Climate Policy Abroad, Emissions at Home: Pollution Reshoring by U.S. Multinationals

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Abstract

Global climate policy has become increasingly uneven, with many host countries of U.S. multinationals adopting stricter climate laws than the United States. We show that greater foreign regulatory exposure leads U.S. firms to re-shore pollution-intensive activity, increasing domestic greenhouse-gas emissions by 0.8% and toxic releases by 7%. Firms headquartered in Democratic-leaning states further redirect this activity to plants in Republican-leaning states, where regulatory pressure is weaker. Managers simultaneously greenwash by downplaying overseas climate risks in earnings calls, and well-intentioned sustainable lenders and financial analysts inadvertently amplify both reshoring and opacity. The resulting domestic pollution worsens air quality and elevates respiratory disease rates, highlighting the substantial public-health costs created by fragmented global climate policy.

Keywords: Reverse Pollution Haven, Climate Change, Political Heterogeneity, Greenwashing

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1 Introduction

Multinational corporations now face a fragmented climate-policy landscape. By 2021, more than thirty host countries of U.S. subsidiaries had enacted stricter and more numerous climate laws than the United States, subjecting American firms to carbon prices, emissions caps, and disclosure mandates abroad while leaving comparable activities at home largely unregulated (Figure 1). This gap, hosting countries with more stringent climate change regulations than the home country, can reverse the classic pollution-haven story.[1] Instead of offshoring to lax regimes, U.S. multinationals may re-shore carbon emission-intensive production to the relatively lenient U.S. Whether foreign climate policy now drives this opposite flow is an open, policy-critical question.

INSERT FIGURE 1 HERE

Using the full universe of national climate laws worldwide, we construct text-based exposure measures that map the statutory scope of each foreign and U.S. regulation onto every publicly listed firm's business description (Kalmenovitz, 2023). Linking these exposures to EPA data on plant-level emissions from 2007–2021, we document a pronounced reverse pollution-haven effect, not only on greenhouse gas, which is the main target of climate change regulations, but also spillover to toxic chemicals. A one-standard-deviation increase in foreign regulatory exposure raises domestic greenhouse-gas emissions by 0.8% and toxic releases by 7%, with the strongest effects in emission-intensive industries and carcinogenic chemicals, and none attributable to shifts in input mix. To identify causality, we instrument foreign reg-

[1]The idea of the "Pollution Havens Hypothesis" is that the laxity of environmental regulations has been assessed as a potential source of comparative advantage that attracts dirty industries. See Taylor (2005); He (2006); Dean, Lovely, and Wang (2009), etc.

ulatory exposure with host country's historical extreme-weather frequency and geographic distance from the United States. These instruments are strong (first-stage F>10) and plausibly exogenous, because both weather history and distance are predetermined relative to contemporary climate lawmaking. The two-stage least squares estimates corroborate our baseline results.

Domestic political heterogeneity magnifies the reverse–pollution-haven effect. Strategic choices are made at corporate headquarters, yet emissions are generated at dispersed production plants. Headquarters based in Democratic leaning states, where environmental norms and enforcement are stricter, perceive foreign climate policy risks more acutely and respond by reallocating pollution-intensive activity to plants in Republican leaning states, where societal and regulatory pressure to curb emissions is weaker (Bisetti et al. 2022; Duchin, Gao, and Xu 2024). This headquarters–plant political mismatch, strict oversight where decisions are made and lax oversight where production occurs, is precisely how firms arrange their re-shored emissions, thereby intensifying domestic pollution.

On the information front, managers significantly underplay overseas climate transition risks. When firms are facing higher foreign climate regulation exposure, firms will disclose a significantly lower level of climate transition risk and adopt a more positive tone in the same-year earnings calls, the voluntary disclosure channel. In contrast, firms comply in 10-K filings, which are subject to the SEC's Climate Change Risk (CCR) rules, and disclose domestic climate risks more objectively than foreign ones. These patterns are consistent with selective disclosure and greenwashing. Meanwhile, financial analysts, who serve as key intermediaries in climate risk price discovery (Sautner et al. 2023b), appear inattentive: they rarely query foreign climate risks and raise climate-related questions chiefly when U.S. policy changes. When analysts do probe climate issues, firms facing stringent foreign climate rules further reduce the salience of those risks in their verbal disclosures.

Well-intentioned sustainable finance can backfire. Our evidence shows that firms whose principal overseas lenders have committed to Science Based Targets Initiative (SBTi) goals, aiming to reduce carbon emissions within their lending portfolios, intensify both pollution reshoring and disclosure opacity in the U.S. Two mechanisms are consistent with this result: (i) overseas lenders possess better information on emissions generated close to them than on those relocated to the United States; and (ii) lenders face a geographic conflict of interest, prioritizing emissions reductions in their own jurisdictions.

Greater foreign exposure also affects real investment and valuation. Exposed firms are less likely to divest emission-intensive U.S. plants and curtail foreign direct investment, reserving green investment for pressure that originates at home. Market prices reflect these frictions: a one-standard-deviation rise in foreign exposure lowers Tobin's Q by 1.5% of the sample mean, whereas domestic exposure has no discernible valuation effect, suggesting that investors regard foreign rules as costlier and more uncertain than comparable U.S. regulations.

Reshoring has clear local costs. Once a county is exposed, through its local plants, to stricter foreign climate regulation, the county's annual 90th-percentile Air Quality Index (AQI) rises by roughly 5% [2], the share of bad-air-quality days nearly doubles, and emergency-department visits for asthma climb by about 3.3% relative to the sample mean. Event-study estimates reveal no pre-treatment trend and show that these effects grow stronger over time.

[2] Higher AQI values indicate poorer air quality. The AQI is derived from concentrations of NO2, O3, CO, PM 2.5, PM10, and SO2. We use the annual 90th percentile of daily AQI to capture upper-tail pollution; results are robust to using the annual maximum daily AQI.

Our study contributes to several strands of the literature. First, we extend work on regulatory arbitrage and pollution substitution by providing, to our knowledge, the first evidence of a reverse pollution-haven pattern. The classic Pollution Haven Hypothesis posits that jurisdictions attract pollution-intensive activity by maintaining weak standards or lax enforcement, leading firms to shift production from stricter, typically high-income countries to laxer ones via outward FDI or by sourcing from dirtier producers (He, 2006; Dean, Lovely, and Wang, 2009; Chung, 2014; Lin et al., 2014; Cai et al., 2016; Li and Zhou, 2017; Ben-David et al., 2021; Shapiro, 2025). Instead, we show that fragmentation in global climate policy, where the United States lags behind, induces U.S. multinationals to reallocate emissions back to the United States. Domestic political heterogeneity amplifies this effect: firms headquartered in Democratic-leaning states respond to stringent foreign regulation by shifting pollution-intensive activity to plants in Republican-leaning states. The reshored emissions include not only CO_2, which has global externalities, but also co-emitted toxic pollutants that impose acute local health and ecological costs on U.S. communities. Our findings underscore how uneven climate ambition fosters institutional competition among advanced economies and can rearrange, rather than reduce, global emissions, highlighting the urgency of closing cross-border regulatory gaps through coordinated standards or border-adjustment mechanisms.

Second, we add to the literature on corporate climate-risk disclosure (Ilhan et al., 2023; Flammer, Toffel, and Viswanathan, 2021; Sautner et al., 2023b; Kölbel et al., 2024) and the broader research on intentional strategic disclosure in earnings conference calls (Kimbrough and Louis, 2011; Larcker and Zakolyukina, 2012; Price et al., 2012; Davis et al., 2015; Call et al., 2024; Carter et al., 2024). Prior work shows that managers tailor the content, timing, and tone of information disclosure in the earnings conference calls to influence investor perceptions. We document a climate-specific manifestation of this behavior: firms systematically downplay the severity and negative tone of foreign transition risks in voluntary channels, especially earnings calls, while remaining fully compliant in mandated 10-K filings and when describing domestic risks. This pattern of selective transparency, most pronounced where external scrutiny is weaker, suggests a greenwashing motive that obscures the underlying relocation of pollution.

Third, our findings speak to ongoing policy debates regarding the effectiveness of financial intermediaries in advancing environmental objectives. Prior studies highlight the role of financial analysts in climate-related price discovery (Sautner et al., 2023b) and document improvements in firm behavior following sustainable lenders' commitments (Kacperczyk and Peydró, 2022; Ellimäki et al., 2023). We find, however, that the same intermediaries can inadvertently facilitate pollution reshoring and strategic disclosure in a fragmented global setting, whether because of limited attention, misaligned incentives, or conflicts of interest. These unintended consequences underscore the potential costs of well-intentioned financial oversight when climate regulations remain uneven across borders.

The remainder of the paper is structured as follows. Section 2 describes the data and sample selection. Section 3 outlines the research design. Section 4 examines the corporate pollution substitution. Section 5 analyzes corporate climate transition risk disclosure. Section 6 explores the role of external monitors. Section 7 evaluates firm-level investment and valuation effects of climate-regulation exposure, and Section 8 assesses its county-level environmental and health consequences. Section 9 concludes the paper.

2 Data and Sample

2.1 Data and Sample Selection

Our sample covers the period from 2007 to 2021 and consists of U.S.-listed firms with non-missing accounting information and plant-level emission data from the EPA's Toxics Release Inventory (TRI) Program and Greenhouse Gas Reporting Program (GHGRP). We obtain accounting data, stock returns, and overseas subsidiary information from Compustat. To reduce the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

2.1.1 Greenhouse Gas and Toxic Chemical Release

Greenhouse gas emissions data are sourced from the EPA's Greenhouse Gas Reporting Program (GHGRP). The GHGRP mandates the reporting of greenhouse gas (GHG) emissions and related information from large GHG sources, fuel and industrial gas suppliers, and CO_2 injection sites in the United States. As the GHGRP data begin in 2010, our analysis of GHG emissions does not include observations from earlier years.

We obtain data on toxic chemical releases and production ratios at the chemical level for each domestic facility of listed firms from the EPA's Toxics Release Inventory (TRI) Program. Since 1987, the EPA TRI has collected chemical-level emissions data from facilities that meet certain criteria—specifically, those that exceed a minimum employment threshold, operate in designated industries, and emit specified hazardous substances.

For each facility, we identify the parent company, defined as the highest-level corporation owning at least 50% of the voting shares, using information from TRI or GHGRP. Following

Akey and Appel (2021), we employ a fuzzy matching algorithm to link parent firm names to those of publicly listed companies. After matching facilities to listed firms, our final sample includes 477 distinct listed firms with 4,737 facility-year observations for GHG emissions, and 822 distinct listed firms with 345,751 chemical-facility-year observations for toxic chemical emissions.[3]

2.1.2 Climate Change Laws of the World

We source data on global climate regulations from the Climate Change Laws of the World database.[4] The database adopts a broad definition of climate change-related laws and policies, encompassing legal documents that are directly relevant to mitigation, adaptation, loss and damage, or disaster risk management. To be included, a law or policy must contain at least one component that is explicitly motivated by climate change concerns. The database provides detailed metadata, including implementation timelines, targeted sectors, keyword classifications (e.g., Energy Demand, Energy Efficiency, Mitigation and Adaptation, Renewables), geographic scope, and the original legal text. For consistency in evaluating regulatory stringency across countries, we restrict our analysis to legislative-type documents.

2.1.3 Climate Transition Risks Disclosure

Measures of firms' disclosed climate transition exposure and risk in earnings conference calls are obtained from Sautner et al. (2023a), who define "exposure" as the share of a

[3]This sample size is comparable to that in Akey and Appel (2021), who successfully matched between 666 and 837 TRI-reporting listed firms per year from 1994 to 2003.

[4]Grantham Research Institute at the London School of Economics and Climate Policy Radar (2023), Climate Change Laws of the World. Available at: `https://climate-laws.org` and `https://app.climatepolicyradar.org/search`. This database focuses exclusively on climate change-related laws and policies, covering all parties to the UNFCCC (196 countries plus the European Union), as well as select territories not formally part of the UN or UNFCCC, such as Taiwan, Palestine, and Western Sahara.

transcript dedicated to climate-related topics, distinct from risk exposure as understood in asset pricing.[5] Using a modified keyword discovery algorithm based on King, Lam, and Roberts (2017), they construct firm-level measures of climate exposure from discussions in both the management presentations and analyst Q&A portions of earnings calls.

To assess the role of analyst attention in shaping climate risk disclosure, we use data from Sautner et al. (2023b), who apply the same methodology to identify and count climate-related conversations initiated by analysts during earnings calls. A "conversation" is defined as the full exchange between an analyst and an executive during the Q&A session, following the approach of Rennekamp, Sethuraman, and Steenhoven (2022).

Corporate disclosure of climate transition risks in 10-K reports follows Kölbel et al. (2024), who apply a BERT-based classifier to identify climate-related sentences within Item 1A ("Risk Factors") of firms' 10-K filings. They construct firm-specific climate risk measures (*rg risk 10K*) based on the proportion of sentences related to climate topics. Kölbel et al. (2024) argues that their method parallels the approach of Sautner et al. (2023a).

3 Research Design

3.1 Dependent Variables

Emission Intensity: To examine domestic plant-level pollution emissions, we measure emission intensity as emissions per unit of capital. Specifically, we scale the emission amount at each facility by the parent firm's total assets in the corresponding year, for both greenhouse gas emissions (GHG) and toxic chemical releases ($Toxic$).

