Outsourcing Climate Change

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Abstract

This paper examines how firms combat climate change and the motivations behind their strategies. Using firm-level carbon emissions and import volume data, we find pervasive evidence of firms outsourcing their emissions to foreign suppliers rather than investing in abatement—a strategy not fully explained by production offshoring, regulatory arbitrage, and supply chain shocks. Instead, our findings reveal that agency problems play a significant role in facilitating corporate carbon outsourcing. While the outsourcing strategy improves short-term profitability, it adversely affects firm value and increases the cost of equity capital, suggesting that investors demand compensation for their exposure to such transition risks.

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

JEL Classifications: G23, G30, G34, M14

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1 Introduction

Climate change has impacted almost every industry worldwide, either directly or indirectly. The global climate crisis and pressures from regulatory authorities, environmental activists, and climate-conscious investors and consumers have compelled corporations to commit publicly to reducing their carbon footprints by around 2050.[1] While their climate actions seem reasonably progressive, a closer analysis reveals that many firms strategically engage in regulatory arbitrage. They capitalize on varying environmental standards within different U.S. states (e.g., Bartram, Hou, and Kim (2022) and across countries (e.g., Li and Zhou, 2017; Ben-David, Jang, Kleimeier, and Viehs, 2021). In other words, companies in areas with stringent greenhouse gas (GHG) emission regulations often shift their operations and high GHG emission sources to regions with more lenient standards. The strategy of firms outsourcing emissions is similar to the well-documented phenomenon of carbon leakage at national, regional, or industry levels (e.g., Babiker, 2005). However, the motivations behind this approach and its environmental consequences remain unclear, whether as a liability or a benefit through more efficient carbon allocation. Notably, no research has yet assessed whether investors have effectively factored in the risks associated with carbon outsourcing, which is part of the broader transition risk.[2] This risk could potentially hinder a firm's shift towards a low carbon economy. Thus, in our study, we explore several possible explanations for firms' emission outsourcing behavior and examine their managerial and financial implications.

One major challenge in combating climate change is carbon leakage, as firms can always move their carbon-intensive production from their home markets with high standards for GHG controls to their global suppliers that still heavily rely on fossil fuels.[3] We propose two plausible motivations for why firms shift their carbon footprints abroad. On the one hand, emission outsourcing may manifest an agency problem associated with corporate insiders' incentives to safeguard their own social status at the cost of overall stakeholder welfare. Their

[1] https://newsroom.accenture.com/news/nearly-all-companies-will-miss-net-zero-goals-without-at-least-doubling-rate-of-carbon-emissions-reductions-by-2030-accenture-report-finds.htm

[2] U.S. Environmental Protection Act (EPA) defines transition risks as how firms manage and adapt to the internal and external pace of change to reduce greenhouse gas emissions and transition to renewable energy.

[3] Note that the emission outsourcing is usually highly correlated with production outsourcing, because countries with low environmental standards also tend to offer an environment with low production cost. Hence, in a subsequent analysis, we shall address this issue.

strategy possibly helps enhance their domestic environmental profile but without curbing global emissions as these firms may have pledged, consistent with the agency cost hypothesis. This hypothesis emphasizes the green-washing intentions of corporate behaviors, given the private benefits of maintaining a high social image, commensurating with a high environmental, social, and governance (ESG) rating. They include positive publicity, increased customer willingness to pay (e.g., Bagnoli and Watts, 2003; Baron, 2008, 2009), more capital from philanthropic investors (e.g., Hartzmark and Sussman, 2019; Ceccarelli, Ramelli, and Wagner, 2021), and better career prospects for the management team (e.g., Cai, Gao, Garrett, and Xu, 2020).

On the other hand, shifting emissions may facilitate the global carbon-reduction goal if firms' own emission reductions are associated with more carbon-efficient production distribution globally, as they leverage their worldwide operations and suppliers to improve operational efficiency and emission performance. The subsequent emission reduction due to carbon leakage can be socially desirable and economically sustainable if foreign suppliers have the capabilities to develop technologies for both operational efficiency and long-term environmental benefits. Consequently, this emission-shifting strategy – an environmental asset – may benefit all stakeholders in the long run. This motivation aligns with the carbon efficiency (i.e., value enhancing) hypothesis.

