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Outsourcing Climate Change

Abstract

This paper examines whether and how firms combat climate change. Our study provides robust evidence that firms outsource part of their carbon emissions to foreign suppliers and shows how internal and external stakeholders significantly shape firms' environmental policies. Furthermore, firms tend to seek a foreign supplier and decrease their emission abatement efforts as pressure to reduce domestic emissions intensifies. These firms are also less incentivized to develop green technologies. Finally, we find that outsourcing emissions has real and economic consequences, with investors demanding a higher carbon premium for their exposures to carbon risks associated with increased outsourced emissions.

Keywords: Outsourcing Emissions, Imports, Stakeholders, Reputational Risk, Green Technologies, Carbon Premium

JEL classification: G23, G30, G34, M14

1. Introduction

Climate change is driving new political and economic realities for countries and businesses worldwide. Many large corporations are integrating climate change into their business strategies in response to pressures from regulatory authorities, environmental activists, and climate-conscious investors and consumers. While their efforts seem reasonably progressive, a closer look reveals that firms are committed only to greenhouse gas (GHG) emissions from their own production and energy consumption (Scopes 1 and 2 emissions, respectively).[1] They largely ignore indirect (Scope 3) emissions generated along their supply chains and in the use of their products, which form the bulk of their total GHG emissions.[2] On the other hand, prior research suggests that firms reduce their local carbon footprints by shifting carbon emissions to states (e.g., Bartram, Hou, and Kim, 2021) or countries with weak environmental regulatory stringency (e.g., Ben-David et al., 2021; Li and Zhou, 2017).[3] Yet, no study has provided direct causal evidence that firms reduce their Scope 1 carbon emissions at the cost of increasing Scope 3 emissions produced by their foreign suppliers[4] and emissions generated from imported goods and services. Nor has existing research examined whether carbon outsourcing presents a risk to a firm and is priced by the financial markets. Thus, a natural question to ask is whether firms' public commitments reflect their marketing ploys or genuine efforts to integrate climate change into their business strategies. To address this important issue, we examine whether and how firms reduce their carbon footprints to tackle global climate change and evaluate the real and economic consequences of their actions.

Our study employs newly available firm-level data on U.S. firms' self-generated Scope 1 emissions and suppliers-produced upstream Scope 3 emissions from Trucost and transaction-level import

[1]For example, the Natural Resources Defense Council's (NRDC) article, "Corporate Honesty and Climate Change: Time to Own Up and Act," (Joshua Axelrod, February 26, 2019) reports that P&G's commitment to halve pollution by 2030 only applies to its Scopes 1 and 2 emissions, but that only accounts for about two percent of its total carbon footprint when indirect or Scope 3 emissions are included.

[2]Carbon Trust research shows that for most companies, Scope 3 emissions represent from 65% to 95% of a company's broader carbon impact. See "Climate experts are worried about the toughest carbon emissions for companies to capture," by Eric Rosenbaum, August 18, 2021. https://www.cnbc.com/2021/08/18/apple-amazon-exxon-and-the-toughest-carbon-emissions-to-capture.html. In our sample of U.S. firms, the average proportion of upstream Scope 3 emissions in a firm's total emissions is 67% for the 2006-2018 period.

[3]Tanaka, Teshima, and Verhoogen (2021) show that after the U.S. tightened the National Ambient Air Quality Standard for lead in 2009, the lead-acid battery-recycling industry rapidly shifted from the U.S. to Mexico.

[4]It is less likely for firms to shift carbon emissions to local suppliers as the latter would face similar environmental regulatory stringency.

information from Panjiva to analyze their actions to combat climate change and curb carbon emissions. Throughout our study, Scope 3 emissions refer to upstream Scope 3 emissions, unless otherwise indicated. After merging the two key databases, our final sample yields 76,356 firm-country-year observations from 1,557 U.S. firms and 210 exporting countries for the 2006-2018 period.[5] These datasets provide granularity relative to those employed in the existing literature and allow us to thoroughly analyze firms' engagements in cutting carbon emissions. As illustrated by Figure 1, the proportion of Scope 1 emissions has fallen as the proportion of Scope 3 emissions has increased. The surge in the proportion of Scope 3 emissions in 2015 possibly reflects both the firms' response to the 2015 Paris Agreement and Trucost's expanded coverage, starting from 2015.[6] Figure 2 shows that both the aggregate carbon footprint (the sum of Scopes 1, 2, and 3) and total imports of U.S. firms are trending upward, suggesting that their carbon emissions and imports are highly correlated and that firms are increasing their carbon emissions through global suppliers.

To begin, we conduct a comprehensive analysis to provide robust evidence that firms reduce carbon footprints through emission offshoring. We first examine the relationship between a firm's Scope 1 and its upstream Scope 3 emissions and investigate how imports play a role in this relationship. Results suggest that a one-standard-deviation increase in tonnes of a firm's average Scope 1 would generate an approximately 19% increase in tonnes of its upstream Scope 3 emissions. The relative share of Scope 1 emissions in a firm's total emissions falls at the expense of the rising proportion of its supplier-generated Scope 3 emissions. We find that a firm's imports further augment the substitutional relationship between its Scope 1 and Scope 3 emissions – demonstrating that U.S. firms outsource part of their pollution to global suppliers to evade their emissions responsibilities.

While we have established that imports play an important role in driving the relationship between Scopes 1 and 3 emissions, our causal inferences of this link may be subject to endogeneity concerns. To circumvent such problems, we exploit several exogenous shocks to U.S. firms' propensity to outsource carbon emissions. In particular, we examine domestic demand shocks to imported emissions caused by legislative pressure and regulatory stringency at the state level. Prior research shows that federal and state judiciaries play a critical role in developing and enforcing environmen-

[5]It is important to stress that the resulting sample only includes observations with country-level imports and firm-level emissions but excludes imports from foreign subsidiaries.

[6]Our results remain robust even after excluding the 2015-2018 sample.

tal regulations in the U.S. (e.g., Shipan and Lowry 2001; Grant, Bergstrand, and Running 2014; Kim and Urpelainen 2017). Thus, firms located in states with intense legislative pressure on environmental consciousness should have stronger incentives to import as a means of outsourcing GHG emissions to their suppliers overseas. Our analysis employs sudden increases in pro-environmental votes in the House and Senate as well as "close-call" Congress election wins by environmentally-conscious candidates as measures of environmental legislature pressure. Unlike landslide victories, close-call wins are more likely to represent unexpected shifts in state-level environmental attitudes and are as good as randomly assigned. Similarly, to gauge the extent of regulatory stringency, we use state-level statutory and executive emission-reduction targets and spikes in Environmental Protection Agency (EPA) state-level facility inspections. Analyses in a triple-interaction framework reveal that imports have a more pronounced mitigating effect on the Scope 1–Scope 3 association following exogenous increases in political pressure and regulatory stringency on environmental issues but not on placebo shocks, consistent with a causal interpretation of firms' carbon outsourcing strategy in curbing their own emissions.

Our analysis further investigates cross-industry and cross-country variations in emissions outsourcing. We find that firms in highly emitting industries or industries requiring abundant polluting inputs have strong incentives to outsource their emission needs. High industry-level emissions are defined as the total Scope 1 emissions generated by each sector, or the amount of emissions each industry produces from inputs used for a $1 million worth of economic activity. We also show that firms are more likely to shift their emission obligations towards exporting countries with laxer environmental regulations, reinforcing our baseline evidence that firms mitigate domestic emissions by moving them to their suppliers abroad.

Next, we explore several plausible mechanisms that explain U.S. firms' pollution management and outsourcing activities. We argue that emission outsourcing may reflect the underlying agency problem – corporate insiders have incentives to maintain reputation and domestic social capital at the cost of overall stakeholder welfare. Social capital is of prime importance as it is commensurate with a high environmental, social, and governance (ESG) rating, which, in turn, offers many benefits to a firm and its insiders, including positive publicity, increased customer willingness to pay (e.g., Bagnoli and Watts, 2003; Baron 2008, 2009), more capital from philanthropic investors (e.g., Ceccarelli, Ramelli, and Wagner 2019; Hartzmark and Sussman 2019), and better career prospects for the management team (e.g., Cai et al. 2020), among others. In maintaining these benefits, firms with higher ESG ratings ("greener" firms) and more ESG-oriented CEOs and directors ("greener" CEOs and directors) face more significant internal pressure to uphold their domestic reputations by shifting pollution-intensive production overseas through upstream supply chains. Thus, it is likely that corporate insiders, such as management and directors, evaluate outsourcing domestic emissions abroad as a less costly and speedier means to curb domestic emissions. We find that carbon outsourcing is more pronounced for greener firms, greener CEOs, and greener directors, thereby supporting the agency view of outsourcing.

On the other hand, existing evidence shows that environmental or greener external stakeholders, such as government customers, corporate customers, and institutional investors, increasingly recognize climate change's rising costs and economic risks. These external stakeholders (principals rather than agents) are concerned about their exposures to climate risk and, therefore, are incentivized to alleviate agency-motivated outsourcing behavior. Thus, they would push against emission offshoring to meet their own climate commitments and pressure firms to transition to a low-carbon world. For example, institutional investors may drive down firms' overall carbon footprints, including domestic and imported emissions, to minimize adverse impacts of climate change on their investments (e.g., Barrot and Sauvagnat 2016; Krüeger, Sautner, and Starks, 2020). Similarly, government customers would also discourage firms' outsourcing behavior as they act in the public interest and emphasize global emission reduction to effectively combat climate change (Hsu, Liang, and Matos 2021). Socially responsible corporate customers would infuse similar socially responsible business behavior in their foreign suppliers; they would be less likely to reduce their carbon footprints at the expense of increasing those of their foreign suppliers (Dai, Liang, and Ng, 2021). Our findings suggest that firms engage less in emission outsourcing when they have more concentrated government customers, greener corporate customers, and greener institutional blockholders, supporting these external mechanisms behind corporate environmental policies.

Finally, we explore the implications of our robust evidence of firms' outsourcing emissions behavior. First, outsourcing emissions to foreign suppliers may be more cost-effective than using pollution abatement to curb direct carbon emissions. Our results suggest that, under increasing pressure to reduce Scope 1 carbon emissions from its own domestic operations, a firm's likelihood of seeking a foreign supplier increases, while its likelihood of investing in pollution abatement activity decreases as its carbon export grows. Second, this outsourcing behavior may imply that firms are less incentivized to develop green technologies that require significant capital investment and long development timelines. Our results support this argument. Third, we evaluate the real and economic consequences of outsourcing carbon footprints. While moving domestic emissions to global supply chains improves short-term profitability, it also raises the implied cost of equity capital. Furthermore, Scope 3 and imported emissions are positively and significantly associated with future stock returns and reputational risks, but not Scope 1. We interpret that cutting direct emissions by outsourcing air pollution to foreign suppliers cannot help lower firms' carbon and reputational risks. Investors instead demand a higher carbon premium for their exposures to carbon risks associated with increased Scope 3 and imported emissions (outsourced emissions).

Our research makes significant contributions to the growing climate finance literature. Prior climate finance studies primarily focus on asset pricing and financial market implications.[7] For example, Bolton and Kacperczyk (2021) find that U.S. firms with higher carbon emissions are associated with larger risk premiums, and Hsu, Li, and Tsou (2020) show a similar spread in average equity returns between high- and low-pollution firms. Engle et al. (2020) use textual analysis and report that stocks of firms with high environmental scores have larger returns during periods with negative news about the future path of climate change. Choi, Gao, and Jiang (2020) document similar results using global data. While this strand of literature examines the extent to which climate risk is priced in financial assets, our study takes a corporate perspective, arguably more fundamental, as firms are the main drivers of climate change. Therefore, we provide the first comprehensive firm-level analysis on whether and how U.S. companies address their full climate impacts. To the best of our knowledge, no prior research has addressed how a firm tackles climate change by examining direct and indirect carbon emissions and jointly with its imports.

Our study is also the first to provide *direct* evidence of the substitutional relationship between a firm's own produced emissions and its outsourced climate pollution. Li and Zhou (2017) document the relationship between trade flow and domestic emissions, whereas Dechezleprêtre et al. (2019),

[7] See Giglio, Kelly, and Stroebel (2021) for an extensive review of the theoretical and empirical literature in climate finance.

Bartram, Hou, and Kim (2021), and Ben-David et al. (2021) focus on how the regulatory environment affects domestic and foreign emissions. However, these studies do not directly show that firms choose one type of emissions in curbing the other. Our empirical design advances this line of research by examining firm-level carbon emission reduction strategies and their real and economic consequences.

Our evidence of how firms combat climate change contributes to the expanding literature on the roles of different stakeholders in shaping a firm's CSR practices. For example, Krüeger, Sautner, and Starks (2020) survey suggests that institutional investors actively engage with the management of their investee firms to reduce their climate risk exposures, and Dyck et al. (2019) find that institutional investors drive firms' CSR performance worldwide. Hsu, Liang, and Matos (2021) document that state-owned enterprises are more responsive to environmental issues, whereas Dai, Liang, and Ng (2021) show that socially responsible corporate customers can infuse similar socially responsible business behavior in suppliers. Our granular analysis offers fresh insights on how internal and external stakeholders exert different influences on firms' environmentally responsible behavior.

The paper proceeds as follows. Section 2 describes the data and sample construction. Section 3 discusses the main results. Section 4 investigates several potential mechanisms that drive corporate environmental policies. Section 5 explores the real and economic consequences of firms' outsourcing behavior. The final section concludes.

2. Data and Summary Statistics

This study employs data from several different sources: (i) direct and indirect GHG emissions for U.S. firms from S&P Global's Trucost; (ii) the U.S. customs import data at the shipment-level from Panjiva; (iii) Senate and House of Representative election outcome data from the U.S. Federal Election Commission (FEC); (iv) congressional voting records on environmental legislations from League of Conservation Voters (LCV); (v) information on state-level GHG emission targets from Center for Climate and Energy Solutions (C2ES); (vi) air pollution-related plant inspection records from EPA's Integrated Compliance Information System for Air (ICIS-Air); (vii) estimated aggregate supply chain emissions level from Carnegie Mellon University Green Design Institute; (viii) facility-level pollution abatement activity information from EPA's Pollution Prevention (P2) database; (ix) country-level environmental regulatory indices from World Economic Forum (WEF); (x) firm-level ESG scores from Refinitiv; (xi) information on executives and boards of director from BoardEx; (xii) corporate and governmental customer data from Factset Revere and Compustat Segment Files; (xiii) Form 13F institutional holdings data from FactSet Ownership; (xiv) innovation output data from Worldwide Patent Statistical Database maintained by European Patent Office (PATSTAT); (xv) firm-level ESG reputational risk data from RepRisk; (xvi) stock returns from CRSP; and (xvii) firm financial information from Compustat.