[5] See also Hassan et al. (2019); Hassan et al. (2023); Hassan et al. (2024a); Hassan et al. (2024b).

Firm Disclosure: To examine firms' disclosure behavior, we use several measures developed by Sautner et al. (2023a) based on earnings call transcripts. The primary measure, *rg expo*, captures disclosed climate transition exposure by quantifying the frequency of climate-related regulatory bigrams appearing in the transcript. In addition, we use *rg risk*, which reflects the extent to which regulatory shocks related to climate change are discussed in conjunction with terms such as "risk" or "uncertainty."

To assess the tone of climate-related disclosure, we use three sentiment-based measures: *rg pos*, the frequency with which regulatory shocks are mentioned alongside positive sentiment words; *rg neg*, their co-occurrence with negative sentiment words; and *rg sent*, defined as the net difference between *rg pos* and *rg neg*.

For comparison with mandatory disclosures, we incorporate climate risk disclosure in 10-K filings using the *rg risk 10K* measure developed by Kölbel et al. (2024), which captures the proportion of climate-related sentences within the "Risk Factors" section (Item 1A) of firms' annual reports.

3.2 Independent Variables

To construct our main independent variable, we measure firms' exposure to environmental regulations based on the relevance of their business activities to specific climate-related laws. Following Kalmenovitz (2023), we compute the cosine similarity between the textual content of Item 1 ("Business") in firms' 10-K reports and the climate regulations documented in the Climate Change Laws of the World database.[6] To ensure the accuracy of the similarity

[6] In Item 1 ("Business") of 10-K reports, firms describe their products, services, and the legal environment in which they operate. The SEC refers to Item 1 as "a good place to start to understand how the company operates."

measure, we rely only on key elements of each regulation, specifically, its title, targeted sectors, keywords, and policy instrument, thus reducing noise from unrelated or overly generic legal language.

Specifically, we calculate the cosine similarity between each pair of company×regulation using the BERT model. For *ForRgExpo*, we aggregate all the overseas climate regulations exposure of the countries in a year in which firms have subsidiaries and then adjust it by foreign income proportion. For *USRgExpo*, we use the same method that takes the climate regulations in the U.S. in a year into account and calculates how firms' business is being exposed to the regulations. The calculations are as follows:

$$ForRgExpo_{i,t} = |\frac{\mathrm{PIFO}_{i,t}}{\mathrm{PI}_{i,t}}| \times \sum_{c \neq \mathrm{US}} \sum_{r \in R_c} \mathrm{Cosine}(\mathrm{Company}_{i,t}, \mathrm{Regulation}_{r,c}) \quad (1)$$

$$USRgExpo_{i,t} = \sum_{c = \mathrm{US}} \sum_{r \in R_c} \mathrm{Cosine}(\mathrm{Company}_{i,t}, \mathrm{Regulation}_{r,c}) \quad (2)$$

where i denotes the firm, t denotes the year, r denotes the regulation, and c denotes the country issuing the regulation.

As a robustness exercise, we substitute the text-based exposure indices with a simpler proxy, the yearly count of climate laws enacted in each host country and in the United States, and the results are consistent.

3.3 Control variables

We control for some firm fundamental characteristics, including firm size (*Size*), growth rate (*Growth*), return on asset (*ROA*), and leverage ratio (*Leverage*). We also control for the number of the firm's overseas subsidiaries($Subsidiaries$).

3.4 Specification

3.4.1 Pollution Substitution

Greenhouse Gas: To assess the impact of both foreign and domestic climate regulation exposure on corporate greenhouse gas emissions at U.S. plants, we estimate the following regression model:

$$GHG_{i,t+1} = \phi ForRgExpo_{i,t} + \theta USRgExpo_{i,t} + \beta Controls_{i,t} + \sigma_i + \delta_i \alpha_t + \epsilon_{i,t} \tag{3}$$

where i denotes the plant and t denotes the year. The analysis is conducted at the plant-year level. We include high-dimensional fixed effects, specifically plant fixed effects (σ_i) and industry-by-year fixed effects ($\delta_i \alpha_t$), where industries are classified at the 2-digit NAICS code level. The error term, $\epsilon_{i,t}$, is clustered at the 2-digit NAICS industry level.

Toxic Chemicals: To analyze toxic chemical emissions, we estimate the following regression model:

$$Toxic_{n,i,t+1} = \phi ForRgExpo_{i,t} + \theta USRgExpo_{i,t} + \beta Controls_{i,t} + \sigma_i + \gamma_n \alpha_t + \delta_i \alpha_t + \epsilon_{n,i,t} \tag{4}$$

where n denotes the chemical, i denotes the plant, and t denotes the year. The analysis is conducted at the plant-chemical-year level. We include high-dimensional fixed effects, specifically plant fixed effects (σ_i), chemical-by-year fixed effects ($\gamma_{n,t}$), and industry-by-year fixed effects ($\delta_i\alpha_t$), where industries are classified according to the 2-digit NAICS code. The error term is denoted by $\epsilon_{n,i,t}$ and clustered at the 2-digit NAICS level.

To test whether the effect on toxic chemical emissions is driven by the reshoring of greenhouse gas emissions, we include an interaction term, $ForRgExpo_{i,t} \times Transition_i$, in Equation (4), and estimate the following regression model:

$$\begin{aligned} Toxic_{n,i,t+1} = \rho ForRgExpo_{i,t} \times Transition_i + \phi ForRgExpo_{i,t} + \theta USRgExpo_{i,t} \\ + \mu Transition_i + \beta Controls_{i,t} + \sigma_i + \gamma_n\alpha_t + \delta_i\alpha_t + \epsilon_{n,i,t} \end{aligned} \tag{5}$$

where $Transition_i$ is a dummy variable equal to one if the plant's parent company operates in an industry that ranks among the top 10 in average greenhouse gas emissions over the sample period. Table 2 presents the industry rankings based on both greenhouse gas and toxic chemical emissions.

3.4.2 Firm Disclosure

To assess the impact of both foreign and domestic climate regulation exposure on firms' disclosed climate transition exposure and risk, we estimate the following regression model:

$$Disclosure_{i,t} = \phi ForRgExpo_{i,t} + \theta USRgExpo_{i,t} + \beta Controls_{i,t} + \sigma_i + \delta_i\alpha_t + \epsilon_{i,t} \tag{6}$$

where i denotes the firm and t denotes the year. The analysis is conducted at the firm-year level. The dependent variable, $Disclosure_{i,t}$, captures firms' disclosed climate transition exposure or risk in earnings conference calls and 10-K reports in year t.[7] We include high-

[7] Reallocating production may take time; thus, when testing the pollution substitution effect, we use emission data from year *t+1*. In contrast, climate-related disclosures in earnings calls and 10-K filings are

dimensional fixed effects, specifically firm fixed effects (σ_i) and industry-by-year fixed effects ($\delta_{s(i),t}$), where industries are classified according to the 2-digit NAICS code. The error term is denoted by $\epsilon_{i,t}$ and clustered at the 2-digit NAICS level.

3.5 Descriptive Statistics

Table 1 presents the descriptive statistics of the key variables used in this study.

INSERT TABLE 1 HERE

Pollution Emission: For the greenhouse gas emission analysis, our sample includes 4,737 plant-year observations. The mean value of *GHG* is 0.362, while the median is 0.0207. For the toxic chemical emission analysis, the sample consists of 345,751 plant-chemical-year observations, with a mean *Toxic* value of 3.715 and a median of 0.0195. Table 2 presents the industry rankings based on average emissions for both greenhouse gases and toxic chemicals during the sample period. The top three industries by average greenhouse gas emissions are NAICS 45 (Retail Trade), 32 (Wood, Paper, Petroleum, Chemicals, Plastics & Rubber Manufacturing), and 48 (Transportation). In contrast, the top three industries by toxic chemical emissions are NAICS 54 (Professional, Scientific, and Technical Services), 56 (Administrative and Support and Waste Management), and 21 (Mining, Quarrying, and Oil and Gas Extraction)

INSERT TABLE 2 HERE

more timely, so we use disclosure data from year t as the dependent variable when examining firms' disclosure behavior.

Regulation Exposure: The mean value of *ForRgExpo*, which captures firms' exposure to foreign climate regulations, is 2.888. We further decompose *ForRgExpo* into two components: *ForRgExpo H*, representing exposure to countries with consistently more stringent climate regulations than the U.S., and *ForRgExpo L*, representing exposure to countries with consistently less stringent regulations. The mean values of *ForRgExpo H* and *ForRgExpo L* are 2.102 and 0.0182, respectively. The mean value of domestic regulation exposure, *USRgExpo*, is 0.255. Figure 2 presents the annual mean values of *ForRgExpo* and *USRgExpo* from 2007 to 2021. Both foreign and domestic exposure measures exhibit increasing trends over the sample period, with the rise in foreign exposure being more pronounced. To illustrate the underlying sources of *ForRgExpo*, Figure 1 shows that, as of 2021, 32 countries hosting U.S. foreign subsidiaries had enacted more climate-related laws than the U.S., the majority of which are located in Europe.

INSERT FIGURE 2 HERE

Disclosed Climate Transition Exposure/Risk: The mean value of *rg expo*, which captures disclosed climate transition exposure, is 9.818, while the mean value of *rg risk*, representing disclosed climate transition risk, is 0.312. Figure 3 plots the annual mean values of *rg expo*, *rg risk*, and *rg sent* over the sample period. Overall, disclosed climate transition exposure, risk, and sentiment remained relatively stable. However, a noticeable increase in both *rg expo* and *rg risk* occurred in 2010–2011, likely reflecting spillover effects from the SEC's 2010 Climate Change Disclosure guidance for 10-K filings to earnings conference calls. A similar uptick is observed after 2019, possibly driven by heightened market attention and public discourse on climate change in recent years.

INSERT FIGURE 3 HERE

Firm Characteristics: Firm size measured by the log value of total assets, *Size*, has a mean value of 7.861 and a median value of 7.929. The average leverage ratio, *Leverage*, is 0.270. The average sales growth rate, *Growth*, is -16.4%, and the average return on assets, *ROA*, is 0.00826. The mean value of *TobinQ* is 1.720. *#Subsidiaries*, the firms' overseas subsidiary number, has a mean value of 31 and a median value of 5. All variables fall within a normal range.

4 Climate Regulation Exposure and Pollution Substitution

In this section, we examine how firms' domestic emissions respond to both foreign and domestic climate regulation exposure using regression analysis. We then adopt an instrumental variable approach to address potential endogeneity concerns. Next, we explore the moderating role of domestic political factors in shaping firms' environmental responses. Finally, we conduct a series of heterogeneity tests.

4.1 Climate Regulation Exposure and Pollution Substitution

4.1.1 Climate Regulation Exposure and Greenhouse Gas Emission Substitution

We begin by examining how domestic greenhouse gas (GHG) emissions respond to both foreign and domestic climate regulation exposure, as specified in Equation (3). Table 3 presents the regression results. Column (1) reports estimates without control variables, while Column (2) includes the full set of controls. Column (3) separately analyzes the effects of exposure to countries with high and low levels of climate regulation stringency, denoted as *ForRgExpo H* and *ForRgExpo L*, respectively.

In both Columns (1) and (2), the estimated coefficients on *ForRgExpo* are significantly positive. In Column (3), the coefficient on *ForRgExpo H* remains significantly positive, whereas the coefficient on *ForRgExpo L* is not statistically significant.[8]

The estimated coefficients on *USRgExpo* are consistently negative but not statistically significant across all specifications. The lack of statistical significance likely has two sources. First, *ForRgExpo* is endogenous: firms facing stricter U.S. climate rules (*USRgExpo*) often respond by expanding abroad, which mechanically raises their foreign-regulation exposure. Once we instrument for *ForRgExpo* in the next section, the coefficient on *USRgExpo* turns significantly negative, showing that this endogeneity had been masking the domestic effect. Second, U.S. climate policy has historically been less comprehensive and stringent than many foreign regimes, so its overall regulatory "bite" may be too weak to produce a large, precisely estimated average effect.

These findings suggest that firms increase their domestic GHG emissions in response to more stringent foreign climate regulations, particularly when the exposure arises from operations in highly regulated countries. In terms of magnitude, the results in Column (2) indicate that a one standard deviation increase in *ForRgExpo* is associated with a 0.003 increase in domestic *GHG*, equivalent to approximately 0.8% of the sample mean.[9]

Taken together, the results in Table 3 provide evidence that firms increase their domestic

[8]The magnitudes of the coefficients on *ForRgExpo H* and *ForRgExpo L* are not directly comparable, as the underlying values of these two variables are not measured on a comparable scale.

[9]For ease of interpretation, *GHG* and *ForRgExpo* are both scaled by 1,000 in the GHG emission regressions. The standard deviation of the scaled *ForRgExpo* in the GHG sample is 0.0657.

GHG emission intensity in response to more stringent climate regulations abroad. This pattern is consistent with the notion of cross-border pollution substitution, likely facilitated by regulatory arbitrage in the context of globally fragmented climate policy regimes.

INSERT TABLE 3 HERE

4.1.2 Climate Regulation Exposure and Toxic Pollution Substitution

We next examine the impact of climate regulation exposure on toxic chemical emission intensity at firms' domestic facilities. Although toxic pollutants are not the direct targets of climate regulations, their emissions may be indirectly affected by firms' production reallocation decisions or may arise as by-products of greenhouse gas (GHG) reshoring.