Our empirical study first examines whether our sample of U.S. firms exhibits emission outsourcing. Unlike existing studies focusing on domestic emissions or trade flow, we exploit the granularity of recently available firm-level data on U.S. firms' self-generated Scope 1 emissions (hereafter Scope 1) and supplier-produced upstream Scope 3 emissions (hereafter Scope 3) from Trucost and transaction-level import information from Panjiva.[4] Including Scope 3 in our analysis offers us an excellent opportunity not only to investigate firms' motives behind their emission mitigation strategies but also to explore the anecdotal evidence that firms are committed only to reducing Scope 1 and 2 emissions (hereafter Scope 2) while ignoring the hard-to-measure indirect Scope 3 generated along a supply chain that account for as much as 95% of their total emissions.[5] Merging the two key databases yields a final

[4]Throughout our study, Scope 3 refers to upstream Scope 3, unless otherwise indicated.

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

sample consisting of 76,356 firm-country-year observations from 1,470 U.S. firms and 210 exporting countries for the 2006-2018 period.[6] As illustrated in Figure 1, on average, the proportion of Scope 1 at the firm level has fallen over time as the proportion of its Scope 3 has increased, especially after the 2015 Paris Agreement,[7] a cursory indication supporting media reports that firms care only about reducing direct emissions at the expense of increasing Scope 3. Figure 2 shows upward trending patterns for both the aggregate carbon footprint and total imports of U.S. firms.[8]

Our main results show pervasive evidence of emission outsourcing by U.S firms. Firms' Scope 1 and Scope 3 are strongly and positively correlated, and their imports play a role in this relationship. For example, for firms with no imports, the elasticity of Scope 3 with respect to Scope 1 is 0.161, indicating that a 1% change in Scope 1 (e.g., 1,770 tonnes of emissions from the median Scope 1) is associated with a 0.161% change in Scope 3 (e.g., 2,134 tonnes from the median Scope 3). However, for firms receiving average import shipment volume from suppliers overseas, the elasticity would weaken by 7.9%, dropping from 0.161 to 0.148. In other words, when a firm imports more from its foreign suppliers, a drop in its Scope 1 would be met with a reduction in suppliers' emissions *but only to a lesser extent*. Thus, firms are curbing their carbon production by imposing a heavier carbon burden on their overseas suppliers, thus attenuating the decline of supplier emissions. We reach a similar conclusion when analyzing the shares of Scope 1 and Scope 3 in total carbon footprint and using both firm-country and firm-level analyses. The relative proportion of Scope 1 falls at the expense of the rising proportion of a firm's supplier-generated Scope 3, and such an inverse relationship is augmented by imports. This finding further substantiates the emission outsourcing effect and suggests that firms are substituting self-generated emissions with increased reliance on foreign suppliers to satisfy their total carbon needs.

Can firms be made accountable for their carbon emissions?" in Special Report ESG Investing, The Economist July 23, 2022. During the 2006-2018 period, the upstream Scope 3 for our sample of U.S. firms account for 67% of an average firm's total emissions.

[6] The resulting sample only includes observations with country-level imports from external suppliers and firm-level emissions but excludes imports from foreign subsidiaries.

[7] The surge in the proportion of Scope 3 in 2015 may reflect both the firms' response to the 2015 Paris Agreement and Trucost's expanded coverage, starting from 2015. Table 6 below shows that our main results remain robust to the subsample analysis, excluding post-2015 observations.

[8] We want to emphasize that, constrained by our data, we cannot separate purchases from domestic and foreign suppliers. While local outsourcing is not our focus, the available data impedes a direct quantification of local outsourcing. For example, similar to corporate customers, many local suppliers are also likely to outsource globally, which could partially manifest as foreign shipments to corporate customers in the U.S.

