in response to the expectation of laxer regulations during the Trump administration, carbon-intensive firms enjoyed a short-run stock price increase (Ramelli et al. 2021). Similarly, Cao et al. (2021) argue that President Trump's unexpected victory might have mitigated concerns about stricter climate and environmental regulations and decreased heightened risks for carbon-intensive companies.

Therefore, based on the findings of prior studies and considering Trump's behaviors and policies that reversed the momentum in the fight against climate change and environmental issues (e.g., withdrawing from the Paris Agreement), we argue that polluting firms' potential regulatory liabilities and risks decreased during the Trump presidency (Hsu et al. 2023), weakening their motivations to engage in green innovation. That is, if regulatory burden is a channel through which firms' toxic release levels drive changes in their green innovation, high-emission companies are expected to reduce their efforts related to green patenting in the years following Trump's election.

To test whether the effect of toxic emissions on corporate green innovation weakened after Trump's election, we first generate an indicator variable, namely, *Post Election*, which equals one if the year is later than 2016 (including years 2017 and 2018); then, we include an interaction term (*Ln(Total Release)*×*Post Election*) in our regressions. We use a sample covering 2015 through 2018 to balance the amount of time on each side of the event in 2016.[27] Our analysis is based on the following model:

$$\begin{aligned} &Green\ Innovation_{i,t+1} \\ &\qquad = \alpha + \beta_1 Toxic\ Emissions_{i,t} \\ &\qquad + \beta_2 Toxic\ Emissions_{i,t} \times Post\ Election_{i,t} \\ &\qquad + \beta_3 Post\ Election_{i,t} + \gamma Controls_{i,t} + FEs + \epsilon_{i,t} \end{aligned} \tag{3}$$

where *i* indexes public firms, and *t* indexes years. The dependent variables are the green innovation proxies in year *t+1*.[28]

Table 5 presents the empirical results where *Post Election* is absorbed by the fixed effects in the specifications. Columns (1) to (3) show that high-emission firms largely reduced their efforts in green innovation after Trump's election, leading to a decrease in the quantity, quality, and value of green patents. Furthermore, the results in Columns (4) and (5) suggest that high-emission firms significantly reduced both their environmental and CCM green innovation. Finally, the coefficient estimates of the interaction term in Columns (6) and (7) for explorative and exploitative green innovation are all negative and statistically significant, implying that firms with high

[27] To avoid the impact of truncation bias on our results and to be consistent with the analysis based on the BP Deepwater Horizon oil spill in Section 6.2, we use a stricter sample period covering the years 2015 through 2018, which correspond to the four years surrounding Trump's election that occurred on November 9, 2016. That is, the years 2019 and 2020 are excluded to mitigate truncation bias.

[28] Our results in Table 5 are generally consistent when we employ the difference-in-differences (DiD) model in the analysis. Specifically, we define a dummy variable, *High Release*, which equals one if a firm's toxic emissions are higher than the median level and zero otherwise. Then, we run the following model:

$$\begin{aligned} &Green\ Innovation_{i,t+1} \\ &\qquad = \alpha + \beta_1 High\ Release_{i,t} \\ &\qquad + \beta_2 High\ Release_{i,t} \times Post\ Election_{i,t} + \beta_3 Post\ Election_{i,t} \\ &\qquad + \gamma Controls_{i,t} + FEs + \epsilon_{i,t} \end{aligned}$$

The regression estimates based on the above model are shown in IA Table 11 of the Internet Appendix.

toxic emission levels dramatically reduced their production of both explorative and exploitative green patents following Trump's election.

[Insert Table 5 about here]

Intuitively, compared with firms headquartered overseas, those headquartered in the U.S. could be more sensitive to changing trends in local environmental policies due to their informational advantages and deep understanding of President Trump's attitudes toward environmental and climate issues. Therefore, U.S. headquartered companies were more likely to expect laxer environmental regulations during the Trump presidency, while overseas firms were less likely to reverse their expectations of policy stringency. We thus hypothesize that Trump's election may have had a stronger impact on firms headquartered in the U.S. than on those headquartered overseas. Therefore, to provide stronger evidence of the regulatory-burden channel, we further exploit Trump's election and estimate a propensity-score-matching-based (PSM) difference-in-difference-in-differences (DDD) model. The results are consistent with our expectations and are presented in IA Table 12 of the Internet Appendix.

Overall, the results support our hypothesis that the unexpected 2016 election of President Trump significantly weakened the relationship between firms' toxic emissions and corporate green innovation due to decreased potential legal liabilities and risks. This finding demonstrates the regulation-induced channel of impact going from firms' toxic emissions to corporate green innovation. This evidence also suggests that (local) environmental and climate policies are an essential factor considered by polluting companies in making decisions on green innovation and that reduced potential regulatory liabilities can weaken high-emission firms' demand for green technologies.

6.2. Environmental awareness: The BP Deepwater Horizon oil spill

To examine the environmental awareness channel, we exploit the BP Deepwater Horizon oil spill that began on April 20, 2010, as a quasi-natural experiment. The Deepwater Horizon oil spill, also known as the BP oil disaster, occurred in the Gulf of Mexico and is regarded as the largest marine oil spill in the history of the petroleum industry (Liang and Renneboog 2017). This unexpected event arguably serves as a shock to the external environmental awareness faced by high-emission firms in extractive industries. If environmental awareness is a channel through which firms' toxic release levels affect green innovation, we should observe that extractive firms with higher toxic emission levels at the time of the Deepwater Horizon oil spill would exhibit better green innovation performance in the years following this event, plausibly because of greater environmental awareness. This test allows us to validate our environmental awareness argument for the positive relationship between toxic emissions and green patenting.

First, using a DiD approach, we investigate whether the Deepwater Horizon event increased the green innovation of firms in extractive industries by enhancing environmental awareness.[29] Our analysis is based on the following specification:

$$\begin{aligned} Green\ Innovation_{i,t} &= \alpha + \beta_1 Treated\ Firm_{i,t} \\ &+ \beta_2 Treated\ Firm_{i,t} \times Post\text{–}2010_{i,t} + \beta_3 Post\text{–}2010_{i,t} \\ &+ \gamma Controls_{i,t} + FEs + \epsilon_{i,t} \end{aligned} \tag{4}$$

where *i* indexes public firms, and *t* indexes years. Following Dyck et al. (2019), we

[29] IA Table 15 of the Internet Appendix shows that treatment and control firms exhibit parallel trends for *Ln(Green Pat)* and *Ln(Tot GPat Cites)* prior to the Deepwater Horizon event (Lemmon and Roberts 2010, Ilhan et al. 2021).

identify *Treated Firm* in extractive industries based on the two-digit SIC code (i.e., SIC 13, Oil and Gas Extraction). *Post-2010* equals one for the years 2010 and 2011 and zero otherwise. The sample period used in the analysis covers the years 2008 through 2011, which correspond to the four years surrounding the event that began on April 20, 2010, ensuring a balance on each side of the Deepwater Horizon event.[30] The two-year pre- and post-event periods are each collapsed into one observation to address serial correlation (Bertrand et al. 2004).[31] The dependent variables are the corporate green innovation proxies in year *t*.[32] We control for industry and year fixed effects in the regressions.[33] In addition, standard errors are clustered at the industry level because this environmental shock mainly affected several specific industries (i.e., extractive industries) (Dyck et al. 2019) and extractive firms are assigned the same treatment

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[30] We use four-year periods surrounding the Deepwater Horizon event to make the analyses consistent with those of Trump's election, which is restricted by truncation bias. However, given that it may take time to change the R&D direction of a company, we conduct robustness checks in the Deepwater Horizon analysis based on longer post periods (i.e., four years, 2010 through 2013). The results are reported in IA Table 16 of the Internet Appendix, and our results are robust.

[31] Dyck et al. (2019) show that after the Deepwater Horizon shock, for extractive firms, ex-ante higher institutional ownership leads to improved environmental performance (measured by the environmental score from the Thomson Reuters ASSET4 ESG database). Therefore, to rule out the impact of institutional ownership on our Deepwater Horizon analysis, we control for total institutional ownership, proxied by *Total IO* and measured over the pre-event period, in the Deepwater Horizon analysis. We collect institutional ownership data from the *Thomson Reuters Institutional (13F) Holdings* database. The results are shown in IA Table 17 of the Internet Appendix. We find that our results in Table 6 are robust after controlling for the impact of institutional ownership. Our results are also consistent when controlling for the interaction terms between *Total IO*, *Treated Firm* and *Post-2010*.

[32] Our analysis follows Dyck et al. (2019), who similarly use the dependent variables in year *t* and the independent and control variables in year *t-1* in their baseline regressions but use the contemporaneous model in the tests based on the BP Deepwater Horizon oil spill. However, the results in Panel A of Table 6 are also robust when the dependent variables are measured in year *t+1*, and the independent and control variables are measured in year *t*.

[33] We cannot use industry-year fixed effects in Model (4) because this is an industry-level analysis. Including industry-year fixed effects will absorb all variations. Similarly, given that including firm fixed effects also absorbs all variations, we do not control firm fixed effects.

status (Abadie et al. 2023).

The regression estimates are reported in Panel A of Table 6. Columns (1) and (2) show the results when the dependent variable is *Ln(Green Pat)*, while Columns (3) and (4) present the results when the dependent variable is *Ln(Tot GPat Cites)*. In Columns (1) and (3), we do not include fixed effects, and in Columns (2) and (4), we include industry and year fixed effects. Across all specifications, the interaction coefficients for *Treated Firm×Post-2010* are positive and statistically significant, suggesting that the unexpected Deepwater Horizon shock imposed a pronounced positive effect on the green patenting efforts of firms in extractive industries.

[Insert Table 6 about here]

Furthermore, we employ a DiD model to examine the impact of the BP Deepwater Horizon oil spill on the relationship between firms' toxic emission levels and corporate green innovation.[34] *Ln(Total Release)* is measured from the pre-event period to avoid the estimated impact in the post-event period being driven by changes in firms' toxic emission levels.[35] We then estimate the following empirical model:

[34] We use settings similar to those in Model (4). Specifically, we identify *Treated* firms in extractive industries based on the two-digit SIC code (i.e., SIC 13, Oil and Gas Extraction). The sample period used in the analysis covers the years 2008 through 2011, which correspond to the four years surrounding the event that began on April 20, 2010, ensuring balance on each side of the event. The two-year pre- and post-event periods are each collapsed into one observation to address serial correlation (Bertrand et al. 2004).

[35] The results in Panel B of Table 6 are robust when *Ln(Total Release)* is the actual total toxic emissions rather than those measured over the pre-event period, and the two-year pre- and post-event periods are not each collapsed into one observation. The results are reported in IA Table 18 of the Internet Appendix.

$$
\begin{aligned}
&Green\ Innovation_{i,t} \\
&\qquad = \alpha + \beta_1 Toxic\ Emissions_{i,t} \\
&\qquad + \beta_2 Toxic\ Emissions_{i,t} \times Post\text{–}2010_{i,t} \times Treated\ Firm_{i,t} \\
&\qquad + \beta_3 Treated\ Firm_{i,t} + \beta_4 Post\text{–}2010_{i,t} \\
&\qquad + \beta' Other\ interactions_{i,t} + \gamma Controls_{i,t} + FEs + \epsilon_{i,t}
\end{aligned} \tag{5}
$$

The DiD estimates are presented in Panel B of Table 6. Columns (1) and (2) show the results for *Ln(Green Pat)*, and Columns (3) to (4) report the results for *Ln(Tot GPat Cites)*. Columns (1) and (3) are without fixed effects, while in Columns (2) and (4), we control for industry and year fixed effects. The coefficients of the triple interaction term (*Ln(Total Release)*×*Treated Firm*×*Post-2010*), capturing the difference in the effect of *Ln(Total Release)* for *Treated* firms relative to *Control* firms after the Deepwater Horizon event, are all positive and statistically significant. The results suggest that for firms in extractive industries, this unexpected incident significantly strengthened the relation between firms' toxic emission levels and their green innovation. This finding is consistent with the environmental awareness-induced channel of effects transferring from firms' toxic releases to their green patenting.

7. Implications of High-Pollution Firms' Green Innovation

7.1. Mitigating toxic air releases

This section explores the value implication of corporate green innovation. Specifically, we examine whether green patents produced by firms mitigate their toxic releases.

