Outsourcing Climate Change

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

Current Version: June 27, 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 (Corresponding author) 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, Wei Jiang, Angie Low, Mancy Luo, Mikael Paaso, Haikun Zhu, and seminar participants at the Erasmus University Rotterdam, Seoul National University, Schulich School of Business, 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 holistic analysis of whether and how U.S. firms address 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 tend to have higher reputational risks and larger future stock returns but are less incentivized to develop clean technologies.

Keywords: Outsourcing, Emissions, Imports, Stakeholders, Stock Performance
JEL classification: G23, G30, G34, M14

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

1. Introduction

Climate change is driving new political and economic realities for businesses. Many large U.S. corporations are integrating climate change into their business strategies in response to pressures from regulatory authorities, environmental activists, climate-conscious consumers, and investors. The Deloitte Resources 2019 Study finds that 84% of the surveyed business decision-makers were aware of the dire U.S. and global climate-change reports issued in late 2018,[2] and two-thirds of these decision-makers have reviewed or changed their energy management strategies in response.[3] Several CEOs also have announced their commitments to move their companies to net-zero carbon emissions. For example, Microsoft has been carbon neutral since 2012, and Amazon is targeting a net-zero carbon footprint by 2040.[4] A natural question that arises is whether U.S. corporations are indeed integrating climate change into their business strategies or their public commitments to a better environment are simply cheap talk. Our study addresses this important question by examining whether and how U.S. firms reduce their carbon footprints to tackle global climate change. Specifically, we investigate whether firms curb their own domestic emissions in the U.S. by outsourcing their carbon pollution to suppliers overseas, resulting in "carbon leakage." We also explore several plausible mechanisms that drive firms' efforts toward reducing carbon emissions and evaluate the economic consequences of their actions.

Since the adoption of the Sustainable Development Goals and the Paris Agreement in 2015, an increasing number of companies recognize the risks and opportunities associated with climate

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

[2] Climate change reports include the U.S. government's Fourth National Climate Assessment and the Intergovernmental Panel on Climate Change's (IPCC) 2018 report.

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

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

change and are taking actions to meet future greenhouse gas (GHG) reduction targets and a 100% renewable electricity commitment (RE100). Thus far, however, there has been little evidence found to support such commitments and actions.[5] Anecdotal media reports suggest that while firms' efforts seem reasonably progressive, a closer look reveals that firms are committed only to GHG emissions from their own production (i.e., Scope 1 emissions) and energy consumption (i.e., Scope 2 emissions).[6] These firms largely ignore indirect emissions from the supply of goods and services used as inputs of their production (i.e., Scope 3 emissions) that form the bulk of their total GHG emissions. 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.[7] 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. Only 4.3 million would be attributed to Scopes 1 and 2, indicating that P&G's GHG target only applies to 2% of its total emissions level. Thus, without accounting for Scope 3 emissions through supply chains, firms fail to fully account for their total GHG emissions attributable to their products.

Recent media mentions and academic studies also argue that while many developed countries have made progress in combating climate change, their efforts look much less impressive once international trade is considered.[8] For example, Ben-David et al. (2020) employ firms' self-reported survey responses about their Scopes 1 and 2 emissions over the 2008-2015 period and find that stricter environmental regulations in the domestic market lead to lower emissions at home but higher emissions abroad. Li and Zhou (2017) link firm-level imports and plant-level toxic emissions information and find that domestic plants pollute less locally as their parent firm imports more from low-wage countries. These studies suggest that firms play whack-a-mole with pollution, bringing carbon emissions down in local markets at the cost of increasing emissions abroad. Their analyses, however, similarly suffer from overlooking the importance of Scope 3 emissions in a firm's climate commitments and hence do not provide a holistic view of whether corporations follow through on

[5]See "What's Really Behind Corporate Promises on Climate Change?" by Peter Eavis and Clifford Krauss, New York Times, February 22, 2021.

[6]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.

[7]See footnote #6.

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

their pledge to a global action plan to fight climate change.

Our study exploits newly available firm-level data on firms' Scopes 1, 2, and 3 emission intensities from Trucost and transaction-level import information from Panjiva to conduct an in-depth analysis of whether and how U.S. firms address climate change. These datasets provide granularity relative to those employed in the existing literature and allow us to thoroughly analyze firms' actions in curbing carbon emissions and evaluate their pricing and welfare implications. Our sample consists of 73,966 firm-country-year observations from 1,254 U.S. firms and 178 exporting countries after merging the two key databases for the 2006-2018 period. It is important to stress that our imports exclude those from foreign subsidiaries. Figure 1 illustrates the evolution of GHG emissions by Scope over time. It shows that firms maintain a reasonably stable carbon footprint (Scope 1) over time while increasing indirect emissions (Scopes 2 and 3) to support their business growth and production needs. The surge in indirect emissions, especially following the 2015 Paris Agreement, points to outsourcing pollution along the supply chain in curbing self-generated emissions. Figure 2 presents the aggregate carbon footprint (Scopes 1, 2, and 3) and total imports of U.S. firms over time. The increasing pattern for both measures further suggests growing popularity in pollution offshoring and, more importantly, that such outsourcing behavior does not represent an efficient emissions allocation strategy. The increasing dependence on foreign suppliers is ineffective in reducing the total carbon footprint of U.S. customers.

To empirically determine the extent to which firms reduce their carbon footprints through exporting pollution, we examine how a firm's own direct emissions (Scope 1) are related to its suppliers' emissions (Scope 3) and how such a relationship is affected by the firm's imports.[9] Using this approach, we find that Scope 1 emissions are positively and significantly associated with Scope 3 emissions, suggesting a high correlation between a firm's own carbon emissions and its suppliers'. These results offer some evidence to pollution outsourcing, as firms with pollution-intensive production are likely the ones that impose the most polluting burden onto their suppliers. We also find that the interaction of Scope 1 emissions and imports exhibits a strong negative association with Scope 3 emissions, suggesting that increasing imports would weaken the positive relationship between Scopes 1 and 3 emissions. A one-standard-deviation increase in the import

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

measure would moderate the positive relationship between Scopes 1 and 3 by about 2%, indicating that when U.S. firms increase their imports, their own Scope 1 emissions fall with a corresponding rise in supplier-generated Scope 3 emissions. This finding complements the time-series emissions trends depicted in Figure 1 and serves as pivotal evidence that U.S. firms rely on outsourcing part of their pollution to global suppliers in satisfying their total emissions needs.

While we have established that imports play an important role in driving the relationship between Scopes 1 and 3 emissions, our causal inferences of this link may be subject to endogeneity concerns. To circumvent such a problem, we exploit several exogenous shocks to U.S. firms' propensity to outsource carbon emissions. Suppose our baseline findings indeed capture the outsourcing effect. In this case, we should observe imports to have a stronger impact with an exogenous increase (decrease) in appetite for imported (domestic) carbon emissions. First, we employ domestic legislative pressure and regulatory stringency in the U.S. as exogenous sources of increase in the demand for imported emissions. Prior research shows that federal and state judiciaries play a critical role in developing and enforcing environmental regulations in the U.S. (e.g., Shipan and Lowry 2001; Grant, Bergstrand, and Running 2014; Kim and Urpelainen 2017). Thus, firms located in states with intense legislative pressure on environmental consciousness, as proxied by a sudden increase in pro-environmental votes in the House and Senate, should have stronger incentives to import as a means of outsourcing GHG emissions to their suppliers overseas. Similarly, we use spikes in state-level facility inspections by the Environmental Protection Agency (EPA) to capture heightened regulatory stringency that should also induce demand for imported emissions. Analyses using triple-difference models reveal a stronger dampening effect of imports on the association between Scopes 1 and 3 as political pressure and regulatory stringency increase, consistent with a causal interpretation of firms' outsourcing pollution in curbing their own emissions.

