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Keywords: green products, environmental incidents, environmental performance, green patents, greenwashing, ChatGPT, machine learning
JEL Classification: G32, L10, L21, Q50, Q51

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1 Introduction

Environmental-friendly and sustainable products (hereafter "green products") have garnered significant attention in recent years among policymakers and researchers in both finance and economics. Regulators worldwide are striving to combat greenwashing in green products. For instance, between 2023 and 2024, the European Union enacted laws banning misleading green product information, enhancing labeling clarity by prohibiting unsubstantiated claims such as "environmentally friendly" or "eco friendly."[1] Similarly, the Federal Trade Commission's 2024 update to the Green Guides will impose stricter guidelines and harsher penalties for deceptive environmental marketing claims.[2]

Moreover, an expanding body of academic research (Sauzet and Zerbib, 2022; Chen, Garlappi, and Lazrak, 2023) is incorporating green products and green consumption into asset pricing models to elucidate the "green premium" observed in financial markets (Pástor, Stambaugh, and Taylor, 2022). However, due to the lack of empirical measures on green products across firms and industries,[3] testing the predictions of these theories remains challenging.[4] Additionally, even the most basic questions about green products remain unresolved, including understanding the incentives for managers to launch green products and evaluating whether these products are the outcome of greenwashing or provide genuine environmental benefits to the society.

In this study, we develop one of the first empirical measures in the literature about firms' green product initiatives using a dataset of 256,512 product-related announcements from U.S.-listed firms in the S&P Capital IQ Key Development database. Leveraging ChatGPT and machine learning, we identify that 3.7% of these announcements pertain to green products. Our key finding is that firms strategically disclose high-quality green products when they are in trouble, as firms increase green product launches by 36% within two years following severe environmental incidents (e.g., oil spills, wildfires, pollution-related fatalities). More importantly, these incident-driven green products are novel and effective, yielding tangible environmental benefits for both *producers* and *customers*. In contrast, green products introduced without such incident triggers

[1] https://www.europarl.europa.eu/news/en/press-room/20240112IPR16772/meps-adopt-new-law-banning-greenwash

[2] https://thirdpartners.com/blog/what-brands-need-to-know-about-the-ftcs-2024-green-guides-update/

[3] An ideal measure would quantify the fraction of a firm's product sales represented by green products during a specific period.

[4] For example, Chen et al. (2023) implicitly assume that firms with high environmental ratings produce green products and are favored by consumers in portfolio sorting analyses. In practice, this is not always the case, as demonstrated by our findings that, in many instances, brown firms launch more green products.

do not demonstrate observable environmental benefits.

We construct our dataset of green and non-green products from 256,512 product-related announcements in the S&P Capital IQ Key Development database. Our identification process for green products involves a two-step methodology. Initially, we generate a candidate pool of green products by filtering announcements containing at least one "green product phrase," which are derived and searched endogenously from the Capital IQ product announcements using supervised machine learning techniques as outlined by King, Lam, and Roberts (2017) and Sautner, Van Lent, Vilkov, and Zhang (2023). This step results in 858 green product phrases (see Figure 1) and 25,642 candidate products. In the second step, we employ ChatGPT to assess the likelihood that each candidate announcement describes a green product. Using a machine learning "steady state" approach to determine probability thresholds, we identify 9,451 announcements (3.7%) as green products. To validate our green product measure, we assess its predictive capability for firms reporting low-carbon products in the CDP questionnaires. Our analysis reveals that a one standard-deviation increase in our green product measure corresponds to a 19% to 38% higher likelihood of firms reporting low-carbon products in the CDP dataset.

The summary statistics on the industry distribution of green products reveal interesting cross-industry variations. Industries such as energy, utilities, textiles, and shipping containers exhibit more than 25% of their products classified as green, whereas traditionally green sectors, including business services and banking, show a comparatively lower percentage. This pattern suggests that green products might be more strategically valuable in traditionally brown industries, where firms can use them to enhance product differentiation from competitors (Albuquerque, Koskinen, and Zhang, 2019). Our regression analyses further confirm that firms in brown industries are more inclined to launch green products (Cohen, Gurun, and Nguyen, 2020).

Next, we commence our core analyses by linking green product launches to severe environmental incidents, analyzing whether incident firms significantly increase their green product launches in response. Unlike previous studies on RepRisk ESG incidents (e.g., Derrien, Krueger, Landier, and Yao (2021) and Gantchev, Giannetti, and Li (2022)), we incorporate event studies to identify the most severe and unexpected environmental incidents. Our sample includes approximately 490 incidents, with an average (median) [-1d, +1d] cumulative abnormal return (CAR) of -5.12% (-3.92%), indicating substantial firm value losses attributable to these events.[5] Our regres-

[5]The RepRisk database does not provide detailed descriptions of each incident. Therefore, we used ChatGPT to

sions reveal that neither observable measures (such as accounting controls, past environmental performance, ESG ratings, and previous green product launches) nor large language models (e.g. ChatGPT) can predict these exogenous incidents.

Using a stacked difference-in-difference (DID) approach with a [-3 year, +3 year] window around each incident (following Bisetti, She, and Zaldokas (2023)), we document that incident firms significantly increase their green product launches within two years post-incident compared to control firms within the same industry. This increase is economically substantial: in each year following an incident, these firms add 37% more green product phrases into new product announcements, and the annual green product ratio rises by 36%. Furthermore, we explore the heterogeneity in responses based on the level of institutional ownership by environmentally-minded investors (Gantchev et al., 2022), measured in the year preceding the incident. Firms with high environmentally-minded institutional ownership tend to respond more rapidly, typically announcing green products in the first year following an incident, whereas firms with low institutional ownership exhibit a slower response.

Taken together, incident firms tend to launch more green products, particularly when under ESG pressure from stakeholders. Relatedly, Duchin, Gao, and Xu (2022) discover that firms under ESG pressure, including those facing RepRisk incidents, are more likely to divest high-pollution plants. However, these divestitures often lead to the sellers forming supplier-customer or joint venture relationships with the buyers, suggesting that such actions may constitute greenwashing rather than genuine sustainability improvements.

Therefore, a key question is whether, in our findings, these incident-driven green products represent genuine green activities or merely greenwashing. We investigate this issue through two channels: (i) examining the quality of the green products, and (ii) assessing the environmental performance of both the green product producers and their customers.

Investigating the first channel, we assess product quality using a novel metric called *product novelty and influence*, as illustrated in Figure 5. This metric is designed to capture products that significantly deviate from a firm's past offerings yet closely resemble its future products.[6] Our stacked DID regressions reveal that most incident-driven green products are both novel and

obtain detailed information about these environmental incidents. Among them, 9 are related to oil spills, 28 involve fires or explosions that ultimately cause toxic emissions, and 15 result in fatalities.

[6]For example, the first-generation iPhone was substantially different from earlier Apple products like the Macintosh and iPod but closely aligned with subsequent iPhone models.

influential, particularly those announced in the first year following incidents. This suggests that pressure from environmentally conscious stakeholders prompts firms to introduce high-quality green products in response to incidents.

However, a natural question emerges: how do incident firms achieve such rapid development of novel and influential green products within a year? One plausible explanation is that these firms might have already developed prototypes or reached advanced stages of R&D prior to the unexpected incidents. When incidents occur, they either accelerate the final stages of product development or strategically disclose the existing high-quality green products (Liu, Sojli, Tham, and Vansteenkiste, 2024). Our stacked DID regressions support this hypothesis, showing that only incident firms with a substantial stock of past green patents (measured within three years prior to incidents) can rapidly launch green products after incidents. Further linking green patents to novel green products, we find that only incident firms with *high-quality* green patent stock are able to announce novel and influential green products.[7]

Next, we examine the impact of incident-driven green products on the environmental performance of both incident firms and their business customers. We formally define "incident-driven green products" by calculating our DID estimator for each incident and selecting the top-tercile incidents that exhibit the most substantial increase in green product launches post-incident. To analyze customers' environmental performance, we merge our stacked DID sample with a supplier $\times$ customer $\times$ year dataset, following Schiller (2018) and Hege, Li, and Zhang (2023). Our findings indicate that when firms introduce green products post-incident, these products are associated with approximately 40% pollution reduction and 20% GHG emission reductions for the incident firms. Similarly, their customers experience a 4% reduction in GHG emissions and a 5% decrease in pollution in water and land usage within three years after their supplier is hitted by incidents and launches new green products. These environmental benefits are not driven by the incidents per se, as we do not find similar evidence for incidents <u>without</u> subsequent green product launches.

One potential concern is the endogeneity of launching green products post-incidents, suggesting that omitted corporate policies of incident firms (e.g., asset sales in Duchin et al. (2022)) may be correlated with green product announcements and improvements in environmental performance. However, it is challenging to conceive of such corporate policies that would sig-

[7] Green patents are identified and measured following the methodologies of Cohen et al. (2020) and Hege, Pouget, and Zhang (2024).

nificantly impact customers' environmental performance without involving (incident) supplier firms' products. Another concern is potential reverse causality: customers may become newly aware of environmental issues following severe incidents involving their suppliers, subsequently reducing their own emissions and pollution. Concurrently, these environmentally conscious customers might pressure their suppliers to innovate more green products. We find no significant changes in customers' supply chain pushing policies in the MSCI and Refinitiv databases surrounding the incidents, therefore rejecting the hypothesis of reverse causality.

A natural question arises: do these environmental benefits extend to green products introduced independently of environmental incidents? Surprisingly, our regression analyses reveal no significant relationship between the number of general green products and improvements in environmental performance for either the product producers or their customers, thereby raising concerns about potential greenwashing. Furthermore, after we use ChatGPT to distinguish between producer-benefit and customer-benefit green products, we still find no evidence that these green products improve environmental performance. These findings are not entirely unexpected in light of recent anti-greenwashing laws by the FTC and EU. Our results underscore the necessity of these regulations, which aim to prevent the arbitrary use of green product claims in firms' advertisements.

To conclude our analysis, we examine the operating performance of incident firms that subsequently launch green products. This allows us to assess whether financial markets and customers recognize the distinct environmental improvements associated with these incident-driven green products. Our findings reveal that incident-driven green products lead to a rapid recovery in sales within three years following the incidents but do not affect gross margins. Additionally, incident-driven green products are associated with a much smaller decrease in firm value compared to incident firms that do not launch green products.

Our paper relates to three strands of literature. The first strand concerns the construction of new textual measures in climate and green finance. For instance, Ardia, Bluteau, Boudt, and Inghelbrecht (2023) develop a daily Media Climate Change Concerns (MCCC) index using climate change news from major U.S. newspapers and newswires. Similarly, Sautner et al. (2023) and Li, Shan, Tang, and Yao (2024) employ machine learning techniques to derive corporate climate exposure measures from companies' conference call information. Additionally, Chen (2022) propose a novel approach to separately measure "walk" and "talk" by applying natural language processing to online job postings, finding that these dimensions have distinct impacts on institutional investors' holdings and stock returns. Furthermore, Bingler, Kraus, Leippold, and Webersinke (2024) introduce ClimateBert, a deep learning algorithm designed to identify climate-related cheap talk in MSCI World index firms' annual reports. Finally, Gourier and Mathurin (2024) construct a news-implied index of greenwashing, revealing that greenwashing has become particularly prominent since 2015. We contribute to this literature by constructing one of the first textual measures of green product launches. Notably, Chiu, Hsu, Li, and Tong (2024) utilize USPTO trademark data to identify green trademarks, finding that peer firms of incident firms apply for more green marks post-incident. Our study complements Chiu et al. (2024) by focusing on the incident firms themselves, employing distinct datasets (Capital IQ product announcements) and methodologies (ChatGPT) to identify green products. While Chiu et al. (2024) examine sales growth associated with green trademarks, our focus is on the environmental performance resulting from incident-driven green products.

Second, our paper contributes to the growing literature investigating RepRisk ESG-related incidents and their consequences. Recently, Gantchev et al. (2022) show that environmental and social (E&S) incidents lead to modest divestitures, but firms with a one-standard-deviation higher E&S-conscious institutional ownership reduce their greenhouse gas emissions by 36.5% post-incident. Similarly, von Beschwitz, Filali-Adib, and Schmidt (2022) focus on mutual funds' reaction to these E&S incidents. Derrien et al. (2021) document that negative ESG news from RepRisk prompts analysts to significantly downgrade their earnings forecasts across all time horizons. Bisetti et al. (2023) demonstrate that U.S. firms reduce imports by 29.9% when their international suppliers face environmental and social incidents. Additionally, Houston, Lin, Shan, and Shen (2022) and Meier, Servaes, Wei, and Xiao (2023) explore household consumption responses to ESG-related incidents. Furthermore, Akey, Lewellen, Liskovich, and Schiller (2023) and Kamiya, Kang, Kim, Milidonis, and Stulz (2021) focus specifically on data breach incidents and incident firms' reactions.[8] Our study contributes to this literature by uncovering the role of green products in repairing corporate environmental issues. We find that incident-driven green products are of high quality and yield genuine environmental benefits. Moreover, while most papers investigating RepRisk incidents treat them as exogenous shocks, often overlooking the endogeneity of these incidents, we employ event study methods to identify the most *severe* and *unexpected* incidents, demonstrating that these incidents are challenging to predict using firm

[8] Akey et al. (2023) also study ESG-related incidents in RepRisk.

controls.[9]

Third, our paper contributes to the emerging literature on products within the intersection of domains of industrial organization, innovation, and corporate finance. For instance, Hoberg and Maksimovic (2022) develop a novel text-based model of product life cycles using 10-K filings, revealing how conditioning on the product life cycle significantly enhances the explanatory power of q in predicting firm investment decisions and underscores a natural ordering of investments throughout the life cycle. Argente, Lee, and Moreira (2024) document that sales of individual products decline steadily as they progress through their life cycles, noting that products rapidly become obsolete due to competition from both newer offerings by the same firm and rival firms.

2 Data and Variable Construction

2.1 Green Product Announcement Data

We compile our dataset of green products and general (non-green) products utilizing the S&P Capital IQ Key Development database. This database provides structured summaries of significant news and events that may influence the market value of securities, covering a wide range of events such as executive changes, mergers and acquisitions, changes in corporate guidance, delayed filings, and SEC inquiries. We focus specifically on news announcements from Capital IQ with EventTypeID = 41, indicating *product-related announcements* pertaining to the introduction, modification, or enhancement of a company's products or services. From these announcements, we extract various data items including company name, company identifier, announcement date, and event detail summaries.[10] After merging this data with CRSP-Compustat, we compile a comprehensive dataset comprising 256,512 product-related announcements spanning from 2002 to 2022.

In the subsequent step, we discern green product announcements (hereafter referred to as

[9]If a firm's environmental management is subpar and it faces a high ex-ante probability of environmental incidents, the market should already incorporate this information. In such cases, investors would not be surprised when incidents occur, and stock prices should not experience abrupt changes. Thus, the incidents we identify using event studies are unexpected by nature.

[10]One potential concern is whether the summarization process by Capital IQ analysts introduces bias by altering the meaning of news articles. To address this concern, we randomly selected 100 news announcements and searched for the original articles in Factiva using the announcement date and company name. Our analysis reveals that the average document cosine similarity between the Capital IQ summary and the original news article is approximately 86%, thus alleviating this concern.

"green products") from the pool of 256,512 product-related announcements by employing the ChatGPT 3.5 AI model. More specifically, for each product announcement document, we ask ChatGPT to analyze and provide a score, ranging from 0 to 1, indicating the probability that the given product is a green product. Since it is challenging and costly to apply the ChatGPT 3.5 model to a large corpus with 256,512 documents, we instead focus on those documents that contain at least one "green product phrase." "Green product phrases" are generated through machine learning techniques as described in Sautner et al. (2023).[11] "Green product phrases" (embedding machine learning tools) together with the ChatGPT API provide us a double validation, enhancing our confidence in the process of identifying green products.

We use three steps to obtain the set of "green product phrases." We begin by compiling an initial set of bigrams related to green and sustainable products, drawing from Sautner et al. (2023) (Table II). From this compilation, we manually select bigrams unequivocally associated with either climate change or environmental impacts. Additionally, we augment this list by identifying words describing green products in McKinsey's report (McKinsey and NielsenIQ, 2023). These two sources collectively enable us to get 58 unique initial bigrams.

Subsequently, we categorize these 58 initial bigrams into four groups with the assistance of ChatGPT. These four groups are: (1) energy-related green products, (2) electric vehicles, (3) general environmentally friendly products, and (4) recyclable and compostable consumer goods. A detailed breakdown is provided in Table A1.

The final stage involves extending the initial set of 58 green bigrams. As noted by King et al. (2017), while humans excel at discerning whether a keyword is pertinent to a specific topic (in this case, green products), identifying all keywords within a corpus is considered a daunting task. Hence, to broaden the scope of bigrams and uncover additional "green product phrases" from product announcements of Capital IQ, we employ the keyword discovery and expansion techniques devised by King et al. (2017). This methodology is applied individually to each of the four categories of initial green bigrams, with the outcomes subsequently consolidated to produce the ultimate set.

After implementing King et al. (2017)'s method, we identified a total of 858 green product phrases. Online Appendix Section B contains details on the machine learning techniques and a

[11] All green product phrases are formulated at the bigram level, meaning each comprises two English words, with a few exceptions included in the initial dictionary set, such as "recyclable" and "compostable."

list of these phrases. Figure 1 presents word clouds illustrating the most commonly occurring green bigrams across each category. For instance, energy-related green products frequently employ terms such as "energy efficiency" and "energy saving," whereas the general green product category often includes "environmental impact" and "environmental friendly."

Equipped with 858 green product phrases, we further narrow down our potential candidates for green products to those containing at least one green product phrase. This step reduces our pool to 25,642 documents. We then use the ChatGPT API + Python to assign a score to each document. We provide ChatGPT with the following task:

> Now, you are an academic researcher. I will provide you with a paragraph and ask you to assign a score from 0 to 1, which represents the probability that the given product description (the paragraph) is a green product. Green products can be renewable and clean energy products, electric vehicles, any general environmental friendly products (related to less air pollution, greenhouse gas emissions, or water and land pollution), recyclable and compostable consumer goods, etc. Please provide a score without detailed commentary.

Figure 2 plots the correlation between the number of "green product phrases" in a product and the ChatGPT probability score. Specifically, we sort product announcements into groups based on the number of "green product phrases" and calculate the average ChatGPT score for each group. Figure 2 shows a monotonic increasing pattern, with the average score consistently higher than 0.8 when conditioned on having more than 5 green phrases. We refer to the threshold of 5 green product phrases and the 0.8 ChatGPT score as the "steady state," as adding more green product phrases beyond this point does not significantly increase the ChatGPT score. Based on this steady state, we use the following formula to identify green products:

$$I[\text{Green Product}]_i = \begin{cases} 1 & \sum_{B \,\in\, \text{Bigrams in Product(i)}} \Big(\mathbf{1}(B \in \text{Green Bigrams})\Big) \geq 5 \;\; or \;\; \text{ChatGPT Score}(i) \geq 0.8 \\ 0 & otherwise \end{cases} \tag{1}$$

Put simply, a product is classified as a green product if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than or equal to 0.8.[12] Therefore, we complement the ChatGPT model with the traditional machine learning approaches described in Sautner et al. (2023).

[12] In a previous version of the paper, we use the following similar definition: a product is classified as a green product if the product announcement contains at least 2 green phrases.

In Table 1, Panel A, we observe that 9,451 (3.7%) product announcements are classified as green products. Notably, the energy-related and general environmental green products are the two largest categories, comprising over 7,000 green products combined. Figure 3 examines the fraction of green products across the Fama-French 48 industries, revealing significant cross-industry variation. Industries like utilities, textiles, and shipping containers have more than 25% of products classified as green, while traditionally green sectors like business services and banking have relatively few green products. Our explanation is that green products in brown industries might better help firms differentiate their products from those of their competitors. Remarkably, the retail and wholesale industries boast 3.6% and 4.3% green products, respectively, aligning with recent economic literature estimating that around 2% to 5% of retail household products carry green labels (Hainmueller and Hiscox, 2015). Finally, to validate our green product measure, we assess its predictive capability for firms reporting low-carbon products in the CDP questionnaires. Table A2 reveals that a one standard-deviation increase in our green product measure corresponds to a 19% to 38% higher likelihood of firms reporting low-carbon products in the CDP dataset.

2.2 Two Measures on Product Quality

With both green products and non-green (general) products at our disposal, we introduce two metrics to evaluate the quality of products announced in the Capital IQ Key Developments. The first metric is based on an event study around product announcement dates. Specifically, we define *product value* as the multiply of the [0d, +1d] (two-day) Cumulative Abnormal Returns (CAR) surrounding the product announcement date and the market capitalization of the company on the day preceding the announcement. We choose the length of the announcement window following Kogan, Papanikolaou, Seru, and Stoffman (2017): We compute the abnormal share turnover around product announcement days, after adjusting for firm-year and calendar day effects in regressions. Figure A1, Panel A, illustrates that the market reacts to product news within the [0d, +1d] window. Interestingly, our coefficients are three times larger than those reported in Kogan et al. (2017), suggesting a higher significance of news regarding new products compared to patent granting announcements by USPTO.