2.1. Firm-level carbon emissions

We obtain disclosed and estimated firm-level GHG emissions data between 2006 and 2018 from Trucost.[8] Over the sample period, the coverage has increased from about 1,000 to 2,800 U.S. firms. The database is constructed following the Greenhouse Gas Protocol standards and incorporates data from Carbon Disclosure Project (CDP). GHG emissions are classified into Scopes 1, 2, and 3. Scope 1 covers direct GHG emissions generated from fossil fuel used in all production and operations of facilities owned or controlled by the firm. Scope 2 accounts for emissions from the firm's consumption of purchased electricity, heat, or steam. Scope 3 refers to indirect GHG emissions caused by activities of the firm but occur from sources not owned or controlled by the firm. In particular, upstream Scope 3 includes those emissions associated with the production and transportation of purchased or acquired materials, business travel, waste disposal, and other outsourced upstream activities that occur up to the point of receipt by the firm. In contrast, downstream Scope 3 emissions are emissions from transportation, distribution, processing, use, and the end-of-life treatment of sold products that occur subsequent to sales by the firm.[9]

To study carbon offshoring to global suppliers, we examine the upstream Scope 3 emissions, an important source of carbon outsourcing for firms in achieving their GHG emission targets. The upstream data from Trucost is composed of both reported and estimated Scope 3 emissions.

[8] An S&P Global representative indicated that sometimes firms' disclosed emissions are slightly lower than what S&P Global estimated. In such cases, S&P Global would reach out to the firms and have the amount of emissions corrected. Given that Scope 1 emissions are much easier to compute, there are fewer differences between firms' disclosed and data providers' estimated amounts.

[9] See http://ghgprotocol.org/standards/scope-3-standard.

Reported GHG emissions are disclosed by the firms of interest directly to CDP, whereas estimated Scope 3 data is constructed using an input-output model that considers both a firm's expenditures across all sectors in which it obtains its inputs and the sector-level emission factors.[10] We measure each GHG emission scope in units of thousand tonnes of CO_2-equivalent emitted in a year and take the natural logarithm transformation to reduce the skewness of sample distribution.

2.2. U.S. corporate seaborne imports

Panjiva provides a unique database of U.S. trades that documents transaction-level details of goods that cross the border. Under the Customs Regulations at 19 CFR (Code of Federal Regulation), firms in the U.S. are required to report shipment details in cargo declarations to the U.S. Customs and Border Protection (CBP). Panjiva relies on such declarations to obtain information on the shippers (i.e., suppliers or logistic companies), consignees (i.e., customers), origin and destination addresses, product descriptions, and container specifications of ocean freight shipments between U.S. firms and foreign entities in over 210 countries for the 2006-2018 period. We use S&P's identification system to link the consignees with the highest-level parent firms available in Compustat.[11] For each of the matched U.S. consignee parent firm, we aggregate the total shipments it receives from an exporting country in a year to obtain import proxies.

More specifically, we construct three alternative measures to capture total import at the firm-exporting country-level. The first measure is the total shipment volume a U.S. firm receives from an exporting country as measured in units of twenty-foot equivalent ($Import\ Volume$). It is obtained from summing the freight shipment volumes across all goods from all external suppliers in a foreign country. Given that our focus is on firms' evasion of their own emission responsibility, we exclude shipments from foreign subsidiaries of U.S. parent firms (i.e., internal suppliers). The second measure is similarly defined as the total number of containers shipped from a foreign country ($Import\ Containers$), and the third measure is the total number of shipments from external

[10] While we also obtain carbon emissions data from Refinitiv and Sustainalytics, Trucost is shown to have a significantly greater time-series and cross-sectional coverage on our sample, especially for Scope 3 emissions. Therefore, we mainly rely on Trucost data for this study.

[11] This approach links part of supplier imports directly to U.S. retail stores rather than the importing firms, resulting in potential underestimation of the outsourcing behavior. Our analysis, therefore, presents a lower bound of emissions offshoring.

suppliers overseas (*Import Count*). All measures are log transformed to reduce skewness. We use *Import Volume* as the primary measure for all subsequent analyses and the remaining two proxies for robustness tests.[12]

Our primary sample intersects these key databases. First, we match Trucost emissions data with publicly-traded companies in Compustat using ISIN as the linking identifier. The merged data forms an initial sample of 15,758 firm-year observations describing the U.S. public firms' carbon emissions level each year. Then, we link the sample to Panjiva imports data by the consignee parent firms. Merging in the shipment information expands our sample to firm-country-year level observations with multiple country-level import values for each U.S. firm in a year. Finally, we exclude financial firms (SIC codes 6000-6900) and remove any observations with missing values for control variables. The selection process yields a final sample of 76,356 firm-country-year observations from 1,557 U.S. firms and 210 exporting countries for the 2006-2018 period.[13] Note that the resulting sample only includes observations with positive country-level imports and firm-level emissions.[14] The actual number of observations varies across analyses, given different model specifications and data availability for the main variables of interest.

2.3. Control variables

We employ the following firm-level control variables throughout our main analyses in Sections 3 and 4. *Assets* is the natural logarithm of total assets. *Tobin's Q* captures the growth opportunities of a firm and is measured as total assets plus the market value of equity minus the book value of equity and deferred taxes divided by total assets. *Leverage* is long-term debt plus short-term debt scaled by total assets. *ROA* measures firm profitability, defined as income before extraordinary items scaled by total assets. *SalesGrowth* is the percentage growth in sales from the previous year to the current year. *Tangibility* is the gross property, plant, and equipment divided by total assets.

[12] All three import measures yield qualitatively similar analysis results.

[13] Trucost has engaged in a major data expansion initiative since the beginning of 2016. To ensure that our findings are not driven by potential sample selection bias, we conduct a battery of robustness tests on the 2006-2015 period subsample. Results remain qualitatively similar to those our main analyses and can be made available upon request.

[14] Such sample selection process eliminates about a thousand unique polluting firms from the Trucost coverage. The alternative approach of including all foreign countries with zero imports to each firm-year allows for a better pollution data coverage but leads to qualitatively similar analysis results. Therefore, all of our reported subsequent analyses follow the main selection approach.

R&D denotes research and development capital stock, computed using the perpetual inventory method where R&D expenses scaled by assets are accumulated over the years with an annual depreciation rate of 15% (Hall, Jaffe, and Trajtenberg 2005). We winsorize all continuous variables at 5% and 95%. Appendix A contains the detailed definition of all variables.

2.4. Summary statistics

Table 1 reports the summary statistics of our key variables. Panel A summarizes the five primary variables in raw form: *Scope 1*, *Scope 3*, *Import Volume*, *Import Container*, and *Import Count*. On average, a U.S. firm produces about 2.2 million tonnes of direct Scope 1 emissions per year and is associated with about 4.1 million tonnes of upstream Scope 3 emissions through its supply chain. In comparison, the median values of emissions are much smaller (0.2 million tonnes and 1.3 million tonnes for Scopes 1 and 3, respectively) and their standard deviations much larger (5.0 million tonnes and 6.5 million tonnes for Scopes 1 and 3, respectively). These statistics suggest skewed distributions with GHG emissions mostly driven by large companies. For these considerations, we employ log emissions and control for firm size in our main analyses. Such findings are largely consistent with CDP's recent report showing that companies' supply chain emissions are immensely greater than their direct emissions.[15] It is evident that a significant portion of a firm's carbon footprint is generated by its suppliers. Hence, the firm must incorporate such large amount of indirect emissions when targeting for carbon neutrality. The average number of shipments from external suppliers in each exporting country is 24, which translates into a total of 34 shipment containers and 41 TEUs in shipment volume for an average firm-country-year. The import measures are also highly skewed as indicated by smaller median values (4 shipments, 5 containers, and 4 TEUs in volume) and larger standard deviations (45 shipments, 68 containers, and 89 TEUs in volume) with respect to the sample means. The summary statistics of their log forms are reported in Panel B.

Panel C presents the summary statistics of the control variables. Our sample consists of mostly large firms with mean total assets of \$8.8 billion (ln(1+\$8,773 million)=9.080) and median of \$7.7

[15] See CDP's "Cascading Commitments Driving Ambitious Action through Supply Chain Engagement," at rack-cdn.com.

billion (ln(1+\$7,690 million)=8.948). An average (median) firm has a Tobin's Q of 1.853 (1.614), a leverage ratio of 26.1% (25.0%), a ROA of 10.8% (10.0%), and an annual sales growth of 4.9% (4.4%). The average (median) tangibility ratio is 53.3% (46.0%), suggesting that physical assets account for about half of a firm's total assets. This statistic is comparable with the average (median) ratio of 51.1% (42.9%) for U.S. manufacturing firms captured in Compustat (SIC codes 2000-3999). R&D capital stock is skewed to the right, with at least 25% of the sample declaring a zero value for R&D expenditures.

3. U.S. Firms and Carbon Outsourcing

In this section, we investigate whether and how U.S. firms outsource their polluting burden and address any endogeneity concerns by exploiting several shocks to firms' propensity to outsource. We further conduct a host of tests on the cross-sectional variation of the carbon outsourcing effect, shedding some light on the underlying mechanisms.

3.1. Scope 1 and upstream Scope 3 emissions

We first estimate the following linear OLS panel regression model to test whether U.S. firms reduce their direct GHG emissions through emission outsourcing.

$$\textit{Scope 3}^{\dagger}_{i,t} = \alpha + \beta_S \textit{Scope 1}^{\dagger}_{i,t} + \beta_{CS}{}' \textit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \tag{1}$$

where $\textit{Scope 3}^{\dagger}{}_{i,t}$ denotes firm i's indirect emissions from its upstream supply chain in year t, alternately measured in either natural logarithm or proportion of total firm emissions (the sum of Scopes 1, 2, and upstream 3 emissions); $\textit{Scope 1}^{\dagger}{}_{i,t}$ is similarly defined as firm i's self-generated emissions in log form or proportion of total emissions; and $\textit{Controls}_{i,t}$ is a vector of firm-specific control variables defined in the preceding section. We also include varying sets of fixed effects (**FE**) to control for unmodeled heterogeneity across firms, countries, and years.[16] Standard errors are clustered at the firm level. The definition of all variables is contained in Appendix A.

[16] We conduct linear regressions on firm-country-year level observations to be consistent with subsequent analyses which include firm-country-specific import measures. Unreported analyses using firm-year level observations yield qualitatively similar results. We also exclude industry fixed effects as they are highly correlated with firm fixed effects.

Table 2 presents the regression estimates of Model (1), with Columns (1)-(3) showing results using the natural logarithm of GHG emissions and Columns (4)-(6) reporting those based on the proportion of emissions. We find that a firm's Scope 1 emissions are strongly correlated with its upstream Scope 3 emissions. The β_S estimates associated with *Ln(Scope 1)* are positive and statistically significant at the 1% level. In terms of economic significance, a one-standard-deviation increase in tonnes of Scope 1 emissions from its mean would lead to an approximately 19% (0.084×4.98 million/2.15 million×100%) increase in upstream Scope 3 emissions. Thus, supply-chain emissions increase with the increase in the firm's own production emissions. Conversely, as the firm reduces its self-generated emissions, so would its suppliers, albeit at a slower speed as reflected by β_S estimates with values less than 1. While our evidence indicates a strong linkage specifically on carbon emissions along the supply chain, it is consistent with Dai, Liang, and Ng's (2021); they show a positive correlation between a firm's overall CSR score and its suppliers' CSR scores.

Columns (4)-(6) reinforce the evidence that firms shift part of their carbon responsibilities to suppliers. In particular, a firm's fraction of Scope 1 emissions is negatively correlated with its fraction of Scope 3 emissions, revealing a substitutional effect between a firm's direct emissions and its indirect emissions along the upstream supply chain. The negative association between the proportions of Scopes 1 and 3 cannot be purely mechanical, because the emission levels of Scopes 1 and 3 co-move in the same direction. Nonetheless, we shall address this concern in subsequent analyses and provide corroborating evidence of U.S. firms' emission outsourcing behavior.

Finally, results suggest that Scope 3 emissions derived from suppliers are more substantial for larger and profitable firms, firms with higher sales growth and tangibility, and firms with lower Tobin's Q and leverage. In contrast, while the fraction of Scope 3 emissions has no relationship with firm characteristics, it is negatively associated with R&D intensity. Perhaps firms more reliant on carbon outsourcing are less likely to innovate, which is a finding we explore later. Overall, these results are consistent across different sets of fixed effects incorporated into the model. For brevity, we show only results using firm and country×year fixed effects in the remaining tables of this study.

3.2. Carbon emissions and imports

The linear regression model (1) alone does not yield sufficient evidence on U.S. firms' carbon outsourcing, especially to suppliers overseas. Therefore, to substantiate these findings, we must evaluate a firm's imports and their impact on the Scope 1–Scope 3 relationship as follows:[17]

$$\begin{aligned} \mathit{Scope\ 3}^{\dagger}_{i,c,t} = \alpha &+ \beta_{SI}\mathit{Scope\ 1}^{\dagger}_{i,t} \times \mathit{Ln(Import)}_{i,c,t} + \beta_{S}\mathit{Scope\ 1}^{\dagger}_{i,t} + \beta_{I}\mathit{Ln(Import)}_{i,t} \\ &+ \beta_{CS}{}'\mathit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where *Scope 3*†, *Scope 1*†, and *Controls* are the same as those in Model (1); $\mathit{Ln(Import)}_{i,c,t}$ denotes each import measure, namely $\mathit{Ln(Import)}_{Volume}$, $\mathit{Ln(Import)}_{Container}$, or $\mathit{Ln(Import)}_{Count}$, for firm i's shipments from exporting country c in year t.[18]

Table 3 reports the regression estimates of Model (2). Results containing $\mathit{Ln(Import)}_{Volume}$ are presented in Columns (1) and (4), $\mathit{Ln(Import)}_{Container}$ in Columns (2) and (5), and $\mathit{Ln(Import)}_{Count}$ in Columns (3) and (6). The β_S estimates in Columns (1)-(3) remain significantly positive with values less than 1, consistent with our prior finding that Scope 1 emissions decrease at a faster rate than Scope 3 emissions. Of particular interest are the sign and significance of β_{SI} estimates, which allow us to infer whether and how firms outsource their carbon pollution abroad. The coefficients on the interaction $Ln(Scope1) \times Ln(Import)$ are negative and significant across Columns (1)-(3), indicating that a firm's imports attenuate the positive correlation between its Scope 1 and upstream Scope 3 emissions. For example, a one-standard-deviation increase in imported shipment volume from its mean would weaken the Scope 1– Scope 3 association by approximately 2%.[19] In other words, suppliers' emission reductions following a firm's own emission reduction become smaller when the firm imports more from overseas. The more a firm imports from its suppliers abroad, the

[17] When analyzing a firm's emissions proportions, we investigate the extent of the substitutional effect between the two carbon types.

[18] In an unreported analysis, we alternatively measure *Import* as a binary indicator capturing whether a firm has received shipments from a foreign country. This approach includes additional sample observations for countries with zero imports to the firm. The results remain qualitatively unchanged.

[19] According to Column (2), the elasticity of Scope 3 emissions with respect to Scope 1 emissions is 0.085 - 0.019$\times$ 0.037 = 0.084, while the shipment volume is held approximately at its mean, but it drops by 1.7% to 0.085 - 0.019$\times$ [0.037 + 0.077] = 0.083 when volume increases by one standard deviation. It is an approximation based on the mean and standard deviation of *Ln(Import Volume)*, which are good proxies for the logarithms of the mean and standard deviations values of *Import Volume* in raw form.

less its suppliers comply with the carbon emission policy of the U.S. customer firm.