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

Our analysis further investigates the countries to which U.S. firms relocate their carbon pollution. First, we examine whether pollution outsourcing is more likely to happen when exporting countries have a lower level of economic development. We contend that less developed countries are more concerned about economic survival than environmental issues and thus have weaker environmental regulations and lower social awareness towards environmental protection. These countries would be less costly alternatives for firms that face fairly intense regulatory and social pressure in the United States. Consistent with our conjecture, we find that the attenuating effect of imports is concentrated in non-OECD countries. Second, we examine outsourcing behaviors toward countries with different legal regimes. As documented in prior research (e.g., La Porta, López-de-Silanes, and Shleifer 2008; Allen, Carletti, and Marquez 2015; Liang and Renneboog 2017), common law countries tend to put more emphasis on shareholder rights, whereas civil law countries are more protective of other stakeholders. Thus, firms should prefer outsourcing more carbon emissions to common law countries, given their weaker environmental protection regulations. Our findings support this prediction. Finally, using the country-level environmental performance index (EPI) and environmental regulation score to capture the strictness of environmental laws and enforcement, we further show that outsourcing effects are stronger among exporting countries with laxer regulations. These findings collectively suggest that pollution outsourcing hinges on the institutional environment of suppliers' countries and complement Figure 2 indicating an inefficient carbon allocation strategy in which U.S. firms shift their emissions toward countries with lower costs of regulatory compliance rather than countries with the greener production process.

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 reputations. 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" management and "green" directors) face greater internal pressure to uphold their domestic reputations by shifting pollution-intensive production overseas through the upstream supply chain. Supporting these internal mechanisms, we find the outsourcing effect to be more pronounced for green firms and firms with green CEOs and green directors.

In contrast to internal stakeholders who reinforce outsourcing, 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 in nature and hence are more concerned about the overall ESG performance of their global supply chain and investee portfolio. They would push against pollution offshoring to reduce any negative 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). 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 carbon 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 evaluate the economic consequences of firms reducing carbon footprints through pollution offshoring. Our results suggest that firms with larger amounts of imported emissions are associated with a higher level of reputational risk and future returns. We argue that investors have difficulties assessing the part of a firm's carbon emissions through imports, possibly explaining why U.S. firms have strong incentives to outsource emissions. Besides regulatory oversight, firms also exploit investor oversight of emissions along the upstream supply chain. Such outsourcing activities disincentivize these firms to develop clean technologies.

Our research makes significant contributions to the growing corporate environmental policy literature. We provide the first comprehensive firm-level analysis 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 level. 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. 2020; 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 both direct and indirect carbon emissions and also jointly with its imports, as highlighted below.

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. (2020) 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 advances 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 examines the economic consequences of firm outsourcing pollution. The final section concludes.

2. Data and Summary Statistics

This study employs data from several different sources: (i) direct and indirect GHG emissions for U.S. firms from S&P Global's Trucost; (ii) the U.S. customs import data at the shipment level from Panjiva; (iii) Senate and House voting records on environmental legislations from League of Conservation Voters (LCV); (iv) plant inspections by EPA from Enforcement and Compliance History Online (ECHO); (v) retail electricity prices from the U.S. Energy Information Administration (EIA); (vi) global natural disaster data from EM-DAT; (vii) tariff and trade records from World Integrated Trade Solution (WITS) provided by World Bank; (viii) firm-level ESG scores from Refinitiv; (ix) information on executives and boards from BoardEx; (x) corporate and governmental customer data from Factset Revere and Compustat Segment Files, respectively; (xi) Form 13F institutional holdings data from FactSet Ownership; (xii) innovation output data from Worldwide Patent Statistical Database maintained by European Patent Office (PATSTAT); (xiii) firm-level ESG reputational risk data from RepRisk; (xiv) information on country-level characteristics from various sources, including International Monetary Fund (IMF), Organization for Economic Cooperation and Development (OECD), World Economic Forum (WEF), and Yale Center for Environmental Law & Policy; (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 2005 and 2018 from Trucost. Over the sample period, the coverage has increased from about 1,000 to 2,700 U.S. firms. The database is constructed following the Greenhouse Gas Protocol standards and 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, the upstream Scope 3 data provided by Trucost include those emissions associated with the production and transportation of purchased materials, business travel, waste disposal, and other outsourced activities. Such information is estimated using an input-output model that considers both the firm's expenditures across all sectors in which it obtains its inputs and the sector-level emission factors. To facilitate the interpretation of carbon emissions across firms of different sizes and operations, we measure each pollution intensity as the quantity of emissions in tonnes of CO_2 equivalent scaled by total assets. All carbon measures take on the natural log form in reducing the skewness of their distributions.

2.2. U.S. corporate seaborne imports

Panjiva provides a unique database of U.S. trades that documents transaction-level details of goods that cross the border. Under the Customs Regulations at 19 CFR (Code of Federal Regulation), firms in the United States are required to report shipment details in cargo declarations to U.S. Customs and Border Protection (CBP). Panjiva relies on such declarations to obtain information on the shippers (i.e., suppliers or logistic companies), consignees (i.e., customers), origin and destination addresses, product descriptions, and container specifications of ocean freight shipments between U.S. firms and foreign entities in over 190 countries for the 2006-2019 period. We use S&P's identification system to link the consignees with the highest-level parent firms available in

Compustat.[10] For each of the matched U.S. consignees, we count the total number of shipments it receives from an exporting country in a year, scaled by the firm's total assets, as a proxy for import intensity.[11] The measure is also log transformed to reduce skewness. Given that we focus on supplier-generated carbon emissions, we exclude shipments from foreign subsidiaries of U.S. parent firms.

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

2.3. Control variables

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

[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.

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

R&D denotes research and development capital stock, computed using the perpetual inventory method where R&D expenses scaled by assets are accumulated over the years with an annual depreciation rate of 15% (Hall, Jafee, and Trajtenberg 2005). We winsorize all continuous variables at 1% and 99%. Appendix A contains the detailed definition of all variables.

2.4. Summary statistics

Table 1 reports the summary statistics of our key variables. Panel A summarizes the four primary variables in raw form (*Scope 1*, *Scope 2*, and *Scope 3*, and *Import*), where emissions are in thousands of tonnes and imports are in the number of shipments. On average, a U.S. firm produces about 2.9 million tonnes of Scope 1 emissions and 1 million tonnes of Scope 2 emissions per year. Through its supply chain, the firm is also associated with about 5.2 million tonnes of Scope 3 emissions. In comparison, the median values of emissions are much smaller (0.17 million tonnes, 0.2 million tonnes, and 1.3 million tonnes for Scopes 1, 2, and 3, respectively). These statistics are largely consistent with CDP's recent report showing that companies' supply chain emissions are immensely greater than their Scopes 1 and 2 emissions.[12] It is evident that the bulk of a firm's emissions is from its suppliers. Hence, the firm must include this large amount of indirect emissions when targeting for carbon neutrality. The standard deviations for Scope 1, Scope 2, Scope 3 emissions are about 9.5 million tonnes, 2.2 million tonnes, and 11.2 million tonnes, respectively. These values are much larger than their respective means, indicating that the quantity of emissions generated are quite skewed. Moreover, statistics suggest that GHG emissions are mostly driven by large companies. For these considerations, we employ log emission intensities for our main analyses. Their summary statistics are reported in Panel B. The average number of shipments from suppliers in each exporting country is 38, and the median number is 4.

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

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

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 Footprints

This section investigates whether and how U.S. firms reduce their carbon footprints and addresses endogeneity concerns by exploiting several shocks on firms' propensity to import GHG emissions. We also conduct a host of tests to determine which countries particularly attract pollution outsourcing from U.S. firms.

3.1. Carbon emissions outsourcing

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

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

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

Of particular interest are the signs and significance of β_S and β_{SI} estimates. They allow us to infer whether and how firms outsource their carbon pollution abroad. The β_S coefficient reflects the link between a U.S. firm's own carbon emissions and those generated by its suppliers. A positive β_S indicates that supply chain emissions increase with the firm's production emissions, suggesting that more pollution-intensive firms are more inclined to shift their polluting burden onto their upstream suppliers. The β_{SI} coefficient provides pivotal evidence of whether U.S. firms outsource carbon emissions. It captures the amplifying or mitigating effect of imports on the association between Scope 1 and Scope 3 emissions. A negative β_{SI} suggests that imports trigger a substitutional relationship between a firm's own emissions and those of its suppliers, an implication that the firm outsources its carbon emissions abroad. In contrast, a positive β_{SI} indicates little outsourcing behavior as imports do not facilitate the substitution of Scope 1 and Scope 3 emissions but instead help align the emission policies of U.S. firms and their overseas suppliers.