Given that air emissions account for a major portion of total toxic emissions (Xu and Kim 2022) and that air releases are the main driver of the positive relationship between toxic emissions and green patenting (as shown in Panel B of IA Table 7), we focus on the toxic chemicals released into the air. First, we calculate the changes in the log pounds of toxic air releases (*ΔLn(Air Release)*) in five different periods, namely, from year –1 to year 1 through year 5. We examine the effects of firms' environmental and CCM green patents on toxic air emissions as follows:

$$\Delta Ln(Air\ Release)_{i,t+1} = \alpha + \beta Green\ Innovation_{i,t} + \gamma Controls_{i,t} + FEs + \epsilon_{i,t}. \tag{6}$$

where *i* indexes public firms, *t* indexes years, and *Δ* indicates the changes from year –1 to year 1 through year 5.[36] Table 7 presents the regression results of changes in the log pounds of toxic air releases on environmental and CCM green innovation. While CCM-related green patents appear to have a short-term negative effect on the change in air emissions (in Column (2); from year –1 to year 1), environmental-related green innovation delivers a far long-lasting and significant impact in controlling toxic air releases (in Columns (3), (5), (7), and (9); from year –1 to year 2 through year 5). Economically, a one-standard-deviation increase in the log number of environmental green patents is associated with 19.30%, 19.06%, 15.94%, and 13.57% decreases in *Δ Ln(Air Release)* from the mean levels for year –1 to year 2 through year 5,

[36] Given that the dependent variables overlap across years, we consider the serial dependency of the standard errors by employing Newey-West standard errors (Newey and West 1987, Petersen 2009). The results in Table 7 are based on Newey-West correction with five lags, and our results are robust when using various lags (one to six lags) in the Newey-West correction. In addition, the results are also consistent without adopting Newey-West correction in the calculation of standard errors.

respectively.[37]

[Insert Table 7 about here]

Overall, these results demonstrate the essential function of corporate green innovation in mitigating toxic (air) emissions. Our findings suggest that environmental green patents can indeed be utilized in daily operations to control pollution. Not surprisingly, CCM green technologies appear to play a minor role in addressing toxic emissions, as they are more likely to mitigate climate-change-related issues. Importantly, these findings alleviate the concern that the green innovation of high-emission firms is merely a greenwashing activity.

7.2. External implications

Next, we investigate the potential benefits of high-pollution firms' green innovation to other firms in helping push the green knowledge frontier (Galasso and Schankerman 2015, Sampat and Williams 2019, Asgharian et al. 2024).

To examine the external implications of green patents, we construct the following two measures of citations received by the firm's green patents filed (and eventually granted): (i) *Ln(InIndGcites),* the natural logarithm of one plus the total number of forward adjusted within-industry citations; and (ii) *Ln(OutIndGcites)*, the natural logarithm of one plus the total number of forward adjusted outside-industry citations.

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[37] Our results in Table 7 remain robust after controlling for production ratios, which capture changes in the output or outcome of processes where a chemical is involved (Akey and Appel 2021). The production ratios are obtained from EPA's Pollution Prevention (P2) dataset. We aggregate the chemical-level production ratios into the company-level through taking the average. Considering the potential data errors, we follow Akey and Appel (2021) and eliminate ratios that fall outside the range of zero to three. The results are presented in IA Table 19 of the Internet Appendix.

The first and second measures capture the number of citations received from companies in the same industry and other industries of the focal firm, respectively.

We explore whether the green patents produced by high-pollution firms have more within-industry and outside-industry citations compared to green patents produced by low-pollution firms by employing the following regression model:

$$Ln(InIndGcites) or Ln(OutIndGcites)_{i,t+1} = \alpha + \beta Toxic\ Emissions_{i,t} + \gamma Controls_{i,t} + FEs + \epsilon_{i,t} \quad (7)$$

where i denotes a public firm and t denotes a year. The dependent variables are the within-industry and outside-industry citations to green patents measured in year $t+1$.[38]

[Insert Table 8 about here]

The results are shown in Table 8. Columns (1) and (2) present the regression results for within-industry citations, and Columns (3) and (4) report the results for outside-industry citations. Columns (1) and (3) do not include fixed effects, while Columns (2) and (4) control for firm and industry-year fixed effects. We find that in all specifications, firms' pollution levels have a significant positive effect on both within-industry and outside-industry citations. This finding suggests that the green patents produced by high-emission firms provide substantial technological support to firms in the same industry and other industries. Thus, we provide significant evidence that the green patenting efforts of high-pollution firms not only address their emissions concerns but also assist firms in other industries in advancing the green knowledge frontier.

[38] Our results in Table 8 are robust when the dependent variables are measured in year t or $t+2$.

7.3. ESG fund flows

The significant increase in ESG investments over the past decades suggests that high-pollution firms might undertake green patenting initiatives to either draw in ESG fund flows or to avoid becoming the target of ESG divestment campaigns (Bofinger et al. 2022). Therefore, we examine how ESG investors, specifically environmentally conscious ones, respond to the green innovation of high-emission firms. This analysis also aims to address a potential alternative explanation of our results: the impetus for green-patenting efforts among high-pollution firms is driven not by their own internal motivations but by ESG fund flows.

First, we collect companies' CSR ratings from the MSCI ESG Stats database (formerly known as KLD) over the sample period from 1991 to 2018. This database contains environmental, social, and governance ratings of large public companies and is widely used in studies exploring the determinants and consequences of firms' CSR performance (e.g., Deng et al. 2013, Lins et al. 2017, Chen et al. 2020). Given that environmentally minded investors may prioritize firms' pollution and green innovation, we focus on companies' environmental performance and calculate the size-adjusted MSCI KLD Environmental Index scores (Pan et al. 2022). We then use the Thomson Reuters Institutional (13F) Holdings database to obtain information on institutional investors' portfolio holdings. We calculate institutions' environmental footprints as the value-weighted average MSCI KLD Environmental Index scores of their portfolio firms.[39] We define institutions with environmental footprints above the median as

[39] Following Pan et al. (2022), we use the portfolio weights at the end of each year. Environmental Index scores of investors' portfolio firms are measured in previous year (*t-1*) because the scores are available to institutions contemporaneously (Hege et al. 2022).

environmentally conscious institutional investors (Hege et al. 2022).[40] Finally, we construct *EnvIO* as the percentage of common shares held by environmentally minded institutions.

[Insert Table 9 about here]

We then examine whether the green patenting efforts of larger polluters lead to higher environmentally conscious institutional ownership. To facilitate interpretation, we designate large polluters using dummy variables based on toxic emissions exceeding the 70th, 75th, or 80th percentiles of the sample distribution (Xu and Kim 2022). The results in Columns (1), (3), and (5) of Table 9 show that emitting firms' green innovation (*Ln(Green Pat)*) does not attract investments from environmentally minded investors, who instead divest from high-emission firms *(Large polluter)*. Even when large polluters generate green patents, they still face divestment from environmentally conscious institutional investors (Columns (2), (4), and (6)).[41] Our findings suggest that the green innovation efforts of high-pollution firms are unable to attract investments from environmentally minded institutional investors. This finding also rules out the possibility that ESG fund flows are driving the positive relationship between firms' green innovation and toxic emission levels.

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[40] Our results in Table 9 are robust when we define institution investors as the institutions with environmental footprints above the 67th (one third) and 75th (one fourth) percentiles of the sample distribution.

[41] As depicted in Table 2, there is a positive relationship between green innovation and firms' toxic emissions. Thus, it is reasonable that the coefficient estimates of the interaction between *Ln(Green Pat)* and *Large polluter* (*Ln(Green Pat)* × *Large polluter*) is statistically significant, while the coefficient of *Large polluter* is insignificant (Columns (2), (4), and (6) of Table 9). This could potentially be explained by the fact that firms with even higher pollution levels among the group of large polluters are more likely to invest in green innovation efforts. Therefore, the interaction term between *Ln(Green Pat)* and *Large polluter* captures the influence of the largest polluters among the group of large polluters.

Taken together with the results in Tables 7 and 8, which demonstrate that high-pollution firms' green patents reduce toxic emissions and advance the green knowledge frontier, our findings suggest that environmentally conscious institutional investors do not consider the productive nature of green innovation in these companies and instead persist with their divestment strategy. Our results indicate that relying on ESG screening, which is a blunt approach to sustainable investment, is unlikely to be an effective strategy for addressing environmental and climate change issues.

8. Do Financial Constraints Hinder High-Emission Firms' Green Patenting Efforts?

Prior literature shows that financial constraints attenuate firms' innovative activities, particularly those involving high risk and uncertainty (Moshirian et al. 2021). Therefore, we examine the green patenting efforts of high-emission firms in the context of financial constraints.

First, prior studies show that relaxing financial constraints improves corporate innovation. For instance, Amore et al. (2013) find that bank-dependent firms innovate more following banking deregulation, and Moshirian et al. (2021) show that stock market liberalization promotes corporate innovation. These findings imply that financial constraints can limit corporate innovative activities and possibly affect firms' green patenting. Second, some existing papers examine the impacts of financial constraints on corporate environmental performance. For example, Cohn and Deryugina (2018) and Xu and Kim (2022) note that financially constrained firms have more hazardous environmental spills and toxic emissions as constraints decrease their spending on environmental protection initiatives. Therefore, it will be of interest to assess how financial constraints affect the green patenting efforts of high-pollution firms.

For our analysis, we use the text-based measures of financial constraints developed by Hoberg and Maksimovic (2015) for the years 1997 through 2015, given the limitations of traditional accounting-based measures (Farre-Mensa and Ljungqvist 2016). Following Xu and Kim (2022), we use the debt-market constraint measure, *HM Debt*, in our analysis. This measure describes a firm's plans to issue debt to solve its liquidity problems. We define a dummy variable, *High HM Debt*, which equals one if the level of debt-market financial constraints is higher than the median and zero otherwise. The regression results are shown in Table 10.

[Insert Table 10 about here]

First, we find that the coefficient estimates of the interaction term between financial constraints and the log pounds of total toxic emissions in Columns (1) and (2) are significantly negative, indicating that financial constraints indeed reduce high-emission firms' overall innovation outputs. Interestingly, this reduction in total innovation appears to be driven by a decrease in nongreen patenting (Columns (3) and (4)). We do not observe any significant decline in green innovation among financially constrained high-pollution firms (Columns (5) and (6)). Furthermore, Columns (7) and (8) show that neither environmental nor CCM patenting is affected by financial constraints. Overall, the findings imply that in the presence of financial constraints, high-emission firms appear to reduce their nongreen patenting efforts more than their green patenting efforts. One possible explanation for these results is that high-emission firms are likely to treat green innovation as an essential innovative activity that is necessary to improve environmental abatement efficiency and address abatement costs.

9. Conclusion

Environmental and climate change issues have gained significant attention in recent years and impact various aspects of financial markets and corporate policies (Hong et al. 2020). Investors and corporate managers are increasingly recognizing the importance of environmental and climate risks (e.g., Alok et al. 2020, Choi et al. 2020, Krueger et al. 2020). Firms' toxic releases, a leading cause of environmental and climate problems, have become a focus of attention among governments, investors, and scholars (Akey and Appel 2019, 2021). In this paper, we link firms' toxic releases to their green innovation measured by green patents, which have the potential to mitigate environmental and climate change problems.

Our empirical findings suggest that firms with high toxic release levels produce more valuable, high-quality green patents than their counterparts with lower levels of toxic releases. Further evidence implies that our results are driven mainly by emissions associated with human health impacts and onsite toxic releases, indicating that firms that impose the most adverse externalities on public health actually exert more efforts toward green innovation. Moreover, we find that high-emission firms use both explorative and exploitative innovation strategies in their green patenting efforts and contribute to the generation of environmental and CCM technologies.

We employ the expansions of the TRI chemical list to mitigate endogeneity concerns. The additions of new chemicals to the TRI reporting list capture the exogenous increases in the corporate toxic releases administered under the TRI program.

We show that the firms reporting emissions of the newly added chemicals significantly increase their green patenting following the implementations of new chemical lists relative to the firms that do not release the newly added chemicals.

We take advantage of two shocks, President Trump's election and the BP Deepwater Horizon oil spill, to examine the channels through which firms' toxic emission levels affect green innovation. First, in the analysis based on Trump's election, we find that high-emission companies, particularly those headquartered in the U.S., significantly reduced their efforts to generate green patents during the Trump administration due to decreased potential regulatory liabilities and risks. Second, our results using the BP Deepwater Horizon oil spill show that extractive firms with higher toxic releases at the time of the Deepwater Horizon shock were more reactive in strengthening their green patenting in the years following this event because of improved external environmental awareness.

Moreover, we examine the implications of corporate green innovation and show that firms' green patents, particularly those related to environmental issues, mitigate toxic (air) releases, indicating that high-pollution companies' green innovation is not simply a form of greenwashing activity. Moreover, we document that the green patents generated by high-pollution firms have greater both within- and outside-industry citations. This finding indicates that their green innovation not only assists their peer firms in the same industries but also helps firms in other industries expand the green technology horizon. However, environmentally conscious institutional investors tend to resort to crude divestment without considering these external implications for high-emission firms. Finally, we find that when facing financial constraints, high-pollution firms sacrifice nongreen patenting rather than green patenting.

Overall, we demonstrate the positive effect of firms' toxic emissions on their green innovation and that this effect can be affected by local environmental and climate policies as well as environmental awareness.