We further verify whether the amplifying effect of imports on the rates at which Scope 1 and upstream Scope 3 emissions decrease contributes to the negative coefficient on the interaction term. When analyzing Scopes 1 and 3 emissions in proportions of total emissions, we find the β_S coefficients on *Propn of Scope 1* to remain negative and statistically significant across Columns (4)-(6). The relative share of Scope 1 emissions falls at the expense of a rising proportion of supplier-generated Scope 3 output. The observed substitutional relationship between Scopes 1 and 3 emissions is further augmented by imports, as shown by the negative coefficient on the interaction between *Propn of Scope 1* and *Ln(Import)*. While U.S. firms decrease their direct carbon output, they do not proportionally reduce their reliance on upstream Scope 3 emissions, leading to carbon leakage.

One may, however, argue that our results reflect the mechanical effects rather than firms' evasion of their emission responsibilities. In particular, imports may mechanically drive the differential reduction rates of Scopes 1 and 3 emissions. Moreover, since a firm has limited control over its suppliers' emissions, it is unsurprising that the reduction in Scope 3 emissions would not be as fast as that in Scope 1 emissions. In the following sections, we explore whether firms' incentives to evade emission duties explain the attenuating effects of their imports, whether such results vary across industries and countries, and whether these firms develop more green innovations and engagement in other pollution abatement activities to offset their carbon footprints along supply chains. If our baseline results are mainly attributed to mechanical effects, we should not expect any significant findings on these issues. Nevertheless, to further alleviate this concern, we use *Ln(Scope 1)* and *Ln(Scope 3)* in the remaining analyses, which facilitate our interpretation of the results and are less subject to the mechanical effect in the percentage change in emissions.

3.3. Identification strategies

Our preceding results suggest that firms' imports play an important role in driving the relationship between Scopes 1 and 3 emissions. However, our causal inferences of this link may be subject to endogeneity concerns. For example, the relationships among Scope 1, Scope 3, and imports may be jointly determined (a simultaneity problem), or driven by other unobservable factors such as production outsourcing (an omitted variable bias). Also, one might argue that suppliers' emissions determine a firm's Scope 1 emissions rather than the other way around (a reverse causality), or high-emitting firms choose high-emissions suppliers (a selection bias). To alleviate these concerns, we employ several exogenous shocks to the incentives for U.S. firms to outsource their carbon emissions. Suppose our baseline findings indeed capture the outsourcing emissions effect. In that case, imports should have a stronger mitigating impact on the Scope 1–Scope 3 relationship with an exogenous increase (decrease) in appetite for imported (domestic) carbon emissions. Specifically, we investigate demand shocks to imported emissions arising from domestic state-level legislative pressure and regulatory stringency.

With the United States being the world's second-largest source of carbon emissions, accounting for 15% of the 2018 global total, environmental protection has become one of the most critical issues in U.S. politics.[20] The U.S. EPA was established in 1970 committed to reducing air pollution, followed by amendments to the Clean Air Act that increased environmental regulatory enforcement. The more recent Clean Power Plan proposed by the EPA in 2014 further aims to combat climate change by cutting down power plants' carbon emissions. There are also significant cross-state variations in environmental policies. For example, California launched its carbon cap-and-trade program in 2013 to reduce GHG emissions to 40% below 1990 levels by 2030 and 80% by 2050. Alternatively, Washington has enacted statutory targets in 2020 to reduce emissions 45% below 1990 levels by 2030, 70% by 2040, and 95% by 2050. These pollution control efforts rely heavily on the states and their abilities to devise implementation plans and enforce policies in ensuring effectiveness (e.g., Grant, Bergstrand, and Running 2014). Such efforts focus not to reduce Scope 3 emissions but to cut domestic state-level GHG emissions. Thus, we employ state-level legislative pressure and regulatory stringency as exogenous sources of increasing demand for outsourcing carbon footprints. If U.S. firms indeed engage in emissions outsourcing, we expect the attenuating effect of imports to be greater for firms in state-years that experience significant increases in such pressure and stringency.

[20] https://www.ucsusa.org/resources/each-countrys-share-co2-emissions

3.3.1. State-level legislative pressure

We analyze Congressional voting patterns in climate-change-related environmental issues to capture domestic legislative pressure. We examine the most critical environmental legislation voted in the House of Representatives and the Senate between 2006 and 2018, as documented by the LCV, and assign a score to each Congress member based on the individual's voting records each year. The score is defined as the number of pro-environmental votes (i.e., voting in favor of a climate-change-rated environmental bill) scaled by the total number of climate-change-rated environmental bills considered in the year. A higher score indicates that the Congress member is more environmentally-conscious. Thus, states with more environmentally-friendly Congress members (i.e., high environmental scores) should have more significant interests in pushing a climate action agenda. We compute an average voting score across all Senate and House members in each state and employ the voting score as a proxy for state-level legislative pressure on environmental protection.

We identify shocks to Congressional voting patterns as state-years that experience score increases by more than three times the average increase during our sample period. We also eliminate any transitory shocks followed by score reversals of a similar level within the next three years and shocks endogenously driven by firm relocation decisions, allowing us to identify our baseline models. There is no noticeable increase in local emission patterns before legislative shocks, suggesting that these shocks are likely independent of firms' domestic carbon production. Instead, they appear to capture sudden spikes in pro-environmental attitudes driven by changes in local policymakers and political parties. For example, in 2006 Pennsylvania's U.S. Senate race, a Democratic member, Bob Casey, Jr., with a lifetime voting score of 90, unseated the incumbent Republican Senator Richard Santorum with a lifetime voting score of 10. In 2008, Michael Bennet, a Democrat with 88, took the Senate seat in Colorado in place of Wayne Allard, a Republican with a voting score of 9. We employ such changes in state-level legislative attitude as exogenous shocks to carbon outsourcing incentives.

We also examine close-call elections during each state-election cycle as exogenous shocks to legislative pressure. Close-call Congress elections won by environmentally-conscious candidates represent sudden shifts in state-level environmental attitudes that are as good as randomly assigned. Unlike landslide victories, close-call election outcomes are most likely independent of the pre-existing state-level environmental conditions and attitudes leading up to the elections. We obtain general election outcomes for the House and the Senate during our sample period from the U.S. FEC. We define *close* elections as those with 5% or less vote-share differences between the winning and runner-up candidates (e.g., the winning candidate receives less than 52.5% of the vote, while the losing candidate receives more than 47.5%). For each state-election cycle, we count the total number of close wins by environmentally-conscious or greener candidates (defined as either a member of the Democratic party or has a lifetime environmental voting score of 60 or above) net of the number of close losses.

We identify shocks to legislative pressure as state-years with a positive net close win count, capturing the local authorities' exogenous increase in environmental awareness. For example, Virginia underwent such a shock during the 2008 election cycle with a net close win count of 2 (2 close wins - 0 close losses). One close win is contributed by the race between a Democratic nominee Glenn Nye, with a lifetime environmental voting score of 75, and the Republican incumbent Thelma Drake, with an environmental voting score of 10, in the House election for District 2. Nye won the election marginally with 52.4% of vote-share. The other win comes from a close victory by a Democratic nominee Tom Perriello (50.1% vote-share), with an environmental score of 79, against the Republican incumbent Virgil Goode, with a lifetime score of 11, in the election for District 5. This approach reflects the sudden heightened legislative pressures on environmental issues primarily driven by random close-call Congress appointments of greener candidates with solid preferences for environmental bills.

To evaluate the impact of state-level legislative pressure on firms' carbon emissions outsourcing behavior, we estimate the following regression model with a triple-interaction effect.

$$\begin{aligned} \mathit{Ln(Scope\ 3)}_{i,t} = \alpha &+ \beta_{SI1}\mathit{Ln(Scope\ 1)}_{i,t} \times Ln(Import)_{i,c,t} \times Treat_{i,t-1} \\ &+ \beta_{SI}\mathit{Ln(Scope\ 1)}_{i,t} \times Ln(Import)_{i,c,t} + \beta_{S1}\mathit{Ln(Scope\ 1)}_{i,t} \times Treat_{i,t-1} \\ &+ \beta_{I1}Ln(Import)_{i,c,t} \times Treat_{i,t-1} + \beta_{S}\mathit{Ln(Scope\ 1)}_{i,t} + \beta_{I}Ln(Import)_{i,c,t} \\ &+ \beta_{1}Treat_{i,t-1} + \beta_{CS}{}'\mathit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where $Treat_{i,t-1}$ is a binary indicator that equals 1 if the state where firm i resides experiences a shock in year $t-1$, and 0 if otherwise. It alternately captures the treatment effect of each exogenous shock. *Ln(Scope 1)*, *Ln(Import)*, *Controls*, and **FE** are the same as those in Model (2). The β_{SI1} parameter of the triple-interaction term captures the incremental impact of imports on the Scope 1–Scope 3 association as driven by firms' incentives to outsource emissions overseas. A negative β_{SI1} suggests a greater attenuating impact on the positive correlation between Scope 1 and upstream Scope 3 emissions, thus a stronger effect of emission outsourcing.

Table 4 presents the regression results of Model (3). Column (1) shows the impact of Congress voting score shocks, where *Treat* is 1 for the next five years if the environmental legislative voting score in year $t-1$ increases by more than three times the average increase in the score during the sample period. Columns (2) and (3) present the effects of close-call election wins by Democratic members and Congress members with a lifetime environmental voting score of 60 or above, respectively. The *Treat* indicator equals 1 for the next two years (i.e. the length of an election cycle) after the close-call election win in year $t-1$. We find the β_{SI1} coefficients to be negative and significant across all three columns, suggesting a stronger outsourcing effect following a sudden increase in state-level legislative pressure, which intensifies local firms' demand for shifting some of their own emission duties to their foreign suppliers. However, when we replicate the analysis of Column (2) with close wins by Republican members, the reported results in Column (4) yield no result.

3.3.2. State-level legislative stringency

We measure state-level regulatory stringency using two approaches. One method determines whether a state has enacted GHG emission targets to reduce statewide carbon output. Many states have set targets as a future percentage reduction compared to a baseline emission level in a benchmark year. For instance, California, Connecticut, Maine, Massachusetts, New York, Oregon, Rhode Island, Vermont, and Washington use a 1990 baseline to measure emission reductions. Colorado, Minnesota, and Nevada use 2006 emissions as the baseline. These states put in place binding statutory requirements or executive actions to achieve their targets. We contend that firms located in these states experience tightened regulatory monitoring and enforcement and, in turn, have stronger incentives to outsource emissions. Thus, to identify shocks to state-level regulatory stringency, we examine whether and the year in which a state enacts a statutory or executive target to limit carbon output, as recorded in C2ES.

Alternatively, we measure state-level regulatory stringency using the facility inspection data obtained from ICIS-Air. Our study defines inspection intensity as the total number of EPA's onsite air pollution compliance evaluations scaled by the total number of air pollution emitting facilities in each state. We contend that firms in states with dramatic increases in onsite inspections have more demand for imported emissions. We identify shocks to inspection patterns as state-years that experience intensity increases by more than three times the average increase during our sample period, excluding any transitory shocks followed by reversals within the next three years, or those driven by changes in the firm location. While inspections themselves are not necessarily exogenous as they may be caused by EPA or state plans or complaints filed by local communities, we argue that a spike in inspection intensity is exogenous to a firm's GHG emissions. Inspections are usually conducted to address multiple environmental concerns simultaneously while assessing many different regulated pollutants. They are triggered by various programs, such as compliance evaluations for Hazardous Air Pollutants, Maximum Achievable Control Technology, Recycling & Emission Reduction Programs, and the Mandatory Greenhouse Gas Reporting Rule.[21] Hence, while other programs may endogenously cause some inspection spikes, they are mainly exogenous for specifically GHG emission concerns. In particular, we find that multiple programs trigger over 43% of the inspections and that less than 1% of the onsite examinations are intended to evaluate compliance with the Mandatory Greenhouse Gas Reporting Rule program.

Similar to the preceding tests, we investigate the impact of state-level regulatory stringency on firms' carbon emissions outsourcing behavior using Model (3) by replacing *Treat* with another binary indicator, *Stringency*. *Stringency* equals 1 for the five years after the state enactment of executive or statutory targets to limit carbon emissions, or equals 1 for the next five years if the one-year lagged average onsite inspection level per facility increases more than three times the average onsite inspection increase in the level over time. Table 5 reports the results. Consistent with the evidence in Table 4, the estimates of β_{SI1} in Columns (1)-(2) are also negative and statistically significant. We also conduct a set of falsification tests to rule out other hypotheses

[21]See https://www.epa.gov/compliance/how-we-monitor-compliance.

possibly associated with endogeneity issues. In particular, Columns (3) and (4) show virtually no result when we estimate the respective models a year before the occurrences of state-level enactment of executive or statutory emissions targets and onsite inspections.

To sum, it is important to stress that such demand shocks do not necessarily increase the absolute level of GHG emissions along the upstream supply chain abroad. Instead, it mainly changes the relative proportion of a firm's Scope 1 and Scope 3 emissions in its overall emissions, resulting from the disproportional rate of change in upstream Scope 3 emissions relative to Scope 1 emissions. These findings also corroborate our argument that U.S. firms' outsourcing behavior drives the mitigating effect of imports found in the baseline analysis.

3.4. Cross-industry and cross-country emissions variations

In this section, we provide more corroborating evidence that corporations reduce their carbon footprints by shifting GHG emissions to their global suppliers.

If firms indeed actively engage in emission outsourcing (rather than simply production outsourcing), their outsourcing activity should increase in high-polluting industries and countries with laxer regulations. There would exist no such evidence in the case of production outsourcing. To conduct our tests, we employ a binary indicator (*Indicator*) to partition our sample into two sub-samples based on industry emission levels of U.S. firms and the environmental regulatory stringency of supplier countries. We then estimate the following triple-interaction model:

$$\begin{aligned} \mathit{Ln(Scope\ 3)}_{i,t} = \alpha &+ \beta_{SI1}\mathit{Ln(Scope\ 1)}_{i,t} \times \mathit{Ln(Import)}_{i,c,t} \times \mathit{Indicator}_t \\ &+ \beta_{SI}\mathit{Ln(Scope\ 1)}_{i,t} \times \mathit{Ln(Import)}_{i,c,t} + \beta_{S1}\mathit{Ln(Scope\ 1)}_{i,t} \times \mathit{Indicator}_t \\ &+ \beta_{I1}\mathit{Ln(Import)}_{i,c,t} \times \mathit{Indicator}_t + \beta_I \mathit{Ln(Import)}_{i,c,t} + \beta_S \mathit{Ln(Scope\ 1)}_{i,t} \\ &+ \beta_1 \mathit{Indicator}_t + \beta_{CS}{}'\mathit{Controls}_{i,t} + \gamma_i + \theta_c + \phi_t + \epsilon_{i,t}. \end{aligned} \tag{4}$$

Model (4) enables us to investigate whether industries requiring abundant polluting inputs are more likely to seek emission outsourcing through foreign suppliers. We construct a binary indicator, *Indicator*, that takes the value of one if the industry is above the median level of emissions and zero if otherwise. Results are presented in Table 6. *Indicator* alternately captures four different representations, namely Fama-French 30 industries with above-median aggregate Scope 1 emissions scaled by total assets in Column (1) and NAICS industries requiring above-median pollution-intensive inputs[22] in Column (2), and countries with below-median enforcement of environmental regulations score (EER) in Column (3) and below-median stringency of the environmental regulation score (SER) in Column (4).[23] The coefficients of the triple-interaction terms are negative and statistically significant across the models. The results suggest that the outsourcing effects are stronger for firms in pollution-intensive sectors and firms that are more likely to outsource GHG emissions to their suppliers from less environmentally regulated countries.[24]

Overall, the subsample results based on the institutional environment offer a more nuanced view of U.S. firms' GHG emission outsourcing. Outsourcing tends to be more pronounced when corporate customers are in high-emitting sectors and their suppliers' countries have laxer environmental regulations.