Our second measure, inspired by Kelly, Papanikolaou, Seru, and Taddy (2021), is termed *product novelty*. This metric gauges the degree to which a product is innovative relative to a firm's prior product portfolio and its influence on the firm's forthcoming product offerings. Using the focal product announcement A of firm f depicted in Figure 5 as an example, we compute its product novelty as follows: Initially, we track firm f's preceding product announcements over the past three years. Subsequently, we calculate the pairwise cosine similarity between product announcement A and these prior announcements (referred to as Products $P1$ and $P2$ in Figure 5). Likewise, we monitor firm f's future product announcements spanning three years and compute pairwise cosine similarity accordingly. The resulting product novelty measure is derived from the disparity between the average similarity to future products ($F1$, $F2$, and $F3$) and the similarity to past products ($P1$ and $P2$). Our computation necessitates at least one past and one future product announcement.[13]

2.3 Environmental Incident Sample

We extract firm-level environmental incidents from RepRisk, a data provider specializing in identifying ESG-related risks for global firms. RepRisk sources negative incidents from various channels, including print and online media, social media platforms like Twitter and blogs, as well as government bodies and regulators. While RepRisk applies its own criteria to assess the severity and media reach of each incident, the specific methodology is undisclosed. To evaluate severity and reach by ourselves, we utilize event studies. Again, we choose the length of the announcement window following Kogan et al. (2017): We compute the abnormal share turnover around environmental incident days, after adjusting for firm-year and calendar day effects.[14] Our main analysis focuses on the bottom 5% of incidents, representing those with the most adverse market response within the [-1d, +1d] event window. This yields 1,067 environmental incidents involving CRSP-Compustat firms. Table 1, Panel B, presents that the mean (median) [-1d, +1d] CAR surrounding these incidents is -5.12% (-3.92%), indicating substantial firm value losses attributable to these events.

The RepRisk database only provides incident categories (e.g., environmental incidents related to carbon emissions) and incident dates, but lacks detailed descriptions of the incidents. Therefore, we used ChatGPT to obtain detailed information about these 1,067 environmental incidents.

[13]Prior to computing pairwise cosine similarity, we preprocess the text by eliminating stop words and excessively frequent words, as outlined in Hoberg and Phillips (2016). Subsequently, we lemmatize and convert all words to lowercase.

[14]Figure A1, Panel B, plots the result.

Among them, 9 are related to oil spills, 28 involve fires or explosions that ultimately cause toxic emissions, and 15 result in fatalities.

We highlight two examples of severe and widely-publicized environmental incidents. The first instance pertains to an oil spill caused by an Amplify Energy pipeline off the coast of Huntington Beach, which the Associated Press describes as "one of the largest oil spills in recent Southern California history." Following the public announcement, regarding the pipeline's involvement in the catastrophic spill, Amplify Energy Corp.'s stock prices plummeted by 44%.

Another notable incident involves the failure of a PG&E Corp. power line possibly causing wildfire in California. The San Francisco-based utility, serving approximately 16 million people, disclosed that one of its high-voltage transmission lines malfunctioned shortly before the Kincade Fire ignited in Sonoma County. The fire resulted in the destruction of numerous homes and the evacuation of thousands. This event led to a loss of -24.52% in PG&E's stock prices within the [-1d, +1d] event window.

2.4 Other Dataset

We collect corporate environmental performance data from the S&P Trucost database, focusing on the external costs related to (i) air pollution, (ii) greenhouse gas emissions, and (iii) land and water pollution directly associated with a firm's operations. Trucost defines external costs as estimates of the monetary value required for society to get rid of the firm's emissions or pollution ex-post. Our emphasis is specifically on direct emissions and pollution, given the often inaccurate nature of data concerning indirect emissions (Hartzmark and Shue, 2022). Differences in emissions between firms can stem from variations in size and is not necessarily indicative of a firm being less environmentally friendly simply because it emits more greenhouse gases due to its larger scale. Hence, we adopt the approach by Hartzmark and Shue (2022) and scale a firm's direct pollution and emissions by its annual sales.

We gather ESG rating data from MSCI, institutional investor data from Refinitiv 13F, and details about supply-chain relationships from Compustat Customer Segment and the FactSet Revere database. Finally, green patents are defined and measured following Cohen et al. (2020) and Hege et al. (2024).

3 Empirical Design

3.1 Stacked Difference-in-Differences

Our primary identification strategy, following Bisetti et al. (2023), employs the stacked Difference-in-Differences (DID) estimator. We opt for stacked DID in response to De Chaisemartin and d'Haultfoeuille (2020)'s findings that the traditional dynamic DID (two-way fixed effect model) yields biased ATT estimates due to the treated observations also serving as control groups in other treated cases. We define our treated group as firm-years experiencing RepRisk environmental incidents, resulting in 1,067 incidents collapsing to 788 firm-year observations. Additionally, we require that, for a given incident, there are no other environmental incidents involving the same firm within the past three years, resulting in 490 incidents, as reported in Table 1, Panel B.[15]

For each treated firm involved in these 490 incidents, we match them with control firms from the same Fama-French 48 industry and year. Control firms are firms without experiencing any incidents throughout our sample period.[16] We restrict our analysis to observations within the [-3 Year, +3 Year] window for both treated and control firms. Our primary DID regressions are formulated as follows:

$$\text{Green\_Product}_{i,c,t} = \sum_{\tau=-3}^{+3} \alpha_\tau I(Treatment)_{i,c,t} \times I(Incident \pm \tau \ Year)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \tag{2}$$

i represents the firm, c denotes the cohort in the stacked DID (totally 490 cohorts), and t signifies the year. $I(Treatment)$ serves as a dummy variable for firms experiencing environmental incidents. $\left\{ I(Incident \pm \tau \ Year) \right\}_{\tau=-3}^{+3}$ consists of seven dummies surrounding the incident year for both treated and control firms. $\gamma_{i\times c}$ is the cohort $\times$ firm fixed effects, and $\delta_{t\times c}$ denotes the year $\times$ cohort fixed effects. Therefore, $\left\{ \alpha_\tau \right\}_{\tau=+1}^{+3}$ identifies our ATT.

3.2 The Predictability of Environmental Incidents

One fundamental assumption in our stacked DID identification is that the occurrence of the 490 environmental incidents is at least partially random and exogenous to any observable

[15] We require this filter to ensure that each of the 490 incidents is an independent event. Under RepRisk's settings, the same incident can reappear in the following year if the risk profile of the incident changes. Consequently, two consecutive incidents involving a firm are not necessarily independent occurrences.

[16] This approach addresses the concern raised by De Chaisemartin and d'Haultfoeuille (2020).

or unobservable firm characteristics. To scrutinize this assumption, we undertake an analysis comparing firm characteristics between those in the treated and control groups, as detailed in Table 1, Panel C, in our stacked DID sample.

At first glance, it appears that the assumption may not hold true, as there are notable distinctions between firms in the treated group and those in the control group across various measures. For instance, treated firms exhibit a higher prevalence of green patents and green products, alongside being larger in size with lower sales growth rates. However, this discrepancy can be partly attributed to the composition of industries represented in the treated group, which primarily consist of brown industries such as Petroleum and Natural Gas, Utilities, and Chemicals (see Table 1, Panel B). This observation aligns with the findings of Cohen et al. (2020), which suggest that brown (energy) firms are more inclined towards innovating green patents.

Therefore, we follow Akey et al. (2023) and investigate the predictability of these severe environmental incidents using regressions with firm and industry-year fixed effects, thereby concentrating on within-firm predictability. Akey et al. (2023) suggests that while the ex-ante probability of data breakage may vary across firms, the timing of such incidents is essentially random. Similarly, these environmental incidents, such as the oil spill by Amplify and the wildfire by PG&E, are also deemed random within a firm's timeline. Table 2 provides empirical evidence testing this notion, where the dependent variable is a dummy indicating the occurrence of an environmental incident. Table 2 demonstrates that neither the past stock of green patents or green products (column 1) nor past environmental performances (column 3) have any predictive power on incidents. The only significant variable is plant, property, and equipment (PPE), which is natural: the more plants a firm possesses, the more likely there are environmental accidents caused by those facilities. Furthermore, in unreported results, we use the MSCI ESG score and its E, S, and G-components, 13F institutional ownership (in fraction), and CEO compensation to predict our incidents. We still find all these controls have no statistical power.

In summary, Table 2 demonstrates that our sample of 490 incidents cannot be predicted by firm-level characteristics after accounting for firm fixed effects. This suggests that our methodology for selecting severe incidents through event studies is effective. Essentially, if a firm's environmental management is subpar and it faces a high ex-ante probability of environmental incidents, the market should already incorporate this information. In such cases, investors would not be surprised when incidents occur, and stock prices should not experience abrupt changes.

Thus, the incidents we identify are unexpected by nature.

3.3 Identify the Incident-Driven Green Products

To identify those incident-driven green products, we estimate a manual DID estimator following the same logic as Equation 2. Specifically, we compute the manual DID as follows:

$$\text{Manual DID}_c = \left(\frac{\text{Number Green Products[t+1:t+3]}_{c,treated}}{\text{Number All Products[t+1:t+3]}_{c,treated}} - \frac{\text{Number Green Products[t-3:t-1]}_{c,treated}}{\text{Number All Products[t-3:t-1]}_{c,treated}} \right) - \left(\frac{\text{Number Green Products[t+1:t+3]}_{c,control}}{\text{Number All Products[t+1:t+3]}_{c,control}} - \frac{\text{Number Green Products[t-3:t-1]}_{c,control}}{\text{Number All Products[t-3:t-1]}_{c,control}} \right) \quad (3)$$

In Equation 3, c represents the cohort, where each incident is assigned a cohort consisting of one treated firm and several control firms. The first component computes the difference in the fraction of green products (among all products) announced within three years after and before the incident. The second component serves as the counterpart for the control firms.[17] The manual DID estimator assesses whether incident firms introduce more green products compared to both their past and the control firms.

We categorize these 490 incidents (cohorts) into terciles based on our manual DID estimator, retaining only the top tercile. These top-tercile incidents exhibit a substantial increase in green product announcements following incidents compared to control firms. Consequently, we designate green products announced after these top-tercile incidents as *incident-driven green products*.

3.4 The Validity of the Product Novelty Measure

To conclude this section, we evaluate the validity of our product novelty measure introduced in Figure 5. This measure assesses the extent to which a product announcement differs from its firm's previous product offerings yet significantly impacts future ones (Kelly et al., 2021). Table 3 presents the results. In Panel A, the dependent variables are either the [0d, +1d] CAR surrounding the product announcement dates or the product value (in million US dollars) as measured in Kogan et al. (2017). The coefficients indicate that an inter-quarter increase in the product novelty measure leads to approximately a 0.48% increase in CAR and a 22.61 million increase in prod-

[17] Given multiple control firms, we calculate the average for them.

uct value. Additionally, the median-split measure, *Product Novelty Dummy*, suggests that novel products, in general, enjoy a higher market valuation.

Turning to Panel B, we interact our key product novelty measure with a dummy variable indicating green products. However, we do not find evidence that novel green products enjoy a higher valuation compared to novel non-green products. Moreover, green products in general are not associated with higher product value or CAR.

4 Do Brown Firms Launch More Green Products?

A central question motivating our study is which types of firms launch more green products: green firms (environmental leaders) or brown firms (environmental laggards)? This inquiry is particularly complex because Cohen et al. (2020) have discovered that brown firms, especially those in the energy sector, develop more green technologies. These green technologies developed by brown firms are not only of higher quality but also exert a more profound influence within the realm of green technology—a phenomenon labeled by Cohen et al. (2020) as the "ESG innovation disconnection puzzle." Building on this, we hypothesize that brown firms may also lead in launching green products, driven by the greater value these products bring to brown firms compared to green firms, at least until the point where brown firms transition to becoming green themselves. When measuring browness at the industry level, green products are more valuable in brown industries since firms in these industries can use green products to better differentiate themselves from competitors.

To explore this hypothesis, we conduct preliminary tests as presented in Table 4, leveraging data at the industry level, consistent with the approach of Cohen et al. (2020). The dependent variable in our analysis is the industry green product ratio, while our key independent variables are the industry medians of pollution or emissions for firms within each respective industry.[18] The coefficients reported in Table 4 suggest that industries characterized by higher emissions or pollution levels (often referred to as brown industries) indeed contribute more to the development of green products, aligning with both the findings of Cohen et al. (2020) and our own hypothesis. Nonetheless, these preliminary findings do not establish any causal relationships. To further investigate it causally, we plan to examine severe environmental incidents as poten-

[18] To enhance comparability, we standardized these environmental variables to have a standard deviation of 1.

tial shocks that could alter firms' perceptions of their "green" or "brown" status, potentially influencing stakeholders' views on these firms' environmental practices.

5 Environmental Incidents and Green Products

5.1 Main Results

This section starts our exploration of severe environmental incidents. Our main investigation is whether firms tend to launch more green products following severe environmental incidents. There are two divergent hypotheses. On one hand, the occurrence of current severe environmental incidents might convey information about the firm's past efforts in corporate environmental management (Kamiya et al., 2021). Stakeholders may utilize this information to reassess the firm's environmental commitment and adjust their expectations for future incident occurrences. Moreover, severe environmental incidents can undermine a firm's reputation in the product market (Akey et al., 2023), potentially leading to divestment by institutional investors (Gantchev et al., 2022) and a decline in purchasing by environmentally-conscious retail and business customers (Meier et al., 2023; Bisetti et al., 2023). In response, incident firms may increase efforts to launch more green products to regain favor with institutional investors and customers.

On the other hand, incident firms may choose not to respond by increasing green products, as suggested by the model in Kamiya et al. (2021). If the occurrence of severe environmental incidents is perceived as merely bad luck and does not signal any change in the probability of future incidents, rational managers and stakeholders may opt for the same risk management strategy (Dessaint and Matray, 2017). However, there is an exception to the above scenario: since incidents in our sample are salient events (on average leading to a 5% decline in firm value), they may prompt investors and managers to rely on heuristics, leading to irrational decisions regarding the launch of more green products (Bordalo, Gennaioli, and Shleifer, 2022).[19] In such cases, the market may not appreciate incident-driven green products in the long run. Ultimately, whether incident firms will launch more green products remains a testable empirical question.

To test this idea, we construct a stacked Difference-in-Difference (DID) sample (details provided in Section 3.1). The treated group comprises incident firms (totaling 490 incidents), while

[19] "It is a common experience that the subjective probability of traffic accidents rises temporarily when one sees a car overturned by the side of the road (Tversky and Kahneman, 1974)."

control groups consist of firms that have never experienced any environmental incidents in our sample. For each treated firm, we match control firms within the same Fama-French 48 industry and year. We restrict observations to treated and control firms within the [-3 Year, +3 Year] window. Our regression specifications are as follows,

$$\text{Green\_Product}_{i,c,t} = \sum_{\tau=1}^{3} \alpha_\tau I(Treatment)_{i,c,t} \times I(Post\ ``\tau"\ yr)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \tag{4}$$

where i represents the firm, c denotes the cohort,[20] and t signifies the calendar year. $I(Treatment)$ serves as a dummy variable for firms experiencing environmental incidents. $\left\{I(Post\ ``\tau"\ yr)\right\}_{\tau=1}^{3}$ consists of three dummies for three consecutive years after the incident year for both treated and control firms. The control variable set $\mathbf{X}$ follows Bolton, Kacperczyk, and Wiedemann (2022) and encompasses Firm Size, ROE, CAPX, PPE, Book-to-Market Ratio, RND, Sales Growth, and the count of any product announcements in year t. $\gamma_{i\times c}$ stands for the firm $\times$ cohort fixed effects, and $\delta_{t\times c}$ denotes the year $\times$ cohort fixed effects. Standard errors are clustered at the cohort $\times$ firm level.

Table 5, Panel A, presents the benchmark results, where we employ two measures to assess firms' green product launch activities, the dependent variable. The first measure, in columns (1) and (2), quantifies the average number of "green product phrases" appearing in each product announcement of firm i in year t, where "green product phrases" are obtained from machine learning (King et al., 2017) and are plotted in Figure 1. The second measure, in columns (3) and (4), represents the annual fraction of green products among all new products launches by firm i. A product is classified as a green product if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8. We follow Bolton et al. (2022)'s green patent ratio measure and use the green product ratio instead of the green product count, as the total number of green products is significantly driven by a firm's innovation and production capacity, and the ratio better captures the firm's green efforts.

Table 5, Panel A, shows that firms involved in environmental incidents significantly increase their launch of green products within the two years following the incident, compared to control firms in the same industry. The magnitude of this increase is also economically significant. For instance, in the first year following the incidents, these firms, on average, incorporate 37%

[20] Each cohort has a single treated firm and multiple matched control firms.

more green product phrases into new products (0.193 ÷ 0.504), and the green product ratio increases by 36% (0.050 ÷ 0.149). In contrast, columns (5) and (6) indicate that firms involved in incidents do not announce more general (both green and non-green) products after the incidents, implying that the impact is only on green products (the denominator of our dependent variables in columns (1)–(4) does not change).[21]

Figure 6 visualizes the results of Table 5, Panel A, where we set the coefficient of $t-3$ equal to 0 (as the benchmark). Panels A and B show a significant increase within two years after incidents in both green product phrases and green product ratio. Crucially, there is a clear parallel trend in the $[t-3, t]$ interval: there is no significant difference in both the level and the changes of green product announcements between treated and control groups. In summary, our results demonstrate that incident firms respond very quickly after incidents by launching more green products.[22]

Our findings contribute to the recent growing accounting literature focusing on innovation disclosure (Glaeser and Lang, 2023), as green product announcements also fall under corporate strategic disclosure. In a related finding, Liu et al. (2024) document that firms under EPA enforcement (or under the threat of future punishments) tend to disclose more green patents, with these patents likely already invented before EPA enforcement. A similar reasoning applies to our main findings: incident firms might have already completed the development of new green products (or prototypes) and choose to announce them after incidents, during periods with real needs of announcing green products. We will come back and test this idea in later sub-sections.

Finally, we perform two important robustness checks. First, we re-estimate the same regressions as in Figure 6 using Compustat quarterly data. The results, displayed in Figure 7, are consistent with our previous findings, although the estimated coefficients are more volatile due to the sparser dependent variable in the quarterly sample. Second, Table A3 in the online appendix demonstrates that our results are robust to different methods in selecting severe en-

[21] We run Poisson regressions in columns (5) and (6) since the dependent variable is a count variable, and we run OLS in columns (1)–(4) as the dependent variables are fractions, with means smaller than 1. Our main dependent variables are not highly skewed, as a result, the Poisson regressions might not lead to unbiased estimator: Poisson regressions impose strong assumptions on the distribution of the error terms and are subject to issues of under-dispersion or over-dispersion (Wooldridge, 2010); (ii) our empirical model introduces many interaction terms (treat × post), and in the case of Poisson regressions, the coefficients of interaction terms become difficult to interpret (Shang, Nesson, and Fan, 2018).

[22] In a recent study, Chiu et al. (2024) use US trademarks to study green products and find that peer firms of those involved in environmental scandals increase their green trademarks. In our work, we do not consider these peer effects, implying that our estimated impact might be even stronger if we did.

vironmental incidents. Specifically, when we use RepRisk's severity measure, we obtain similar results.

5.2 Heterogeneity on Environmental-minded Stakeholders

In this section, we delve into the heterogeneity of impacts of environmental incidents by considering environmentally conscious stakeholders, namely institutional investors and business customers. We commence our analysis by focusing on institutional investors. Following the methodology in Gantchev et al. (2022), we rank all 13F institutions in each year-quarter based on their value-weighted portfolio firm's MSCI environmental ratings. We define "environmentally conscious (E-C) institutional investors" as those in the top tercile of each year-quarter cohort. Then, we aggregate the environmentally conscious institutional ownership at the company level and divide both the treatment and control groups in Table 5, Panel A, into two categories: high and low E-C institutional ownership.[23] In Table 5, Panel B, columns (1) to (3) present regressions based on incident and control firms with both high E-C institutional ownership. Panel B reveals an orthogonal time pattern: when incident firms experience high E-C ownership, they swiftly launch green products—within the first year—while their launch is slower in the absence of high E-C institutional ownership (see Panel B columns (4) to (6)). Our finding is consistent with Gantchev et al. (2022) that, after environmental incidents, E-C institutional investors might opt to divest, exerting significant pressure on the management team of the incident firm to quickly improve their "corporate green image" (Admati and Pfleiderer, 2009).

In Panel C of Table 5, we turn to focusing on environmentally conscious customers. We define E-C business customers as those whose MSCI ESG scores are above the median in a given year among all customer firms. Consequently, we restrict our regression sample (both treated and control firms) to firms with at least one business customer identified from the Compustat customer segment and FactSet Revere. This subset is ten times smaller than the benchmark sample in Panel A of Table 5. The results in Panel C reveal that only incident firms with E-C business customers actively respond by launching green products following severe environmental incidents. This finding aligns with Schiller (2018) and Dai, Liang, and Ng (2021), which suggests that customer firms can influence supplier firms to improve their ESG performance.

[23] We utilize institutional ownership information from year t-1, one year prior to the incident year.

5.3 Heterogeneity on Product Quality (Novelty)

On one hand, we document that incident firms tend to launch more green products, particularly when under ESG pressure from stakeholders. On the other hand, Duchin et al. (2022) discover that firms under ESG pressure, including those facing RepRisk incidents, are more likely to divest high-pollution plants. However, these divestitures often lead to the sellers forming supplier-customer or joint venture relationships with the buyers, suggesting that such actions may constitute greenwashing rather than genuine sustainability improvements.

Therefore, a key question is whether, in our findings, those incident-driven green products represent genuine green activities or merely greenwashing. We investigate this issue through two channels: (i) examining the quality of the green products, and (ii) assessing the environmental performance of both the green product producers and their customers. This subsection focuses on the first channel.

We measure the quality of green and non-green products using our product novelty and influential measure (hereafter simply call it the novelty measure), detailed in Section 2.2. In summary, a product has a high novelty score if its description is significantly different from the firm's past product portfolios but very similar to its future offerings. Consider the first generation of the iPhone: it was very different from previous Apple products like the Macintosh and iPod but highly similar to subsequent iPhone models (see Figure 5). In Table 3, we show that the product novelty measure is positively associated with both the announced CAR and the value of products.

