Outsourcing Climate Change

Rui Dai, Rui Duan, Hao Liang, and Lilian Ng*

Current Version: September 14, 2021

*Dai is from WRDS, The Wharton School, University of Pennsylvania, Philadelphia, USA; Duan is from WU Vienna University of Economics and Business; Ng is from the Schulich School of Business, York University, Toronto, Canada; Liang from Singapore Management University. Authors' email information: Dai: rui.dai.wrds@outlook.com; Duan: rui.duan@wu.ac.at; Liang: hliang@smu.edu.sg; Ng: Email: lng@schulich.york.ca. We thank Robin Döttling, Anne Jacqueminet, Wei Jiang, Valerie Karplus (discussant), Andrew King, Angie Low, Mancy Luo, Basma Majerbi, Lakshmi Naaraayanan (discussant), Mikael Paaso, Nora Pankratz (discussant), Nicholas Poggioli, Michael Toffel, Michael Viehs (discussant), Haikun Zhu, and seminar participants at the 2021 Alliance for Research on Corporate Sustainability, 2021 Asian Bureau of Finance and Economic Research's Annual Conference, Erasmus University Rotterdam, 2021 Global Research Alliance for Sustainable Finance and Investment (GRASFI) conference, 2021 International Workshop on Financial System Architecture & Stability, National Chung Cheng University, 2021 Principles for Responsible Investment Academic Network, Schulich School of Business; Seoul National University, Singapore Management University, and WRDS for their helpful comments and suggestions.

Outsourcing Climate Change

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 combat climate change. We find robust evidence that U.S. firms' imports amplify the substitutional relationship between their direct and indirect carbon emissions, suggesting that these firms outsource part of their pollution to suppliers overseas. Our key evidence is further substantiated by quasi-natural experiments associated with exogenous shocks to U.S. firms' propensity to outsource carbon emissions. We also 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 are less incentivized to develop clean technologies, have higher reputational risks, and larger future stock returns.

Keywords: Outsourcing Emissions, Imports, Stakeholders, Reputational Risk, Green Technologies
JEL classification: G23, G30, G34, M14

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. While firms' efforts seem reasonably progressive, a closer look reveals that firms are committed only to green house gas (GHG) emissions from their own production (i.e., Scope 1 emissions) and energy consumption (i.e., Scope 2 emissions).[1] They largely ignore indirect emissions from the supply of goods and services used as inputs of their production (i.e., upstream Scope 3 emissions) that form the bulk of their total GHG emissions. Prior studies indicate that averaging across all US sectors, upstream Scope 3 emissions represent 74% of a firm's total carbon footprint (Matthews, Hendrickson, Weber 2008).[2] For example, the Natural Resources Defense Council (NRDC) reports that P&G's commitments to halve pollution by 2030 only apply to Scopes 1 and 2 emissions.[3] NRDC alleges that if P&G were to include all its emissions from the production of its raw materials to the disposal of its products, its carbon emissions would be about 215 million metric tons of GHG per year. To be more accurate, only 4.3 million metric tons of GHG would be attributed to Scopes 1 and 2 emissions, indicating that P&G's GHG target applies to only 2% of its total emission level. Thus, if Scope 3 emissions are overlooked, firms have failed to fully account for their total GHG emissions attributable to their products. A natural question that arises is whether U.S. corporations are indeed integrating climate change into their business strategies or are their public commitments to a better environment simply cheap talk. To address this important issue, we examine whether and how U.S. firms reduce their carbon footprints to tackle global climate change and evaluate the consequences of their actions.

Prior academic research suggests that firms reduce carbon emissions by exporting their pollution to foreign countries.[4] For example, Ben-David et al. (2021) employ firms' self-reported survey responses about their Scopes 1 and 2 emissions over the 2008-2015 period and find that stricter

[1]See "Corporate Honesty and Climate Change: Time to Own Up and Act," by Joshua Axelrod at the Natural Resources Defense Council (NRDC), a not-for-profit organization whose work is to help safeguard the air, water, and environment.

[2]The proportion of upstream Scope 3 emissions in our sample of firms averages at 67% for the 2007-2018 period.

[3]See footnote #6.

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

environmental regulations in the domestic market lead to lower emissions at home but higher emissions abroad. Li and Zhou (2017) 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 indirect 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.

Our study exploits newly available firm-level data on firms' self-generated Scope 1 emissions and suppliers-produced upstream Scope 3 emissions from Trucost and transaction-level import information from Panjiva to conduct an in-depth analysis of U.S. firms' actions to combat climate change.[5] After merging the two key databases, our final sample yields 76,356 firm-country-year observations from 1,557 U.S. firms and 210 exporting countries for the 2007-2018 period. It is important to stress that the resulting sample only includes observations with country-level imports and firm-level emissions but excludes imports from foreign subsidiaries. These datasets provide granularity relative to those employed in the existing literature and allow us to thoroughly analyze firms' engagements in curbing carbon emissions. Figure 1 illustrates time-series trends in average proportions of Scopes 1 and 3 emissions to total emissions (Scopes 1, 2, and 3) at the firm level. The graphs show that the proportion of Scope 1 emissions has been falling through time as the proportion of upstream Scope 3 emissions increases. It seems likely that the surge in the proportion of indirect Scope 3 emissions in 2015 reflects firms' response to the 2015 Paris Agreement and that they curb their own domestic emissions in the U.S. by shifting their carbon pollution to suppliers overseas, resulting in "carbon leakage."[6] Figure 2 presents the aggregate carbon footprint (Scopes 1, 2, and 3) and total imports of U.S. firms over time. The upward time trend in both measures further suggests growing popularity in pollution offshoring.

[5] An earlier version of this study includes a firm's indirect emissions, Scope 2, which account for emissions from the firm's consumption of purchased electricity, heat, or steam. However, because Scope 2 emissions contribute an insignificantly small proportion of a firm's total GHG emissions, the exclusion of Scope 2 emissions has no material effect on the results. To conserve space, our current paper excludes reporting results on Scope 2 emissions, and throughout our study, Scope 3 emissions refer only to upstream Scope 3 emissions, which form the largest proportion of a firm's total footprint.

[6] Note that Trucost has expanded their sample in 2015 and also improved their methodology in estimating Scope 3 emissions. According to Trucost, its technical team has re-estimated the previously computed Scope 3 emissions to improve the accuracy of the estimates. Nevertheless, our results remain robust, even excluding the expanded sample.

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

While we have established that imports play an important role in driving the relationship between Scopes 1 and 3 emissions, our causal inferences of this link may be subject to endogeneity concerns. To circumvent such problems, we exploit several exogenous shocks to U.S. firms' propensity to outsource carbon emissions. Suppose our baseline findings indeed capture the outsourcing effect. In this case, imports should have a larger mitigating impact on the linkage between Scope 1 and Scope 3 emissions following an exogenous increase in the demand for imported carbon emissions. In particular, we examine demand shocks to imported emissions arising from domestic state-level legislative pressure and regulatory stringency. 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; Kim and Urpelainen 2017). Thus, firms located in states with intense legislative pressure on environmental consciousness should have stronger incentives to import as a means of outsourcing GHG emissions to their suppliers overseas. Our analysis employs sudden increases in pro-environmental votes in the House and Senate as well as close-call Congress election wins by environmentally-conscious candidates as measures of environmental legislature pressure. Similarly, to gauge the extent of regulatory stringency, we use state-level statutory and executive emission-reduction targets and spikes in Environmental Protection Agency (EPA) state-level facility inspections. Analyses in a triple-interaction framework reveal that imports have a more pronounced mitigating effect on the Scope 1–Scope 3 association following exogenous increases in political pressure and regulatory stringency on environmental issues, consistent with a causal interpretation of firms' outsourcing behavior in curbing their own emissions.

Our analysis further investigates cross-industry and cross-country variations in emissions outsourcing. First, we examine whether pollution outsourcing is concentrated in pollution-intensive industries. We employ two approaches to capture industry-level emissions. One approach is to aggregate the total Scope 1 emissions generated by each sector. An alternative method is to investigate the amount of emissions each industry produces from inputs used for a $1 million worth of economic activity. The results show that firms in highly emitting industries or industries requiring abundant polluting inputs have stronger incentives to outsource their emission needs. Second, we investigate whether firms are prone to outsource to supplier countries with lower environmental regulation enforcement scores (EER) or stringency scores (SER). We find that firms are more likely to shift their emission obligations towards exporting countries with laxer environmental regulations.

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 domestic social reputation. A high environmental, social, and governance (ESG) rating provides many benefits to a firm and its internal stakeholders, including increased customer willingness to pay (e.g., Bagnoli and Watts, 2003; Baron 2008, 2009), the attraction of more capital from altruistic investors (e.g., Ceccarelli, Ramelli, and Wagner 2019; Hartzmark and Sussman 2019), and better career prospects for the management team (e.g., Dai et al. 2019; Cai et al. 2020), among others. In maintaining these benefits, firms with higher ESG ratings (hereafter "green" firms) and more ESG-oriented CEOs and directors (hereafter "green" CEOs and "green" directors) face greater internal pressure to uphold their domestic reputation by shifting pollution-intensive production overseas through the upstream supply chain. The outsourcing effect is more pronounced for green firms, firms with green CEOs, and those with green directors, thereby supporting the internal mechanisms.

In contrast, environmentally-conscious corporate customers and institutional investors (hereafter "green" corporate customers and "green" institutional investors) should exert strong external pressure to alleviate such behavior. These stakeholders are usually international and hence are more concerned about the overall ESG performance of their global supply chain and investee portfolio. Thus, they would push against pollution offshoring to reduce any adverse spillover effects on the ESG ratings of their associated foreign companies. Furthermore, these stakeholders may drive down the overall carbon footprint, including domestic and imported emissions, to minimize adverse impacts of climate change on their investments (e.g., Barrot and Sauvagnat 2016; Krueger, Sautner, and Starks, 2020). Similarly, government customers would also discourage firms' outsourcing behavior as they act in the public interest and emphasize global emissions reduction in effectively combating climate change. Our findings suggest that firms engage less in emissions outsourcing when they have more concentrated government customers, green corporate customers, and green institutional blockholders. The results lend support to these external mechanisms behind corporate environmental policies.

