Outsourcing Climate Change

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Abstract

This paper exploits newly available information on firms' direct (own production) and indirect (supplier-generated) carbon emission intensities and transaction-level imports to conduct an in-depth analysis of whether and how U.S. firms address climate change. We find robust evidence that when firms increase their imports, their own emissions fall with a corresponding rise in supplier-generated emissions. Several quasi-natural experiments further support this pivotal evidence that U.S. firms outsource some of their pollutions abroad. We show that firms, management, and directors with desires to maintain high environmental standings and environmentally-conscious customers and investors play a role in corporate environmental policies. Finally, firms with more imported emissions tend to have higher reputational risks and larger future stock returns but are less incentivized to develop clean technologies.

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JEL classification: G23, G30, G34, M14

We are now in a world where companies work to enhance corporate values by integrating climate change into their business strategies, rather than considering environmental actions simply as costs.[1]

1. Introduction

Climate change is driving new political and economic realities for businesses. Many large U.S. corporations are integrating climate change into their business strategies in response to pressures from regulatory authorities, environmental activists, climate-conscious consumers, and investors. The Deloitte Resources 2019 Study finds that 84% of the surveyed business decision-makers were aware of the dire U.S. and global climate-change reports issued in late 2018, and two-thirds of these decision-makers have reviewed or changed their energy management strategies in response.[2] Several CEOs also have announced their commitments to move their companies to net-zero carbon emissions. For example, Microsoft has been carbon neutral since 2012, and Amazon is targeting a net-zero carbon footprint by 2040.[3] A natural question that arises is whether U.S. corporations are indeed integrating climate change into their business strategies or their public commitments to a better environment are simply cheap talk. Our study addresses this important question by examining whether and how U.S. firms reduce their carbon footprints to tackle climate change. Specifically, we investigate whether firms curb their own domestic emissions in the U.S. by outsourcing their carbon pollution to suppliers overseas, resulting in "carbon leakage." We also explore the underlying mechanisms that drive firms' efforts toward reducing direct emissions and evaluate the economic consequences of their actions by analyzing pricing and welfare implications of their emission-reducing efforts.

Since the adoption of the Sustainable Development Goals and the Paris Agreement in 2015,[4]

[1] See Foreword of Mr. Yoshiaki Harada, Minister of the Environment, Government of Japan in CDP Disclosure Insight Action "Cascading Commitments Driving Ambitious Action through Supply Chain Engagement." https://6fefcbb86e61af1b2fc4-c70d8ead6ced550b4d987d7c03fcdd1d.ssl.cf3.rackcdn.com/cms/reports/documents/000/004/072/original/CDP_Supply_Chain_Report_2019.pdf?1550490556

[2] The study is based on 600 online interviews with business decision-makers responsible for energy management practices at companies with more than 250 employees across all industries. https://www2.deloitte.com/content/dam/insights/us/articles/5065_Global-resources-study/DI_Global-resources-study.pdf

[3] https://www.bizjournals.com/seattle/news/2020/01/16microsoft-tech-carbon-negative-brad-smith-nadella.html

[4] https://unfoundation.org/what-we-do/issues/sustainable-development-goals/?gclid=CjwKCAjw0_T4BRBlEiwAwoEiAf_P6BRIxqStMpkNl2lp3P-_yqTVnYy9v17fyNskzWaqc4ZO7Olh3hoCLiAQAvD_BwE

an increasing number of companies recognize the risks and opportunities associated with climate change and are taking actions to meet future greenhouse gas (GHG) reduction targets and a 100% renewable electricity commitment (RE100). Thus far, however, there has been little evidence found to support such commitments and actions. Anecdotal media reports suggest that while firms' efforts seem reasonably progressive, a closer look reveals that firms are committed only to GHG emissions from their own production (i.e., Scope 1 emissions) and energy consumption (i.e., Scope 2 emissions). These firms largely ignore indirect emissions from the supply of goods and services used as inputs of their production (i.e., Scope 3 emissions) that form the bulk of their total GHG emissions.[5] For example, according to a previous mention of P&G by the Natural Resources Defense Council, the company's commitments to halve pollution by 2030 only apply to Scopes 1 and 2 emissions.[6] P&G emits about 215 million metric tons of GHG per year, only 4.3 million of which are attributed to Scopes 1 and 2. Hence, the GHG target only applies to 2% of P&G's total emissions level, and a 50% reduction will only lead to a minuscule decrease in the firm's carbon footprint by 1%. Without accounting for Scope 3 emissions through supply chains, firms fail to fully account for their total GHG emissions attributable to their products.

Recent media mentions and academic studies also argue that while many developed countries have made progress in combating climate change, their efforts look much less impressive once international trade is considered.[7] For example, Ben-David et al. (2020) employ firms' self-reported survey responses about their Scopes 1 and 2 emissions over the 2008-2015 period and find that stricter environmental regulations in the domestic market lead to lower emissions at home but higher emissions abroad. Li and Zhou (2017) link firm-level imports and plant-level toxic emissions information and find that domestic plants pollute less locally as their parent firm imports more from low-wage countries. These studies suggest that firms play whack-a-mole with pollution, bringing carbon emissions down in local markets at the cost of increasing emissions abroad. Their analyses, however, similarly suffer from overlooking the importance of Scope 3 emissions in a firm's climate commitments and hence do not provide a holistic view of whether corporations follow through on their pledge to a global action plan to fight climate change.

[5]https://www.nrdc.org/sites/default/files/issue-tissue-how-americans-are-flushing-forests-down-toilet-report.pdf

[6]NRDC is a not-for-profit organization whose work is to help safeguard the air, water, and environment. See, also, the preceding footnote.

[7]https://www.nytimes.com/2018/09/04/climate/outsourcing-carbon-emissions.html.

Our study exploits newly available firm-level data on firms' Scopes 1, 2, and 3 emission intensities from TruCost and transaction-level import information from Panjiva to conduct an in-depth analysis of whether and how U.S. firms address climate change. These datasets provide granularity relative to those employed in the existing literature and allow us to thoroughly analyze firms' actions in curbing carbon emissions and evaluate the pricing and welfare implications of their approach to climate change. Our sample consists of 73,966 firm-country-year observations from 1,254 U.S. firms and 178 exporting countries after merging the two key databases for the 2006-2018 period.

To determine the extent to which firms export carbon pollution in reducing their own emissions, we examine whether and how firms' Scope 1 emissions and imports are related to their Scope 3 emissions.[8] Using this approach, we find that Scope 1 emissions are positively and significantly associated with Scope 3 emissions, suggesting a high correlation between a firm's own carbon emissions and its suppliers'. These results offer some evidence to pollution outsourcing, as firms with pollution-intensive production are likely the ones that impose the most polluting burden onto their suppliers. We also find that the interaction of Scope 1 emissions and imports exhibits a strong negative association with Scope 3 emissions. A one-standard-deviation increase in the import measure would moderate the positive relationship between Scopes 1 and 3 by about 2%, indicating that when U.S. firms increase their imports, their own Scope 1 emissions fall with a corresponding rise in supplier-generated Scope 3 emissions. Such a finding serves as pivotal evidence that U.S. firms outsource some of their pollution abroad.

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 a problem, we exploit several exogenous shocks to imported emissions. If our baseline findings indeed capture the outsourcing effect, we should observe imports to have a stronger (weaker) impact with an exogenous increase (decrease) in carbon emissions associated with the imports. First, we employ domestic legislative pressure and regulatory stringency in the U.S. as exogenous sources of increase in the demand for imported emissions. Prior research shows that federal and state judiciaries play a critical role in developing and enforcing environmental regulations in the U.S. (e.g., Shipan and Lowry 2001; Grant, Bergstrand, and Running 2014;

[8] Our results remain materially unaffected if we examine the total indirect emissions from Scopes 2 and 3 (hereafter "Scopes 2 + 3") instead.

Kim and Urpelainen 2017). Thus, firms located in states with intense legislative pressure on environmental consciousness, as proxied by a sudden increase in pro-environmental votes in the House and Senate, should have stronger incentives to import as a means of outsourcing GHG emissions to their suppliers overseas. Similarly, we use spikes in state-level facility inspections by the Environmental Protection Agency (EPA) to capture heightened regulatory stringency that should also induce demand for imported emissions. Analyses reveal a stronger dampening effect of imports on the association between Scopes 1 and 3 as political pressure and regulatory stringency increase, consistent with a causal interpretation of firms' outsourcing behavior in curbing their own emissions.

In an alternative approach, we consider state-level electricity rate spikes, import tariff reductions, and natural disasters in exporting countries as exogenous shocks to the supply of carbon emissions. The retail electricity rate represents the price of the domestic emission supply. Thus, firms residing in states that experience a drastic increase in electricity price should have a stronger incentive to seek imported emissions in curbing their heightened emissions costs. Tariff reduction also decreases the cost of imported pollution relative to domestic emission supply, thereby increasing the outsourcing effect of imports. Finally, we explore exogenous shocks related to natural disasters in exporting countries that should disrupt their trading with U.S. firms in the short-term, weakening their import effects on Scope 3 emissions. Overall, these three quasi-natural experiments collectively provide corroborating evidence that imports have a causal impact on the interplay between a firm's own Scope 1 emissions and the indirect Scope 3 emissions through its supply chains.

Our analysis further investigates the countries to which U.S. firms relocate their carbon pollution. First, we examine whether pollution outsourcing is more likely to happen when exporting countries have a lower level of economic development. We contend that less developed countries are more concerned about economic survival than environmental issues and thus have weaker environmental regulations and lower social awareness towards environmental protection. These countries would be less costly alternatives for firms that face fairly intense regulatory and social pressure in the United States. Consistent with our conjecture, we find that the attenuating effect of imports is concentrated in emerging economies and non-OECD countries. Second, we examine outsourcing behaviors toward countries with different legal regimes. As documented in prior research (e.g., La

Porta, López-de-Silanes, and Shleifer 2008; Allen, Carletti, and Marquez 2015; Liang and Renneboog 2017), common law countries tend to place fewer *ex ante* restrictions on managerial behaviors in support of private market outcomes and shareholder values, whereas civil law countries are more protective of other stakeholders through state intervention of private sectors. Thus, firms should prefer exporting countries with a common law origin to those with a civil law origin. Our findings support this prediction. Finally, using the country-level environmental performance index (EPI), stringency of environmental regulation score (SER), and GHG emission intensity to capture the strictness of environmental laws and enforcement, we further show that outsourcing effects are stronger among exporting countries with laxer regulations. Overall, the findings lend support to our *prior* that pollution outsourcing hinges on the institutional environment of suppliers' countries.

Next, we explore several plausible internal and external mechanisms that explain U.S. firms' pollution management and outsourcing activities. Possible internal mechanisms may stem from the desire for firms, management, and board members to maintain their environmental standings. Prior studies show that corporate social responsibility (CSR) or environmental social, and governance (ESG) engagements can help firms build a social reputation (e.g., Fombrun and Shanley 1990), increase environmental, social, and governance-(ESG-)oriented investors (e.g., Ceccarelli, Ramelli, and Wagner 2019; Hartzmark and Sussman 2019), attract more productive employees (Burbano 2016), and expand new markets for environmentally-friendly products (Arora and Gangopadhyay 1995), among others.[9] Such benefits would propel firms with high ESG ratings (hereafter "green" firms) to uphold their domestic standards by shifting pollution-intensive production overseas through the upstream supply chain. Management and board members also reflect their own environmental standards through firm actions (Bènabou and Tirole 2010). In maintaining their established prosocial reputation, ESG-oriented CEOs and directors (hereafter "green" management and "green" directors) would be more inclined to curb domestic emissions from firms' production by importing polluting goods from global suppliers. Supporting these internal mechanisms, we find that the imports' outsourcing effect is more pronounced for green firms and firms with green CEOs and green directors.