Table 6 re-estimates our baseline results by differentiating between green & novel and green & non-novel products.[24] The dependent variables are always the ratio between A and B, where A and B are presented in the first row of Table 6. These dependent variables are simple decomposition of dependent variables in Table 5. For example, columns (3), (4), (7), and (8) are the first two parts on the right-hand side of the following equation,

$$\frac{\text{Number of Green Products}}{\text{Number of Product Announcements}} = \frac{\text{Number of Green \& Novel Products}}{\text{Number of Product Announcements}} + \frac{\text{Number of Green \& Non-Novel Products}}{\text{Number of Product Announcements}} \tag{5}$$

The coefficients in Table 6 indicate that: (i) incident firms launching green products in the first year after incidents tend to introduce novel green products (columns (1) – (4)); (ii) green products

[24] We conduct a median split using the whole Capital IQ product announcement sample, including both green and non-green product announcements.

launched in the second and third years are more likely to be non-novel (columns (5) – (6)). Combined with the results in Table 5 Panel B, a clearer pattern emerges: under pressure from environmentally conscious institutional investors, incident firms accelerate the launch of green products, and these early products are often novel and of high quality. This evidence counters the greenwashing hypothesis as in Duchin et al. (2022).

5.4 Incident-Driven Green Products and Green Patents

Given our findings that incident firms expedite the launch of green products (in the first year following incidents), and strikingly, these products tend to be novel, a compelling question emerges: how do they achieve such rapid development of novel green products? One plausible explanation is that these firms might have already developed prototypes or reached advanced stages of R&D prior to the unexpected incidents. This hypothesis aligns with Liu et al. (2024), who document that firms under EPA enforcement (or the threat of future punishments) tend to disclose more green patents, with these patent technologies likely already invented before the enforcement.

To test this hypothesis, we split both our treatment and control samples into two groups: those with and those without green patent stocks. Green patent stocks are defined as the total number of green patents applied to the USPTO within three years before the incident year for both treated and control firms. Green patents are identified and measured following the methodologies of Cohen et al. (2020) and Hege et al. (2024).

Table 7, Panel A (B) presents DID regressions for both treated and control firms with non-zero (zero) green patent stocks prior to incidents. The contrasting results in Panels A and B indicate that only incident firms with green patent stocks significantly increase the launch of green products in the first two years following an incident. This finding supports our hypothesis: firms capable of responding by launching green (and novel) products have already developed green technology in-house.

This evidence suggests that the ability to quickly introduce green products after an incident is not merely a reactionary measure but rather a strategic deployment of existing innovations. These firms likely have advanced R&D processes and prototypes that can be rapidly brought to market under ESG pressures. Thus, the presence of green patent stocks appears to be a crucial determinant in whether an incident firm can swiftly and effectively respond with high-quality, novel green products.

Lastly, in Panel C of Table 7, we directly examine the relationship between green patent quality and the launch of novel green products. For firms with positive green patent stocks, we further categorize them into high and low-quality green patent stocks based on the median number of citations received by their green patents each year. The results demonstrate that high-quality green patent stocks significantly drive the rapid introduction of novel green products. While the coefficients in columns (2) and (4) are not statistically significant, their magnitudes are substantially larger compared to those in columns (6) and (8), which represent firms with only low-quality green patent stocks. This suggests that the presence of high-quality green patents is crucial for the prompt launch of innovative green products, emphasizing the critical role of patent quality in fostering genuine environmental advancements (Cohen et al., 2020).

5.5 Incident-Driven Green Products and Product Value

To conclude this section, we examine the value of green products launched after incidents, where the product value is calculated similar as in Kogan et al. (2017).[25] We conduct our tests again using DID with the firm-year level dataset. Our new dependent variable is the annual median value of green products. Each firm-year observation in the regressions must have at least one green product announcement in Capital IQ.

Table 8 and Figure 8 present our regression results. Due to the noisy nature and large standard deviation of the product value measure in Table 8, we either take the natural log of the values or winsorize them at the 10% and 90% levels. The coefficients in Table 8 indicate that the value of green products announced one year after incidents is $26 million higher. In contrast, there is no significant increase in value when firms launch non-green products following incidents. These results align with our previous findings in Table 6, which show that green products launched one year after incidents are usually of higher quality (i.e., they are novel) and therefore,

[25]It is equal to the multiply of the [0d, +1d] (two-day) cumulative abnormal returns (CAR) surrounding the product announcement date and the market capitalization of the company on the day preceding the announcement. We choose the length of the announcement window following Kogan et al. (2017): We compute the abnormal share turnover around product announcement days, after adjusting for firm-year and calendar day effects in regressions. Figure A1, Panel A, illustrates that the market reacts to product news within the [0d, +1d] window. Interestingly, our coefficients are three times larger than those reported in Kogan et al. (2017), suggesting a higher significance of news regarding new products compared to patent granting announcements by USPTO.

naturally enjoy higher product value.

6 Incident-Driven Green Products and Environmental Benefits

The previous section's findings indicate that firms increase the launch of green products in response to environmental incidents, particularly under pressure from environmentally-conscious stakeholders. Notably, these incident-driven green products are often novel and influential, as evidenced by our product novelty measure. However, the novelty and influence of these products do not entirely dispel concerns of greenwashing. As a result, this section explores whether these incident-driven green products genuinely deliver environmental benefits to society. Section 6.1 examines the environmental performance of green product producers, Section 6.2 evaluates the environmental improvements for customers of green products, and Section 6.3 employs ChatGPT again to distinguish between producer-benefit and customer-benefit green products.

6.1 Producer's Environmental Performance

Before focusing on the environmental performance of green product producers, we first define "incident-driven green products." Using the stacked DID sample in Table 5, we calculate a manual DID measure to determine if an incident firm significantly increases green product launches for each of the 490 incidents, as shown in Equation 3. We then categorize these incidents into terciles based on our DID estimator, retaining only the top tercile. To verify, we estimate the DID regression as in Panel B of Figure 6 using only top-tercile incidents, plotting the results in Figure A2. The figure shows that within three years following top-tercile incidents, firms increase their annual green product fraction by about 20%, or 133% of the sample mean for treated firms. Finally, we define these green products launched within three years after these top-tercile incidents as incident-driven green products.

To assess the impact of incident-driven green products on the environmental performance of the incident firms (producers), we re-estimate the DID regression, focusing exclusively on the top-tercile incidents firms (launching 20% more green products after incidents) as the treatment group.[26] In Figure 9, we employ the air pollution intensity of the incident firms (and their control

[26]The control group contains firms in the same Fama-French 48 industry that never have any incidents in our

counterparts) as the dependent variable.[27] The coefficients in Panel A indicate that incident firms launching 20% more green products following incidents experience a reduction in air pollution intensity by 20% to 40% of a standard deviation within the three years post-incident. The air pollution reduction is likely driven by green products but not the incident itself as, in Panel B, we repeat our DID analysis but replacing the top tercile incident firms with mid- and bottom-tercile ones, and we do not find any pollution reductions after incidents.

Similarly, Figure 10 Panel A shows that top-tercile incident firms enjoy a reduction of 20% greenhouse gas emissions in the third year following the incident, while Panel B shows that mid- and bottom-incident firms do not experience a similar emission reduction.

A potential issue with the analysis is the simultaneity of green product launches and environmental improvements, both occurring within three years following the incidents. It is conceivable that other ESG-related corporate policies (omitted variables), which are highly correlated with green product launches, may drive better environmental improvements in the incident firms. For instance, Akey et al. (2023) discover that firms involved in RepRisk E&S incidents enhance their post-incident CSR scores. Similarly, Duchin et al. (2022) argue that firms are more likely to divest pollution assets following such incidents.

Due to the difficulty of providing exogenous variation on green products, we next examine the environmental performance of the incident firm's customer firms. Since these customers are not directly affected by environmental incidents and incident firms' product policies are the primary influence on their environmental impact, this approach offers stronger evidence that green products effectively enhance environmental outcomes.

6.2 Customer's Environmental Performance

To evaluate customer firms' environmental performance, we construct a supplier firm $\times$ customer firm $\times$ year panel following Schiller (2018) and Hege et al. (2023). We merge FactSet supply chain data with Compustat customer segment data and further match it to our stacked DID sample. In the treated group, suppliers experience severe environmental incidents and rapidly launch green products (identified by the top-tercile treated group). We aim to see if these incident-driven green products of suppliers improve the environmental performance of

dataset.

[27] We standardize the dependent variable, setting the standard deviation to 1.

their customer firms.

Figure 11 Panels A and B display the DID regressions using the top-tercile treated group.[28] We ensure that supply chain relationships existed before the incident year for both treated and control groups. Figure 11 shows that customers experience an average 4% reduction in GHG emissions and 5% less pollution in water and land usage within three years after their supplier is affected by incidents and introduces new green products. The omitted variable is less concerning because it is difficult to imagine any incident firms' (suppliers') corporate policies that improve their customers' environmental behavior not through their products. In general, customers can push suppliers to adopt greener practices, but the reverse relationship is less evident (Schiller, 2018; Dai et al., 2021).

Our final concern is potential reverse causality: customers may become newly aware of environmental issues following severe incidents involving their suppliers, subsequently reducing their own emissions and pollution. Concurrently, these environmentally conscious customers might pressure their suppliers, who have experienced incidents, to innovate more green products. To address this concern, we conduct placebo tests by substituting our dependent variables in Figure 11 with ESG policy variables of the customers. The results of these tests are presented in the online appendix, Figure A3. In Panel A, we employ a dummy variable that equals one if firms use environmental or sustainable criteria when selecting their suppliers and sourcing partners.[29] The results show that customer firms benefiting from incident-driven green products do not modify their supply chain sustainability policies. Panel B indicates that these customers do not experience changes in their environmental scores, as per MSCI ratings. These findings are inconsistent with the reverse causality hypothesis. The results in Figure A3 are *not inconsistent* with the findings in Bisetti et al. (2023), which show that customer firms cut trade relationships following their suppliers' E&S incidents. This occurs because customer firms can constantly maintain a stringent ESG policy but choose to enforce it after such incidents.

Thus, a more plausible explanation is that supplier firms, in response to severe incidents, launch numerous green products, such as compostable bags. Customers then benefit from these new green products, leading to reduced water and land pollution, given that non-compostable

[28]The regressions incorporate supplier × customer fixed effects to mitigate selection effects and supply chain dynamics. For example, Bisetti et al. (2023) document that after RepRisk E&S incidents, customer firms tend to cease trading with incident supplier firms. Hege et al. (2023) find that climate patents attract new customers to suppliers with innovative climate technologies.

[29]This variable is identified as En_En_RR_DP058 in the Refinitiv ESG database.

bags can contribute significantly to land pollution. Additionally, when we substitute top-tercile incident firms with mid- and bottom-tercile ones in Figure A4, we do not observe reductions in emissions and pollution for their customers, suggesting that the observed effects are driven by incident-driven green products rather than the incidents themselves.

6.3 Producer-Benefit and Customer-Benefit Green Products

To further sharpen causality between incident-driven green products and environmental benefits, we employed ChatGPT to classify each of the 9,451 green products into either producer-benefit or customer-benefit categories. Producer-benefit products are those that enable producers to improve their environmental performance, while customer-benefit products aid customers in enhancing their environmental practices (Bena and Simintzi, 2022). Of these, 3,695 are classified as producer-benefit green products, and 4,721 are classified as customer-benefit green products.[30] Subsequently, we estimate our manual DID measure (Equation 3) separately for these two types of green products and identify the top-tercile incident firms that launch producer-benefit and customer-benefit green products, respectively.

In Figure 12, we observe that firms responding to environmental incidents by introducing more producer-benefit green products tend to achieve greater reductions in air pollution for themselves (the producers) compared to their customers, as depicted in Panels A and B. Conversely, when firms respond with more customer-benefit green products, the impact is more pronounced on their customers rather than on the firms themselves, as illustrated in Panels C and D.

7 General Green Products and Environmental Benefits

In the previous section, we posited that incident-driven green products confer significant environmental benefits to both producers and consumers. A natural question follows: do these benefits extend to green products introduced independently of environmental incidents?

Table 9 explores this by examining the relationship between annual number of (general)

[30] The remaining products are identified as both customer-benefit and producer-benefit by ChatGPT, and we exclude these green products in the subsequent analyses.

green products announced by firms and environmental performance for both producers and customers. Panels A and B assess the producers' direct pollution intensity and GHG emission intensity over the next three years. We find no evidence that green products reduce pollution or emissions. This holds even when distinguishing between producer-benefit and customer-benefit green products in Panel B. Panels C and D focus on customers' environmental performance, again revealing no significant correlation.

In summary, general green products do not seem to deliver environmental benefits, at least not as measured by Trucost environmental metrics. This outcome may not be surprising, considering the recent policy discussions surrounding greenwashing and the actual effectiveness of green products. For instance, between 2023 and 2024, the European Union (EU) adopted new laws banning greenwashing and misleading product information. These regulations aim to make product labeling clearer and more trustworthy by prohibiting the use of general environmental claims such as "environmentally friendly," "natural," "biodegradable," "climate neutral" or "eco" without proof.[31] [32] The Federal Trade Commission is preparing for its once-a-decade update to the Green Guides, scheduled for release in 2024. Green Guides provides guidance on how brands can make legitimate environmental marketing claims about their products. The update promises stricter guidelines and harsher penalties for companies playing fast and loose with their environmental marketing.[33] Finally, Gourier and Mathurin (2024) recently construct a news-implied index of greenwashing, and the index reveals that greenwashing has become particularly prominent after 2015.

The last remaining question is why incident-driven green products are so effective in contrast to general green products. We conjecture that this discrepancy might be explained by experience effects. Malmendier (2021) defines experience effects as an updating process modeled as a form of generalized Bayesian learning (Bissiri, Holmes, and Walker, 2016), with a loss function wherein individuals assign more weight to negative shocks they have personally experienced. These effects are not limited to individual investors but are also prevalent among professional corporate managers. For example, Dessaint and Matray (2017) find that managers become more risk-averse and hold more cash after experiencing hurricanes in nearby counties. Similarly, experiencing severe environmental incidents might enhance managers' awareness of environmental protection

[31] https://www.europarl.europa.eu/news/en/press-room/20230918IPR05412/eu-to-ban-greenwashing-and-improve-c
[32] https://www.europarl.europa.eu/news/en/press-room/20240112IPR16772/meps-adopt-new-law-banning-greenwash
[33] https://thirdpartners.com/blog/what-brands-need-to-know-about-the-ftcs-2024-green-guides-update/

and further incentivize them to undertake genuine green initiatives and avoid greenwashing (Demski, Capstick, Pidgeon, Sposato, and Spence, 2017).

8 Incident-Driven Green Products and Operating Performance

To conclude our analyses, we examine whether financial markets and customers can discern or anticipate the superior effectiveness of incident-driven green products relative to general green products. Figure 13 presents the natural logarithm of sales within a [-3, +3] year window around environmental incidents. Panel A focuses on the top-tercile incidents—those followed by a 20% or greater increase in green product launches—in our DID analysis, while Panel B considers the remaining incidents.

Both panels reveal a notable decline in sales following severe environmental incidents. Notably, in Panel A, the decline occurs more contemporaneously, whereas in Panel B, the sales decrease is observed in year $t+1$. We posit that firms launching a higher volume of green products in year $t-1$ engage with more environmentally conscious customers (as detailed in Table 5, Panel C), who exhibit a more immediate response to such incidents. The observed sales recovery in Panel A, but not in Panel B, suggests that green products play a critical role in customer retention. Figure 14 further explores gross margins surrounding these incidents, finding no significant changes. Combined, Figures 13 and 14 indicate that incident-driven green products facilitate sales recovery through increased quantities rather than elevated prices.

Lastly, Figure 15 investigates market-to-book ratios within the [-3, +3] year window, revealing that incident-driven green products mitigate substantial value loss stemming from environmental incidents.

9 Conclusions

This study provides novel empirical insights into the dynamics of green product launches following environmental incidents, employing a large dataset of 256,512 product-related announcements from U.S.-listed firms. Our findings highlight a significant and novel contribution to the discourse on corporate environmental strategies and their implications.

The analysis reveals that firms experiencing severe environmental incidents significantly increase their green product launches in the two years following these events. This response is not merely a superficial or opportunistic maneuver; rather, it reflects genuine efforts to restore corporate reputations and align with environmental expectations. The increase in green product launches—by 36%—demonstrates a substantial shift towards more sustainable practices in response to negative environmental impacts. Importantly, these green products are found to be novel and effective, contributing real environmental benefits, such as reductions in pollution and greenhouse gas emissions, for both producers and customers.

In contrast, green products introduced independently of such incidents do not show similar improvements in environmental performance. This finding casts doubt on the effectiveness of non-incident-driven green products, suggesting that they might often be instances of greenwashing rather than substantive environmental progress. The study's novel metric of product novelty and influence further supports the notion that incident-driven green products are not only innovative but also align closely with the firms' future product trajectories.

Our results also shed light on the role of institutional ownership in shaping corporate responses to environmental incidents. Firms with high environmentally-minded institutional ownership are quicker to launch green products, suggesting that stakeholder pressure can accelerate genuine environmental improvements. Conversely, firms with lower levels of such ownership exhibit slower responses, underscoring the role of investor influence in driving sustainable corporate behavior.

Overall, this study advances our understanding of corporate green product strategies, highlighting that incident-driven green products can lead to substantial environmental benefits and mitigate the negative financial impacts of environmental crises. However, it also emphasizes the need for rigorous regulatory frameworks to prevent greenwashing and ensure that green product claims genuinely contribute to environmental sustainability.

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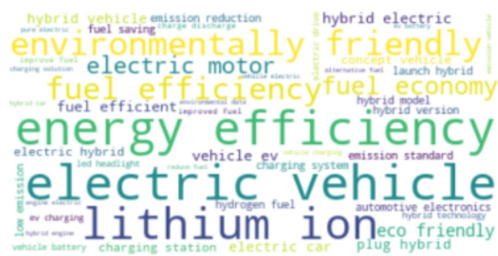
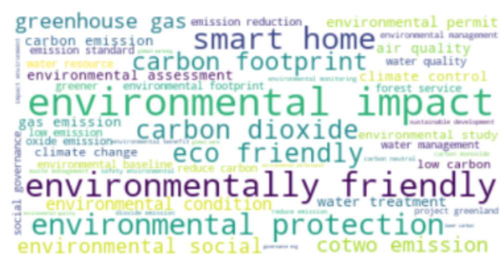
Figure 1. Word Clouds of Green Product Phrases

This figure depicts word clouds showcasing green product phrases utilized to identify green product announcements in the S&P Capital IQ Key Development database. We employ machine learning techniques, similar to those described in Sautner et al. (2023), to generate these green product phrases. Detailed procedures are outlined in *Online Appendix Section B*. Green product phrases are subsequently classified into four distinct groups: (1) energy-related green products; (2) electric vehicles; (3) general environmentally friendly products; and (4) recyclable and compostable consumer products.

(a) Green Products (Energy-Related)

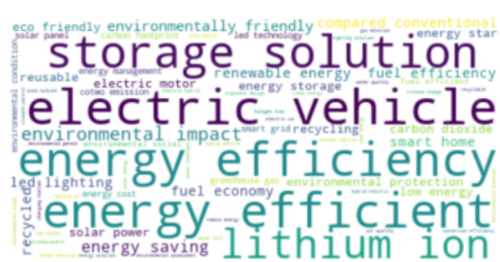


(b) Green Products (Electric Vehicle)



(c) Green Products (General Environmental)

(d) Green Products (Recyclable/Compostable)



(e) Green Products (All)

Figure 2. Correlation between ChatGPT Scores and the Number of Green Product Phrases

This figure shows the correlation between the number of "green product phrases" in product announcements and the ChatGPT probability score. For each document, we ask ChatGPT-3.5 to analyze and provide a score from 0 to 1, indicating the likelihood that the document describes a green product. We sort product announcements into groups based on the number of "green product phrases" and then calculate the average ChatGPT score for each group. The y-axis represents the average ChatGPT score.

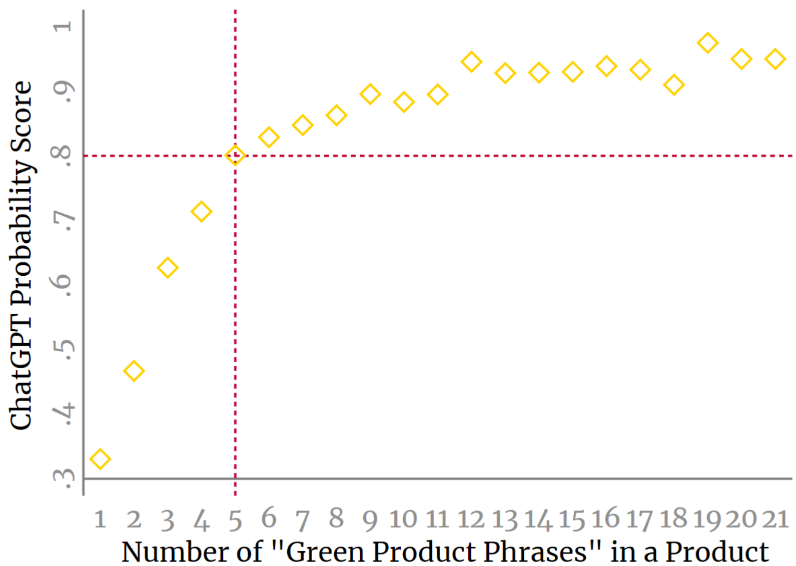


Figure 3. Fraction of Green Products in Fama-French 48 Industries

This figure illustrates the fraction of green products in each of the Fama-French 48 industries. A product is classified as green if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8. The green bar stands for the fraction of green products among all product announcements made by firms in a given industry.