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

Second, the coefficients on the interaction term, *Scope 1* × *Import*, are all negative and significant, with β_{SI} estimates ranging from -0.088 ($t-$stat$= -2.34$) in Column (4) to -0.104 ($t-$stat$= -2.68$) in Column (1). These results suggest that when a firm increases its imports, the positive correlation between its Scope 1 and Scope 3 emissions becomes weaker. A one-standard-deviation increase in *Import* from its mean attenuates the *Scope1-Scope 3* association by 2.4% and the *Scope1-Scope 2+3* association by about 1.7%.[13] Similarly, Column (4) reveals that the elasticity of *Scope 2+3* for *Scope 1* decreases from 0.0605 to 0.0595, or a 1.68% reduction, with the increase in import intensity. This direct evidence of pollution outsourcing indicates that when U.S. firms increase their imports, their Scope 1 emissions fall at the expense of rising supplier-generated Scope 3 emissions. Such an import-induced substitution effect complements Figure 1 in showing that U.S. firms rely heavily on Scope 3 emissions to satisfy their total carbon needs while curbing Scope 1 emissions. This finding is broadly consistent with the economic literature in environmental policies. Prior research suggests that U.S. environmental regulations drive down energy-intensive manufacturing output and that about half of the decline in domestic production for these industries is offset by an increase in net imports from countries not implementing emission mitigation policies (e.g., Ho, Morgenstern, and Shih 2008; Aldy 2017).

Finally, the positive and significant coefficient on *Import* may be mechanically driven. Companies with more imports from global suppliers also tend to have more Scope 3 emissions. Furthermore, the findings indicate that emissions from suppliers are greater for smaller U.S. corporate customers, customers with lower market-to-book value but greater profitability, sales growth, and tangibility. Except for sales growth, these results remain robust when the dependent variable is *Scope 2+3*. The results are also consistent across the two different sets of fixed effects that we employ. For brevity, we only report results using *Scope 3* and firm, country×year fixed effects in subsequent analyses.[14]

3.2. Identification strategies

Thus far, our results suggest that firms' imports play an important role in driving the relationship between Scopes 1 and 3 emissions. However, our causal inferences of this link may be subject to endogeneity concerns. For example, U.S. firms may choose countries of imports for other production cost considerations than carbon emissions. Therefore, the association between *Scope1* and *Scope 3* mechanically weakens as firms increase imports from foreign suppliers subject to emissions policies

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

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

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 carbon emissions. If our baseline findings indeed capture the outsourcing pollution effect, imports should have a stronger mitigating impact on the *Scope1–Scope 3* relationship with an exogenous increase (decrease) in appetite for imported (domestic) carbon emissions net of provision. In particular, we examine demand shocks to imported emissions arising from domestic legislative pressure and regulatory stringency as well as supply shocks stemming from regional carbon price spikes, import tariffs reductions, and global supply chain disruptions due to natural disasters.

3.2.1. State-level legislative pressure and regulatory stringency

With the United States being the world's second-largest source of carbon emissions, accounting for 15% of the global total by 2018, environmental protection has become one of the most critical issues in U.S. politics.[15] The U.S. EPA was established in 1970 committed to reducing air pollution, followed by amendments to the Clean Air Act that increased environmental regulatory enforcement. The more recent Clean Power Plan proposed by the EPA in 2014 further aims to combat climate change by cutting carbon emissions of power plants. These pollution control efforts rely heavily on the states and their abilities to devise implementation plans and enforce policies in ensuring effectiveness (e.g., Grant, Bergstrand, and Running 2014). Thus, we employ state-level legislative pressure and regulatory stringency as exogenous sources of increase in the demand for imported emissions.

We analyze Congressional voting patterns in climate-change-related environmental issues to capture domestic legislative pressure. We examine the most critical environmental legislation voted in the House and the Senate between 2006 and 2019, as documented by the LCV, and assign a score to each Congress member based on his/her voting records each year. The score is defined as the number of pro-environmental votes scaled by the total number of environmental legislations considered in the year. A higher score indicates that the Congress member is more environmen-

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

tally conscious. States consisting of more environmentally friendly Congress members should have greater interests in pushing forward a climate action agenda. To proxy for state-level legislative pressure on environmental protection, we compute the average voting scores separately across the Senate and House of Representatives in each state. We argue that firms located in states with a dramatically heightened legislative pressure, potentially due to elections of more environmentally conscious members in the Senate or the House, should have stronger incentives to import as a means of offshoring GHG emissions.

Legislative pressure shocks are identified as state-years that experience score increases by more than three times the average increase during our sample period. We eliminate any transitory shocks followed by score reversals of a similar level within the next three years and shocks endogenously driven by firm relocation decisions. Such an identification test satisfies the exclusion restriction. There is no noticeable increase in the local-emission pattern before legislative shocks, suggesting that these shocks are likely independent of firms' domestic carbon production. Instead, they appear to capture sudden rises 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,[16] unseated incumbent Republican Senator Richard Santorum with a lifetime voting score of 10. Similarly, in 2008 Colorado's U.S. Senate race, Wayne Allard, a Republican with a voting score of 9, lost his senate seat to Michael Bennet, a Democrat with 88. We employ such senate races as exogenous shocks to environmental policies.

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

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

where $Treat_{i,t-1}$ is a binary indicator that equals 1 if the state where firm i resides in experiences a shock in the average House or Senate score at year $t-1$, and 0 otherwise. The coefficient of the

[16] A higher value indicates that the member is more likely to vote in favor of pro-environmental policies.

triple interaction term $Scope\ 1 \times Import \times Treat$ captures the incremental impact of imports on the *Scope1–Scope 3* association for firms that are more likely to demand pollution overseas through imports. A negative β_{SI1} suggests a stronger substitutional relationship between a firm's own emissions and its suppliers' emissions given increased desire to outsource pollution.

We measure state-level regulatory stringency using the facility inspection data obtained from ECHO. Inspection intensity is defined as the total number of onsite air pollution compliance evaluations conducted by EPA scaled by the total number of air pollution emitting facilities in each state. We contend that firms located in states with tightened regulatory monitoring and enforcement should have more robust demand for imported emissions. To test this prediction, we repeat model (2) while redefining $Treat_{i,t-1}$ as 1 if the one-year lagged inspection intensity increases by more than three times the average increase during the sample period. We again eliminate any transitory shocks followed by reversals within the next three years and shocks driven by changes in the firm location. Our unreported time-series analysis shows no consistent pattern indicating significant increases in firms' local carbon emissions drive these shocks. Furthermore, inspections can be conducted to simultaneously address multiple environmental concerns while assessing many different regulated pollutants.[17] Thus, while these inspection shocks would increase the regulatory pressure on carbon production, they may be initially triggered by other regulatory programs or environmental problems than those associated with GHG.

Table 3 reports regression estimates of model (2). Columns (1) and (2) show the impact of legislative pressure from the House and the Senate on U.S. firms' environmental policies, whereas Column (3) presents the effect of state-level regulatory stringency. The β_{SI1} estimates are negative and significant at the 1% level in Column (1) and at the 5% level in Columns (2) and (3). These results suggest a stronger dampening effect of imports with an exogenous increase in the demand for imported emissions. According to Column (2), for example, a one-standard-deviation increase in *Import* would attenuate the *Scope1-Scope 3* relationship by about 14.2% for firms experiencing a shock to the House voting score, in stark contrast to a 1.8% reduction for other U.S. firms.[18]

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

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

We find a similar increase from a 2% mitigating effect to 10.7% following a shock to state-level regulatory stringency, as shown in Column (3). These findings corroborate our argument that the outsourcing behavior of U.S. firms drives the mitigating effect of imports observed in the baseline analysis.