4. The Mechanisms

Thus far, we have shown robust evidence that firms care about reducing Scope 1 emissions even though such carbon mitigation is achieved partly through outsourcing their air pollution abroad. This section explores several plausible firm-level mechanisms that can explain firms' emission management and outsourcing activities.

[22] In this approach, we incorporate the total carbon footprint of the industry and its whole supply chain. It enables us to investigate whether industries requiring abundant polluting inputs are more likely to seek pollution outsourcing through foreign suppliers. We obtain an estimate of GHG emissions resulting from a $1 million worth of economic activity in each industry from Carnegie Mellon University (http://www.eiolca.net/). This estimate is generated using the Economic Input-Output Life Cycle Assessment approach, which in essence captures all emissions produced throughout the supply chain, starting from the raw inputs up to the production of $1 million worth of output. We group the industries by NAICS in this case, given it is the default industry classification in the I-O estimate.

[23] The EER and SER scores are obtained from World Economic Forum's Travel & Tourism Competitiveness Reports, and higher scores represent more stringent environmental policies.

[24] We also conduct subsample analyses using Model (1) and obtain qualitatively similar results.

4.1. Internal mechanisms

We contend that emission outsourcing may reflect an underlying agency problem. Corporate insiders, such as management and directors, understand the importance of their firms' reputations and domestic social capital. Thus, their desire to build a good reputation and social capital could incentivize them to go green for themselves. Our earlier findings indicate that outsourcing part of firms' direct GHG emissions is a less costly and faster strategy, even at the expense of the overall stakeholder welfare. Therefore, we posit that firms with higher ESG ratings (*Greenness*) are more inclined to subtly shift emissions overseas in reducing self-generated GHG emissions to maintain their own reputation.

Prior research suggests that a high ESG score can benefit firms with better product quality signaling (e.g., Fisman, Heal, and Nair 2006; Siegel and Vitaliano 2007), increased customer loyalty and willingness to pay (e.g., Bagnoli and Watts, 2003; Baron 2008, 2009), and attraction of more or cheaper sources of capital from altruistic investors (e.g., Ceccarelli, Ramelli, and Wagner 2019; Hartzmark and Sussman 2019), among others. Such benefits would propel greener firms to uphold their domestic social images and environmental standings. Social reputations are generally built on firms' observable ESG efforts but typically remain silent on the emissions along their supply chain. Thus, greener firms would have stronger incentives to outsource air pollution in maintaining a good front. We test this mechanism by employing the triple-interaction model (3). $Treat_{i,t-1}$ is replaced with $Firm\ Greenness\ _{i,t-1}$ to capture firm i's established reputation at year $t-1$. $Firm\ Greenness$ is measured as the decile ranking of its ESG score, defined as a combined score obtained from Refinitiv based on the reported information in the environmental, social and corporate governance pillars with an ESG controversies overlay.

Executives and directors with a pro-environmental image (i.e., greener executives and board of directors) should similarly have reinforcing effects on emission outsourcing. The reputations of these internal stakeholders can be tied to their firms' reputations. They take credit for their firms' strong social images and receive private benefits, including better career prospects, among others (Bénabou and Tirole 2010; Cai et al. 2020). Thus, greener executives and directors would also influence corporate environmental policies in maintaining their own established reputation and prestige.

Existing studies document that managers and directors play a critical role in their firm's ESG performance (e.g., Davidson, Dey, and Smith 2019; Iliev and Roth 2020). Following this strand of literature, we argue that firms with greener CEOs and directors would face greater internal pressure to drive down direct Scope 1 emissions through emission outsourcing. In testing these mechanisms, $Treat_{i,t-1}$ is replaced, alternately, with $CEO\ Greenness_{i,t-1}$ and $Board\ Greenness_{i,t-1}$ to capture CEO's and board of directors' established social reputation as revealed by their past five years of employment. For each CEO in a given year, we assign a decile ranking based on the average score of her current and past employers' ESG ratings over the past five years. $CEO\ Greenness_{i,t-1}$ ranks the average scores over years $t-5$ to $t-1$. A higher ranking denotes a greener CEO for firm i. We compute *Board Greenness* in a similar fashion. Specifically, $Board\ Greenness_{i,t-1}$ is the decile ranking based on the average ESG scores of the directors' previously affiliated firms, serving as board members, in years $t-5$ to $t-1$. We obtain information on the CEO's and directors' past work experiences from BoardEx.

Table 7 presents regression results for all three internal mechanisms. The β_{SI1} estimate is -0.002 with its $t-$statistic varying from -1.70 to -2.02, indicating that the mitigating effect of imports in the baseline result is amplified by the firm's, CEO's, and board's ESG ratings. This finding is consistent with our expectation that companies, CEOs, and directors with reputation of greenness have stronger incentives to outsource emissions in curbing their own Scope 1 emissions.

4.2. External mechanisms

Unlike corporate insiders who are internal stakeholders, external stakeholders, such as government and corporate customers and institutional investors, may have different expectations. These external stakeholders are concerned about their overall exposures to climate risk and may care about carbon footprints along the whole value chain. As a result, they have incentives to alleviate agency-motivated outsourcing behavior. They would push against emission offshoring to reduce any adverse spillover effects on the ESG ratings of their associated foreign suppliers. External stakeholders typically reside or have portfolios in different countries and are usually concerned about their reputation of greenness not within the U.S. but internationally. Previous research documents their pivotal influences on corporate environmental policies. For example, Dai, Liang, and Ng

(2021) show that corporate customers shape foreign suppliers' social and environmental policies. Other work suggests that large institutional blockholders can pressure for changes in corporate environmental policies through private engagement, proxy voting, and threats of exit (e.g., Starks, Venkat, and Zhu 2017; Dyck et al. 2019; Gantchev, Giannetti, and Li 2020; Krüeger, Sautner, and Starks 2020). We, therefore, examine whether external stakeholders exercise such powerful influences to deter firms' outsourcing behavior.

Government and greener corporate customers should be more concerned about the global community's overall environmental externalities of corporate actions. Government customers act in the public interest and address social issues arising from market failures and negative externalities. As global warming and other environmental issues become increasingly acute and pressing, governments are compelled to reduce firms' overall carbon footprints in the interest of public welfare (Hsu, Liang, and Matos 2021). Furthermore, previous research suggests that green corporate customers tend to impose their ESG preferences on their suppliers (Dai, Liang, and Ng 2021). Other research shows that climate change constitutes extreme weather events leading to significant losses on affected firms propagating through the supply chain (Barrot and Sauvagnat 2016). These two strands of the literature suggest that greener customers would be more attentive to the adverse impact of climate risk on their performance and exert influences to curb total emissions. Hence, we expect the outsourcing effect to be less pronounced when a firm has more concentrated government and greener corporate customers. We apply the triple-interaction model (3) to explore these external stakeholders' incentives. In this model, $Treat_{i,t-1}$ is replaced with $Gov\ Customer_{i,t-1}$ and $Customer\ Greenness_{i,t-1}$. The former is defined as the percentage of firm i's sales to its largest government customer identified in the Compustat Segments file at year $t-1$. $Customer\ Greenness_{i,t-1}$ represents the percentage of firm i's largest corporate customer with the above industry-median ESG score.[25]

We also argue that environmentally-conscious institutional investors, who typically have international exposures, are more concerned about the overall ESG performance of their global investment portfolios. Particularly, ESG-oriented investors are more likely to consider and manage the

[25]Alternative definitions of customer concentration include (i) the percentage sales to major customers individually accounting for at least 10% of firm i's total revenue; and (ii) the sum of percentage sales squared of major customers yield qualitatively similar results.

climate risk of their investments (Krueger, Sautner, and Starks 2020). To minimize the negative impact of climate risk on portfolio performance, these stakeholders would focus on reducing a firm's total contribution to global warming rather than the narrowly defined Scope 1 emissions. Thus, our analysis focuses on greener block institutional investors with half of their portfolio holdings invested in green firms ranked in the top quintile of the Refinitiv ESG score distribution each year (*Blockholder Greenness*).[26]

Table 8 presents the results for all three external mechanisms. Columns (1), (2), and (3) record the impacts of government customers, greener corporate customers, and greener block investors on a firm's carbon footprint management, respectively. The coefficient on the triple-interaction term is consistently positive and statistically significant at the 5% level across the columns. Thus, consistent with our expectations, government customers, greener customers, and greener blockholders reduce global environmental externalities by restricting their associated firms from outsourcing emissions to other countries.

It is essential to highlight the stark differences in our results between internal and external mechanisms. On the one hand, the internal channels reflect agents' incentives to commit to social images in the local community, inducing them to cut their self-generated carbon emissions by increasing overseas supplier emissions. On the other hand, the external mechanisms capture external stakeholders' incentives to reduce their global exposure to climate risk, discouraging firms from outsourcing emissions to international suppliers.

5. Real and economic consequences of emission outsourcing

We have provided pivotal evidence that U.S. firms reduce their Scope 1 emissions at home by outsourcing part of their carbon pollution to foreign suppliers from less developed countries with weaker environmental regulations. This section, therefore, explores the real and economic consequences of firms' actions. Specifically, we investigate whether outsourcing emission activity is associated with pollution mitigation initiatives and has implications for firms' profitability, valuation, reputational risk, and stock prices.

[26] Blockholders are defined as institutional investors that hold at least 5% of a firm's total shares outstanding.

5.1. Real consequences

5.1.1. Emission mitigation initiatives

Our key evidence suggests that increasing the proportion of Scope 3 emissions and imports is a less costly business strategy to tackle climate change. If, indeed, this is the case, we should expect firms to put less effort into local-emission mitigation initiatives as they shift part of their carbon emissions overseas. Therefore, we test whether a firm is more likely to: (i) engage a foreign supplier that it can outsource its emissions, (ii) reduce pollution abatement measures locally, and (iii) invest less in green technology. To conduct such analyses, we adopt a more granular measure of emission outsourcing – imported emissions (*Ln(Import CO_2)*). *Ln(Import CO_2)* measures the magnitude of emissions attributed to imported goods and is an estimate of outsourced GHG emissions based on a \$1 million worth of output through the Economic Input-Output Life Cycle Assessment (EIO-LCA) model. Primarily based on the economic input-output accounting and Intergovernmental Panel on Climate Change's second assessment report, the model quantifies standardized carbon emissions generated along the supply chain from imported products to a firm based on its primary industry. Appendix A offers a detailed explanation of this variable.

Table 9 presents regression results at the firm level, while controlling for *Age*, *Size*, *Tobin's Q*, *Leverage*, *PPE*, *ROA*, *CapEx*, *R&D*, *HHI*, and different fixed effects. In Column (1), we conduct a linear probability model in which we regress a binary variable, *Foreign Supplier*, on the domestic portion of a firm's Scope 1 emissions as estimated by multiplying the aggregate Scope 1 value with the ratio of domestic assets to total assets. *Foreign Supplier* is defined as one if the firm has at least one foreign supplier in the following year and zero if otherwise. The result shows a positive and statistically significant coefficient on domestic *Ln(Scope 1)*, suggesting that when a firm faces mounting pressure to reduce direct carbon emissions from its domestic production, its likelihood of seeking a foreign supplier to outsource its air pollution increases.

In Column (2), we also conduct a linear probability model in which we regress a binary variable, *Pollution Abatement*, on a firm's Scope 1, Scope 2, and imported CO_2. Following Appel and Akey (2019), *Pollution Abatement* measures a firm's investment in abatement activities associated with reducing the number of hazardous substances entering the waste stream.[27] *Pollution Abatement* equals one if the firm reports at least one abatement activity in year $t+1$ that reduces a chemical production in the following activity categories: 1) operating practices, 2) inventory control, 3) spill and leakage, 4) raw material modifications, 5) process modifications, 6) cleaning and degreasing, 7) surface preparation and finishing, or 8) product modifications and zero if otherwise. We find the coefficient of *Ln(Scope 1)* to be positive and statistically significant, whereas that of *Ln(Imported* CO_2*)* to be negative and statistically significant. For more pollution-intensive firms (i.e., the higher their Scope 1 emissions), the growing pressure to reduce carbon emissions will increase firms' likelihood of investing in abatement measures in the future, but this likelihood will decrease for those that choose to outsource instead.

Finally, in Column (3), we report the results from regressing the natural logarithm of the number of green patents filed by a firm two years ahead ($Green\ Innovation_{i,t+2}$), accommodating for the time taken to innovate.[28] We use the International Patent Classifications (IPC) to classify green patents and focus on those IPCs identified as environmentally sound technologies by United Nations Framework Convention on Climate Change. This regression result reported in Column (3) also includes the firm's direct emissions from own production (*Ln(Scope 1)*) and through supply-chains (*Ln(Scope 3)*). Economic theory suggests that firms may innovate as a differentiation strategy to gain competitive advantages over their rivals (e.g., Aghion et al. 2005). While firms can invest more in green R&Ds gearing toward environmental patents to offset any potential adverse regulatory shocks and remain competitive, this strategy is more costly. It also demands a longer-term commitment than simply outsourcing emissions abroad. Our results reveal a myopic environmental preference among firms that may have more flexibility to reduce their carbon footprints through outsourcing emissions to foreign suppliers. *Ln(Import* CO_2*)* is negatively related to green innovation output, while neither direct emissions nor indirect supplier-induced carbon emissions bear any significant effect on *Green Innovation*. For example, the estimate of *Ln(import* CO_2*)* coefficient is -0.049 ($t-$statistic=-2.44), and the unreported estimate for the 3-year ahead green innovation is -0.063 ($t-$statistic=-2.87), Thus, the more carbon intensively firms import, the less likely they will

[27] Note that firms do not report dollar amounts spent on pollution abatement activities but only disclose their efforts to reduce pollution emissions in their annual EPA's Toxic Release Inventory (TRI) fillings.

[28] Results remain qualitatively similar when we employ the number of green patents filed three years ahead.

engage in environmental innovation.

These results suggest that U.S. firms do not actively pursue carbon neutrality through offsetting their emissions outsourcing by launching pollution abatement efforts and deploying clean technologies. Our findings are also broadly in line with the work of Cohen, Nguyen, and Gurun (2020), who show that firms from oil, gas, and energy-producing sectors ("brown" firms) with lower ESG scores are key green innovators in the U.S. Moreover, these brown firms produce significantly higher quality green innovation, suggesting that "bad apples" (i.e., firms in heavily-polluted industries) can do good by being critical innovators in the U.S. green patent landscape. On the other hand, our study potentially reveals the true incentive of U.S. firms that outsource carbon footprints. These firms appear unwilling or unable to develop green technology that requires significant capital investments and long development timelines, indicating that "good apples" (i.e., firms with lower Scope 1 emissions) can do bad by avoiding green innovation.