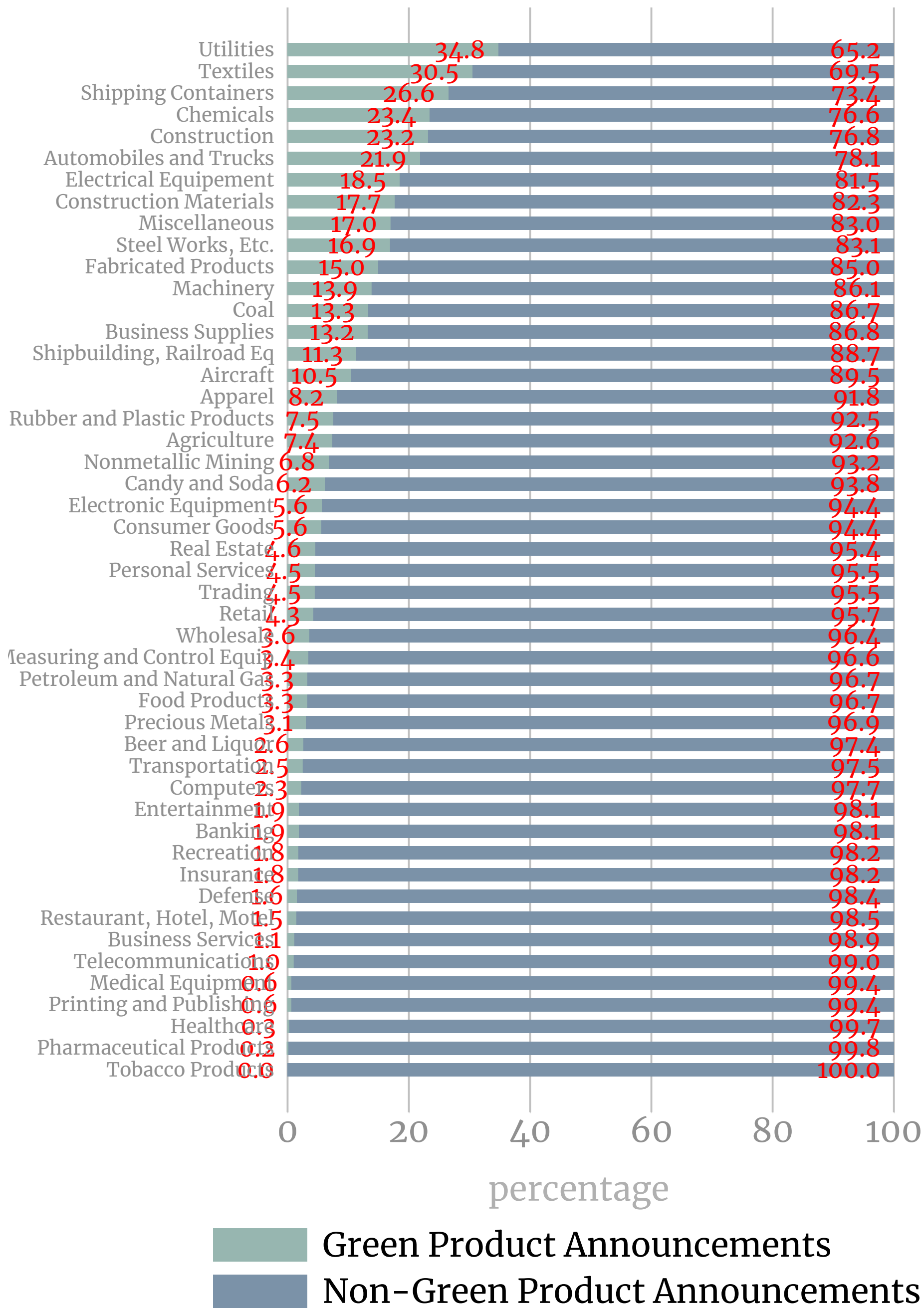


Figure 4. Industry Distribution of Green Product Announcements

This figure illustrates the industry distribution of both green and all (green and non-green) product announcements across the Fama-French 48 industry categories. The blue bar presents non-green products, while the green bar specifically focuses on green products. A product is classified as a green product if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8.

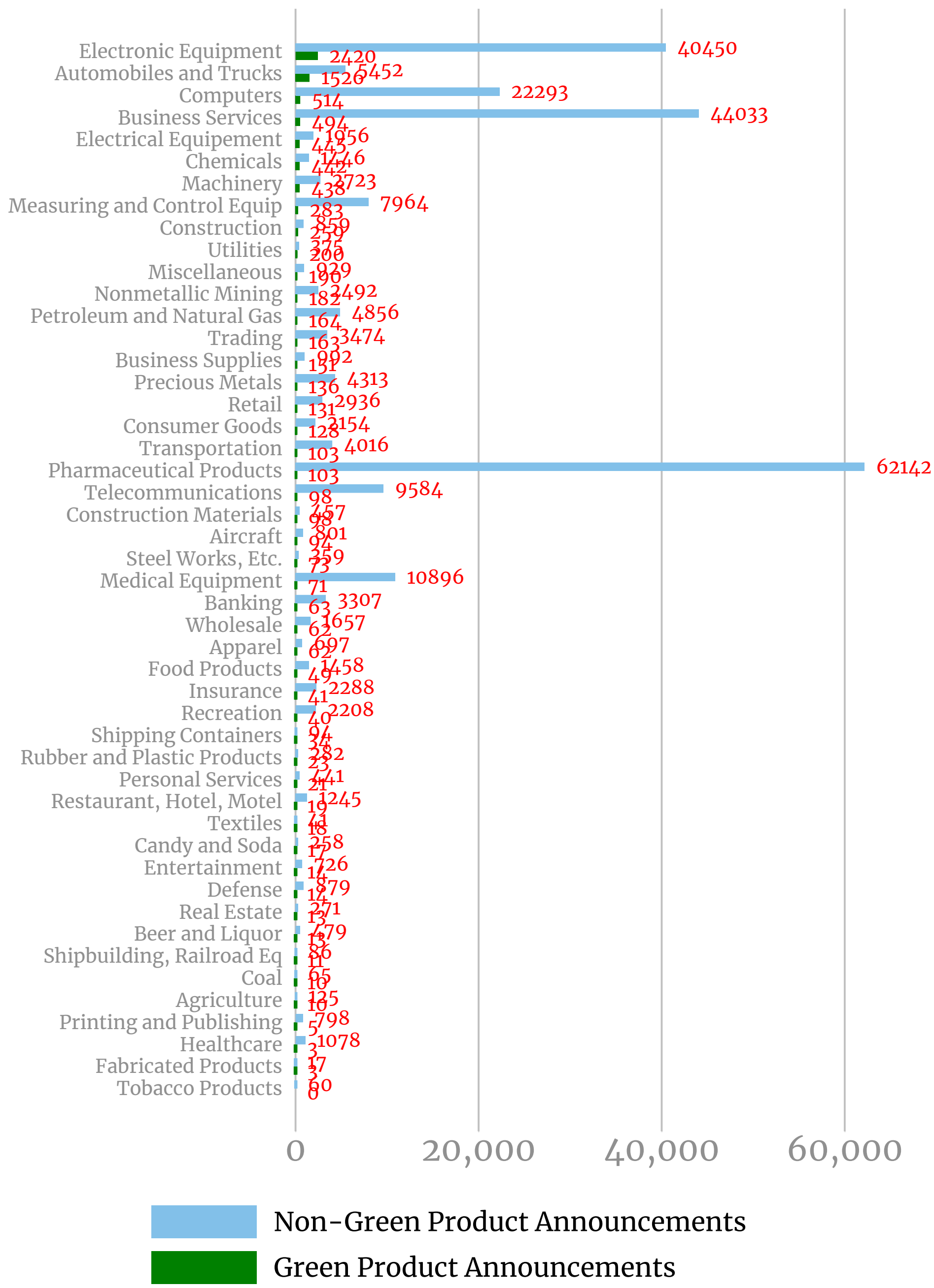


Figure 5. Construction of the Product Novelty Measure

This figure illustrates the construction of the product novelty measure. Using the focal product announcement A of firm f as an example, we calculate its product novelty as follows: First, we track firm f's past product announcements within the past three years. We then compute the pair-wise cosine similarity between product announcement A and these previous announcements (denoted as Products $P1$ and $P2$ in the figure below). Similarly, we track the future three-year product announcements of firm f and calculate pair-wise cosine similarity. The final product novelty measure is determined by the difference between the average similarity to future products ($F1$, $F2$, and $F3$) and the similarity to past products ($P1$ and $P2$). Our calculation requires at least one past and one future product announcement. Before computing pair-wise cosine similarity, we preprocess the text by removing stop words and excessively frequent words, following the approach outlined in Hoberg and Phillips (2016), and then lemmatize and convert all words to lowercase.

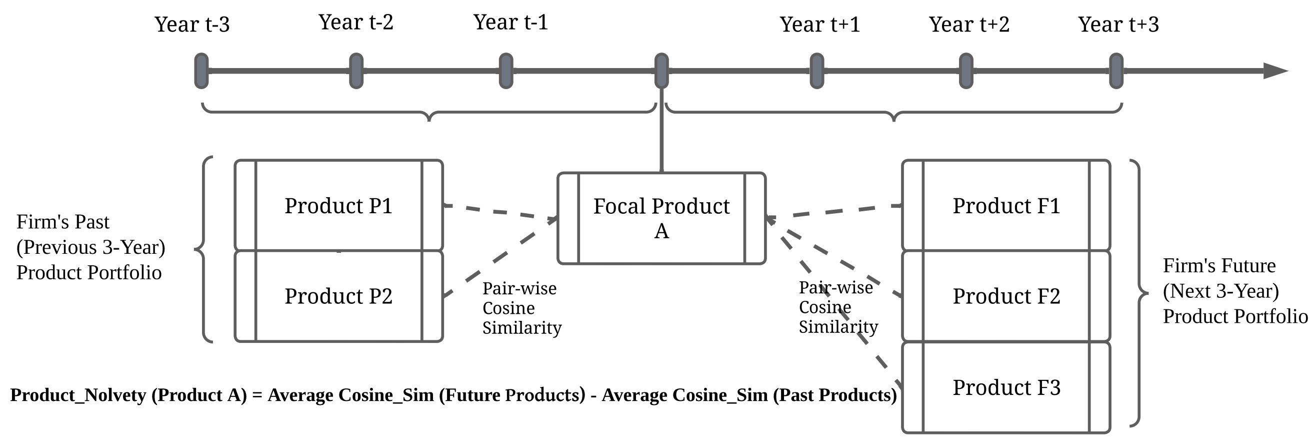


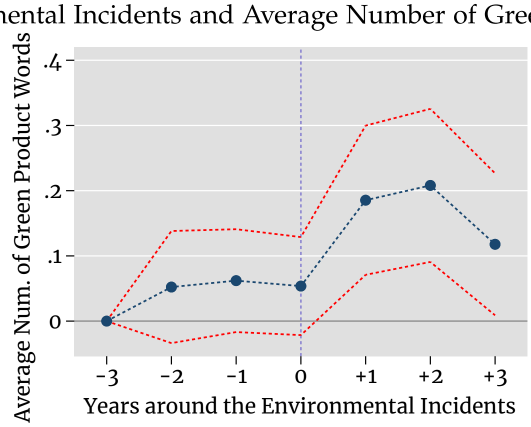
Figure 6. Environmental Incidents and Green Product Announcements

This figure presents stacked difference-in-difference (DID) regressions investigating post-incident green product announcements. Environmental incidents are sourced from the RepRisk database. We focus on the bottom 5% of incidents, representing those with the most negative market response in the [-1d, +1d] event window. Additionally, for each incident, we require that no other environmental incidents involving the firm occurred within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year. We only keep observations for treated and control firms within the [-3 Year, +3 Year] window. Our regressions are as follows,

$$\text{Green\_Product}_{i,c,t} = \sum_{\tau=-3}^{+3} \alpha_\tau I(Treatment)_{i,c,t} \times I(Incident \pm \tau \ Year)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \quad (6)$$

i represents the firm, c denotes the cohort in the stacked DID, and t signifies the year. In Panel A, the dependent variable is the average number of "green product phrases" appearing in each product announcement of firm i in year t, while in Panel B, it is the fraction of green products among all product announcements of firm i in year t. A product is classified as a green product if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8. $I(Treatment)$ serves as a dummy variable for firms experiencing environmental incidents. $\left\{I(Incident \pm \tau \ Year)\right\}_{\tau=-3}^{+3}$ consists of seven dummies surrounding the incident year for both treated and control firms. The control variable set $\mathbf{X}$ encompasses Firm Size, ROE, CAPX, PPE, Book-to-Market Ratio, RND, Sales Growth, and the count of any product announcements in year t. We control for cohort $\times$ year F.E. and cohort $\times$ firm F.E. Standard errors are clustered at the cohort $\times$ firm level, and confidence intervals are plotted at the 90% confidence level.

Panel A: Environmental Incidents and Average Number of Green Product Phrases



Panel B: Environmental Incidents and Fraction of Green Products

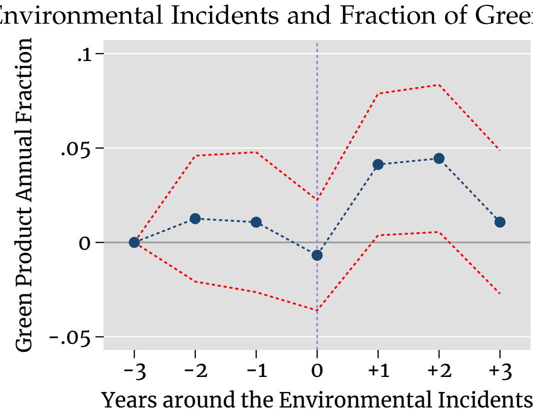


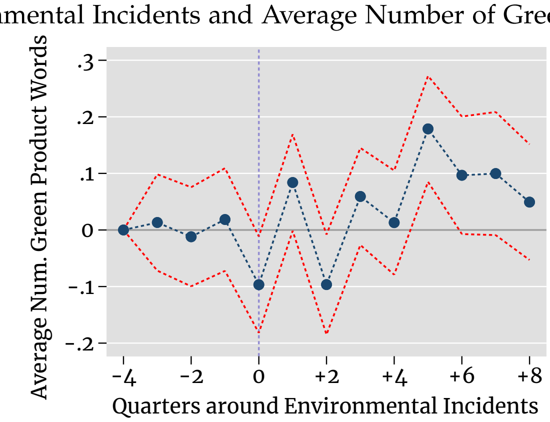
Figure 7. Environmental Incidents and Green Product Announcements (Quarterly Sample)

This figure presents stacked difference-in-difference (DID) regressions investigating post-incident green product announcements using the Compustat Quarterly data as our regression sample. Environmental incidents are sourced from the RepRisk database, focusing on the bottom 5% of incidents with the most negative market response in the [-1d, +1d] event window. Additionally, we ensure that no other environmental incidents involving the firm occurred within the past 12 quarters. For each treated firm, we match control firms within the same Fama-French 48 industry and year-quarter, retaining observations within the [-4 Quarter, +8 Quarter] window. Our regressions are formulated as follows:

$$\text{Green\_Product}_{i,c,y\text{-}q} = \sum_{\tau=-4}^{+8} \alpha_\tau I(\mathit{Treatment})_{i,c,y\text{-}q} \times I(\mathit{Incident} \pm \tau\ \mathit{Year})_{i,c,y\text{-}q} + \beta \mathbf{X}_{i,c,y\text{-}q} + \gamma_{i\times c} + \delta_{y\text{-}q\times c} + \phi_{q\times f} + \varepsilon_{i,c,y\text{-}q} \tag{7}$$

Here, i represents the firm, c denotes the cohort in the stacked DID, and y-q signifies the year-quarter. In Panel A, the dependent variable is the average number of "green product phrases" appearing in each product announcement of firm i in year-quarter yq, while in Panel B, it is the fraction of green products among all product announcements of firm i in year-quarter yq. $I(\mathit{Treatment})$ serves as a dummy variable for firms experiencing environmental incidents. $\left\{I(\mathit{Incident} \pm \tau\ \mathit{Year})\right\}_{\tau=-4}^{+8}$ consists of 13 dummies surrounding the incident year-quarter for both treated and control firms. The control variable set $\mathbf{X}$ encompasses Firm Size, Book Leverage, CASH, PPE, Book-to-Market Ratio, Sales Growth (all variables are at the quarterly level), and the count of any product announcements in yq. We control for cohort $\times$ year-quarter F.E., firm $\times$ quarter F.E., and cohort $\times$ firm F.E. Standard errors are clustered at the cohort $\times$ firm level, and confidence intervals are plotted at the 90% confidence level.

Panel A: Environmental Incidents and Average Number of Green Product Phrases



Panel B: Environmental Incidents and Quarterly Fraction of Green Products

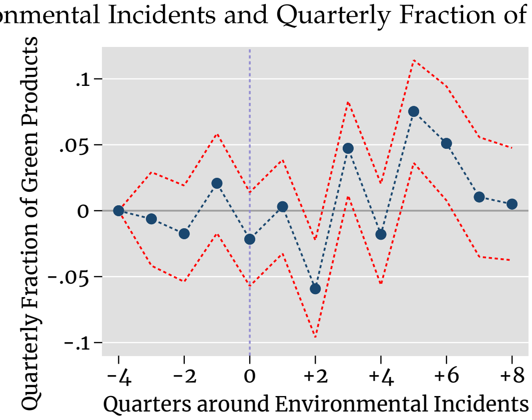


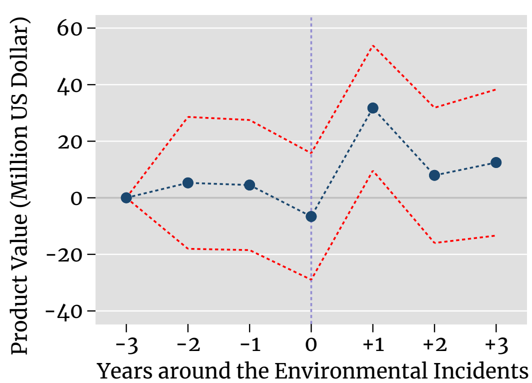
Figure 8. Environmental Incidents and Green Product Value

This figure presents stacked difference-in-difference (DID) regressions investigating the post-incident value of green product announcements. Environmental incidents are sourced from the RepRisk database, focusing on the bottom 5% of incidents with the most negative market response in the [-1d, +1d] event window. Additionally, for each incident, we require that no other environmental incidents involving the firm occurred within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year. We only keep observations for treated and control firms within the [-3 Year, +3 Year] window. The dependent variable, *Product Value*, is equal to [0d, +1d] CAR around the product announcement date multiplied by the market capitalization of the company on the day preceding the announcement. Due to noise, we winsorize this variable at the 10% and 90% levels. Our regressions are as follows:

$$\text{Product\_Value}_{i,c,t} = \sum_{\tau=-3}^{+3} \alpha_\tau I(\mathit{Treatment})_{i,c,t} \times I(\mathit{Incident} \pm \tau\ \mathit{Year})_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \tag{8}$$

Here, i represents the firm, c denotes the cohort in the stacked DID, and t signifies the year. $I(\mathit{Treatment})$ serves as a dummy variable for firms experiencing environmental incidents. $\left\{I(\mathit{Incident} \pm \tau\ \mathit{Year})\right\}_{\tau=-3}^{+3}$ consists of seven dummies surrounding the incident year for both treated and control firms. In Panel A, the dependent variable is the annual median of green product value. In Panel B, it is the annual median for non-green products. A product is classified as a green product if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8. The control variable set $\mathbf{X}$ encompasses Firm Size, ROE, CAPX, PPE, Book-to-Market Ratio, RND, Sales Growth, and the count of any product announcements in year t. We control for cohort $\times$ year F.E. and cohort $\times$ firm F.E. Standard errors are clustered at the cohort $\times$ firm level, and confidence intervals are plotted at the 90% confidence level.

Panel A: Annual Median Value of Green Products



Panel B: Annual Median Value of Non-Green Products

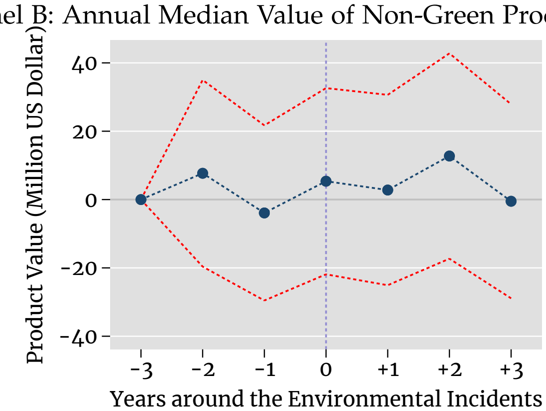


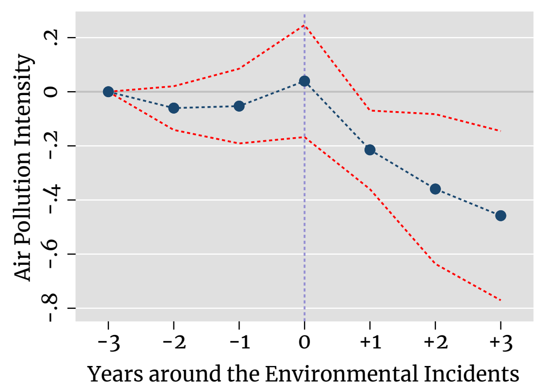
Figure 9. Environmental Incidents and Post-Incident Air Pollution Intensity

This figure presents stacked difference-in-difference (DID) regressions investigating post-incident air pollution intensity. Environmental incidents are sourced from the RepRisk database. We focus on the bottom 5% of incidents, representing those with the most negative market response in the [-1d, +1d] event window. Additionally, for each incident, we require that no other environmental incidents involving the firm occurred within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year. We only keep observations for treated and control firms within the [-3 Year, +3 Year] window. Our regressions are as follows,

$$\text{Air\_Pollution}_{i,c,t} = \sum_{\tau=-3}^{+3} \alpha_\tau \overline{I(Treatment)}_{i,c,t} \times I(Incident \pm \tau\ Year)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \tag{9}$$

i represents the firm, c denotes the cohort in the stacked DID, and t signifies the year. The dependent variable is the firm's air pollution cost scaled by sales. The air pollution cost is defined as the external cost of pollutants released to air by the consumption of fossil fuels and production processes which are owned or controlled by the company. Data are from S&P Trucost. In Panel A, we only include treated firms with their manual diff-in-diff estimator of post-incident green products in the top tercile. These treated firms are matched to control firms within the same Fama-French 48 industry and year. In Panel B, we use the remaining treated groups. The construction of the manual diff-in-diff estimator follows Figure 6 Panel B. $\overline{I(Treatment)}$ serves as a dummy variable for firms experiencing environmental incidents and announcing many green products after incidents (captured by the top tercile of the DID estimator in Figure 6 Panel B). $\left\{I(Incident \pm \tau\ \ Year)\right\}_{\tau=-3}^{+3}$ consists of seven dummies surrounding the incident year for both treated and control firms. The control variable set $\mathbf{X}$ encompasses Firm Size, ROE, CAPX, PPE, Book-to-Market Ratio, RND in year t. We control for cohort $\times$ year F.E. and cohort $\times$ firm F.E. Standard errors are clustered at the cohort $\times$ firm level, and confidence intervals are plotted at the 90% confidence level.