To investigate this relationship, we estimate regressions based on Equations (4) and (5). Table 4 presents the results. Columns (1) and (2) report estimates from Equation (4), excluding and including control variables, respectively. Column (3) incorporates an interaction term, $ForRgExpo \times Transition$, as specified in Equation (5), and Column (4) examines the separate effects of high and low foreign regulation exposure, *ForRgExpo H* and *ForRgExpo L*.

In Columns (1) and (2), the coefficients on *ForRgExpo* are significantly positive, indicating that foreign regulation exposure is associated with higher domestic toxic chemical emissions. However, in Column (3), the main effect of *ForRgExpo* becomes negative and statistically insignificant once the interaction term is included. Importantly, the coefficient on the interaction term $ForRgExpo \times Transition$ is significantly positive, suggesting that the increase in toxic emissions is concentrated in industries with higher average carbon intensity, consistent with the idea that toxic pollution may increase as a by-product of GHG reshoring. In Column (4), the coefficient on *ForRgExpo H* is significantly positive, whereas the coefficient on *ForRgExpo L* remains positive but statistically insignificant. This pattern mirrors the findings for GHG emissions, implying that foreign climate regulation in highly regulated countries is the primary driver of toxic pollution substitution.

Additionally, the estimated coefficients on *USRgExpo* are significantly negative across all specifications, indicating that U.S. domestic climate regulation is effective in reducing firms' toxic chemical emission intensity. The coefficient on toxic releases stays negative largely because toxic discharges are not subject to the same endogeneity pressures: climate regulations focus chiefly on greenhouse gases, so variation in toxic emissions is unlikely to be driven by firms' strategic responses to those rules. After we address the potential endogenous issues using the IV approach, the estimated coefficients on *USRgExpo* remain significantly negative.

To ensure that this result is not driven by increased production, Column (5) examines changes in *Production*, measured as output when a specific chemical is used as an input at a given domestic plant. The coefficient on *ForRgExpo* is statistically insignificant, suggesting that foreign regulatory exposure does not lead to higher production levels. This finding supports the interpretation that the rise in toxic emissions reflects pollution substitution rather than output expansion.

In terms of magnitude, Column (2) indicates that a one standard deviation increase in *ForRgExpo* is associated with a 0.264 increase in *Toxic*, equivalent to approximately 7% of the sample mean.[10] In sum, the results indicate that U.S. firms significantly increase both domestic GHG and toxic chemical emission intensity in response to more stringent foreign

[10] The standard deviation of *ForRgExpo* in the toxic chemical emissions sample is 8.29.

climate regulations. Crucially, these increases are not attributable to higher production but instead reflect pollution-shifting behavior consistent with regulatory arbitrage.

INSERT TABLE 4 HERE

4.2 Identification Strategy: Instrumental Variables Approach

Our baseline estimates may be subject to endogeneity concerns. Firms may endogenously choose the countries in which to establish foreign operations based on the stringency of local environmental regulations. Similarly, firms might adjust their international business scope in response to shifts in regulatory intensity. These factors raise concerns about reverse causality in the relationship between foreign regulation exposure and domestic emissions. Moreover, despite the inclusion of a rich set of firm characteristics and multiple layers of fixed effects, omitted variable bias may persist.

To address endogeneity concerns, we employ an instrumental-variables (IV) strategy that leverages two exogenous sources of variation in firms' foreign regulatory exposure. The first instrument, $ExtremeWeather$, is the historical count of extreme-weather days in host countries. Prior research shows that such climate-related disasters significantly increase the likelihood of enacting or tightening climate legislation and strengthen public support for climate policies (Rowan, 2023; Cologna et al., 2025). The second instrument, $HostingProximity$, is the geographic distance, measured at the industry aggregated level, from the United States to each host country.[11] Existing studies find that geographic proximity facilitates international trade, cross-border mergers and acquisitions, and equity portfolio investment by reducing

[11] For clearer interpretation, we use the inverse of geographic distance between the United States and each host country when constructing the $HostingProximity$.

transportation costs and information asymmetries (Grosse and Trevino, 1996; Rossi and Volpin, 2004; Portes and Rey, 2005). Accordingly, nearer countries are more likely to host U.S. subsidiaries.

For the exclusion restriction, the extreme-weather measure is long-run historical rather than contemporaneous, making it predetermined with respect to current U.S. operations, while distance is a time-invariant geographic constant. After controlling for plant fixed effects, industry-year fixed effects, and chemical fixed effects, neither $ExtremeWeather$ nor $ForDistance$ has a credible direct link to the emission intensity of firms' domestic plants.

Table 5 reports the two-stage least squares (2SLS) estimation results. Columns (1) and (2) are results based on greenhouse gas emissions, and Columns (3) and (4) are results based on toxic pollution emissions. Columns (1) and (3) present the first-stage regressions for greenhouse gas and toxic chemical emissions, respectively. Both instruments exhibit significantly positive coefficients on *ForRgExpo*, and the associated F-statistics exceed the conventional threshold of 10, mitigating concerns about weak instruments. In both specifications, Hansen J-test p-values exceed 0.1, supporting the validity of the over-identifying restrictions. Columns (2) and (4) present the second-stage results. The estimated coefficients on *ForRgExpo* remain positive and statistically significant for both emissions outcomes, reinforcing our baseline findings. These results suggest that foreign climate regulation causally increases domestic pollution levels, consistent with a pollution reshoring mechanism.

Taken together, the IV analysis confirms that our main results are not driven by endogenous selection or omitted variable bias. Exposure to stricter foreign climate regulations leads to a measurable increase in pollution at U.S. domestic facilities.

INSERT TABLE 5 HERE

4.3 State Politics, Climate Regulation Exposure and Pollution Substitution

In this section, we examine how domestic political heterogeneity in mediating firms' environmental responses. Specifically, we test the within-U.S. reallocation of emissions and find evidence consistent with political arbitrage. Prior research shows that state-level political ideology shapes environmental norms and regulatory enforcement, with Democratic-leaning states generally imposing stricter environmental regulations than Republican-leaning states (Bisetti et al. 2022; Duchin, Gao, and Xu 2024). In our sample, a substantial share of firms have headquarters and facilities located in states with differing political orientations.[12]

Since corporate headquarters typically set production strategies, firms headquartered in Democratic-leaning states where environmental norms and regulatory pressures are stronger may be more attuned to foreign climate regulation risks. However, emissions occur at production facilities, which often operate under state-level rules. Facilities in Republican-leaning states generally face weaker environmental enforcement. We hypothesize that, in response to stricter foreign climate regulations, firms with Democratic-leaning headquarters are more likely to reallocate emission-intensive production to their domestic facilities located in Republican-leaning states. This reflects a form of political arbitrage, allowing firms to

[12] In the greenhouse gas emission sample, for firms headquartered in Democratic-leaning states, 32% of their plants are located in the Republican-leaning states; for firms headquartered in Republican-leaning states, 20% of their plants are located in the Democratic-leaning states. In the toxic chemical emission sample, for firms headquartered in Democratic-leaning states, 42% of their plants are located in the Republican-leaning states; for firms headquartered in Republican-leaning states, 33% of their plants are located in the Democratic-leaning states.

comply with external pressures while minimizing domestic regulatory costs.

To test this hypothesis, we use state-level presidential vote share data from the MIT Election Data and Science Lab. We define $DemoHQ$ as an indicator equal to one if a firm's headquarters is located in a state where the Democratic candidate received more votes than the Republican candidate in the most recent presidential election. We classify production facilities as located in Democratic or Republican states based on the same criteria. We also introduce an interaction term, $ForRgExpo \times DemoHQ$, into our pollution substitution regression framework. To address potential endogeneity concerns that firms may select locations based on political or environmental regulatory considerations, we also conduct a robustness test using a swing-state subsample following Akey (2015). This subsample includes only firms headquartered in states where the presidential vote margin falls within ± 2 percentage points, thereby minimizing bias from strategic location choices related to political climate.

Table 6 reports the results. Columns (1)–(4) focus on GHG emissions; Columns (5)–(8) examine toxic chemical emissions. Across all the columns, the main variable of interest is the interaction term $ForRgExpo \times DemoHQ$, and we also control for $DemoHQ$. Columns (1), (2), (5), and (6) use observations from plants in Republican-leaning states; Columns (3), (4), (7), and (8) use those in Democratic-leaning states. Odd columns present full sample estimates, while even columns report results for the swing-state subsample. The estimated coefficients on $ForRgExpo \times DemoHQ$ are significantly positive for all plants in Republican-leaning states for the tests of both GHG and toxic chemical emissions. These results support the hypothesis that firms with Democratic-leaning headquarters disproportionately shift emission-intensive production to Republican-leaning states in response to foreign climate regulation exposure.

INSERT TABLE 6 HERE

4.4 Heterogeneous Tests

In this subsection, we conduct heterogeneity analyses across industries and chemical types.

4.4.1 Brown vs Green Industry

First, we split the sample based on the average level of industry emissions for both GHG and toxic chemicals. Industries ranked in the top half in terms of average emissions are classified as brown industries, while those in the bottom half are classified as green industries. We examine the pollution substitution effect separately for GHG and toxic chemicals within each group. Table 7 presents the results. The estimated coefficients on *ForRgExpo* are significantly positive for the brown industry sample, as shown in Columns (1) and (3), indicating that firms in emission-intensive industries are more likely to increase domestic pollution in response to foreign regulatory pressure. In contrast, the coefficients for the green industry sample, shown in Columns (2) and (4), are negative and statistically insignificant. These results suggest that the pollution substitution effect is primarily concentrated in brown industries.

INSERT TABLE 7 HERE

4.4.2 Carcinogenic vs non-carcinogenic Chemicals

Second, for toxic chemical releases, we examine heterogeneity based on chemical type, specifically, carcinogenic versus non-carcinogenic chemicals.[13] To do so, we include an interaction term, $ForRgExpo \times CancerChemical$, in Equation (4), where $CancerChemical$ is an indicator variable equal to one if the chemical is classified as carcinogenic. Table 8 presents the results. Columns (1) and (2) report estimates without and with control variables, respectively. In both specifications, the estimated coefficients on the interaction term $ForRgExpo \times CancerChemical$ are significantly positive, indicating that pollution reshoring is more pronounced for carcinogenic chemicals.

For example, in Column (2), the coefficient on $ForRgExpo \times CancerChemical$ is 0.036, while the coefficient on $ForRgExpo$ is 0.027. This implies that the magnitude of reshoring for carcinogenic chemicals is roughly twice as large as that for non-carcinogenic chemicals.

INSERT TABLE 8 HERE

5 Corporate Climate Transition Risks Disclosure

In this section, we shift focus from real actions to disclosure behavior, examining how firms disclose their exposure to climate regulations in both foreign and domestic markets through public information disclosure.

[13]EPA's Integrated Risk Information System (IRIS) program systematically identifies and characterizes the health hazards of environmental chemicals. We retrieve each substance's "cancer" or "non-cancer" classification from the IRIS Advanced Search Chemical Details page (https://iris.epa.gov/AdvancedSearch/).

5.1 Firms' Disclosure Incentives

U.S.-listed multinationals report to investors in the United States but operate under both domestic and foreign climate regulations. Because domestic stakeholders know far less about conditions abroad, firms can exploit this information gap and reveal only the foreign risks they choose to highlight (Dvořák 2005). Such selective transparency is plausible for two reasons. First, there is still no consensus on whether climate risk is financially material (Matsumura, Prakash, and Vera-Muñoz 2024). Second, climate disclosures are largely qualitative, making it hard for outsiders to gauge a firm's true exposure (Giglio, Kelly, and Stroebel 2021). These frictions create room for strategic, or "greenwashed", climate reporting. By downplaying foreign-regulation risks, firms can mask the pollution substitution documented earlier, reduce regulatory scrutiny, and appeal to stakeholders' prosocial preferences.

5.2 Climate Regulation Exposure and Disclosed Climate Transition Exposure/Risk

To this end, we examine firms' climate risk disclosure patterns by comparing their actual climate regulation exposure with their disclosed climate transition exposure and risk levels, using the regression model specified in Equation (6). Under the SEC's Climate Change Risk (CCR) rules, firms are required to disclose climate-related risks in their 10-K filings.[14] In contrast, climate risk disclosures during earnings conference calls are voluntary. We exploit this distinction to compare firms' disclosure behavior across two channels, mandatory

[14]These disclosures typically appear in Item 1A ("Risk Factors") and Item 7 ("MD&A") of the 10-K reports.

disclosure in 10-K reports and voluntary disclosure in earnings calls, to assess whether firms present consistent information across these venues.

Table 9 presents the regression results. The dependent variables in Columns (1) to (4) are measures of disclosed corporate climate transition exposure and risk from earnings conference calls, constructed by Sautner et al. (2023a). Columns (5) and (6) use measures of climate transition risk disclosed in 10-K reports, based on the methodology of Kölbel et al. (2024). For each test, we assess the effect of total foreign regulatory exposure (*ForRgExpo*), as well as its decomposition into exposure to more and less stringent foreign regulatory environments, *ForRgExpo H* and *ForRgExpo L*, respectively.