5.2. Economic consequences

5.2.1. Firm profitability, operating efficiency, and valuation

It is plausible that firms outsourcing carbon emissions pass on production and emission costs to their overseas suppliers and, in turn, generate greater profitability by achieving operating efficiency. To test this relationship, we estimate the following model,

$$\begin{aligned} ROA_{,i,t+1} \quad = \quad & \alpha + \beta_1 \; Ln(Scope\ 3)_{i,t} + \beta_2 Ln(Scope\ 1)_{i,t} + \beta_3 Ln(Import\ CO_2)_{i,t} \\ & + \beta'_{CS} Controls_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned} \tag{5}$$

where ROA is a proxy for firm profitability in year $t+1$ and is computed as the operating income before depreciation scaled by total assets. *Controls* denotes a vector of variables, including firm size measured by total assets, Tobin's Q, R&D, advertising expenditure, firm leverage, capital expenditure, cash holdings, income volatility, return on equity, and growth in EPS. As in our baseline regression, we control for potential time-series dependence in the residuals by clustering standard errors at the firm level. Model (5) also includes firm-fixed effects to control for unobservable omitted firm-specific factors and adds year-fixed effects to control for time-specific shocks influencing all firms. Column (1) of Table 10 highlights the estimated coefficients of the key variables in Model (5).

We find that *ROA* is uncorrelated with *Ln(Scope 1)* and *Ln (Import* CO_2*)* but is positively and significantly related to *Ln(Scope 3)*. Firms are able to produce considerably higher profits when they shift their emissions to suppliers, thereby allowing them to reduce direct emissions domestically by adopting a lean production process. Notably, the finding of no significant correlation exists for imported CO_2 indicates that the benefits may derive from the upstream carbon emissions rather than the carbon emission intensity of imported goods.

Next, we examine the sources of firm profitability by decomposing the profitability measure into operating profit margins, as measured by earnings before interest and taxes scaled by sales (EBIT Margin) and operating efficiency, as measured by the ratio of sales to assets (*Asset Utilization*). *EBIT Margin* gauges the extent to which prices exceed marginal costs, whereas *Asset Utilization* measures how efficiently firms employ their assets to generate sales. We, therefore, reestimate Model (5) using *EBIT Margin* and *Asset Utilization* as dependent variables and report their estimates in Columns (2) and (3), respectively. The coefficient of *Ln(Scope 3)* is positive and statistically significant, while that of *Ln(Scope 1)* is negative but insignificant. The positive link between Scope 3 emissions and *ROA* is potentially due to larger profit margins and improved operational efficiency. Possibly, firms mitigate direct Scope 1 emissions to improve profitability and look good financially through increasing Scope 3 and, to a lesser extent, carbon emission intensity of imported goods.

A natural question that arises is whether the improved profitability associated with Scope 3 emissions translates into a lower cost of equity capital and enhanced firm valuation. We test this prediction by reestimating Model (5) with the implied cost of equity capital (*ICC*) and Tobin's Q as alternate dependent variables. Our analysis employs the average of four different estimates for the cost of equity capital implied in share prices and analyst forecasts suggested in the literature (Claus and Thomas, 2001; Gebhardt, Lee, and Swaminathan, 2001; Easton, 2004; Ohlson and Juettner-Nauroth, 2005). We use Tobin's Q, the ratio of the market value of equity plus total assets minus book value of equity to total assets, as a proxy for firm value. Columns (4) and (5) indicate that both *Ln(Scope 3)* and *Ln(Import* CO_2*)* are positive and statistically significantly related to *ICC*, but that only the former is negative, albeit marginally, associated with *Tobin's Q*. These results suggest that outsourcing carbon pollution raises climate transition risk and information asymmetry, resulting in increased cost of equity capital and reduced firm value.

5.2.2. *Stock returns and reputational risk*

We have shown that the positive association between Scope 3 emissions and firm profitability is accompanied by a rise in the implied cost of equity capital and a fall in firm value. We next analyze the pricing implications of air pollution outsourcing activities by investigating whether financial markets efficiently price in the stocks of firms that exploit outsourcing to reduce carbon emissions. Prior research provides increasing evidence that financial markets play a role in pricing carbon exposure. For example, carbon emissions increase with firms' cost of capital (Chava, 2014) and carbon risk premium (Hsu, Li, and Tsou, 2019; Bolton and Kacperczyk, 2021).

Motivated by this strand of literature, our analysis follows Bolton and Kacperczyk (2021) and examines the relationships between monthly stock returns and different sources of firm-level carbon emissions using the following model,

$$\begin{aligned} \textit{Stock Return}_{i,m,t+1} &= \alpha + \beta_1 \textit{Ln(Scope 1)}_{i,t} + \beta_2 \textit{Ln(Scope 3)}_{i,t} + \beta_3 \textit{Ln(Import CO}_2\textit{)}_{i,t} \\ &\quad + \beta'_{CS} \textit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned} \tag{6}$$

where $\textit{Stock Return}_{i,m,t+1}$ is the monthly stock return of firm i in month m of year $t+1$. Model (6) controls for firm-specific characteristics that are previously shown to predict stock returns, and they include firm-specific *Size*, *BM*, *Leverage*, *PPE*, *CapEx*, *Momentum*, *Volatility*, *Beta*, and *HHI* at year t. It also includes firm and month fixed effects and incorporates standard errors clustered at the firm level. Results are reported in Columns (1)-(4) of Table 11. Consistent with Bolton and Kacperczyk (2021), we find that carbon emissions are all positive and significantly associated with stock returns. However, when we estimate these different sources of emissions jointly, Column (4) shows that only the coefficients on *Ln(Import* CO_2*)* and *Ln(Scope 3)* are positive and significant and that the statistical significance of *Ln(Scope 1)* disappears. The statistically significant carbon risk premium attached to Scope 3 and imported emissions implies that forward-looking investors seek compensation for holding stocks of carbon outsourcers associated with more substantial carbon risks.

We conduct another test to substantiate our findings of carbon risk premium associated with outsourced emissions. Specifically, we evaluate whether sources of carbon emissions are linked to firms' reputational risks. Reputational risk is the risk of possible damage or threat to a firm's reputation that typically results in the potential loss to the firm's social capital, financial capital, and/or market capitalization. Firms can suffer severe reputational damage, or face mounting legal and financial challenges due to ESG and business conduct incidents. Furthermore, technology and social media have increasingly enabled various stakeholders, including customers, employees, and activists, to expose companies' unethical ESG behavior to a large audience much more quickly.[22] Such reputational risk typically affects the "loyalty" of key stakeholders (including customers and suppliers across the global supply chain) to stay with the firm to offset the adverse effect of market-wide systematic shocks, thus can be considered as a source of systematic risk.[29] Therefore, we expect environmentally responsible firms to display a lower ESG-induced reputational risk. That is, firms with less carbon footprint along the global value chain have a lower reputational risk.

We test a cross-sectional relationship between a firm's reputational risk (*RepRisk*) and its sources of carbon emissions by replacing the dependent variable of Model (5) with *RepRisk* β, an estimate of a firm's reputational risk at year t. We estimate *RepRisk* β as follows. Each year, we rank the firms in our sample based on their reputational risk scores, as provided by RepRisk,[30] and divide them into two portfolios of stocks with high and low reputational risk scores. We compute daily returns on a reputational risk factor by taking the difference in daily returns between the low and high reputational-risk score portfolios. We then regress individual stock returns on the returns of the reputational risk factor and Fama-French-Carhart four factors. The coefficient on the reputational risk factor is our estimate of *RepRisk* $\beta_{i,t}$. We repeat this procedure each year to obtain yearly estimates of each firm's *RepRisk* $\beta_{i,t}$.

[22] Knowledge@Wharton, "Social Media Shaming: Can Outrage Be Effective?" November 20, 2015, http://knowledge.wharton.upenn.edu/article/social-media-shaming-can-outrage-be-effective. See, also, Johnson (2020) on how publicizing firms' socially undesirable actions may enhance firms' incentives to avoid such actions.

[29] Albuquerque, Koskinen, and Zhang (2020) show that the systematic risk is lower for firms with higher CSR scores and that the ESG-systematic risk relationship is more pronounced for firms with greater product differentiation.

[30] RepRisk, an ESG data science provider, quantifies the reputational risk scores of companies based on their exposures to ESG and business conduct risks and annually highlights companies that are most exposed to such risks. https://finance.yahoo.com/news/reprisk-most-controversial-companies-report-130000270.html

It is important to point out that when we regress returns of the reputational risk factor against the returns on Fama-French-Carhart four factors, the alpha estimate of -3% per annum is statistically significant at the 5% level.[31] Similar to Edmans (2011), we interpret that the reputational risk factor's underperformance reflects the difficulty of incorporating intangibles into traditional valuation models. Even though our primary purpose is to examine which source of firm-level carbon emissions relates to a firm's systematic reputational risk, the results are consistent with this interpretation.

Columns (5)-(8) of Table 11 present the results showing how each CO_2 emission variable is related to *RepRisk* β, separately and jointly. Consistent with Columns (1)-(4), the findings suggest that the market attaches a high systematic risk associated with ESG reputation for firms shifting their emissions overseas. *RepRisk* β is positive and significantly related to both *Ln(Import* CO_2*)* and *Ln(Scope 3)*, while not with *Ln(Scope 1)*. The magnitude and statistical significance of both *Ln(Import* CO_2*)* and *Ln(Scope 3)* coefficients become even stronger when they are estimated jointly. Overall, investors have appropriately factored in the risk premium and reputational risk of outsourced emissions. Thus, firms bear a larger risk premium and face a greater reputational risk when they move their carbon emissions abroad.

In summary, our evidence suggests that only firms' Scope 3 and imported emissions are positively and significantly associated with their future stock returns and reputational risks. Firms may attempt to combat climate change by outsourcing carbon emissions to their global supply chains but still are unable to reduce carbon premiums and reputational risks. Investors instead demand compensation for their exposures to carbon risks associated with their increased Scope 3 and imported emissions.

6. Conclusion

Climate change is a real and undeniable global threat, and its effects are already apparent. Yet, while companies recognize the risks associated with climate change and are taking actions to reduce their carbon footprints, there is little evidence of whether corporations follow through on their

[31] The spread between the low and high RRI portfolio tends to have an upward trend except for the early stage of the Subprime Crisis period and 2019.

pledge to a global action plan to fight climate change. Our study exploits several newly available firm-level emissions and imports data to conduct an in-depth holistic analysis of firms' actions in curbing carbon emissions and evaluate the real and economic consequences of their environmental policy. We find robust evidence that U.S. corporations reduce direct carbon emissions in local markets at the expense of increasing indirect emissions through outsourcing polluted products abroad. Combating climate change is not only the sole responsibility of corporations but also the responsibility of various corporate stakeholders. Our analyses suggest that environmentally-conscious CEOs, boards of directors, customers, and institutional blockholders are channels that drive firms' incentives to tackle climate change.

Our evidence that U.S. firms reduce their carbon footprints through outsourcing carbon emissions reveals a dark side of global supply chains. Therefore, environmentally-conscious investors and consumers should carefully investigate a firm's Scope 1 emissions and all of the emissions that its activities and products produce to evaluate better how green the firm truly is.

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Figure 1

Proportions of Direct vs. Supplier-Induced Carbon Emissions of U.S. Firms for the 2007-2017 Period

This figure depicts the time series of the average proportion of direct (Scope 1) carbon emissions to total emissions (Scopes 1, 2, and 3) and the average proportion of indirect (upstream Scope 3) carbon emissions to total emissions across U.S. firms.

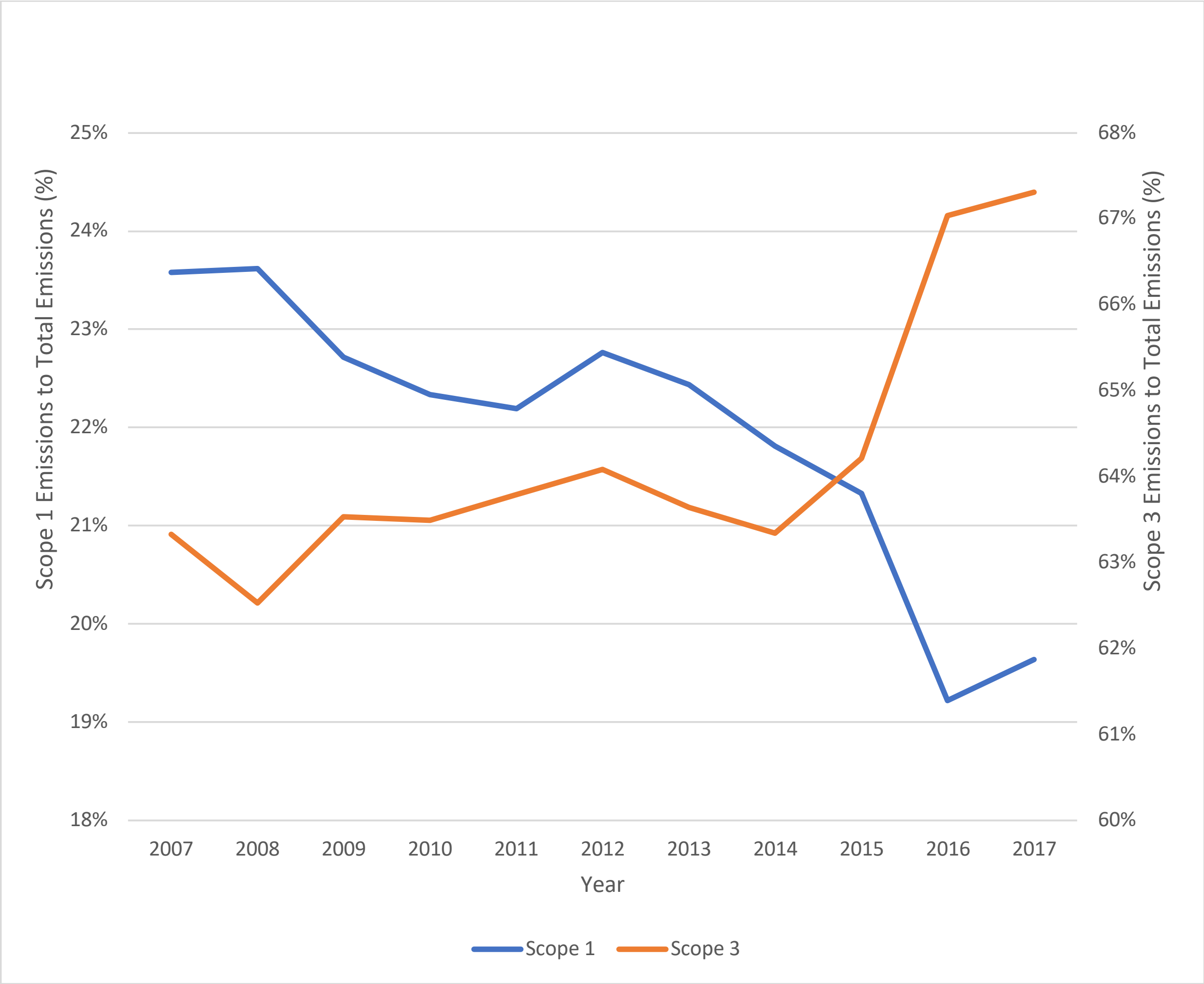

Figure 2

Total Carbon Emissions (Scopes 1, 2, and Upstream 3) and Imports of U.S. Firms for the 2007-2017 Period

This figure shows the aggregate carbon emissions (the sum of Scopes 1, 2, and 3) and total import shipments (millions) of U.S. firms over time.