Panel A: Incidents **with** Post Green Products (Incidents with DID Estimator in Top Tercile)



Panel B: Incidents **without** Post Green Products (Remaining Incidents Sample)

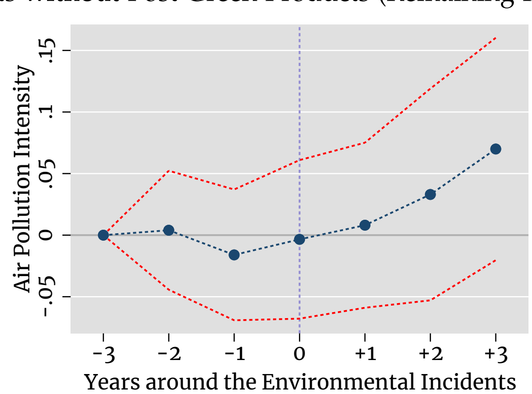


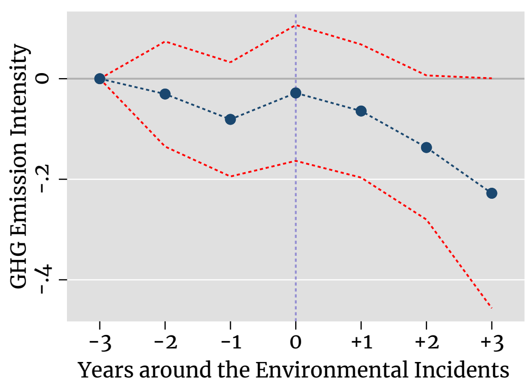
Figure 10. Environmental Incidents and Post-Incident GHG Emission Intensity

This figure presents stacked difference-in-difference (DID) regressions investigating post-incident green house gas emission intensity. Environmental incidents are sourced from the RepRisk database. We focus on the bottom 5% of incidents, representing those with the most negative market response in the [-1d, +1d] event window. Additionally, for each incident, we require that no other environmental incidents involving the firm occurred within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year. We only keep observations for treated and control firms within the [-3 Year, +3 Year] window. Our regressions are as follows,

$$\text{GHG\_Emission}_{i,c,t} = \sum_{\tau=-3}^{+3} \alpha_\tau \overline{I(Treatment)}_{i,c,t} \times I(Incident \pm \tau\ Year)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \tag{10}$$

i represents the firm, c denotes the cohort in the stacked DID, and t signifies the year. The dependent variable is the firm's GHG emission cost scaled by sales. The GHG emission cost is defined as the external cost of greenhouse gas (GHG) emissions released to air by the consumption of fossil fuels and production processes which are owned or controlled by the company. Data are from S&P Trucost. In Panel A, we only include treated firms with their manual diff-in-diff estimator of post-incident green products in the top tercile. These treated firms are matched to control firms within the same Fama-French 48 industry and year. In Panel B, we use the remaining treated groups. The construction of the manual diff-in-diff estimator follows Figure 6 Panel B. $\overline{I(Treatment)}$ serves as a dummy variable for firms experiencing environmental incidents and announcing many green products after incidents (captured by the top tercile of the DID estimator in Figure 6 Panel B). $\left\{I(Incident \pm \tau\ Year)\right\}_{\tau=-3}^{+3}$ consists of seven dummies surrounding the incident year for both treated and control firms. The control variable set $\mathbf{X}$ encompasses Firm Size, ROE, CAPX, PPE, Book-to-Market Ratio, RND in year t. We control for cohort $\times$ year F.E. and cohort $\times$ firm F.E. Standard errors are clustered at the cohort $\times$ firm level, and confidence intervals are plotted at the 90% confidence level.

Panel A: Incidents **with** Post Green Products (Incidents with DID Estimator in Top Tercile)



Panel B: Incidents **without** Post Green Products (Remaining Incidents Sample)

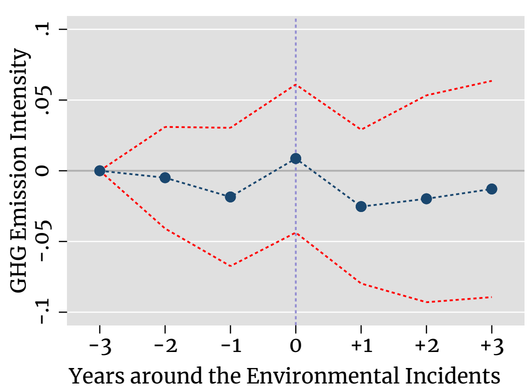


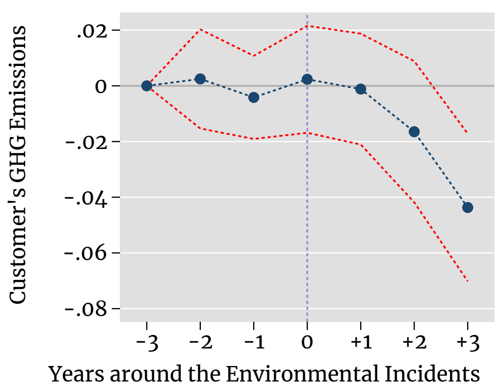
Figure 11. Incident-Driven Green Products and Customers' Environmental Performance

This figure presents stacked difference-in-difference (DID) regressions investigating incident-driven green products and customers' environmental performances. Environmental incidents are sourced from the RepRisk database. We focus on the bottom 5% of incidents, representing those with the most negative market response in the [-1d, +1d] event window. Additionally, for each incident, we require that no other environmental incidents involving the firm occurred within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year. We only keep observations for treated and control firms within the [-3 Year, +3 Year] window. Our regressions are as follows,

$$\text{Environmental\_Performance}_{j,c,t} = \sum_{\tau=-3}^{+3} \alpha_\tau \overline{I(Treatment)}_{i,j,c,t} \times I(Incident \pm \tau\ Year)_{i,j,c,t} + \beta_1 \mathbf{X}_{i,c,t} + \beta_2 \mathbf{X}_{j,c,t} + \gamma_{i \times c \times j} + \delta_{t \times c} + \varepsilon_{i,j,c,t} \quad (11)$$

i represents the incident firm (and its matched control-group firm), j denotes its business customer, c denotes the cohort in the stacked DID, and t signifies the year. The dependent variable is the business customer's environmental performances. Data are from S&P Trucost. We only include treated firms with their manual diff-in-diff estimator of post-incident green products in the top tercile. These treated firms are matched to control firms within the same Fama-French 48 industry and year. The construction of the manual diff-in-diff estimator follows Figure 6 Panel B. $\overline{I(Treatment)}$ serves as a dummy variable for firms experiencing environmental incidents and announcing many green products after incidents (captured by the top tercile of the DID estimator in Figure 6 Panel B). $\left\{I(Incident \pm \tau\ Year)\right\}_{\tau=-3}^{+3}$ consists of seven dummies surrounding the incident year for both treated and control firms. The control variable set $\mathbf{X}$ encompasses Firm Size, ROE, CAPX, PPE, Book-to-Market Ratio, RND in year t for both firm i and j, separately. We control for cohort $\times$ year F.E. and cohort $\times$ firm $\times$ customer firm F.E. Standard errors are clustered at the cohort $\times$ customer firm level, and confidence intervals are plotted at the 90% confidence level.

Panel A: Incidents **with** Post Green Products and Customers' CO2 emissions



Panel B: Incidents **with** Post Green Products and Customers' Land & Water Pollution

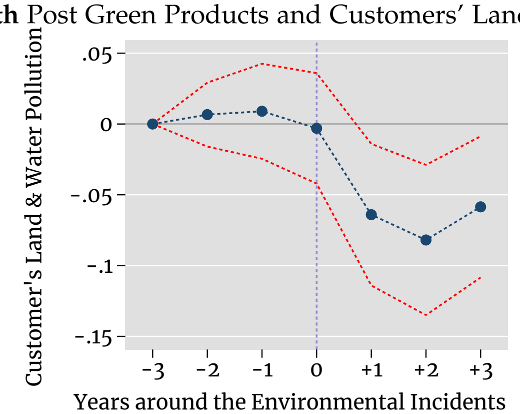
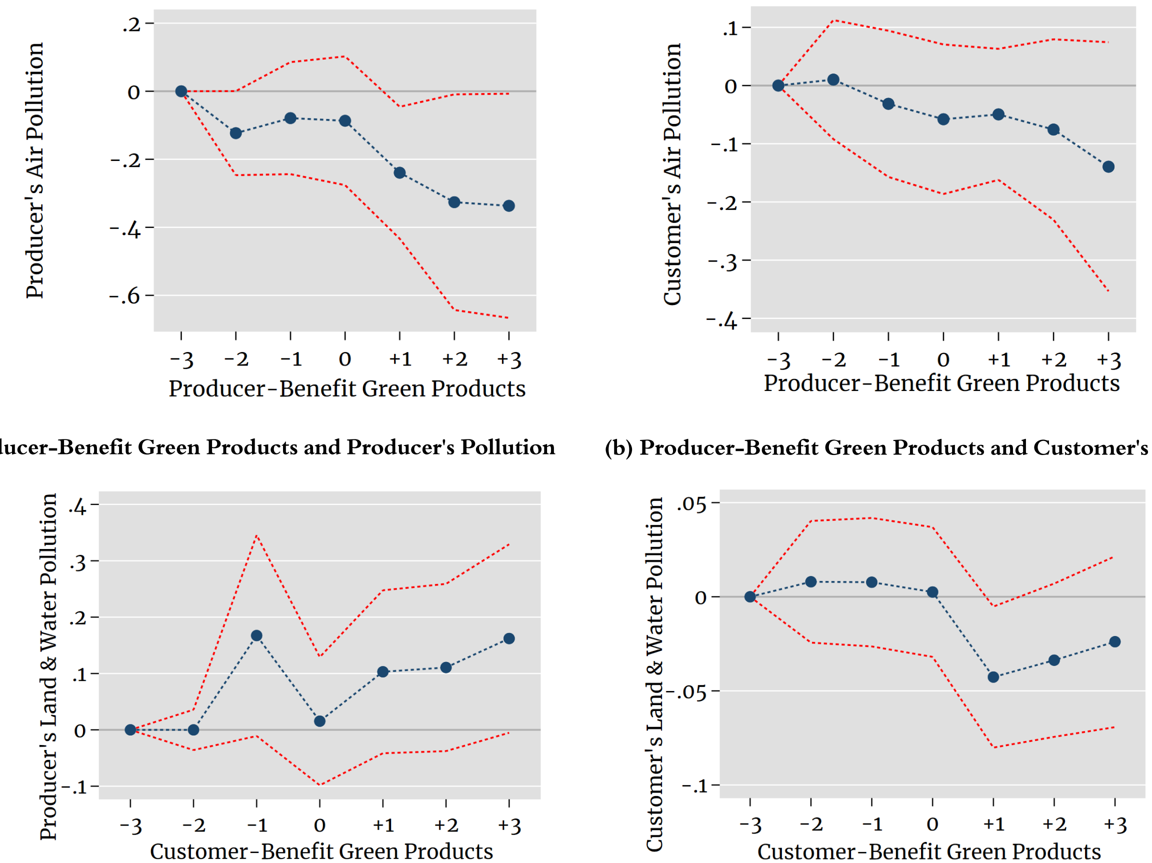


Figure 12. Producer-Benefit and Consumer-Benefit Green Products

This figure examines the impacts of producer-benefit and customer-benefit green products on the environmental performance of producers and customers. We utilized ChatGPT to distinguish between producer- and customer-benefit green products. Subsequently, we manually estimated a DID measure for each category and selected the top tercile for analysis. Panels A and B present results for the top-tercile treated group of producer-benefit green products, while Panels C and D display results for the top-tercile treated group of customer-benefit green products.



(a) Producer-Benefit Green Products and Producer's Pollution

(b) Producer-Benefit Green Products and Customer's Pollution

(c) Customer-Benefit Green Products and Producer's Pollution

(d) Customer-Benefit Green Products and Customer's Pollution

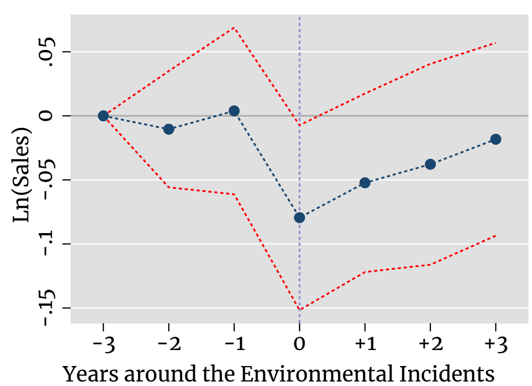
Figure 13. Environmental Incidents and Annual Sales

This figure presents stacked difference-in-difference (DID) regressions investigating post-incident annual sales. Environmental incidents are sourced from the RepRisk database. We focus on the bottom 5% of incidents, representing those with the most negative market response in the [-1d, +1d] event window. Additionally, for each incident, we require that no other environmental incidents involving the firm occurred within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year. We only keep observations for treated and control firms within the [-3 Year, +3 Year] window. Our regressions are as follows,

$$\ln(\text{Sales}_{i,c,t}) = \sum_{\tau=-3}^{+3} \alpha_\tau \overline{I(Treatment)}_{i,c,t} \times I(Incident \pm \tau\ Year)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \tag{12}$$

i represents the firm, c denotes the cohort in the stacked DID, and t signifies the year. The dependent variable is the natural logarithm of annual sales. In Panel A, we only include treated firms with their manual diff-in-diff estimator of post-incident green products in the top tercile. These treated firms are matched to control firms within the same Fama-French 48 industry and year. In Panel B, we use the remaining treated groups. The construction of the manual diff-in-diff estimator follows Figure 6 Panel B. $\overline{I(Treatment)}$ serves as a dummy variable for firms experiencing environmental incidents and announcing many green products after incidents (captured by the top tercile of the DID estimator in Figure 6 Panel B). $\left\{I(Incident \pm \tau\ \ Year)\right\}_{\tau=-3}^{+3}$ consists of seven dummies surrounding the incident year for both treated and control firms. The control variable set $\mathbf{X}$ encompasses Firm Size, ROE, CAPX, PPE, Book-to-Market Ratio, RND in year t. We control for cohort $\times$ year F.E. and cohort $\times$ firm F.E. Standard errors are clustered at the cohort $\times$ firm level, and confidence intervals are plotted at the 90% confidence level.

Panel A: Incidents **with** Post Green Products (Incidents with DID Estimator in Top Tercile)



Panel B: Incidents **without** Post Green Products (Remaining Incidents Sample)

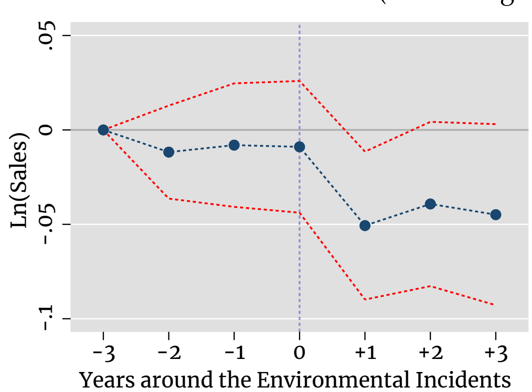


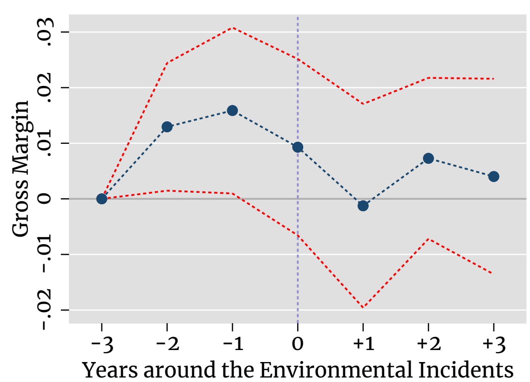
Figure 14. Environmental Incidents and Gross Margin

This figure presents stacked difference-in-difference (DID) regressions investigating post-incident gross margin. Environmental incidents are sourced from the RepRisk database. We focus on the bottom 5% of incidents, representing those with the most negative market response in the [-1d, +1d] event window. Additionally, for each incident, we require that no other environmental incidents involving the firm occurred within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year. We only keep observations for treated and control firms within the [-3 Year, +3 Year] window. Our regressions are as follows,

$$\text{Gross Margin}_{i,c,t} = \sum_{\tau=-3}^{+3} \alpha_\tau \overline{I(Treatment)}_{i,c,t} \times I(Incident \pm \tau\ Year)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \quad (13)$$

i represents the firm, c denotes the cohort in the stacked DID, and t signifies the year. The dependent variable is the gross margin. Gross margin is equal to net profits ($REVT - COGS$) scaled by total revenue ($REVT$). In Panel A, we only include treated firms with their manual diff-in-diff estimator of post-incident green products in the top tercile. These treated firms are matched to control firms within the same Fama-French 48 industry and year. In Panel B, we use the remaining treated groups. The construction of the manual diff-in-diff estimator follows Figure 6. $\overline{I(Treatment)}$ serves as a dummy variable for firms experiencing environmental incidents and announcing many green products after incidents (captured by the top tercile of the DID estimator in Figure 6 Panel B). $\left\{I(Incident \pm \tau\ \ Year)\right\}_{\tau=-3}^{+3}$ consists of seven dummies surrounding the incident year for both treated and control firms. The control variable set $\mathbf{X}$ encompasses Firm Size, ROE, CAPX, PPE, Book-to-Market Ratio, RND in year t. We control for cohort $\times$ year F.E. and cohort $\times$ firm F.E. Standard errors are clustered at the cohort $\times$ firm level, and confidence intervals are plotted at the 90% confidence level.

Panel A: Incidents **with** Post Green Products (Incidents with DID Estimator in Top Tercile)



Panel B: Incidents **without** Post Green Products (Remaining Incidents Sample)

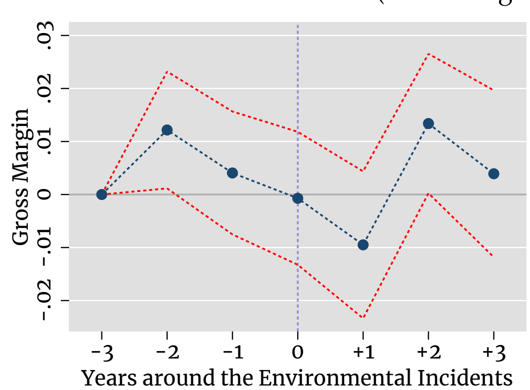


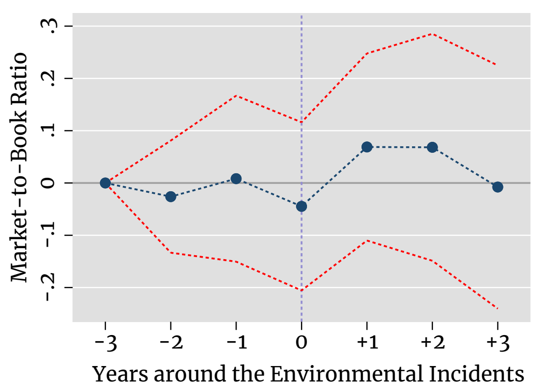
Figure 15. Environmental Incidents and Market-to-Book Ratio

This figure presents stacked difference-in-difference (DID) regressions investigating post-incident market-to-book ratio. Environmental incidents are sourced from the RepRisk database. We focus on the bottom 5% of incidents, representing those with the most negative market response in the [-1d, +1d] event window. Additionally, for each incident, we require that no other environmental incidents involving the firm occurred within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year. We only keep observations for treated and control firms within the [-3 Year, +3 Year] window. Our regressions are as follows,

$$\text{M/B}_{i,c,t} = \sum_{\tau=-3}^{+3} \alpha_\tau \overline{I(Treatment)}_{i,c,t} \times I(Incident \pm \tau\ Year)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \tag{14}$$

i represents the firm, c denotes the cohort in the stacked DID, and t signifies the year. The dependent variable is the market-to-book ratio. In Panel A, we only include treated firms with their manual diff-in-diff estimator of post-incident green products in the top tercile. These treated firms are matched to control firms within the same Fama-French 48 industry and year. In Panel B, we employ the remaining treated groups. The construction of the manual diff-in-diff estimator follows Figure 6 Panel B. $\overline{I(Treatment)}$ serves as a dummy variable for firms experiencing environmental incidents and announcing many green products after incidents (captured by the top tercile of the DID estimator in Figure 6 Panel B). $\left\{I(Incident \pm \tau\ \ Year)\right\}_{\tau=-3}^{+3}$ consists of seven dummies surrounding the incident year for both treated and control firms. The control variable set $\mathbf{X}$ encompasses Firm Size, ROE, CAPX, PPE, and RND in year t. We control for cohort $\times$ year F.E. and cohort $\times$ firm F.E. Standard errors are clustered at the cohort $\times$ firm level, and confidence intervals are plotted at the 90% confidence level.