External stakeholders, such as customers and shareholders, may also play an important role

[9] Throughout this paper, we use the expressions CSR and ESG interchangeably.

in driving firms' efforts toward combating climate change. We contend that government and environmentally-responsible corporate customers (hereafter "green" customers) are more concerned about the overall environmental externalities across a broader community. Given their pivotal influences in shaping suppliers' environmental policies (e.g., Dai, Liang, and Ng 2020), these customers can push U.S. firms to shrink the overall carbon footprint, including domestic and imported emissions. Institutional blockholders with a strong focus on sustainable investing (hereafter "green" blockholders) may further drive an overall reduction in GHG emissions. These large shareholders are becoming increasingly concerned about the adverse impacts of climate change on their investments and can exert powerful influences on portfolio companies to combat climate risks through private engagement and proxy voting (e.g., Krueger, Sautner, and Starks 2020). Our findings suggest that firms engage less in carbon outsourcing when they have more concentrated government customers, green customers, and green blockholders. The results lend support to these external mechanisms behind corporate environmental policies.

Finally, we evaluate the economic consequences of firms reducing carbon footprints through pollution offshoring. Our results suggest that firms with larger amounts of imported emissions are associated with a higher level of reputational risk and future returns. We argue that investors have difficulties assessing the part of a firm's carbon emissions through imports, possibly explaining why U.S. firms have strong incentives to outsource emissions. Besides regulatory oversight, firms also exploit investor oversight of emissions along the upstream supply chain. Such outsourcing activities disincentivize these firms to develop clean technologies.

Our research makes significant contributions to the growing corporate environmental policy literature. We provide the first comprehensive firm-level analysis of whether and how U.S. companies address their full climate impacts. Prior research mainly examines direct carbon emissions from firms' own production but omits substantial indirect emissions from product inputs (e.g., Li and Zhou 2017; Ben-David et al. 2020). Without considering all emission sources, one cannot fully analyze whether or not a firm reduces its overall pollution or simply externalizes it through the supply chain. To the best of our knowledge, no prior research has addressed how a firm tackles climate change by examining both direct and indirect carbon emissions. In analyzing both types of emissions in association with international trade, our study is also the first to provide *direct* evidence of the substitutional relationship between produced and outsourced pollution. Li and Zhou and Ben-David et al. focus on how international trade and regulatory environment affect domestic or foreign emissions but fail to directly show that firms choose one type of emissions in curbing the other.

Our work also contributes to the pollution haven literature in environmental economics. The pollution haven hypothesis suggests that relocation of pollution-intensive production is likely from countries with high income and strict environmental regulations to countries with low income and lax regulations. Thus far, empirical tests have been limited to aggregate country, state, or industry level analyses and often produced conflicting results (e.g., Grossman and Krueger 1995; Antweiler, Copeland, and Taylor 2001; Ederington, Levinson, and Minier, 2005; Wagner and Timmins, 2009; Levinson 2009, 2010). Our paper advances this research by utilizing firm-level data to empirically support such a hypothesis. In a battery of tests against country characteristics, we provide evidence consistent with pollution-intensive production shifting towards countries with weaker environmental awareness and standards.

This paper further advances the CSR literature. Prior studies highlight the roles of external stakeholders in shaping a firm's CSR practices. For example, Dyck et al. (2019) find that institutional investors drive firms' CSR performance worldwide. Hsu, Liang, and Matos (2020) document that state-owned enterprises are more responsive to environmental issues, particularly in emission mitigation and reduction in natural resource usage. Dai, Liang, and Ng (2020) show that socially responsible corporate customers can infuse similar socially responsible business behavior in suppliers. We add to this strand of literature by offering evidence that these stakeholders can also push firms to take a global perspective on GHG reduction.

The remainder of the paper is organized 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 examines the economic consequences of firm outsourcing pollution. 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 TruCost; (ii) the U.S. customs import data at the shipment level from Panjiva; (iii) Senate and House voting records on environmental legislations from League of Conservation Voters (LCV); (iv) plant inspections by EPA from Enforcement and Compliance History Online (ECHO); (v) retail electricity prices from the U.S. Energy Information Administration (EIA); (vi) global natural disaster data from EM-DAT; (vii) tariff and trade records from World Integrated Trade Solution (WITS) provided by World Bank; (viii) ESG scores from Refinitiv; (ix) information on executives and boards from BoardEx; (x) corporate and government customer data from Factset Revere and Compustat Segment Files, respectively; (xi) Form 13F institutional holdings data from FactSet Ownership; (xii) innovation output data from Worldwide Patent Statistical Database maintained by European Patent Office (PATSTAT); (xiii) information on country-level characteristics from various sources, including International Monetary Fund (IMF), Organization for Economic Cooperation and Development (OECD), World Economic Forum (WEF), and Yale Center for Environmental Law & Policy; (xiv) stock returns from CRSP; and (xv) firm financial information from Compustat.

2.1. Firm-level carbon emissions

TruCost offers firm-level GHG emissions data between 2005 and 2018. Over the sample period, the coverage has increased from about 1,000 to 2,700 U.S. firms. The database is constructed following the Greenhouse Gas Protocol standards and distinguishes between three different corporate emissions types: 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, the upstream Scope 3 data provided by Trucost include those emissions associated with the production and transportation of purchased materials, business travel, waste disposal, and other outsourced activities. Such information is estimated using an input-output model that considers both the firm's expenditures across all sectors in which it obtains its inputs and the sector-level emission factors. To facilitate the interpretation of carbon emissions across firms of different sizes and operations, we measure each pollution intensity as the quantity of emissions in tonnes of CO_2 equivalent scaled by total assets. All carbon measures take on the natural log form in reducing the skewness of their distributions.

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 United States are required to report shipment details in cargo declarations to 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 190 countries for the 2006-2019 period. We use S&P's identification system to link the consignees with the highest-level parent firms available in Compustat. For each of the matched U.S. consignees, we count the total number of shipments it receives from an exporting country in a year, scaled by the firm's total assets, as a proxy for import intensity.[10] We again take the natural logarithm of the measure to reduce skewness.

Our primary sample intersects these key databases. First, we match the emissions data with publicly traded companies in Compustat using ISIN as the linking identifier. We use the merged data to form an initial sample of 15,764 firm-year observations describing the U.S. public firms' pollution levels each year. Then, the sample is linked to imports data by the highest-level parent firms. Merging in the trade information expands our sample to firm-country-year level observations with multiple country-level import intensities for each U.S. firm in a year. The resulting sample only includes observations with positive imports and emissions. Finally, we exclude financial and regulated utility firms (SIC codes 4900-4999 and 6000-6900) and remove any observations with missing values for control variables. This merging of databases yields a final sample of 73,966 firm-country-year observations from 1,254 U.S. firms and 178 exporting countries for the 2006-2018

[10] We obtain similar analysis results using import measures without scaling.

period. The actual number of observations varies across analyses, given different 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. *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, Jafee, and Trajtenberg 2005). We winsorize all continuous variables at 1% and 99%. 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 four primary variables in raw form (*Scope 1*, *Scope 2*, and *Scope 3*, and *Import*), where emissions are in thousands of tonnes and imports are in the number of shipments. On average, a U.S. firm produces about 2.9 million tonnes of Scope 1 emissions and 1 million tonnes of Scope 2 emissions. Through its supply chain, the firm is also associated with about 5.2 million tonnes of Scope 3 emissions. In comparison, the median values of emissions are much smaller (0.17 million tonnes, 0.2 million tonnes, and 1.3 million tonnes for Scopes 1, 2, and 3, respectively). These statistics are largely consistent with the Carbon Disclosure Project's (CDP) recent report showing that companies' supply chain emissions are immensely greater than their Scopes 1 and 2 emissions.[11] It is evident that the bulk of a firm's emissions is from its suppliers. Hence, the firm must include this large amount of indirect emissions when targeting for carbon neutrality. The standard deviations for

[11]See CDP's "Cascading Commitments Driving Ambitious Action through Supply Chain Engagement."

Scope 1, Scope 2, Scope 3 emissions are about 9.5 million tonnes, 2.2 million tonnes, and 11.2 million tonnes, respectively. These values are much larger than their respective means, indicating that the quantity of emissions generated are quite skewed. Moreover, statistics suggest that GHG emissions are mostly driven by large companies. For these considerations, we employ log emission intensities for our main analyses. Their summary statistics are reported in Panel B. The average number of shipments from suppliers in each exporting country is 38, and the median number is 4. We also scale this variable by the firm's total assets and employ the natural logarithm throughout the study.

Panel C presents the summary statistics of the control variables. Our sample consists of mostly large firms with mean total assets of $8.52 billion (ln(1+$8,524 million)=9.051) and median of $7.44 billion (ln(1+$7,443 million)=8.915). An average (median) firm has a Tobin's Q of 1.841 (1.638), a leverage ratio of 25.6% (24.5%), a ROA of 10.9% (10.3%), and an annual sales growth of 4.8% (4.5%). The average (median) tangibility ratio is 51.8% (44.7%), suggesting that physical assets account for about half of a firm's total assets. 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 Footprints

This section investigates whether and how U.S. firms reduce their carbon footprints and establish causality by exploiting several exogenous shocks to supply and demand of imported GHG emissions. We also conduct a host of tests to determine which countries particularly attract pollution outsourcing from U.S. firms.

3.1. Carbon emissions outsourcing

To test whether U.S. firms reduce their own GHG emissions through pollution outsourcing, we estimate the following regression model.

$$\begin{aligned} \mathit{Scope\ 3}_{i,t} = \alpha + \beta_{SI}\mathit{Scope\ 1}_{i,t} \times \mathit{Import}_{i,c,t} + \beta_S \mathit{Scope\ 1}_{i,t} + \beta_I \mathit{Import}_{i,c,t} \\ + \beta_{CS}{}' \mathit{Controls}_{i,t} + \gamma_i + \theta_c + \phi_t + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where *Scope* $3_{i,t}$ is firm i's indirect supply chain emissions in year t; *Scope* $1_{i,t}$ is firm i's direct emissions; $Import_{i,c,t}$ is its imports from country c; $Controls_{i,t}$ is a vector of firm-specific control variables defined in the preceding section; γ_i, θ_c, and ϕ_t denote firm, country, and year fixed effects, respectively, to account for unmodeled heterogeneity across firms, countries, and years. We also estimate alternative specifications of Model (1) by employing firm and country×year fixed effects to control for any omitted time-varying country characteristics, and by replacing *Scope* $3_{i,t}$ with *Scope* $2{+}3_{i,t}$ to capture firm i's total indirect emissions. Standard errors are clustered at the firm-year level.

Of particular interest are the signs and significance of β_S and β_{SI} estimates. They allow us to infer whether and how firms outsource their carbon pollution abroad. The β_S coefficient reflects the link between a U.S. firm's own carbon emissions with those generated by its suppliers. A positive β_S indicates that supply chain emissions increases with the firm's production emissions, suggesting that more pollution-intensive firms are more inclined to shift their polluting burden onto their upstream suppliers. The β_{SI} coefficient provides pivotal evidence on whether U.S. firms outsource carbon emissions. It captures the amplifying or mitigating effect of imports on the association between Scope 1 and Scope 3 emissions. A negative β_{SI} suggests that imports trigger a substitutional relationship between a firm's own emissions and those of its suppliers, an implication that the firm outsources its carbon emissions abroad. In contrast, a positive β_{SI} indicates little to no outsourcing behavior as imports do not facilitate the substitution of Scope 1 and Scope 3 emissions.

Table 2 presents results of Model (1). The dependent variable is *Scope 3* for Columns (1) and (2) and is *Scope 2+3* in Columns (3) and (4). Columns (1) and (3) control for firm, country, and year fixed effects, and Columns (2) and (4) control for firm and country×year fixed effects. The table reveals several important findings. First, the domestic carbon emissions from a firm's own production and operations are highly associated with its suppliers' emissions, as shown by the positive and significant β_S estimates across all four specifications. The estimates range from 0.112 ($t-$stat = 6.35) in Column (1) to 0.138 ($t-$stat = 7.88) in Column (4). A one-standard-deviation increase in *Scope 1* would lead to a 4.9% ($1.478/3.350 \times (0.112 - 0.104 \times 0.008)$) increase in *Scope 3* and a 6.1% ($1.478/3.350 \times (0.138 - 0.088 \times 0.008)$) increase in *Scope 2+3*, while holding it Import at its mean. We attribute these results to the emission outsourcing behavior of pollution-intensive firms but need more confirming evidence, as shown below. Our findings also reinforce Dai, Liang, and Ng's (2020) finding of a positive spillover of CSR practices from customers to global suppliers.