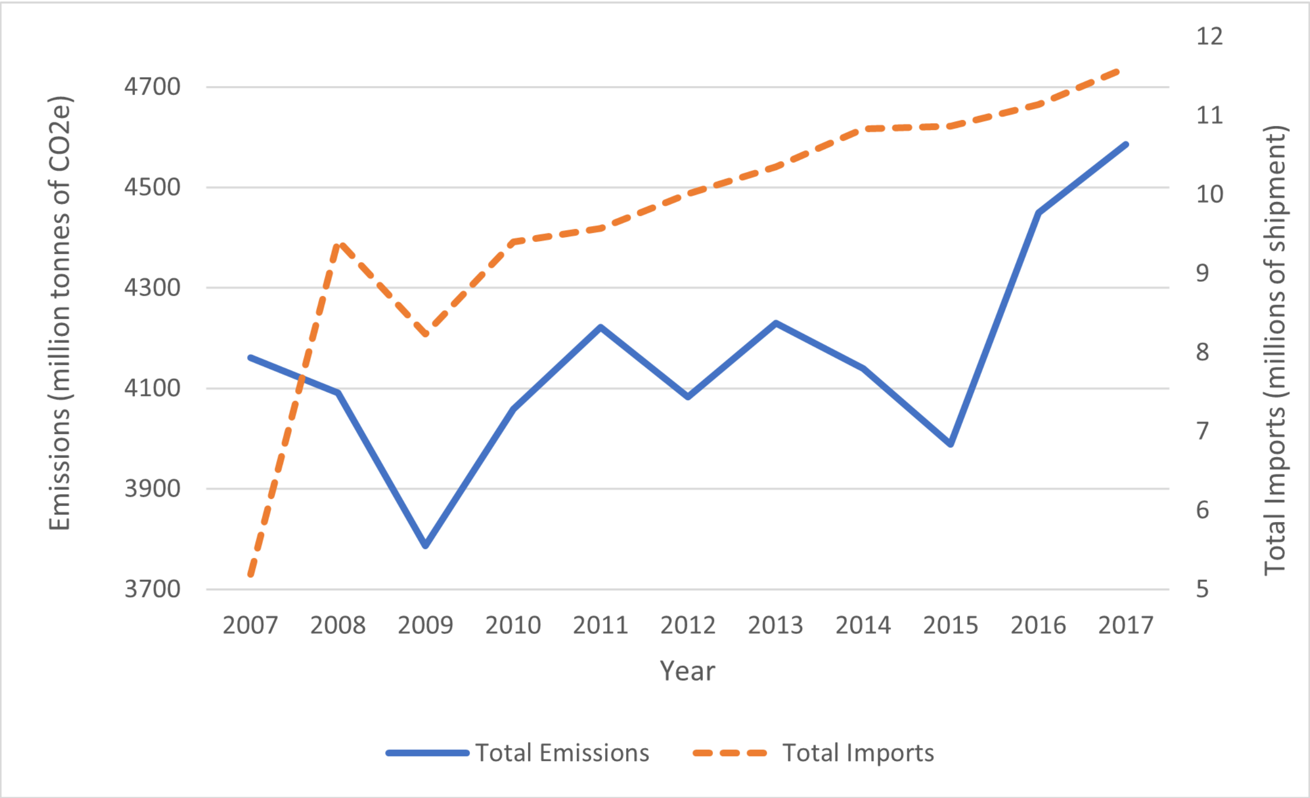

Table 1
Summary Statistics

This table presents summary statistics of the variables in our baseline analysis over the entire sample period from 2006 to 2018. It shows the number of observations (# Obs), mean (Mean), standard deviation (Stdev), minimum (Min), the 25th percentile (P25), median (Median), 75th percentile (P75) and maximum (Max) of each variable. The key variables in raw values show the summary statistics of Scope 1 and upstream Scope 3 emissions reported in thousands of tonnes and *Imports* measured in the number of shipments, number of shipment containers, and shipment volume (Twenty-Foot Equivalent Unit or TEU). The remaining variables are defined in the Appendix. All continuous variables are winsorized at the 5% and 95% of their distribution.

Variable	Obs	Mean	Stdev	Min	P25	Median	P75	Max
Panel A: Key Variables in Raw Values								
Carbon Emissions								
Scope 1 ('000 tonnes)	76,356	2154.832	4979.683	8.772	47.996	176.987	890.000	19335.910
Scope 3 ('000 tonnes)	76,356	4072.593	6513.327	100.040	418.070	1325.301	4257.182	25775.830
Imports								
Import Count	76,356	23.843	45.030	1.000	1.000	4.000	19.000	179.000
Import Container	76,356	34.054	67.737	1.000	2.000	5.000	25.000	271.000
Import Volume (TEU)	76,356	41.474	89.061	0.010	1.000	4.000	26.405	356.150
Panel B: Key Variables in Natural Logarithm								
Ln(Scope 1)	76,356	12.397	2.127	9.079	10.779	12.084	13.699	16.777
Ln(Scope 3)	76,356	14.136	1.538	11.513	12.943	14.097	15.264	17.065
$\text{Ln(Import)}_{Count}$	76,356	0.023	0.042	0.001	0.001	0.004	0.019	0.165
$\text{Ln(Import)}_{Container}$	76,356	0.032	0.061	0.001	0.002	0.005	0.025	0.240
$\text{Ln(Import)}_{Volume}$	76,356	0.037	0.077	0.000	0.001	0.004	0.026	0.305
Panel C: Control Variables (Main)								
Assets	76,356	9.080	1.400	6.718	7.999	8.948	10.143	11.796
Tobin's Q	76,356	1.853	0.826	0.921	1.232	1.614	2.223	4.021
Leverage	76,356	0.261	0.150	0.005	0.152	0.250	0.359	0.571
ROA	76,356	0.108	0.060	0.009	0.064	0.100	0.145	0.235
SalesGrowth	76,356	0.049	0.126	-0.199	-0.023	0.044	0.115	0.321
Tangibility	76,356	0.533	0.320	0.108	0.266	0.460	0.775	1.167
R&D	76,356	0.088	0.131	0.000	0.000	0.018	0.129	0.467

Table 2
The Relationship between Scope 1 and Scope 3 Emissions

This table reports results from the regression of a firm's supplier carbon emissions (*Scope 3*) on its direct emissions (*Scope 1*) as follows.

$$\textit{Scope 3}^{\dagger}_{i,t} = \alpha + \beta_S \textit{Scope 1}^{\dagger}_{i,t} + \beta_{CS}{}' \textit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t},$$

where the vector of *Controls* includes firm-specific *Assets*, *Tobin's Q*, *Leverage*, *ROA*, *SalesGrowth*, *Tangibility*, and *R&D*, and † denotes that the emission is alternately measured in natural log in Columns (1)-(3) and in a proportion to total emissions (Scope 1 + Scope 2 + Upstream Scope 3) in Columns (4)-(6). The definition of variables is detailed in Appendix A. The regression model controls for varying sets of fixed effects (**FE**) including firm, country, and year FE, firm×country and year FE, and firm and country×year FE. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at the 10%, 5%, and 1% levels, respectively.

	Definition of *Scope 3*†					
	Ln(Scope 3)			Propn of Scope 3		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Scope 1†	0.084***	0.084***	0.083***	-0.847***	-0.847***	-0.857***
	(5.57)	(5.66)	(5.49)	(-21.74)	(-21.82)	(-21.75)
Assets	0.706***	0.705***	0.694***	-0.002	-0.002	-0.002
	(19.89)	(19.91)	(19.13)	(-0.39)	(-0.38)	(-0.37)
Tobin's Q	-0.036**	-0.037**	-0.035**	0.003	0.003	0.003
	(-2.36)	(-2.41)	(-2.23)	(1.11)	(1.12)	(1.11)
Leverage	-0.117*	-0.116*	-0.120**	0.012	0.012	0.012
	(-1.90)	(-1.91)	(-1.99)	(0.71)	(0.71)	(0.67)
ROA	2.244***	2.233***	2.138***	0.022	0.023	0.021
	(9.69)	(9.85)	(9.46)	(0.67)	(0.72)	(0.62)
SalesGrowth	0.143***	0.144***	0.160***	0.008	0.008	0.007
	(3.80)	(3.82)	(4.14)	(1.02)	(1.04)	(0.98)
Tangibility	0.449***	0.446***	0.467***	-0.009	-0.009	-0.008
	(4.47)	(4.44)	(4.65)	(-0.60)	(-0.60)	(-0.51)
R&D	0.072	0.079	0.063	-0.173***	-0.170***	-0.175***
	(0.24)	(0.27)	(0.21)	(-3.03)	(-2.99)	(-2.92)
# Obs	76,195	75,886	66,742	76,195	75,886	66,742
Firm, Country, Year FE	Yes	No	No	Yes	No	No
Firm, Country×Year FE	No	Yes	No	No	Yes	No
Firm×Country, Year FE	No	No	Yes	No	No	Yes
Adj. R^2	0.989	0.989	0.989	0.979	0.979	0.977

Table 3
The Effect of Imports on the Scope 1–Scope 3 Emissions Link

This table reports results from the regression of a firm's supplier carbon emissions (*Scope 3*) on its direct emissions (*Scope 1*), imports (*Ln(Import)*), and their interaction, as follows.

$$\begin{aligned} Scope\ 3^{\dagger}_{i,t} &= \alpha + \beta_{SI} Scope\ 1^{\dagger}_{i,t} \times Ln(Import)^{\ddagger}_{i,c,t} + \beta_S Scope\ 1^{\dagger}_{i,t} + \beta_I Ln(Import)^{\ddagger}_{i,t} \\ &+ \beta_{CS}{}' Controls_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where the vector of *Controls* is as defined in Table 2. † denotes that the emission is alternately measured in natural log in Columns (1)-(3) and in a proportion to total emissions (Scope 1 + Scope 2 + Scope 3) in Columns (4)-(6). $Ln(Import)^{\ddagger}$ is measured by $Ln(Import)_{Volume}$, $Ln(Import\ )_{Container}$, and $Ln(Import)_{Count}$ in Columns (1), (2), and (3), (or Columns (4), (5), and (6)), respectively. The definition of variables is detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at the 10%, 5%, and 1% levels, respectively.

	Definition of *Scope 3*†					
	Ln(Scope 3)			Propn of Scope 3		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Scope 1† × Ln(Import)‡	-0.019***	-0.021***	-0.029**	-0.040**	-0.047**	-0.068**
	(-2.82)	(-2.67)	(-2.31)	(-2.51)	(-2.32)	(-2.05)
Scope 1†	0.085***	0.085***	0.085***	-0.846***	-0.846***	-0.846***
	(5.71)	(5.71)	(5.71)	(-21.81)	(-21.82)	(-21.85)
Ln(Import)$_{Volume}$	0.248***			0.009***		
	(3.02)			(2.71)		
Ln(Import)$_{Container}$		0.274***			0.011***	
		(2.86)			(2.68)	
Ln(Import)$_{Count}$			0.371**			0.017***
			(2.44)			(2.68)
Assets	0.704***	0.704***	0.705***	-0.002	-0.002	-0.002
	(19.92)	(19.92)	(19.92)	(-0.39)	(-0.39)	(-0.38)
Tobin's Q	-0.037**	-0.037**	-0.037**	0.003	0.003	0.003
	(-2.42)	(-2.42)	(-2.42)	(1.11)	(1.11)	(1.11)
Leverage	-0.117*	-0.116*	-0.116*	0.012	0.012	0.012
	(-1.92)	(-1.91)	(-1.91)	(0.70)	(0.71)	(0.71)
ROA	2.233***	2.234***	2.234***	0.024	0.024	0.024
	(9.85)	(9.85)	(9.85)	(0.72)	(0.72)	(0.72)
SalesGrowth	0.144***	0.144***	0.144***	0.008	0.008	0.008
	(3.81)	(3.81)	(3.81)	(1.04)	(1.04)	(1.04)
Tangibility	0.446***	0.446***	0.446***	-0.009	-0.009	-0.009
	(4.44)	(4.44)	(4.44)	(-0.60)	(-0.60)	(-0.59)
R&D	0.079	0.079	0.079	-0.170***	-0.170***	-0.170***
	(0.27)	(0.27)	(0.27)	(-2.99)	(-2.99)	(-2.99)
# Obs	75,886	75,886	75,886	75,886	75,886	75,886
Firm, Country×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.988	0.988	0.988	0.979	0.979	0.979

Table 4
Legislative Pressure and Firms' Carbon Emissions

This table presents tests of shocks to legislative pressure and close-call elections using the following regression model with triple-interaction effects:

$$
\begin{aligned}
\mathit{Ln(Scope\ 3)}_{i,t} \quad = \quad & \alpha + \beta_{SI1}\mathit{Ln(Scope\ 1)}_{i,t} \times \mathit{Ln(Import)}^{\ddagger}_{i,c,t} \times Treat_{i,t-1} + \beta_{SI}\mathit{Ln(Scope\ 1)}_{i,t} \times \mathit{Ln(Import)}^{\ddagger}_{i,c,t} \\
& + \beta_{S1}\mathit{Ln(Scope\ 1)}_{i,t} \times Treat_{i,t-1} + \beta_{I1}\mathit{Ln(Import)}^{\ddagger}_{i,c,t} \times Treat_{i,t-1} + \beta_{S}\mathit{Ln(Scope\ 1)}_{i,t} \\
& + \beta_{I}\mathit{Ln(Import)}^{\ddagger}_{i,c,t} + \beta_{1}Treat_{i,t-1} + \beta_{CS}{}'\mathit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t},
\end{aligned}
$$

where *Treat* is a binary indicator that alternately captures four different representations. In Column (1), *Treat* equals one for five years if the lagged state-average Congress member environmental voting score increases more than three times the mean score increase over time, where environmental voting score is defined as the number of votes each Congress member made in favor of the environmental bills scaled by the total number of climate change-specific environmental legislations considered in the year; such shock must not revert back within the next three years, and it must not be driven by changes in firm locations. In Columns (2)-(3), a shock to each state depends on the number of close-election wins relative to close-election losses for environmentally-conscious candidates. For each house and senate candidate elected in a state-election year, a close-win (close-loss) is defined as a win (loss) where the vote-share difference between the winning and runner-up candidates is 5% or less (i.e. within a 2.5% bandwidth from the 50% threshold for winning elections). Close-wins (close-losses) are summed across all environmentally-conscious candidates, where an environmentally-conscious candidate is a Democrat for Column (2) or has a lifetime environmental voting score of 60 or above for Column (3). *Treat* equals one for the next two years if the number of close-wins net of close-losses is greater than 0, and 0 otherwise. In Column (4), we repeat the test in Column (2) with Republicans being the close-win candidates. It serves as a placebo test to close-call election analysis. $\mathit{Ln(Import)}^{\ddagger}$ is measured by $\mathit{Ln(Import)}_{Volume}$. *Ln(Scope 1)* and *Ln(Scope 3)* are a firm's Scope 1 and upstream Scope 3 emissions, measured in natural log. *Controls* are as defined in Table 2. The definition of variables is contained in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Full Sample	Close-Election Sample		
		Definition of *Treat*		
	Congress	Democrat	Green Candidate	Republican
Variable	(1)	(2)	(3)	(4)
Ln(Scope 1)×Ln(Import)$_{Volume}$×Treat	-0.015*	-0.088*	-0.079*	0.018
	(-1.78)	(-1.91)	(-1.76)	(1.26)
Ln(Scope 1)×Ln(Import)$_{Volume}$	-0.002	-0.033*	-0.044*	-0.013**
	(-0.54)	(-1.75)	(-1.69)	(-1.96)
Ln(Scope 1)×Treat	-0.002	0.015**	0.025**	0.022***
	(-0.34)	(2.21)	(2.42)	(2.59)
Ln(Import)$_{Volume}$×Treat	0.178*	0.975*	0.783	-0.190
	(1.72)	(1.72)	(1.47)	(-1.12)
Ln(Scope 1)	0.087***	0.127***	0.125***	0.090***
	(5.76)	(4.66)	(4.22)	(4.01)
Ln(Import)$_{Volume}$	0.031	0.493*	0.670**	0.150*
	(0.65)	(1.95)	(2.07)	(1.93)
Treat	0.037	-0.167**	-0.303**	-0.262**
	(0.44)	(-2.02)	(-2.34)	(-2.54)
# Obs	75,886	36,482	28,435	21,551
Controls	Yes	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.989	0.989	0.989	0.988