In Columns (1) and (2), we use *rg expo* as the dependent variable, which captures the disclosed climate regulatory exposure based on the frequency of specified bigrams in earnings call transcripts. In Column (1), the coefficient on *ForRgExpo* is negative but not statistically significant, implying that firms may be less inclined to highlight their regulatory exposure when host-country climate rules tighten, yet this tendency is not statistically distinguishable from zero. The coefficient on *USRgExpo* is positive but also insignificant. In Column (2), the coefficient on *ForRgExpo H* is significantly negative, while the coefficient on *ForRgExpo L* is not, indicating that firms reduce discussion of regulatory exposure particularly when operating in more stringently regulated countries.

In Columns (3) and (4), the dependent variable is *rg risk*, which reflects the extent to which firms frame regulatory shocks as risks or uncertainties during earnings conference calls. In Column (3), the significantly negative coefficient on *ForRgExpo* indicates that firms disclose lower levels of climate transition risk when exposed to stricter foreign regulations. In Column (4), the coefficient on *ForRgExpo H* is significantly negative, while the coefficient on

ForRgExpo L is not, reinforcing the pattern that strategic underreporting of climate transition risks is concentrated among firms exposed to highly regulated foreign jurisdictions. By contrast, the significantly positive coefficient on *USRgExpo* suggests that domestic regulatory exposure is associated with increased risk disclosure.

Quantitatively, based on the estimates in Column (4), a one standard deviation increase in *ForRgExpo* is associated with a 0.0624 decrease in *rg risk*, relative to a sample mean of 20%.[15] A one standard deviation increase in *USRgExpo* corresponds to a 0.104 increase in *rg risk*, relative to a sample mean of 33%.

In Columns (5) and (6), we examine disclosure in 10-K reports using *rg risk 10K* as the dependent variable, following the measure developed by Kölbel et al. (2024). In Column (5), the coefficients on both *ForRgExpo* and *USRgExpo* are positive but statistically insignificant, indicating no meaningful change in disclosed climate transition risk in 10-K filings in response to either foreign or domestic regulation. Similarly, in Column (6), neither *ForRgExpo H* nor *ForRgExpo L* is statistically significant.

INSERT TABLE 9 HERE

5.3 Climate Regulation Exposure and Disclosure Sentiment

We further examine the sentiment of climate-related regulatory disclosures using three measures: *rg pos*, which captures instances where climate-related regulatory shocks are discussed alongside positive tone words; *rg neg*, which captures mentions alongside negative tone words; and *rg sent*, defined as the net difference between *rg pos* and *rg neg*.

[15] For ease of interpretation, *ForRgExpo* is scaled by 10 in the tests of disclosure regressions. The standard deviation of *ForRgExpo* after scaling is 0.78.

Table 10 presents the results. Column (1) shows that firms' use of positive tone in climate transition risk disclosure does not significantly change in response to foreign regulation exposure. However, in Column (2), the coefficient on *ForRgExpo* is significantly negative, indicating that firms adopt a less negative tone when exposed to more stringent foreign climate regulations. As a result, the overall sentiment becomes more positive, as shown by the significantly positive coefficient on *ForRgExpo* in Column (3).

Regarding domestic exposure, the coefficient on *USRgExpo* is significantly positive in Column (2), suggesting that negative sentiment in disclosure increases with domestic climate regulation exposure. In contrast, the coefficients on *USRgExpo* are positive but insignificant in Column (1) and negative but insignificant in Column (3). This divergence in patterns implies that while firms downplay foreign regulatory risks through more positive sentiment, they tend to emphasize the risks of domestic regulation using a more negative tone.

INSERT TABLE 10 HERE

Overall, the results suggest that firms strategically downplay their exposure to foreign climate transition risks. Specifically, when facing more stringent foreign climate regulations, firms disclose less information, report lower levels of perceived risk, and adopt a less negative tone. This pattern of strategic disclosure is observed exclusively in earnings conference calls where disclosure is voluntary and does not extend to mandatory disclosures in 10-K filings. Importantly, this behavior does not apply to domestic climate risk exposure, further underscoring the selective nature of the disclosure. These findings are consistent with a greenwashing strategy, whereby firms obscure forthcoming pollution substitution activities by downplaying their exposure to foreign regulatory pressures in public communications.

6 The Role of External Monitors

In this section, we examine how external monitors, including financial analysts and sustainable creditors, are shaping firms' arbitrage behaviors in this context.

6.1 Financial Analysts

Given that one of the key functions of financial analysts is to facilitate risk price discovery, Sautner et al. (2023b) shows that analysts often raise values-related climate concerns during earnings conference calls. Moreover, portfolios that incorporate insights from these values-based questions earn higher returns, driven by investor flow effects. However, little is known about the role of financial analysts in the context of fragmented global climate change regulations and the potential for firm-level regulatory arbitrage, particularly in the domain of information disclosure. To this end, we first examine whether financial analysts respond to both foreign and domestic climate regulation exposures, with a primary focus on climate-related exchanges between analysts and managers during the Q&A sessions of earnings conference calls. In addition, we analyze how managers respond to these climate-related inquiries.

We obtain data on climate-related conversations from Sautner et al. (2023b), who parse the Q&A portions of earnings calls into distinct "conversations." Each conversation captures the complete exchange between a single analyst and any executive, and those involving climate-related questions are classified as climate conversations. Based on this dataset, we find that 87% of the disclosed content related to climate transition risks in our sample arises during the Q&A sessions when managers respond to analysts' climate-related questions. In contrast, such disclosures are rarely initiated voluntarily during the management presentation portion of the call.

Table 11 presents the empirical results. In Columns (1) and (2), we use the number of climate-related conversations (*climateconv*) as the dependent variable. Column (1) reports OLS estimates, while Column (2) reports results from a Poisson regression. The estimated coefficients on *ForRgExpo* are not statistically significant, suggesting that greater foreign regulatory exposure does not prompt more climate-related questions from analysts. In contrast, the coefficients on *USRgExpo* are significantly positive, indicating that analysts are more responsive to domestic climate regulatory exposure. The differing responses of analysts to foreign versus domestic regulatory exposure may stem from their relative disadvantage in accessing local information abroad or reflect limited overall market demand for information on overseas climate risks.

Columns (3) and (4) shift the focus to managerial disclosure behavior in climate-related conversations with analysts, especially in response to foreign regulation. To test this, we include an interaction term, $ForRgExpo \times \ln(climateconv)$, where *climateconv* captures the extent of analyst pressure. The estimated coefficients on the interaction term are significantly negative when the dependent variables are *rg expo* and *rg risk*, indicating that firms systematically reduce the quantity and tone of disclosed climate transition risks during analyst conversations when facing greater foreign regulation exposure. This behavior is consistent with strategic disclosure and greenwashing incentives under fragmented regulatory oversight.

INSERT TABLE 11 HERE

6.2 Sustainable Lenders

Next, we examine the role of sustainable lenders. Specifically, we examine whether banks, one of the most influential players in coordinating climate action, are effectively monitoring firms' disclosure practices and real actions regarding pollution emissions. Since the inception of global fossil fuel divestment campaigns in 2011, an increasing number of companies, including financial institutions, have pledged to reduce their carbon footprints. Since 2015, many banks worldwide have gradually committed to the Science Based Targets Initiative (SBTi), aiming to reduce carbon emissions within their lending portfolios (Kacperczyk and Peydró 2022).[16] The SBTi is a collaborative effort between the Carbon Disclosure Project, the UN Global Compact, the World Resources Institute, and the World Wide Fund for Nature. Its core mission is to mobilize the private sector to set science-based targets for achieving net-zero emissions.

To assess how SBTi lenders influence firms' strategic disclosure and pollution substitution, we focus on non-U.S. lenders that have committed to SBTi, excluding U.S. lenders to avoid confounding effects related to their domestic environmental quality preferences. We define an indicator variable, $SBTi$, which equals one after a firm's non-U.S. lenders commit to carbon neutrality under SBTi and zero otherwise. We incorporate the interaction term $ForRgExpo \times SBTi$ into our regressions, testing both the pollution substitution and strategic disclosure.

Table 12 presents the results. Columns (1) to (4) report findings for the pollution substitution. We separate the sample into the brown (in Columns (1) and (3)) and green

[16] A list of SBTi lenders is provided in the Appendix Table A2.

industries(in Columns (2) and (4)).[17] The estimated coefficients on $ForRgExpo \times SBTi$ are significantly positive for the brown industries for both greenhouse gas and toxic chemical emissions, but negative and not significant for the green industry. The results show that re-shoring greenhouse gas and toxic pollution to domestic plants in the brown industries intensifies after firms' non-U.S. lenders commit to SBTi. Columns (5) to (6) focus on the strategic disclosure. The estimated coefficient on $ForRgExpo \times SBTi$ are both significantly negative when the dependent variables are *rg expo* and *rg risk*, indicating that firms downplay their disclosed climate transition risks more prominently after their non-U.S. lenders commit to sustainable investment.

There are some potential reasons why sustainable lenders fail to function as effective monitors in firms' emissions in this context. From the banks' perspective, first, emissions abroad are more visible to foreign lenders due to closer geographical distance, compared to U.S. domestic ones, thus easier to monitor. Second, foreign lenders have conflicts of interest in their monitoring role in this context. In specific, they care more about pollution within a closer distance to them because it poses a direct threat to their health and surrounding environment, compared to pollution in the U.S.

From the firms' perspective, to maintain their relationship with these international lenders, firms will try to meet the expectations of overseas sustainable lenders, by transferring emissions back to the U.S. at the expense of domestic welfare to maintain a green image internationally. At the same time, firms would like to manipulate disclosure for greenwashing purposes. This aligns with Duchin, Gao, and Xu (2024), which finds that firms emphasize sustainability efforts in conference calls without a corresponding decline in pollution levels

[17] The definition of brown and green industries is the same as in the prior section.

through divesting pollutive plants. Thus, sustainable lenders may inadvertently encourage greater regulatory arbitrage in both emissions and disclosure for multinational firms.

INSERT TABLE 12 HERE

7 Firm Level Consequence Analysis

In this section, we analyze the firm-level consequences of climate regulation exposure, focusing on firms' foreign and domestic asset market investment decisions, green investment, and Tobin's Q. Table 13 presents the main results.

INSERT TABLE 13 HERE

From the perspective of asset market investment, Duchin, Gao, and Xu (2024) shows that firms divest pollutive plants in response to environmental pressures. While their analysis centers on the U.S. domestic market, we extend the inquiry to examine how global climate regulation exposure affects firms' investment behavior in both foreign and domestic markets. In Column (1), the dependent variable is *Plant Divestment*, sourced from Duchin, Gao, and Xu (2024), defined as a dummy indicating whether a firm divested pollutive industrial plants in the U.S. in a given year. We adopt the same logit model specification used in their study. The estimated coefficient on *ForRgExpo* is significantly negative, indicating that greater exposure to foreign climate regulation is associated with a lower likelihood of divesting domestic pollutive plants. This finding supports our pollution substitution hypothesis: firms may retain domestic pollutive assets to support high-emission production activities reshored from abroad.

Next, we investigate the impact of climate regulatory exposure on firms' international expansion. Columns (2) and (3) use as dependent variables *Sub Growth H* and *Sub Growth L*, which measure the growth rate of foreign subsidiaries in highly and weakly regulated countries, respectively. The independent variables *ForRgExpo H* and *ForRgExpo L* capture foreign regulatory exposure in each context. Both coefficients are significantly negative, suggesting that stringent foreign regulations deter firms from expanding their international footprint, regardless of the regulatory stringency of the host country.

In Column (4), we examine the effect of climate regulation exposure on green investment. Following Accetturo et al. (2024), we construct the *Green Investment* dummy equal to one if at least one keyword from the climate regulatory dictionary developed by Sautner et al. (2023a) appears in the accompanying notes of the 10-K report for that year, and the firm reports positive capital expenditures. The estimated coefficient on *ForRgExpo* is negative but not statistically significant, whereas the coefficient on *USRgExpo* is significantly positive. These results imply that firms respond to domestic regulatory pressure by investing more in green upgrades, but foreign regulatory exposure does not yield a similar response, potentially because firms can rely on pollution substitution to adapt to foreign constraints without altering their innovation strategy.

Finally, Column (5) explores the market valuation response using Tobin's Q as the outcome variable. The significantly negative coefficient on *ForRgExpo* suggests that stricter overseas climate regulation reduces firm value. Quantitatively, a one standard deviation increase in *ForRgExpo* is associated with a 1.5% decline in Tobin's Q within the current year. In contrast, the coefficient on *USRgExpo* is not statistically significant. The divergence in effects between foreign and domestic exposure likely reflects differences in enforcement intensity and compliance costs between jurisdictions.

8 County Air Quality and Respiratory Disease Rates

Air pollution is a leading determinant of respiratory illness. Short-term spikes in fine particulates, ozone, and other criteria pollutants raise emergency-department (ED) visits for respiratory diseases (Dominici et al., 2006; Zanobetti and Schwartz, 2011; Di et al., 2017; Liu et al., 2019; Alexander and Schwandt, 2022). Building on this evidence, we test whether the pollution re-shoring triggered by foreign climate regulations worsens U.S. air quality and respiratory health.

We adopt the staggered difference-in-differences framework of Callaway and Sant'Anna (2021). A county enters treatment in the first year in which its locally operating parent firms become exposed to foreign climate regulation from hosting countries with consistently higher levels than the US, and it remains in treatment thereafter.