While we have shown that imports play an important role in driving the relationship between Scope 1 and 3, our causal inferences of this link may be subject to endogeneity concerns. To circumvent such problems, we exploit several exogenous shocks to U.S. firms' propensity to outsource carbon emissions caused by local legislative pressure and regulatory stringency changes at the state level. Firms located in states with intense legislative pressure on environmental consciousness should have stronger incentives to import as a means of outsourcing GHG emissions to their suppliers overseas. Our analysis employs sharp increases in pro-environmental votes by the House and Senate as well as "close-call" Congress election wins by environmentally-conscious candidates as shocks to environmental legislature pressure. Unlike landslide victories, close-call wins are more likely to represent unexpected shifts in state-level environmental attitudes and are as good as randomly assigned. Similarly, to gauge the extent of regulatory stringency, we exploit state-level statutory and executive emission-reduction targets and spikes in Environmental Protection Agency (EPA) state-level facility inspections. Analyses in a triple-interaction framework reveal that imports have a more pronounced mitigating effect on the Scope 1–Scope 3 association following exogenous increases in political and regulatory pressures on environmental issues but not on placebo shocks, consistent with a causal interpretation of firms' carbon outsourcing strategy in curbing their own emissions. These regulatory shocks are unlikely associated with supply chain disruptions due to natural disasters, trade wars, etc.

The key findings are robust to a battery of additional tests. In particular, the impact of imports is asymmetric to the direction of Scope 1 movement – the attenuating effect on Scope 3 can only be observed for firms attempting to reduce, rather than increase, their own carbon production. Such a finding serves as a critical piece of evidence confirming emission outsourcing. We also rule out alternative interpretations of our results, including (i) estimation errors of Scope 3; (ii) production outsourcing; and (iii) outsourcing to reduce labor costs. Emission offshoring is more pronounced for firms in highly emitting industries and for supplier countries with laxer environmental regulations, further confirming that U.S. firms shift part of their pollution to evade their own carbon reduction responsibilities.

Having confirmed that firms outsource their emissions to their foreign suppliers, we explore whether such a strategy is consistent with the agency cost hypothesis or the carbon efficiency hypothesis. First, our analysis establishes that a firm's ESG rating exhibits a negative and statistically significant relationship with only its direct carbon emissions, indicating that firms' social status is primarily driven by self-disclosed Scope 1 while remain silent on the value-chain induced emissions. In other words, to elevate social status, corporate managers need to focus on mitigating their firms' Scope 1. Consistent with this evidence, we find that a firm tends to shift more pollution-intensive production overseas when it has a higher ESG rating, when the management is more entrenched, CEO and directors associated with higher past ESG track records, and when its executive compensation package contains ESG performance metrics. These results align with the agency cost hypothesis and suggest the firms are green washing at the expense of suppliers' pollution. While corporate insiders are incentivized to outsource emissions abroad, climate conscious stakeholders, who increasingly recognize the rising costs and economic risks associated with climate change, may push against emission offshoring and pressure firms to transition to a low-carbon economy. As a result, these stakeholders, including government customers, corporate customers, and institutional investors, act as governance mechanisms to alleviate agency-motivated outsourcing behavior. For example, institutional investors, who are usually universal investors, may drive down firms' overall carbon footprints, including domestic and imported emissions, to minimize adverse impacts of climate change on their investments (e.g., Dyck, Lins, Roth, and Wagner, 2019; Krüeger, Sautner, and Starks, 2020). Similarly, government customers typically act in the public interest and emphasize global emission reduction to effectively combat climate change (Hsu, Liang, and Matos, 2021. Unlike environmental regulations, which often have ambiguous effects on firm behavior (e.g., emission outsourcing), government customers may directly influence their supplier firms' corporate decisions to push for the intended corporate actions and correct market failures. Furthermore, socially responsible corporate customers would infuse similar socially responsible business behavior in both domestic and foreign suppliers (Dai, Liang, and Ng, 2021); thus, they are less likely to encourage firm actions that adversely impact their global supply chain. The moderating effects of governance mechanisms further corroborate the agency-based explanation of emission outsourcing.

Second, we examine whether emission shifting is associated with carbon efficiency, because foreign suppliers are in an advantageous position to reduce carbon emissions more effectively than firms themselves or domestic suppliers. To implement this test, we construct a metric that estimates a firm's aggregated amount of imported GHG emissions from all its foreign suppliers (hereafter "Outsourced Emissions"). We find no evidence suggesting carbon efficiency as the firm's motive for outsourcing emissions, nor do we find that such strategies reduce a firm's overall emissions. Consistent with these results, firms are likely to engage a foreign supplier while less inclined to invest in pollution abatement activity and green technologies as their carbon export grows. It is plausible that outsourcing carbon may be more cost-effective than using pollution abatement measures and developing green technologies that require significant capital investment and long development timelines. Taken together, both types of evidence support the agency cost hypothesis against the carbon efficiency hypothesis.