Second, the coefficients on the interaction term, *Scope 1* × *Import*, are all negative and significant, with β_{SI} estimates ranging from -0.088 ($t-$stat= -2.34) in Column (4) to -0.104 ($t-$stat= -2.68) in Column (1). These results suggest that when a firm increases its imports, the positive correlation between its Scope 1 and Scope 3 emissions becomes weaker. A one-standard-deviation increase in *Import* from its mean attenuates the *Scope1-Scope 3* association by 2.4% and the *Scope1-Scope 2+3* association by about 1.7%.[12] Similarly, Column (4) reveals that the elasticity of *Scope 2+3* for *Scope 1* decreases from 0.0605 to 0.0595, or a 1.68% reduction, with the increase in import intensity. This direct evidence of pollution outsourcing indicates that when U.S. firms increase their imports, their own Scope 1 emissions fall at the expense of rising supplier-generated Scope 3 emissions. Such import-induced substitution effect is broadly consistent with the economic literature in environmental policies. Prior research suggests that U.S. environmental regulations drive down energy-intensive manufacturing output and that about half of the decline in domestic production for these industries is offset by an increase in net imports from countries that are not implementing emission mitigation policies (e.g., Ho, Morgenstern, and Shih 2008; Aldy 2017).

Finally, the positive and significant coefficient on *Import* may be mechanically driven. Companies with more imports from global suppliers also tend to have more Scope 3 emissions. Furthermore, the findings indicate that emissions from suppliers are greater for smaller U.S. corporate customers, customers with lower market-to-book value but greater profitability, sales growth, and tangibility. Except for sales growth, these results remain robust when the dependent variable is *Scope 2+3*. The results are also consistent across the two different sets of fixed effects that we employ. For brevity, we only report results using *Scope 3* and firm, country×year fixed effects in subsequent analyses.[13]

[12] According to Column (1), the elasticity of *Scope 3* with respect to *Scope 1* is $0.138 - 0.088 \times 0.008 = 0.111$ while *Import* is held at its mean, but it drops by 2.44% to $0.138 - 0.088 \times (0.008 + 0.026) = 0.108$ when *Import* increases by one-standard-deviation.

[13] Results using firm, year, and country fixed effects are shown in an earlier version of this paper and are available upon request.

3.2. Identification strategies

Thus far, our 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, U.S. firms may choose countries of imports for other production cost considerations than carbon emissions. Therefore, the *Scope1-Scope 3* association mechanically weakens as firms increase imports from foreign suppliers subject to emissions policies in their own countries. Thus, our findings may simply reflect fewer suppliers' ability to complying with their U.S. customer firm's emissions policy rather than a substitution of Scope 1 for Scope 3 emissions arising from pollution outsourcing. To alleviate endogeneity concerns, we employ several exogenous shocks to imported GHG emissions. If our baseline findings indeed capture the outsourcing pollution effect, we should expect an exogenous increase (decrease) in imported carbon emissions to exhibit a stronger (weaker) impact on the *Scope1-Scope 3* relationship. In particular, we examine demand shocks to imported emissions arising from domestic legislative pressure and regulatory stringency as well as supply shocks stemming from regional carbon price spikes, import tariffs reductions, and global supply chain disruptions due to natural disasters.

3.2.1. 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 global total by 2018, environmental protection has become one of the most critical issues in U.S. politics.[14] 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 carbon emissions of power plants. 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). Thus, we employ state-level legislative pressure and regulatory stringency as exogenous sources of increase in the demand for imported emissions.

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

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 and the Senate between 2006 and 2019, as documented by the LCV, and assign a score to each Congress member based on his/her voting records each year. The score is defined as the number of pro-environmental votes scaled by the total number of environmental legislations considered in the year. A higher score indicates that the Congress member is more environmentally conscious. States consisting of more environmentally friendly Congress members should have greater interests in pushing forward a climate action agenda. To proxy for state-level legislative pressure on environmental protection, we compute the average voting scores separately across the Senate and House of Representatives in each state. We argue that firms located in states with a dramatically heightened legislative pressure, potentially due to elections of more environmentally conscious members in the Senate or the House, should have stronger incentives to import as a means of offshoring GHG emissions. Legislative pressure shocks are identified as state-years that experience score increases by more than three times the average increase during our sample period. We 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.

To evaluate the impact of demand shocks to carbon emissions, we estimate the following regression model with a triple-interaction effect:

$$\begin{aligned} \textit{Scope 3}_{i,t} = \alpha &+ \beta_{SI1} \textit{Scope 1}_{i,t} \times Import_{i,c,t} \times Treat_{t-1} + \beta_S \textit{Scope 1}_{i,t} + \beta_{SI} \textit{Scope 1}_{i,t} \times Import_{i,c,t} \\ &+ \beta_{S1} \textit{Scope 1}_{i,t} \times Treat_{t-1} + \beta_1 Treat_{t-1} + \beta_{I1} Import_{i,c,t} \times Treat_{t-1} + \beta_I Import_{i,c,t} \\ &+ \beta_{CS}' Controls_{i,t-1} + \gamma_i + \theta_c + \phi_t + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where $Treat_{i,t-1}$ is a binary indicator that equals 1 if the state where firm i resides in experiences a shock in the average House or Senate score at year $t-1$, and 0 otherwise. The coefficient of the triple interaction term $\textit{Scope } 1 \times Import \times Treat$ captures the incremental impact of imports on the *Scope1-Scope 3* association for firms that are more likely to demand pollution overseas through imports. A negative β_{SI1} suggests a stronger substitutional relationship between a firm's own emissions and those of its suppliers given increased desire to outsource pollution.

We measure state-level regulatory stringency using the facility inspection data obtained from ECHO. Inspection intensity is defined as the total number of onsite air pollution compliance evaluations conducted by EPA scaled by the total number of air pollution emitting facilities in each state. We contend that firms located in states with tightened regulatory monitoring and enforcement should have more robust demand for imported emissions. To test this prediction, we repeat Model (6) while redefining $Treat_{i,t-1}$ as 1 if the one-year lagged inspection intensity increases by more than three times the average increase during the sample period. We again eliminate any transitory shocks followed by reversals within the next three years and shocks driven by changes in the firm location.

Table 3 reports regression estimates of Model (6). Columns (1) and (2) show the impact of legislative pressure from the House and the Senate on U.S. firms' environmental policies, whereas Column (3) presents the effect of state-level regulatory stringency. The β_{SI1} estimates are negative and significant at the 1% level in Column (1) and at the 5% level in Columns (2) and (3). These results suggest a stronger dampening effect of imports with an exogenous increase in the demand for imported emissions. According to Column (2), for example, a one-standard-deviation increase in *Import* would attenuate the *Scope1-Scope 3* relationship by about 14.2% for firms experiencing a shock to the House voting score, in stark contrast to a 1.8% reduction for other U.S. firms.[15] We find a similar increase from a 2% mitigating effect to 10.7% following a shock to state-level regulatory stringency, as shown in Column (3). These findings corroborate our argument that the outsourcing behavior of U.S. firms drives the mitigating effect of imports observed in the baseline analysis.

3.2.2. Supply shocks to carbon emissions

Alternatively, we consider state-level electricity rate spikes, import tariff reductions, and natural disasters in exporting countries as exogenous shocks to the supply of carbon emissions. Prior research suggests that climate change policies increase the cost of carbon supply and, in turn,

[15] As shown in Column (2), the elasticity of *Scope 3* with respect to *Scope 1* is $0.106-0.071\times0.008 = 0.105$ for control firms while holding *Import* at its mean, but it drops by 1.18% to $0.106 - 0.071 \times (0.008 + 0.026) = 0.104$ when *Import* increases by one-standard-deviation. In contrast, the elasticity declines from $0.106 - (0.071 + 0.482) \times 0.008 = 0.102$ to $0.106 - (0.071 + 0.482) \times (0.008 + 0.026) = 0.087$, or a 14.2% reduction, for treated firms.

raise the energy and electricity prices that end-users face. Using simulated models, Aldy and Pizer (2014, 2015) and Aldy (2017) show that higher energy and electricity rates induced by carbon pricing policies have significant adverse effects on energy-intensive manufacturing firms, including production cost increases, production declines, and job cuts. Drawn from this strand of literature, we employ spikes in retail electricity prices as our first supply shock to domestic emissions for U.S. firms. We contend that electricity price spikes reflect increases in the cost of domestic carbon supply. Thus, firms located in states with a dramatic rise in electricity price should have more substantial incentives to seek imported carbon supply in curbing their heightened emissions and production costs. We test this prediction by re-estimating Model (6) with $Treat_{i,t-1}$ taking the value of 1 if the one-year lagged state-average retail electricity rate rises by more than three times the average increase over the sample period. Such shock must not revert within the next three years, and a change in firm locations must not drive it.

We exploit large import tariff reductions across different industries in the U.S. as another quasi-natural experiment. Tariff reductions decrease the cost of foreign emission supply, thereby inducing firms to trade internationally for pollution outsourcing. We obtain the lowest available tariff rates applied by the U.S. on each commodity (measured at the 6-digit HS level) and exporting country in a given year from WITS World Bank. Using the product concordance table provided by WITS, we map the commodity types to their corresponding Fama-French 30 industries and measure tariffs using the average applied rates for each industry-country in a year. Following prior literature (e.g., Huang, Jennings, and Yu 2017), we identify large tariff reduction events as industry-country-years that experience tariff rate decreases relative to the previous year by more than three times the average tariff rate reduction during our sample period. To ensure that these reduction events reflect only non-transitory changes in imported pollution, we exclude declines, followed by tariff increases of a similar level within the next three years. The treatment indicator, $Treat_{i,c,t-1}$, equals 1 for the five years following a large tariff cut in year $t-1$ and 0 otherwise.

We also consider natural disasters that cause unexpected disruptions to global suppliers' operations as an identification strategy. These events have substantial short-term effects on the production output of affected supplier firms. We expect such shocks to temporarily slow down imported carbon supply to U.S. corporate customers, weakening the mitigating effect of imports from the affected countries. For this experiment, $Treat_{i,c,t-1}$ equals 1 if the supplying country c has at least one major natural disaster incidence during year $t-1$.

Table 4 presents the regression results for the three sets of experiments. The impacts of electricity price spikes, tariff reductions, and disaster incidences are shown in Columns (1), (2), and (3), respectively. The coefficient of the triple-interaction term $Scope\ 1 \times Import \times Treat$ is negative and statistically significant in Columns (1) and (2), whereas it is significantly positive in Column (3). These findings suggest a more substantial dampening effect of imports when facing exogenous reductions to the cost of emission outsourcing, but a weaker effect with a decrease in foreign carbon supply. As shown in Column (1), a one-standard-deviation increase in *Import* would attenuate the *Scope1*-*Scope 3* relationship by 12.1% for firms facing higher electricity rates, significantly stronger than the import effects found for other firms. We observe a similar increase from an insignificant impact to 8.8% moderation following large tariff cuts in Column (2). In contrast, Column (3) reveals that the mitigating effect reduces from 3.2% to 1.2% after a disaster shock to the supply of imported emissions. The *Treat* variable is omitted from the model because we control for country×year fixed effects.

All the above results collectively indicate a causal interpretation of our crucial finding that firms outsource emissions to overseas suppliers in curbing their domestic carbon footprints.