3.2.2. Supply shocks to carbon emissions

Alternatively, we consider state-level electricity rate spikes, import tariff reductions, and natural disasters in exporting countries as exogenous shocks to the supply of carbon emissions. Prior research suggests that climate change policies increase the cost of carbon supply and, in turn, raise the energy and electricity prices that end-users face. Using simulated models, Aldy and Pizer (2014, 2015) and Aldy (2017) show that higher energy and electricity rates induced by carbon pricing policies have significant adverse effects on energy-intensive manufacturing firms, including production cost increases, production declines, and job cuts. Drawn from this strand of literature, we employ spikes in retail electricity prices as our first supply shock to domestic emissions for U.S. firms. We contend that electricity price spikes reflect increases in the cost of domestic carbon supply. Thus, firms located in states with a dramatic rise in electricity price should have more substantial incentives to seek imported carbon supply in curbing their heightened emissions and production costs. We test this prediction by re-estimating model (2) with $Treat_{i,t-1}$ taking the value of 1 if the one-year lagged state-average retail electricity rate rises by more than three times the average increase over the sample period. Such a shock must not revert within the next three years, and a change in firm locations must not drive it.

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

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

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

All the above results collectively support the "carbon outsourcing" interpretation of our crucial finding on the substitutional relationship between Scopes 1 and 3 emissions.

3.3. Destination countries

In preceding sections, we have established that U.S. corporations reduce their carbon footprints by shifting GHG emissions to their global suppliers through imports. We now turn to examine the destination countries to which those U.S. firms relocate their pollution. To do so, we partition our sample based on whether suppliers are residing in countries with a lower level of economic development, weaker stakeholder protection, and laxer stringent environmental regulations. We employ a binary indicator to differentiate destination countries along each of these criteria and estimate the following triple-interaction model:

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

where *Indicator* is a binary indicator that alternately captures four different representations, namely non-OECD countries, common-law countries, countries with below-median stringency of environmental regulation (SER), and countries with below-median environmental performance index (EPI). Model (3) allows us to directly test U.S. firms' outsourcing preferences in destination countries.[19] Such an approach differs from prior studies (e.g., Li and Zhou 2017; Ben-David et al. 2020) that infer preferences without showing substitutional relationships between firms' self-generated emissions and those from different exporting countries.

First, we examine whether pollution outsourcing is more likely to occur when destination countries have a lower level of economic development. We contend that less developed economies typically lack the proper institutional and organizational framework to enforce stringent environmental regulations. Poorer countries are also more concerned about daily economic survival than environmental sustainability and have a weaker social awareness of environmental issues. These countries offer more cost-effective alternatives for corporations that face fairly intense regulatory and social pressure in the United States (e.g., California Cap-and-Trade Program, Clean Air Act; National Energy Conservation Policy Act). Thus, U.S. firms should be more inclined to outsource

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

GHG emissions to less-developed exporting countries. We employ a binary indicator that equals one if the destination country is a non-OECD member country and zero if it is an OECD member country. OECD countries are generally high-income economies with average GDP per capita reaching 3.6 times that of non-OECD countries by 2019.[20] Furthermore, as OECD pushes for better social policies, its fellow members should have environmental standards that are more comparable to the United States than do non-OECD countries. Thus, the benefit of pollution outsourcing would be small for OECD destinations compared to non-OECD nations. Column (1) of Table 5 reports estimation results from the triple-interaction model (3). Consistent with our prediction, we find the attenuating effect of imports to be more pronounced for the non-OECD than OECD destination countries. The coefficient on the triple-interaction term is -0.079 ($t-$stat$= -1.90$) and statistically significant at the 10% level. Such outsourcing preference is broadly consistent with existing studies (e.g., Taylor 2005; Li and Zhou 2017) that document a shift of pollution-intensive production toward low-wage countries.

Second, we examine firms' pollution outsourcing towards countries with different legal regimes. Prior research suggests that common law countries rely more heavily on private market outcomes to maximize value in the interest of shareholders (e.g., La Porta, López-de-Silanes, and Shleifer 2008; Allen, Carletti, and Marquez 2015; Liang and Renneboog 2017). They tend to put more emphasis on shareholder rights vis-a-vis stakeholder welfare. In contrast, civil law countries are more protective of other stakeholders' interests through state intervention of private sectors. A common law regime suggests relatively inefficient regulations against climate change, whereas a civil law system may reflect stricter regulatory protection of environmental stakeholders. Thus, U.S. firms may find it easier to relocate their emissions to destination countries with a common law origin than a civil law origin, especially when they share a similar legal framework (i.e., the common law). We define a binary indicator equals one if the exporting country is a common-law country and zero if otherwise. Column (2) reports that the outsourcing effect is concentrated in common law countries – the coefficient of the triple-interaction term is negative and highly statistically significant (i.e., -0.103 with $t-$stat$= -3.30$).

Finally, we test explicitly how the outsourcing effect varies across countries with varying degrees

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

of environmental regulatory stringency. We use a country's Stringency of Environmental Regulation (SER) score provided by the WEF's Travel & Tourism Competitiveness Reports and Environmental Performance Index (EPI) provided by Yale Center for Environmental Law & Policy. EPI comprehensively measures the environmental health and ecosystem vitality of 180 countries regarding how close they are to established environmental policy targets. Our study specifically examines the score that captures the policy targets essential to combating climate change. We use the binary indicator to denote a country that is below the median SER or EPI score of the sample of countries and show their results in Columns (3) and (4). The coefficients of *Scope 1*$\times$*Import*$\times$*Inidcator* are positive and statistically significant at the 5% level, thereby corroborating our argument that less environmentally regulated countries attract pollution outsourcing. Taken together with Figure 2, these findings indicate an inefficient carbon allocation strategy in which U.S. firms outsource their pollution to countries with lower costs associated with GHG production than countries with the more carbon-efficient production process.

3.4. Industry emissions

We further investigate how industry characteristics affect carbon production decisions. First, we examine whether outsourcing is concentrated among pollution-intensive industries, measured at the Fama-French 30 industry level and defined as those with above-median aggregate Scope 1 emissions. Column (1) of Table 6 reports the results from re-estimating model (3) with such polluting-industry indicator. Similar to those shown in Table 5, the coefficient of the triple-interaction term is negative and statistically at the 5% level, indicating that highly polluting industries are more likely to outsource their emissions production to their suppliers. Alternatively, we incorporate the total carbon footprint of the industry and its whole supply chain. Alternatively, we incorporate the total carbon footprint of the industry and its whole supply chain. This approach enables us to investigate whether industries requiring an abundance of 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

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

essence captures all emissions produced throughout supply chain, starting from the raw inputs up to the production of $1 million worth of output. Again, we construct a binary indicator that takes the value of one if the industry is above the median level of emissions and zero if otherwise. Results are reported in Column (2) of Table 6. The significant triple-interaction term suggests that firms requiring carbon-intensive inputs turn to foreign suppliers for pollution outsourcing.

Overall, the results of Tables 5 and 6 reveal a more nuanced view of U.S. corporations' pollution outsourcing preferences based on destination countries' institutional environments and the extent of pollution of each industry. Such outsourcing is more likely to occur when the exporting countries have a lower level of economic development, less stakeholder-oriented legal regime, and laxer environmental regulations, or when industries are highly polluted.

4. The Mechanisms

This section explores several possible mechanisms that drive firms' pollution management and outsourcing activities. To facilitate our discussion, we group them into two types of mechanisms: internal and external mechanisms. Internal mechanisms arise from firms, management, and board members' desire to maintain 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 own greenness can dictate its corporate environmental policy. We posit that firms with higher social and environmental ratings (i.e., green firms) are more inclined to shift pollution overseas in reducing self-generated GHG. Prior research suggests that companies can "do well by doing good." 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 and 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 (2). $Treat_{i,t-1}$ 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.

Green executives and board members should similarly have reinforcing effects on pollution 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, executives and directors with a pro-environmental image (i.e., green executives and directors) would also influence corporate policies in maintaining their own established reputation and prestige. Existing studies document that managers and directors play a critical role in their firm's 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 pollution outsourcing. In testing these mechanisms, $Treat_{i,t-1}$ is replaced with $Green\ CEO_{i,t-1}$ and $Green\ Director_{i,t-1}$ to capture managers and directors' established social reputation as revealed by their past five-year of employment. For each CEO in a given year, we assign a ranking based on the average score of his/her current and past employers' environmental scores over the past five years. $Green\ CEO_{i,t-1}$ measures the average scores over years $t-5$ to $t-1$. A higher score denotes a greener CEO for firm i. We compute *Green Directors* in a similar fashion. Specifically, $Green\ Director_{i,t-1}$ is the average of firm i's director scores over the past five years of their experiences serving as board members in any corporation. We obtain information on the CEO's and directors' past work experience from BoardEx and manually match these stakeholders with Dun & Bradstreet database for their experience in private firms.