Finally, our analysis indicates that moving domestic emissions to global supply chains improves short-term profitability while raising the implied cost of equity capital and reducing firm valuation. Overall, emission outsourcing assists corporate management in maintaining their firm's social status but at the expense of higher reputational risk and a more significant carbon risk premium.

Our research makes significant contributions to the growing climate finance literature. Prior climate finance studies primarily focus on asset pricing and financial market implications.[9] For example, Bolton and Kacperczyk (2021) find that U.S. firms with higher carbon emissions are associated with more significant risk premiums, and Hsu, Li, and Tsou (2022) show a similar spread in average equity returns between high- and low-pollution firms. Engle, Giglio, Kelly, Lee, and Stroebel (2020) use textual analysis and report that stocks of firms with high environmental scores have larger returns during periods with negative news about the future path of climate change. Choi, Gao, and Jiang (2020) document similar results using global data. While this strand of literature examines the extent to which climate risk is priced in financial assets, our study takes a corporate perspective, arguably more fundamental, as firms are the main drivers of climate change. Therefore, we conduct the first comprehensive firm-level analysis of whether and how U.S. companies address their full climate impacts. To the best of our knowledge, no prior research has addressed how a firm tackles climate change by examining direct and indirect carbon emissions and jointly with its imports.

Our study contributes to the carbon offshoring literature by providing *direct* evidence of

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

the substitutional relationship between a firm's own produced emissions and its outsourced carbon pollution and, more importantly, its motives. For instance, Li and Zhou (2017) document the relationship between trade flow and domestic emissions. In contrast, Dechezleprêtre, Gennaioli, Martin, Muûls, and Stoerk (2019), Bartram, Hou, and Kim (2022), and Ben-David, Jang, Kleimeier, and Viehs (2021) focus on how the regulatory environment affects domestic and foreign emissions separately. But they do not directly show that firms choose one type of emissions in managing the other. Our empirical design advances this line of research by examining the motivations for firm-level carbon emission reduction strategies.

Our work expands prior literature on the roles of different stakeholders in shaping a firm's corporate social responsibility (CSR) practices. For example, Krüeger, Sautner, and Starks' (2020) survey suggests that institutional investors actively engage with the management of their investee firms to reduce their climate risk exposures, and Dyck, Lins, Roth, and Wagner (2019) find that institutional investors drive firms' CSR performance worldwide. Hsu, Liang, and Matos (2021) document that state-owned enterprises are more responsive to environmental issues, whereas Dai, Liang, and Ng (2021) show that socially responsible corporate customers can infuse similar socially responsible business behavior in suppliers. Our granular analysis offers insights into how corporate insiders and external stakeholders influence firms' environmentally responsible behavior.

2 Data and Summary Statistics

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

2.1 Firm-level carbon emissions

We obtain disclosed and estimated firm-level GHG emissions data between 2006 and 2018 from Trucost.[10] Over the sample period, the coverage has increased from about 1,000 to 2,800 U.S. firms. The database is constructed following the Greenhouse Gas Protocol standards and incorporates data from Carbon Disclosure Project (CDP). GHG emissions are classified into Scope 1, 2, and 3. Scope 1 covers direct GHG emissions generated from fossil fuel used in all production and operations of facilities owned or controlled by the firm. Scope 2 accounts for emissions from the firm's consumption of purchased electricity, heat, or steam. Scope 3 refers to indirect GHG emissions caused by activities of the firm but occur from sources not owned or controlled by the firm. In particular, upstream Scope 3 includes those emissions associated with the production and transportation of purchased or acquired materials, business travel, waste disposal, and other outsourced upstream activities that occur up to the point of receipt by the firm. In contrast, downstream Scope 3 includes emissions from transportation, distribution, processing, use, and the end-of-life treatment of sold products that occur subsequent to sales by the firm.[11]

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

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

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

Scope 3. Reported GHG emissions are disclosed by the firms of interest directly to CDP, whereas estimated Scope 3 data is constructed using an input-output model that considers both a firm's expenditures across all sectors in which it obtains its inputs and the sector-level emission factors.[12] We measure each GHG emission scope in units of thousand tonnes of CO_2-equivalent emitted in a year and take the natural logarithm transformation to reduce the skewness of sample distribution.