Table 5
State Regulatory Stringency and Firm Carbon Emissions

This table presents tests of shocks to state regulatory stringency using the following regression model with triple-interaction effects:

$$\begin{aligned} Ln(Scope\ 3)_{i,t} \quad = \quad & \alpha + \beta_{SI1} Ln(Scope\ 1)_{i,t} \times Ln(Import)^{\ddagger}_{i,c,t} \times Stringency_{i,t-1} + \beta_{SI} Ln(Scope\ 1)_{i,t} \times Ln(Import)^{\ddagger}_{i,c,t} \\ & + \beta_{S1} Ln(Scope\ 1)_{i,t} \times Stringency_{i,t-1} + \beta_{I1} Ln(Import)^{\ddagger}_{i,c,t} \times Stringency_{i,t-1} + \beta_S Ln(Scope\ 1)_{i,t} \\ & + \beta_I Ln(Import)^{\ddagger}_{i,c,t} + \beta_1 Stringency_{i,t-1} + \beta_{CS}{}' Controls_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where *Stringency* is a binary indicator that alternately captures four different representations. In Column (1), a shock at the state-level is when a state enacts an executive/statutory target to limit its GHG emissions, and *Stringency* equals one for the next five years if the state enacts a GHG emission target in year $t-1$. In Column (2), *Stringency* equals one for five years if the lagged EPA onsite inspection intensity increases more than three times the average inspection increase in the state; such shock must not revert back within the next three years, and it must not be driven by changes in firm locations. Columns (3) and (4) conduct the tests in the year before the state-level statutory/executive target and EPA inspection spike, serving as placebo tests to state-level regulatory stringency shocks. *Ln(Import)*‡ is measured by *Ln(Import)*$_{Volume}$. *Ln(Scope 1)* and *Ln(Scope 3)* are a firm's Scope 1 and upstream Scope 3 emissions, measured in natural log. *Controls* are as defined in Table 2. The definition of variables is detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	State-Level Shocks		Placebo Tests	
	Definition of *Stringency*			
	GHG Target	Onsite	GHG Target	Onsite
Variable	(1)	(2)	(3)	(4)
Ln(Scope 1)×Ln(Import)$_{Volume}$×Stringency	-0.024*	-0.056**	-0.039	-0.028
	(-1.77)	(-2.02)	(-1.42)	(-0.66)
Ln(Scope 1)×Ln(Import)$_{Volume}$	-0.007**	-0.012**	-0.007***	-0.017***
	(-2.28)	(-2.07)	(-2.82)	(-2.77)
Ln(Scope 1)×Stringency	0.023**	-0.003	0.018	0.011
	(2.09)	(-0.36)	(1.11)	(1.06)
Ln(Import)$_{Volume}$×Stringency	0.296*	0.752**	0.460	0.348
	(1.75)	(2.23)	(1.41)	(0.66)
Ln(Scope 1)	0.100***	0.086***	0.079***	0.085***
	(6.12)	(5.72)	(5.53)	(5.68)
Ln(Import)$_{Volume}$	0.086**	0.156**	0.092***	0.233***
	(2.38)	(2.19)	(2.91)	(2.98)
Stringency	-0.279**	0.067	-0.208	-0.131
	(-2.11)	(0.63)	(-1.13)	(-1.08)
# Obs	75,886	75,886	75,886	75,886
Controls	Yes	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.990	0.989	0.990	0.989

Table 6
Industry Carbon Emissions and Supplier Environmental Regulations

This table reports results using the triple-interaction model regression of a firm's supplier carbon emissions (*Ln(Scope 3)*) on its direct emissions (*Ln(Scope 1)*), imports (*Ln(Import)$_{Volume}$*), and a binary indicator capturing the firm's industry emission level and its outsourcing-country environmental regulatory stringency, and their triple interaction (*Ln(Scope 1)* × *Ln(Import)*)× *Indicator*), as follows.

$$\begin{aligned} \textit{Ln(Scope 3)}_{i,t} &= \alpha + \beta_{SI1} \textit{Ln(Scope 1)}_{i,t} \times \textit{Ln(Import)}^{\ddagger}_{i,c,t} \times \textit{Indicator}_t + \beta_{SI} \textit{Ln(Scope 1)}_{i,t} \times \textit{Ln(Import)}^{\ddagger}_{i,c,t} \\ &\quad + \beta_{S1} \textit{Ln(Scope 1)}_{i,t} \times \textit{Indicator}_t + \beta_{I1} \textit{Ln(Import)}^{\ddagger}_{i,c,t} \times \textit{Indicator}_t + \beta_S \textit{Ln(Scope 1)}_{i,t} \\ &\quad + \beta_I \textit{Ln}(\textit{Import})^{\ddagger}_{i,c,t} + \beta_1 \textit{Indicator}_t + \beta_{CS}{}' \textit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where *Indicator* is a binary indicator that alternately captures four different representations, namely above-median emission industries measured based on the Fama-French 30 industries in Column (1) and NAICS industries requiring above-median pollution-intensive inputs in Column (2), and countries with below-median enforcement of environmental regulations score (EER) in Column (3) and below-median stringency of environmental regulation score (SER) in Column (4). The *Indicator* coefficient is not reported in the last two columns as it is subsumed by country × year fixed effect. *Ln(Import)*‡ is measured by *Ln(Import)$_{Volume}$*. *Ln(Scope 1)* and *Ln(Scope 3)* are a firm's Scope 1 and upstream Scope 3 emissions, measured in natural log. *Controls* are as defined in Table 2. The definition of variables is detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Definition of *Indicator*			
	Above-Median Emissions		Country with Below-Median	
	FF Industries	NAICS Industries	EER	SER
Variable	(1)	(2)	(3)	(4)
Ln(Scope 1) × Ln(Import)$_{Volume}$× Indicator	-0.026**	-0.029**	-0.006*	-0.006**
	(-2.15)	(-2.17)	(-1.86)	(-2.00)
Ln(Scope 1) × Ln(Import)$_{Volume}$	-0.002	-0.003	-0.004*	-0.004**
	(-0.27)	(-0.34)	(-1.93)	(-1.98)
Ln(Scope 1) × Indicator	0.016	-0.004	0.001	0.002
	(1.40)	(-0.35)	(1.03)	(1.18)
Ln(Import)$_{Volume}$× Indicator	0.329**	0.379**	0.082*	0.078*
	(2.19)	(2.34)	(1.83)	(1.93)
Ln(Scope 1)	0.075***	0.085***	0.084***	0.084***
	(4.74)	(5.25)	(5.72)	(5.73)
Ln(Import)$_{Volume}$	0.038	0.054	0.055**	0.057**
	(0.40)	(0.45)	(2.10)	(2.14)
Indicator	-0.164	0.086		
	(-1.26)	(0.71)		
# Obs	75,886	74,910	72,569	72,569
Controls	Yes	Yes	Yes	Yes
Firm, CountryxYear FE	Yes	Yes	Yes	Yes
Adj. R^2	0.989	0.989	0.989	0.989

Table 7
Internal Mechanisms

This table reports results showing the various internal mechanisms (*Internal*) through which a firm's direct emissions (*Ln(Scope 1)*) and imports ($Ln(Import)_{Volume}$) affect its suppliers' emissions (*Ln(Scope 3)*), using the following model specification.

$$\begin{aligned} Ln(Scope\ 3)_{i,t} \quad = \quad & \alpha + \beta_{SI1} Ln(Scope\ 1)_{i,t} \times Ln(Import)^{\ddagger}_{i,c,t} \times Internal_{t-1} + \beta_{SI} Ln(Scope\ 1)_{i,t} \times Ln(Import)^{\ddagger}_{i,c,t} \\ & + \beta_{S1} Ln(Scope\ 1)_{i,t} \times Internal_{t-1} + \beta_{I1} Ln(Import)^{\ddagger}_{i,c,t} \times Internal_{t-1} + \beta_S Ln(Scope\ 1)_{i,t} \\ & + \beta_I Ln(Import)^{\ddagger}_{i,c,t} + \beta_1 Internal_{t-1} + \beta_{CS}{}' Controls_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where *Internal* alternately represents: (1) Firm Greenness as proxied by the decile ranking of a firm's ESG score; (2) CEO Greenness, the decile ranking of average ESG score of firms in which the CEO has worked during the past five years; (3) Board Greenness, the decile ranking of average ESG score of firms affiliated with the directors during the past five years. $Ln(Import)^{\ddagger}$ is measured by $Ln(Import)_{Volume}$. *Ln(Scope 1)* and *Ln(Scope 3)* are a firm's Scope 1 and upstream Scope 3 emissions, measured in natural log. *Controls* are as defined in Table 2. The definition of variables is detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Definition of *Internal*		
	Firm Greenness	CEO Greenness	Board Greenness
Variable	(1)	(2)	(3)
Ln(Scope 1) × $\text{Ln(Import)}_{Volume}$× Internal	-0.002**	-0.002*	-0.002*
	(-2.02)	(-1.70)	(-1.78)
Ln(Scope 1) × $\text{Ln(Import)}_{Volume}$	0.004	0.007	0.008
	(0.94)	(1.37)	(1.47)
Ln(Scope 1) × Internal	-0.002*	-0.009***	-0.009***
	(-1.78)	(-2.73)	(-2.68)
$\text{Ln(Import)}_{Volume}$× Internal	0.019*	0.023*	0.023*
	(1.81)	(1.66)	(1.72)
Ln(Scope 1)	0.101***	0.140***	0.137***
	(4.99)	(4.87)	(4.76)
$\text{Ln(Import)}_{Volume}$	-0.036	-0.084	-0.084
	(-0.66)	(-1.25)	(-1.31)
Internal	0.021*	0.115***	0.113***
	(1.76)	(2.94)	(2.88)
# Obs	65,101	64,034	64,566
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Adj. R^2	0.988	0.988	0.988

Table 8
External Mechanisms

This table reports results showing the various external mechanisms (*External*) through which a firm's direct emissions (*Ln(Scope 1)*) and imports ($Ln(Import)_{Volume}$) affect its suppliers' emissions (*Ln(Scope 3)*), using the following model specification.

$$\begin{aligned} Ln(Scope\ 3)_{i,t} \quad = \quad & \alpha + \beta_{SI1} Ln(Scope\ 1)_{i,t} \times Ln(Import)^{\ddagger}_{i,c,t} \times External_{t-1} + \beta_{SI} Ln(Scope\ 1)_{i,t} \times Ln(Import)^{\ddagger}_{i,c,t} \\ & + \beta_{S1} Ln(Scope\ 1)_{i,t} \times External_{t-1} + \beta_{I1} Ln(Import)^{\ddagger}_{i,c,t} \times External_{t-1} + \beta_S Ln(Scope\ 1)_{i,t} \\ & + \beta_I Ln(Import)^{\ddagger}_{i,c,t} + \beta_1 External_{t-1} + \beta_{CS}{}' Controls_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where *External* alternately represents: (1) Govt Customer, the percentage sales to a firm's largest government customer; (2) Customer Greenness, the percentage sales to a firm's largest corporate customer with above industry-median ESG score; (3) Blockholder Greenness, the percentage of shares owned by blockholders with at least half of their portfolio holdings invested in green firms ranked in the top quintile on their ESG scores. $Ln(Import)^{\ddagger}$ is measured by $Ln(Import)_{Volume}$. *Ln(Scope 1)* and *Ln(Scope 3)* are a firm's Scope 1 and upstream Scope 3 emissions, measured in natural log. *Controls* are as defined in Table 2. The definition of variables is detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Definition of *External*		
	Govt Customer	Customer Greenness	Blockholder Greenness
Variable	(1)	(2)	(3)
Ln(Scope 1) × $Ln(Import)_{Volume}$ × External	0.002**	0.379***	0.865**
	(2.09)	(2.67)	(2.04)
Ln(Scope 1) × $Ln(Import)_{Volume}$	-0.029***	-0.072***	-0.022***
	(-2.69)	(-3.10)	(-3.52)
Ln(Scope 1) × External	0.001	-0.016	-0.183***
	(1.01)	(-0.17)	(-2.78)
$Ln(Import)_{Volume}$× External	-0.028**	-4.167***	-8.856*
	(-2.02)	(-2.60)	(-1.82)
Ln(Scope 1)	0.062***	0.096***	0.083***
	(2.93)	(3.09)	(5.55)
$Ln(Import)_{Volume}$	0.402***	0.842***	0.281***
	(3.00)	(3.11)	(3.54)
External	-0.005	-0.010	2.455***
	(-0.57)	(-0.01)	(2.96)
# Obs	32,142	14,778	72,115
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Adj. R^2	0.990	0.990	0.989