We source the county-level Air Quality Index (AQI) from the Environmental Protection Agency (EPA)'s Air Quality System (AQS). The AQI combines concentrations of NO_2, O_3, CO, PM_2.5, PM_{10}, and SO_2. The AQI ranges from 0 to 500, with higher values indicating worse air quality. Our analysis considers two air-quality outcomes. The first is *Annual Top AQI*, the annual 90th Percentile Air Quality Index (AQI) within a county. The second outcome is *Bad Day Ratio*, the yearly ratio of "bad" days, the total of "Hazardous", "Very Unhealthy", and "Unhealthy" days to Days with AQI.

To gauge health effects, we use county-level, age-adjusted ED visit rates (per 10,000 inhabitants) for asthma among all ages. These data come from the National Environmental

Public Health Tracking Network.[18]

Table 14 reports the CSDID estimation results. Across counties, treatment is followed by worse air quality and higher asthma ED visits. *Annual Top AQI* rises by 3.15 (5% of the mean 63.5), *Bad Day Ratio* increases by 0.003 (100% of its mean 0.003), and *Asthma ED Visits* increase by 0.014 per 10,000 (3.3% of the mean 0.427). Cohort- and calendar-average ATTs are similar in magnitude, indicating the effects are broad-based rather than driven by a particular adoption cohort or year.

INSERT TABLE 14 HERE

For the Event-time dynamics, the pre-treatment average is near zero and statistically indistinguishable from it, supporting parallel trends. Post-treatment averages are positive and statistically significant (Post avg: +4.794 for AQI; +0.004 for Bad Day Ratio; +0.020 for Asthma ED), consistent with effects that emerge at treatment and persist thereafter. Event-study figures (Figure 4 and Figure 5) mirror this pattern: no discernible pre-trend, followed by a sustained deterioration in air quality and an uptick in asthma ED visits after exposure, and post-treatment effects strengthen over time.

INSERT FIGURE 4 HERE

INSERT FIGURE 5 HERE

Taken together, the evidence indicates that pollution reshored in response to foreign regulation imposes measurable local environmental and health costs in the United States.

[18] We scaled the age-adjusted ED visit rates by 100 to ease interpretation.

9 Conclusion

This paper shows that fragmented climate policy can reverse the classic pollution-haven logic. When U.S. multinationals face stricter rules abroad, they reallocate pollution-intensive activity back to the United States, raising domestic GHG and toxic releases; locally, upper-tail AQI worsens and asthma ED visits rise, with no pre-trend and effects that strengthen over time. An IV strategy supports a causal interpretation. Reshoring is shaped by domestic politics, Democratic-HQ firms shift activity to plants in Republican-leaning states, and by information frictions: firms downplay overseas transition risks in voluntary disclosures while complying in 10-Ks. Intermediaries matter: financial analysts rarely interrogate foreign-policy exposure, and firms whose principal overseas lenders have SBTi commitments intensify both reshoring and disclosure opacity. Real decisions and prices move accordingly, exposed firms curtail foreign investment, are less likely to divest dirty U.S. plants, and trade at lower Tobin's Q when foreign exposure rises.

These findings have three policy implications. First, reducing cross-border regulatory gaps, via tighter U.S. standards, credible border adjustments, or coordination of carbon pricing, would limit incentives to re-site emissions domestically. Second, disclosure rules should explicitly require firms to report exposures to foreign climate policies and to reconcile mandated filings with voluntary communications, curbing selective transparency. Third, guidelines for sustainable finance should penalize displacement rather than only local footprint to avoid pushing pollution across borders.

Our analysis has limits. We focus on U.S. outcomes and do not estimate the net global change in emissions; we measure exposure from statutory text rather than enforcement intensity; and health effects are observed over a medium-run horizon with available county-level data. Future work could quantify global net emissions, incorporate facility-level abatement investments and enforcement variation, and examine whether recent policy changes reduce the reshoring margin.

Overall, the evidence indicates that well-intentioned but uneven climate policies can reconfigure where pollution is produced, what is disclosed about it, and who bears its costs. Closing regulatory and informational seams, domestically and across borders, appears central to decarbonization without domestic environmental backsliding.

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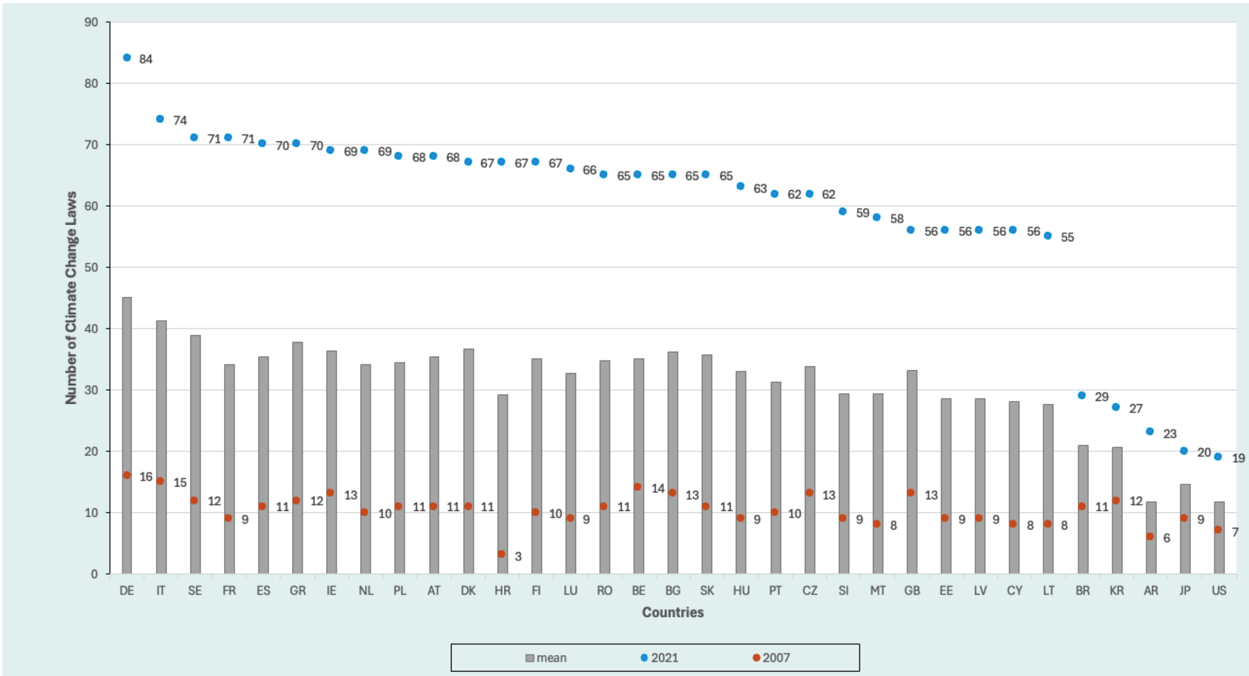


Figure 1: Number of Climate Change Laws across Countries

This figure presents the average number of climate change laws across selected countries from 2007 to 2021, and values in 2007 and 2021. The countries shown include the U.S. and those with more climate change laws than the U.S. in 2021 where U.S.-listed firms have overseas subsidiaries.

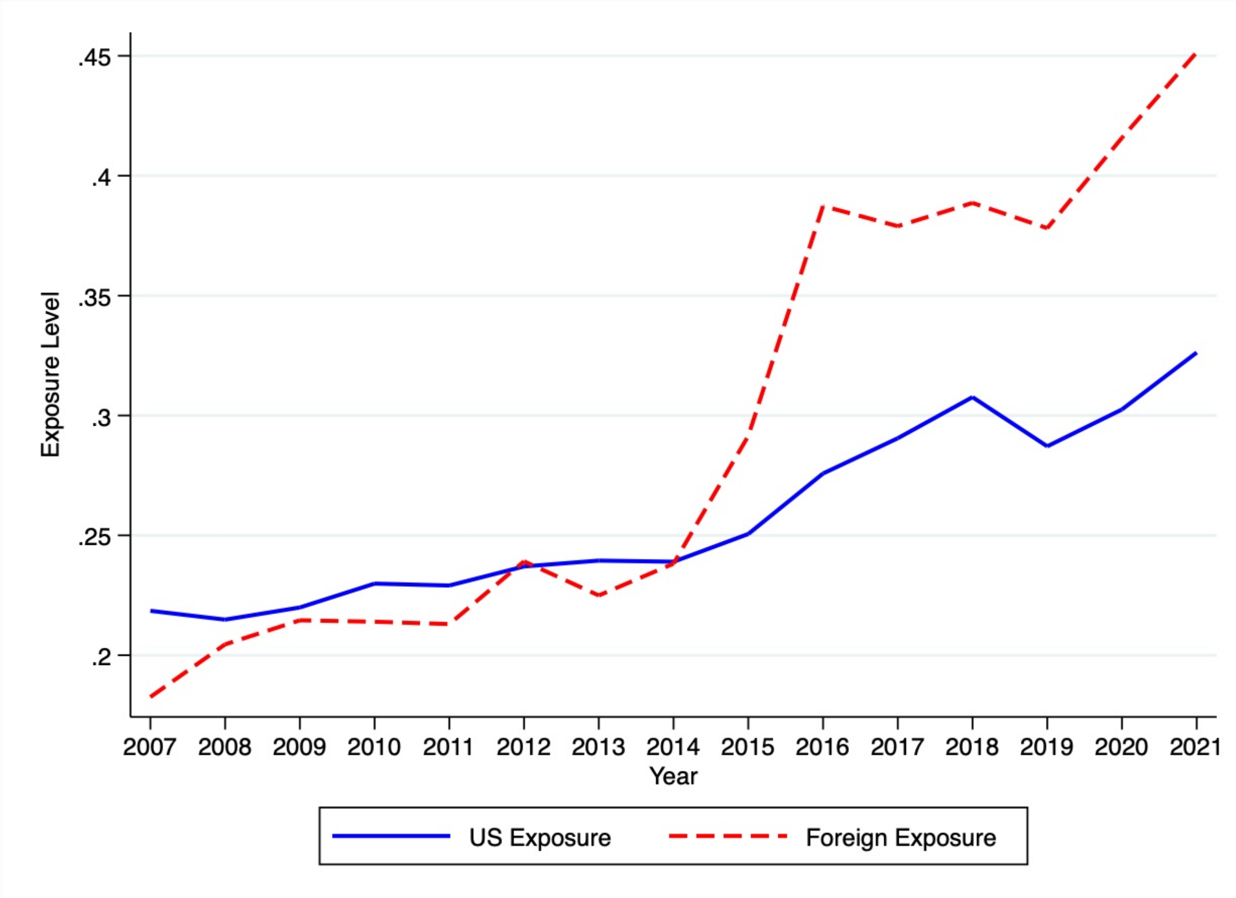


Figure 2: US and Foreign Climate Change Regulation Exposure across Years

This figure illustrates the climate change regulation exposure from the US and foreign countries from 2007 to 2021. The measures are self-constructed based on the cosine similarity between the textual content of Item 1 ("Business") in firms' 10-K reports and the climate regulations documented in the Climate Change Laws of the World database.