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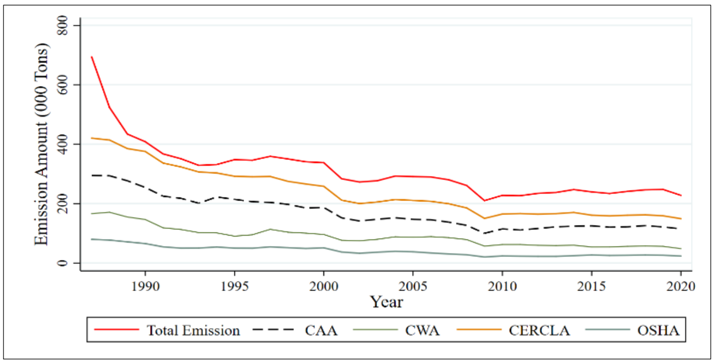
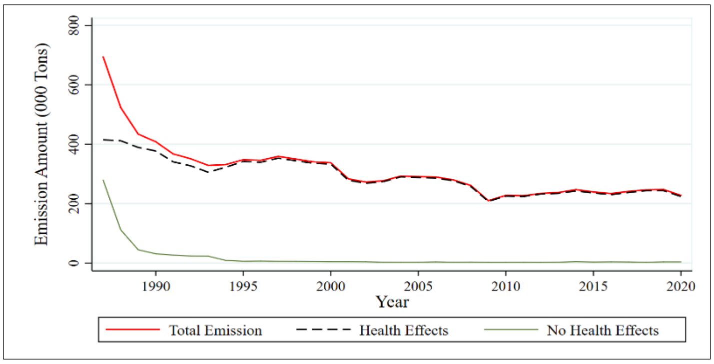
Figure 1. Toxic Release Time Series

This figure shows the time series of toxic releases for public firms in our sample from 1987 through 2020. In Panel A, we include the total toxic emission volumes (in thousands of tons) and toxic emissions under various EPA acts (including the Clean Air Act (CAA), Clean Water Act (CWA), Compensation and Liability Act (CERCLA), and Compensation and Liability Act (CERCLA)) (in thousands of tons). Panel B presents the time series of toxic releases grouped by health effects (including emissions with and without health effects, namely, *Health Effects Emission* and *No Health Effects Emission*, respectively). Additionally, we include toxic emissions released onsite and offsite in Panel C and show the time series of toxic releases grouped by physical properties (including air, water, and ground releases) in Panel D.

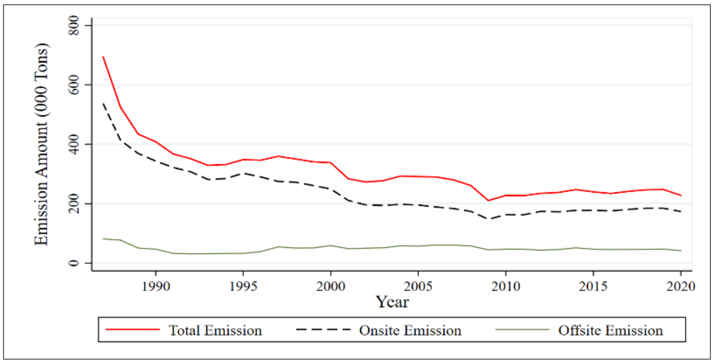
Panel A. Toxic emissions under various EPA regulations



Panel B. Toxic emissions grouped by health effects



Panel C. Toxic emissions released onsite and offsite



Panel D. Toxic emissions grouped by physical properties

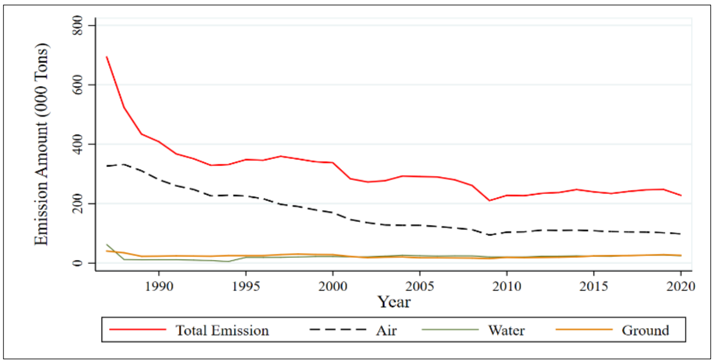


Table 1. Summary Statistics

The final sample consists of 20,712 firm-year observations for 1,562 unique firms during 1987-2020. Panel A presents the statistics on corporate green innovation. Panel B reports the descriptive statistics on the corporate toxic emissions. The raw release levels are shown in 1000 pounds (labeled "(1000s)"). Finally, Panel C shows the descriptive statistics on the firm characteristics. All the firm-level continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix.

Variables	Mean	Median	Std. Dev.	p25	p75
Panel A: Corporate green innovation					
Green Pat	1.94	0.00	7.53	0.00	0.00
Ln(Green Pat)	0.36	0.00	0.84	0.00	0.00
Ln(Tot GPat Cites)	0.29	0.00	0.77	0.00	0.00
Ln(GPat(Tot Env))	0.17	0.00	0.52	0.00	0.00
Ln(GPat(Tot CCM))	0.30	0.00	0.76	0.00	0.00
Ln(Explorative GPat)	0.21	0.00	0.58	0.00	0.00
Ln(Exploitative GPat)	0.15	0.00	0.50	0.00	0.00
Ln(Avg GPat Real Value)	0.46	0.00	1.00	0.00	0.00
Ln(Avg GPat Nominal Value)	0.57	0.00	1.23	0.00	0.00
Ln(Tot GPat Real Value)	0.71	0.00	1.59	0.00	0.00
Ln(Tot GPat Nominal Value)	0.84	0.00	1.82	0.00	0.00
Panel B: Corporate toxic emissions					
Total Release (1000s)	1532.05	55.54	5620.91	4.86	427.78
CAA Release (1000s)	737.29	22.90	2752.23	0.59	214.13
CWA Release (1000s)	381.24	8.72	1620.84	0.02	89.15
CERCLA Release (1000s)	1101.45	40.71	4094.75	2.88	322.81
OSHA Release (1000s)	163.99	1.46	603.62	0.00	41.05
Air Release (1000s)	549.61	28.08	1831.54	1.21	210.18
Water Release (1000s)	49.90	0.00	260.23	0.00	0.14
Ground Release (1000s)	347.20	0.00	1794.42	0.00	0.01
Health Effects Release (1000s)	1449.57	50.58	5305.10	4.12	401.05
No Health Effects Release (1000s)	23.49	0.00	115.89	0.00	0.14
RSEI Hazard (1000s)	9.828e+08	125027.67	5185134604.62	1008.00	22038096.00
Onsite Release (1000s)	1233.37	33.61	4631.23	1.50	300.85
Offsite Release (1000s)	152.22	0.93	581.28	0.00	33.25
Ln(Total Release)	10.26	10.92	4.05	8.49	12.97
Ln(CAA Release)	8.89	10.04	4.68	6.38	12.27
Ln(CWA Release)	7.59	9.07	4.94	2.86	11.40
Ln(CERCLA Release)	9.81	10.61	4.22	7.96	12.68
Ln(OSHA Release)	6.35	7.29	5.01	0.00	10.62
Ln(Air Release)	9.18	10.24	4.37	7.10	12.26
Ln(Water Release)	2.59	0.00	4.10	0.00	4.95
Ln(Ground Release)	2.52	0.00	4.72	0.00	2.48
Ln(Health Effects Release)	10.12	10.83	4.13	8.32	12.90
Ln(No Health Effects Release)	2.42	0.00	4.18	0.00	4.94
Ln(RSEI Hazard)	18.24	18.64	7.30	13.82	23.82
Ln(Onsite Release)	9.51	10.42	4.46	7.31	12.61
Ln(Offsite Release)	6.05	6.83	5.03	0.00	10.41
Panel C: Firm characteristics					
Capex/Assets	0.05	0.04	0.04	0.03	0.07
ROA	0.09	0.09	0.08	0.06	0.13
PPE/Assets	0.32	0.29	0.18	0.18	0.43
Profit Margin	0.08	0.09	0.44	0.05	0.14
Tobin's q	1.69	1.42	0.97	1.14	1.92
Leverage	0.46	0.45	0.18	0.34	0.56
Ln(Market Equity)	6.95	7.00	2.12	5.50	8.44
Cash	0.07	0.04	0.08	0.01	0.10
R&D/Assets	0.02	0.01	0.04	0.00	0.03

Table 2. Firms' Toxic Emissions and Green Innovation

This table presents regression estimates of firms' quantity and quality of green patents on total toxic emissions (measured by pounds in natural logarithm). Columns (1) and (2) show the results for total R&D expenses. Columns (3) and (4) report the results for the quantity of green patents. Finally, Columns (5) and (6) present the results for the quality of green patents. For odd columns, the dependent variables are calculated in year *t+1*, while for even columns, they are measured in year *t+2*. All dependent variables are multiplied by 1000. The sample period is from 1987 to 2020. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, and *Cash*, while *R&D/Assets* is included in Columns (3) to (6). Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) RD/AT (t+1)	(2) RD/AT (t+2)	(3) Ln(Green Pat) (t+1)	(4) Ln(Green Pat) (t+2)	(5) Ln(Tot GPat Cites) (t+1)	(6) Ln(Tot GPat Cites) (t+2)
Ln(Total Release)	0.213	0.147	8.635***	10.154***	6.400**	9.212**
	(1.336)	(0.943)	(2.773)	(2.908)	(2.045)	(2.573)
Capex/Assets	19.154***	17.395***	-181.110	-232.467*	-72.771	-116.085
	(3.092)	(3.025)	(-1.428)	(-1.783)	(-0.542)	(-0.827)
ROA	-10.133*	-8.559	-176.946*	-189.653*	-240.111**	-252.349**
	(-1.835)	(-1.407)	(-1.865)	(-1.922)	(-2.447)	(-2.372)
PPE/Assets	12.826***	10.858**	98.144	160.732**	39.445	84.964
	(2.859)	(2.357)	(1.259)	(2.026)	(0.530)	(1.105)
Profit Margin	-2.172**	6.040	-9.079	-6.741	-4.196	12.631
	(-2.387)	(1.616)	(-0.852)	(-0.739)	(-0.407)	(1.248)
Tobin's q	1.516**	0.838	0.897	9.941	-5.943	1.751
	(2.364)	(1.291)	(0.078)	(0.842)	(-0.503)	(0.141)
Leverage	3.031	3.598	38.526	28.795	52.417	19.091
	(1.286)	(1.519)	(0.757)	(0.545)	(1.053)	(0.351)
Ln(Market Equity)	-1.050*	-0.885	69.121***	73.371***	76.203***	78.159***
	(-1.773)	(-1.564)	(5.295)	(5.320)	(5.847)	(5.716)
Cash	13.179**	15.307*	-14.611	57.058	61.247	118.934
	(2.087)	(1.917)	(-0.163)	(0.604)	(0.618)	(1.171)
R&D/Assets			-150.117	-185.721	435.756	512.612
			(-0.326)	(-0.380)	(0.994)	(1.060)
Observations	20,712	18,965	20,712	18,965	20,712	18,965
Adjusted R-squared	0.835	0.839	0.763	0.767	0.692	0.695
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3. Nature of High-Emission Firms' Green Innovation

Panel A presents the results on whether high-emission firms produce green patents with high values. Columns (1) and (2) of Panel A show regression results for the total (real and nominal) patent values, while Columns (3) and (4) of Panel A report the results for the average (real and nominal) patent values. Panel B analyzes which categories of green patents are primarily focused on by high-emission firms. The dependent variables are shown in an abbreviated format for readability; only *Var.* of *Ln(GPat(Var.))* are presented as dependent variables in this table. Panel C analyzes which types of innovation strategies are used by high-emission firms in green innovation. Columns (1) and (2) of Panel C show the results for the log number of explorative and exploitative green patents filed, respectively. The sample period is from 1987 to 2020. All dependent variables are calculated in year *t+1* and are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Toxic emissions and corporate innovation value

	(1) Ln(Tot GPat Real Value)	(2) Ln(Tot GPat Nominal Value)	(3) Ln(Avg GPat Real Value)	(4) Ln(Avg GPat Nominal Value)
Ln(Total Release)	13.326**	15.477**	6.918*	8.718*
	(2.281)	(2.241)	(1.690)	(1.741)
Observations	20,712	20,712	20,712	20,712
Adjusted R-squared	0.720	0.706	0.598	0.598
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes

Panel B: Specific categories of green innovation

Dependent Variables➔ *Ln(GPat(Var.))*	(1) Env Mgt	(2) Water Adapt	(3) CCM Energy	(4) CCM GH Gases	(5) CCM Transport	(6) CCM Build	(7) CCM Waste	(8) CCM Goods	(9) Tot Env	(10) Tot CCM
Ln(Total Release)	6.539***	0.302	3.584**	0.544*	1.980	-0.053	1.645**	5.546***	6.884***	6.697**
	(3.181)	(0.861)	(2.098)	(1.856)	(1.233)	(-0.032)	(2.146)	(2.650)	(3.229)	(2.286)
Observations	20,712	20,712	20,712	20,712	20,712	20,712	20,712	20,712	20,712	20,712
Adjusted R-squared	0.690	0.397	0.622	0.375	0.695	0.632	0.312	0.653	0.701	0.740
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Toxic emissions and green innovation strategy