2.2 U.S. corporate seaborne imports

Panjiva provides a unique database of U.S. trades that documents transaction-level details of goods that cross the border. Under the Customs Regulations at 19 CFR (Code of Federal Regulation), firms in the U.S. are required to report shipment details in cargo declarations to the U.S. Customs and Border Protection (CBP). Panjiva relies on such declarations to obtain information on the shippers (i.e., suppliers or logistic companies), consignees (i.e., customers), origin and destination addresses, product descriptions, and container specifications of ocean freight shipments between U.S. firms and foreign entities in over 210 countries for the 2006-2018 period. We use S&P's identification system to link the consignees with the highest-level parent firms available in Compustat.[13] For each of the matched U.S. consignee parent firm, we aggregate the total shipments it receives from an exporting country in a year to obtain import proxies.

We employ the total shipment volume measured in twenty-foot equivalent units (TEU) to capture the total import at the firm-exporting country level. This measure, denoted by $Ln(Import)$, is obtained from summing the freight shipment volumes across all goods from all external suppliers in a foreign country and is log transformed to reduce skewness. As our focus is on firms' evasion of their own emission responsibility, we exclude shipments from foreign subsidiaries of U.S. parent firms (i.e., internal suppliers). Untabulated results of two alternative import measures, namely the total number of containers shipped from a foreign country and the total number of shipments from external suppliers overseas, yield

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

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

qualitatively similar results.

Our primary sample intersects these key databases. First, we match Trucost emissions data with publicly-traded companies in Compustat using ISIN as the linking identifier. The merged data forms an initial sample of 15,758 firm-year observations describing the U.S. public firms' carbon emissions level each year. Then, we link the sample to Panjiva imports data by the consignee parent firms. Merging in the shipment information expands our sample to firm-country-year level observations with multiple country-level import values for each U.S. firm in a year. For robustness, we also examine firm-year level observations. Finally, we exclude financial firms (SIC codes 6000-6900) and remove any observations with missing values for control variables. The selection process yields a final sample of 76,356 firm-country-year observations from 1,470 U.S. firms and 210 exporting countries for the 2006-2018 period. Note that the resulting sample only includes observations with positive country-level imports and firm-level emissions.[14] The actual number of observations varies across analyses, given different model specifications and data availability for the main variables of interest. Online Appendix Table IA1 reports the distribution of sample firms across industries, and our sample does not appear to concentrate only in a few industries.

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 interest and taxes scaled by total assets. *SalesGrowth* is the percentage growth in sales from the previous year to the current year. *Tangibility* is the gross property, plant, and equipment divided by total assets. *R&D* denotes research and development capital stock, computed using the perpetual inventory method where R&D expenses scaled by assets are accumulated over the years with an annual depreciation rate of 15% Hall, Jaffe, and

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

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

2.4 Summary statistics

Table 1 reports the summary statistics of our key variables. Panel A summarizes our three primary variables: *Scope 1*, *Scope 3*, and *Import*. On average, a U.S. firm produces about 2.2 million tonnes of Scope 1 annually and is associated with about 4.1 million tonnes of upstream Scope 3 through its supply chain. In comparison, the median emissions values are much smaller (0.2 million and 1.3 million tonnes for Scope 1 and 3, respectively), and their standard deviations much larger (5.0 million and 6.5 million tonnes for Scope 1 and 3, respectively). These skewed distributions with GHG emissions are mostly driven by large companies. For these considerations, we employ log emissions and control for firm size throughout analyses. Such observations are largely consistent with CDP's recent report showing that companies' supply chain emissions are immensely greater than their direct emissions.[15]

On average, *Scope 1* accounts for 18.6% of the firm's total carbon needs, whereas *Scope 3* accounts for 66.9%. A significant portion of a firm's carbon footprint is generated by its suppliers. A firm, on average, increases its Scope 1 by 2.5% each year (%Δ Scope 1) and its Scope 3 by a larger magnitude of 4.8% (%Δ Scope 3), emphasizing that Scope 3 is increasing faster than Scope 1. Below, we will show that firms are, indeed, increasing their reliance on supplier-induced carbon emissions over time.