Finally, we explore the implications of our robust evidence of firms' emissions outsourcing behavior. First, this behavior may imply that firms are less incentivized to develop green technologies that require significant capital investment and long development timelines. We show that U.S. firms innovate less when they import more, possibly indicating that investing in green technologies is more challenging and immensely costly. Second, we evaluate the reputational risk and pricing implications of firms outsourcing carbon footprints. Our analysis indicates that firms with larger imported emissions are associated with higher reputational risk and future returns. Notably, estimating and collecting carbon emissions along the supply chain is complicated and challenging. Thus, it is not surprising that investors exhibit difficulty assessing a firm's carbon emissions from imports and foreign suppliers to diversify a firm's reputational risk and price in these emissions.

Our research makes significant contributions to the growing corporate environmental policy literature. We provide the first comprehensive firm-level analysis on whether and how U.S. companies address their full climate impacts. Existing studies in environmental economics have examined whether firms displace their pollution towards regions with weaker environmental protection and documented 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). However, most of their empirical tests are limited to aggregate country, state, or industry level analyses. They often rely on indirect inferences through trade and capital flow rather than direct evidence from emissions levels. Recent work more directly assesses firm-level pollution (e.g., Li and Zhou 2017; Bartram, Hou, and Kim 2019; Dechezleprêtre et al. 2019; Ben-David et al. 2021; Shive and Forster 2020), but they largely focus on emissions from firm's own production while omitting substantial pollution from product inputs. Without considering all emission sources, one cannot thoroughly analyze whether 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 direct and indirect carbon emissions and jointly with its imports.

In examining both types of emissions associated 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 (2017) document the relationship between trade flow and domestic emissions, whereas Bartram, Hou, and Kim (2019), Dechezleprêtre et al. (2019), and Ben-David et al. (2021) focus on how the regulatory environment affects domestic and foreign emissions. These studies fail to directly show that firms choose one type of emissions in curbing the other. Our empirical design advances this research.

This paper further expands the corporate social responsibility (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 natural resource usage reduction. 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 offers supporting evidence and pricing implications of firms' actions. The final section concludes.

2. Data and Summary Statistics

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

2.1. Firm-level carbon emissions

We obtain firm-level GHG emissions data between 2006 and 2018 from Trucost. Over the sample period, the coverage has increased from about 1,000 to 2,800 U.S. firms. The database is constructed following the Greenhouse Gas Protocol standards and incorporates data from Carbon Disclosure Project (CDP). GHG emissions are distinguished between three different 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, upstream Scope 3 includes those emissions associated with the production and transportation of purchased or acquired materials, business travel, waste disposal, and other outsourced upstream activities that occur up to the point of receipt by the firm. In contrast, downstream Scope 3 emissions are related to the transportation, distribution, processing, use, and the end-of-life treatment of sold products that occur subsequent to sales by the firm.[7]

For the purpose of studying carbon offshoring to global suppliers, we examine solely the upstream emissions. CDP estimates that over 43% of Scope 3 emissions are driven by firms through their purchases of goods and services,[8] suggesting that upstream suppliers can be an important source of carbon outsourcing for firms in achieving their GHG targets. The upstream data from Trucost is composed of both reported and estimated Scope 3 emissions. Reported GHG emissions are disclosed by the firms of interest directly to CDP, whereas estimated Scope 3 data is constructed using an input-output model that considers both a firm's expenditures across all sectors in which it obtains its inputs and the sector-level emission factors.[9] We measure each GHG emission scope in units of thousand tonnes of CO_2-equivalent emitted in a year and take the natural logarithm transformation to reduce the skewness of sample distribution.

2.2. U.S. corporate seaborne imports

Panjiva provides a unique database of U.S. trades that documents transaction-level details of goods that cross the border. Under the Customs Regulations at 19 CFR (Code of Federal Regulation), firms in the U.S. are required to report shipment details in cargo declarations to the U.S. Customs and Border Protection (CBP). Panjiva relies on such declarations to obtain information on the shippers (i.e., suppliers or logistic companies), consignees (i.e., customers), origin and destination addresses, product descriptions, and container specifications of ocean freight shipments between U.S. firms and foreign entities in over 210 countries for the 2006-2018 period. We use S&P's identification system to link the consignees with the highest-level parent firms available in Compustat.[10] For each of the matched U.S. consignee parent firm, we aggregate the total shipments

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

[8]See CDP's 2016 Climate Change Report "Tracking Progress on Corporate Climate Action."

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

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

it receives from an exporting country in a year to obtain import proxies.

More specifically, we construct three alternative measures to capture total import at the firm-exporting country-level. The first measure is the total shipment volume a U.S. firm receives from an exporting country as measured in units of twenty-foot equivalent ($Import\ Volume$). It is obtained from summing the freight shipment volumes across all goods from all external suppliers in a foreign country. Given that our focus is on firms' evasion of their own emission responsibility, we exclude shipments from foreign subsidiaries of U.S. parent firms (i.e., internal suppliers). The second measure is similarly defined as the total number of containers shipped from a foreign country ($Import\ Containers$), and the third measure is the total number of shipments from external suppliers overseas ($Import\ Count$). All measures are log transformed to reduce skewness. We use $Import\ Volume$ as the primary measure for all subsequent analyses and the remaining two proxies for robustness tests.[11]

Our primary sample intersects these key databases. First, we match Trucost emissions data with publicly traded companies in Compustat using ISIN as the linking identifier. The merged data forms an initial sample of 15,758 firm-year observations describing the U.S. public firms' pollution level each year. Then, we link the sample to Panjiva imports data by the consignee parent firms. Merging in the shipment information expands our sample to firm-country-year level observations with multiple country-level import values for each U.S. firm in a year. Finally, we exclude financial firms (SIC codes 6000-6900) and remove any observations with missing values for control variables. The selection process yields a final sample of 76,356 firm-country-year observations from 1,557 U.S. firms and 210 exporting countries for the 2006-2018 period.[12] Note that the resulting sample only includes observations with positive country-level imports and firm-level emissions.[13] The actual number of observations varies across analyses, given different model specifications and data availability for the main variables of interest.

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

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

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

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, Jaffe, and Trajtenberg 2005). We winsorize all continuous variables at 5% and 95%. Appendix A contains the detailed definition of all variables.

2.4. Summary statistics

Table 1 reports the summary statistics of our key variables. Panel A summarizes the five primary variables in raw form: *Scope 1*, *Scope 3*, *Import Volume*, *Import Container*, and *Import Count*. On average, a U.S. firm produces about 2.2 million tonnes of direct Scope 1 emissions per year and is associated with about 4.1 million tonnes of upstream Scope 3 emissions through its supply chain. In comparison, the median values of emissions are much smaller (0.2 million tonnes and 1.3 million tonnes for Scopes 1 and 3, respectively) and the standard deviations much larger (5.0 million tonnes and 6.5 million tonnes for Scopes 1 and 3, respectively). These statistics suggest skewed distributions with GHG emissions mostly driven by large companies. For these considerations, we employ log emissions and control for firm size in our main analyses. Such findings are largely consistent with CDP's recent report showing that companies' supply chain emissions are immensely greater than their direct emissions.[14] It is evident that a significant portion of a firm's carbon footprint is generated by its suppliers. Hence, the firm must incorporate

[14] See CDP's "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.

such large amount of indirect emissions when targeting for carbon neutrality. The average number of shipments from external suppliers in each exporting country is 24, which translates into a total of 34 shipment containers and 41 TEUs in shipment volume for an average firm-country-year. The import measures are also highly skewed as indicated by smaller median values (4 shipments, 5 containers, and 4 TEUs in volume) and larger standard deviations (45 shipments, 68 containers, and 89 TEUs in volume) with respect to the sample means. The summary statistics of their log forms are reported in Panel B.

Panel C presents the summary statistics of the control variables. Our sample consists of mostly large firms with mean total assets of $8.8 billion (ln(1+$8,773 million)=9.080) and median of $7.7 billion (ln(1+$7,690 million)=8.948). An average (median) firm has a Tobin's Q of 1.853 (1.614), a leverage ratio of 26.1% (25.0%), a ROA of 10.8% (10.0%), and an annual sales growth of 4.9% (4.4%). The average (median) tangibility ratio is 53.3% (46.0%), suggesting that physical assets account for about half of a firm's total assets. This statistic is comparable with the average (median) ratio of 51.1% (42.9%) for U.S. manufacturing firms captured in Compustat (SIC codes 2000-3999). R&D capital stock is skewed to the right, with at least 25% of the sample declaring a zero value for R&D expenditures.

3. U.S. Firms and Carbon Outsourcing

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

3.1. Scope 1 and upstream Scope 3 emissions

In testing whether U.S. firms reduce their direct GHG emissions through pollution outsourcing, we first estimate the following linear OLS panel regression model.

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

where *Scope 3*$^{\dagger}{}_{i,t}$ denotes firm i's indirect emissions from its upstream supply chain in year t, alternately measured in either natural logarithm or proportion to total firm emissions defined as the sum of Scopes 1, 2, and upstream 3 emissions; *Scope 1*$^{\dagger}{}_{i,t}$ is similarly defined as firm i's self-generated emissions in log form or proportion to total emissions; and $Controls_{i,t}$ is a vector of firm-specific control variables defined in the preceding section. We also include varying sets of fixed effects (**FE**) to control for unmodeled heterogeneity across firms, countries, and years.[15] Standard errors are clustered at the firm level. The definition of all variables is contained in Appendix A.