	(1) Ln(Explorative GPat)	(2) Ln(Exploitative GPat)
Ln(Total Release)	6.080***	4.665**
	(2.814)	(2.118)
Observations	20,712	20,712
Adjusted R-squared	0.707	0.661
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry-year FE	Yes	Yes

Table 4. Identification: Expansions of TRI Chemical List

This table analyzes the effect of expansions of the TRI chemical list on corporate green innovation by employing a cohort-based DiD approach. Specifically, for each chemical-list expansion year, we construct a cohort consisting of treatment firms reporting emissions of the newly added chemicals after the expansion and control firms within the same 2-digit SIC industries of treatment firms that do not emit any added chemicals. Each cohort includes firm-year observations for the five years before and the five years after the new regulation (i.e., list expansion) becomes effective. For each cohort, we require that companies do not report new chemicals required by the other TRI chemical list expansions. Finally, we pool all cohorts together to form the final sample, which contains the major TRI list expansions in 1990, 1991, 1994, 1995, 2000, 2011, 2012, 2014, 2015, 2016, 2017, and 2019. *Treat* is a dummy variable that equals one for treatment groups and zero for control groups. *Post* is a dummy variable that equals one for the five years after the expansions of the TRI chemical list and zero for the five years before the expansions. The sample period is from 1987 to 2020. All dependent variables are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Ln(Green Pat)	Ln(Tot GPat Cites)
Treat × Post	103.966***	84.624***
	(3.265)	(2.748)
Treat	-52.260	-36.818
	(-1.594)	(-1.519)
Post	-7.671*	-9.681**
	(-1.948)	(-2.366)
Observations	11,721	11,721
Adjusted R-squared	0.779	0.730
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry-year FE	Yes	Yes

Table 5. Effect of the 2016 Election of President Trump

This table analyzes the effect of President Trump's election in 2016. Columns (1) through (3) show the results for the quantity, quality, and value of green innovation, respectively. Columns (4) and (5) report the results for the quantity of environmental (Env) and climate change mitigation (CCM) patents. Finally, Columns (4) and (5) present the results for the quantity of explorative and exploitative green patents. The sample period is from 2015 through 2018, which corresponds to the four years surrounding Trump's election on November 9, 2016. All dependent variables are calculated in year *t+1* and are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Green Patents			Env & CCM		Explorative & Exploitative	
	Ln(Green Pat)	Ln(Tot GPat Cites)	Ln(Tot GPat Real Value)	Ln(GPat(Tot Env))	Ln(GPat(Tot CCM))	Ln(Explorative GPat)	Ln(Exploitative GPat)
Ln(Total Release) × Post Election	-15.714***	-19.591***	-29.996***	-8.590***	-17.295***	-8.627**	-9.143**
	(-3.119)	(-3.508)	(-2.876)	(-2.732)	(-3.112)	(-2.486)	(-2.489)
Ln(Total Release)	2.296	7.247	-8.852	3.111	3.589	-1.147	0.513
	(0.359)	(1.264)	(-0.638)	(0.711)	(0.614)	(-0.244)	(0.145)
Post Election	-	-	-	-	-	-	-
Observations	2,079	2,079	2,079	2,079	2,079	2,079	2,079
Adjusted R-squared	0.791	0.496	0.727	0.792	0.719	0.705	0.685
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Effect of the BP Deepwater Horizon Oil Spill

This table presents regression estimates of the effects of the BP Deepwater Horizon oil spill for the years 2008 through 2011, which correspond to the four years surrounding the event that began on April 20, 2010. Panel A reports the overall impact of the BP Deepwater Horizon oil spill on the *Treated* firms, which are identified by the two-digit Standard Industrial Classification (SIC) code (i.e., SIC 13, Oil and Gas Extraction). Panel B presents the difference-in-differences regression results to examine the impact of the BP Deepwater Horizon oil spill on the relationship between firms' toxic emission levels and corporate green innovation. Columns (1) and (3) do not include fixed effects, while Columns (2) and (4) include industry and year fixed effects. Standard errors are clustered at the industry level. The two-year pre- and post-event periods are each collapsed into one observation, and *Ln(Total Release)* is the total toxic emissions measured over the pre-event period. All dependent and independent variables are calculated for year *t*. All dependent variables are multiplied by 1000. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Robust t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The overall effect of the BP Deepwater Horizon oil spill

	(1)	(2)	(3)	(4)
	Ln(Green Pat)		Ln(Tot GPat Cites)	
Treated Firm × Post-2010	281.612***	259.676***	169.131***	155.552***
	(7.298)	(10.270)	(4.185)	(4.170)
Treated Firm	-39.863		298.911**	
	(-0.264)		(2.380)	
Post-2010	-9.082		-48.631***	
	(-0.498)		(-3.042)	
Observations	1,229	1,224	1,229	1,224
Adjusted R-squared	0.281	0.353	0.240	0.310
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

Panel B: Difference-in-differences regressions

	(1)	(2)	(3)	(4)
	Ln(Green Pat)		Ln(Tot GPat Cites)	
Ln(Total Release) × Treated Firm × Post-2010	45.401**	63.326***	35.548**	50.862***
	(2.519)	(6.364)	(2.309)	(5.330)
Ln(Total Release)	17.060**	16.706*	12.232*	12.834*
	(2.497)	(1.881)	(1.831)	(1.688)
Treated Firm	603.606***	-	657.576***	-
	(3.918)		(4.592)	
Post-2010	7.627	-	-23.418	-
	(0.179)		(-0.549)	
Observations	1,198	1,194	1,198	1,194
Adjusted R-squared	0.276	0.347	0.233	0.302
Other Interactions	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

Table 7. Corporate Green Innovation and Toxic Air Releases

This table presents the results from regression estimates of changes in the log pounds of toxic air releases on environmental and CCM green innovation. Changes in the log pounds of toxic air releases (*ΔLn(Air Release)*) are calculated for five different periods, namely, from year –1 to year 1 through year 5. Then, the following regression specification is used in the analysis: $\Delta Ln(Air\ Release)_{i,t+1} = \alpha + \beta Green\ Innovation_{i,t} + \gamma Controls_{i,t} + FEs + \epsilon_{i,t}$. The sample period is from 1987 to 2020. Firm-level controls include lagged *Capex/assets*, *ROA*, *PPE/assets*, *Profit margin*, *Tobin's q*, *Leverage*, *Ln (market equity)*, *Cash*, and *R&D/assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. *Newey-West correction* with five lags is employed in the calculation of standard errors. Standard errors are clustered at the firm and year level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Year −1 to Year 1		Year −1 to Year 2		Year −1 to Year 3		Year −1 to Year 4		Year −1 to Year 5	
	Δ Ln(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)
Ln(GPat(Tot Env))	-0.082		-0.148**		-0.197***		-0.207***		-0.210**	
	(-1.660)		(-2.133)		(-3.120)		(-3.016)		(-2.476)	
Ln(GPat(Tot CCM))		-0.068		-0.084		-0.102		-0.077		-0.080
		(-1.209)		(-1.229)		(-1.459)		(-1.038)		(-0.988)
Observations	18,737	18,737	17,154	17,154	15,747	15,747	14,505	14,505	13,352	13,352
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. External Implications of High-Pollution Firms' Green Innovation

This table presents the results on whether high-emission firms' green patents have more within-industry and outside-industry citations. *Ln(InIndGcites)* is the natural logarithm of one plus the total number of forward adjusted within-industry citations received by the firm's green patents filed and eventually granted. *Ln(OutIndGcites)* is the natural logarithm of one plus the total number of forward adjusted outside-industry citations received by the firm's green patents filed and eventually granted. We define within-industry and outside-industry based on four-digit SIC in our analysis. Our results are robust when within-industry and outside-industry are defined based on two-digit or three-digit SIC. Columns (1) and (2) show the regression results for within-industry citations, while Columns (3) and (4) report the results for outside-industry citations. Columns (1) and (3) do not include fixed effects, while Columns (2) and (4) include firm and industry-year fixed effects. The sample period is from 1987 to 2020. All dependent variables are calculated in year *t+1* and are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Ln(InIndGcites)	Ln(InIndGcites)	Ln(OutIndGcites)	Ln(OutIndGcites)
Ln(Total Release)	13.633***	4.891**	10.819***	5.018**
	(5.432)	(2.135)	(4.663)	(2.154)
Observations	21,165	20,712	21,165	20,712
Adjusted R-squared	0.123	0.548	0.122	0.540
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry-year FE	No	Yes	No	Yes

Table 9. Large Polluters' Green Innovation and Environmentally Conscious Institutional Ownership

This table examines whether larger polluters' green innovation efforts lead to higher environmentally conscious institutional ownership. *EnvIO* is defined as the percentage of common shares held by environmentally conscious institutions. *Large polluter* is defined as firms with total toxic emissions above the 70th, 75th, and 80th percentiles of the sample distribution. All dependent variables are calculated in year *t+1* and are multiplied by 1000. The sample period is from 1992 to 2019. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, and *Cash*, while *R&D/Assets* is included in Columns (3) to (6). Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	70th percentile		75th percentile		80th percentile	
	(1)	(2)	(3)	(4)	(5)	(6)
	EnvIO	EnvIO	EnvIO	EnvIO	EnvIO	EnvIO
Ln(Green Pat)	-3.397	3.071	-3.610	2.840	-3.504	2.566
	(-0.732)	(0.613)	(-0.781)	(0.609)	(-0.760)	(0.550)
Large polluter	-18.000**	-9.593	-22.401***	-10.848	-17.032*	-0.447
	(-2.402)	(-1.258)	(-2.980)	(-1.496)	(-1.866)	(-0.054)
Ln(Green Pat) × Large polluter		-17.304**		-21.624***		-26.586***
		(-2.167)		(-3.282)		(-4.126)
Observations	12,927	12,927	12,927	12,927	12,927	12,927
Adjusted R-squared	0.711	0.712	0.711	0.712	0.711	0.712
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10. The Effect of Financial Constraints

This table analyzes the effect of financial constraints. Columns (1) and (2) report the results for the quantity and quality of total patents. Columns (3) and (4) present the results for the quantity and quality of nongreen patents. Columns (5) and (6) show the regression results for the quantity and quality of green patents. Columns (7) and (8) present the results for environmental (Env) and CCM patents. To address the missing values in the financial constraint variable (i.e., *HM Debt*), we follow Hoberg and Maksimovic (2015) to include a dummy (i.e., *No HM Debt Information*) to capture the missing observations. The sample period is from 1997 to 2015. All dependent variables are calculated in year *t+1* and are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total innovation		Nongreen innovation		Green innovation		Env & CCM	
	Ln(All Pat)	Ln(Tot AllPat Cites)	Ln(nonGPat)	Ln(Tot NGPat Cites)	Ln(Green Pat)	Ln(Tot GPat Cites)	Ln(GPat(Tot Env))	Ln(GPat(Tot CCM))
Ln(Total Release)	27.163***	27.954***	28.915***	29.303***	9.291*	9.073	7.129*	8.163*
	(3.282)	(3.207)	(3.525)	(3.432)	(1.794)	(1.631)	(1.817)	(1.659)
Ln(Total Release) × High HM Debt	-9.169**	-8.572**	-9.410**	-8.972**	-1.461	-3.181	-1.778	-0.906
	(-2.183)	(-2.004)	(-2.249)	(-2.117)	(-0.572)	(-1.183)	(-0.915)	(-0.379)
High HM Debt	107.811**	96.638**	109.035**	97.664**	18.841	23.018	21.775	9.322
	(2.252)	(1.964)	(2.281)	(1.986)	(0.678)	(0.767)	(1.075)	(0.359)
No HM Debt Information	11.384	-3.568	10.686	-5.263	6.473	3.727	20.279	-0.020
	(0.388)	(-0.117)	(0.369)	(-0.171)	(0.336)	(0.187)	(1.539)	(-0.001)
Observations	11,384	11,384	11,384	11,384	11,384	11,384	11,384	11,384
Adjusted R-squared	0.915	0.902	0.915	0.902	0.830	0.761	0.755	0.821
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix

Table A.1. Variable Definitions

Variables	Definition
Dependent Variables:	
Ln(Green Pat)	Natural logarithm of one plus the number of green patents filed (and eventually granted).
Ln(Tot GPat Cites)	Natural logarithm of one plus the total number of forward adjusted citations received by the firm's green patents filed and eventually granted. Each patent's adjusted citation count is calculated by dividing the citation count it receives by the average number of citations received by all patents in the same industry and year as the focal firm (Mudambi and Swift 2014), where the industry is defined at the three-digit SIC code level.
Ln(GPat(Env Mgt))	Natural logarithm of one plus the number of green patents filed (and eventually granted) that are classified as environmental management technologies.
Ln(GPat(Water Adapt))	Natural logarithm of one plus the number of green patents filed (and eventually granted) that are classified as water-related adaptation technologies.
Ln(GPat(CCM Energy))	Natural logarithm of one plus the number of green patents filed (and eventually granted) that are classified as climate change mitigation technologies related to energy generation, transmission or distribution.
Ln(GPat(CCM GH Gases))	Natural logarithm of one plus the number of green patents filed (and eventually granted) that are classified as climate change mitigation technologies related to capture, storage, sequestration or disposal of greenhouse gases.
Ln(GPat(CCM Transport))	Natural logarithm of one plus the number of green patents filed (and eventually granted) that are classified as climate change mitigation technologies related to transportation.
Ln(GPat(CCM Build))	Natural logarithm of one plus the number of green patents filed (and eventually granted) that are classified as climate change mitigation technologies related to buildings.
Ln(GPat(CCM Waste))	Natural logarithm of one plus the number of green patents filed (and eventually granted) that are classified as climate change mitigation technologies related to wastewater treatment or waste management.
Ln(GPat(CCM Goods))	Natural logarithm of one plus the number of green patents filed (and eventually granted) that are classified as climate change mitigation technologies in the production or processing of goods.
Ln(GPat(Tot Env))	Natural logarithm of one plus the number of green patents filed (and eventually granted) that are classified as environmental technologies. It includes the green patents classified as environmental management and water-related adaptation technologies.
Ln(GPat(Tot CCM))	Natural logarithm of one plus the number of green patents filed (and eventually granted) that are classified as climate change mitigation technologies.
Ln(Explorative GPat)	Natural logarithm of one plus the number of explorative green patents filed (and eventually granted). A green patent is categorized as explorative if at least 60% of its citations (i.e., patents cited by the focal patent) do not refer to existing knowledge, which includes all the patents that the firm invented and all the patents that were cited by the firm's patents filed over the past five years.
Ln(Exploitative GPat)	Natural logarithm of one plus the number of exploitative green patents filed (and eventually granted). A green patent is categorized as exploitative if at least 60% of its citations (i.e., patents cited by the focal patent) are based on the firm's existing knowledge, which includes all the patents that the firm invented and all the patents that were cited by the firm's patents filed over the past five years.
Ln(Tot GPat Real Value)	Natural logarithm of one plus the total value of green innovation deflated to 1982 (million) dollars using the consumer price index (CPI). Value of innovation is constructed as the product of the estimate of the stock return due to the value of the patent and market capitalization of the firm divided by the number of patents granted to the same firm on the same day and multiplied by 2.27 (=1/(1-0.56)), where 0.56 is the unconditional probability of a successful patent application (Kogan et al. 2017).
Ln(Tot GPat Nominal Value)	Natural logarithm of one plus the total value of green innovation in millions of nominal dollars. Value of innovation is constructed as above.

Ln(Avg GPat Real Value)	Natural logarithm of one plus [the total value of green innovation deflated to 1982 (million) dollars using the consumer price index (CPI) scaled by the total number of green patents filed].
Ln(Avg GPat Nominal Value)	Natural logarithm of one plus [the total value of green innovation in millions of nominal dollars scaled by the total number of green patents filed].
Ln(All Pat)	Natural logarithm of one plus the number of both green and nongreen patents filed (and eventually granted).
Ln(nonGPat)	Natural logarithm of one plus the number of nongreen patents filed (and eventually granted).
Ln(Tot AllPat Cites)	Natural logarithm of one plus the total number of forward adjusted citations received by the firm's all patents filed and eventually granted.
Ln(Tot NGPat Cites)	Natural logarithm of one plus the total number of forward adjusted citations received by the firm's nongreen patents filed and eventually granted.
Ln(InIndGcites)	Natural logarithm of one plus the total number of forward adjusted within-industry citations received by the firm's green patents filed and eventually granted.
Ln(OutIndGcites)	Natural logarithm of one plus the total number of forward adjusted outside-industry citations received by the firm's green patents filed and eventually granted.
Key Independent Variables:	
Ln(Total Release)	Natural logarithm of one plus the pounds of total toxic releases administered under the TRI program.
Ln(CAA Release)	Natural logarithm of one plus the pounds of toxic releases administered under the Clean Air Act.
Ln(CWA Release)	Natural logarithm of one plus the pounds of toxic releases administered under the Clean Water Act.
Ln(CERCLA Release)	Natural logarithm of one plus the pounds of toxic releases administered under the Comprehensive Environmental Response, Compensation, and Liability Act.
Ln(OSHA Release)	Natural logarithm of one plus the pounds of toxic releases administered by the Occupational Safety and Health Administration.
Ln(Air Release)	Natural logarithm of one plus the pounds of toxic releases through air.
Ln(Water Release)	Natural logarithm of one plus the pounds of toxic releases through water.
Ln(Ground Release)	Natural logarithm of one plus the pounds of toxic releases through ground.
Ln(Health Effects Release)	Natural logarithm of one plus the pounds of toxic releases associated with health effects.
Ln(No Health Effects Release)	Natural logarithm of one plus the pounds of toxic releases not associated with health effects.
Ln(RSEI Hazard)	Natural logarithm of one plus the toxic releases multiplied by EPA's Risk-Screening Environmental Indicators (RSEI) toxicity weight.
Ln(Onsite Release)	Natural logarithm of one plus the pounds of total toxic releases to air, water and land onsite at the facility.
Ln(Offsite Release)	Natural logarithm of one plus the pounds of total toxic releases reported as transferred to offsite locations for release or disposal.
Control Variables:	
Capex/Assets	Ratio of capital expenditure to total assets.
Cash	Ratio of cash holdings to total assets.
Leverage	Sum of long-term and short-term debt divided by total assets.
Ln(Market Equity)	Natural logarithm of the market value of equity
PPE/Assets	Ratio of fixed assets to total assets.
Profit Margin	Ratio of operating income after depreciation to total sales.
R&D/Assets	Maximum (0, Research and development expense scaled by total assets)
ROA	Ratio of operating income after depreciation to total assets.
Tobin's q	Tobin's q is calculated as (total assets + market value of equity - book value of equity) divided by total assets.

Internet Appendix

for "Toxic Emissions and Corporate Green Innovation"

This Internet Appendix reports the tables and figures for additional evidence or tests that are not shown in the main manuscript of the paper. Specifically, Section I presents the details of company name string-matching process. Section II reports the additional tests and summary statistics. Section III reports the results of the survey that are based on the responses of the members of the Australian Corporate Treasury Association (ACTA). The survey results provide important insights into the motivations behind green innovation and help support our hypothesis.

In summary, this Internet Appendix contains the following sections, tables and figures.

I. Company Name String-Matching Process

II. Additional Robustness Tests and Summary Statistics:

- IA Table 1. Firms' Toxic Emissions and Green Innovation (Sample Ends in 2017)
- IA Table 2. Summary Statistics - Subcategories of Green Innovation
- IA Table 3. Firms' Toxic Emissions and Green Innovation (Poisson Estimation)
- IA Table 4. Firms' Toxic Emission Intensities and Green Innovation
- IA Table 5. Toxic Emissions Under Various EPA Acts
- IA Table 6. Toxic Emissions Grouped by Health Effects
- IA Table 7. Toxic Emissions Grouped by Release Sites and Physical Properties
- IA Table 8. Firms' Toxic Emissions and Green Innovation (Excluding the Energy Sector)
- IA Table 9. Industry-Level Average of Green Patents and Total Releases
- IA Table 10. Identification: Expansions of TRI Chemical List (DiD-IV)
- IA Table 11. Effect of President Trump's 2016 Election (DiD Analysis) – Alternative Measure
- IA Table 12. Effect of President Trump's 2016 Election: PSM-DDD Analysis
- IA Table 13. Test of Parallel Trends for Trump's Election Analysis

III. Survey Results:

Ⅰ. *Company Name String-Matching Process*

The TRI toxic emissions data do not contain company-level identifiers (e.g., GVKEY, PERMCO) but record the historical names of establishments' parent firms. Therefore, we employ a string-matching process to match the TRI plants to Compustat companies. Using historical parent company names is crucial for our matching. For instance, Google, Inc., went public through an initial public offering (IPO) in 2004, and in October 2015, Google was reorganized as a wholly owned subsidiary of Alphabet, Inc. As a result, GVKEY 160329 should be linked to the historical parent names "Google, Inc.," from 2004 through 2014 and to "Alphabet, Inc.," from 2015 through 2020. Since Compustat only provides the most up-to-date parent firm names, following Xu and Kim (2022), we obtain historical company names from CRSP and supplement the data with name information from 10K, 10-Q, and 8-K filings using the SEC Analytical Package of Wharton Research Data Service (WRDS) to ensure the accuracy of the matching. We then use the CRSP/Compustat Linking Table from WRDS to match the obtained historical company names to the Compustat firms identified by GVKEYs.

The string-matching process is labor intensive, and the first step is cleaning the historical firm names in both the TRI and Compustat/CRSP/SEC datasets. Specifically, we convert the historical names of parent companies to uppercase letters, remove all punctuation marks to keep alphanumeric characters, and standardize the common "full form" words to consistent abbreviations and acronyms (e.g., substitute "corporation" with "corp" and "international" with "intl"). Next, we use a string-matching command (i.e., -reclink- package) in Stata to generate similarity scores between the deduplicated TRI parent names and Compustat/CRSP/SEC historical company names. We then rank the potential matches according to similarity scores (from high to low) and manually check and assess the potential matches by comparing the alphanumeric characters and the effective periods of the historical parent names in the TRI and Compustat/CRSP/SEC datasets. The matches with similarity scores equal to 100% are also manually checked to ensure accuracy. We then exclude matched names from the total deduplicated TRI parent names and conduct the next iteration. Each iteration includes both data cleaning and manual checking and assessment. Specifically, according to spurious matches in the previous iteration, we further perform additional standardization for the common “full form” words before each subsequent iteration. After five iterations, the percentage of correct matches became excessively low; therefore, we end our string-matching process. Finally, the matching results generated in the iterations are combined.

Ⅱ. *Additional Robustness Tests and Summary Statistics*

In this section, we present the results of additional robustness checks and descriptive statistics.

IA Table 1. Firms' Toxic Emissions and Green Innovation (Sample Ends in 2017)

This table presents OLS regression estimates of firms' quantity and quality of green patents on total toxic emissions (measured by pounds in natural logarithm). Columns (1) and (2) show the results for total R&D expenses. Columns (3) and (4) report the results for the quantity of green patents. Finally, Columns (5) and (6) present the results for the quality of green patents. For odd columns, the dependent variables are calculated in year *t+1*, while for even columns, they are measured in year *t+2*. All dependent variables are multiplied by 1000. The sample period is from 1987 to 2017. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, and *Cash*, while *R&D/Assets* is included in Columns (3) to (6). Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) RD/AT (t+1)	(2) RD/AT (t+2)	(3) Ln(Green Pat) (t+1)	(4) Ln(Green Pat) (t+2)	(5) Ln(Tot GPat Cites) (t+1)	(6) Ln(Tot GPat Cites) (t+2)
Ln(Total Release)	0.235	0.155	9.243***	10.802***	7.409**	9.958***
	(1.466)	(0.989)	(2.826)	(2.976)	(2.276)	(2.723)
Capex/Assets	18.074***	16.966***	-166.452	-239.194*	-86.147	-130.714
	(2.887)	(2.936)	(-1.309)	(-1.825)	(-0.656)	(-0.946)
ROA	-7.950	-7.901	-107.841	-137.014	-180.728**	-213.180**
	(-1.450)	(-1.279)	(-1.202)	(-1.470)	(-1.963)	(-2.116)
PPE/Assets	13.085***	10.918**	91.118	169.385**	44.919	94.726
	(2.857)	(2.342)	(1.083)	(2.071)	(0.595)	(1.236)
Profit Margin	-2.062**	6.087	-9.247	-8.324	-4.303	11.586
	(-2.157)	(1.636)	(-0.878)	(-0.939)	(-0.423)	(1.146)
Tobin's q	1.474**	0.807	7.418	13.359	0.088	4.542
	(2.214)	(1.225)	(0.619)	(1.114)	(0.008)	(0.371)
Leverage	3.146	3.751	39.994	32.434	53.496	21.490
	(1.303)	(1.566)	(0.774)	(0.613)	(1.111)	(0.402)
Ln(Market Equity)	-1.131*	-0.887	58.542***	67.988***	69.145***	74.868***
	(-1.878)	(-1.564)	(4.206)	(4.775)	(5.271)	(5.460)
Cash	13.706**	15.416*	-52.326	47.549	35.045	109.424
	(2.099)	(1.887)	(-0.561)	(0.499)	(0.353)	(1.084)
R&D/Assets			-256.700	-259.915	276.620	418.564
			(-0.538)	(-0.523)	(0.634)	(0.867)
Observations	19,701	18,469	19,701	18,469	19,701	18,469
Adjusted R-squared	0.836	0.839	0.785	0.782	0.719	0.709
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

IA Table 2. Summary Statistics - Subcategories of Green Innovation

This table presents the summary statistics on the subcategories of corporate green innovation. The final sample consists of 20,712 firm-year observations for 1,562 unique firms during 1987-2020. All variables in this table are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix.