Panel A: Incidents **with** Post Green Products (Incidents with DID Estimator in Top Tercile)



Panel B: Incidents **without** Post Green Products (Remaining Incidents Sample)

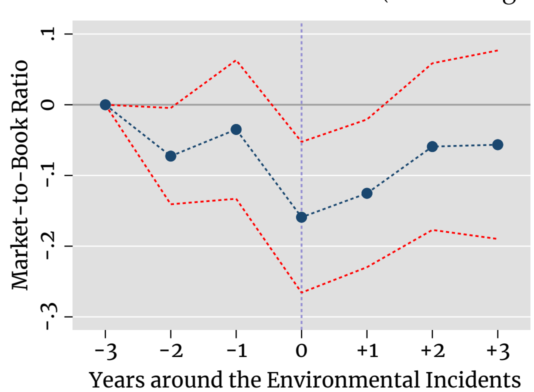


Table 1. Summary Statistics

This table presents summary statistics for three samples utilized in the analyses. Panel A provides summary statistics for the product announcement sample sourced from the Capital IQ Key Development Database. We select all news announcements from Capital IQ with EventTypeID = 41 (product-related announcements). A product is classified as a green product if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8. The specific type of green products (such as energy-related) requires at least two distinct "green product phrases" from the phrase set of that specific type. Product value is calculated as [0d, +1d] CAR around the product announcement date multiplied by the market capitalization of the company on the day preceding the announcement (Unit: Million US Dollar). Panel B reports summary statistics for the RepRisk environmental incident sample. We focus on the bottom 5% of incidents with the most negative market response in the [-1d, +1d] event window. Environmental Incidents (Used in Regressions) requires that no environmental incidents involving the firm occurred within the past 12 quarters. Panel C presents summary statistics for the stacked Diff-in-Diff regression sample. Each treated firm among 490 incidents is matched to control firms within the same Fama-French 48 industry and year. We only retain observations for treated and control firms within the [-3 Year, +3 Year] window. The variable definition and construction can be found in *Online Appendix Section A*.

Panel A: Product Announcement Sample (Capital IQ Key Development Database)

Sample Period: 2001 – 2022			
Number of Total Product Announcements:			256,512
Number of Green Product Announcements			
— Total:			9,451
— Energy-Related:			3,519
— Electric Vehicle:			2,365
— General Environmental:			3,531
— Recyclable and Compostable:			795
	Mean	Median	Num. Obs.
Product Announcement CAR [0d, +1d]			
— Green Product:	0.24%	0.05%	8,837
— Non-Green Product:	0.28%	0.08%	237,049
Product Value (Million US Dollar)			
— Green Product:	6.374	0.384	8,836
— Non-Green Product:	8.276	0.264	236,986
Product Novelty			
— Green Product:	0.003	0.002	8,541
— Non-Green Product:	-0.0004	-0.0002	234,612

Panel B: RepRisk Environmental Incident Sample

Number of Environmental Incidents (Bottom 5%):			1,067
Number of Firm-Year with Environmental Incidents:			788
Number of Firm-Year with Environmental Incidents (Used in Regressions):			490
Fama-French Industries with the most Incidents (Used in Regressions):			
— Petroleum and Natural Gas:			111
— Utilities:			53
— Chemicals:			27
	Mean	Median	Num. Obs.
Incident CAR [-1d, +1d]	-5.12%	-3.92%	1,067

Panel C: Stacked Diff-in-Diff Sample

	Treated Group			Control Group		
Variable	Mean	Median	Num. Obs.	Mean	Median	Num. Obs.
Average Number of Green Product Phrases	0.504	0.000	1,427	0.262	0.000	125,227
Fraction of Green Products	0.149	0.000	1,427	0.071	0.000	125,227
Number of Annual Product Announcements	8.233	3.000	1,427	4.898	2.000	125,227
Number of Green Patents	13.423	0.000	1,427	1.973	0.000	125,227
Firm Size	9.251	9.520	1,427	7.073	6.935	125,159
PPE	8.516	8.887	1,326	6.127	6.093	119,956
ROE	0.060	0.110	1,403	-0.064	0.048	120,608
BM	0.531	0.435	1,427	0.608	0.475	125,084
LEV	0.467	0.454	1,422	0.369	0.294	124,496
CAPX	0.076	0.045	1,400	0.082	0.041	120,437
RND	0.013	0.000	1,403	0.054	0.000	120,697
Sales Growth	0.071	0.041	1,372	0.118	0.068	115,787

Table 2. The Predictability of RepRisk Environmental Incidents

This table investigates the predictability of RepRisk environmental incidents, focusing on the bottom 5% of universal RepRisk environmental incidents with the most negative market response in the [-1d, +1d] event window. Additionally, we stipulate that each incident must not have had any previous environmental incidents involving the same firm within the past 12 quarters. The sample filtering results in a total of 490 incidents. The dependent variable in the regressions is a dummy variable equal to 1 if firm i experiences an incident in year t, and the incident is among the 490 severe incidents. Green patents are defined and measured following Cohen et al. (2020) and Hege et al. (2024). Firm-level stock for green patents, all patents, green products, and all products are measured within the past three years, while all other control variables are measured in year $t-1$. External costs for air pollution, GHG emissions, and land & water pollution only account for direct pollution and emissions caused by the firm. Standard errors are clustered at the firm level, with statistical significance denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

	(1) I(Incident)	(2) I(Incident)	(3) I(Incident)
Num. Green Patents (Past Three Years)	-0.002	-0.001	-0.001
	(0.002)	(0.001)	(0.002)
Num. All Patents (Past Three Years)	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)
Num. Green Products (Past Three Years)	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Num. All Products (Past Three Years)	0.001	0.000	0.000
	(0.001)	(0.001)	(0.002)
Firm Size (Lag)		0.001	-0.002
		(0.002)	(0.005)
ROE (Lag)		-0.000	0.000
		(0.000)	(0.001)
CAPX (Lag)		0.000	0.002
		(0.001)	(0.001)
PPE (Lag)		0.005***	0.011**
		(0.002)	(0.005)
RND (Lag)		-0.000	-0.001
		(0.000)	(0.001)
SALE (Lag)		0.000	0.006
		(0.002)	(0.005)
M/B Ratio (Lag)		0.001*	0.001
		(0.000)	(0.001)
Gross Margin (Lag)		-0.000	-0.001
		(0.001)	(0.001)
External Cost – Air Pollution (Lag)			-0.000
			(0.002)
External Cost – GHG Emissions (Lag)			0.003
			(0.003)
External Cost – Land & Water Pollution (Lag)			-0.001
			(0.002)
Firm F.E.	Y	Y	Y
Industry × Year F.E.	Y	Y	Y
Num. Obs.	94577	65579	28342
Adj. R^2	0.023	0.016	0.018

Table 3. Product Novelty, Green Products, and Product Value

This table examines the relationships among product novelty, green products, and product value. In both Panel A and B, the dependent variable is either the event-study cumulative abnormal return in the [0d, +1d] event window surrounding the date of product announcements (denoted as *CAR[0, 1]*) or the product value (denoted as *Prod_Value*). *Prod_Value* represents the [0d, +1d] CAR around the product announcement date multiplied by the market capitalization of the company on the day preceding the announcement. To address noise, we winsorize this variable at the 10% and 90% levels. *Product_Novelty* is a continuous measure capturing the extent to which a given product announcement differs from previous product portfolios of the firm and is similar to future product offerings. The construction follows the methodology outlined in Figure 5. *Product_Novelty_Dummy* is a dummy variable equal to 1 if *Product_Novelty* is above the sample median. I(Green Product) is a dummy variable for green products. A product is classified as a green product if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8. Standard errors are clustered at the firm level, with statistical significance denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Value of Novel Products	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAR[0, 1]	CAR[0, 1]	Prod_Value	Prod_Value	CAR[0, 1]	CAR[0, 1]	Prod_Value	Prod_Value
Product_Novelty	0.019***	0.019***	83.403***	90.437***				
	(0.003)	(0.003)	(16.255)	(16.433)				
Product_Novelty_Dummy					0.001***	0.001***	5.503***	5.834***
					(0.000)	(0.000)	(1.648)	(1.718)
Num_Product_Words	-0.000*	-0.000	0.027	0.035	-0.000*	-0.000	0.026	0.033
	(0.000)	(0.000)	(0.033)	(0.033)	(0.000)	(0.000)	(0.033)	(0.033)
Num_Previous_Products	-0.000***	-0.000	0.028	-0.034	-0.000***	-0.000	0.027	-0.035
	(0.000)	(0.000)	(0.039)	(0.046)	(0.000)	(0.000)	(0.039)	(0.046)
Num_Future_Products	-0.000	0.000	0.006	-0.047	-0.000	0.000	0.006	-0.047
	(0.000)	(0.000)	(0.068)	(0.096)	(0.000)	(0.000)	(0.068)	(0.097)
Year-Month F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Firm F.E.		Y		Y		Y		Y
N	197127	196947	197090	196911	197127	196947	197090	196911
Adj. R^2	0.007	0.026	0.003	-0.006	0.007	0.026	0.003	-0.006

Panel B. Interact with Green Products	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAR[0, 1]	CAR[0, 1]	Prod_Value	Prod_Value	CAR[0, 1]	CAR[0, 1]	Prod_Value	Prod_Value
I(Green Product)	-0.001	0.000	-6.175*	-1.271	-0.000	0.001	-9.644*	-5.522
	(0.000)	(0.000)	(3.702)	(4.624)	(0.001)	(0.001)	(5.215)	(5.897)
Product_Novelty	0.012***	0.013***	26.634***	31.692***				
	(0.002)	(0.002)	(7.999)	(8.581)				
I(Green Product) × Product_Novelty	-0.010	-0.009	3.018	14.778				
	(0.008)	(0.009)	(36.245)	(41.849)				
Product_Novelty_Dummy					0.001***	0.001***	4.063***	4.372***
					(0.000)	(0.000)	(1.201)	(1.220)
I(Green Product) × Product_Novelty_Dummy					-0.001	-0.001	6.268	7.786
					(0.001)	(0.001)	(6.503)	(6.697)
Year-Month F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Firm F.E.		Y		Y		Y		Y
N	197127	196947	197090	196911	197127	196947	197090	196911
Adj. R^2	0.007	0.026	0.003	-0.006	0.007	0.026	0.003	-0.006

Table 4. Do Brown Industries Launch More Green Products?

This table examines whether firms within brown industries are more likely to launch green products. The observations are at the industry (Fama-French 48 industries) × year level. The dependent variable is the fraction of green products among all products launched by firms in industry j during year t. A product is classified as a green product if it meets either of the following criteria: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8. The independent variables are the industry median of firm-level variables. Standard errors are clustered at the industry level. Statistical significance is indicated by *, **, and ***, representing significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Industry Fraction of Green Products					
GHG Emissions (Industry Median)	0.041***			0.041***		
	(0.013)			(0.014)		
Air Pollution (Industry Median)		0.041***			0.045***	
		(0.013)			(0.012)	
Land & Water Pollution (Industry Median)			0.034**			0.025*
			(0.014)			(0.013)
Firm Size (Industry Median)				-0.019	-0.012	-0.031*
				(0.016)	(0.016)	(0.016)
ROE (Industry Median)				0.019**	0.021***	0.018**
				(0.007)	(0.008)	(0.008)
CAPX (Industry Median)				-0.030***	-0.032***	-0.019*
				(0.010)	(0.011)	(0.011)
PPE (Industry Median)				0.044**	0.036**	0.061***
				(0.017)	(0.016)	(0.015)
BM (Industry Median)				0.019*	0.017	0.023*
				(0.011)	(0.012)	(0.013)
RND (Industry Median)				0.011	0.009	0.007
				(0.010)	(0.009)	(0.010)
Sales Growth (Industry Median)				-0.011**	-0.013**	-0.014**
				(0.005)	(0.006)	(0.006)
HHI				-0.005	-0.006	-0.008
				(0.010)	(0.010)	(0.011)
Year F.E.	Y	Y	Y	Y	Y	Y
N	966	964	889	966	964	889
adj. R^2	0.170	0.171	0.139	0.232	0.238	0.224

Table 5. Environmental Incidents and Frequency of Green Products

This table presents stacked difference-in-difference (DID) regressions investigating post-incident green product announcements. Environmental incidents are sourced from the RepRisk database. We focus on the bottom 5% of incidents, representing those with the most negative market response in the [-1d, +1d] event window. Additionally, for each incident, we require that no other environmental incidents involving the firm occurred within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year. We only keep observations for treated and control firms within the [-3 Year, +3 Year] window. Our regressions are as follows,

$$\text{Green\_Product}_{i,c,t} = \sum_{\tau=1}^{3} \alpha_\tau I(Treatment)_{i,c,t} \times I(Post\ \tau yr)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \tag{15}$$

Where i represents the firm, c denotes the cohort in the stacked DID, and t signifies the year. Panel A reports the benchmark regressions. The dependent variable in columns 1 and 2 (Average Num. Green Product Words) is the average number of green product phrases appearing in each product announcement of firm i in year t. Columns 3 and 4 (Fraction of Green Products) represent the fraction of green products among all product announcements of firm i in year t. A product is classified as a green product if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8. Columns 5 and 6 (Number of All Product Announce) represent the number of all product announcements by firm i in year t, using Poisson regressions. In Panel B, we median-split both the treated firms (490 incident firms) and control firms by MSCI environmental scores of their business customer firms. Each treated and control firm must have at least one customer firm reported in the FactSet Revere Supply Chain database, and its MSCI environmental score must not be missing. We measure both the supply chain relationships and customer firms' environmental score in the year preceding the incidents. In Panel C, we median-split both the treated firms (490 incident firms) and control firms by the level of fraction of institutional ownership held by environmental-minded institutional investors. Environmental-minded institutional investors are those institutions with value-weighted portfolio-level environmental score in the top tercile among all institutions in the corresponding year-quarter. Standard errors are clustered at the cohort × firm level, with statistical significance denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Full Sample	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	Poisson	Poisson
Dependent Var. =	Average Num. Green Product Words		Fraction of Green Products		Number of All Product Announce	
I(Treatment) × I(Post 1yr)	0.193***	0.147**	0.050**	0.035*	0.103	0.074
	(0.073)	(0.073)	(0.020)	(0.019)	(0.093)	(0.081)
I(Treatment) × I(Post 2yr)	0.196***	0.179***	0.052***	0.043**	0.079	0.040
	(0.066)	(0.068)	(0.019)	(0.019)	(0.082)	(0.068)
I(Treatment) × I(Post 3yr)	0.127*	0.097	0.030	0.014	-0.100	-0.135
	(0.071)	(0.065)	(0.024)	(0.021)	(0.172)	(0.142)
I(Post 1yr)	0.014**		0.002		0.004	
	(0.006)		(0.002)		(0.008)	
I(Post 2yr)	0.038***		0.007**		0.022*	
	(0.008)		(0.003)		(0.013)	
I(Post 3yr)	0.018*		0.003		0.036**	
	(0.010)		(0.003)		(0.018)	
Firm-level Controls	Y	Y	Y	Y	Y	Y
Year F.E.	Y		Y		Y	
Cohorts × Year F.E.		Y		Y		Y
Cohorts × Firm F.E.	Y	Y	Y	Y	Y	Y
N	103,594	103,479	103,594	103,479	103,594	103,479
Adj. R^2	0.505	0.533	0.479	0.498		

Panel B. Split Sample with Environmental-Conscious Institutional Ownership	(1)	(2)	(3)	(4)	(5)	(6)
	High E-C Institutional Ownership			*Low E-C Institutional Ownership*		
	OLS	OLS	Poisson	OLS	OLS	Poisson
Dependent Var. =	Average Num. Green Product Words	Fraction of Green Products	Total Number All Products	Average Num. Green Product Words	Fraction of Green Products	Total Number All Products
I(Treatment) × I(Post 1yr)	0.166***	0.063***	0.056	0.034	0.028	0.074
	(0.057)	(0.020)	(0.069)	(0.062)	(0.025)	(0.087)
I(Treatment) × I(Post 2yr)	0.078	0.022	0.062	0.392***	0.090***	0.040
	(0.060)	(0.021)	(0.053)	(0.066)	(0.027)	(0.103)
I(Treatment) × I(Post 3yr)	0.083	0.026	-0.158	0.067	-0.023	0.152
	(0.060)	(0.021)	(0.127)	(0.071)	(0.029)	(0.103)
Firm-level Controls	Y	Y	Y	Y	Y	Y
Cohorts × Year F.E.	Y	Y	Y	Y	Y	Y
Cohorts × Firm F.E.	Y	Y	Y	Y	Y	Y
N	30,311	30,311	30,311	20,771	20,771	20,771
Adj. R^2	0.501	0.462		0.568	0.526	

Panel C. Split Sample with the Customer's Environmental Score	(1)	(2)	(3)	(4)	(5)	(6)
	High Customer's Environmental Score			*Low Customer's Environmental Score*		
	OLS	OLS	Poisson	OLS	OLS	Poisson
Dependent Var. =	Average Num. Green Product Words	Fraction of Green Products	Total Number All Products	Average Num. Green Product Words	Fraction of Green Products	Total Number All Products
I(Treatment) × I(Post 1yr)	0.278***	0.037	0.096	-0.006	0.023	0.064
	(0.089)	(0.025)	(0.078)	(0.111)	(0.025)	(0.069)
I(Treatment) × I(Post 2yr)	0.109	0.043	0.063	-0.209*	-0.019	0.044
	(0.098)	(0.027)	(0.084)	(0.126)	(0.028)	(0.069)
I(Treatment) × I(Post 3yr)	0.081	0.058*	-0.184*	-0.114	-0.025	-0.062
	(0.117)	(0.032)	(0.103)	(0.145)	(0.032)	(0.070)
Firm-level Controls	Y	Y	Y	Y	Y	Y
Cohorts × Year F.E.	Y	Y	Y	Y	Y	Y
Cohorts × Firm F.E.	Y	Y	Y	Y	Y	Y
N	11,246	11,246	11,246	12,656	12,656	12,656
Adj. R^2	0.665	0.604		0.566	0.560	

Table 6. Environmental Incidents and Frequency of Green (Non-Green) and Novel (Non-Novel) Products

This table presents stacked difference-in-difference (DID) regressions investigating post-incident green product announcements, extending the analysis from Table 5 to differentiate between novel-green and non-novel-green products. Environmental incidents are sourced from the RepRisk database, focusing on the bottom 5% of incidents with the most negative market response in the [-1d, +1d] event window. Additionally, each incident is required to have had no other environmental incidents involving the firm within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year, retaining observations for treated and control firms within the [-3 Year, +3 Year] window. Our regressions follow the equation:

$$\text{Green\_Product}_{i,c,t} = \sum_{\tau=1}^{3} \alpha_\tau I(Treatment)_{i,c,t} \times I(Post\ \tau yr)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \tag{16}$$

Where i represents the firm, c denotes the cohort in the stacked DID, and t signifies the year. The dependent variables are the ratios of A and B, where A and B are shown in the top row of the table. The control variable set $\mathbf{X}$ encompasses Firm Size, ROE, CAPX, PPE, Book-to-Market Ratio, and RND in year t. Standard errors are clustered at the cohort $\times$ firm level, with statistical significance denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	A = (Total Green Product Words in Novel Products)		A = (Number of Green & Novel Products)		A = (Total Green Product Words in Non-Novel Products)		A = (Number of Green & Non-Novel Products)		A = (Number of Non-Green & Novel Products)		A = (Number of Non-Green & Non-Novel Products)	
	B = (Number of Products)		B = (Number of Products)		B = (Number of Products)		B = (Number of Products)		B = (Number of Products)		B = (Number of Products)	
Dependent Var. =	A ÷ B		A ÷ B		A ÷ B		A ÷ B		A ÷ B		A ÷ B	
I(Treatment) × I(Post 1yr)	0.073**	0.086***	0.029***	0.039***	0.008	0.003	-0.000	-0.007	-0.050	-0.041	0.022	0.009
	(0.032)	(0.030)	(0.009)	(0.014)	(0.022)	(0.022)	(0.012)	(0.013)	(0.034)	(0.036)	(0.034)	(0.036)
I(Treatment) × I(Post 2yr)	0.072	0.067	0.004	-0.001	0.058**	0.057**	0.017	0.012	-0.031	-0.024	0.009	0.013
	(0.045)	(0.044)	(0.011)	(0.017)	(0.029)	(0.028)	(0.016)	(0.015)	(0.034)	(0.037)	(0.034)	(0.037)
I(Treatment) × I(Post 3yr)	0.054	0.049	0.015	0.002	0.053*	0.050*	0.009	0.012	-0.043	-0.024	0.020	0.010
	(0.042)	(0.040)	(0.011)	(0.017)	(0.032)	(0.029)	(0.018)	(0.016)	(0.040)	(0.039)	(0.038)	(0.040)
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y		Y		Y		Y		Y		Y	
Cohorts × Year F.E.		Y		Y		Y		Y		Y		Y
Cohorts × Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	86676	86475	86676	86475	86676	86475	86676	86475	86676	86475	86676	86475
Adj. R^2	0.345	0.376	0.312	0.328	0.296	0.303	0.321	0.340	0.073	0.075	0.067	0.064

Table 7. Environmental Incidents, Green Patent Stock, and Frequency of Green Products

This table presents stacked difference-in-difference (DID) regressions investigating post-incident green product announcements, extending the analysis from Table 5 to differentiate between incident firms with and without green patent stock. Green patent stock refers to the number of green patents invented by the firm i within the past three years. Environmental incidents are sourced from the RepRisk database, focusing on the bottom 5% of incidents with the most negative market response in the [-1d, +1d] event window. Additionally, each incident is required to have had no other environmental incidents involving the firm within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year, retaining observations for treated and control firms within the [-3 Year, +3 Year] window. Our regressions follow the equation:

$$\text{Green\_Product}_{i,c,t} = \sum_{\tau=1}^{3} \alpha_\tau I(Treatment)_{i,c,t} \times I(Post\ \tau yr)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \tag{17}$$