3.3. Destination countries

In preceding sections, we have established that U.S. corporations reduce their carbon footprints by shifting GHG emissions to their global suppliers through imports. We now turn to examine the destination countries to which those U.S. firms relocate their pollution. To do so, we partition our sample based on whether suppliers are residing in countries with a lower level of economic development, weaker stakeholder protection, and laxer stringent environmental regulations. By re-estimating our baseline model (1) on subsamples of countries, we directly observe U.S. firms' outsourcing preferences in destination countries. Such an approach differs from prior studies (e.g., Li and Zhou 2017; Ben-David et al. 2020) that infer preferences without showing substitutional relationships between firms' self-generated emissions and those from different exporting countries.

First, we examine whether pollution outsourcing is more likely to happen when destination countries have a lower level of economic development. We contend that less developed or emerging economies typically lack the proper institutional and organizational framework to enforce stringent environmental regulations. Poorer countries are also more concerned about daily economic survival than environmental sustainability, and hence have a weaker social awareness towards environmental issues. These countries offer more cost-effective alternatives for corporations that face fairly intense regulatory and social pressure in the United States (e.g., California Cap-and-Trade Program, Clean Air Act; National Energy Conservation Policy Act). Thus, U.S. firms should be more inclined to outsource GHG emissions to less developed exporting countries. Results shown in Table 5 support our conjecture. In Columns (1) and (2), we define developed and emerging economies based on IMF classifications and find the outsourcing effect to concentrate in the emerging market subsample. More specifically, the coefficient of the interaction term *Scope 1* $\times$ *Import* is negative and statistically significant only for emerging destination countries but not for developed economies. In Columns (3) and (4), we classify our sample as Non-OECD and OECD countries. OECD members are generally high-income economies with average GDP per capita reaching 3.6 times that of Non-OECD countries by 2019.[16] Furthermore, as OECD pushes for better social policies, its fellow members should have environmental standards that are more comparable to the United States than do Non-OECD countries. Thus, the cost benefits of pollution outsourcing would be small for OECD destinations compared to Non-OECD nations. Supporting our *prior*, we find the attenuating effect of imports to be more pronounced in the Non-OECD than OECD subsample. Such outsourcing preference is broadly consistent with existing studies (e.g., Taylor 2005; Li and Zhou 2017) that suggest a shift of pollution-intensive production toward low-wage countries.

Second, we examine firms' pollution outsourcing towards countries with different legal regimes. Prior research suggests that common law countries rely more heavily on private market outcomes to maximize value in the interest of shareholders (e.g., La Porta, López-de-Silanes, and Shleifer 2008; Allen, Carletti, and Marquez 2015; Liang and Renneboog 2017). They tend to place fewer *ex ante* restrictions on managerial behaviors and impose *ex post* sanctions in response to inappropriate or unacceptable actions. In contrast, civil law countries are more protective of other

[16] Data on GDP per capita is obtained from OECD website: http://www.oecd.org/sdd/productivity-stats/.

stakeholders' interests through state intervention of private sectors. They rely more heavily on rules-based mechanisms that restrict managerial behavior *ex ante*. A common law regime suggests inefficient regulations against climate change, whereas a civil law system may reflect stricter regulatory protection of environmental stakeholders. Thus, U.S. firms may find it easier to relocate their emissions to destination countries with a common law origin than a civil law origin, especially when they share a similar legal framework (i.e., the common law). We partition exporting countries into subsamples by their legal origins. As shown in Columns (5) and (6), the outsourcing effect is concentrated in common law countries. Specifically, the coefficient of the interaction term is -0.203 ($t-$stat$= -3.66$) in the common law sample but insignificantly different from zero in the civil law sample.

Finally, we test explicitly how the outsourcing effect varies across countries with varying degrees of environmental regulatory stringency and emission intensity. In particular, we divide our sample into two based on a country's Stringency of Environmental Regulation (SER) score, as provided by the WEF's Travel & Tourism Competitiveness Reports. Countries with above-median SER score are grouped into the High-SER sample, while the remaining are grouped into the Low-SER sample. As reported in Columns (1) and (2) of Table 6, the outsourcing effect is more pronounced in the low-SER group. These results corroborate our argument that less environmentally regulated countries attract pollution outsourcing. We next divide our sample based on a country's Environmental Performance Index (EPI), as provided by Yale Center for Environmental Law & Policy. EPI comprehensively measures the environmental health and ecosystem vitality of 180 countries regarding how close they are to established environmental policy targets. Columns (3) and (4) report the results for Low-EPI and High-EPI samples, respectively. Consistent with all prior findings, the mitigating effect of import is concentrated in the Low-EPI sample. A country's emission intensity, defined as total GHG emissions per dollar value of GDP, may also reflect its environmental standards. Columns (5) and (6) indicate that the outsourcing effect stems mainly from the subsample of exporting countries with above-median emission intensity, possibly resulting from laxer environmental regulations.

Overall, the subsample analyses recorded in Tables 5 and 6 suggest a more nuanced view of U.S. corporations' pollution outsourcing preferences based on destination countries' institutional environments. Such outsourcing is more likely to occur when the exporting countries have a lower level of economic development, less stakeholder-oriented legal regime, and laxer environmental regulations.

4. The Mechanisms

This section explores several possible mechanisms that drive firms' pollution management and outsourcing activities. To facilitate our discussion, we group them into two types of mechanisms: internal and external mechanisms. Internal mechanisms arise from firms, management, and board members' desire to maintain high environmental standings, whereas external mechanisms stem mainly from other corporate stakeholders, such as corporate customers and investors, who are committed to reducing carbon footprints. We examine how each mechanism influences a firm's environmental policy.

4.1. Internal mechanisms

A firm's own greenness can dictate its corporate environmental policy. We posit that firms with higher environmental ratings (i.e., green firms) are more inclined to reduce self-generated GHG emissions. Prior research suggests that companies can "do well by doing good". ESG engagements can benefit firms with better product differentiation (e.g., Fisman, Heal, and Nair 2006; Siegel and Vitaliano 2007; Fernandez-Kranz and Santalo 2010; Flammer 2015); increased customer willingness to pay (e.g., Bagnoli and Watts, 2003; Baron 2008, 2009), and improved employee morale and retention (e.g., Turban and Greening 1997; Burbano 2016), among others. In maintaining these benefits, green firms are propelled to uphold their social images and environmental standings. Greener firms should thus have stronger incentives to curb their own Scope 1 emissions, potentially at the expense of rising supplier-generated Scope 3 emissions. We test this mechanism by employing the triple-interaction model (6). $Treat_{i,t-1}$ is replaced with $Green\ Scores_{i,t-1}$ to capture firm i's established reputation at year $t-1$. *Green Score* is measured using the Refinitiv Environmental score, which is a continuous score on a scale of 1 to 100. A higher score denotes a greener firm.

We also examine the impacts of executives and board members on their firms' carbon footprints.

The reputation of these internal stakeholders can be tied to the reputation of their firm. They take credit for their firms' strong social images and receive private benefits, including better career prospects, among others (Bénabou and Tirole, 2010; Dai et al. 2019; Cai et al. 2020). Thus, executives and directors with a pro-environmental image (i.e., green executives and directors) would influence corporate policies in maintaining their own established reputation and prestige. Existing studies document that managers and directors play a critical role in their firm's CSR 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, which should, at least in part, be achieved through pollution outsourcing. In testing these mechanisms, $Treat_{i,t-1}$ is replaced with $Green\ CEO_{i,t-1}$ and $Green\ Director_{i,t-1}$ to capture managers and directors' established social reputation as revealed by their past five-year of employment. For each CEO in a given year, we assign a decile ranking based on the average score of his/her current and past employers' environmental scores over the past five years. $Green\ CEO_{i,t-1}$ measures the stakeholder's average decile scores over years $t-5$ to $t-1$. A higher score denotes a greener CEO for firm i. We compute *Green Directors* in a similar fashion. Specifically, $Green\ Director_{i,t-1}$ is the average of firm i's director scores over the past five years of their experiences serving as board members in any corporation. We obtain information on the CEO's and directors' past work experience from BoardEx.

Table 7 presents the regression results for all three internal mechanisms. Columns (1), (2), and (3) show the impacts of a firm, management, and director greenness on corporate environmental policy, respectively. The coefficient of the triple-interaction term is negative and statistically significant across all three columns. Specifically, the β_{SI1} estimate is -0.594 ($t-$stat$=-1.95$) in Column (1) when interacting *Scope 1* $\times$ *Import* with *Green Score*, indicating that the mitigating effect of imports in the baseline result is amplified by the firm's own environmental standing. This finding is consistent with our expectation that greener companies have stronger incentives to reduce their own Scope 1 emissions, leading to more intensive pollution outsourcing toward global suppliers. The β_{SI1} estimates are -0.136 ($t-$stat$=-1.89$) and -0.141 ($t-$stat$=-1.95$) for *Green CEO* and *Green Directors* interactions, suggesting that firms with greener CEOs and directors are also more likely to outsource GHG emissions overseas as driven by the increased pressure to reduce the firms' own carbon footprints.

4.2. External mechanisms

External stakeholders, such as customers and shareholders, may also play an important role in driving corporate climate actions. Previous research demonstrates that corporate stakeholders have their own social preferences and can exert powerful influences on firms to align with their interests. For example, Dai, Liang, and Ng (2019) show that corporate customers shape suppliers' social and environmental policies. Other work suggests that large 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; Krueger, Sautner, and Starks 2020; Gantchev, Giannetti, and Li 2020). In this section, we investigate specifically how their social preferences affect the outsourcing behavior of U.S. firms.

We contend that, unlike green internal stakeholders, government customers discourage pollution outsourcing as a means of reducing direct domestic carbon emissions. Governments have different objectives from private enterprises. They act in the public interest and address social issues arising from market failures and negative externalities. As environmental issues become increasingly acute and pressing, governments are compelled to reduce pollution for the sake of public welfare (Hsu, Liang, and Matos 2020). To effectively combat climate change, U.S. governments should be more concerned about total GHG reductions in the global community rather than simply relocating polluting sources.[17] Firms benefit from lower business risk when supplying to government customers and are, therefore, driven to satisfy these customers' demands (Cohen and Li 2020). Hence, we expect the outsourcing effect to be less pronounced when a firm has more concentrated government customers. We apply the same triple-interaction approach in Model (6) to explore such an external mechanism. In this model, $Treat_{i,t-1}$ is replaced with $Largest\ Gov\ Customer_{i,t-1}$. It is defined as the percentage of firm i's sales to the largest major government customer identified in Compustat Segments file at year $t-1$, where a major customer accounts for at least 10% of a firm's total sales. We also employ alternative customer concentration measures, including the sum of sales and the sum of squared sales to all major government customers scaled by firm i's total sales revenue. Given

[17] https://unfoundation.org/blog/post/7-ways-u-s-states-are-leading-climate-action/.

that the results are qualitatively similar, we only report those of the *Largest Gov Customer*.external mechanism. In this model, $Treat_{i,t-1}$ is replaced with $Largest\ Gov\ Customer_{i,t-1}$. It is defined as the percentage of firm i's sales to the largest major government customer identified in Compustat Segments file at year $t-1$, where a major customer accounts for at least 10% of a firm's total sales. We also employ alternative customer concentration measures, including the sum of sales and the sum of squared sales to all major government customers scaled by firm i's total sales revenue. Given that the results are qualitatively similar, we only report those of the *Largest Gov Customer*.

Environmentally-conscious corporate customers (i.e., green corporate customers) may influence corporate climate action in two opposite directions. On the one hand, green customers may impose high environmental standards on the suppliers to align with their own social reputations. U.S. firms facing a strong external pressure to "do good" may resort to reducing direct GHG output through pollution outsourcing. In such a case, we expect the outsourcing effect of imports to be stronger for U.S. firms with more concentrated green corporate customers. On the other hand, green customers may be more concerned about the overall impact of carbon emissions on global warming and are more attentive to all environmental externalities associated with their suppliers' production. Given their pivotal influences on suppliers' social and environmental policies (Dai, Liang, and Ng 2020), these customers can push U.S. firms to shrink the overall carbon footprint, including both domestic and imported emissions. This hypothesis predicts a weaker outsourcing effect for firms with more green customers. To determine the dominating effect, we replace *Treat* with *Green Customers* in Model (6). $Green\ Customers_{i,t-1}$ captures the percentage of firm i's green corporate customers in year $t-1$, where green customers are those emitting lower than industry-median carbon emissions per dollar value of total assets.