The annual average shipment volume from external suppliers in each exporting country is 41 TEUs, which sums up to an average firm-level volume of about 376 TEUs in aggregate across all supplying countries. To facilitate the interpretation of our firm-level analysis in Table 2 and 3, the firm-level aggregate shipment volume (Import (Firm-Level)) is obtained from the sample, including all carbon-emitting firms irrespective of their importing conditions. These import measures are also highly skewed, as indicated by a significantly smaller median value of 4 TEUs from each exporting country (or 9 TEUs at the aggregate firm level) with a large standard deviation of 89 TEUs (or 823 TEUs at the aggregate firm level).

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

Hence, we employ their log form in all our regression models.

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

3 Emission Outsourcing, Imports, and U.S. Firms

This section starts by examining evidence for emission shifting. Unlike prior research, our work leverages the granularity of recently available firm-level data on U.S. firms' Scope 1, upstream Scope 3, and import information, permiting us to establish a *direct* evidence that firms are replacing their own pollution with a higher reliance on outsourced emissions. We further exploit several shocks to firms' propensities to outsource to address possible endogeneity concerns about our key results. Finally, the section conducts several robustness tests to rule out alternative interpretations of our key evidence and investigates cross-sectional variation in the carbon outsourcing effect.

3.1 Scope 1, upstream Scope 3, and imports

We employ the following OLS panel regression model to evaluate the impact of a firm's imports on the relationship between direct emissions (Scope 1) and supplier-induced emissions (Scope 3).

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

where $Scope\ 3^{\dagger}{}_{i,t}$ is alternately measured in either natural logarithm (log) or proportion of total firm emissions (the sum of Scope 1, 2, and upstream 3) in year t; $Scope\ 1^{\dagger}{}_{i,t}$ is similarly defined in the log form or proportion of total emissions.[16] $Ln(Import)_{i,c,t}$ denotes firm i's shipment volume from exporting country c in year t; and $Controls_{i,t}$ is a vector of firm-specific control variables defined in the preceding section. We also include varying sets of fixed effects (**FE**) to control for unobserved heterogeneity across firms, countries, and years. Standard errors are clustered at the firm level. The definition of all variables is contained in Appendix A. In Model (1), the β_S parameter dictates the strength of the correlation between Scope 1 and 3, while the sign of β_{SI} parameter underscores the role of imports in the Scope 1–Scope 3 relationship.

We first estimate Model (1) without imports and present the results in Table 2. Results in Columns (1)-(3) are based on the log of GHG emissions, whereas those in Columns (4)-(6) use the proportion of total emissions. Note that Columns (1)-(2) and (4)-(5) report models estimated based on the firm-country level, and the remaining two columns report those estimated at the firm level. The firm-level analysis serves as a robustness check to that conducted at the firm-country level and is used to gauge the economic significance of firm-wide outsourcing behavior. However, in most subsequent tests, we stick to the firm-country-level analysis that allows us to consider cross-sectional heterogeneities in supplier countries.

Results show that a firm's Scope 1 correlate strongly with its upstream Scope 3 across all model specifications. The β_S estimates associated with *Ln(Scope 1)* are positive and statistically significant at the 1% level. For example, in Column (2), the elasticity of Scope 3 with respect to Scope 1 is 0.152: a 1% change in Scope 1 for an average firm (e.g., 1,770 tonnes of emissions from the median Scope 1 level) is associated with a 0.152% change in Scope 3 in the same direction (e.g., 2,014 tonnes of emissions from the median Scope 3 level).[17] This finding is consistent with carbon outsourcing as it suggests that more pollution-intensive firms are more inclined to shift their polluting burden onto their upstream suppliers,

[16] Throughout this study, when variables are measured in the log form, we add unity to the variable before taking the log. Analyzing a firm's emissions proportions allows one to evaluate the extent of the substitutional effect between the two carbon types.

[17] A 1% change in Scope 1 corresponds to a change of 1% × 176,987 tonnes = 1,769.87 tonnes from its median value, whereas a 0.152% change in Scope 3 corresponds to a change of 0.152% × 1,325,301 tonnes = 2,104.45 tonnes from its median value.

resulting in higher Scope 3. Columns (4)-(6) reinforce the evidence of emission outsourcing. A negative coefficient on *Scope 1/Total Emissions* suggests a substitutional effect between the two types of emissions. Below, we provide more evidence that this negative Scope 1–Scope 3 association is due to the disproportionate Scope 3 decrease induced by imports.