Table 2 presents the regression estimates of model (1), with Columns (1)-(3) showing results using the natural logarithm of GHG emissions and Columns (4)-(6) reporting those based on the proportion of emissions. We find that a firm's Scope 1 emissions are strongly correlated with its upstream Scope 3 emissions. The β_S estimates associated with *Ln(Scope 1)* are positive and statistically significant at the 1% level. In terms of economic significance, a one-standard-deviation increase in tonnes of Scope 1 emissions from its mean would lead to an approximately 19% (0.084×4.98 million/2.15 million$\times$100%) increase in upstream Scope 3 emissions. Thus, the finding that supply chain emissions increase with the firm's own production emissions suggests that more pollution-intensive firms are more inclined to shift their polluting burden onto their upstream suppliers. Conversely, as a firm reduces its own emissions, so would its suppliers, albeit at a slower speed as reflected by β_S estimates with values less than 1. While our findings suggest a strong linkage specifically on carbon emissions along the supply chain, they are also consistent with Dai, Liang, and Ng (2020), who show a positive correlation between a firm's overall CSR score and its suppliers' CSR scores.

Columns (4)-(6) provide reinforcing evidence that firms shift part of their carbon responsibilities to suppliers. In particular, a firm's fraction of Scope 1 emissions is negatively correlated with its fraction of Scope 3 emissions, revealing a substitutional effect between a firm's self-generated emissions and emissions along the upstream supply chain. If the proportions of Scopes 1 and 3 in a firm's total emissions are relatively stable, it would be less likely to find the firm's relative share of Scope 1 to decrease with its share of suppliers' emissions increases. In other words, the correlations

[15]We conduct linear regressions on firm-country-year level observations to be consistent with subsequent analyses which include firm-country-specific import measures. Unreported analyses using firm-year level observations yield qualitatively similar results.

between Scopes 1 and 3 emissions and between their relative proportions are more broadly consistent with carbon outsourcing rather than an indication of their mechanical relationships. Hence, while the emission levels of Scopes 1 and 3 co-move in the same direction, their proportions change in opposite directions. These findings but We, therefore, address this concern in subsequent analyses and provide evidence reinforcing U.S. firms' pollution outsourcing behavior.

Finally, results suggest that the level of emissions from suppliers is greater for larger and profitable firms, firms with higher sales growth and tangibility, and firms with lower Tobin's Q and leverage. However, these characteristics have no bearing on Scope 3 emissions proportion. Instead, only R&D intensity is negatively associated with the fraction of Scope 3 emissions, suggesting that firms more reliant on carbon outsourcing are less likely to innovate in green technologies, a finding that we will explore in a later section. These findings are also consistent across different sets of fixed effects that we employ, but for brevity, the remaining tables of our study only present results using firm and country×year fixed effects.

3.2. Carbon emissions and imports

The linear regression model (1) alone does not provide sufficient evidence on U.S. firms' carbon outsourcing, especially to suppliers overseas. To provide corroborating evidence of this outsourcing effect, it is imperative that our analysis incorporates a firm's imports and their impact on the Scope 1–Scope 3 relationship as follows:[16]

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

where *Scope 3*†, *Scope 1*†, and *Controls* are the same as those in model (1); $\textit{Ln(Import)}_{i,c,t}$ denotes each import measure, namely $\textit{Ln(Import)}_{Volume}$, $\textit{Ln(Import)}_{Container}$, or $\textit{Ln(Import)}_{Count}$, for firm i's shipments from exporting country c in year t.[17]

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

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

Table 3 reports the regression estimates of model (2). Results containing $Ln(Import)_{Volume}$ are presented in Columns (1) and (4), $Ln(Import)_{Container}$ in Columns (2) and (5), and $Ln(Import)_{Count}$ in Columns (3) and (6). The β_S estimates in Columns (1)-(3) remain significantly positive with values less than 1, consistent with our prior finding that Scope 1 emissions decrease at a faster rate than Scope 3 emissions. Of particular interest are the sign and significance of β_{SI} estimates, which allow us to infer whether and how firms outsource their carbon pollution abroad. The coefficients on the interaction $Ln(Scope1) \times Ln(Import)$ are negative and significant across Columns (1)-(3), indicating that a firm's imports attenuate the positive correlation between its Scope 1 and upstream Scope 3 emissions. For example, a one-standard-deviation increase in imported shipment volume from its mean would weaken the Scope 1– Scope 3 association by approximately 2%.[18] In other words, suppliers' emission reductions following a firm's own emission reduction become smaller when the firm imports more from overseas. This finding potentially suggests that the more a firm imports from its suppliers abroad, the less its suppliers comply with the carbon emission policy of the U.S. customer firm.

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

One may, however, argue that our results simply reflect the mechanical effects rather than firms' evasion of their emission responsibilities. In particular, imports may mechanically drive the

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

differential reduction rates of Scope 1 and upstream Scope 3 emissions. Moreover, since a firm has limited control over its overseas suppliers' emissions, it is unsurprising that the reduction in overseas Scope 3 emissions would not be as fast as that in Scope 1 emissions. In the following sections, we explore whether firms' incentives to evade emission duties explain the attenuating effects of their imports, whether such effects vary across industries and countries, and whether these firms develop more green innovations to offset their carbon footprints along supply chains. If our baseline results are mainly attributed to mechanical effects, we should not expect any significant findings on these issues.

3.3. 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 rather than exporting carbon emissions. Therefore, the association between Scope 1 and Scope 3 emissions may mechanically weaken 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 on the incentives for U.S. firms to outsource their carbon emissions. Suppose our baseline findings indeed capture the outsourcing pollution effect. In that case, imports should have a stronger mitigating impact on the Scope 1–Scope 3 relationship with an exogenous increase (decrease) in appetite for imported (domestic) carbon emissions. In particular, we examine demand shocks to imported emissions arising from domestic state-level legislative pressure and regulatory stringency.

With the United States being the world's second-largest source of carbon emissions, accounting for 15% of the 2018 global total, environmental protection has become one of the most critical issues in U.S. politics.[19] 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.

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

The more recent Clean Power Plan proposed by the EPA in 2014 further aims to combat climate change by cutting down power plants' carbon emissions. There are also significant cross-state variations in environmental policies. For example, California launched its carbon cap-and-trade program in 2013 to reduce GHG emissions to 40% below 1990 levels by 2030 and 80% by 2050. Alternatively, Washington has enacted statutory targets in 2020 to reduce emissions 45% below 1990 levels by 2030, 70% by 2040, and 95% by 2050. These pollution control efforts rely heavily on the states and their abilities to devise implementation plans and enforce policies in ensuring effectiveness (e.g., Grant, Bergstrand, and Running 2014). Thus, we employ state-level legislative pressure and regulatory stringency as exogenous sources of increasing demand for outsourcing carbon footprints. If U.S. firms indeed engage in emissions outsourcing, we expect the attenuating effect of imports to be greater for firms in state-years that experience significant increases in such pressure and stringency.

3.3.1. State-level legislative pressure

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

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

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

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

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

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

where $Pressure_{i,t-1}$ is a binary indicator equal 1 if the state where firm i resides experiences a shock in year $t-1$, and 0 otherwise. It alternately captures the treatment effect of each exogenous shock. *Ln(Scope 1)*, *Ln(Import)*, *Controls*, and **FE** are the same as those in model (2). The β_{SI1} parameter of the triple interaction term $\mathit{Ln(Scope\ 1)} \times Ln(Import) \times Treat$ captures the incremental impact of imports on the Scope 1–Scope 3 association as driven by firms' incentives to outsource emissions overseas. A negative β_{SI1} suggests a greater decrease in the proportion of a firm's own emissions relative to the decrease of its overseas suppliers' emissions, thus a stronger effect of emissions outsourcing.

Table 4 presents the regression results of model (3). Column (1) shows the impact of Congress voting score shocks, where *Treat* is 1 for the next five years if the environmental legislative voting score in year $t-1$ increases by more than three times the average increase in the score during the sample period. Columns (2) and (3) present the effects of close-call election wins by green Democratic members and Congress members with a lifetime environmental voting score of 60 or above, respectively. The *Treat* indicator equals 1 for the next two years after the close-call election win in year $t-1$ until the next election cycle. We find the β_{SI1} coefficients to be negative and significant across all three columns, suggesting a stronger outsourcing effect following a sudden increase in state-level legislative pressure, which intensifies local firms' demand for shifting some of their own emission duties to their foreign suppliers.

3.3.2. State-level legislative stringency

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

Alternatively, we measure state-level regulatory stringency using the facility inspection data obtained from ICIS-Air. Our study defines inspection intensity as the total number of EPA's onsite air pollution compliance evaluations scaled by the total number of air pollution emitting facilities in each state. We contend that firms in states with dramatic increases in onsite inspections have more demand for imported emissions. We identify shocks to inspection patterns as state-years that experience intensity increases by more than three times the average increase during our sample period, eliminate any transitory shocks followed by reversals within the next three years, and shocks driven by changes in the firm location. While inspections themselves are not necessarily exogenous as they may be caused by EPA or state plans or complaints filed by local communities, we argue that a spike in inspection intensity is exogenous to a firm's GHG emissions. Inspections are usually conducted to simultaneously address multiple environmental concerns while assessing many different regulated pollutants. They are triggered by various programs, such as compliance evaluations for Hazardous Air Pollutants, Maximum Achievable Control Technology, Recycling & Emission Reduction Programs, and the Mandatory Greenhouse Gas Reporting Rule.[20] Hence,

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

while some inspection spikes may be endogenously caused by other programs, ithey are mainly exogenous for GHG concerns. In particular, we find that over 43% of the inspections are triggered by multiple programs, and that less than 1% of the onsite examinations was intended to evaluate compliance with the Mandatory Greenhouse Gas Reporting Rule program.

Similar to the preceding tests, we investigate the impact of state-level regulatory stringency on firms' carbon emissions outsourcing behavior using a a triple-interaction-effect regression model (3) by replacing *Pressure* with another binary indicator, *Stringency*. Results are reported in Table 5. Column (1) of the table shows the effect of state enactment of executive or statutory targets to limit carbon emissions, where *Stringency* equals 1 for all years starting one year after the enactment. Column (2) presents the effect of state-level inspection spikes with *Stringency* equals 1 for the next five years if the one-year lagged average onsite inspection level per facility increases more than three times the average onsite inspection increase in the level over time. Consistent with the evidence in Table 4, the estimates of β_{SI1} are also negative and statistically significant.