Like green corporate customers, environmentally-conscious institutional investors (green investors) may also affect outsourcing efforts in either direction. In protecting their own reputation,[18] green institutions may exert influences to curb the direct emissions of their portfolio companies, which could induce pollution outsourcing in response. Alternatively, these large shareholders may drive down carbon pollution out of their concerns over climate risks (e.g., Krueger et al. 2020). To effectively reduce the adverse impacts of climate change on their investments, green institutional

[18] Krueger et al. (2020) show that the protection of the investors' reputations is one of the most prevalent motives for incorporating environmental preferences into portfolio decisions.

investors would instead focus on total GHG reductions. *Green Blockholders*$_{i,t-1}$ is measured as the percentage of firm i's shares owned by green blockholders in year $t-1$, where a blockholder holds at least 5% of the firm's total shares outstanding; a green institution has at least 50% of its portfolio invested in green firms; and a green firm is ranked in the top quintile of the Refinitiv ESG score distribution each year.

Table 8 presents the results for all three external mechanisms. Columns (1), (2), and (3) record the impacts of government customers, green corporate customers, and green investors on a firm's pollution management, respectively. As shown in Column (1), the coefficient on *Scope 1* $\times$ *Import* $\times$ *Largest Gov Customer* is positive and statistically significant at the 1% level. This finding indicates a weaker mitigating effect of imports for firms supplying to large government customers, consistent with our conjecture that government customers limit pollution outsourcing activities. We similarly find the triple-interaction coefficients for *Green Customers* and *Green Blockholders* to be positive and statistically significant. They support the notion that green customers and investors reduce global environmental externalities by restricting their associated firms from outsourcing emissions to other countries.

It is essential to highlight the stark differences in results between internal and external mechanisms. The internal mechanisms we identify are related to a firm's past ESG performance and its environmental-conscious CEO and directors. Our findings likely reflect their commitments to social images in the local community. Such local reputational commitments incentivize the firm to reduce self-generated carbon emissions at the expense of increasing supplier pollution overseas. In contrast, the external mechanisms are all related to the pressures from a firm's external stakeholders, who may be concerned about environmental issues across a broader community. As a result, these external stakeholders discourage the firm from outsourcing emissions to suppliers.

5. Economic Consequences

This section examines the economic consequences of firms' carbon reduction efforts. Specifically, we investigate whether a firm's engagement in pollution outsourcing activity influences its reputational risk and stock performance and then evaluate the welfare implications of this activity.

5.1. Reputational Risk

In this section, we study whether different sources of a firm's carbon emissions affect its reputational risk. 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.[19] 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.[20] Drawn from prior findings that firms use ESG as a product differentiation strategy (e.g., Flammer 2015; Albuquerque, Koskinen, Zhang 2020), we expect environmentally-responsible firms to display a lower ESG-induced reputational risk. That is, firms that pollute more have a higher reputational risk.

To test our prediction, we examine the cross-sectional variation between firms' reputational risks and different sources of carbon emissions using the following model specification,[21]

$$\begin{aligned} \textit{RepRisk}\ \beta_{i,t} \quad = \quad & \alpha + \beta_1 \text{Imported CO}_{2_{i,t}} + \beta_2 \textit{Scope 1 CO}_{2_{i,t}} + \beta_3 \textit{Scope 2 CO}_{2_{i,t}} \\ & + \beta_4 \textit{Scope 3 CO}_{2_{i,t}} + \beta'_{CS} \textit{Controls}_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where *RepRisk* $\beta_{i,t}$ is an estimate of a firm's reputational risk at year t; *Scope 1* CO_2, *Scope 2* CO_2, *Scope 3* CO_2, and *Imported* CO_2 are defined as the log of one plus the emissions variable. Model (3) also includes firm-level *Assets*, *Tobin's Q*, *R&D*, *PPE*, *Leverage*, *CapEx*, *Cash*, *Income Volatility*, and *ROA*, as well as firm and month fixed effects as controls. We estimate *RepRisk* $\beta_{i,t}$ as follows. Each year, we rank the firms in our sample based on their reputational risk scores and divide them into portfolios of high and low reputational risk. We compute daily returns on a reputational risk factor by taking the difference in returns between the low and high reputational

[19] RepRisk, an ESG data science provider, quantifies the reputational risks of companies based on their exposure 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

[20] 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.

[21] 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.

risk portfolios. We then regress individual stock returns on the returns of the reputational risk factor and Fama-French 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 firms' *RepRisk* $\beta_{i,t}$.

It is important to point out that when we regress returns of the reputational risk factor against the returns on the Fama-French four factors, the alpha estimate of -3% per annum is statistically significant at the 5% level. Similar to Edmans (2011), we interpret that the reputational risk factor's underperformance reflects the difficulty in incorporating intangibles into traditional valuation models. Nevertheless, our main purpose is to examine which source of firm-level carbon emissions is related to a firm's systematic reputational risk.

Table 9 reports the regression estimates of Model (3). Columns (1)-(4) show the results of separate effects of each CO_2 emission variable on *RepRisk* β, and Column (5) report those of their joint effects. We find that a firm's reputational risk is strongly and positively related to only *Imported* CO_2, but shows no relationship with *Scope 1* CO_2, *Scope 2* CO_2, and *Scope 3* CO_2. The magnitude and statistical significance of *Imported* CO_2 remain materially unaffected even when it is estimated jointly with the other sources of carbon emissions (Column (5)). Consistent with our prediction, firms with larger amounts of imported emissions are associated with a higher level of reputational risk. It appears that investors have difficulty assessing the amount of a firm's carbon emissions through imports, compared to its Scopes 1, 2, and 3 emissions, possibly explaining why companies can actively (but also unnoticeably) export their pollution to foreign suppliers.

5.2. Stock Return Performance

We also analyze the pricing implications of 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 downside risk (Ilhan, Sautner, and Vilkov 2019). Bansal, Kiku, and Ochoa (2014) document that the financial market prices in long-run climate risks as proxied by temperature, while Hong, Li, and Xu (2019) suggest that stock markets incorporate climate risk information from natural disasters with a significant delay. Hsu, Li, and Tsou (2019) and Starks, Venkat, and Zhu (2020) find that polluting firms are associated with higher stock returns and lower credit ratings, respectively. Bolton and Kacperczyk (2020a, 2020b) find that stock returns are positively correlated with carbon emissions, but Dai and Meyer-Brauns (2020) document no reliable empirical relation between different emission metrics and average stock returns.

Motivated by this strand of literature, our analysis focuses on market efficiency and climate risks. If markets correctly price in different sources of a firm's carbon exposure, these emission sources should have no predictive power for future stock returns. Conversely, if carbon emissions have return predictability, then the markets are inefficient and investors have not factored in firms' carbon exposure. We test the return predictive powers of the different sources of firm-level carbon emissions using the following model,

$$\begin{aligned} \textit{Stock Return}_{i,m,t} &= \alpha + \beta_1 \text{Imported CO}_{2_{i,t-1}} + \beta_2 \textit{Scope 1 CO}_{2_{i,t-1}} + \beta_3 \textit{Scope 2 CO}_{2_{i,t-1}} \\ &\quad + \beta_4 \textit{Scope 3 CO}_{2_{i,t-1}} + \beta'_{CS} \textit{Controls}_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where $\textit{Stock Return}_{i,m,t}$ is the monthly stock return of firm i in month m of year t, and *Scope 1* CO_2, *Scope 2* CO_2, *Scope 3* CO_2, and *Imported* CO_2 are measured at year $t-1$. *Controls* include firm-specific *Size*, *BM*, *Leverage*, *PPE*, *CapEx*, *Momentum*, *Volatility*, *Beta*, and *HHI* at year $t-1$. Model (4) also includes firm and month fixed effects and incorporates standard errors clustered at the firm-year level. We estimate the effect of each source of carbon emissions separately and jointly on future stock returns. Results are reported in Table 10.

In Columns (1)-(4), the coefficients on the emission variables are positive and statistically significant at the 1% level, consistent with the notion that stocks with greater climate risk exposures also have greater future stock returns. In Column (5), we evaluate the joint impacts of the emission variables and find that while the signs of emission variables remain positive, only the coefficient on *Imported* CO_2 remains unaffected and is statisically significant at the 1% level. The coefficient on *Scope 3* CO_2 becomes marginally significant at the 10% level. These results are intriguing and somewhat corroborate those in Table 9 on reputational risks. In particular, the market sufficiently prices a firm's Scopes 1 and 2 emissions (i.e., emissions of the firm's own production and operation), and to a certain degree, its Scope 3 emissions. Combined, the results of Tables 9 and 10 explain why U.S. firms have a strong incentive to outsource emissions. Besides regulatory oversight, these firms also exploit investor oversight or unawareness of their emissions along the upstream supply chain.

5.3. Green Innovation and Carbon Emissions

We now investigate whether firms are incentivized to develop clean technologies in response to political and social pressures to reduce carbon emissions. Economic theory suggests that firms may innovate as a differentiation strategy to gain competitive advantages over their rivals (e.g., Aghion et al. 2005). Therefore, we conjecture that firms invest more in green R&Ds gearing toward environmental patents to offset any potential adverse regulatory shocks and remain competitive.

To test the prediction, we regress a firm's future green innovative output on its imported carbon emissions as well as Scopes 1, 2, and 3 emissions as follows.

$$\begin{aligned} \textit{Green Innovation}_{i,t+1} \quad = \quad & \alpha + \beta_1 \text{Imported CO}_{2i,t} + \beta_2 \textit{Scope 1 CO}_{2i,t} + \beta_3 \textit{Scope 2 CO}_{2i,t} \quad (5) \\ & + \beta_4 \textit{Scope 3 CO}_{2i,t} + \beta'_{CS} \textit{Controls}_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where $\textit{Green Innovation}_{i,t+1}$ is measured as the one-year ahead number of clean patents filed by each firm, where clean patents are classified based on their the International Patent Classifications (IPC) by Dechezlepretre, Martin, and Mohnen (2013), who focus on identifying the clean IPCs for four sectors: energy, automotive, fuel, and lighting. *Controls* include firm-specific *Age*, *Size*, *Tobin's Q*, *Leverage*, *PPE*, *ROA*, *CapEx*, *R&D*, and *HHI*. The results are shown in Table 11.

The table reveals one distinct finding. There is little evidence that firms that reduce their carbon footprints through outsourcing pollution to foreign suppliers have a desire to develop clean technologies. Imported CO_2 emissions are negatively correlated with green innovation output, while none of the direct and indirect carbon emissions significantly affect green innovation. For example, the coefficient estimates of *Imported* CO_2 are between -0.024 ($t-$statistic$= -2.37$) and -0.027 ($t-$statistic$= -2.42$) and are all statistically significant at the 5% level. In contrast, the coefficients on *Scope 1* CO_2, *Scope 2* CO_2, and *Scope 3* CO_2 are not statistically different from zero. Adding *Scope 1* CO_2, *Scope 2* CO_2, and *Scope 3* CO_2, separately or jointly, to the model has virtually no effect on the magnitude of the *Imported* CO_2 coefficient.[22] The more firms import, the less likely they will engage in environmental innovation. These results are in line with the work of Cohen, Nguyen, and Gurun (2020). While their evidence suggests that "bad apples" (i.e., firms in heavily-polluted industries, including oil, gas, and energy) can do good by being critical innovators in the U.S. green patent landscape, our findings show that "good apples" (i.e., firms with lower Scope 1 emissions) can do bad by evading green innovation.