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

4.2. External mechanisms

Unlike green internal stakeholders, environmentally-responsible external stakeholders, such as green customers and green investors, should play an important role in discouraging pollution outsourcing efforts. 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; Krueger, Sautner, and Starks 2020; Gantchev, Giannetti, and Li 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 overall environmental externalities of corporate actions in the global community. These customers usually have global supply chains and tend to impose their social preferences on their suppliers (Dai, Liang, and Ng 2020). Thus, in maintaining the overall ESG performance of their global supply network, green customers would push against pollution outsourcing of U.S. firms to alleviate any displaced polluting burden added onto their foreign suppliers. In addition to international network considerations, customers may also drive total GHG reductions out of climate change concerns. 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 pollution for the sake of public welfare (Hsu, Liang, and Matos 2020). To effectively combat climate change, they would emphasize a firm's overall carbon footprint instead of only direct emissions. Green corporate customers should be more attentive to the adverse impacts of climate risks on their performance. Climate change constitutes extreme weather events leading to significant losses on affected firms that propagate through the supply chain (Barrot and Sauvagnat 2016). These customers would also exert influences to curb total emissions. Hence, we expect the outsourcing effect to be less pronounced when a firm has more concentrated government customers and green corporate customers.

We apply the triple-interaction model (2) to explore these external mechanisms. In this model, $Treat_{i,t-1}$ is replaced by $Largest\ Gov\ Customer_{i,t-1}$ and $Green\ Customers_{i,t-1}$. The former is defined as the percentage of firm i's sales to the largest major government customer identified in Compustat Segments file at year $t-1$, where a major customer accounts for at least 10% of a firm's total sales. We also employ alternative customer concentration measures, including the sum of sales and the sum of squared sales to all major government customers scaled by firm i's total sales revenue. Given that the results are qualitatively similar, we only report those of the *Largest Gov Customer*. $Green\ Customers_{i,t-1}$ captures the percentage of firm i's green corporate customers in year $t-1$, where green customers are those emitting lower than industry-median carbon emissions per dollar value of total assets.

We contend that environmentally-conscious institutional investors would similarly alleviate pollution outsourcing. Like green customers, they have international exposure and are more concerned about the overall ESG performance of their global investment portfolios. These investors would influence pollution outsourcing to reduce any adverse spillover effects on the ESG ratings of their portfolio firms overseas. Furthermore, ESG-oriented investors are more likely to consider and manage the climate risks of their investments (Krueger, Sautner, and Starks 2020). To minimize the negative impact of climate risks 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. $Green\ Blockholders_{i,t-1}$ is measured as the percentage of firm i's shares owned by green blockholders in year $t-1$, where a blockholder holds at least 5% of the firm's total shares outstanding. A green institution has at least 50% of its portfolio invested in green firms, identified as those 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 pollution management, respectively. As shown in Column (1), the coefficient on *Scope 1* $\times$ *Import* $\times$ *Largest Gov Customer* is positive and statistically significant at the 1% level. This finding indicates a weaker mitigating effect of imports for firms supplying to large government customers, consistent with our conjecture that government customers limit pollution outsourcing activities. We similarly find the triple-interaction coefficients for *Green Customers* and *Green Blockholders* to be positive and statistically significant. They support the notion that green customers and investors reduce global environmental externalities by restricting their associated firms from outsourcing emissions to other countries.

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

5. Economic Consequences

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

5.1. Reputational Risk

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] As firms employ ESG as a product differentiation strategy (e.g., Flammer 2015; Albuquerque, Koskinen, Zhang 2020), they would likely behave responsibly and not jeopardize their reputation. We, therefore, expect environmentally-responsible firms to display a lower ESG-induced reputational risk. That is, firms that pollute less have a lower reputational risk.

We test our prediction by examining the cross-sectional variation between firms' reputational risks and different sources of carbon emissions. To facilitate comparisons between our findings and those of existing studies such as Bolton and Kacperczyk (2020a, b), the remainder of our analyses employs the natural logarithm of one plus the amounts of carbon emissions, namely, *Scope 1* CO_2, *Scope 2* CO_2, *Scope 3* CO_2, and *Imported* CO_2 (i.e., carbon emissions generated from imported shipments).[23] Accordingly, our model specification is as follows:[24]

$$\begin{aligned} \textit{RepRisk}\ \beta_{i,t} \quad = \quad & \alpha + \beta_1 \textit{Imported}\ CO_{2i,t} + \beta_2 \textit{Scope 1}\ CO_{2i,t} + \beta_3 \textit{Scope 2}\ CO_{2i,t} \\ & + \beta_4 \textit{Scope 3}\ CO_{2i,t} + \beta_{CS}' \textit{Controls}_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where *RepRisk* $\beta_{i,t}$ is an estimate of a firm's reputational risk at year t; *Scope 1* CO_2, *Scope 2* CO_2, *Scope 3* CO_2, and *Imported* CO_2 are defined as the log of one plus the emissions variable. Model (4) also includes firm-level *Assets*, *Tobin's Q*, *R&D*, *PPE*, *Leverage*, *CapEx*, *Cash*, *Income Volatility*, and *ROA*, as well as firm and month fixed effects as controls. We estimate *RepRisk* $\beta_{i,t}$ as follows. Each year, we rank the firms in our sample based on their reputational risk scores, as provided by RepRisk,[25] 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

[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.

[23] Unlike the variables employed in the preceding sections, *Scope 1* CO_2, *Scope 2* CO_2, *Scope 3* CO_2, and *Imported* CO_2 are not scaled by a firm's total assets.

[24] 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.

[25] 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

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 firms' *RepRisk* $\beta_{i,t}$'s.

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.[26] Similar to Edmans (2011), we interpret that the reputational risk factor's underperformance reflects the difficulty in incorporating intangibles into traditional valuation models. Nevertheless, our main purpose is to examine which source of firm-level carbon emissions is related to a firm's systematic reputational risk.

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

5.2. Stock Return Performance

We also analyze the pricing implications of pollution outsourcing activities by investigating whether financial markets efficiently price in the stocks of firms that exploit outsourcing to reduce carbon emissions. Prior research provides increasing evidence that financial markets play a role in pricing carbon exposure. For example, carbon emissions increase with firms' cost of capital (Chava

[26]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.

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

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

$$\begin{aligned} \textit{Stock Return}_{i,m,t} \quad &= \quad \alpha + \beta_1 \textit{Imported } CO_{2_{i,t-1}} + \beta_2 \textit{Scope 1 } CO_{2_{i,t-1}} + \beta_3 \textit{Scope 2 } CO_{2_{i,t-1}} \\ &\quad + \beta_4 \textit{Scope 3 } CO_{2_{i,t-1}} + \beta'_{CS} \textit{Controls}_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned} \tag{5}$$

where $\textit{Stock Return}_{i,m,t}$ is the monthly stock return of firm i in month m of year t, and *Scope 1* CO_2, *Scope 2* CO_2, *Scope 3* CO_2, and *Imported* CO_2 are measured at year $t-1$. *Controls* include firm-specific *Size*, *BM*, *Leverage*, *PPE*, *CapEx*, *Momentum*, *Volatility*, *Beta*, and *HHI* at year $t-1$. Model (5) also includes firm and month fixed effects and incorporates standard errors clustered at the firm-year level. We estimate the effect of each source of carbon emissions separately and jointly on future stock returns. Results are reported in Table 10.