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

3.4. Cross-industry and cross-country emissions variations

In 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 explore cross-industry and cross-country variations in emissions outsourcing. To do so, we employ a binary indicator (*Indicator*) to partition our sample into two sub-samples based on industry emission levels of US firms and the environmental regulatory stringency of supplier countries. We then estimate the following triple-interaction model:

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

This approach enables us to investigate whether industries requiring abundant polluting inputs are more likely to seek pollution outsourcing through foreign suppliers. We obtain an estimate of GHG emissions resulting from a $1 million worth of economic activity in each industry from Carnegie Mellon University.[21] This estimate is generated using the Economic Input-Output Life Cycle Assessment approach, which in essence captures all emissions produced throughout the supply chain, starting from the raw inputs up to the production of $1 million worth of output. Again, we construct a binary indicator, *Indicator*, that takes the value of one if the industry is above the median level of emissions and zero if otherwise. Results are presented in Table 6. *Indicator* alternately captures four different representations, namely above-median emission industries measured based on the Fama-French 30 industres in Column (1) and NACIS industries in Column (2), and countries with below-median enforcement of environmental regulations score (EER) in Column (3) and below-median stringency of environmental regulation score (SER) in Column (4).[22] The coefficients of the triple interactioin terms are negative and statistically significant across the models. The results suggest that the outsourcing effects are stronger for firms in high-emitting sectors and firms that are more likely to outsource GHG emissions to their suppliers that are in less environmentally regulated countries.[23]

Overall, the subsample results suggest a more nuanced view on the outsourcing of GHG emissions by US public companies based on institutional environment. Such outsourcing is more likely to happen when corporate customers are in high-emitting sectors and when suppliers' countries have laxer environmental regulations.

[21] http://www.eiolca.net/.

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

[23] We also conduct sub-sample analyses using model (1) and obtain qualitatively similar results.

4. The Mechanisms

We explore several firm-level mechanisms that drive firms' emission 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 good social reputations domestically, whereas external mechanisms stem mainly from other corporate stakeholders, such as governmental and corporate customers and investors, who are committed to reducing global carbon footprints. We examine how each mechanism influences a firm's environmental policy.

4.1. Internal mechanisms

A firm's concern about its own reputation of being green among its stakeholders can dictate its corporate environmental policy. We posit that firms with higher social and environmental ratings (i.e., "green" firms) are more inclined to subtly shift emissions overseas in reducing self-generated GHG to maintain their own reputation. Prior research suggests that a high ESG score can benefit firms with better product quality signaling (e.g., Fisman, Heal, and Nair 2006; Siegel and Vitaliano 2007), increased customer willingness to pay (e.g., Bagnoli and Watts, 2003; Baron 2008, 2009), and attraction of more or cheaper sources of capital from altruistic investors (e.g., Ceccarelli, Ramelli, and Wagner 2019; Hartzmark and Sussman 2019), among others. Such benefits would propel green firms to uphold their domestic social images and environmental standings. Social reputations are generally built on firms' observable ESG efforts but typically remain silent on the emissions along their supply chain. Thus, greener firms would have stronger incentives to outsource pollution in maintaining a good front. We test this mechanism by employing the triple-interaction model (3). $Treat_{i,t-1}$ 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.

Executives and directors with a pro-environmental image (i.e., green executives and directors) should similarly have reinforcing effects on emissions outsourcing. 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, green executives and directors would also influence corporate environmental policies in maintaining their own established reputation and prestige. Existing studies document that managers and directors play a critical role in their firm's ESG performance (e.g., Davidson, Dey, and Smith 2019; Iliev and Roth 2020). Following this strand of literature, we argue that firms with greener CEOs and directors would face greater internal pressure to drive down direct Scope 1 emissions through emissions outsourcing. In testing these mechanisms, $Treat_{i,t-1}$ is replaced, alternately, with $Green\ CEO_{i,t-1}$ and $Green\ Board_{i,t-1}$ to capture CEO's and board of directors' established social reputation as revealed by their past five years of employment. For each CEO in a given year, we assign a ranking based on the average score of her current and past employers' environmental scores over the past five years. $Green\ CEO_{i,t-1}$ measures the average scores over years $t-5$ to $t-1$. A higher score denotes a greener CEO for firm i. We compute *Green Board* in a similar fashion. Specifically, $Green\ Board_{i,t-1}$ is the average of firm i's board score over the past five years of its directors' experiences serving as board members in any corporation. We obtain information on the CEO's and directors' past work experiences from BoardEx and manually match these stakeholders with Dun & Bradstreet database for their experiences in private firms.

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

4.2. External mechanisms

Unlike green internal stakeholders, environmentally-conscious external stakeholders who may care about carbon footprints along the whole value chain, such as green customers and green investors, should play an important role in discouraging emission outsourcing efforts. These external stakeholders typically reside or have their portfolios in different countries and are usually concerned about their reputation of being green not within the U.S. but internationally. Previous research documents their pivotal influences on corporate environmental policies. For example, Dai, Liang, and Ng (2020) show that corporate customers shape suppliers' social and environmental policies. Other work suggests that large institutional blockholders can pressure for changes in corporate environmental policies through private engagement, proxy voting, and threats of exit (e.g., Starks, Venkat, and Zhu 2017; Dyck et al. 2019; Gantchev, Giannetti, and Li 2020; Krueger, Sautner, and Starks 2020). In this section, we determine whether external stakeholders exercise such powerful influences to deter firms' outsourcing behavior.

Government and green corporate customers should be more concerned about the global community's overall environmental externalities of corporate actions. Government customers act in the public interest and address social issues arising from market failures and negative externalities. As global warming and other environmental issues become increasingly acute and pressing, governments are compelled to reduce firms' overall carbon footprints in the interest of public welfare (Hsu, Liang, and Matos 2020). Furthermore, prior research suggests that green corporate customers tend to impose their ESG preferences on their suppliers (Dai, Liang, and Ng 2020). Other research shows that climate change constitutes extreme weather events leading to significant losses on affected firms propagating through the supply chain (Barrot and Sauvagnat 2016). These two strands of the literature suggest that green customers would be more attentive to the adverse impact of climate risk on their performance and exert influences to curb total emissions. Hence, we expect the outsourcing effect to be less pronounced when a firm has more concentrated government and green corporate customers. We apply the triple-interaction model (3) to explore these external mechanisms. In this model, $Treat_{i,t-1}$ is replaced by $Gov\ Customer_{i,t-1}$ and $Green\ Customers_{i,t-1}$. The former is defined as the percentage of firm i's sales to government customers identified in the Compustat Segments file at year $t-1$. $Green\ Customers_{i,t-1}$ represent 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.

We contend that environmentally-conscious institutional investors, who typically have international exposures, are more concerned about the overall ESG performance of their global investment portfolios. Particularly, ESG-oriented investors are more likely to consider and manage the climate risk of their investments (Krueger, Sautner, and Starks 2020). To minimize the negative impact of climate risk on portfolio performance, these stakeholders would focus on reducing a firm's total contribution to global warming rather than the narrowly defined Scope 1 emissions. Thus, our analysis focuses on green block institutional investors with at least 50% of their portfolios invested in green firms (*Green Blockholders*).[24] We define green firms as those with ranking in the top 20% 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 carbon footprint management, respectively. The coefficient on the triple-interaction term is consistently positive and statistically significant at the 5% level across the columns. Thus, consistent with our expectations, government customers, green customers, and green blockholders reduce global environmental externalities by restricting their associated firms from outsourcing emissions to other countries.

It is essential to highlight the stark differences in our results between internal and external mechanisms. The internal mechanisms are related to a firm and its internal stakeholders' commitments to social images in the local community. Such local reputational commitments incentivize the firm to disproportionally change its self-generated carbon emissions and supplier emissions overseas. In contrast, the external mechanisms are related to the influences of external stakeholders, who tend to have a global perspective on ESG performance. As a result, they discourage the firm from outsourcing emissions to global suppliers.

5. Implications

In this section, we explore the implications of firms' emissions outsourcing behavioor. First, we investigate whether there is any evidence that firms develop clean technologies in response to political and social pressures to reduce carbon emissions. Second, we examine how a firm's engagement in pollution outsourcing activity influences its reputational risk and stock performance.

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

5.1. Green innovation and 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). While firms can invest more in green R&Ds gearing toward environmental patents to offset any potential adverse regulatory shocks and remain competitive, our preceding evidence seems to suggest that outsourcing emissions to foreign suppliers is a less costly alternative. To examine this issue, we regress a firm's green innovation on its *Ln(Import)*, *Ln(Scope 1)* and *Ln(Scope 3)* as follows:

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

where $\mathit{Green\ Innovation}_{i,t+1}$ is measured as the numbers of two-year or three-year ahead clean patents filed by each firm, accommodating for the time taken to innovate. *Ln(Import* CO_2*)* is the log of the amount of carbon emissions produced by imports. We follow Dechezlepretre, Martin, and Mohnen (2013) to use the International Patent Classifications (IPC) to classify clean patents. We focus on four sectors, namely, energy, automotive, fuel, and lighting, that allow us to distinguish between clean and dirty patents more accurately. *Controls* include firm-specific *Age*, *Size*, *Tobin's Q*, *Leverage*, *PPE*, *ROA*, *CapEx*, *R&D*, and *HHI*. The results are shown in Table 9.

The table reveals one distinct finding. There is little evidence that firms that reduce their carbon footprints through outsourcing emissions to foreign suppliers have a desire to develop clean technologies. *Ln(Import* CO_2*)* negatively correlates with green innovation output, while neither direct emissions nor indirect supplier-induced carbon emissions bear any significant effect on green innovation. For example, the estimates of *Ln(import* CO_2*)* coefficient are between -0.044 (2-year ahead green innovation) and -0.063 (3-year ahead green innovation) and statistically significant at 1% and 5% levels. In contrast, adding *Ln(Scope 1)* and *Ln(Scope 3)*, separately or jointly, to the model has virtually no effect on the magnitude of the *Ln(Import* CO_2*)* coefficient. Thus, the more firms import, the less likely they will engage in environmental innovation.