6. Conclusion

Climate change is a real and undeniable global threat, and its effects are already apparent. While companies recognize the risks associated with climate change and are taking actions to reduce their carbon footprints, there is little evidence whether corporations follow through on their 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 pricing and welfare implications 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. Figure 1 provides graphical evidence of how firms curb their carbon footprints by increasing supplier-induced carbon emissions, especially following the 2015 Paris Agreement. Combating climate change is not only the sole responsibility of corporations but also the responsibilities 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.

Combating climate change demands international cooperation. A single country cannot solve its own climate problem, even if it can achieve a carbon-neutral economy. Countries need coordinated action to protect what is ultimately a shared climate. Our results call for international engagements

[22] Untabulated results also show that when *Scope 1* CO_2, *Scope 2* CO_2, and *Scope 3* CO_2 are estimated alone with the control variables, none of their coefficients are statistically signficant, suggesting that these emissions play no role in influencing a firms' green innovation output.

between policymakers and other stakeholders to support cost-effective policy measures to mitigate global climate risks and support low carbon investments. Also, these results might be useful for nations to revise their climate action plans as set out under the 2015 Paris Climate Agreement, and to close the gap between what they have pledged and what is needed. While government and individual actions are vital to addressing global warming, corporations, with their influence and power in today's world, have an even larger role to play. They are able to drive policy change, shape consumer preferences, and rapidly respond to the necessities of climate change at a scale and pace beyond any other political or private entity. Purposeful corporate action is not only necessary as climate change accelerates by the day, it is also a global obligation. Companies should take full responsibility for their climate footprints.

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Figure 1
Direct vs. Supplier-Induced Carbon Emissions During the 2007-2017 Period

This figure depicts the time series of firms' direct (Scope 1) and indirect (Scopes 2 and 3) carbon emissions, together with their total assets.

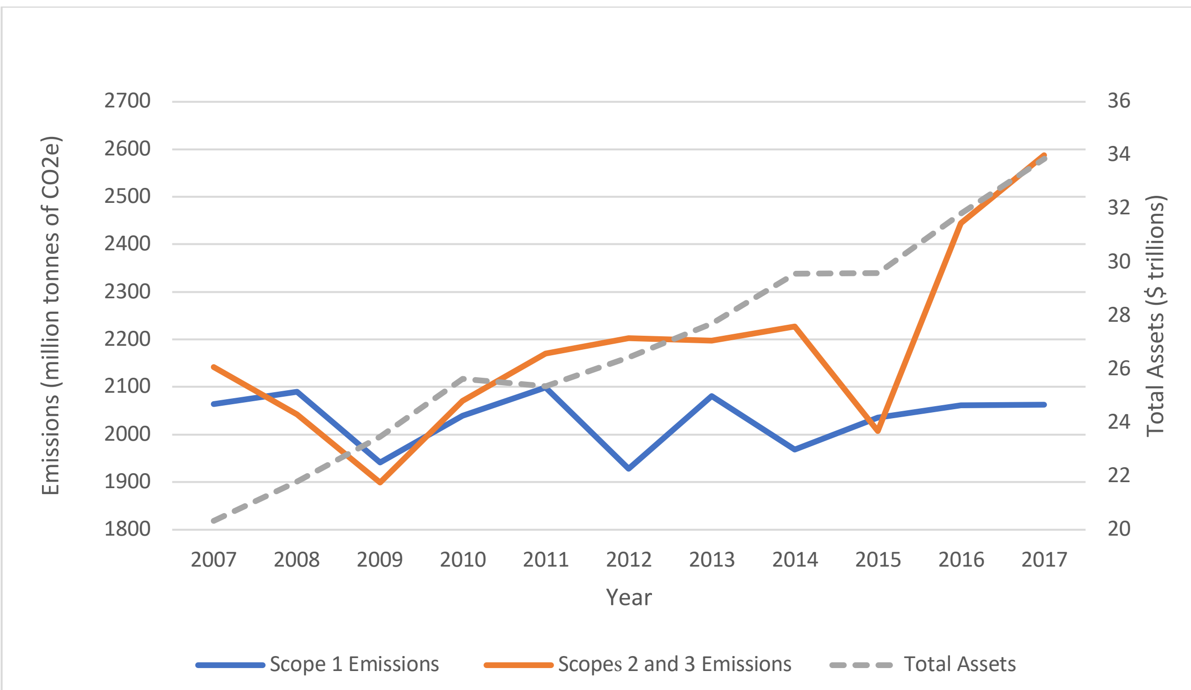

Table 1
Summary Statistics

This table presents summary statistics of the variables in our baseline analysis over the entire sample period from 2007 to 2019. It shows the 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 Scopes 1, 2, and 3 emissions reported in thousands of tonnes and *Import* is in the number of shipments. The remaining variables are defined in the Appendix.

Variable	Observations	Mean	Stdev	Min	P25	Median	P75	Max
Key Variables in Raw Values								
Scope 1 ('000 tonnes)	73,966	2880.81	9472.83	2.31	46.70	165.59	785.58	63000.00
Scope 2 ('000 tonnes)	73,966	1001.93	2211.28	3.48	59.73	208.72	917.93	14000.00
Scope 3 ('000 tonnes)	73,966	5219.11	11200.00	28.27	416.97	1305.63	4309.13	67200.00
Import (# Shipments)	73,966	37.977	112.553	1.000	1.000	4.000	20.000	836.000
Key Variables								
Scope 1	73,966	3.350	1.478	0.420	2.344	3.141	4.151	7.039
Scope 3	73,966	5.086	0.921	2.807	4.495	5.160	5.688	7.276
Scope $2+3$	73,966	5.305	0.902	2.993	4.771	5.376	5.921	7.331
Import	73,966	0.008	0.026	0.000	0.000	0.001	0.003	0.195
Control Variables								
Assets	73,966	9.051	1.321	7.018	7.987	8.915	10.098	11.404
Tobin's Q	73,966	1.841	0.740	0.988	1.252	1.638	2.241	3.468
Leverage	73,966	0.256	0.141	0.035	0.149	0.245	0.353	0.518
ROA	73,966	0.109	0.055	0.026	0.066	0.103	0.146	0.214
SalesGrowth	73,966	0.048	0.114	-0.155	-0.023	0.045	0.116	0.260
Tangibility	73,966	0.518	0.304	0.127	0.261	0.447	0.747	1.086
R&D	73,966	0.098	0.135	0.000	0.000	0.025	0.157	0.426

Table 2
The Effect of Imports on Firms' CO_2 Emissions

This table reports results from the regression of a firm's indirect emissions (*Scope 3* or *Scope 2+3*) on its direct emissions (*Scope 1*), imports (*Import*), and their interaction (*Scope 1* $\times$ *Import*) as follows.

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

where the vector of *Controls* includes firm-specific *Assets*, *Tobin's Q*, *Leverage*, *ROA*, *SalesGrowth*, *Tangibility*, and *R&D*. The definition of variables is contained in Appendix A. The regression model includes two different sets of fixed effects (**FE**) such as firm, country, and year or firm and country-year. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for firm-year clustering. *, **, *** are significance levels denoted at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable			
	Scope 3		Scopes $2+3$	
Variable	(1)	(2)	(3)	(4)
Scope 1 $\times$ Import	-0.104**	-0.097**	-0.098**	-0.088**
	(-2.68)	(-2.45)	(-2.64)	(-2.34)
Scope 1	0.112***	0.112***	0.138***	0.138***
	(6.35)	(6.51)	(7.73)	(7.88)
Import	0.355**	0.329**	0.325**	0.285**
	(2.65)	(2.39)	(2.57)	(2.20)
Assets	-0.156***	-0.157***	-0.151***	-0.152***
	(-4.41)	(-4.45)	(-4.73)	(-4.77)
Tobin's Q	-0.026**	-0.027**	-0.028**	-0.028**
	(-2.35)	(-2.38)	(-2.46)	(-2.49)
Leverage	-0.061	-0.061	-0.057	-0.057
	(-0.75)	(-0.75)	(-0.82)	(-0.83)
ROA	2.084***	2.068***	1.943***	1.926***
	(7.99)	(8.09)	(8.27)	(8.38)
SalesGrowth	0.073*	0.072*	0.049	0.047
	(1.81)	(1.80)	(1.29)	(1.28)
Tangibility	0.374**	0.375**	0.366***	0.366***
	(2.94)	(2.99)	(3.20)	(3.26)
R&D	0.157	0.149	0.261	0.256
	(0.74)	(0.71)	(1.18)	(1.18)
Firm, Country, Year FE	Yes	No	Yes	No
Firm, Country$\times$Year FE	No	Yes	No	Yes
Observations	73,966	73,659	73,966	73,659
Adj. R^2	0.968	0.969	0.969	0.969

Table 3
Shocks to Legislative Pressure and State Regulatory Stringency

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

$$\begin{aligned} \textit{Scope 3}_{i,t} \;=\; & \alpha + \beta_{SI1}\textit{Scope 1}_{i,t} \times \textit{Import}_{i,c,t} \times \textit{Treat}_{t-1} + \beta_{SI}\textit{Scope 1}_{i,t} \times \textit{Import}_{i,c,t} \\ & + \beta_{S1}\textit{Scope 1}_{i,t} \times \textit{Treat}_{t-1} + \beta_{I1}\textit{Import}_{i,c,t} \times \textit{Treat}_{t-1} + \beta_{S}\textit{Scope 1}_{i,t} \\ & + \beta_{I}\textit{Import}_{i,c,t} + \beta_{1}\textit{Treat}_{t-1} + \beta_{CS}{}'\textit{Controls}_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where *Treat* is a binary indicator that alternately captures three different representations. *Treat* equals one if the one-year lagged average voting score on climate change-specific environmental legislations for the House of Representatives (House) in Column (1) or the Senate in Column (2) increases more than three times the average increase in the voting score over time. In Column (3), *Treat* equals one if the one-year lagged average onsite inspection level per facility (Onsite) increases more than three times the average onsite inspection increase in the level over time. Note that for every *Treat* variable, the change must not revert within the next three years, and the change in firm locations must not drive the shock. *Scope 1, Scope 2, Imports*, *Controls*, and **FE** are those defined in Table 2. The definition of variables is contained in Appendix A. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for firm-year clustering. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Legislative Pressure		State-Level Regulatory Stringency
	Treat=House	Treat=Senate	Treat=Onsite
Variable	(1)	(2)	(3)
Scope 1 × Import × Treat	-0.309***	-0.482**	-0.341**
	(-4.50)	(-2.44)	(-2.58)
Scope 1 × Import	-0.077	-0.071**	-0.081*
	(-1.74)	(-2.36)	(-2.12)
Scope 1 × Treat	0.021**	0.001	-0.005
	(2.63)	(0.08)	(-0.55)
Import × Treat	0.926***	1.413*	0.935**
	(3.58)	(2.15)	(2.97)
Scope 1	0.105***	0.106***	0.107***
	(6.26)	(6.40)	(6.41)
Import	0.294*	0.267**	0.290*
	(1.98)	(2.53)	(2.11)
Treat	-0.035	0.001	0.036
	(-1.28)	(0.02)	(1.26)
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Observations	66,333	66,333	66,333
Adj. R^2	0.969	0.969	0.969

Table 4
Electricity Price Spikes, Import Tariff Reductions, and Natural Disasters

This table presents tests of shocks to electricity prices and import tariffs, and natural disasters occurring in the exporting country using the following regression model with triple-interaction effects:

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

where *Treat* is a binary indicator that alternately captures three different representations. In Column (1), *Treat* equals one if the one-year lagged average electricity price increases more than four times the average price increase over time (Price Spikes). In Column (2), *Treat* equals one for the next five years if the lagged applied tariff rate for the exporting country and industry reduces more than three times the average decrease in rates over time (i.e., a time-series average for each country-sector) (Tariff Drops). In Column (3), *Treat* (Disaster) equals one if the exporting country has more than one natural disaster incidence during the year (with at least US$1 million of damage). Note that for every *Treat* variable, the change must not revert within the next three years, and the change in firm locations must not drive the shock. *Scope 1, Scope 2, Imports*, *Controls*, and **FE** are those defined in Table 2. The definition of variables is contained in Appendix A. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for firm-year clustering. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Treat=Price Spikes	Treat=Tariff Drops	Treat=Disaster
Variable	(1)	(2)	(3)
Scope 1 × Import × Treat	-0.600**	-0.465*	0.083**
	(-3.32)	(-1.90)	(2.42)
Scope 1 × Import	-0.059	-0.082	-0.134**
	(-1.36)	(-1.57)	(-2.85)
Scope 1 × Treat	0.030**	0.028**	0.001
	(2.74)	(2.48)	(0.52)
Import × Treat	1.950***	1.637*	-0.186
	(3.32)	(2.16)	(-1.70)
Scope 1	0.105***	0.114***	0.112***
	(6.38)	(5.69)	(6.50)
Import	0.225	0.283	0.417**
	(1.56)	(1.74)	(2.62)
Treat	-0.074***	-0.079**	
	(-2.46)	(-2.55)	
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Observations	66,333	49,177	49,177
Adj. R^2	0.969	0.959	0.959

Table 5
The Effect of Imports on Firms' CO_2 Emissions by Outsourcing Country Type

This table reports subsample results using the baseline regression of a firm's indirect (*Scope 3*) emissions on its direct (*Scope 1*) emissions, imports (*Import*), and their interaction (*Scope 1 × Import*), by outsourcing country type, as follows.

$$Scope\ 3_{i,t} \quad = \quad \alpha + \beta_{SI} Scope\ 1_{i,t} \times Import_{i,c,t} + \beta_S Scope\ 1_{i,t} + \beta_I Import_{i,c,t} + \beta_{CS}{}' Controls_{i,t-1} + \mathbf{FE} + \epsilon_{i,t},$$

where the vector of *Controls* includes firm-specific *Assets*, *Tobin's Q*, *Leverage*, *ROA*, *SalesGrowth*, *Tangibility*, and *R&D*. The definition of variables is contained in Appendix A. The regression model includes firm and country-year fixed effects (**FE**). The subsamples are grouped based on the country, where Scope 3 emissions are derived, namely, emerging vs. developed countries in Columns (1)-(4), non-OECD vs. OECD countries in Columns (5)-(8), and common law vs. civil law countries in Columns (9)-(12). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for firm-year clustering. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Emerging vs. Developed Markets		Non-OECD vs. OECD Countries		Common Law vs. Civil Law Countries	
	Emerging	Developed	Non-OECD	OECD	Common Law	Civil Law
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Scope 1 × Import	-0.099***	-0.103	-0.146**	-0.074	-0.203***	-0.074
	(-3.29)	(-1.29)	(-3.04)	(-1.56)	(-3.66)	(-1.77)
Scope 1	0.106***	0.116***	0.104***	0.117***	0.105***	0.116***
	(5.79)	(6.86)	(5.91)	(6.65)	(6.66)	(6.32)
Import	0.386***	0.284	0.470**	0.271	0.630***	0.271*
	(3.27)	(1.11)	(2.82)	(1.70)	(3.52)	(1.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,010	39,079	31,883	41,610	23,250	49,175
Adj. R^2	0.968	0.969	0.968	0.969	0.969	0.968

Table 6

The Effect of Imports on Firms' CO_2 Emissions by Environmental Regulation

This table reports subsample results using the baseline regression of a firm's indirect (*Scope 3*) emissions on its direct (*Scope 1*) emissions, imports (*Import*), and their interaction (*Scope 1* × *Import*), by the country environmental regulation, as follows.

$$Scope\ 3_{i,t} \quad = \quad \alpha + \beta_{SI} Scope\ 1_{i,t} \times Import_{i,c,t} + \beta_S Scope\ 1_{i,t} + \beta_I Import_{i,c,t} + \beta_{CS}{}' Controls_{i,t-1} + \mathbf{FE} + \epsilon_{i,t},$$

where the vector of *Controls* includes firm-specific *Assets*, *Tobin's Q*, *Leverage*, *ROA*, *SalesGrowth*, *Tangibility*, and *R&D*. The definition of variables is contained in Appendix A. The regression model includes firm and country-year fixed effects (**FE**). The subsamples are grouped based on the below (Low) and above median (High) of yearly cross-section rankings of countries' stringency of environmental regulation, environmental performance on climate change, and country-level emissions. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for firm-year clustering. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Regulatory Stringency		Environmental Performance		Country Emissions	
	Low	High	Low	High	Low	High
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Scope 1 × Import	-0.225***	-0.088*	-0.174***	-0.067	-0.074	-0.117**
	(-3.52)	(-1.99)	(-3.25)	(-1.60)	(-1.02)	(-3.03)
Scope 1	0.093***	0.115***	0.109***	0.114***	0.113***	0.109***
	(4.28)	(6.90)	(6.02)	(6.68)	(6.19)	(6.13)
Import	0.775**	0.292*	0.558**	0.251	0.209	0.489***
	(3.04)	(1.96)	(3.01)	(1.77)	(0.83)	(3.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,787	56,495	27,636	43,739	45,284	19,281
Adj. R^2	0.967	0.969	0.968	0.969	0.968	0.968

Table 7
Internal Mechanisms

This table reports results showing the various internal mechanisms (*Internal*) through which a firm's direct (*Scope 1*) emissions and imports (*Import*) affect indirect (*Scope 3*) emissions, using the following model specification.

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

where *Internal* alternately represents a firm's: (1) Green score, which represents its environmental score; (2) Green CEO, who is determined by the CEO's past five years of experience working in an ESG-oriented firm (or firms). (3) Green Directors, who are measured by the firm's board of direcrors' past five years of experience working in an ESG-oriented firm (or firms). *Controls* include firm-specific *Assets*, *Tobin's Q*, *Leverage*, *ROA*, *SalesGrowth*, *Tangibility*, and *R&D*. The definition of variables is contained in Appendix A. **FE** are firm and country-year fixed effects. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for firm-year clustering. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Definition of Each Internal Mechanism (*Internal*)		
	Green Score	Green CEO	Green Directors
Variable	(1)	(2)	(3)
Scope 1 × Import × Internal	-0.594*	-0.136*	-0.141*
	(-1.95)	(-1.89)	(-1.95)
Scope 1 × Import	0.165	0.516	0.559
	(1.28)	(1.42)	(1.53)
Scope 1 × Internal	-0.030	-0.006	-0.006
	(-0.75)	(-1.149)	(-1.66)
Import × Internal	0.116***	0.507*	0.523*
	(4.36)	(2.07)	(2.13)
Scope 1	1.849*	0.128***	0.130***
	(2.01)	(4.41)	(4.55)
Import	-0.527	-2.011	-2.144
	(-1.35)	(-1.65)	(-1.76)
Internal	0.245*	0.033*	0.035**
	(2.05)	(2.71)	(2.95)
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Observations	63,021	61,981	62,512
Adj. R^2	0.969	0.969	0.969

Table 8
External Mechanisms

This table reports results showing the various external mechanisms (*External*) through which a firm's direct (*Scope 1*) emissions and imports (*Import*) affect indirect (*Scope 3*) emissions, using the following model specification.

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

where *External* alternately represents the firm's: (1) Largest Govt Customer is its largest government customer; (2) Green Customers are measured by corporate customers with below industry-median CO_2 emissions; (3) Green Blockholders are institutional investors with at least 50% of their portfolio firms with below industry-median environmental rating scores. *Controls* include firm-specific *Assets*, *Tobin's Q*, *Leverage*, *ROA*, *SalesGrowth*, *Tangibility*, and *R&D*. The definition of variables is contained in Appendix A. **FE** are firm and country-year fixed effects. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for firm-year clustering. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Definition of Each External Mechanism (*External*)		
	Largest Govt Customer	Green Customers	Green Blockholders
Variable	(1)	(2)	(3)
Scope 1 × Import × External	0.088***	0.464**	1.525*
	(3.66)	(2.93)	(2.05)
Scope 1 × Import	-0.114**	-0.295***	-0.117**
	(-2.57)	(-3.58)	(-2.66)
Scope 1 ×External	0.001	-0.034**	-0.258***
	(0.62)	(-2.30)	(-3.54)
Import × External	0.084***	0.116***	0.112***
	(3.53)	(5.41)	(6.30)
Scope 1	-0.249***	-1.292**	-1.704
	(-4.04)	(-2.39)	(-0.63)
Import	0.414**	0.924***	0.361**
	(2.77)	(3.19)	(2.37)
External	0.000	0.131**	1.090***
	(0.16)	(2.51)	(5.79)
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Observations	31,544	56,641	70,000
Adj. R^2	0.977	0.970	0.968

Table 9
Reputational Risk and Various Sources of Firms' CO_2 Emissions

This table reports regression results showing effects of a firm's various sources of CO_2 emissions, including CO_2 emissions from imported input goods (Imported CO_2), its direct emissions from own production (*Scope 1* CO_2), indirect emissions from the generation of purchased energy (*Scope 2* CO_2), and through supply-chains (*Scope 3* CO_2) on the firm's systematic risk associated with ESG practices, using the following model specification.

$$\begin{aligned} RepRisk\ \beta_{,i,t} &= \alpha + \beta_1 \text{Imported CO}_{2i,t} + \beta_2 Scope\ 1\ CO_{2i,t} + \beta_3 Scope\ 2\ CO_{2i,t} \\ &\quad + \beta_4 Scope\ 3\ CO_{2i,t} + \beta'_{CS} Controls_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where $RepRisk\ \beta_{i,t}$ is the factor loading obtained from regressing individual firms' daily stock returns against returns on the zero-investment portfolio constructed from taking the difference in daily value-weighted returns between high and low reputational-risk portfolios and those of the Fama-French 4-factor model in a given year. *Controls* include firm-specific *Assets*, *Tobin's Q*, *R&D*, *PPE*, *Leverage*, *CapEx*, *Cash*, *Income Volatility*, and *ROA*. The definition of variables is contained in Appendix A. **FE** are firm and country-year fixed effects. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for firm-year clustering. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

Variable	(1)	(2)	(3)	(4)	(5)
Imported CO^2	0.058**				0.059**
	(2.53)				(2.85)
Scope 1		-0.014			-0.045
		(-0.46)			(-1.01)
Scope 2			0.032		-0.003
			(0.69)		(-0.06)
Scope 3				0.184	0.201
				(1.42)	(1.40)
Assets	0.091	0.108	0.078	-0.032	-0.020
	(0.83)	(0.94)	(0.70)	(-0.34)	(-0.22)
Tobin's Q	0.165**	0.172***	0.169***	0.162**	0.164**
	(2.97)	(3.16)	(3.15)	(2.99)	(3.00)
R&D	-2.684*	-2.503*	-2.602*	-2.964*	-2.925*
	(-2.07)	(-1.93)	(-1.91)	(-2.10)	(-2.11)
PPE	-2.984	-2.361	-2.620	-3.090	-2.809
	(-1.45)	(-1.14)	(-1.25)	(-1.34)	(-1.27)
Leverage	-0.302	-0.280	-0.274	-0.258	-0.267
	(-1.35)	(-1.26)	(-1.24)	(-1.18)	(-1.20)
CapEx	0.396	0.598	0.620	0.713	0.659
	(0.47)	(0.72)	(0.74)	(0.86)	(0.80)
Cash	0.148	0.151	0.164	0.191	0.179
	(1.03)	(1.08)	(1.14)	(1.26)	(1.22)
Income Volatility	-0.008*	-0.009*	-0.009*	-0.008	-0.008*
	(-2.08)	(-2.05)	(-1.98)	(-1.80)	(-1.86)
ROA	0.910	0.822	0.783	0.525	0.512
	(1.07)	(0.91)	(0.89)	(0.70)	(0.69)
	-0.732	-0.708	-0.975	-2.085	-1.903
	(-0.78)	(-0.70)	(-0.89)	(-1.20)	(-1.15)
Observations	5,904	5,615	5,615	5,615	5,615
Firm, Month FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.314	0.316	0.316	0.318	0.319