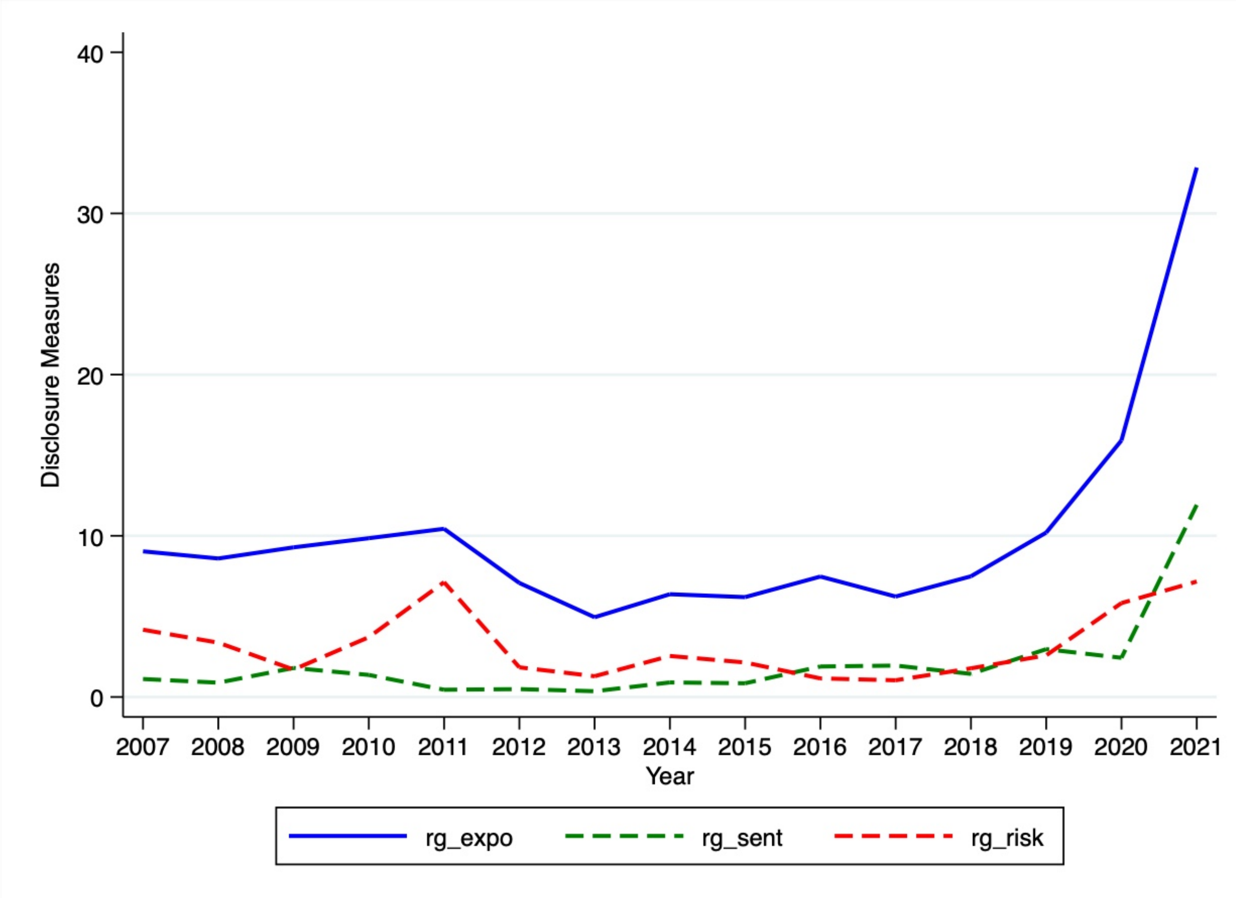
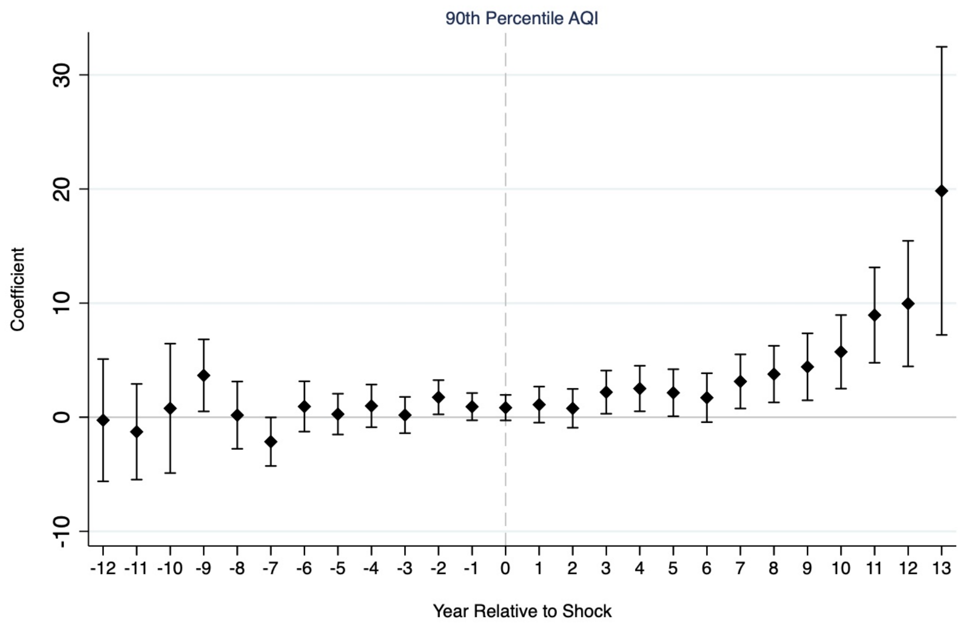
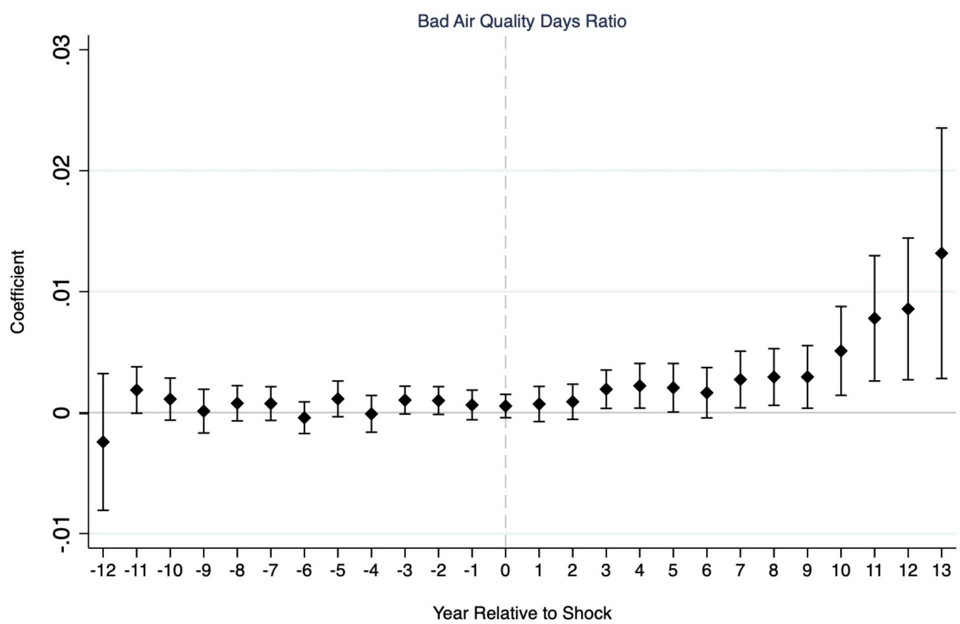


Figure 3: Disclosed Climate Transition Exposure, Risk, and Sentiment

This figure illustrates the disclosed Climate Transition Exposure, Risk, and Sentiment in firms' earnings conference calls. The measures are constructed by Sautner et al. (2023a) based on earnings call transcripts.



(a) Annual Top AQI



(b) Bad Days Ratio

Figure 4: The impact of Foreign Climate Regulation Exposure on Air Quality

This figure presents estimated coefficients of counties' first-time foreign climate regulation exposure on air quality, based on the difference-in-differences framework of Callaway and Sant'Anna (2021). The 90% confidence intervals are shown. Air quality is measured using Annual 90th Percentile AQI and the ratio of bad days to Days with AQI, sourced from the EPA's Air Quality System (AQS).

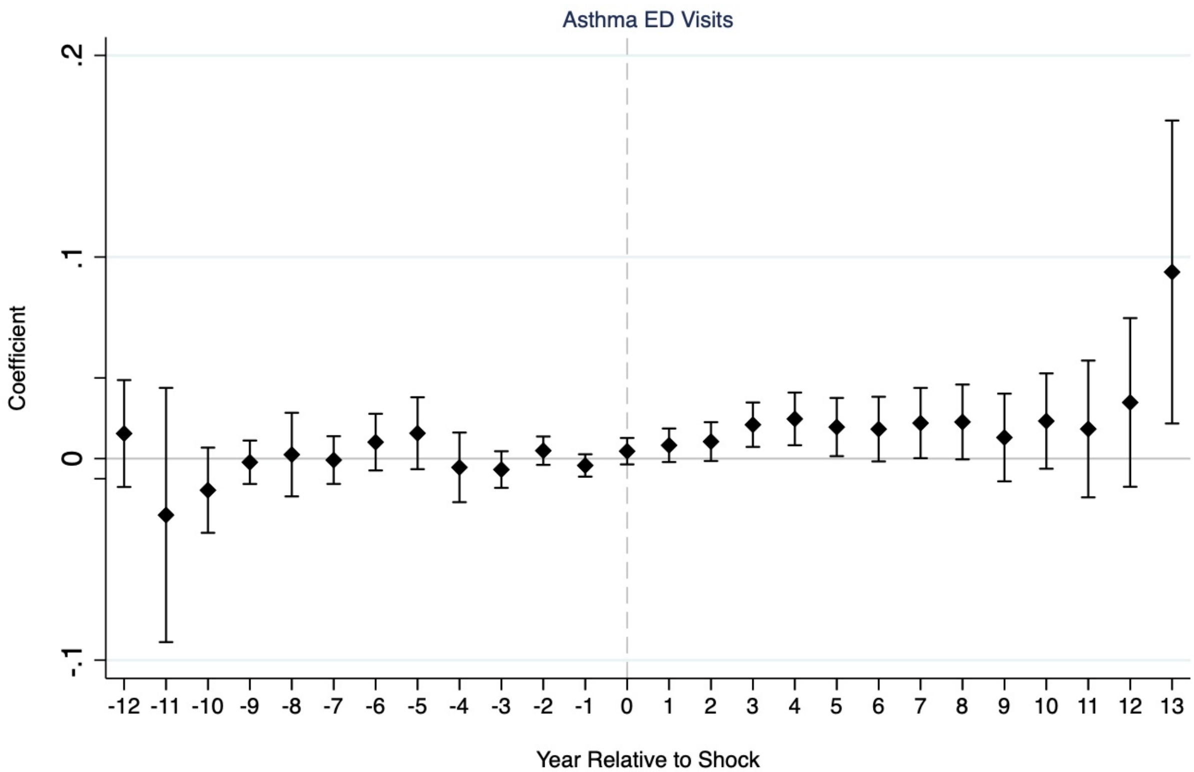


Figure 5: The impact of Foreign Climate Regulation Exposure on Asthma ED Visit Rates

This figure presents estimated coefficients of counties' first-time foreign climate regulation exposure on their Asthma ED Visit Rates, based on the difference-in-differences framework of Callaway and Sant'Anna (2021). The 90% confidence intervals are shown. Asthma ED Visit Rates are Age-adjusted Emergency Department Visit Rates per 10,000, obtained from the National Environmental Public Health Tracking Network.

Table 1: Summary Statistics

This table presents summary statistics for the variables used in this study, including plant-year level greenhouse gas emissions, plant-chemical-year level toxic pollution emissions, firm-year level climate regulation exposure, fundamentals, and climate transition risk disclosure. The full sample consists of all non-financial U.S.-listed firms with plant emission records from the EPA and non-missing values for the relevant variables. The sample period spans from 2007 to 2021 for most variables, except for greenhouse gas emissions, which are available from 2010 onward. See the Appendix for detailed variable definitions.

VARIABLES	N	Mean	SD	P1	P10	P25	P50	P75	P90	P99
Plant-Year Greenhouse Gas Emission										
GHG	4,737	0.362	1.184	0.00015	0.0008	0.0036	0.0207	0.151	0.795	8.229
Plant-Chemical-Year Toxic Pollution Emission										
Toxic	345,751	3.715	16.76	0	0	0.0001	0.0195	0.544	4.848	91.62
Firm-Year Climate Change Regulatory Exposure										
ForRgExpo	11,936	2.888	7.804	0	0	0	0	0.570	10.22	39.09
ForRgExpo H	11,936	2.102	5.886	0	0	0	0	0.203	7.458	29.45
ForRgExpo L	11,936	0.0182	0.129	0	0	0	0	0	0	0.607
USRgExpo	11,936	0.255	0.340	0	0	0	0	0.682	0.744	0.793
Firm-Year Fundamentals										
Size	11,936	7.861	1.876	2.855	5.525	6.678	7.929	9.096	10.28	11.68
Leverage	11,936	0.270	0.203	0	0.008	0.133	0.256	0.365	0.507	0.934
Growth	11,936	-0.164	4.014	-16.35	-1.813	-0.646	-0.017	0.325	1.304	15.92

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VARIABLES	N	Mean	SD	P1	P10	P25	P50	P75	P90	P99
ROA	11,936	0.0083	0.499	-0.583	-0.061	0.009	0.038	0.075	0.115	0.254
TobinQ	10,869	1.720	0.969	0.675	0.966	1.138	1.426	1.956	2.771	6.489
Green Investment	11,936	0.158	0.365	0	0	0	0	0	1	1
#Subsidiaries	11,936	31.043	1.824	0	0	0	5	33	90	356
Firm-Year Climate Transition Risk Disclosure										
rg expo	11,936	9.818	33.00	0	0	0	0	0	26.15	169.9
rg risk	11,936	0.312	2.933	0	0	0	0	0	0	10.40
rg pos	11,936	3.888	16.65	0	0	0	0	0	8.248	82.55
rg neg	11,936	1.974	10.70	0	0	0	0	0	0	44.68
rg sent	11,936	1.914	15.41	-23.00	0	0	0	0	0	67.52
rg risk 10*K*	11,936	33.89	86.56	0	0	0	0	0	121.2	420.7
#climateconv	11,936	4.478	6.169	0	0	0	2	7	13	26

Table 2: Industrial GHG and Toxic Emission Ranks

This table reports the industry rankings at the 2-digit NAICS level based on average greenhouse gas and toxic chemical emissions during the sample period. A smaller rank indicates higher average emissions.