Where i represents the firm, c denotes the cohort in the stacked DID, and t signifies the year. Panel A requires that both treated firms and control firms have non-zero green patent stock. Panel B requires zero green patent stock. The dependent variable in columns 1 and 2 (Average Num. Green Product Words) is the average number of green product phrases appearing in each product announcement of firm i in year t. Columns 3 and 4 (Fraction of Green Products) represent the fraction of green products among all product announcements of firm i in year t. A product is classified as a green product if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8. Columns 5 and 6 (Number of All Product Announce) represent the number of all product announcements by firm i in year t, using Poisson regressions. The control variable set $\mathbf{X}$ encompasses Firm Size, ROE, CAPX, PPE, Book-to-Market Ratio, and RND in year t. Standard errors are clustered at the cohort × firm level, with statistical significance denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Treated Firms and Controls Firms Both with Green Patent Stock

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	Poisson	Poisson
Dependent Var. =	Average Num. Green Product Words		Fraction of Green Products		Number of All Product Announce	
I(Treatment) × I(Post 1yr)	0.333***	0.298***	0.061**	0.041	0.158	0.139
	(0.115)	(0.107)	(0.028)	(0.026)	(0.098)	(0.093)
I(Treatment) × I(Post 2yr)	0.278***	0.243***	0.044*	0.034	0.127	0.109
	(0.093)	(0.093)	(0.025)	(0.024)	(0.093)	(0.070)
I(Treatment) × I(Post 3yr)	0.198*	0.151	0.035	0.012	-0.115	-0.166
	(0.105)	(0.104)	(0.031)	(0.034)	(0.192)	(0.160)
Firm-level Controls	Y	Y	Y	Y	Y	Y
Year F.E.	Y		Y		Y	
Cohorts × Year F.E.		Y		Y		Y
Cohorts × Firm F.E.	Y	Y	Y	Y	Y	Y
N	14388	14240	14388	14240	14388	14240
Adj. R^2	0.625	0.635	0.551	0.561		

Panel B. Treated Firms and Controls Firms Both without Green Patent Stock

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	Poisson	Poisson
Dependent Var. =	Average Num. Green Product Words		Fraction of Green Products		Number of All Product Announce	
I(Treatment) × I(Post 1yr)	0.064	-0.023	0.041	0.023	0.111	0.091
	(0.091)	(0.092)	(0.027)	(0.024)	(0.095)	(0.081)
I(Treatment) × I(Post 2yr)	0.136	0.064	0.047*	0.022	0.108	0.068
	(0.090)	(0.098)	(0.026)	(0.027)	(0.108)	(0.101)
I(Treatment) × I(Post 3yr)	0.003	-0.028	0.011	-0.015	0.168	0.106
	(0.092)	(0.088)	(0.037)	(0.029)	(0.120)	(0.124)
Firm-level Controls	Y	Y	Y	Y	Y	Y
Year F.E.	Y		Y		Y	
Cohorts × Year F.E.		Y		Y		Y
Cohorts × Firm F.E.	Y	Y	Y	Y	Y	Y
N	48983	48910	48983	48910	48983	48910
Adj. R^2	0.451	0.498	0.464	0.486		

Panel C. High Quality vs. Low Quality Green Patent Stock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated & Control Firms have:	**High Quality** Green Patent Stock				**Low Quality** Green Patent Stock			
	A = (Total Green Product Words in **Novel** Products)		A = (Number of Green & **Novel** Products)		A = (Total Green Product Words in **Novel** Products)		A = (Number of Green & **Novel** Products)	
	B = (Number of Products)		B = (Number of Products)		B = (Number of Products)		B = (Number of Products)	
Dependent Var. =	A ÷ B		A ÷ B		A ÷ B		A ÷ B	
I(Treatment) × I(Post 1yr)	0.160**	0.090	0.049**	0.049	0.074	0.006	0.023	0.016
	(0.075)	(0.073)	(0.024)	(0.032)	(0.055)	(0.040)	(0.020)	(0.023)
I(Treatment) × I(Post 2yr)	0.026	0.014	-0.023	-0.018	0.012	-0.001	-0.014	-0.022
	(0.075)	(0.072)	(0.023)	(0.021)	(0.067)	(0.058)	(0.021)	(0.019)
I(Treatment) × I(Post 3yr)	0.050	-0.009	0.002	-0.026	-0.006	-0.076	-0.006	-0.057**
	(0.096)	(0.102)	(0.029)	(0.032)	(0.065)	(0.070)	(0.029)	(0.027)
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y		Y		Y		Y	
Cohorts × Year F.E.		Y		Y		Y		Y
Cohorts × Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y
N	10025	9882	10025	9882	7695	7562	7695	7562
Adj. R^2	0.431	0.477	0.360	0.377	0.336	0.363	0.284	0.291

Table 8. Environmental Incidents and Value of Green and Non-Green Product

This figure presents stacked difference-in-difference (DID) regressions investigating the post-incident value of green product announcements. Environmental incidents are sourced from the RepRisk database, focusing on the bottom 5% of incidents with the most negative market response in the [-1d, +1d] event window. Additionally, for each incident, we require that no other environmental incidents involving the firm occurred within the past three years. For each treated firm, we match control firms within the same Fama-French 48 industry and year. We only keep observations for treated and control firms within the [-3 Year, +3 Year] window. The dependent variable, *Product Value*, is equal to [0d, +1d] CAR around the product announcement date multiplied by the market capitalization of the company on the day preceding the announcement. Due to noise, we winsorize this variable at the 10% and 90% levels. Our regressions are as follows:

$$\text{Product\_Value}_{i,c,t} = \sum_{\tau=-3}^{+3} \alpha_\tau I(Treatment)_{i,c,t} \times I(Incident \pm \tau\ Year)_{i,c,t} + \beta \mathbf{X}_{i,c,t} + \gamma_{i\times c} + \delta_{t\times c} + \varepsilon_{i,c,t} \tag{18}$$

Here, i represents the firm, c denotes the cohort in the stacked DID, and t signifies the year. $I(Treatment)$ serves as a dummy variable for firms experiencing environmental incidents. $\left\{I(Incident \pm \tau\ Year)\right\}_{\tau=-3}^{+3}$ consists of seven dummies surrounding the incident year for both treated and control firms. In Panel A, the dependent variable is the annual median of green product value. In Panel B, it is the annual median for non-green products. A product is classified as a green product if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8. The control variable set $\mathbf{X}$ encompasses Firm Size, ROE, CAPX, PPE, Book-to-Market Ratio, RND, Sales Growth, and the count of any product announcements in year t. We control for cohort $\times$ year F.E. and cohort $\times$ firm F.E. Standard errors are clustered at the cohort $\times$ firm level, and confidence intervals are plotted at the 90% confidence level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Var. = Annual Median Value of New Products							
	Green Products				Non-Green Products			
	US Dollar Million		Take Log		US Dollar Million		Take Log	
I(Treatment) × I(Post 1yr)	22.655***	26.014***	1.767**	2.104**	-1.725	-1.562	-0.266	-0.203
	(8.666)	(9.546)	(0.778)	(0.881)	(3.986)	(3.738)	(0.419)	(0.397)
I(Treatment) × I(Post 2yr)	14.013	3.572	1.169	0.602	1.884	2.641	0.259	0.327
	(9.782)	(12.106)	(0.849)	(0.997)	(4.685)	(4.526)	(0.484)	(0.474)
I(Treatment) × I(Post 3yr)	5.840	-0.988	0.772	0.342	0.489	0.555	-0.015	0.031
	(11.906)	(13.003)	(1.060)	(1.042)	(4.680)	(4.609)	(0.502)	(0.500)
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y		Y		Y		Y	
Cohorts × Year F.E.		Y		Y		Y		Y
Cohorts × Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y
N	10,857	9,551	10,857	9,551	96,544	96,335	96,544	96,335
Adj. R^2	0.010	0.001	0.009	-0.027	0.037	0.033	0.027	0.023

Table 9. General Green Products and Environmental Benefits

This table investigates the relationship between general green products and the environmental performance of both producers and customers. In Panels A and B, the dependent variables are the environmental performance metrics of producer firms over the next three years. Panels C and D examine the environmental performance of customer firms over the same period. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Producer's Environmental Benefits

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var. =	Producer's Air Pollution	Producer's GHG Emissions	Producer's Air Pollution	Producer's GHG Emissions	Producer's Air Pollution	Producer's GHG Emissions
Period =	$t+1$	$t+1$	$t+2$	$t+2$	$t+3$	$t+3$
Producer's Num. Green Products	0.003	0.002	0.002	0.004	0.005*	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Producer's Firm Control	Y	Y	Y	Y	Y	Y
Producer's Firm F.E.	Y	Y	Y	Y	Y	Y
Producer's Industry × Year F.E.	Y	Y	Y	Y	Y	Y
N	27,306	27,306	23,434	23,434	20,044	20,044
adj. R^2	0.817	0.901	0.824	0.906	0.828	0.908

Panel B. Producer's Environmental Benefits (Distinguish Producer- and Customer-Benefit Green Products)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var. =	Producer's Air Pollution	Producer's GHG Emissions	Producer's Air Pollution	Producer's GHG Emissions	Producer's Air Pollution	Producer's GHG Emissions
Period =	$t+1$	$t+1$	$t+2$	$t+2$	$t+3$	$t+3$
Producer's Num. Producer-Benefit Green Prod	-0.001	0.005**	-0.001	0.004	0.002	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Num. Consumer-Benefit Green Prod	0.004*	-0.001	0.003	0.002	0.004	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Producer's Firm Control	Y	Y	Y	Y	Y	Y
Producer's Firm F.E.	Y	Y	Y	Y	Y	Y
Producer's Industry × Year F.E.	Y	Y	Y	Y	Y	Y
N	27,306	27,306	23,434	23,434	20,044	20,044
adj. R^2	0.817	0.901	0.824	0.906	0.828	0.908

Panel C. Customer's Environmental Benefits

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var. =	Customer's GHG Emissions	Customer's Land Pollution	Customer's GHG Emissions	Customer's Land Pollution	Customer's GHG Emissions	Customer's Land Pollution
Period =	$t+1$	$t+1$	$t+2$	$t+2$	$t+3$	$t+3$
Producer's Num. Green Products	-0.002	0.002	0.000	0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Producer's Firm Control	Y	Y	Y	Y	Y	Y
Customer's Firm Control	Y	Y	Y	Y	Y	Y
Producer's Firm × Customer Firm F.E.	Y	Y	Y	Y	Y	Y
Customer's Industry × Year F.E.	Y	Y	Y	Y	Y	Y
N	110,893	60,489	81,504	44,923	62,294	34,498
adj. R^2	0.967	0.974	0.964	0.973	0.963	0.972

Panel D. Customer's Environmental Benefits (Distinguish Producer- and Customer-Benefit Green Products)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var. =	Customer's GHG Emissions	Customer's Land Pollution	Customer's GHG Emissions	Customer's Land Pollution	Customer's GHG Emissions	Customer's Land Pollution
Period =	$t+1$	$t+1$	$t+2$	$t+2$	$t+3$	$t+3$
Producer's Num. Producer-Benefit Green Prod	-0.000	0.001	0.000	0.001	0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Num. Consumer-Benefit Green Prod	-0.001	0.001	-0.001	-0.001	-0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Producer's Firm Control	Y	Y	Y	Y	Y	Y
Customer's Firm Control	Y	Y	Y	Y	Y	Y
Producer's Firm × Customer Firm F.E.	Y	Y	Y	Y	Y	Y
Customer's Industry × Year F.E.	Y	Y	Y	Y	Y	Y
N	110,893	60,489	81,504	44,923	62,294	34,498
adj. R^2	0.967	0.974	0.964	0.973	0.963	0.972

Internet Appendix for

"The Incident-Driven Green Products"

A. Table for Variables Definition and Construction

B. Details about Construction of "Green Product Phrases"

C. Empirical Results Not Included in the Paper

A Table for Variables Definition and Construction

Variable Name	Definition of Variable	Data Source
Firm-Year Variable		
Average Green Product Phrases	The average number of "green product phrases" appearing in each product announcement of firm i in year t. Calculated as the total number of "green product phrases" appearing in the product announcements of firm i in year t divided by the number of product announcements of firm i in year t	Capital IQ Key Development
Fraction of Green Products	The fraction of green product announcements among all product announcements by firm i in year t. A product is classified as a green product if one of the following two criteria is met: (i) the product announcement contains at least five green phrases, or (ii) ChatGPT assigns a score greater than 0.8.	Capital IQ Key Development
Product Novelty	A text-based measure of product novelty. Novel products are defined as those significantly different from the firm's previous product offerings and similar to its future products. Detailed constructions can be found in Figure 5.	Capital IQ Key Development
Product Novelty (Dummy)	Dummy equal to 1 if the product novelty measure is above the sample median. Detailed constructions of the product novelty measure can be found in Figure 5.	Capital IQ Key Development
Green Product Value	The median of the value of green products issued by firm i in year t. The value of a green product is equal to [0d, +1d] CAR around the product announcement date multiplied by the market capitalization of the company on the day preceding the announcement. Due to noise, we winsorize this variable at the 10% and 90% levels.	Capital IQ Key Development
Firm Size	The natural logarithm of firm's total assets (Compustat Item: AT)	CRSP-Compustat
PPE	The natural logarithm of firm's value of plants, properties, and equipments (PPE)	CRSP-Compustat
CAPX	The capital expenditure of the firm. Measured as the capital expenditure ($CAPX$) scaled by total assets (AT)	CRSP-Compustat
RND	The research and development expenditure of the firm. Measured as the R&D expenditure (RND) scaled by total assets (AT). RND is set to be zero if it is missing in CRSP-Compustat	CRSP-Compustat
ROE	Return on Equity. Measured as the income before extraordinary items (IB) scaled by book equity value. Book equity value is measured by stockholders equity (SEQ). SEQ is relaced by $CEQ + PSTK$ when SEQ is missing.	CRSP-Compustat
SALE	The natural logarithm of total sales	CRSP-Compustat
M/B	Market-to-Book Ratio. Measured as the market value of equity ($CSHO \times PRCC\_F$) scaled by book value of equity ($SEQ + TXDITC - PSTK$). M/B is required to be positive.	CRSP-Compustat
GM	Gross Margin. Measured as net profits ($REVT - COGS$) scaled by total revenue ($REVT$).	CRSP-Compustat

Continued on next page

Appendix A continued from previous page

Variable name	Definition of variable	Data Source
Direct Cost - Air Pollution	Firm's direct air pollution cost scaled by sales. The air pollution cost is defined as the external cost of pollutants released to air by the consumption of fossil fuels and production processes which are owned or controlled by the company	S&P Trucost
Direct Cost - GHG Emissions	Firm's GHG emission cost scaled by sales. The GHG emission cost is defined as the external cost of greenhouse gas (GHG) emissions released to air by the consumption of fossil fuels and production processes which are owned or controlled by the company.	S&P Trucost
Direct Cost - Land & Water Pollution	Firm's land & water pollution cost scaled by sales. The land & water pollution cost is defined as the external cost pollutants released to land and water by the company due to its own activities.	S&P Trucost

B Details about Construction of "Green Product Phrases"

This section outlines the methods for constructing "green product phrases" used to identify green products in the S&P Capital IQ Key Development database. All green product phrases are formed at the bigram level, meaning each consists of two English words, except for a few special cases included in the initial dictionary set, such as "recyclable" and "compostable." The employed machine learning methods, as documented in King et al. (2017) and Sautner et al. (2023), are utilized to obtain the complete set of "green product phrases." The main procedures are as follows.

B.1 Obtain the Initial Set of Bigrams

We begin by compiling a set of bigrams related to green and sustainable products, drawing from the research of Sautner et al. (2023) (Table II). From this compilation, we manually select bigrams unequivocally associated with either climate change or environmental impacts. Additionally, we augment this list by identifying words describing green products, as detailed in McKinsey's report (McKinsey and NielsenIQ, 2023). These two steps collectively enable us to identify 58 unique initial bigrams.

Subsequently, we categorize these 58 initial bigrams into four groups of green products with the assistance of ChatGPT. These four groups encompass: (1) energy-related green products, (2) electric vehicles, (3) general environmentally friendly products, and (4) recyclable and compostable consumer goods. A detailed breakdown of each group's components is provided in Table A1.

B.2 Expand the Set of "Green Product Phrases"

According to King et al. (2017), while the human brain is adept at determining whether a keyword is relevant to a given topic, the task of identifying all keywords is deemed a "near-impossible task" for humans. Therefore, to expand the initial set of bigrams and extract further "green product phrases" from product announcements in Capital IQ, we utilize the keyword discovery methods developed by King et al. (2017). This methodology is applied individually for each category of initial green bigrams, with the results subsequently amalgamated to form a final set.

In the initial step, we commence by cleaning and processing a corpus comprising 256,512 texts concerning firms' product announcements. This process involves converting all words to lowercase, removing non-alphabetical characters and stop words, and lemmatizing them. The list of stop words encompasses those identified by King et al. (2017), from NLTK, as well as those sourced from the website of Loughran and MacDonald (with the exception of certain special stop words such as 'green' and 'paris', among others).

Following the identification of a given initial set of bigrams (e.g., the 19 energy-related bigrams), we proceed with their expansion. We determine whether a product is classified as green across all 256,512 texts, with a product announcement qualifying as green if it contains at least one of the 19 energy-related bigrams. For example, let us assume we identify 500 green products, constituting the treated group. Subsequently, we randomly select an additional 500 non-green products from the remaining announcement texts to form the control group.

Following this, we utilize the 1000-text corpus as a training sample to train machine learning models. Consistent with the methodology outlined in King et al. (2017), we employ various machine learning models, including Logit, SVM, Tree model, and Random Forest. These models are then leveraged to predict the classification of the remaining 255,512 texts (256,512 − 1000). We establish a criterion whereby at least two-thirds of the models must predict a given product as green for it to be classified as a green product. For instance, let's suppose we identify an additional 200 green products through this process.

In the next step, we combine the initial green products (500) with the newly identified ones (200) and reverse-engineer the machine-learning (ML) process to trace back the bigrams that best discriminate between green and non-green products. Specifically, we identify those green product bigrams that appear most frequently in the 700 green product announcements and meanwhile least frequently in the remaining announcements.

Finally, we scrutinize the top 500 newly identified green product phrases to ensure their relevance to climate change, green products, and environmental-friendly claims. Valid phrases are then added to the initial set of 19 energy-related bigrams. This entire process is repeated multiple times to ensure the exhaustive extraction of all green product words. Importantly, this procedure is carried out separately for each set of bigrams, totaling four sets: (1) energy-related green products, (2) electric vehicles, (3) general environmentally friendly products, and (4) recyclable and compostable consumer goods. Both the initial bigram sets and the expanded ones are listed in Table A1.

Table A1. Bigram Lists Used to Identify Green Products

A.1 Initial Bigram List (Energy-Related Green Products)
Total 19 bigrams: green building, renewable energy, clean energy, wind power, wind energy, green energy, ocean energy, energy saving, solar energy, renewable natural, energy environment, clean power, solar farm, clean technology, onshore wind, solar pv, electrical energy, solar installation, sustainable energy
A.2 Expanded Bigram List with Machine Learning (Energy-Related Green Products)
Total 245 bigrams: green building, renewable energy, clean energy, wind power, wind energy, green energy, ocean energy, energy saving, solar energy, renewable natural, clean power, solar farm, clean technology, onshore wind, green technology, solar pv, electrical energy, solar installation, sustainable energy, energy efficiency, energy efficient, energy storage, solar panel, wind turbine, energy management, solar cell, led lighting, energy cost, energy environmental, photovoltaic pv, solar system, reduce energy, solar installation, wind farm, solar project, energy solution, solar module, save energy, solar wind, pv module, saving technology, cost energy, wind solar, solar photovoltaic, conversion efficiency, saving energy, energy water, lighting solution, solar inverter, turbine solar, pv system, solar powered, solar power, wind project, storage solution, water energy, rooftop solar, pv inverter, photovoltaic solar, energy conservation, saving performance, battery energy, solar solution, solar technology, solar generation, energy solar, led technology, solar array, pv panel, reducing energy, reduction energy, offshore wind, efficient energy, saving led, clean renewable, renewable source, efficiency energy, efficiency solar, resource solar, voltage solar, launch solar, residential solar, led fixture, solar storage, commercial solar, led bulb, display solar, reduced energy, pv solar, photovoltaic system, generation solar, solar solar, led luminaires, renewable electricity, led luminaire, photovoltaic module, solar battery, solar application, solution solar, solar facility, pv cell, megawatt solar, home solar, daylight harvesting, energy renewable, performance solar, wavefront energy, led energy, saving efficiency, installation solar, energy wind, solar production, solar market, efficiency technology, wind generation, solar product, solar electricity, supply renewable, energy reduce, efficiency reliability, efficiency renewable, efficient solar, solar electric, onshore wind, solar thermal, solar program, energy climate, clean diesel, renewable resource, renewable electricity, renewable fuel, end tidal, technology clean, reduces energy, technology solar, source solar, film solar, application solar, gas renewable, integrated solar, cell solar, thermal energy, intelligent energy, efficient solar, powered solar, saving lighting, efficient lighting, prototype solar, powerbuoy wave, wave condition, wave power, solar company, commercial rooftop, photovoltaic panel, renewable generation, pv installation, efficient lighting, innovative energy, silicon solar, panel solar, generated solar, advanced solar, turbine wind, source renewable, efficiency led, wind powered, electricity renewable, battery solar, hydrogen fuel, wave energy, system renewable, energy reduction, pv array, solar international, scale solar, efficient led, solar industry, generation solar, compared conventional, cost solar, module solar, energy loss, innovative solar, dimmable led, output solar, daylight harvesting, crystalline solar, production solar, kw solar, inverter solar, build solar, grid solar, micro grid, off grid, solar charging, solar customer, solar charger, efficient home, rooftop system, clean solar, rooftop installation, photovoltaic cell, install solar, pv energy, optimize energy, ascent solar, company solar, cut energy, line solar, brightness led, solar launch, efficient ethernet, integrated photovoltaic, photovoltaic inverter, ethernet eee, storage solar, lighting solar, manufacture solar, manufacturer solar, solar manufacturer, electricity solar, voltage solar, solar monitoring, solar tracking, solar rooftop, integration solar, solar generated, design solar, solar installers, solar led, produce solar, mounted solar, wind power, tidal energy, tidal power, wavefront energy, geothermal energy, hydro energy, oceanic energy, waste energy, biofuel, energy star, brightness led, led brightness, lower energy, saving power, solar access, green hydrogen, home energy, halogen free, renewable power, energy carbon, green power, hydrogen technology, smart grid, energy emission
B.1 Initial Bigram List (Electric Vehicle Related Green Products)
Total 7 bigrams: electric car, electric vehicle, battery electric, battery power, electric motor, electrical vehicle, electric hybrid