Table 10
Future Stock Returns and Sources of CO_2 Emissions of Firms

This table reports regression results showing effects of a firm's various sources of CO_2 emissions, including CO_2 emissions from imported input goods (Imported CO_2), direct emissions from its own production (*Scope 1 CO_2*), indirect emissions from the generation of purchased energy (*Scope 2 CO_2*), and through supply-chains (*Scope 3 CO_2*) on monthly future stock returns, using the following model specification.

$$\begin{aligned} \textit{Stock Return}_{i,m,t} &= \alpha + \beta_1 \text{Imported CO}_{2i,t-1} + \beta_2 \textit{Scope 1 CO}_{2i,t-1} + \beta_3 \textit{Scope 2 CO}_{2i,t-1} \\ &\quad + \beta_4 \textit{Scope 3 CO}_{2i,t-1} + \beta'_{CS} \textit{Controls}_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where *Stock Return*$_{i,m,t}$ is the monthly stock return of firm i in month m of year t. *Controls* include firm-specific *Size*, *BM*, *Leverage*, *PPE*, *CapEx*, *Momentum*, *Volatility*, *Beta*, and *HHI*. The definition of variables is contained in Appendix A. **FE** are firm and month fixed effects. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for firm-year clustering. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

Variable	(1)	(2)	(3)	(4)	(5)
Imported CO_2	0.002***				0.002***
	(3.12)				(3.16)
Scope 1 CO_2		0.001*			0.000
		(1.86)			(0.78)
Scope 2 CO_2			0.002*		0.001
			(2.10)		(0.75)
Scope 3 CO_2				0.006**	0.005*
				(2.37)	(1.94)
Size	-0.019***	-0.019***	-0.019***	-0.020***	-0.020***
	(-6.62)	(-6.64)	(-6.76)	(-7.64)	(-7.64)
BM	0.008*	0.008*	0.007*	0.007*	0.007*
	(1.99)	(2.04)	(1.99)	(1.86)	(1.81)
Leverage	0.006	0.006	0.006	0.006	0.006
	(0.88)	(0.94)	(0.88)	(0.91)	(0.87)
PPE	-0.002	-0.003	-0.003	-0.005	-0.005
	(-0.60)	(-0.97)	(-1.16)	(-1.64)	(-1.69)
CapEX	-0.040	-0.038	-0.038	-0.037	-0.038
	(-0.99)	(-0.93)	(-0.95)	(-0.96)	(-1.01)
Momentum	0.001	0.002	0.002	0.002	0.002
	(0.69)	(0.70)	(0.75)	(0.96)	(1.00)
Volatility	0.030	0.030	0.031	0.030	0.030
	(1.07)	(1.08)	(1.09)	(1.09)	(1.10)
Beta	0.005	0.005	0.005	0.005	0.005
	(1.10)	(1.09)	(1.12)	(1.15)	(1.17)
HHI	0.003	0.003	0.003	0.003	0.003
	(0.55)	(0.41)	(0.46)	(0.42)	(0.49)
Observations	62,978	62,978	62,978	62,978	62,978
Firm, Month FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.303	0.302	0.303	0.303	0.303

Table 11
Green Innovation and Firms' Various Sources of CO_2 Emissions

This table reports regression results showing effects of a firm's various sources of CO_2 emissions, including CO_2 emissions from imported input goods (Imported CO_2), its direct emissions from own production (*Scope 1* CO_2), indirect emissions from the generation of purchased energy (*Scope 2* CO_2), and through supply-chains (*Scope 3* CO_2) on its *Green Innovation*, using the following model specification.

$$\begin{aligned} \textit{Green Innovation}_{i,t+1} &= \alpha + \beta_1 \text{Imported } \mathrm{CO_2}_{i,t} + \beta_2 \textit{Scope 1 } CO_{2\,i,t} + \beta_3 \textit{Scope 2 } CO_{2\,i,t} \\ &\quad + \beta_4 \textit{Scope 3 } CO_{2\,i,t} + \beta'_{CS} \textit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where $\textit{Green Innovation}_{i,t+1}$ is the number of green patents filed by firm i in year *t+1*, where clean patents are classified based on their the International Patent Classifications (IPC). *Controls* include firm-specific *Size*, *Age*, *Tobin's Q*, *Leverage*, *PPE*, *ROA*, *CapEx*, *R&D*, and *HHI*. The definition of variables is contained in Appendix A. **FE** are firm and country-year fixed effects. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for firm-year clustering. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

Variable	(1)	(2)	(3)	(4)
Imported CO_2	-0.024**	-0.025**	-0.025**	-0.027**
	(-2.37)	(-2.26)	(-2.26)	(-2.42)
Scope 1 CO_2		-0.006	-0.007	-0.010
		(-0.65)	(-0.82)	(-1.05)
Scope 2 CO_2			0.006	-0.001
			(0.40)	(-0.09)
Scope 3 CO_2				0.031
				(1.77)
Age	0.178**	0.192**	0.190**	0.188**
	(2.48)	(2.45)	(2.38)	(2.34)
Size	0.000	0.002	0.001	-0.003
	(0.00)	(0.17)	(0.10)	(-0.31)
Tobin's Q	0.004	0.004	0.005	0.008
	(0.37)	(0.36)	(0.42)	(0.64)
Leverage	0.016	0.013	0.012	0.009
	(0.33)	(0.23)	(0.22)	(0.15)
PPE	-0.007	-0.006	-0.008	-0.021
	(-0.24)	(-0.17)	(-0.25)	(-0.64)
ROA	-0.035	-0.034	-0.040	-0.088
	(-0.37)	(-0.36)	(-0.44)	(-0.92)
CapEx	-0.104	-0.136	-0.136	-0.128
	(-0.82)	(-0.97)	(-0.99)	(-0.98)
R&D	0.499	0.496	0.494	0.479
	(0.72)	(0.69)	(0.68)	(0.66)
HHI	-0.109	-0.108	-0.108	-0.109
	(-1.34)	(-1.29)	(-1.29)	(-1.29)
	-0.450*	-0.453*	-0.469*	-0.629**
	(-1.97)	(-1.90)	(-2.00)	(-2.53)
Observations	5,203	4,845	4,845	4,845
Firm × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.579	0.585	0.584	0.585

Appendix A

Variable Definition and Data Source

Variable	Definition and Data Source
Measures of Firm-level CO_2 Emissions and Imports	
Scope 1	ln(1 + Scope 1 emissions/customer total asset) (TruCost & Compustat)
Scope 3	ln(1 + Scope 3 emissions/customer total asset) (TruCost & Compustat)
Scope 2+3	ln(1 + Scopes 2+3 emissions/customer total asset) (TruCost & Compustat)
Import	ln(1 + the number of shipments from suppliers in each exporting country / customer total asset) (TruCost & Compustat)
Imported CO^2	Firm-level imported pollution each year is defined as the log of one plus total CO_2 emissions from all imported shipments across all exporting countries. The variable is measured as the log sum of product-weighted CO_2 emissions (per $1M) over all the imported goods for a firm over a given year. The CO_2 emissions of each import transaction is based on BEA Input-Output through HS code reported to US ports. (Carnegie Mellon University-Economic Input-Output Life Cycle Assessment, Peter K. Schott's Website, and Panjiva)
Scope 1 CO^2	ln(1 + Scope 1 emissions) (TruCost)
Scope 2 CO^2	ln(1 + Scope 3 emissions) (TruCost)
Scope 3 CO^2	ln(1 + Scopes 3 emissions) (TruCost)
Identification Variables	
House	A binary variable equals 1 if the lagged increase in the House of Representative voting score is more than four times larger than the average score increase in the state, where House voting score is defined as the number of pro-environment votes on climate change-specific legislations from each House of Representative member in the firm headquarter state divided by the total number of climate change-specific legislations in a given year, averaged across all House members in that state and year (League of Conservation Voters)
Senate	A binary variable equals 1 if the lagged increase in the Senate voting score is more than four times larger than the average score increase in the state, where Senate voting score is defined as the number of pro-environment votes from each Senator in the firm headquarter state divided by the total number of environmental legislations n a given year, averaged across all Senators in that state and year(League of Conservation Voters)
Onsite	A binary variable equals 1 if the lagged increase in onsite inspections is more than four times larger than the average inspection increase in the state, where an onsite inspection is defined as the total number of onsite air pollution compliance evaluations conducted by EPA across all facilities located in the firm headquarter state divided by the total number of emitting facilities in that state and year (ECHO)
Price Spikes	A binary variable equals 1 if the lagged increase in electricity rates is more than four times larger than the average price increase in the state, where an electricity rate is defined as the average retail electricity rate for the firm headquarter state and year (EIA)
Tariff Drops	A binary variable equals 1 for the next five years if the lagged reduction in tariff is more than four times larger than the average tariff reduction for the specific exporting country and industry, where tariff is measured by the average effectively applied rate for each Frama-French 30 industry and exporting country (WITS World Bank)
Disaster	A binary variable equals 1 if an exporting country is ranked in the top quintile on the number of major disasters occurring during the year, where major disasters are those natural disasters causing at least one million dollars of damage (EM-DAT)

Appendix A – Continued

Variable Definition and Data Source

Variable	Definition and Data Source
Internal Mechanism Variables	
Green Score	A firm's score associated with the environmental pillar of a CSR Rating (Asset4)
Green CEO	A firm's Green CEO is determined by the CEO's past five years of experience working in a firm or firms. Within each year, firms are formed into deciles based on their environmental scores. For a Green CEO at a given year, we calculate the CEO's firm's average decile ranks over years -5 to -1 and then take the average of the ranks and assign this rank as the CEO's environmental score for the year (BoardEx & Asset4)
Green Directors	A firm's Green Directors is determined by taking the average of the ranks of all its directors' past five years of experience working in a firm or firms. Within each year, firms are formed into deciles based on their environmental scores. For each director at a given year, we calculate the director's firm's average decile ranks over years -5 to -1 and then take the average of the ranks and assign this rank as the director's environmental score for the year. We then take an equal-weighted average of ranks of the board of directors. (BoardEx & Asset4)
External Mechanism Variables	
Large Gov Customer	Sales percentage to the largest major government customers of a firm, where major customers each accounts for at least 10% of the firm's total sales (Compustat Customer Segment)
Green Customers	Percentage of green corporate customers defined as the number of green corporate customers divided by the total number of corporate customers, where green customers are those with below the industry-median GHG emissions per dollar of total assets (Revere & TruCost)
Green Blockholders	Percentage of a firm's shares owned by green blockholders in a given year, where blockholders are institutional investors each holding at least 5% of a firm's shares outstanding, and green investors are those institutions with at least 50% of their portfolio invested in green firms ranked in the top quintile on the ESG score among all firms in a year (FactSet Ownership & ASSET4)
Pricing and Welfare Implications	
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.
Stock Return	Monthly Return of firm i's primary shares over year t (CRSP)
Clean Innovation	One-year ahead number of clean patents filed by each firm, where clean patents are classified based on the International Patent Classifications (IPC) Dechezlepretre, Martin, and Mohnen (2013). (PATSTAT)

Appendix A – Continued

Variable Definition and Data Source

Variable	**Definition and Data Source**
Control Variables	
Assets	ln(1 + total asset) (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 leverage scaled by total asset (Compustat)
ROA	Eearnings before interest and taxes scaled by total asset (Compustat)
SalesGrowth	Percentage change in sales (Compustat)
Tangibility	Gross property, plant, and expenditure scaled by total asset (Compustat)
R&D	Cumulative R&D expenditure over time since 1985 with a decay rate of 15% each year (Compustat)
Control Variables Related to Welfare and Pricing 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)
Momemtum	Cumulative monthly stock return over one-year period (CRSP)
Volatility	Monthly stock return volatility over one-year period (CRSP)
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)