GHG Emission Industry Rank

NAICS	**Industry**	**Rank**
45	Retail Trade	1
32	Wood, Paper, Petroleum, Chemicals, Plastics & Rubber Manufacturing	2
48	Transportation	3
22	Utilities	4
42	Wholesale Trade	5
51	Information	6
21	Mining, Quarrying, and Oil and Gas Extraction	7
72	Accommodation and Food Services	8
31	Food, Beverage, Textile, Apparel, Leather Manufacturing	9
33	Fabricated Metals, Machinery, Computers, Electronics, Transportation Equipment Manufacturing	10
56	Administrative and Support and Waste Management	11
11	Agriculture, Forestry, Fishing and Hunting	12

Toxic Emission Industry Rank

NAICS	**Industry**	**Rank**
54	Professional, Scientific, and Technical Services	1
56	Administrative and Support and Waste Management	2
21	Mining, Quarrying, and Oil and Gas Extraction	3
31	Food, Beverage, Textile, Apparel, Leather Manufacturing	4
33	Fabricated Metals, Machinery, Computers, Electronics, Transportation Equipment Manufacturing	5
22	Utilities	6
42	Wholesale Trade	7
32	Wood, Paper, Petroleum, Chemicals, Plastics & Rubber Manufacturing	8
48	Transportation	9
51	Information	10
23	Construction	11
53	Real Estate and Rental and Leasing	12
44	Retail Trade	13
11	Agriculture, Forestry, Fishing and Hunting	14
61	Information	15
45	Retail Trade	16

Table 3: Climate Regulation Exposure and Greenhouse Gas Substitution

This table presents results examining the impact of climate regulation exposure on corporate greenhouse gas substitution. The dependent variable is *GHG*, the greenhouse gas release amount at a specific plant scaled by the firm's total assets in a year, and then scaled by 10^3. In Columns (1) and (2), the key independent variable is *ForRgExpo*, which is firms' exposure to all overseas climate regulations in host countries of their subsidiaries in a year, and then scaled by 10^3. Column (3) presents results examining the impact of climate regulation exposure on corporate climate transition risk disclosure from higher- and lower-regulated countries or regions. *ForRgExpo H* is a firm's exposure to overseas climate regulations of higher-regulated host countries. *ForRgExpo L* is a firm's exposure to overseas climate regulations of lower-regulated host countries. *USRgExpo* is a firm's exposure to domestic climate regulations in a year. All control variables remain consistent as discussed in the data section. Robust t-statistics are reported in parentheses. The error term is clustered at the 2-digit NAICS industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
		GHG	
$ForRgExpo$	0.034***	0.043*	
	(6.69)	(2.06)	
$ForRgExpo\ H$			0.070***
			(3.62)
$ForRgExpo\ L$			2.678
			(0.99)
$USRgExpo$	-0.142	-0.056	-0.056
	(-1.76)	(-0.73)	(-0.73)
Controls	N	Y	Y
Plant FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
$Adj.R^2$	0.860	0.879	0.879
Observations	4,737	4,737	4,737

Table 4: Climate Regulation Exposure and Toxic Pollution Substitution

This table presents results examining the impact of climate regulation exposure on corporate toxic pollution gas substitution. In Columns (1) to (4), the dependent variable is *Toxic*, a specific toxic chemical release amount at a specific plant scaled by the firm's total assets in a year. The dependent variable is *Production* in Column (5). The key independent variable is *ForRgExpo* in Columns (1), (2), and (5). In Column (3), the key independent variable is the interaction term, $ForRgExpo \times Transition$. $Transition$ is a dummy identifying the top 10 industries with high greenhouse gas emissions. In Column (4), the key independent variables are *ForRgExpo H* and *ForRgExpo L*. All control variables remain consistent as discussed in the data section. Robust t-statistics are reported in parentheses. The error term is clustered at the 2-digit NAICS industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	$Toxic$				$Production$
$ForRgExpo$	0.015*	0.033**	-0.023		0.002
	(1.96)	(2.60)	(-1.50)		(0.10)
$ForRgExpo \times Transition$			0.072**		
			(2.44)		
$ForRgExpo\ H$				0.039**	
				(2.24)	
$ForRgExpo\ L$				0.091	
				(0.33)	
$USRgExpo$	-2.514***	-2.464***	-2.500***	-2.454***	-0.335
	(-4.95)	(-4.69)	(-4.98)	(-4.65)	(-0.65)
Controls	N	Y	Y	Y	Y
Plant FE	Y	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y	Y
Chemical × Year FE	Y	Y	Y	Y	Y
$Adj.R^2$	0.306	0.312	0.312	0.312	0.387
Observations	345,751	345,751	345,751	345,751	345,751

Table 5: IV Regression: Climate Regulation Exposure and Pollution Substitution

This table presents 2SLS regression results that examine the causal relation between climate regulation exposure and pollution substitution. Instrument variables for $ForRgExpo$ are $ExtremeWeather$, the historical average number of annual extreme weathers in firms' hosting countries, and $HostingProximity$, the sum of the inverse CES-consistent weighted distances ($distwces$, from CEPII GeoDist Database) from the U.S. to each firm's foreign host country, aggregated within the same industry. Columns (1) and (2) are results based on greenhouse gas emissions, and Columns (3) and (4) are results based on toxic pollution emissions. All control variables remain consistent as discussed in the data section. Robust t-statistics are reported in parentheses. The error term is clustered at the 2-digit NAICS industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	GHG		$Toxic$	
	1 Stage	2 Stage	1 Stage	2 Stage
$ExtremeWeather$	0.007***		7.806***	
	(3.27)		(10.29)	
$HostingProximity$	0.144*		35.061***	
	(1.95)		(3.07)	
$ForRgExpo$		24.211***		0.119*
		(4.75)		(1.90)
$USRgExpo$	0.001	-0.155**	0.260	-2.822***
	(0.21)	(-2.22)	(0.24)	(-4.20)
Controls	Y	Y	Y	Y
Plant FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
Chemical × Year FE	-	-	Y	Y
First-Stage SW F	23.19		92.97	
Hansen J (p)	0.3393		0.5497	
Observations	4,737	4,737	345,751	345,751

Table 6: State Politics, Climate Regulation Exposure and Pollution Substitution

This table presents results examining the impact of state politics on the relationship between climate regulation exposure and corporate pollution substitution decisions. We identify the state's political leaning according to the majority of the state's votes for the presidential candidate in the most recent presidential elections. The dependent variable is *GHG* in Columns (1)–(4), and *Toxic* in Columns (5)–(8). The main variable of interest is the interaction term $ForRgExpo \times DemoHQ$, where $DemoHQ$ is an indicator equal to one if the firm's headquarters is located in a Democratic-leaning state. We also control for $DemoHQ$. Columns (1), (2), (5), and (6) use observations from plants in Republican-leaning states; Columns (3), (4), (7), and (8) use those in Democratic-leaning states. Columns (1), (3), (5), and (7) present full sample estimates, while Columns (2), (4), (6), and (8) reports results for the swing-state subsample, defined as firms headquartered in states where the vote margin is within ± 2 percentage points. All control variables remain consistent as discussed in the data section. Robust t-statistics are reported in parentheses. The error term is clustered at the 2-digit NAICS industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GHG				*Toxic*			
	RepuPlant		DemoPlant		RepuPlant		DemoPlant	
$ForRgExpo \times DemoHQ$	0.134*	2.305**	-0.931	-2.879	0.033**	0.045*	0.006	0.046
	(1.97)	(4.06)	(-0.87)	(-1.29)	(2.32)	(2.17)	(0.33)	(1.65)
$ForRgExpo$	0.010	1.882***	0.927	1.657	0.016	-0.015	0.018	0.008
	(0.12)	(8.23)	(0.86)	(1.53)	(0.83)	(-1.31)	(0.92)	(0.62)
$USRgExpo$	0.012	-0.028	0.012	-0.088	-3.077***	-2.108***	-1.460***	-1.958***
	(0.11)	(-2.12)	(0.14)	(-1.27)	(-5.18)	(-12.54)	(-4.31)	(-3.64)
Plant FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry*Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Chemical*Year FE	-	-	-	-	Y	Y	Y	Y
$Adj.R^2$	0.873	0.965	0.909	0.973	0.312	0.355	0.335	0.469
Observations	2,616	196	2,015	160	200,082	21,055	141,324	12,718

Table 7: Brown/Green Industry, Climate Regulation Exposure and Pollution Substitution

This table presents results examining the industry emissions heterogeneity on the corporate pollution substitution decisions. In Columns (1) and (2), the dependent variable is *GHG*. In Columns (3) and (4), the dependent variable is *Toxic*. The key independent variables are *ForRgExpo* and *USRgExpo*. We rank the industries according to the industrial average emission during the sample period and define the top half as brown industries and the bottom half as green industries. Columns (1) and (3) report results based on brown industries, and Columns (2) and (4) report results based on green industries. All control variables remain consistent with those used in the baseline regressions. Robust t-statistics are reported in parentheses. The error term is clustered at the 2-digit NAICS industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	GHG		*Toxic*	
	Brown	Green	Brown	Green
ForRgExpo	0.063***	-0.016	0.033**	-0.002
	(20.38)	(-0.79)	(2.52)	(-0.10)
USRgExpo	-0.171	-0.003	-2.491***	0.688
	(-1.10)	(-0.24)	(-4.52)	(1.27)
Controls	Y	Y	Y	Y
Plant FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
Chemical × Year FE	-	-	Y	Y
$Adj.R^2$	0.875	0.967	0.312	0.509
Observations	2,492	2,220	323,872	21,196

Table 8: Cancer Chemicals, Climate Regulation Exposure and Pollution Substitution

This table presents results examining the toxic chemical heterogeneity, carcinogenic versus non-carcinogenic chemicals, on the corporate pollution substitution decisions. The dependent variable is *Toxic*. The key independent variable is the interaction term, $ForRgExpo \times CancerChemical$. *CancerChemical* is a dummy equaling one if the released chemical is carcinogenic, and zero otherwise. All control variables remain consistent with those used in the baseline regressions. Robust t-statistics are reported in parentheses. The error term is clustered at the 2-digit NAICS industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	$Toxic$	
$ForRgExpo \times CancerChemical$	0.033*	0.036*
	(1.81)	(2.06)
$ForRgExpo$	0.009	0.027**
	(1.23)	(2.64)
$USRgExpo$	-2.514***	-2.467***
	(-4.94)	(-4.66)
Controls	N	Y
Plant FE	Y	Y
Industry × Year FE	Y	Y
Chemical × Year FE	Y	Y
$Adj.R^2$	0.306	0.312
Observations	345,751	345,751

Table 9: Climate Regulation Exposure and Disclosed Climate Transition Risks

This table presents results examining the impact of climate regulation exposure on corporate climate transition risk disclosure. The dependent variable is *rg expo* in Columns (1) and (2), measurements of disclosed climate transition exposure; and *rg risk* in Columns (3) and (4), measurements of disclosed climate transition risk, based on conference call transcripts by Sautner et al. (2023a). In Columns (5) and (6), the dependent variable is *rg risk 10K*, a measurement of climate transition exposure based on the 10-K reports by Kölbel et al. (2024). The key independent variables in the odd-numbered columns are *ForRgExpo* and *USRgExpo*, while the even-numbered columns use *ForRgExpo H*, *ForRgExpo L*, and *USRgExpo* as the main explanatory variables. All control variables remain consistent with those used in the baseline regressions. Robust t-statistics are reported in parentheses. The error term is clustered at the 2-digit NAICS industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	rg expo		*rg risk*		*rg risk 10K*	
ForRgExpo	-0.568		-0.080***		1.082	
	(-1.18)		(-5.97)		(0.86)	
ForRgExpo H		-11.854***		-1.010***		15.960
		(-3.22)		(-13.67)		(1.03)
ForRgExpo L		1.350		-0.156		-7.294
		(0.35)		(-1.06)		(-1.48)
USRgExpo	2.195	2.227	0.407*	0.411*	4.479	4.856
	(1.67)	(1.73)	(1.84)	(1.83)	(0.79)	(0.90)
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y	Y	Y
$Adj.R^2$	0.442	0.442	0.0601	0.0601	0.818	0.819
Observations	11,936	11,936	11,936	11,936	11,249	11,249

Table 10: Climate Regulation Exposure and Disclosure Sentiment

This table presents results examining the impact of climate regulation exposure on corporate climate transition risk disclosure sentiment. The dependent variable is *rg pos*, disclosure with positive tone words, in Column (1); *rg neg*, disclosure with negative tone words, in Column (2), and *rg sent*, the net difference between *rg pos* and *rg neg*, in Column (3). The key independent variables are *ForRgExpo* and *USRgExpo*. All control variables remain consistent with those used in the baseline regressions. Robust t-statistics are reported in parentheses. The error term is clustered at the 2-digit NAICS industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) *rg pos*	(2) *rg neg*	(3) *rg sent*
ForRgExpo	0.014	-0.270***	0.283**
	(0.07)	(-2.99)	(2.67)
USRgExpo	-0.327	1.183**	-1.510
	(-0.52)	(2.13)	(-1.60)
Controls	Y	Y	Y
Firm FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
$Adj.R^2$	0.290	0.166	0.146
Observations	11,936	11,936	11,936

Table 11: Climate Regulation Exposure, Analysts' Attention, and Disclosed Climate Transition Risks