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

5.2. Reputational risk and future stock returns

We evaluate 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. Furthermore, technology and social media have increasingly enabled various stakeholders, including customers, employees, and activists, to expose companies' unethical ESG behavior to a large audience much more quickly.[22] Such reputational risk typically affects the "loyalty" of key stakeholders (including customers and suppliers across the global supply chain) to stay with the firm to offset adverse effect of market-wide systematic shocks, thus can be considered as a source of systematic risk.[25] We, therefore, expect environmentally-responsible firms to display a lower ESG-induced reputational risk. That is, firms with less carbon footprint along the global value chain have a lower reputational risk.

To implement our test, we jointly evaluate the impacts of Scope 1, upstream Scope 3, and imported emissions on a firm's reputational risk. The carbon footprint of each shipment is esti-

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

[25] 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.

mated using the 4-digit product code for each product (HS Code provided by Panjiva) and the industry/product average emission based on the Economic Input-Output Life Cycle Assessment for the imported goods in each standard container (TEU). We then take the average CO_2 assessment among all HS-codes associated with a shipment as the imported CO_2 intensity measure for the shipment (*Ln(Import* CO_2*)*). We then test a cross-sectional relationship between a firm's reputational risk (*RepRisk*) and its sources of carbon emissions, as follows.

$$
\begin{aligned}
RepRisk\ \beta_{,i,t} &= \alpha + \beta_1 Ln(Import\ CO_2)_{i,t} + \beta_2 Ln(Scope\ 1)_{i,t} + \beta_3\ Ln(Scope\ 3)_{i,t} \\
&\quad + \beta_{CS}' Controls_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \qquad (6)
\end{aligned}
$$

where *RepRisk* β is an estimate of a firm's reputational risk at year t; *Ln(Scope 1)* and *Ln(Scope 3)* are defined earlier. Model (6) also includes firm-level *Assets*, *Tobin's Q*, *R&D*, *Advertising Expenditure*, *PPE*, *Leverage*, *CapEx*, *Cash*, *Income Volatility*, and *ROA*, as well as firm and year fixed effects as controls. We estimate *RepRisk* β as follows. Each year, we rank the firms in our sample based on their reputational risk scores, as provided by RepRisk,[26] and divide them into two portfolios of stocks with high and low reputational risk scores. We compute daily returns on a reputational risk factor by taking the difference in daily returns between the low and high reputational-risk score portfolios. We then regress individual stock returns on the returns of the reputational risk factor and Fama-French-Carhart four factors. The coefficient on the reputational risk factor is our estimate of *RepRisk* $\beta_{i,t}$. We repeat this procedure each year to obtain yearly estimates of each firm's *RepRisk* $\beta_{i,t}$.

It is important to point out that when we regress returns of the reputational risk factor against the returns on Fama-French-Carhart four factors, the alpha estimate of -3% per annum is statistically significant at the 5% level.[27] Similar to Edmans (2011), we interpret that the reputational risk factor's underperformance reflects the difficulty in incorporating intangibles into traditional valuation models. Even though our main purpose is to examine which source of firm-level carbon emissions is related to a firm's systematic reputational risk, the results are consistent with this

[26]RepRisk, an ESG data science provider, quantifies the reputational risk scores 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

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

interpretation.

Table 10 reports the regression estimates of model (6). Columns (1)-(3) show the results of separate effects of each CO_2 emission variable on *RepRisk* β, and Column (4) reports those of their joint effects. We find that a firm's reputational risk is positively related to *Ln(Import* CO_2*)* and *Ln(Scope 3)*, while not with *Ln(Scope 1)*. The magnitude and statistical significance of both *Ln(Import* CO_2*)* and *Ln(Scope 3)* coefficients become even stronger when they are estimated jointly (Column (4)). It is not surprising to find that firms with larger amounts of imported and upstream Scope 3 emissions are associated with a higher level of reputational risk. For many companies, collecting data on emissions throughout their supply chains is challenging, and this offers an excuse for some firms only to take responsibility for their direct emissions. Understandably, it would be more difficult for investors to assess the amount of a firm's carbon emissions arising from imports and suppliers that would enable them to diversify such risk.

We next 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,

$$\begin{aligned}\textit{Future Return}_{i,m,t} &= \alpha + \beta_1 \textit{Ln(Import CO}_2\textit{)}_{i,t-1} + \beta_2 \textit{Ln(Scope 1)}_{i,t-1} + \beta_3 \textit{Ln(Scope 3)}_{i,t-1} \\ &\quad + \beta'_{CS}\textit{Controls}_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned} \tag{7}$$

where $\textit{Future Return}_{i,m,t}$ is the monthly stock return of firm i in month m of year t. Model (7) controls for firm-specific characteristics that are previously shown to predict stock returns, and they include firm-specific *Size*, *BM*, *Leverage*, *PPE*, *CapEx*, *Momentum*, *Volatility*, *Beta*, and *HHI* at year $t-1$. It also includes firm and month fixed effects and incorporates standard errors clustered at the firm-year level. Results are reported in Column (5) of Table 10. Consistent with the findings in Column (3), only the coefficients on $\textit{Ln(Import CO}_2\textit{)}$ and *Ln(Scope 3)* are positive and strongly significant at conventional levels. The market sufficiently prices a firm's Scope 1 emissions but not its imported and Scope 3 emissions. Combined, the results of Table 10 explain why U.S. firms have a strong incentive to outsource emissions. Besides regulatory oversight, these firms can exploit investor oversight or unawareness of their emissions along the upstream supply chain.

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 of 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. 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.

Our evidence that U.S. firms reduce their carbon footprints through outsourcing pollution reveals a dark side of global supply chains. Environmentally-conscious investors and consumers should not only carefully investigate a firm's Scope 1 emissions but also all of the emissions that its activities and products produce to better evaluate how green the firm truly is.

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 between policymakers and other stakeholders to support cost-effective policy measures to mitigate global climate risks and support low carbon investments. These results might also 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 can drive policy change, shape consumer preferences, and rapidly respond to climate change necessities 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, but it is also an international obligation. Companies should take full responsibility for their climate footprints.

References

Albuquerque, R., Koskinen, Y., Zhang, C., 2019. Corporate social responsibility and firm risk. *Management Science* 65(10), 4451-4469.

Aldy, J.E., 2017. Frameworks for evaluating policy approaches to address the competitiveness concerns of mitigating greenhouse gas emissions. *National Tax Journal* 70(2), 395–420.

Aldy, J.E., Kotchen, M.J., Leiserowitz, A.A., 2012. Willingness to pay and political support for a US national clean energy standard. *Nature Climate Change* 2(8), 596–599.

Aldy, J.E., Pizer, W.A., 2014. The employment and competitiveness impacts of power-sector regulations. In Coglianese, Cary, Adam M. Finkel, and Christopher Carrigan (eds.), Does Regulation Kill Jobs, 70–88. University of Pennsylvania Press, Philadelphia, PA.

Allen, F., Carletti, E. and Marquez, R., 2015. Deposits and bank capital structure. *Journal of Financial Economics*, 118(3), pp.601-619.

Aldy, J.E., Pizer, W.A., 2015. The competitiveness impacts of climate change mitigation policies. *Journal of the Association of Environmental and Resource Economists* 2(4), 565–595.

Aghion, P., Bloom, N. Blundell R. Griffith, R., and Howitt P., 2005. Competition and innovation: an inverted-U relationship. *Quarterly Journal of Economics*, 120, 701-728.

Antweiler, W., Copeland, B. R., Taylor, M. S., 2001. Is free trade good for the environment? *American Economic Review* 91(4), 877–908.

Bagnoli, M. and Watts, S.G., 2003. Selling to socially responsible consumers: Competition and the private provision of public goods. *Journal of Economics & Management Strategy*, 12(3), pp.419-445.

Bansal, R., Kiku, D., Ochoa, M., 2014. Climate change and growth risks, Working paper, Duke University.

Baron, D.P., 2008. Managerial contracting and corporate social responsibility. *Journal of Public Economics*, 92(1-2), pp.268-288.

Baron, D.P., 2009. A positive theory of moral management, social pressure, and corporate social performance. *Journal of Economics & Management Strategy*, 18(1), 7-43.

Bartram, S.M., Hou, K., Kim, S., 2019. Real effects of climate policy: Financial constraints and spillovers. Fisher College of Business Working Paper, (2019-03), p.004.

Barrot, J.N., Sauvagnat, J., 2016. Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics*, 131(3), 1543-1592.

Bénabou, R., Tirole, J., 2010. Individual and corporate social responsibility. *Economica* 77, 1-19.

Ben-David, I., Jang, Y., Kleimeier, S., Viehs, M., 2021. Exporting pollution: where do multinational firms emit CO_2? *Economic Policy*, Forthcoming.

Bolton, P., Kacperczyk, M., 2020a. Do investors care about carbon risk?" *Journal of Financial Economics*, forthcoming.

Bolton, P., Kacperczyk, M., 2020b. Carbon premium around the world. CEPR Discussion Paper No. DP14567.

Cai, X., Gao, N., Garrett, I. and Xu, Y., 2020. Are CEOs judged on their companies' social reputation?. *Journal of Corporate Finance*, 64, p.101621.

Ceccarelli, M., Ramelli, S., Wagner, A.F., 2019. When investors call for climate responsibility, how do mutual funds respond? Swiss Finance Institute Research Paper.

Chava, S., 2014. Environmental externalities and cost of capital. *Management Science* 60(9), 2223-2247.

Cohen, L., Gurun, U.G., Nguyen, Q.H. 2020. The ESG-innovation disconnect: evidence from green patenting. NBER Working Paper 27990.

Dai, X., Gao, F., Lisic, L.L. and Zhang, I., 2019. Corporate Social Performance and Managerial Labor Market. Available at SSRN 3510664.

Dai, R., Liang, H., Ng, L., 2020. Socially responsible corporate customers. *Journal of Financial Economics*, Forthcoming.

Dai, W., Meyer-Brauns, P., 2020. Greenhouse gas emissions and expected returns. Working Paper, Dimensional Fund Advisors.