	N	Mean	Median	Std. Dev.	p25	p75
Ln(GPat(Env Mgt))	20712	0.16	0.00	0.50	0.00	0.00
Ln(GPat(Water Adapt))	20712	0.01	0.00	0.08	0.00	0.00
Ln(GPat(CCM Energy))	20712	0.10	0.00	0.40	0.00	0.00
Ln(GPat(CCM GH Gases))	20712	0.01	0.00	0.09	0.00	0.00
Ln(GPat(CCM Transport))	20712	0.08	0.00	0.38	0.00	0.00
Ln(GPat(CCM Build))	20712	0.08	0.00	0.35	0.00	0.00
Ln(GPat(CCM Waste))	20712	0.03	0.00	0.16	0.00	0.00
Ln(GPat(CCM Goods))	20712	0.14	0.00	0.46	0.00	0.00

IA Table 3. Firms' Toxic Emissions and Green Innovation (Poisson Estimation)

This table presents Poisson regression estimates of firms' quantity and quality of green patenting on total toxic emissions (measured by pounds in natural logarithm). Columns (1) to (4) show the results from Poisson regression, while Columns (5) to (8) present the results from estimating linear regressions of the log of one plus the outcome ("log1plus" regressions) where the sample is restricted to the sample usable in Poisson regression (Cohn et al. 2022). The regression coefficients reported in Columns (1) to (4) are incidence rate ratios (IRRs). For odd columns, the green innovation measures are calculated in year *t+1*, while for even columns, they are measured in year *t+2*. Columns (1), (2), (5), and (6) show the results for firms' quantity of green patenting, while Columns (3), (4), (7), and (8) present the results for firms' quality of green patenting. All dependent variables are multiplied by 1000. The sample period is from 1987 to 2020. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust z-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Poisson				Log1plus Poisson Sample			
	Green Pat (t+1)	Green Pat (t+2)	Tot GPat Cites (t+1)	Tot GPat Cites (t+2)	Ln(Green Pat) (t+1)	Ln(Green Pat) (t+2)	Ln(Tot GPat Cites) (t+1)	Ln(Tot GPat Cites) (t+2)
Ln(Total Release)	1.049**	1.059**	1.086**	1.106***	16.031**	19.779**	12.686*	19.337**
	(2.099)	(2.247)	(2.407)	(2.651)	(2.274)	(2.504)	(1.723)	(2.287)
Capex/Assets	0.335	0.270*	0.824	0.360	-362.350	-520.684	-122.053	-396.933
	(-1.222)	(-1.649)	(-0.163)	(-0.885)	(-1.118)	(-1.616)	(-0.325)	(-1.047)
ROA	0.937	0.999	0.885	1.310	66.808	-41.661	-57.914	-77.296
	(-0.082)	(-0.001)	(-0.129)	(0.348)	(0.219)	(-0.136)	(-0.180)	(-0.238)
PPE/Assets	0.818	1.091	0.859	1.094	232.112	341.278*	32.535	149.476
	(-0.352)	(0.160)	(-0.197)	(0.112)	(1.183)	(1.768)	(0.163)	(0.736)
Profit Margin	0.528	0.674	0.726	0.859	-398.605	-270.970	-344.045	-137.271
	(-0.922)	(-0.660)	(-0.370)	(-0.209)	(-1.493)	(-0.965)	(-1.246)	(-0.564)
Tobin's q	0.985	1.005	1.043	1.107**	8.443	21.155	-6.207	1.111
	(-0.287)	(0.109)	(0.762)	(2.090)	(0.401)	(0.996)	(-0.276)	(0.048)
Leverage	0.820	0.839	0.577	0.590	53.723	32.333	66.340	-40.304
	(-0.681)	(-0.625)	(-1.365)	(-1.411)	(0.490)	(0.288)	(0.617)	(-0.347)

Ln(Market Equity)	1.322***	1.280***	1.238***	1.195**	126.648***	126.339***	138.795***	135.200***
	(3.565)	(3.086)	(2.903)	(2.254)	(4.549)	(4.262)	(4.811)	(4.410)
Cash	0.821	1.196	1.826	0.582	-60.560	54.440	156.720	234.771
	(-0.436)	(0.364)	(0.737)	(-0.769)	(-0.300)	(0.262)	(0.659)	(0.987)
R&D/Assets	0.217	0.167	0.085	0.058**	-733.370	-723.677	293.051	302.678
	(-1.002)	(-1.299)	(-1.618)	(-2.361)	(-0.998)	(-0.961)	(0.398)	(0.390)
Observations	9,624	8,969	8,805	8,166	9,624	8,969	8,805	8,166
Adjusted R-squared					0.737	0.742	0.681	0.684
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

IA Table 4. Firms' Toxic Emission Intensities and Green Innovation

This table presents OLS regression estimates of firms' quantity and quality of green patents on total toxic emission intensities. The proxies for toxic emission intensities are (1) *Ln(Total Release/Assets)*, defined as the natural logarithm of one plus [the pounds of total toxic releases scaled by total assets]; (2) *Ln(Total Release/Revenue)*, defined as the natural logarithm of one plus [the pounds of total toxic releases scaled by total revenues]. The results are consistent without taking natural logarithm of the emission intensity measures. Columns (1) and (2) report the results for the quantity of green patents. Columns (3) and (4) present the results for the quality of green patents. The dependent variables are calculated in year *t+1*. All dependent variables are multiplied by 1000. The sample period is from 1987 to 2017. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, and *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Ln(Green Pat)	Ln(Green Pat)	Ln(Tot GPat Cites)	Ln(Tot GPat Cites)
Ln(Total Release/Assets)	349.641*		289.885*	
	(1.699)		(1.759)	
Ln(Total Release/Revenue)		222.649*		186.847*
		(1.679)		(1.731)
Observations	20,712	20,712	20,712	20,712
Adjusted R-squared	0.762	0.762	0.692	0.692
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes

IA Table 5. Toxic Emissions Under Various EPA Acts

This table shows the regression results of firms' green patenting on toxic emissions administered under various EPA acts. The toxic emissions measures include the log pounds of toxic releases regulated under the Clean Air Act (CAA), the Clean Water Act (CWA), the Comprehensive Environmental Response, Compensation and Liability Act (CERCLA), and the Occupational Safety and Health Act (OSHA) (Xu and Kim 2022). Panel A presents the regression results, and Panel B reports the correlation matrix for releases under various acts. The sample period is from 1987 to 2020. All dependent variables are calculated in year *t+1* and are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Toxic emissions under various EPA regulations

	(1) Ln(Green Pat)	(2) Ln(Green Pat)	(3) Ln(Green Pat)	(4) Ln(Green Pat)
Ln(CAA Release)	5.820**			
	(1.998)			
Ln(CWA Release)		6.391**		
		(2.221)		
Ln(CERCLA Release)			7.904***	
			(2.606)	
Ln(OSHA Release)				6.534**
				(2.390)
Observations	20,712	20,712	20,712	20,712
Adjusted R-squared	0.763	0.763	0.763	0.763
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes

Panel B: Correlation matrix for emissions under various acts

	Total Release	CAA Release	CWA Release	CERCLA Release	OSHA Release
Total Release	1.00				
CAA Release	0.91***	1.00			
CWA Release	0.81***	0.74***	1.00		
CERCLA Release	0.96***	0.94***	0.82***	1.00	
OSHA Release	0.81***	0.83***	0.83***	0.83***	1.00

IA Table 6. Toxic Emissions Grouped by Health Effects

This table presents the regression estimates of firms' green patenting on toxic emissions grouped by health effects. The toxic emissions measures include the log pounds of the releases associated with health effects (*Ln(Health Effects Release)*), releases weighted by the RSEI toxicity score (*Ln(RSEI Hazard)*), and releases not associated with health effects (*Ln(No Health Effects Release)*). The sample period is from 1987 to 2020. All dependent variables are calculated in year *t+1* and are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Ln(Green Pat)	(2) Ln(Green Pat)	(3) Ln(Green Pat)	(4) Ln(Green Pat)	(5) Ln(Green Pat)
Ln(Health Effects Release)	7.544**			7.499**	
	(2.515)			(2.498)	
Ln(RSEI Hazard)		3.870**			3.842**
		(2.282)			(2.264)
Ln(No Health Effects Release)			0.906	0.646	0.616
			(0.399)	(0.284)	(0.271)
Observations	20,712	20,712	20,712	20,712	20,712
Adjusted R-squared	0.763	0.763	0.762	0.763	0.763
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes

IA Table 7. Toxic Emissions Grouped by Release Sites and Physical Properties

This table presents the regression estimates of firms' green patenting on toxic emissions grouped by release sites and physical properties. In Panel A, we group the toxic missions based on the release sites, including onsite and offsite emissions, and Panel B presents the regression results based on physical properties. In Panel A, Column (1) shows the results for the total onsite releases, and Column (2) presents the results for the total offsite releases. Finally, we include both *Ln(Onsite Release)* and *Ln(Offsite Release)* in a single regression in Column (3) of Panel A. In Panel B, Columns (1) to (3) show the results for air releases, water releases, and ground releases, respectively, and Column (4) includes all these releases in one regression. The sample period is from 1987 to 2020. All dependent variables are calculated in year *t+1* and are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Onsite and offsite releases

	(1) Ln(Green Pat)	(2) Ln(Green Pat)	(3) Ln(Green Pat)
Ln(Onsite Release)	9.193***		8.728***
	(3.009)		(2.970)
Ln(Offsite Release)		3.029	1.958
		(1.406)	(0.950)
Observations	20,712	20,712	20,712
Adjusted R-squared	0.763	0.763	0.763
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes

Panel B: Physical properties

	(1) Ln(Green Pat)	(2) Ln(Green Pat)	(3) Ln(Green Pat)	(4) Ln(Green Pat)
Ln(Air Release)	10.376***			10.189***
	(3.364)			(3.283)
Ln(Water Release)		3.511		1.936
		(1.107)		(0.614)
Ln(Ground Release)			0.198	-0.796
			(0.075)	(-0.303)
Observations	20,712	20,712	20,712	20,712
Adjusted R-squared	0.763	0.762	0.762	0.763
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes

IA Table 8. Firms' Toxic Emissions and Green Innovation (Excluding the Energy Sector)

This table presents regression estimates of firms' quantity and quality of green patents on total toxic emissions after excluding the energy sector. The energy sector includes industries with the first two digits of SIC equal to 10 (Metal, Mining), 12 (Coal Mining), 13 (Oil & Gas Extraction), 14 (Nonmetallic Minerals, Except Fuels), 29 (Petroleum & Coal Products), or 49 (Electric, Gas, & Sanitary Services) (Cohen et al. 2023). Columns (1) and (2) show the results for total R&D expenses. Columns (3) and (4) report the results for the quantity of green patents. Finally, Columns (5) and (6) present the results for the quality of green patents. For odd columns, the dependent variables are calculated in year *t+1*, while for even columns, they are measured in year *t+2*. All dependent variables are multiplied by 1000. The sample period is from 1987 to 2020. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, and *Cash*, while *R&D/Assets* is included in Columns (3) to (6). Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) RD/AT (t+1)	(2) RD/AT (t+2)	(3) Ln(Green Pat) (t+1)	(4) Ln(Green Pat) (t+2)	(5) Ln(Tot GPat Cites) (t+1)	(6) Ln(Tot GPat Cites) (t+2)
Ln(Total Release)	0.251	0.209	7.473**	9.040**	6.483**	8.869**
	(1.425)	(1.218)	(2.229)	(2.419)	(1.981)	(2.370)
Capex/Assets	24.034***	19.353***	-267.287*	-292.329**	-177.762	-173.283
	(3.150)	(2.756)	(-1.946)	(-2.023)	(-1.221)	(-1.114)
ROA	-11.508*	-13.268*	-231.584**	-263.889**	-299.726***	-338.009***
	(-1.777)	(-1.924)	(-2.183)	(-2.315)	(-2.730)	(-2.731)
PPE/Assets	14.428***	14.626**	141.573	203.020**	77.650	124.879
	(2.670)	(2.551)	(1.539)	(2.177)	(0.922)	(1.438)
Profit Margin	-3.274***	10.290***	0.804	3.890	6.545	12.506
	(-3.872)	(4.729)	(0.113)	(0.474)	(1.095)	(1.430)
Tobin's q	1.612**	1.040	1.652	10.203	-4.645	2.450
	(2.354)	(1.598)	(0.137)	(0.823)	(-0.374)	(0.186)
Leverage	3.503	3.995	38.179	25.834	46.541	17.154
	(1.402)	(1.592)	(0.715)	(0.466)	(0.891)	(0.302)
Ln(Market Equity)	-1.081*	-0.979	76.248***	81.621***	79.576***	83.253***
	(-1.666)	(-1.579)	(5.367)	(5.419)	(5.610)	(5.628)
Cash	13.832**	16.439*	-12.437	62.212	50.108	129.069
	(2.070)	(1.955)	(-0.133)	(0.631)	(0.484)	(1.218)
R&D/Assets			-125.531	-156.521	434.139	475.899
			(-0.271)	(-0.318)	(0.986)	(0.983)
Observations	18,476	16,887	18,476	16,887	18,476	16,887
Adjusted R-squared	0.830	0.835	0.760	0.765	0.689	0.693
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

IA Table 9. Industry-Level Average of Green Patents and Total Releases

This table presents the average number of green patents and average total toxic releases (in thousands of pounds) for each two-digit SIC industry in our final sample. Energy sectors include 10 (Metal, Mining), 12 (Coal Mining), 13 (Oil & Gas Extraction), 14 (Nonmetallic Minerals, Except Fuels), 29 (Petroleum & Coal Products), and 49 (Electric, Gas, & Sanitary Services).