Table 9
Pollution Reduction Activities and Firm Carbon Emissions

This table reports regression results showing the effects of a firm's Scope 1, Scope 3, and imported carbon emissions on its pollution reduction activities, including the likelihood of seeking at least one foreign supplier, the likelihood of adopting a pollution abatement measure, and the development of green innovation, in Columns (1), (2), and (3), respectively. We estimate the following model,

$$\begin{aligned} Activity_{i,t+j} &= \alpha + \beta_1 Ln(Scope\ 1)_{i,t} + \beta_2 Ln(Scope\ 3)_{i,t} + \beta_3 Ln(Import\ CO_2)_{i,t} + \beta'_{CS} Controls_{i,t} \\ &\quad + \mathbf{FE} + \epsilon_{i,t}. \end{aligned}$$

where *Activity*, alternately, represents *Foreign Supplier*, *Pollution Abatement*, and *Green Innovation*. *Foreign Supplier* equals 1 if the firm imports from at least one foreign supplier in the following year; 0 otherwise. Following Appel and Akey (2019), we employ a binary indicator (*Pollution Abatement*) to measure a firm's investment in abatement activities associated with reducing the amount of hazardous substances entering the waste stream. *Pollution Abatement* equals 1 if the firm reports at least one abatement activity in year $t+1$ that reduces a chemical production in the following categories: 1) operating practices, 2) inventory control, 3) spill and leakage, 4) raw material modifications, 5) process modifications, 6) cleaning and degreasing, 7) surface preparation and finishing, or 8) product modifications; 0 otherwise. *Green Innovation* is the log number of green patents filed by the firm in year *t+2*, where green patents are those classified as environmentally sound technologies by WIPO based on their IPC patent classes. Results in Columns (1) and (2) are estimated using a linear probability model, and those in Column (3) are based on a linear regression model. The firm's sources of CO_2 emissions include direct emissions from its own production (*Ln(Scope 1)*), emissions from its suppliers (*Ln(Scope 3)*), and more specifically emissions from imported input goods (*Ln(Import CO_2)*). In Column (1)†, *Ln(Scope 1)* denotes only the domestic portion of Scope 1 emissions, where we use the ratio of total assets net of foreign assets to total assets as a multiplier for the domestic component of a firm's own emissions. *Controls* include firm-specific *Age*, *Size*, *Tobin's Q*, *Leverage*, *PPE*, *ROA*, *CapEx*, *R&D*, and *HHI*. The definition of variables is detailed in Appendix A. The model controls for either firm and year fixed effects, or firm, chemical, and year fixed effects. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Foreign Supplier	Pollution Abatement	Green Innovation
Variable	(1)†	(2)	(3)
Ln(Scope 1)	0.006*	0.029**	-0.016
	(1.69)	(2.54)	(-0.64)
Ln(Scope 3)		-0.005	-0.014
		(-0.13)	(-0.39)
Ln(Imported CO_2)		-0.019**	-0.049**
		(-1.99)	(-2.44)
# Obs	7,412	12,837	4,470
Controls	Yes	Yes	Yes
Firm, Year FE	Yes	No	Yes
Firm, Chemical, Year FE	No	Yes	No
Adj. R^2	0.826	0.399	0.751

Table 10
Firm Profitability, Operating Efficiency, and Carbon Emissions

This table reports regression results showing the effects of a firm's Scope 1, Scope 3, and imported carbon emissions on its operating performance in Columns (1)-(3), implied cost of equity in Column (4), and firm value in Column (5). We estimate the following model,

$$\begin{aligned}\text{Firm Performance}_{,i,t+1} \quad &= \quad \alpha + \beta_1 \textit{Ln(Scope 1)}_{i,t} + \beta_2 \ \textit{Ln(Scope 3)}_{i,t} + \beta_3 \textit{Ln(Import CO}_2\textit{)}_{i,t} \\ &\quad + \beta_{CS}' \textit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t},\end{aligned}$$

where *Firm Performance* is alternately defined by Return on Assets (ROA), EBIT Margin, Asset Utilization, implied cost of equity capital (ICC), and Tobin's Q. The firm's sources of CO_2 emissions include direct emissions from its own production (*Ln(Scope 1)*), emissions from its suppliers (*Ln(Scope 3)*), and more specifically emissions from imported input goods (*Ln(Import* CO_2*)*). *Controls* include firm-specific *Assets*, *Tobin's Q* (except in Column (5)), *R&D*, *Advertising Expenditure*, *Leverage*, *CapEx*, *Cash*, *Income Volatility*, *ROE*, and *EPS Growth*. The definition of variables is detailed in Appendix A. The model controls for firm and year fixed effects. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	ROA	EBIT Margin	Asset Utilization	ICC	Tobin's Q
Variable	(1)	(2)	(3)	(4)	(5)
Ln(Scope 1)	0.001	-0.000	-0.001	-0.001	0.007
	(0.91)	(-0.10)	(-0.18)	(-1.19)	(0.33)
Ln(Scope 3)	0.011***	0.015**	0.130***	0.012***	-0.064*
	(2.64)	(2.20)	(4.40)	(4.13)	(-1.91)
Ln(Import CO_2)	0.001	0.003	-0.002	0.001*	-0.013
	(0.72)	(0.96)	(-0.31)	(1.66)	(-0.51)
# Obs	7,077	7,077	7,077	5,781	6,537
Controls	Yes	Yes	Yes	Yes	Yes
Firm, Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.746	0.715	0.940	0.485	0.821

Table 11
Reputational Risk, Stock Returns, and Carbon Emissions

This table reports regression results showing effects of a firm's Scope 1, Scope 3, and imported carbon emissions on a firm's future stock returns in Columns (1)-(4) and its systematic reputational risk associated with ESG practices in Columns (5)-(8). The models are presented as follows:

$$Stock\ Returns_{,i,t+1}\ or\ RepRisk\ \beta_{,i,t} \quad = \quad \alpha + \beta_1 Ln(Scope\ 1)_{i,t} + \beta_2\ Ln(Scope\ 3)_{i,t} + \beta_3 Ln(Import\ CO_2)_{i,t} + \beta'_{CS} Controls^{\dagger}_{i,t} + \mathbf{FE} + \epsilon_{i,t},$$

where *Stock Returns*$_{i,t+1}$ are the monthly returns in year $t+1$, and *RepRisk* $\beta_{i,t}$ is the factor loading obtained from regressing individual firms' daily stock returns on the difference between high and low reputational-risk quintile portfolios and those of the Fama-French-Carhart 4-factor model in year t. The firm's sources of CO_2 emissions include direct emissions from its own production (*Ln(Scope 1)*), emissions from its suppliers (*Ln(Scope 3)*), and more specifically emissions from imported input goods (*Ln(Import* CO_2*)*). Columns (1)-(4) employ the usual firm-level control variables that can predict future stock returns, including *Size*, *BM*, *Leverage*, *PPE*, *CapEx*, *Momentum*, *Return Volatility*, *Beta*, and *HHI*. *Controls*† for Columns (5)-(8) are firm-specific *Assets*, *Tobin's Q*, *R&D*, *Advertising Expenditure*, *Leverage*, *CapEx*, *Cash*, *Income Volatility*, *ROA* that can potentially affect *RepRisk* $\beta_{i,t}$ and measured at $t-1$. The definition of variables is detailed in Appendix A. The model controls for either firm and month fixed effects, or firm and year fixed effects. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Stock Returns at year $t+1$				RepRisk β at year t			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Scope 1)	0.001**			0.001	-0.023			-0.041
	(2.23)			(1.44)	(-0.83)			(-1.47)
Ln(Scope 3)		0.004**		0.004**		0.115**		0.137***
		(2.43)		(2.09)		(2.29)		(2.69)
Ln(Import CO_2)			0.001**	0.001*			0.037*	0.049**
			(2.00)	(1.86)			(1.65)	(2.03)
# Obs	67,916	67,916	67,916	67,916	6,068	6,068	6,386	6,068
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, Month FE	Yes	Yes	Yes	Yes				
Firm, Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Adj. R^2	0.030	0.030	0.030	0.030	0.361	0.362	0.363	0.364

Appendix Table A

Variable Definition and Data Source

Variable	**Definition and Data Source**
Measures of Firm-level Carbon Emissions and Imports	
Ln(Scope 1)	ln(1 + Scope 1 emissions), where Scope 1 refers to direct GHG emissions that occur from sources controlled or owned by the firm (e.g., emissions associated with fuel combustion in boilers, furnaces, vehicles). (Trucost)
Ln(Scope 3)	ln(1 + upstream Scope 3 emissions), where upstream Scope 3 refers to indirect GHG emissions caused by activities of the firm but occur from the firm's suppliers. (Trucost)
Propn of Scope 1	The ratio of Scope 1 emissions to total emissions (Scope 1 + Scope 2 + Upstream Scope 3), where Scope 2 emissions are indirect emissions from the generation of purchased electricity, steam, heating and cooling consumed by the reporting firm. (Trucost)
Propn of Scope 3	The ratio of upstream Scope 3 emissions to total emissions (Scope 1 + Scope 2 + Upstream Scope 3). (Trucost)
Ln(Import)$_{Volume}$	ln(1 + the volume of shipment, measured in twenty-foot equivalent unit, from suppliers in each exporting country). (Panjiva)
Ln(Import)$_{Container}$	ln(1 + the number of shipment containers from suppliers in each exporting country). (Panjiva)
Ln(Import)$_{Count}$	ln(1 + the number of shipments from suppliers in each exporting country). (Panjiva)
Ln(Import CO_2)	ln(1 + the aggregated amount of estimated GHG emission imported from suppliers overseas). The aggregated amount of GHG emissions is measured as metric tons of CO_2 equivalent into the air from the production of all imported goods (per $1 million economic activity) over all shipment containers (in the unit of TEU) in a given year. In particular, we adopted the EIO-LCA GHG emission model from Carnegie Mellon. We use the industry code corresponding to the imported goods and importer's primary industry codes as input and output industry codes, respectively, to approximate the outsourced CO_2 emission intensity at shipment level. The imported good's industry is based on the six-digit HS Code from Panjiva and the HS to NAICS table from Peter K. Schott Website, and the importer's primary industry NAICS code is from Compustat. The EIO-LCA GHG emission model is constructed from the BEA Input-Output model, the IPCC Second Assessment Report, and other resources. (Panjiva & EIO-LCA & Peter K. Schott Website & Compustat)
Identification Variables	
Congress	A binary variable equals 1 for five years if the lagged state-level average Congress member environmental voting score increases more than three times the mean score increase over time (i.e. time-series average of score increase), and the score does not revert back within the next three years and it is not driven by changes in firm locations. Congress member environmental voting score is defined as the number of votes each Congress member made in favor of the environmental bills scaled by the total number of climate change-specific environmental legislations considered in the year. The average is then taken across each state to proxy for the overall environmental-consciousness of a state. (League of Conservation Voters)
Democrat	A binary variable equals 1 for the next two years after the close-call election win by Democratic candidates in year $t-1$ until the next election cycle. (League of Conservation Voters)
Green Candidate	A binary variable equals 1 for the next two years after the close-call election win by a candidate with a lifetime environmental voting score of at least 60% in year $t-1$ until the next election cycle, where lifetime voting score is defined as the average of all the historical scores recorded for the candidate. (League of Conservation Voters)

Appendix A – Continued

Variable Definition and Data Source

Variable	Definition and Data Source
Identification Variables – Continued	
Republican	A binary variable equals 1 for the next two years after the close-call election win by Republican candidates in year $t-1$ until the next election cycle. (League of Conservation Voters)
GHG Target	A binary variable equals 1 for five years starting from one year after the state enactment of executive or statutory targets to limit carbon emissions. (C2ES)
Onsite	A binary variable equals 1 for the next five years if the lagged increase in onsite inspection intensity is more than three times the average inspection increase in the state, where an onsite inspection intensity is defined as the total number of onsite air pollution compliance evaluations conducted by EPA across all facilities located in the state divided by the total number of emitting facilities in that state and year. (ICIS-Air)
Internal Mechanism Variables	
Firm Greenness	The decile ranking of a firm's ESG score, defined as a combined score based on the reported information in the environmental, social and corporate governance pillars with an ESG controversies overlay. (Refinitiv ESG)
CEO Greenness	The decile ranking of a CEO's previously associated firm ESG scores in the past 5 years, where associated firms are those in which the CEO has worked. For each CEO, an average ESG score is taken across all associated firms over years $t-5$ to $t-1$ and a decile ranking is assigned among all CEOs. (BoardEx & Refinitiv ESG)
Board Greenness	The decile ranking of directors' previously affiliated firm ESG scores in the past 5 years. For each director, an average ESG score is taken across all affiliated firms over years $t-5$ to $t-1$. An average score across all directors of the firm is then taken before a decile ranking is assigned. (BoardEx & Refinitiv ESG)
External Mechanism Variables	
Gov Customer	Percentage sales to a firm's largest government customer. (Compustat Customer Segment)
Customer Greenness	Percentage sales to a firm's largest corporate customer with above industry-median ESG score. (Revere & Refinitiv ESG)
Blockholder Greenness	Percentage of shares owned by blockholders with at least half of their portfolio holdings invested in green firms ranked in the top quintile on their ESG scores. (FactSet Ownership & Refinitiv ESG)
Pollution Reduction Activities	
Foreign Supplier	A binary variable that equals 1 if the firm has at least one foreign supplier in the following year and 0 if otherwise. (Revere)
Pollution Abatement	A binary variable that equals 1 if the firm reports at least one abatement activity in the following year that reduces a chemical production in one of the activity categories: 1) operating practices, 2) inventory control, 3) spill and leakage, 4) raw material modifications, 5) process modifications, 6) cleaning and degreasing, 7) surface preparation and finishing, and 8) product modifications, and 0 if otherwise. (EPA's Pollution Preventation database)
Green Innovation	Two-year ahead log number of green patents filed by the firm, where green patents are those classified as environmentally sound technologies by WIPO based on their IPC patent classes. (PATSTAT & WIPO)

Appendix A – Continued

Variable Definition and Data Source

Variable	Definition and Data Source
Operating Performance, Reputational Risk, and Stock Returns	
EBIT Margin	Earnings before interest and taxes scaled by sales. (Compustat)
ROA	Operating income before depreciation scaled by total assets. (Compustat)
Asset utilization	The ratio of sales to total assets (Compustat).
ICC	Implied cost of equity calculated by taking the average of four different cost of equity estimates following the methodologies outlined in Claus and Thomas (2001), Gebhardt, Lee, and Swaminathan (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005). (IBES)
RepRisk β	The factor loading on the difference between the daily value-weighted return of two portfolios based on firm-level reputational risk based on ESG-related news after controlling Fama-French-Carhart 4 Factors. (RepRisk & CRSP)
Stock Returns	Monthly stock returns. (CRSP)
Control Variables (Main)	
Assets	ln(1 + total assets). (Compustat)
Tobin's Q	Total assets plus the market value of equity minus the book value of equity minus deferred taxes divided by total assets. (Compustat)
Leverage	Total debt scaled by total assets. (Compustat)
ROA	Earnings before interest and taxes scaled by total assets. (Compustat)
SalesGrowth	Annual percentage change in sales. (Compustat)
Tangibility	Gross property, plant, and equipment scaled by total assets. (Compustat)
R&D	Cumulative R&D expenditure scaled by total assets over time since 1985 with a decay rate of 15% each year, where missing values for R&D expenditure are replaced by zero. (Compustat)
Control Variables (Implications)	
Age	ln(1 + current fiscal year of a firm − the first year the firm appears in Compustat). (Compustat)
Size	ln(1 + market capitalization). (Compustat)
BM	Book value of equity divided by market value of equity. (Compustat)
PPE	ln(1 + gross property, plant, and equipment). (Compustat)
CapEx	Capital expenditure divided by total assets. (Compustat)
Advertising Expenditure	Advertising expenditure divided by total assets. (Compustat)
Momentum	Cumulative monthly stock return over one-year period. (CRSP)
Return Volatility	Monthly stock return volatility over one-year period. (CSRP)
Beta	CAPM beta calculated over one-year period. (CRSP)
HHI	Herfindahl-Hirschman index measured by the summation of sales-based squared market share of each firm within the same 3-digit SIC industry. (Compustat)
Cash	Cash and marketable securities divided by (total assets − cash and marketable securities). (Compustat)
Income Volatility	Standard deviation of income before extraordinary items per share over the past five years. (Compustat)
ROE	Earnings before interest and taxes scaled by the book value of equity. (Compustat)
EPS Growth	The difference between current year and previous year earnings per share divided by the previous year earnings per share. (Compustat)