Continued from previous page
B.2 Expanded Bigram List with Machine Learning (Electric Vehicle Related Green Products)
Total 140 bigrams: electric car, electric vehicle, electric motor, electrical vehicle, electric hybrid, charging station, vehicle charging, hybrid electric, vehicle ev, plug hybrid, hybrid vehicle, vehicle charging, ev charging, hybrid version, pure electric, vehicle battery, engine electric, fuel efficiency, electric drive, concept vehicle, hybrid car, hybrid model, hybrid engine, environmentally friendly, eco friendly, hydrogen fuel, charging system, vehicle hybrid, ev battery, fuel efficient, hybrid technology, plug electric, charging infrastructure, vehicle electric, drive electric, ev charger, vehicle charger, energy vehicle, electric suv, electric motorcycle, friendly vehicle, electric powered, electric bus, motor electric, car electric, charging solution, battery vehicle, hybrid plug, car sharing, charge discharge, alternative fuel, hybrid drive, electric mobility, car charging, car battery, ev hybrid, charge electric, charging electric, hybrid concept, hybrid powertrain, electric driving, hybrid sport, diesel hybrid, future electric, electrified vehicle, ev model, fuel saving, charge ev, reduce fuel, reduction fuel, electric powertrain, ev electric, electric propulsion, full electric, metal hydride, tesla model, electric plug, motor battery, charger electric, emission electric, automotive electronics, hybrid propulsion, vehicle electrification, electrified vehicle, renewable fuel, lithium ion, launch hybrid, energy efficiency, improved fuel, electric engine, emission reduction, clean diesel, reduced emission, vehicle emission, hybrid truck, hybrid equipped, led headlight, car charger, hybrid bus, battery ev, vehicle electrical, electric scooter, hybrid sedan, model hybrid, hydrogen powered, electric sedan, emission car, reducing fuel, powered electric, electrically powered, electric truck, ev plug, ev driving, engine hybrid, fuel reduce, efficiency fuel, reduced fuel, reduces fuel, save fuel, improvement fuel, hybrid motorcycle, fuel economy, clean diesel, low emission, emission standard, oxides emission, emission car, emission vehicle, emission free, voc free, lower fuel, detailed environmental, harmful emission, environmental data, improving fuel, improve fuel, environmental profile, solution environmental, product environmentally, enhanced environmental, technology environmentally, compliance environmental, engine efficiency, efficiency engine
C.1 Initial Bigram List (General Green (Environmental-Friendly) Products)
Total 22 bigrams: green product, climate change, greenhouse gas, gas emission, emission reduction, co2 emission, air quality, clean air, carbon emission, carbon dioxide, water resource, air pollution, pollution reduction, carbon tax, global warm, environmental footprint, environmental benefit, eco friendly, carbon neutral, environmental concern, carbon intensity, sustainability goal
C.2 Expanded Bigram List with Machine Learning (General Green (Environmental-Friendly) Products)
Total 411 bigrams: green product, climate change, greenhouse gas, gas emission, emission reduction, cotwo emission, air quality, clean air, carbon emission, carbon dioxide, water resource, air pollution, pollution reduction, carbon tax, global warm, environmental footprint, environmental benefit, eco friendly, carbon neutral, environmental concern, carbon intensity, sustainability goal, air quality, carbon neutral, environmental service, environmentally responsible, reduce greenhouse, environmental protection, environmental impact, impact environment, environmentally responsible, environmentally conscious, dioxide emission, environmental impact, environmentally friendly, global warming, carbon footprint, reduce carbon, environmental protection, emission reducing, reduce emission, warming potential, reduce environmental, reducing carbon, gas ghg, ghg emission, impact environment, emission standard, environmental performance, ton carbon, carbon credit, water quality, carbon monoxide, reduction carbon, gas carbon, reducing greenhouse, environmental quality, environmental social, sustainable solution, reduction greenhouse, water treatment, environmental sustainability, reducing environmental, emission compared, nox emission, reduced environmental, oxide nox, consumption carbon, environment friendly, air purifier, reduced carbon, emission carbon, sustainable development, launch carbon, nitrous oxide, carbon capture, environmental assessment, emission level, emission control, wastewater treatment, reduced emission, carbon offset, reduces emission, environmentally responsible, pollution control, air purification, reduction emission, consumption emission, reducing emission, meet environmental, significant environmental, emission regulation, social governance, emission ton, environment climate, carbon intensity, reduces carbon, global climate, emission reduced, saving emission, meet sustainability, waste management, total carbon,

Continued from previous page

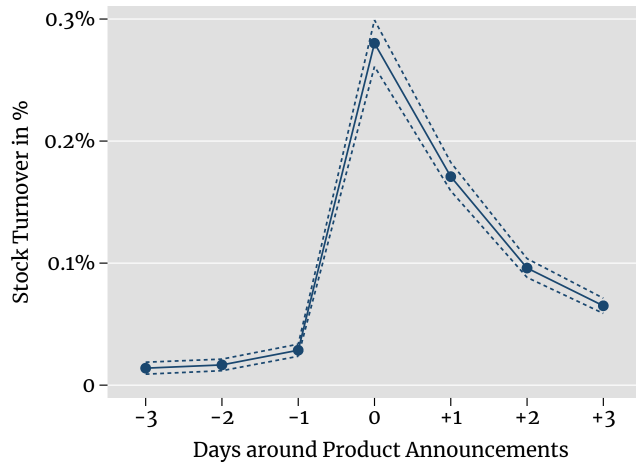
economic environmental, cost carbon, diesel emission, dioxide equivalent, efficiency emission, cost environmental, environmentally sustainable, amount carbon, ultra emission, governance esg, emission equivalent, tonne carbon, consumption greenhouse, ozone depletion, cut carbon, improve air, exhaust emission, environmentally conscious, smaller environmental, air pollutant, fight climate, saving environmentally, fewer greenhouse, emission nitrogen, emission metric, carbon reduction, transition carbon, process carbon, global carbon, level carbon, environmental regulation, environmental technology, oxide emission, environmental issue, emission technology, net carbon, water resource, carbon economy, social environmental, emission management, carbon neutrality, sulfur dioxide, air filter, project environmental, nitrogen carbon, protect environment, sustainability initiative, minimize environmental, sustainability program, cut emission, offset carbon, ultra clean, carbon management, saving environmental, purification process, impact climate, product environmental, environmental clean, environmental legislation, water saving, low carbon, emit carbon, carbon sequestration, climate control, offset emission, carbon neutral, reduces greenhouse, gas recirculation, esg factor, made renewable, environmental monitoring, emission limit, launched carbon, responsible product, impact environmental, improved environmental, launch environmental, released atmosphere, reduce water, environmental stewardship, positive environmental, planting tree, gas reduction, emission solution, ton emission, nox reduction, emission production, emission tonne, eco efficient, preparation environmental, waste disposal, environmentally safe, capture storage, environmental permit, environmental risk, environmental responsibility, environmental requirement, environmental product, reduces environmental, carbon market, product environmentally, performance environmental, emission cost, emission equivalent, global emission, global environmental, efficient environmentally, social responsibility, socially responsible, emission requirement, toxic gas, water pollution, environmental management, environmental review, euro emission, environmental baseline, environmental policy, emission mitigat, environmental standard, project greenland, environmental awareness, environment protection, waste reduction, equivalent emission, improve environmental, set environmental, emission improve, emission improved, montreal protocol, waste landfill, emission produced, emission source, emission performance, emission test, emission truck, tier emission, potential environmental, recirculation egr, environmental effect, required environmental, biodiversity conservation, protection biodiversity, international environmental, minimal environmental, launch environmentally, environmental solution, environmental factor, assessment environmental, kyoto protocol, paris agreement, aquifer protection, generation emission, water reuse, water purification, commitment environmental, climate action, carbon impact, reducing waste, announces environmental, eliminating carbon, eliminate carbon, greener , environmental credits, eliminate toxic, reduce cotwo, reduced cotwo, eliminate cotwo, reducing cotwo, environmental contamination, mitigate environmental, climate technology, low emission, reduced waste, reduce waste, reduce gas, reduced gas, lower carbon, safety environmental, water management, environmental study, study environmental, environmental condition, zone climate, low environmental, environmental consultant, lower emission, final environmental, reduction cotwo, lower environmental, application environmental, including environmental, percentage renewable, ton cotwo, consumption cotwo, approved environmental, baseline environmental, water efficient, clean water, affected environmental, draft environmental, reduce toxic, water environmental, guided environmental, effective environmentally, submitted environmental, purification technology, completion environmental, key environmental, forest service, complete environmental, engineering environmental, tonne cotwo, update environmental, process environmental, responsible production, feature environmentally, commitment sustainability, stringent emission, ongoing environmental, climate controlled, cotwo capture, emission computed, program environmental, green initiative, water conservation, emission intensity, scope emission, submission environmental, climate related, environmental design, level environmental, environment natural, based environmental, development environmental, cotwo equivalent, sustainability strategy, addition environmental, waste treatment, environmental compliance, environmentally sound, smart home, design environmental, report environmental, stringent environmental, responsible investment, environmental license, requirement environmental, net emission, emission product, commitment sustainable, sustainably sourced, low cotwo, environmental affair, air emission, cotwo reduction, cotwo solution, equivalent emission, cost environmentally,

Continued from previous page review environmental, additional environmental, emission lower, preliminary environmental, management environmental, methane emission, water environment, oxygen carbon, carbon fuel, progress environmental, environmental safety, friendly sustainable, low nox, emission approximately, sustainability effort, environmental health, receipt environmental, environment water, sustainability performance, environmentally sensitive, friendly green, support sustainable, efficiency environmental, climate risk, standard environmental, lower greenhouse, plan environmental, carbon free, environmental engineering, integrated environmental, ozone depleting, efficient climate, full environmental, launch climate, cotwo footprint, environment energy, making environmentally, aquifer protection, voluntary carbon, safe environmentally, environmental friendly, commenced environmental, minimizing environmental, climate impact, groundwater monitoring, sustainable environmentally, performance environmentally, sustainability report, subject environmental, sustainability commitment, released atmosphere, address environmental, environmental advantage, clean burning, adverse environmental, negative environmental, launched green, resource environmental, emission target, environmental initiative, certification environmental, environmental control, environmental program, environmental goal, emission cotwo
D.1 Initial Bigram List (Recyclable Green Products)
Total 10 bigrams: recycled plastic, reusable bag, recyclable, recycled, reusable, compostable, biodegradable, planet friendly, zero waste, eco friendly
D.2 Expanded Bigram List with Machine Learning (Recyclable Green Products)
Total 62 bigrams: recycled plastic, reusable bag, recyclable, recycled, reusable, compostable, recycling, biodegradable, planet friendly, zero waste, eco friendly, friendly product, environmentally friendly, fully recyclable, launch eco, packaging solution, bio based, circular economy, sustainable packaging, recycled material, biodegradable polymer, recycling technology, friendly material, sustainable product, recycling program, ergonomic design, consumer recycled, recycling process, environmentally sustainable, eco conscious, line eco, reduce waste, natural organic, made recycled, recycled paper, feature eco, recycled paper, recycled content, sustainable packaging, recycled polyester, environmentally conscious, recyclable packaging, recycled fiber, plastic waste, sustainable material, cleaning product, biodegradable compostable, recycled paperboard, bottle recycled, environment friendly, environmental sustainability, recyclable plastic, recycled resin, packaging recyclable, recycled polyethylene, sustainability goal, artificial meat, percentage organic, organic ingredients, certified organic, usda organic, truly organic, percentage natural, recycle ready

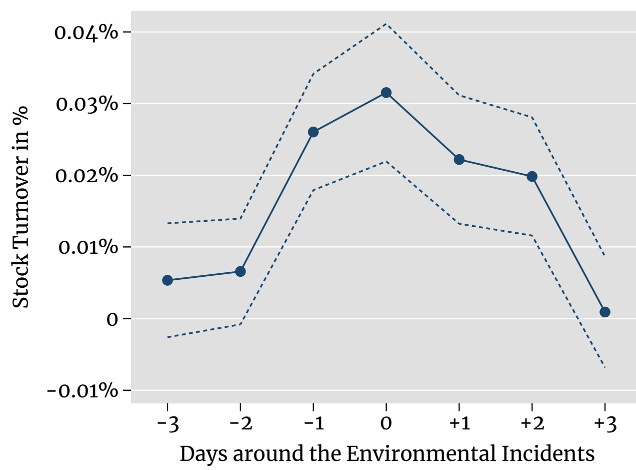
C Empirical Results Not Included in the Paper

Figure A1. Abnormal Stock Turnover Rates

Panel A: Turnover around Product Announcements

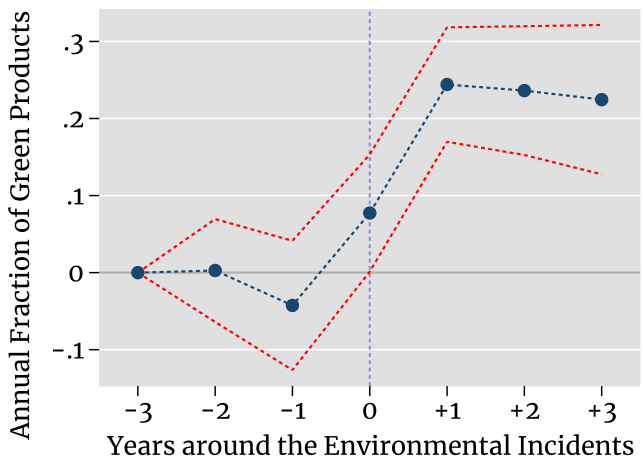


Panel B: Turnover around Environmental Incidents



Note: In this figure, we plot the abnormal stock turnover surrounding product announcements in Panel A and surrounding RepRisk environmental incidents in Panel B. Detailed regression methodologies are based on Kogan et al. (2017).

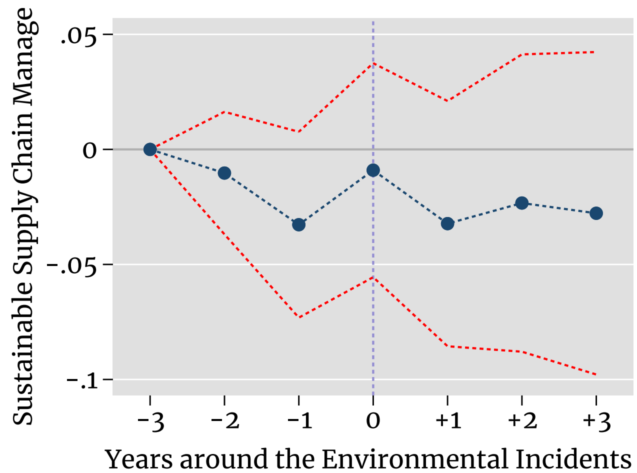
Figure A2. Verification Test about Manual Diff-in-Diff Estimator in the Top Tercile



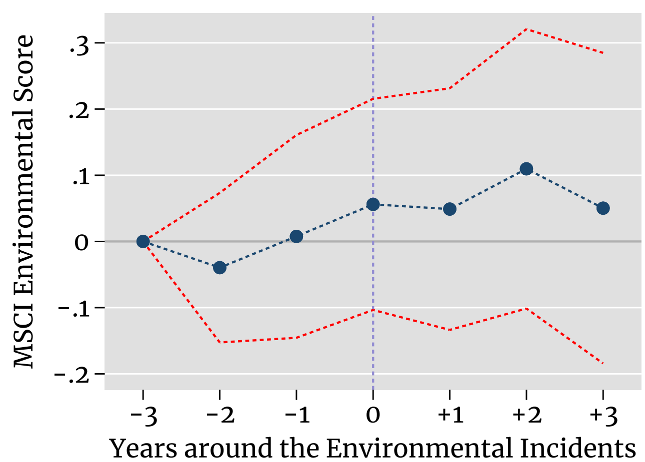
Note: Using a stacked DID sample in Table 5, we calculate a manual DID measure to determine if an incident firm significantly increases green product launches for each of the 490 incidents, as shown in Equation 3. We then categorize these incidents into terciles based on our DID estimator, retaining only the top tercile. To verify, we estimate the DID regression as in Panel B of Figure 6 using only top-tercile incidents, plotting the results in Figure A2. This shows that within two years following top-tercile incidents, firms increase their green product fraction by about 20%, or 133% of the sample mean for treated firms.

Figure A3. Placebo Tests for Incident-Driven Green Products

Panel A: Incidents **with** Post Green Products and Customer's Supply Chain Policy



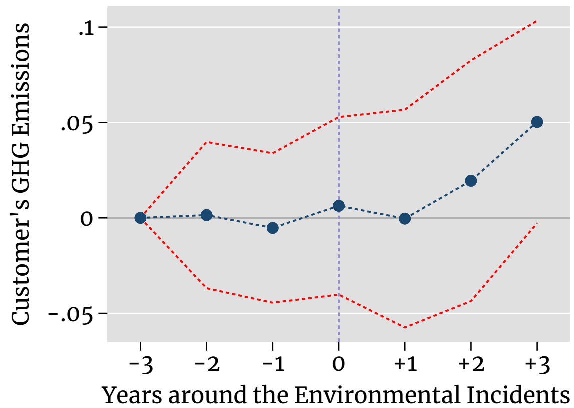
Panel B: Incidents **with** Post Green Products and Customer's Environmental Socre



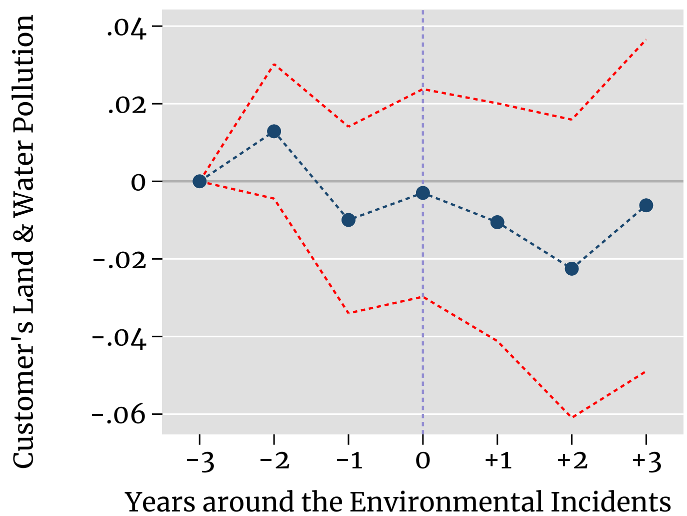
Note: In Panel A, the dependent variable is a dummy variable equal to 1 if the customer company uses environmental or sustainable criteria in selecting their suppliers and sourcing partners. In Panel B, the dependent variable is the customer firm's MSCI environmental score, which ranges from 0 to 10.

Figure A4. Incidents without Green Products and Customers' Environmental Performance

Panel A: Incidents **without** Post Green Products and Customers' CO2 emissions



Panel B: Incidents **without** Post Green Products and Customers' Land & Water Pollution



Note: This is the placebo test for Figure 11. Here, we use the mid- and bottom-tercile incidents to conduct DID analyses.

Table A2. Validity Tests of Green Product Measure

	(1)	(2)	(3)	(4)
	I[Low Carbon Product]			
Annual Fraction of Green Products	0.381***	0.334***	0.189***	0.188***
	(0.042)	(0.045)	(0.049)	(0.051)
Firm-Level Controls	N	Y	N	Y
Year F.E.	Y	Y	Y	Y
Industry F.E.	N	N	Y	Y
N	2029	1888	2027	1886
Adj. R^2	0.042	0.089	0.188	0.267

Note: The dependent variable, *I[Low Carbon Product]*, is a dummy variable equal to 1 if the firm reports in the CDP questionnaire that it sells low-carbon products or services. The data are sourced from CDP questionnaires spanning 2016 to 2022.

Table A3. Environmental Incidents and Frequency of Green Products (Use the Alternative Sample of Incidents)

Panel A. Full Sample	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	Poisson	Poisson
Dependent Var. =	Average Num. Green Product Words		Fraction of Green Products		Number of All Product Announce	
I(Treatment) × I(Post 1yr)	0.152***	0.112**	0.031**	0.021	-0.060	-0.031
	(0.051)	(0.045)	(0.014)	(0.014)	(0.062)	(0.067)
I(Treatment) × I(Post 2yr)	0.129**	0.099**	0.036*	0.020	-0.064	-0.039
	(0.052)	(0.048)	(0.019)	(0.019)	(0.073)	(0.072)
I(Treatment) × I(Post 3yr)	0.024	-0.006	0.002	-0.005	-0.116	-0.098
	(0.040)	(0.045)	(0.017)	(0.017)	(0.087)	(0.075)
I(Post 1yr)	-0.010**		-0.004**		0.008	
	(0.005)		(0.002)		(0.008)	
I(Post 2yr)	-0.003		-0.004*		0.010	
	(0.006)		(0.002)		(0.011)	
I(Post 3yr)	-0.025***		-0.010***		0.015	
	(0.007)		(0.003)		(0.015)	
Firm-level Controls	Y	Y	Y	Y	Y	Y
Year F.E.	Y		Y		Y	
Cohorts × Year F.E.		Y		Y		Y
Cohorts × Firm F.E.	Y	Y	Y	Y	Y	Y
N	109941	109908	109941	109908	109941	109908
Adj. R^2	0.511	0.554	0.522	0.547		

Note: This table replicates the regression analysis from Table 5, with only one difference: we include all environmental incidents categorized as *"High Reach"* by RepRisk.