In Columns (1)-(4), the coefficients on the emission variables are positive and statistically significant at the 1% level, consistent with the notion that stocks with greater climate risk exposures also have greater future stock returns. In Column (5), we evaluate the joint impacts of the emission variables and find that while the signs of emission variables remain positive, only the coefficient on *Imported* CO_2 remains unaffected and is statisically significant at the 1% level. The coefficient on *Scope 3* CO_2 becomes marginally significant at the 10% level. These results are intriguing and somewhat corroborate those in Table 9 on reputational risks. In particular, the market sufficiently prices a firm's Scopes 1 and 2 emissions (i.e., emissions of the firm's own production and operation), and to a certain degree, its Scope 3 emissions. Scope 3 emissions measure the overall emissions released by a firm's suppliers, but the firm may not necessarily factor in these emissions in its carbon reduction policy. Combined, the results of Tables 9 and 10 explain why U.S. firms have a strong incentive to outsource emissions. Besides regulatory oversight, these firms also exploit investor oversight or unawareness of their emissions along the upstream supply chain.

5.3. Green Innovation and Carbon Emissions

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

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

$$\begin{aligned} \textit{Green Innovation}_{i,t+1} \quad = \quad & \alpha + \beta_1 \textit{Imported } CO_{2i,t} + \beta_2 \textit{Scope 1 } CO_{2i,t} + \beta_3 \textit{Scope 2 } CO_{2i,t} \\ & + \beta_4 \textit{Scope 3 } CO_{2i,t} + \beta'_{CS} \textit{Controls}_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \qquad (6) \end{aligned}$$

where $\textit{Green Innovation}_{i,t+1}$ is measured as the one-year ahead number of clean patents filed by each firm. 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 11.

The table reveals one distinct finding. There is little evidence that firms that reduce their carbon footprints through outsourcing pollution to foreign suppliers have a desire to develop clean technologies. Imported CO_2 emissions are negatively correlated with green innovation output, while none of the direct and indirect non-supplier-induced carbon emissions significantly affect green innovation. For example, the coefficient estimates of *Imported* CO_2 are between -0.024 ($t-$statistic$= -2.37$) and -0.027 ($t-$statistic$= -2.42$) and are all statistically significant at the 5% level. In contrast, the coefficients on *Scope 1* CO_2, *Scope 2* CO_2, and *Scope 3* CO_2 are not statistically different from zero. Adding *Scope 1* CO_2, *Scope 2* CO_2, and *Scope 3* CO_2, separately or jointly, to the model has virtually no effect on the magnitude of the *Imported* CO_2 coefficient.[27] The more firms import, the less likely they will engage in environmental innovation.

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. 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 other other hand, our study potentially reveals the true incentive of U.S. firms that outsource pollution. It is possible that these firms are unwilling or unable to develop green technology that requires significant capital and long development timelines, indicating that "good apples" (i.e., firms with lower Scope 1 emissions) can do bad by avoiding green innovation.

6. Conclusion

Climate change is a real and undeniable global threat, and its effects are already apparent. While companies recognize the risks associated with climate change and are taking actions to reduce their carbon footprints, there is little evidence 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

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

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., 2020. Exporting pollution: where do multinational firms emit CO_2? Working Paper. Ohio State University.

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

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

Direct vs. Supplier-Induced Carbon Emissions for the 2007-2017 Period

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

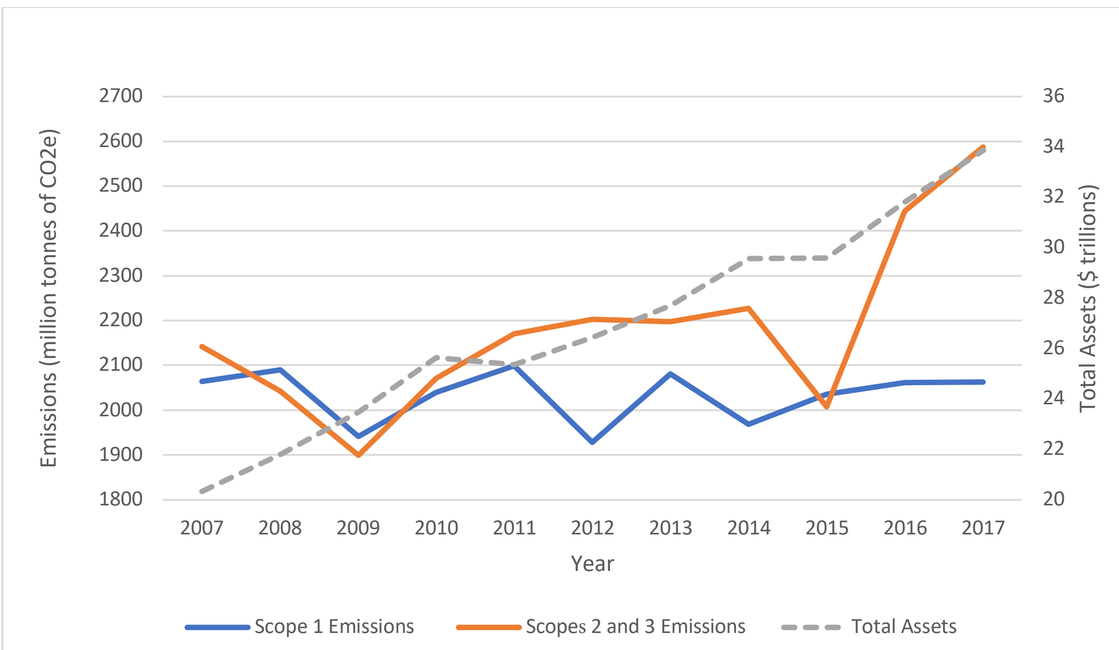

Figure 2

Total Carbon Footprint (Scopes 1, 2, and 3) and Imports for the 2007-2017 Period

This figure shows the aggregate carbon footprint (the sum of Scopes 1, 2, and 3) and total imports of U.S. firms over time.

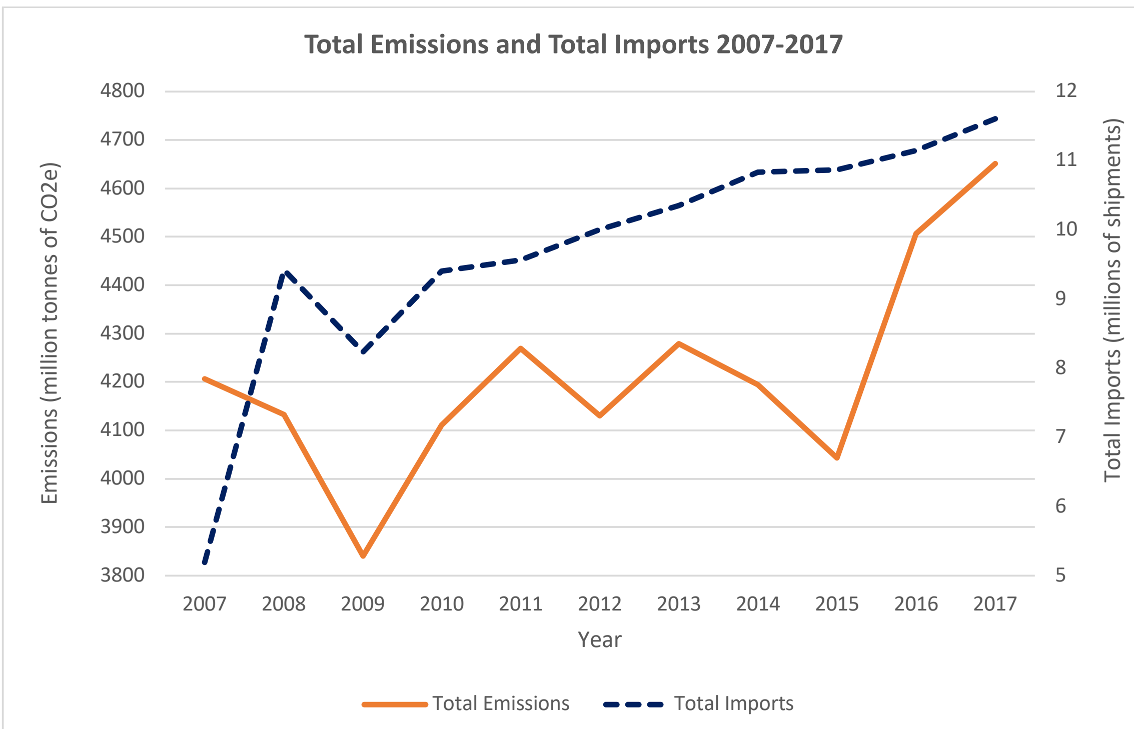

Table 1
Summary Statistics

This table presents summary statistics of the variables in our baseline analysis over the entire sample period from 2007 to 2019. It shows the mean (Mean), standard deviation (Stdev), minimum (Min), the 25th percentile (P25), median (Median), 75th percentile (P75) and maximum (Max) of each variable. The key variables in raw values show the summary statistics of Scopes 1, 2, and 3 emissions reported in thousands of tonnes and *Import* is in the number of shipments. The remaining variables are defined in the Appendix. All continuous variables are winsorized at the 1% and 99% of their distribution.