Davidson, R.H., Dey, A. and Smith, A.J., 2019. CEO materialism and corporate social responsibility. *The Accounting Review*, 94(1), pp.101-126.

Davis, S.J., Caldeira, K., 2010. Consumption-based accounting of CO_2 emissions. *Proceedings of the National Academy of Sciences* 107, 5687-5692.

Dechezleprêtre, A., Martin, R., Mohnen, M., 2013. Knowledge spillovers from clean and dirty technologies: a patent citation analysis. Working Paper.

Dechezleprêtre, A., Gennaioli, C., Martin, R., Muûls, M., Stoerk, T., 2019. Searching for carbon leaks in multinational companies. Working Paper.

Dyck, A., Lins, K.V., Roth, L. and Wagner, H.F., 2019. Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics*, 131(3), pp.693-714.

Ederington, J., Levinson, A. and Minier, J., 2005. Footloose and pollution-free. *Review of Economics and Statistics*, 87(1), pp.92-99.

Edmans, A., 2011. Does the stock market fully value intangibles? employee satisfaction and equity prices. *Journal of Financial Economics* 101, 621-640.

Fisman, R., Heal, G. and Nair, V., 2006. A model of corporate philanthropy. *Columbia University and University of Pennsylvania.*

Fombrun, C., Shanley, M., 1990. What's in a name? Reputation building and corporate strategy. *Academy of Management Journal* 33, 233–258.

Gantchev, N., Giannetti, M. and Li, R., 2020. Does Money Talk? Market Discipline through Selloffs and Boycotts. CEPR Discussion Papers 14098.

Grant, D., Bergstrand, K., Running, K., 2014. Effectiveness of US state policies in reducing CO_2 emissions from power plants. *Nature Climate Change* 4, 977-982.

Grossman, G. M., Krueger, A. B., 1995. Economic growth and the environment. *Quarterly Journal of Economics* 110, 353–377.

Hartzmark, S. M., Sussman, A. B., 2019. Do investors value sustainability? a natural experiment examining ranking and fund flows. *Journal of Finance* 74, 2789–2837.

Hall, B.H., Jaffe, A. and Trajtenberg, M., 2005. Market value and patent citations. *RAND Journal of Economics*, pp.16-38.

Ho, M,S., Morgenstern, R., Shih, J.-S. 2008. Impact of carbon price policies on U.S. industry. RFF DP 08-37. Resources for the Future, Washington, DC.

Hong, H., Li, F.W., Xu, J., 2019. Climate risks and market efficiency. *Journal of Econometrics* 208(1), 265-281.

Hsu, P-H., Li, K., Tsou, C-Y., 2019. The pollution premium. Working paper.

Hsu, P.H., Liang, H., Matos, P., 2020. Leviathan Inc. and corporate environmental engagement. *Management Science*, Forthcoming.

Huang, Y., Jennings, R. and Yu, Y., 2017. Product market competition and managerial disclosure of earnings forecasts: Evidence from import tariff rate reductions. *The Accounting Review*, 92(3), pp.185-207.

Ilhan, E., Sautner, Z., Vilkov, G., 2019. Carbon tail risk. SSRN: https://ssrn.com/abstract=3204420 or http://dx.doi.org/10.2139/ssrn.3204420.

Iliev, P. and Roth, L., 2020. Do Directors Drive Corporate Sustainability?. Available at SSRN 3575501.

Johnson, M.S., 2020. Regulation by shaming: deterrence effects of publicizing violations of workplace safety and health laws. *American Economic Review* 110(6), 1866-1904.

Kim, S.E., Urpelainen, J., 2017. The polarization of American environmental policy: a regression discontinuity analysis of Senate and House cotes, 1971–2013. *Review of Policy Research* 34(4), 456–484.

Krüeger, P., Sautner, Z., Starks, L.T., 2020. The importance of climate risks for institutional investors. *The Review of Financial Studies* 33(3), 1067–1111 .

La Porta, R., Lopez-de-Silanes, F. and Shleifer, A., 2008. The economic consequences of legal origins. *Journal of Economic Literature*, 46(2), pp.285-332.

Levinson, A., 2009. Technology, international trade, and pollution from U.S. manufacturing. *American Economic Review* 99(5), 2177–2192.

Levinson, A., 2010. Offshoring pollution: Is the United States increasingly importing polluting goods? *Review of Environmental Economics and Policy* 4(1), 63–83.

Li, X., Zhou, Y.M., 2017. Offshoring Pollution while Offshoring Production? *Strategic Management Journal* 38, 2310–2329.

Liang, H., Renneboog, L., 2017. On the foundations of corporate social responsibility. *The Journal of Finance*, 72(2), pp.853-910.

Matthews, H. S., Hendrickson, C. T., Weber, C. L., 2008. The importance of carbon footprint estimation boundaries. *Environmental Science & Technology* 42(16), 5839-5842.

Raghunandan, A., Rajgopal S., 2020. Do the socially responsible walk the talk? Working Paper, London School of Economics.

Seltzer, L., Starks, L., Zhu, Q., 2020. Climate regulatory risks and corporate bonds. 2021 AFA Paper.

Shapiro, J.S., Walker, R., 2018. Why Is pollution from US manufacturing declining? The roles of environmental regulation, productivity, and trade. *American Economic Review*108(12), 3814–3854.

Shive, S.A., Forster, M.M., 2020. Corporate governance and pollution externalities of public and private firms. *The Review of Financial Studies*, 33(3), 1296-1330.

Siegel, D.S. and Vitaliano, D.F., 2007. An empirical analysis of the strategic use of corporate social responsibility .*Journal of Economics & Management Strategy*, 16(3), pp.773-792.

Shipan, C.R., Lowry, W.R. William R., 2001. Environmental policy and party divergence in Congress. *Political Research Quarterly* 54 (2), 245-263

Starks, L.T., Venkat, P. and Zhu, Q., 2017. Corporate ESG profiles and investor horizons. Available at SSRN 3049943.

Taylor, M. S., 2005. Unbundling the pollution haven hypothesis. *The B.E. Journal of Economic Analysis & Policy* 4(2), 1–28.

Wagner, U.J. and Timmins, C.D., 2009. Agglomeration effects in foreign direct investment and the pollution haven hypothesis. *Environmental and Resource Economics*, 43(2), pp.231-256.

Figure 1

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

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

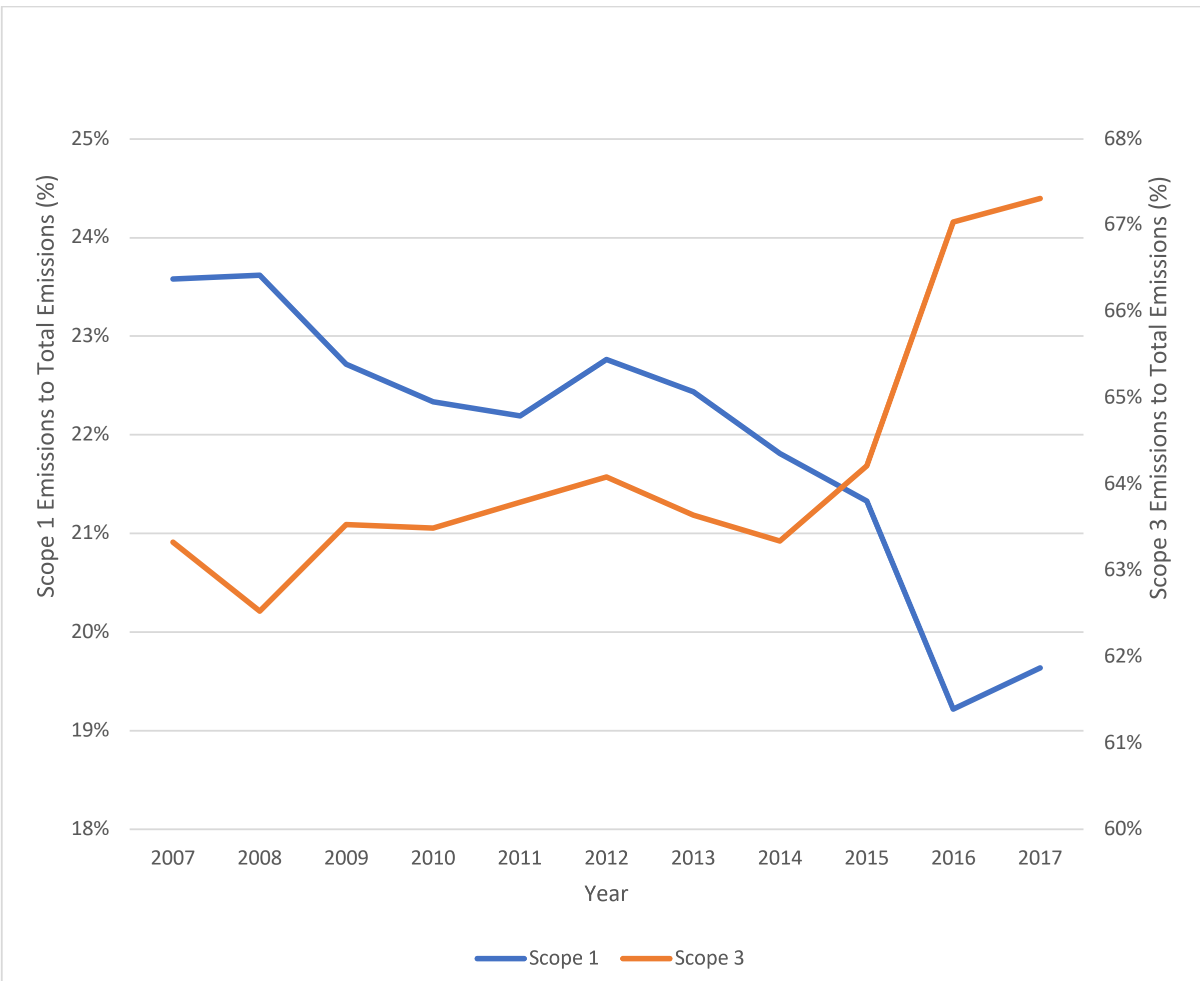

Figure 2

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

This figure shows the aggregate carbon emissions (the sum of Scopes 1, 2, and 3) and total volume of imports (millions of twenty-four equivalent units or TEU) of U.S. firms over time.