2-digit SIC	Industry	Green Patent	Total Release (1000s)
10	Metal, Mining	0.28	16627.84
12	Coal Mining	0	435.55
13	Oil & Gas Extraction	2.23	549.97
14	Nonmetallic Minerals, Except Fuels	0.42	834.41
15	General Building Contractors	0.07	39.78
16	Heavy Construction, Except Building	3.6	32.87
17	Special Trade Contractors	0	61.46
20	Food & Kindred Products	0.13	1039.6
21	Tobacco Products	0.56	627.66
22	Textile Mill Products	0.1	315.26
23	Apparel & Other Textile Products	0	65.29
24	Lumber & Wood Products	0.07	898.91
25	Furniture & Fixtures	0.38	608.82
26	Paper & Allied Products	1.29	4415.06
27	Printing & Publishing	0.03	268.39
28	Chemical & Allied Products	2.28	1237.71
29	Petroleum & Coal Products	5.16	2579.33
30	Rubber & Miscellaneous Plastics Products	0.28	425.11
31	Leather & Leather Products	0	375.9
32	Stone, Clay, & Glass Products	0.75	754.54
33	Primary Metal Industries	0.28	3404.87
34	Fabricated Metal Products	0.48	561.99
35	Industrial Machinery & Equipment	2.98	191.76
36	Electronic & Other Electric Equipment	3.33	190.07
37	Transportation Equipment	4.61	623.28
38	Instruments & Related Products	1.23	345.82
39	Miscellaneous Manufacturing Industries	0.1	135.89
40	Railroad Transportation	0	16.39
42	Trucking & Warehousing	0	166.9
44	Water Transportation	0.01	34.59
45	Transportation by Air	0	193.25

46	Pipelines, Except Natural Gas	0	692.71
47	Transportation Services	0	0.57
48	Communications	1.36	368.54
49	Electric, Gas, & Sanitary Services	0.11	7653.86
50	Wholesale Trade – Durable Goods	0.71	494.7
51	Wholesale Trade – Nondurable Goods	0.11	799.02
52	Building Materials & Gardening Supplies	0.05	646.51
53	General Merchandise Stores	0.15	50.56
54	Food Stores	0	87.04
55	Automative Dealers & Service Stations	0	524.34
56	Apparel & Accessory Stores	0	70.91
57	Furniture & Homefurnishings Stores	0.06	198.05
58	Eating & Drinking Places	0	24.84
59	Miscellaneous Retail	0.31	3.52
61	Nondepository Institutions	0	2
64	Insurance Agents, Brokers, & Service	0	811.03
65	Real Estate	0	9.59
67	Holding & Other Investment Offices	0.09	9.1
70	Hotels & Other Lodging Places	0	9.46
72	Personal Services	0	5.99
73	Business Services	4.24	69.6
75	Auto Repair, Services, & Parking	0.17	16.69
78	Motion Pictures	0.5	0.09
80	Health Services	0.19	8.78
82	Educational Services	0	30.49
87	Engineering & Management Services	0.15	70.06
99	Non-Classifiable Establishments	11.38	457.24

IA Table 10. Identification: Expansions of TRI Chemical List (DiD-IV)

This table analyzes the effect of expansions of the TRI chemical list on corporate green innovation by employing a cohort-based instrumented DiD (DiD-IV) approach. Specifically, for each chemical-list expansion year, we construct a cohort consisting of treatment firms reporting emissions of the newly added chemicals after the expansion and control firms within the same 2-digit SIC industries of treatment firms that do not emit any added chemicals. Each cohort includes firm-year observations for the five years before and the five years after the new regulation (i.e., list expansion) becomes effective. For each cohort, we require that companies do not report new chemicals required by the other TRI chemical list expansions. Finally, we pool all cohorts together to form the final sample, which contains the major TRI list expansions in 1990, 1991, 1994, 1995, 2000, 2011, 2012, 2014, 2015, 2016, 2017, and 2019. *Treat* is a dummy variable that equals one for treatment groups and zero for control groups. *Post* is a dummy variable that equals one for the five years after the expansions of the TRI chemical list and zero for the five years before the expansions. In the first stage (Column (1)), we regress total toxic releases on the variables that capture the exogenous shocks of TRI list expansions. In the second stage (Columns (2) and (3)), we regress corporate green innovation on the instrumented total toxic emissions predicted from the first-stage regressions. In Column (2), corporate green innovation is measured by *Ln(Green Pat)*, while in Column (3), corporate green innovation is measured by *Ln(Tot GPat Cites)*. The sample period is from 1987 to 2020. All dependent variables are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	First-stage	Second-stage	
	Ln(Total Release)	Ln(Green Pat)	Ln(Tot GPat Cites)
Treat × Post	0.561***		
	(5.632)		
Treat	0.009		
	(0.067)		
Post	0.001		
	(0.017)		
$\widehat{\text{Ln(Total Release)}}$		157.472**	129.241**
		(2.175)	(2.001)
Observations	11,721	11,721	11,721
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes

IA Table 11. Effect of President Trump's 2016 Election (DiD Analysis) – Alternative Measure

This table analyzes the effect of President Trump's election in 2016 based on the difference-in-differences (DiD) model. Columns (1) through (3) show the results for the quantity, quality, and value of green innovation, respectively. Columns (4) and (5) report the results for the quantity of environmental (Env) and climate change mitigation (CCM) patents. Finally, Columns (6) and (7) present the results for the quantity of explorative and exploitative green patents. To test whether the effect of toxic emissions on corporate green innovation weakened after Trump's election, we first generate an indicator variable, namely, *Post Election*, which equals one if the year is later than 2016 (including years 2017 and 2018); then, we replace a continuous interaction term (*Ln(Total Release)*×*Post Election*) in Table 5 with a dummy interaction term (*High Release*×*Post Election*) in our regressions. *High Release* is a dummy variable that equals one if a firm's toxic emissions are higher than the median level and zero otherwise. The sample period is from 2015 through 2018, which corresponds to the four years surrounding Trump's election on November 9, 2016. All dependent variables are calculated in year *t+1* and are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets.* Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Green Patents			Env & CCM		Explorative & Exploitative	
	Ln(Green Pat)	Ln(Tot GPat Cites)	Ln(Tot GPat Real Value)	Ln(GPat(Tot Env))	Ln(GPat(Tot CCM))	Ln(Explorative GPat)	Ln(Exploitative GPat)
High Release × Post Election	-96.083**	-125.299***	-211.834***	-71.623***	-99.736**	-45.649	-53.704*
	(-2.457)	(-2.743)	(-2.957)	(-2.736)	(-2.380)	(-1.546)	(-1.718)
High Release	62.665*	100.603**	184.086**	25.545	70.457*	50.889	35.492
	(1.741)	(2.295)	(1.984)	(1.417)	(1.915)	(1.330)	(1.373)
Post Election	-	-	-	-	-	-	-
Observations	2,079	2,079	2,079	2,079	2,079	2,079	2,079
Adjusted R-squared	0.790	0.495	0.727	0.792	0.717	0.704	0.684
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

IA Table 12. Effect of President Trump's 2016 Election: PSM-DDD Analysis

This table analyzes the effect of President Trump's 2016 election based on the PSM-DDD model. Panels A and B compare the distributional properties of the *Treated*, *Nontreated*, and *Control* firms. The *Treated* firms are defined as those with headquarters located in the U.S. *Nontreated* firms are defined as those with headquarters located in other countries. *Control* firms are a subset of the *Nontreated* firms matched to the *Treated* firms based on the propensity score matching algorithm. Each *Treated* firm is matched to one *Control* firm. Panel C reports the propensity-score-matching-based difference-in-difference-in-differences regression results. Specifically, Columns (1) report the results when the dependent variable is *Ln(Green Pat)*, while Columns (2) show the results when the dependent variable is *Ln(Tot GPat Cites)*. The sample period is from 2015 through 2018, which corresponds to the four years surrounding Trump's election on November 9, 2016. All dependent variables are calculated in year *t+1* and are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. Standard errors are clustered at the firm level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Means for Treated and Nontreated firms in the pre-Trump-election period (Pre-Match)				
	Treated	Nontreated	Difference	Mean test p-value
Capex/Assets	0.042	0.048	-0.006	0.126
ROA	0.083	0.069	0.014	0.211
PPE/Assets	0.297	0.342	-0.045	0.077*
Profit Margin	0.100	0.108	-0.008	0.642
Tobin's q	1.822	1.912	-0.091	0.464
Leverage	0.463	0.440	0.023	0.308
Ln(Market Equity)	7.916	9.423	-1.507	0.000***
Cash	0.090	0.073	0.017	0.091*
R&D/Assets	0.020	0.024	-0.004	0.323

Panel B: Means for Treated and Control firms in the pre-Trump-election period (Post-Match)				
	Treated	Control	Difference	Mean test p-value
Capex/Assets	0.048	0.045	0.003	0.616
ROA	0.074	0.092	-0.017	0.199
PPE/Assets	0.365	0.326	0.039	0.349
Profit Margin	0.120	0.145	-0.024	0.295
Tobin's q	1.830	1.960	-0.130	0.629
Leverage	0.432	0.451	-0.019	0.501
Ln(Market Equity)	9.302	9.471	-0.169	0.518
Cash	0.070	0.074	-0.004	0.731
R&D/Assets	0.024	0.025	-0.001	0.916

Panel C: PSM-DDD regressions		
	(1)	(2)
	Ln(Green Pat)	Ln(Tot GPat Cites)
High Release × US HQ × Post Election	-973.089*	-1,611.843***
	(-1.723)	(-3.675)
High Release	-254.418	120.849
	(-0.821)	(0.617)
US HQ	-	-

Post Election	-	-
Observations	136	136
Adjusted R-squared	0.549	0.059
Other Interactions	Yes	Yes
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry-year FE	Yes	Yes

We define *Treated* firms as those with headquarters located in the U.S. and *Nontreated* firms as those with headquarters located in other countries. The *Control* firms are a subset of the *Nontreated* firms matched with the *Treated* firms based on a propensity score matching algorithm. The procedure is based on a one-to-one nearest-neighbor matching of the *Treated* and *Control* firms falling within the common support of the estimated propensity scores. The matching results and regression estimates are reported in IA Table 12. *US HQ* is a dummy variable that equals one when a firm's headquarters is in the U.S. and zero otherwise; similarly, *Post Election* equals one when the observed year is later than 2016 and zero otherwise. Based on the continuous variable, *Ln(Total Release)*, we define a dummy variable, *High Release*, which equals one if a firm's toxic emissions are higher than the median level and zero otherwise.

Panels A and B of IA Table 12 compare firms in the treatment, nontreatment, and control groups. Panel A shows that firms with U.S. headquarters differ substantially from those with overseas headquarters in several dimensions (e.g., *Ln(Market Equity)*, *PPE/Assets*, *Cash*). Panel B of IA Table 12 shows that after matching, we find no significant differences in the means of the covariates between the *Control* and *Treated* groups.[45]

Panel C reports the PSM-based DDD regression results, where *US HQ* and *Post Election* are omitted because of collinearity with fixed effects. Column (1) reports the results when the dependent variable is *Ln(Green Pat)*, while Column (2) shows the results when the dependent variable is *Ln(Tot GPat Cites)*. The coefficient estimates of the triple interaction term (*High Release*×*US HQ*×*Post Election*) in Columns (1) and

[45] IA Table 13 of the Internet Appendix shows that treatment and control firms exhibit parallel trends for *Ln(Green Pat)* and *Ln(Tot GPat Cites)* prior to Trump's election (Lemmon and Roberts 2010, Ilhan et al. 2021).

(2) are all negative and statistically significant (at the 10% and 1% levels, respectively), indicating that local high-emission firms significantly reduced green patenting, especially decreasing the quality of green innovation, compared with those headquartered overseas following Trump's election. These results suggest that high-emission firms actively adjust their corporate policies regarding green innovation when the local environment and climate policy change.[46]

[46] Our results are not driven by the sample composition because high- and low-emission companies are approximately equally distributed among firms with U.S. headquarters and those with overseas headquarters. The detailed sample composition is shown in Panel A of IA Table 14 of the Internet Appendix.