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

Table 2
The Effect of Imports on Firms' CO_2 Emissions

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

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

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

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

Table 3
Shocks to Legislative Pressure and State Regulatory Stringency

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

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

where *Treat* is a binary indicator that alternately captures three different representations. *Treat* equals one if the one-year lagged average voting score on climate change-specific environmental legislations for the House of Representatives (House) in Column (1) or the Senate in Column (2) increases more than three times the average increase in the voting score over time. In Column (3), *Treat* equals one if the one-year lagged average onsite inspection level per facility (Onsite) increases more than three times the average onsite inspection increase in the level over time. Note that for every *Treat* variable, the shock must not revert within the next three years and must not be driven by a voluntary move of firm location from a state with lower legislative pressure to a state with higher legislative pressure. *Scope 1, Scope 2, Import*, *Controls*, and **FE** are the same as 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 and at the year level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

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

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

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

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

where *Treat* is a binary indicator that alternately captures three different representations. In Column (1), *Treat* equals one if the one-year lagged average electricity price increases more than three times the average price increase over time (Price Spikes). In Column (2), *Treat* equals one for the next five years if the lagged applied tariff rate for the exporting country and industry reduces more than three times the average decrease in rates over time (i.e., a time-series average for each country-sector) (Tariff Drops). In Column (3), *Treat* (Disaster) equals one if the exporting country has more than one natural disaster incidence during the year (with at least US$1 million of damage). Note that for every *Treat* variable, the shock must not revert within the next three years and must be not be driven by a change in firm locations across the states. *Scope 1, Scope 2, Imports*, *Controls*, and **FE** are the same 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 and at the year level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

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

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

This table reports results using the triple-interaction model regression of a firm's indirect (*Scope 3*) emissions on its direct (*Scope 1*) emissions, imports (*Import*), outsourcing-country type (proxied by a binary indicator), and their triple interaction (*Scope 1* $\times$ *Import*)$\times$, by outsourcing country type, as follows.

$$\begin{aligned} Scope\ 3_{i,t} &= \alpha + \beta_{SI1} Scope\ 1_{i,t} \times Import_{i,c,t} \times Indicator_t + \beta_{SI} Scope\ 1_{i,t} \times Import_{i,c,t} \\ &+ \beta_{S1} Scope\ 1_{i,t} \times Indicator_t + \beta_{I1} Import_{i,c,t} \times Indicator_t + \beta_S Scope\ 1_{i,t} \\ &+ \beta_I Import_{i,c,t} + \beta_1 Indicator_t + \beta_{CS}{}' Controls_{i,t-1} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

where *Indicator* is a binary indicator that alternately captures four different representations, namely non-OECD countries (Column (1)), common-law countries (Column (2)), countries with below-median stringency of environmental regulation (SER) (Column (3)), and countries with below-median environmental performance index (EPI) (Column (4)). Note that the *Indicator* coefficient is not reported, 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 the Binary Indicator (Indicator)			
	Non-OECD Country	Common-Law Country	Country with Below-Median SER	Country with Below-Median EPI
Variable	(1)	(2)	(3)	(4)
Scope 1 × Import × Indicator	-0.079*	-0.103***	-0.135**	-0.096**
	(-1.90)	(-3.30)	(-2.47)	(-2.45)
Scope 1 × Import	-0.064	-0.073*	-0.082*	-0.065
	(-1.58)	(-1.80)	(-2.03)	(-1.75)
Scope 1 × Indicator	0.000	0.000	0.001	0.002
	(0.23)	(0.37)	(0.67)	(1.47)
Scope 1	0.112***	0.113***	0.111***	0.112***
	(6.56)	(6.53)	(6.63)	(6.58)
Import × Indicator	0.185	0.279**	0.415**	0.265**
	(1.43)	(2.74)	(2.29)	(2.23)
Import	0.254*	0.265*	0.284*	0.243*
	(1.82)	(1.85)	(2.04)	(1.90)
Controls	Yes	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes	Yes
Observations	73,659	72,589	70,447	71,539
Adj. R^2	0.969	0.969	0.969	0.969

Table 6
The Effect of Imports on Firms' CO_2 Emissions by Industry Emissions

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

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

where *Indicator* is a binary indicator that alternately captures firms in Fama-French (FF) 30 industries with above-median emissions (Column (1)) and North American Industry Classification System (NAICS) industries with above-median emissions based on the Input-Output tables (Column (2)). Note that the *Indicator* coefficient is not reported, because it is subsumed by country × 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 the Binary Indicator (Indicator)	
	FF Industries with Above-Median Emissions	NACIS Industries with Above-Median Emissions
Variable	(1)	(2)
Scope 1 × Import × Indicator	-0.215**	-0.176**
	(-2.64)	(-2.21)
Scope 1 × Import	0.075	0.021
	(1.02)	(0.49)
Scope 1 × Indicator	-0.008	0.016
	(-0.60)	(0.84)
Scope 1	0.117***	0.099***
	(6.45)	(4.84)
Import × Indicator	0.565**	0.655**
	(2.42)	(2.50)
Import	-0.097	-0.098
	(-0.50)	(-0.63)
Indicator	0.031	0.012
	(0.81)	(0.19)
Controls	Yes	Yes
Firm, Country×Year FE	Yes	Yes
Observations	73,659	72,682
Adj. R^2	0.969	0.969

Table 7
Internal Mechanisms

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

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

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

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

Table 8
External Mechanisms

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

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

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

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

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

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

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

where *RepRisk* $\beta_{i,t}$ is the factor loading obtained from regressing individual firms' daily stock returns on the difference between high and low reputational-risk 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*, *PPE*, *Leverage*, *CapEx*, *Cash*, *Income Volatility*, and *ROA*. 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 and at the year level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

Variable	(1)	(2)	(3)	(4)	(5)
Imported CO_2	0.058**				0.059**
	(2.53)				(2.85)
Scope 1 CO_2		-0.014			-0.045
		(-0.46)			(-1.01)
Scope 2 CO_2			0.032		-0.003
			(0.69)		(-0.06)
Scope 3 CO_2				0.184	0.201
				(1.42)	(1.40)
Assets	0.091	0.108	0.078	-0.032	-0.020
	(0.83)	(0.94)	(0.70)	(-0.34)	(-0.22)
Tobin's Q	0.165**	0.172***	0.169***	0.162**	0.164**
	(2.97)	(3.16)	(3.15)	(2.99)	(3.00)
R&D	-2.684*	-2.503*	-2.602*	-2.964*	-2.925*
	(-2.07)	(-1.93)	(-1.91)	(-2.10)	(-2.11)
PPE	-2.984	-2.361	-2.620	-3.090	-2.809
	(-1.45)	(-1.14)	(-1.25)	(-1.34)	(-1.27)
Leverage	-0.302	-0.280	-0.274	-0.258	-0.267
	(-1.35)	(-1.26)	(-1.24)	(-1.18)	(-1.20)
CapEx	0.396	0.598	0.620	0.713	0.659
	(0.47)	(0.72)	(0.74)	(0.86)	(0.80)
Cash	0.148	0.151	0.164	0.191	0.179
	(1.03)	(1.08)	(1.14)	(1.26)	(1.22)
Income Volatility	-0.008*	-0.009*	-0.009*	-0.008	-0.008*
	(-2.08)	(-2.05)	(-1.98)	(-1.80)	(-1.86)
ROA	0.910	0.822	0.783	0.525	0.512
	(1.07)	(0.91)	(0.89)	(0.70)	(0.69)
Firm, Year FE	Yes	Yes	Yes	Yes	Yes
Observations	5,904	5,615	5,615	5,615	5,615
Adj. R^2	0.314	0.316	0.316	0.318	0.319