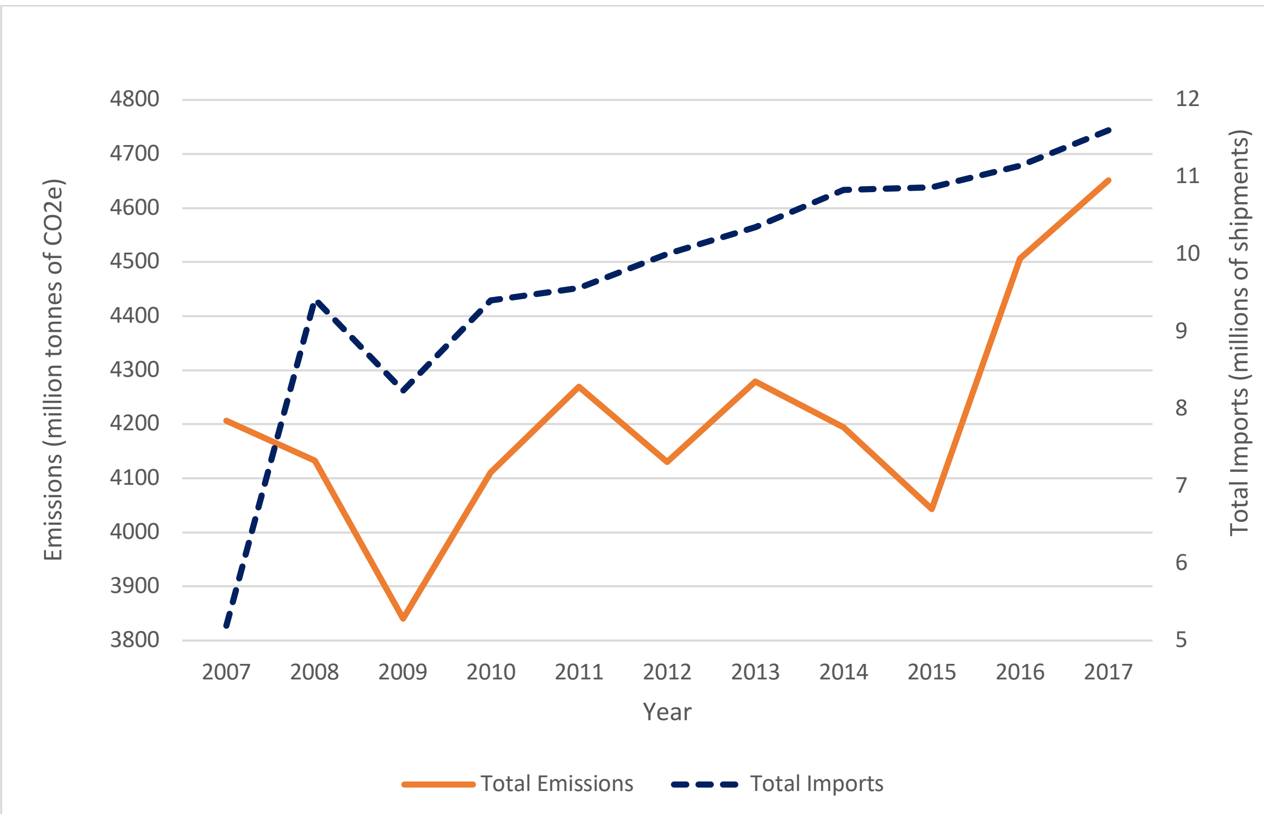

Table 1
Summary Statistics

This table presents summary statistics of the variables in our baseline analysis over the entire sample period from 2007 to 2018. It shows the number of observations (# Obs), mean (Mean), standard deviation (Stdev), minimum (Min), the 25th percentile (P25), median (Median), 75th percentile (P75) and maximum (Max) of each variable. The key variables in raw values show the summary statistics of Scope 1 and upstream Scope 3 emissions reported in thousands of tonnes and *Imports* measured in the number of shipments, number of shipment containers, and shipment volume (Twenty-Foot Equivalent Unit or TEU). The remaining variables are defined in the Appendix. All continuous variables are winsorized at the 1% and 99% of their distribution.

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

Table 2
The Relationship between Scope 1 and Scope 3 Emissions

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

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

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

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

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

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

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

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

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

Table 4
Legislative Pressure and Firms' Carbon Emissions

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

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

where *Pressure* is a binary indicator that alternately captures three different representations. In Column (1), *Pressure* equals one for five years if the lagged average Congress member voting score based on climate change-specific environmental legislations increases more than three times the mean score over time; the change must not revert back within the next three years, and the shock must not be driven by the change in firm locations. In Columns (2)-(3), a shock to each state depends on the number of close-election wins relative to close-election losses for environmentally-conscious candidates. For each house and senate candidate elected in a state-election year, a close-win (close-loss) is defined as a win (loss) where the vote-share difference between the winning and runner-up candidates is 5% or less. Close-wins (close-losses) are summed across all environmentally-conscious candidates (other candidates), where an environmentally-conscious candidate is a democrat for Column (2) or has a lifetime environmental voting score of 60 or above for Column (3). *Pressure* equals one for the next two years if the number of close-wins net of close-losses is greater than 0, and 0 otherwise. *Ln(Import)*‡ is measured by *Ln(Import)*$_{Volume}$. *Ln(Scope 1* and *Ln(Scope 3* are a firm's Scope 1 and upstream Scope 3 emissions, measured in natural log. *Controls* are the same as those 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 clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Definition of *Pressure*		
	Congress	Green Democrat	Voting Score
Variable	(1)	(2)	(3)
Ln(Scope 1)×Ln(Import)$_{Volume}$×Pressure	-0.015*	-0.088*	-0.079*
	(-1.78)	(-1.91)	(-1.76)
Ln(Scope 1)×Ln(Import)$_{Volume}$	-0.002	-0.033*	-0.044*
	(-0.54)	(-1.75)	(-1.69)
Ln(Scope 1)×Pressure	-0.002	0.015**	0.025**
	(-0.34)	(2.21)	(2.42)
Ln(Import)$_{Volume}$×Pressure	0.178*	0.975*	0.783
	(1.72)	(1.72)	(1.47)
Ln(Scope 1)	0.087***	0.127***	0.125***
	(5.76)	(4.66)	(4.22)
Ln(Import)$_{Volume}$	0.031	0.493*	0.670**
	(0.65)	(1.95)	(2.07)
Pressure	0.037	-0.167**	-0.303**
	(0.44)	(-2.02)	(-2.34)
# Obs	75,886	36,482	28,435
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Adj. R^2	0.989	0.989	0.989

Table 5
State Regulatory Stringency and Firms' Carbon Emissions

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

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

where *Stringency* is a binary indicator that alternately captures two different representations. In Column (1), a shock at the state-level is when a state enacts an executive/statutory target to limit its GHG emissions, and *Stringency* equals one for five years, starting one year after the state enacts a GHG target. In Column (2), *Stringency* equals one for five years 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. $\textit{Ln(Import)}^{\ddagger}$ is measured by $\textit{Ln(Import)}_{Volume}$. *Ln(Scope 1* and *Ln(Scope 3* are a firm's Scope 1 and upstream Scope 3 emissions, measured in natural log. *Controls* are the same as those 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 clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Definition of *Stringency*	
	GHG Target	Onsite
Variable	(1)	(2)
Ln(Scope 1)×Ln(Import)$_{Volume}$×Stringency	-0.024*	-0.056**
	(-1.77)	(-2.02)
Ln(Scope 1)×Ln(Import)$_{Volume}$	-0.007**	-0.012**
	(-2.28)	(-2.07)
Ln(Scope 1)×Stringency	0.023**	-0.003
	(2.09)	(-0.36)
Ln(Import)$_{Volume}$×Stringency	0.296*	0.752**
	(1.75)	(2.23)
Ln(Scope 1)	0.100***	0.086***
	(6.12)	(5.72)
Ln(Import)$_{Volume}$	0.086**	0.156**
	(2.38)	(2.19)
Stringency	-0.279**	0.067
	(-2.11)	(0.63)
# Obs	75,886	75,886
Controls	Yes	Yes
Firm, Country×Year FE	Yes	Yes
Adj. R^2	0.99	0.989

Table 6
Industry Emissions and Supplier Environmental Regulations

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

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

where *Indicator* is a binary indicator that alternately captures four different representations, namely above-median emission industries measured based on the Fama-French 30 industres in Column (1) and NACIS industries in Column (2), and countries with below-median enforcement of environmental regulations score (EER) in Column (3) and below-median stringency of environmental regulation score (SER) in Column (4). Note that the *Indicator* coefficient is not reported in the last two columns because it is subsumed by country $\times$ year fixed effect. 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**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level and at the year level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

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

Table 7
Internal Mechanisms

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

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

where *Internal* alternately represents a firm's: (1) Green Score as proxied by Refinitiv's ESG Combined Score; (2) Green CEO, the average Green Score of firms in which the CEO has worked during the past five years; (3) Green Director, the average Green Score of the director's affiliated firms during the past five years. *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 clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

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

Table 8
External Mechanisms

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

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

where *External* alternately represents the firm's: (1) Govt Customer, the percentage sales to its largest government customer; (2) Green Customers, the percentage sales to its largest corporate customers with above industry-median ESG Combined score; (3) Green Blockholder, the percentage of shares owned by green blockholders with at least half of their portfolio invested in green firms ranked in the top quintile based on their ESG combined 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 clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Definition of *External*		
	Govt Customer	Green Customers	Green Blockholders
Variable	(1)	(2)	(3)
Ln(Scope 1) × Ln(Import)$_{Volume}$ × External	0.002**	0.379***	0.865**
	(2.57)	(2.67)	(2.04)
Ln(Scope 1) × Ln(Import)$_{Volume}$	-0.030***	-0.072***	-0.022***
	(-2.70)	(-3.10)	(-3.52)
Ln(Scope 1) × External	0.000	-0.016	-0.183***
	(0.40)	(-0.17)	(-2.78)
Ln(Import)$_{Volume}$× External	-0.024**	-4.167***	-8.856*
	(-2.41)	(-2.60)	(-1.82)
Ln(Scope 1)	0.063***	0.096***	0.083***
	(2.94)	(3.09)	(5.55)
Ln(Import)$_{Volume}$	0.408***	0.842***	0.281***
	(3.01)	(3.11)	(3.54)
External	0.001	-0.010	2.455***
	(0.13)	(-0.01)	(2.96)
# Obs	32,142	14,778	72,115
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Adj. R^2	0.990	0.990	0.989