IA Table 13. Test of Parallel Trends for Trump's Election Analysis

This table compares the mean yearly growth rates for *Ln(Green Pat)* and *Ln(Tot GPat Cites)* between the *Treated* and *Control* (after matching) firms from 2015 to 2016 (two years before President Trump's election on November 9, 2016). The *Treated* firms consist of those with U.S. headquarters, and *Control* firms comprise those with overseas headquarters after matching. We conduct the test following Ilhan et al. (2021) and Lemmon and Roberts (2010). The fourth column presents the *p-value* of a difference-in-means test, which tests the null hypothesis that the mean values of the two groups of firms are the same. The last column reports the Wilcoxon *p-value* of the two-sample Wilcoxon–Mann–Whitney test, which tests the null hypothesis that the two groups are taken from populations with the same median.

	Treatment Firms	Control Firms	Difference	*p-value*	Wilcoxon *p-value*
Ln(Green Pat) Growth	-0.052	-0.106	0.054	0.559	0.630
Ln(Tot GPat Cites) Growth	-0.037	-0.046	0.009	0.930	0.972

IA Table 14. Sample Composition for Trump's Election Analysis

This table presents the composition of the sample for 2015 through 2018, which correspond to the four years surrounding Trump's election on November 9, 2016. Panel A shows the sample composition based on toxic emissions levels and headquarters locations. Panel B reports the top 10 industries ranked by the number of observations for firms with non-U.S. headquarters.

Panel A: Sample composition based on toxic emissions level and headquarters locations

Groups	Low Toxic Emissions	High Toxic Emissions	Total
Non-U.S. Headquarters	66	70	136
U.S. Headquarters	966	977	1943
Total	1032	1047	2079

Panel B: Top 10 industries ranked by the number of observations for firms with non-U.S. headquarters

Industry	2-digit SIC	Frequency	Percentage (%)
Chemical & Allied Products	28	30	22.06
Electronic & Other Electric Equipment	36	22	16.18
Metal, Mining	10	12	8.82
Primary Metal Industries	33	12	8.82
Instruments & Related Products	38	12	8.82
Industrial Machinery & Equipment	35	8	5.88
Transportation Equipment	37	8	5.88
Electric, Gas, & Sanitary Services	49	8	5.88
Petroleum & Coal Products	29	7	5.15
Oil & Gas Extraction	13	6	4.41

IA Table 15. Test of Parallel Trends for the Deepwater Horizon Event Analysis

This table compares the mean yearly growth rates for *Ln(Green Pat)* and *Ln(Tot GPat Cites)* between the *Treated* and *Control* firms from 2008 to 2009 (two years before the Deepwater Horizon event on April 20, 2010). The *Treated* firms consist of those in extractive industries based on the two-digit SIC code (i.e., SIC 13, Oil and Gas Extraction), and *Control* firms comprise those in other industries. We perform the test following Ilhan et al. (2021) and Lemmon and Roberts (2010). The fourth column presents the *p-value* of a difference-in-means test, which tests the null hypothesis that the mean values of the two groups of firms are the same. The last column reports the Wilcoxon *p-value* of the two-sample Wilcoxon–Mann–Whitney test, which tests the null hypothesis that the two groups are taken from populations with the same median.

	Treatment Firms	Control Firms	Difference	*p-value*	Wilcoxon *p-value*
Ln(Green Pat) Growth	-0.066	-0.018	-0.048	0.623	0.741
Ln(Tot GPat Cites) Growth	-0.057	-0.026	-0.031	0.796	0.504

IA Table 16. Effect of the BP Deepwater Horizon Oil Spill (Extended Post Periods)

This table presents regression estimates of the effects of the BP Deepwater Horizon oil spill for the years 2008 through *2013*, which correspond to the two-year pre- and *four-year* post-event periods surrounding the event that began on April 20, 2010. *Treated* firms are identified by the two-digit Standard Industrial Classification (SIC) code (i.e., SIC 13, Oil and Gas Extraction). Columns (1) and (2) show the results when the dependent variable is *Ln(Green Pat)*, while Columns (3) to (4) show the results when the dependent variable is *Ln(Tot GPat Cites)*. Columns (1) and (3) do not include fixed effects, while Columns (2) and (4) include industry and year fixed effects. Standard errors are clustered at the industry level. The two-year pre- and *four-year* post-event periods are each collapsed into one observation, and *Ln(Total Release)* is the total toxic emissions measured over the pre-event period. All dependent and independent variables are calculated for year *t*. All dependent variables are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Robust t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Ln(Green Pat)		Ln(Tot GPat Cites)	
Ln(Total Release) × Treated Firm × Post-2010	38.167**	61.479***	33.055**	54.973***
	(2.065)	(5.675)	(2.260)	(6.108)
Ln(Total Release)	17.701**	17.969**	12.972*	14.136*
	(2.622)	(2.044)	(1.955)	(1.872)
Treated Firm	612.965***		669.523***	
	(4.144)		(4.729)	
Post-2010	-42.121		-60.162	
	(-1.051)		(-1.548)	
Observations	1,198	1,194	1,198	1,194
Adjusted R-squared	0.278	0.346	0.234	0.305
Other Interactions	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

IA Table 17. Effect of the BP Deepwater Horizon Oil Spill (Controlling for Institutional Ownership)

Different from Table 6, *Total IO*, which is the total institutional ownership measured over the pre-event period, is included as a control variable. *Treated* firms are identified by the two-digit Standard Industrial Classification (SIC) code (i.e., SIC 13, Oil and Gas Extraction). Columns (1) and (2) show the results when the dependent variable is *Ln(Green Pat)*, while Columns (3) to (4) show the results when the dependent variable is *Ln(Tot GPat Cites)*. Columns (1) and (3) do not include fixed effects, while Columns (2) and (4) include industry and year fixed effects. Standard errors are clustered at the industry level. The two-year pre- and post-event periods are each collapsed into one observation, and *Ln(Total Release)* is the total toxic emissions measured over the pre-event period. All dependent and independent variables are calculated for year *t*. All dependent variables are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Robust t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Ln(Green Pat)		Ln(Tot GPat Cites)	
Ln(Total Release) × Treated Firm × Post-2010	202.291***	221.458***	174.974***	193.208***
	(7.019)	(10.882)	(7.965)	(11.127)
Ln(Total Release)	20.151**	24.075*	14.868*	19.667*
	(2.384)	(1.973)	(1.752)	(1.863)
Treated Firm	5,944.970***		8,136.973***	
	(13.499)		(20.800)	
Post-2010	37.265		4.384	
	(0.697)		(0.097)	
Total IO	-497.686***	-744.645***	-353.239***	-557.333***
	(-2.836)	(-3.734)	(-2.836)	(-3.297)
Observations	948	945	948	945
Adjusted R-squared	0.297	0.383	0.259	0.343
Other Interactions	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

IA Table 18. BP Deepwater Horizon Oil Spill (Without Observations Collapsed)

This table presents difference-in-differences regression results for the effects of the BP Deepwater Horizon oil spill for the years 2008 through 2011, which correspond to the four years surrounding the spill that began on April 20, 2010. Different from Table 6, the two-year pre- and post-event periods are *NOT* each collapsed into one observation, and *Ln(Total Release)* is the actual total toxic emissions rather than those measured over the pre-event period. *Treated* firms are identified by the two-digit Standard Industrial Classification (SIC) code (i.e., SIC 13, Oil and Gas Extraction). Columns (1) and (2) show the results when the dependent variable is *Ln(Green Pat)*, while Columns (3) to (4) present the results when the dependent variable is *Ln(Tot GPat Cites)*. Columns (1) and (3) do not include fixed effects, while Columns (2) and (4) include industry and year fixed effects. Standard errors are clustered at the industry level. All dependent and independent variables are calculated in year *t*. All dependent variables are multiplied by 1000. Firm-level controls include lagged *Capex/Assets*, *ROA*, *PPE/Assets*, *Profit Margin*, *Tobin's q*, *Leverage*, *Ln(Market Equity)*, *Cash*, and *R&D/Assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Robust t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Difference-in-differences regressions				
	(1)	(2)	(3)	(4)
	Ln(Green Pat)		Ln(Tot GPat Cites)	
Ln(Total Release) × Treated Firm × Post-2010	129.552***	155.424***	39.349***	60.708***
	(8.961)	(8.254)	(2.980)	(3.624)
Ln(Total Release)	17.155**	17.214**	12.398*	13.102*
	(2.618)	(2.286)	(1.839)	(1.927)
Treated Firm	566.450***		572.567***	
	(5.687)		(5.056)	
Post-2010	69.202		9.619	
	(1.448)		(0.291)	
Observations	2,481	2,480	2,481	2,480
Adjusted R-squared	0.259	0.334	0.211	0.283
Other Interactions	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

IA Table 19. Corporate Green Innovation and Toxic Air Releases (Controlling for Production Ratio)

Different from Table 7, *Production Ratio*, is included as a control variable. *Production Ratio* is defined as the firm-level average of the ratios of current-year to previous-year output at chemical level (Akey and Appel 2021). Changes in the log pounds of toxic air releases (*ΔLn(Air Release)*) are calculated in five different periods, namely, from year –1 to year 1 through year 5. Then, the following regression specification is used in the analysis: $\Delta Ln(Air\ Release)_{i,t+1} = \alpha + \beta Green\ Innovation_{i,t} + \gamma Controls_{i,t} + FEs + \epsilon_{i,t}$. The sample period is from 1987 to 2020. Firm-level controls include lagged *Capex/assets*, *ROA*, *PPE/assets*, *Profit margin*, *Tobin's q*, *Leverage*, *Ln (market equity)*, *Cash*, and *R&D/assets*. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Table A.1 in the appendix. Firm fixed effects and industry-year fixed effects are included in all regressions. *Newey-West correction* with five lags is employed in the calculation of standard errors. Standard errors are clustered at the firm and year level (robust t-statistics are reported in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Year −1 to Year 1		Year −1 to Year 2		Year −1 to Year 3		Year −1 to Year 4		Year −1 to Year 5	
	Δ Ln(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)	ΔLn(Air Release)
Ln(GPat(Tot Env))	-0.082		-0.147**		-0.197***		-0.207***		-0.210**	
	(-1.659)		(-2.130)		(-3.122)		(-3.017)		(-2.480)	
Ln(GPat(Tot CCM))		-0.068		-0.084		-0.102		-0.077		-0.080
		(-1.210)		(-1.223)		(-1.458)		(-1.040)		(-0.989)
Production Ratio	0.109	0.109	0.132	0.132	0.031	0.031	0.008	0.008	-0.132	-0.131
	(1.304)	(1.302)	(1.663)	(1.661)	(0.319)	(0.313)	(0.079)	(0.075)	(-1.247)	(-1.242)
Observations	18,737	18,737	17,154	17,154	15,747	15,747	14,505	14,505	13,352	13,352
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

III. A Survey of Executives

Survey and the Respondents

One of the co-authors of the paper conducted a survey among executives in Australia aimed at collecting information on general corporate policies and decision-making, which included a specific section on climate and environmental issues. In May 2022, the online survey was distributed to approximately 900 members of the Australian Corporate Treasury Association (ACTA). The process yielded 129 responses, with participation primarily from treasures (52%), followed by directors and CFOs (25%). The remaining survey participants held positions including research fellow, head of department, treasury manager, senior treasury analyst, treasury accountant, and assistant treasurer.

The respondents were from a wide range of industries, including financial services, education, mining, utilities, agriculture, manufacturing, and government departments. About 52% of the respondents' firms are listed on the Australian Stock Exchange, with the rest listed on the London Stock Exchange, New York Stock Exchange, Frankfurt Stock Exchange, New Zealand Stock Exchange, and Tokyo Stock Exchange. In terms of size, approximately half (52.68 percent) of the respondents' organizations have annual revenue of above $1 billion, while 19.35 percent generate annual revenue that is less than $250 million. In terms of investments, Asia-Pacific region accounts for the majority of respondents' investment (62.43%), followed by North America (13.73 percent), Africa (3.38 percent), Middle East (3.34 percent), Western Europe (2.87 percent), South America (1.63 percent), and Eastern Europe (1.35 percent).

Determinants of Firms' Green Innovation

To understand what factors are dominant in driving firms' green innovation, the survey asked the respondents to rank the importance of several determinants of producing green patents. The determinants include (i) level of (toxic) emissions; (ii) level of environmental abatement costs; (iii) environmental/climate awareness; (iv) managers' personal characteristics and preferences; (v) increase in climate change activism; (vi) climate change regulations/policies; (vii) shareholder/stakeholder pressure; (viii) local climate vulnerability. The result of this survey question is summarized in IA Figure 1.

IA Figure 1 shows that a significant proportion of the respondents (27.59 percent) strongly agreed that shareholder and stakeholder pressure is a crucial factor in determining firms' green innovation efforts, followed closely by the level of toxic emissions (24.14 percent). The remaining determinants (e.g., abatement costs, environmental awareness, increase in activism, regulations, and local climate vulnerability), ranging from approximately 12 percent to 18 percent, have relatively similar proportions. Interestingly, managers' personal characteristics and preferences are perceived as the most neutral determinant, with a percentage of 55.17 percent.

[Insert IA Figure 1 about here]

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IA Figure 1. Important Determinants of Firms' Efforts to Produce Green Patents