This table presents results examining the impact of climate regulation exposure on analysts' climate-related questions during conference calls, as well as the interaction between regulation exposure and analysts' questions on corporate climate transition risk disclosure. In Columns (1) and (2), the dependent variable is *#climateconv*, the number of climate-related questions analysts ask during conference calls. Column (1) reports OLS estimates; Column (2) reports Poisson estimates. Columns (3) and (4) examine climate risk disclosure outcomes with *rg expo* and *rg risk* as dependent variables. *ln_climateconv* is the log of *#climateconv* plus one. All control variables are consistent with those used in the baseline regressions. Robust t-statistics are reported in parentheses. The error term is clustered at the 2-digit NAICS industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	#climateconv		Disclosure	
	OLS	PPML	*rg expo*	*rg risk*
ForRgExpo	-0.072	-0.019	0.326	-0.031*
	(-0.95)	(-0.79)	(0.59)	(-1.87)
USRgExpo	0.910***	0.186***	1.134	0.374*
	(3.32)	(3.54)	(0.89)	(1.81)
ForRgExpo × *ln_climateconv*			-0.852**	-0.050***
			(-2.19)	(-3.15)
ln_climateconv			4.800**	0.147*
			(2.69)	(2.03)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
$Adj.R^2$	0.748	0.5563	0.448	0.0606
Observations	11,936	10,169	11,936	11,936

Table 12: Cross-sectional Test: SBTi Bank, Climate Regulation Exposure, and Firm Response

This table presents results examining how firms' non-US creditors' commitment to the Science-Based Targets Initiative (SBTi) affects both firms' strategic disclosure and pollution substitution. *SBTi* is an indicator equal to one after a firm's non-US creditors are committed to carbon neutrality under the SBTi, and zero otherwise. We include the interaction term of *ForRgExpo* and *SBTi* in the baseline regression. Columns (1) to (4) report the results testing pollution substitution for firms in the brown and green industries, respectively. Columns (1) and (2) use *GHG* as the dependent variable. Columns (3) and (4) use *Toxic* as the dependent variable. Columns (1) and (3) report brown industry subsample results and Columns (2) and (4) report green industry subsample results. Columns (5) to (6) report the results testing strategic disclosure, with *rg expo* and *rg risk* as dependent variables. All control variables follow the baseline specification. Robust t-statistics are reported in parentheses. The error term is clustered at the 2-digit NAICS industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	GHG		*Toxic*		Disclosure	
	Brown	Green	Brown	Green	*rg expo*	*rg risk*
$ForRgExpo \times SBTi$	9.403***	-1.794	0.074**	-0.008	-3.999***	-0.313***
	(4.71)	(-1.72)	(3.24)	(-0.16)	(-3.62)	(-4.49)
$SBTi$	0.020	0.024	-1.390	-0.518	2.872	0.180
	(0.99)	(1.90)	(-1.68)	(-0.54)	(1.42)	(1.74)
$USRgExpo$	-0.169	-0.002	-2.480***	0.691	2.250	0.411*
	(-1.08)	(-0.18)	(-4.74)	(1.26)	(1.69)	(1.84)
$ForRgExpo$	0.063***	-0.015	0.029*	-0.001	-0.361	-0.064***
	(20.50)	(-0.65)	(2.35)	(-0.07)	(-0.72)	(-3.18)
Controls	Y	Y	Y	Y	Y	Y
Plant FE	Y	Y	Y	Y	-	-
Industry × Year FE	Y	Y	Y	Y	Y	Y
Chemical × Year FE	-	-	Y	Y	-	-
Firm FE	-	-	-	-	Y	Y
$Adj.R^2$	0.875	0.967	0.312	0.509	0.442	0.0601
Observations	2,492	2,220	323,872	21,196	11,936	11,936

Table 13: Climate Regulation Exposure and Firm-level Consequences

This table presents results examining how climate regulation exposure affects firms' divestment in the asset market. In Column (1), the dependent variable is *Plant Divestment*, a dummy indicating whether a firm divests domestic pollutive plants, sourced from Duchin, Gao, and Xu (2024). In Columns (2) and (3), the dependent variable is the foreign subsidiaries' number growth rate for worldwide, higher-regulated host countries, and lower-regulated host countries, respectively. In Column (4), the dependent variable is *Green Investment*, a dummy suggesting whether the firms are making green investments related to climate transition risks. In Column (5), the dependent variable is Tobin's Q. All control variables remain consistent with those used in the baseline regressions. Robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) *Plant Divestment*	(2) *Sub Growth H*	(3) *Sub Growth L*	(4) *Green Investment*	(5) *Tobin Q*
ForRgExpo	-0.369**			-0.043	-0.031***
	(-2.57)			(-1.17)	(-4.82)
ForRgExpo H		-3.188***			
		(-5.46)			
ForRgExpo L			-0.253***		
			(-3.67)		
USRgExpo	0.360	0.209**	0.018	2.703***	0.020
	(1.12)	(2.49)	(0.49)	(25.75)	(0.47)
Controls	Y	Y	Y	Y	Y
Firm FE	-	Y	Y	-	Y
Industry × Year FE	Y	Y	Y	Y	Y
$Adj.R^2$	0.1823	-0.0193	0.0771	0.1606	0.712
Observations	11,302	7,208	7,208	12,010	10,866

Table 14: County Air Quality and Respiratory Disease Rates

This table presents results examining how climate regulation exposure affects County Air Quality and Respiratory Disease Rates, based on the difference-in-differences framework of Callaway and Sant'Anna (2021). A county enters treatment in the first year in which its locally operating parent firms become exposed to foreign climate regulation from hosting countries with consistently higher levels than the US, and it remains in treatment thereafter. In Column (1), the dependent variable is *Annual Top AQI*, 90th Percentile AQI during the year. In Column (2), the dependent variable is *Bad Day Ratio*, the ratio of bad days to Days with AQI. Bad days include "Hazardous", "Very Unhealthy", and "Unhealthy" days in the EPA's Air Quality System (AQS). In Column (3), the dependent variable is *Asthma ED Visits*, Age-adjusted Emergency Department Visit Rates per 10,000, obtained from the National Environmental Public Health Tracking Network.

	(1) *Annual Top AQI*	(2) *Bad Day Ratio*	(3) *Asthma ED Visits*
Average Treatment Effect on Treated			
ATT	3.15**	0.003**	0.014*
	(2.51)	(2.15)	(1.84)
ATT by Group			
GAverage	2.723***	0.002**	0.012*
	(2.57)	(2.35)	(1.72)
ATT by Calendar Period			
CAverage	3.316***	0.003**	0.012*
	(2.58)	(2.07)	(1.73)
ATT by Periods Before and After treatment			
Pre avg	0.503	0.0004	-0.002
	(1.13)	(0.96)	(-0.46)
Post avg	4.794***	0.004**	0.020**
	(2.82)	(2.33)	(1.97)

Table A1: Variable Definition

Variable	Definition	Source
Plant Emission Data		
GHG	Greenhouse gas release amount at a specific plant scaled by the firm total assets in a year.	GHGRP Program
Toxic	A specific toxic chemical release amount at a specific plant scaled by the firm total assets in a year.	TRI Program
Production	The change in production output when a specific chemical is used as an input at a specific plant, which is scaled to (1,5).	TRI Program
Corporate Climate Change Regulation Exposure Variables		
ForRgExpo	Firm's exposure to overseas climate regulations where its subsidiaries are located in: $\lvert\frac{\mathrm{PIFO}_{i,t}}{\mathrm{PI}_{i,t}}\rvert \times \sum_{c \neq \mathrm{US}} \sum_{r \in R_c} \mathrm{Cosine}(\mathrm{Company}_{i,t}, \mathrm{Regulation}_{r,c})$, where i denotes the firm, t denotes the year, r denotes the regulation, and c denotes the country issuing the regulation. The cosine similarity is calculated between firms' Item 1 ("Business") in 10-K reports and specific climate regulation in the Climate Change Laws of the World database through the BERT (Bidirectional Encoder Representations from Transformers) model. The environmental laws of EU apply for all countries within EU.	Climate Policy Radar Database
USRgExpo	Firm's exposure to US domestic climate regulations: $USRgExpo_{i,t} = \sum_{c=\mathrm{US}} \sum_{r \in R_c} \mathrm{Cosine}(\mathrm{Company}_{i,t}, \mathrm{Regulation}_{r,c})$ where i denotes the firm, t denotes the year, r denotes the regulation, and c denotes the country issuing the regulation. The cosine similarity is calculation is the same as in *ForRgExpo*.	Climate Policy Radar Database
Firm Characteristics		
Size	Log value of firm total assets.	Compustat
Leverage	Long-term debt to total assets.	Compustat
Growth	Annual sales growth rate.	Compustat

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VARIABLES	Definition	Source
ROA	Ratio of income before extraordinary items to total assets.	Compustat
Subsidiaries	The log value of one plus the number of firms' overseas subsidiaries.	Compustat
TobinQ	$(csho * prcc_f + at - ceq)/at$, and then multiplied by 10^2.	Compustat
Green Investment	An indicator that equals one if at least one keyword from the climate regulatory dictionary developed by Sautner et al. (2023a) appears in the accompanying notes of the 10-K report for that year, and the firm reports positive capital expenditures.	Self Construct
SBTi	An indicator that equals one after a firm's non-US creditor are committed to carbon neutrality under the SBTi, and zero otherwise.	Dealscan
Sub Growth H	The annual growth rate in the number of firms' foreign subsidiaries located in higher-regulated host countries.	Self Construct
Sub Growth L	The annual growth rate in the number of firms' foreign subsidiaries located in lower-regulated host countries.	Self Construct
Plant Divestment	An indicator equal to one if a firm divested pollutive industrial plants in the U.S. in a given year, and zero otherwise.	Duchin, Gao, and Xu (2024)
DemoHQ	An indicator equal to one if the firm's headquarters is located in a Democratic-leaning state, and zero otherwise.	MIT Election Data and Science Lab
Instrumental Variables		
Extreme Weather	The average number of extreme weather days experienced by a country during the pre-sample period (2000–2006).	EM-DAT
Hosting Proximity	The sum of the inverse CES-consistent weighted distances (*distwces*) from the U.S. to each firm's foreign host country, aggregated within the same industry.	CEPII GeoDist Database
Corporate Climate Transition Risk Disclosure Variables		

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VARIABLES	Definition	Source
rg expo	Relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of earnings conference calls, which is the count number of such bigrams divided by the total number of bigrams in the transcripts, and then multiplied by 10^5.	Sautner et al. (2023a)
rg risk	Relative frequency with which bigrams that capture regulatory shocks related to climate change are mentioned together with the words "risk" or "uncertainty" (or synonyms thereof) in one sentence in the transcripts of earnings conference calls, which is the count number of such bigrams divided by the total number of bigrams in the transcripts, and then multiplied by 10^5.	Sautner et al. (2023a)
rg pos	Relative frequency with which bigrams that capture regulatory shocks related to climate change are mentioned together with positive tone words that are summarized by Loughran and McDonald (2011) in one sentence in the transcripts of earnings conference calls, which is the count number of such bigrams divided by the total number of bigrams in the transcripts, and then multiplied by 10^5.	Sautner et al. (2023a)
rg neg	Relative frequency with which bigrams that capture regulatory shocks related to climate change are mentioned together with negative tone words that are summarized by Loughran and McDonald (2011) in one sentence in the transcripts of earnings conference calls, which is the count number of such bigrams divided by the total number of bigrams in the transcripts, and then multiplied by 10^5.	Sautner et al. (2023a)

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VARIABLES	Definition	Source
rg sent	The overall sentiments of bigrams that capture regulatory shocks related to climate change are mentioned in the transcripts of earnings conference calls, which is the count number of positive bigrams less negative bigrams divided by the total number of bigrams in the transcripts, and then multiplied by 10^5.	Sautner et al. (2023a)
#climateconv	The number of climate-related conversations during conference calls in a year. A "conversation" is the full exchange between an analyst and an executive in the Q&A portion of the call.	Sautner et al. (2023b)
rg risk 10K	Relative frequency with which sentences that capture regulatory shocks related to climate change in Item 1.A (for firms to self-identify those risks that they see as significant risk factors to their business)of the 10-K report, which is the count number of such sentences divided by the total number of sentences in the transcripts, and then multiplied by 10^3.	Kölbel et al. (2024)
Corporate Climate Transition Risk Disclosure Variables		
Annual Top AQI	The AQI combines concentrations of NO_2, O_3, CO, PM_2.5, PM_{10}, and SO_2. The AQI ranges from 0 to 500, with higher values indicating worse air quality.	EPA's Air Quality System
Bad Day Ratio	The ratio of bad days to Days with AQI. Bad days include "Hazardous", "Very Unhealthy", and "Unhealthy" day. It is categorized as follows: Good (0–50), Moderate (51–100), Unhealthy for Sensitive Groups (101–150), Unhealthy (151–200), Very Unhealthy (201–300), and Hazardous (301–500).	EPA's Air Quality System

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VARIABLES	Definition	Source
Asthma ED Visits	Age-adjusted Emergency Department Visit Rates per 10,000, and then scaled by 100.	National Environmental Public Health Tracking Network

Table A2: List of Committed Lenders

This table lists lenders that committed to SBTi, the year of commitment, and the headquarter of each bank.

Banks	Commitment Year	Headquarter Country
AXA Group	2015	France
Bank Colombia	2015	Colombia
Bank of Australia	2015	Australia
ING	2015	Netherlands
Westpac Banking Corp	2015	Australia
BNP Paribas	2016	France
Credit Agricole	2016	France
HSBC	2016	United Kingdom
Metlife	2016	United States
Societe Generale	2016	France
ABN AMRO	2018	Netherlands
BBVA	2018	Spain
Compass Bank	2018	United States
LaSalle	2018	United States
Raiffeisen Bank	2018	Austria
Standard Chartered Bank	2018	United Kingdom
Swedbank	2018	Sweden
Y Bank	2018	India