Table 9
Green Innovation and Firms' Various Sources of Carbon 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 (*Ln(Import CO_2)*), its direct emissions from own production (*Ln(Scope 1)*) and through supply-chains (*Ln(Scope 3)*) on its *Green Innovation*, using the following model specification.

$$\textit{Green Innovation}_{i,t+j} \quad = \quad \alpha + \beta_1 \textit{Ln(Import CO}_2)_{i,t} + \beta_2 \textit{Ln(Scope 1)}_{i,t} + \beta_3 \textit{Ln(Scope 3)}_{i,t} + \beta'_{CS} \textit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t},$$

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

	2-Year Ahead Green Innovation				3-Year Ahead Green Innovation			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Import CO_2)	-0.044**			-0.049**	-0.056***			-0.063***
	(-2.50)			(-2.44)	(-2.87)			(-2.87)
Ln(Scope 1)		-0.015		-0.016		-0.013		-0.012
		(-0.64)		(-0.64)		(-0.53)		(-0.45)
Ln(Scope 3)			-0.016	-0.014			-0.027	-0.030
			(-0.44)	(-0.39)			(-0.64)	(-0.67)
# Obs	4,809	4,470	4,470	4,470	4,198	3,920	3,920	3,920
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.746	0.751	0.751	0.751	0.744	0.744	0.744	0.746

Table 10
Reputational Risk, Future Returns, and Firm-Level Carbon 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 (*Ln(Import CO_2)*), its direct emissions from own production (*Ln(Scope 1)*), and indirect emissions from upstream supply-chains (*Ln(Scope 3)*) on the firm's systematic risk associated with ESG practices in Columns (1)-(4) and future stock returns in Column (5). The models for the first four columns are given by the following specification:

$$\begin{aligned} \textit{RepRisk } \beta_{,i,t} &= \alpha + \beta_1 \textit{Ln(Import } CO_2)_{i,t} + \beta_2 \textit{Ln(Scope 1)}_{i,t} + \beta_3 \textit{ Ln(Scope 3)}_{i,t} \\ &\quad + \beta'_{CS} \textit{Controls}_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where *RepRisk* $\beta_{i,t}$ is the factor loading obtained from regressing individual firms' daily stock returns on the difference between high and low reputational-risk quintile portfolios and those of the Fama-French-Carhart 4-factor model in a given year. *Controls* include firm-specific *Assets*, *Tobin's Q*, *R&D*, *Advertising Expenditure*, *Leverage*, *CapEx*, *Cash*, *Income Volatility*, *ROA*, and firm and year fixed effects **FE**.

In Column (5), we regress monthly future stock returns on the three sources of firm-level CO_2 emissions, firm-level control variables, and firm-month fixed effects.

$$\begin{aligned} \textit{Future Return}_{,i,t+1} &= \alpha + \beta_1 \textit{Ln(Import } CO_2)_{i,t} + \beta_2 \textit{Ln(Scope 1)}_{i,t} + \beta_3 \textit{ Ln(Scope 3)}_{i,t} \\ &\quad + \beta'_{CS} \textit{Controls}_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where firm-level control variables include *Size*, *BM*, *Leverage*, *PPE*, *CapEx*, *Momentum*, *Return Volatility*, *Beta*, *HHI*, and firm and month **FE**. The definition of variables is contained in Appendix A. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Dep Var = RepRisk β				Dep Var= Future Return
Variable	(1)	(2)	(3)	(4)	(5)
Ln(Import CO_2)	0.037*			0.049**	0.050**
	(1.65)			(2.03)	(2.04)
Ln(Scope 1)		-0.023		-0.041	-0.044
		(-0.83)		(-1.47)	(-1.58)
Ln(Scope 3)			0.115**	0.141***	0.137***
			(2.29)	(2.74)	(2.69)
# Obs	6,386	6,068	6,068	6,068	67,867
Controls	Yes	Yes	Yes	Yes	Yes
Firm, Year FE	Yes	Yes	Yes	Yes	
Firm, Month FE					Yes
Adj. R^2	0.361	0.362	0.363	0.364	0.029

Appendix Table A

Variable Definition and Data Source

Variable	Definition and Data Source
Measures of Firm-level Carbon Emissions and Imports	
Ln(Scope 1)	ln(1 + Scope 1 emissions), where Scope 1 refers to direct GHG emissions owned or controlled by the firm. (Trucost & Compustat)
Ln(Scope 3)	ln(1 + upstream Scope 3 emissions), where upstream Scope 3 refers to indirect GHG emissions that occur in the firm's supply chain. (Trucost & Compustat)
Propn of Scope 1	The ratio of Scope 1 emissions to total emissions (Scope 1 + Scope 2 + Upstream Scope 3), where Scope 2 emissions are indirect emissions from the generation of purchased electricity, steam, heating and cooling consumed by the reporting firm. (Trucost & Compustat)
Propn of Scope 3	The ratio of upstream Scope 3 emissions to total emissions (Scope 1 + Scope 2 + Upstream Scope 3). (Trucost & Compustat)
Ln(Import)$_{Volume}$	ln(1 + the volume of shipment, measured in TEU, from suppliers in each exporting country). (Panjiva & Compustat)
Ln(Import)$_{Container}$	ln(1 + the number of shipment containers from suppliers in each exporting country). (Panjiva & Compustat)
Ln(Import)$_{Count}$	ln(1 + the number of shipments from suppliers in each exporting country). (Panjiva & Compustat)
Ln(Import CO_2)	ln(1 + the aggregated amount of GHG (metric tons of CO_2 equivalent) into the air from the production of all imported goods (per $1 million) over all shipment containers (in the unit of TEU) in a given year. When there are various imported goods (based on the six-digit HS Code) in each shipment, the amount is an average weighting of GHG from the productions of all imported goods. (Panjiva & EIO-LCA & Peter K. Schott Website)
Identification Variables	
Congress	A binary variable equals 1 for five years if the lagged average Congress member voting score based on climate change-specific environmental legislations increases more than three times the mean score over time; the change must not revert back within the next three years, and the shock must not be driven by the change in firm locations. (League of Conservation Voters)
Green Democrat	A binary variable equals 1 for the next two years after the close-call election win by green candidates in year $t-1$ until the next election cycle. Green candidates are defined as members of the Democratic party. (League of Conservation Voters)
Voting Score	A binary variable equals 1 for the next two years after the close-call election win by Congress members with a lifetime environmental voting score of at least 60 in year $t-1$ until the next election cycle. (League of Conservation Voters)
GHG Target	A binary variable equal to 1 for all years starting from one year after the state enactment of executive or statutory targets to limit carbon emissions. (C2ES)
Onsite	A binary variable equals 1 if the lagged increase in onsite inspections is more than three 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)

Appendix A – Continued

Variable Definition and Data Source

Variable	**Definition and Data Source**
Internal Mechanism Variables	
Green Score	A firm's overall ESG score. (Refinitiv ESG)
Green CEO	A firm's Green CEO is determined by the CEO's past five years of experience working in a firm or firms. For a Green CEO at a given year, we calculate the CEO's firm's average environmental score over years -5 to -1 and then assign this score as the CEO's environmental score for the year. (BoardEx & Refinitiv ESG)
Green Board	A firm's Green Board is determined by taking the average of environmental scores of all its directors' past five years of experience working in a firm or firms. For each director at a given year, we calculate the director's affiliated firm's average score over years -5 to -1 and then assign this score as the director's environmental score for the year. We then take an equal-weighted average of scores of the board of directors. (BoardEx & Refinitiv ESG)
External Mechanism Variables	
Gov Customer	Sales percentage to a firm's government customers. (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 & Refinitiv ESG)
Green Technology, Reputational Risk, and Future Return	
Green Innovation	Two- or three-year ahead number of clean patents filed by each firm, where clean patents are classified based on the International Patent Classifications (IPC) in Dechezlepretre, Martin, and Mohnen (2013). (PATSTAT)
RepRisk β	The factor loading on the difference between the daily value-weighted return of two portfolios based on firm-level reputational risk based on ESG-related news after controlling Fama-French-Carhart 4 Factors. (RepRisk)
Future Return	Monthly stock returns of firm i over year t (CRSP)

Appendix A – Continued

Variable Definition and Data Source

Variable	**Definition and Data Source**
Control Variables (Main)	
Assets	ln(1 + total assets). (Compustat)
Tobin's Q	Total assets plus the market value of equity minus the book value of equity minus deferred taxes divided by total assets. (Compustat)
Leverage	Total debt scaled by total assets. (Compustat)
ROA	Earnings before interest and taxes scaled by total assets. (Compustat)
SalesGrowth	Annual percentage change in sales. (Compustat)
Tangibility	Gross property, plant, and expenditure scaled by total assets. (Compustat)
R&D	Cumulative R&D expenditure scaled by total assets over time since 1985 with a decay rate of 15% each year, where missing values for R&D expenditure are replaced with zero. (Compustat)
Control Variables (Additional)	
Age	ln(1 + current fiscal year of a firm − the first year the firm appears in Compustat. (Compustat)
Size	ln(1 + market capitalization). (Compustat)
BM	Book value of equity divided by market value of equity. (Compustat)
PPE	ln(1 + gross property, plant, and equipment). (Compustat)
CapEx	Capital expenditure divided by total assets. (Compustat)
Advertising Expenditure	Advertising expenditure divided by total assets. (Compustat)
Momemtum	Cumulative monthly stock return over one-year period (CRSP)
Return 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)