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

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

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

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

Variable	(1)	(2)	(3)	(4)	(5)
Imported CO_2	0.002***				0.002***
	(3.12)				(3.16)
Scope 1 CO_2		0.001*			0.000
		(1.86)			(0.78)
Scope 2 CO_2			0.002*		0.001
			(2.10)		(0.75)
Scope 3 CO_2				0.006**	0.005*
				(2.37)	(1.94)
Controls	Yes	Yes	Yes	Yes	Yes
Firm, Month FE	Yes	Yes	Yes	Yes	Yes
Observations	62,978	62,978	62,978	62,978	62,978
Adj. R^2	0.303	0.302	0.303	0.303	0.303

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

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

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

where *Green Innovation*$_{i,t+1}$ is the number of green patents filed by firm i in year *t+1*, where clean patents are classified based on their the International Patent Classifications (IPC). *Controls* include firm-specific *Size*, *Age*, *Tobin's Q*, *Leverage*, *PPE*, *ROA*, *CapEx*, *R&D*, and *HHI*. The definition of variables is contained in Appendix A. **FE** are firm and year fixed effects. 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.

Variable	(1)	(2)	(3)	(4)
Imported CO_2	-0.024**	-0.025**	-0.025**	-0.027**
	(-2.37)	(-2.26)	(-2.26)	(-2.42)
Scope 1 CO_2		-0.006	-0.007	-0.010
		(-0.65)	(-0.82)	(-1.05)
Scope 2 CO_2			0.006	-0.001
			(0.40)	(-0.09)
Scope 3 CO_2				0.031
				(1.77)
Controls	Yes	Yes	Yes	Yes
Firm, Year FE	Yes	Yes	Yes	Yes
Observations	5,203	4,845	4,845	4,845
Adj. R^2	0.579	0.585	0.584	0.585

Appendix A

Variable Definition and Data Source

Variable	Definition and Data Source
Measures of Firm-level CO_2 Emissions and Imports	
Scope 1	ln(1 + Scope 1 emissions/customer total asset), where Scope 1 refers to direct GHG emissions generated from fossil fuel used in all production and operations of facilities owned or controlled by the firm. (Trucost & Compustat)
Scope 3	ln(1 + Scope 3 emissions/customer total asset), where Scope 3 refers to indirect GHG emissions caused by activities of the firm but occur from source not owned or controlled by the firm. (Trucost & Compustat)
Scope 2+3	ln(1 + Scopes 2+3 emissions/customer total asset), where Scope 2 refers to GHG emissions from the firm's consumption of purchased electricity, heat, or steam. (Trucost & Compustat)
Import	ln(1 + the number of shipments from suppliers in each exporting country / customer total asset) (Panjiva & Compustat)
Imported CO_2	Firm-level imported pollution each year is defined as the log of one plus total CO_2 emissions from all imported shipments across all exporting countries. The variable is measured as the log sum of product-weighted CO_2 emissions (per $1M) over all the imported goods for a firm over a given year. The CO_2 emissions of each import transaction is based on BEA Input-Output through HS code reported to US ports. (Carnegie Mellon University-Economic Input-Output Life Cycle Assessment, Peter K. Schott's Website, and Panjiva)
Scope 1 CO_2	ln(1 + Scope 1 emissions). (Trucost)
Scope 2 CO_2	ln(1 + Scope 3 emissions) (Trucost)
Scope 3 CO_2	ln(1 + Scopes 3 emissions) (Trucost)
Identification Variables	
House	A binary variable equal to 1 if the lagged increase in the House of Representative voting score is more than three times larger than the average score increase in the state, where House voting score is defined as the number of pro-environment votes on climate change-specific legislations from each House of Representative member in the firm headquarter state divided by the total number of climate change-specific legislations in a given year, averaged across all House members in that state and year (League of Conservation Voters)
Senate	A binary variable equal to 1 if the lagged increase in the Senate voting score is more than three times larger than the average score increase in the state, where Senate voting score is defined as the number of pro-environment votes from each Senator in the firm headquarter state divided by the total number of environmental legislations n a given year, averaged across all Senators in that state and year(League of Conservation Voters)
Onsite	A binary variable equal to 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)
Price Spikes	A binary variable equal to 1 if the lagged increase in electricity rates is more than three times larger than the average price increase in the state, where an electricity rate is defined as the average retail electricity rate for the firm headquarter state and year (EIA)
Tariff Drops	A binary variable equal to 1 for the next five years if the lagged reduction in tariff is more than three times larger than the average tariff reduction for the specific exporting country and industry, where tariff is measured by the average effectively applied rate for each Frama-French 30 industry and exporting country (WITS World Bank)
Disaster	A binary variable equal to 1 if an exporting country is ranked in the top quintile on the number of major disasters occurring during the year, where major disasters are those natural disasters causing at least one million dollars of damage (EM-DAT)

Appendix A – Continued

Variable Definition and Data Source

Variable	**Definition and Data Source**
Internal Mechanism Variables	
Green Score	A firm's score associated with the environmental pillar of a CSR Rating (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 scores over years −5 to −1 and then assign this score as the CEO's environmental score for the year (BoardEx & Refinitiv ESG)
Green Directors	A firm's Green Directors 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 firm's average scorees 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	
Large Gov Customer	Sales percentage to the largest major government customers of a firm, where major customers each accounts for at least 10% of the firm's total sales (Compustat Customer Segment)
Green Customers	Percentage of green corporate customers defined as the number of green corporate customers divided by the total number of corporate customers, where green customers are those with below the industry-median GHG emissions per dollar of total assets (Revere & Trucost)
Green Blockholders	Percentage of a firm's shares owned by green blockholders in a given year, where blockholders are institutional investors each holding at least 5% of a firm's shares outstanding, and green investors are those institutions with at least 50% of their portfolio invested in green firms ranked in the top quintile on the ESG score among all firms in a year (FactSet Ownership & Refinitiv ESG)
Pricing and Welfare Implications	
RepRisk β	The factor loading on the difference between the daily value-weighted return of two portfolios based on firm-level reputational risk based on ESG-related news after controlling Fama-French-Carhart 4 Factors. (RepRisk)
Stock Return	Monthly Return of firm i's primary shares over year t (CRSP)
Green Innovation	One-year ahead number of clean patents filed by each firm, where clean patents are classified based on the International Patent Classifications (IPC) Dechezlepretre, Martin, and Mohnen (2013). (PATSTAT)

Appendix A – Continued

Variable Definition and Data Source

Variable	**Definition and Data Source**
Control Variables	
Assets	ln(1 + total asset) (Compustat)
Tobin's Q	Total assets plus the market value of equity minus the book value of equity minus deferred taxes divided by total assets(Compustat)
Leverage	Total debt scaled by total asset (Compustat)
ROA	Eearnings before interest and taxes scaled by total asset (Compustat)
SalesGrowth	Annual percentage change in sales (Compustat)
Tangibility	Gross property, plant, and expenditure scaled by total asset (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 Related to Welfare and Pricing Implications	
Age	Ln (1 + current fiscal year of a firm − the first year the firm appears in Compustat (Compustat)
Size	Ln (1 + market capitalization) (Compustat)
BM	Book value of equity divided by market value of equity (Compustat)
PPE	Ln (1 + gross property, plant, and equipment) (Compustat)
CapEx	Capital expenditure divided by total assets (Compustat)
Momemtum	Cumulative monthly stock return over one-year period (CRSP)
Volatility	Monthly stock return volatility over one-year period (CRSP)
Beta	CAPM beta calculated over one-year period (CRSP)
HHI	Herfindahl-Hirschman index measured by the summation of sales-based squared market share of each firm within the same 3-digit SIC industry (Compustat)
Cash	Cash and marketable securities divided by (total assets − cash and marketable securities) (Compustat)
Income Volatility	Standard deviation of income before extraordinary items per share over the past five years (Compustat)