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

We next estimate the full Model (1) and report the results in Table 3 in a format quite similar to that of Table 2. The sign and magnitude of β_S estimates are broadly consistent with those presented in Table 2. For example, a β_S estimate of 0.161 in Column (2) indicates that the elasticity of Scope 3 to Scope 1 is 0.161 for firms without imports. However, the β_{SI} estimate of -0.040 suggests that increasing import shipment volume would dampen such elasticity. For firms receiving an average of 375.76 TEU in shipment volume from their foreign suppliers, the elasticity would weaken by 7.9% to 0.148.[18] Hence, when firms import from their foreign suppliers, reductions in their self-generated emissions will coincide with decreases in their suppliers' emissions but only to a lesser extent. In other words, firms curb their carbon production by imposing a heavier carbon burden on overseas suppliers. Columns (3)-(4) produce a similar conclusion using the proportion analysis, suggesting that imports disproportionately increase firms' reliance on upstream Scope 3 as a substitute for direct carbon output. Again, this finding emphasizes the outsourcing effect and alleviates the concern that the negative Scope 1–Scope 3 relative share relationship may be purely mechanical.

[18]The elasticity of Scope 3 with respect to Scope 1 given zero import volume is 0.161 - 0.040 × 0 = 0.161, but it drops to 0.161 - 0.04 × ln(1+375.76 TEU/1,000) = 0.148 (or by 0.148/0.161 - 1 = -7.9%) for firms with an average import volume of 375.76 TEU. The discrepancy between the elasticity of 0.152 from the linear regression results in Table 2 and that of 0.148 can be attributed to differences in how average imports are defined. Note that Table 2 shows the elasticity for an average firm, holding the log-transformed import value ln(1 + import volume/1,000) at its average (i.e., 0.215 corresponding to an actual volume of 239.52 TEU), whereas the elasticity of 0.148 is calculated based on the actual average level of shipment volume.

3.2 Identification strategies

Our causal inferences of the attenuating import effect on the Scope 1–Scope 3 link may be subject to endogeneity concerns. For example, the relationships among Scope 1, Scope 3, and imports may be jointly determined (a simultaneity problem), or driven by other unobservable factors such as production outsourcing and supply chain disruptions (omitted variable biases). It is also plausible that there is a reverse causality in the Scope 1–Scope 3 relationship or a selection bias in heavy polluting firms choosing high-emissions suppliers. To alleviate these concerns, we employ several exogenous shocks to the incentives for U.S. firms to limit their local direct emissions and shift their carbon burden offshore. Specifically, we investigate shocks from domestic state-level legislative pressure and regulatory stringency on environmental issues. Suppose our baseline findings capture the emission outsourcing effect. Then, imports should have a stronger mitigating impact on the Scope 1–Scope 3 relationship with an exogenous increase (decrease) in appetite for foreign (domestic) carbon production.

3.2.1 *State-level legislative pressure*

With the United States being the world's second-largest source of carbon emissions, accounting for 15% of the 2018 global total, environmental protection has become one of the most critical issues in U.S. politics.[19] Its pollution control efforts rely heavily on the states and their enforcement policies to ensure emissions mitigation effectiveness (e.g., Grant, Bergstrand, and Running, 2014). But these efforts focus on cutting direct domestic state-level GHG emissions, which may have the unintended effect of incentivizing firms to outsource their carbon footprints elsewhere. Thus, we employ state-level legislative pressure and regulatory stringency as exogenous sources of an increasing propensity for carbon outsourcing.

We analyze Congressional voting patterns in climate-change-related environmental issues between 2006 and 2018, as documented by the LCV, to capture domestic legislative pressure. The more environmentally-conscious are the state legislators, the more likely they would vote in favor of pro-environmental Congressional bills. First, we assign a score to each Congress member based on the individual's voting records each year, where the score, expressed in the form of a percentage ratio, is the number of pro-environmental votes scaled by the total number of climate-change-rated environmental bills considered in the year. Next, we compute

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

an average voting score across all Senate and House members in each state and employ the voting score as a proxy for state-level legislative pressure on environmental protection. States with more environmentally-friendly Congress members (i.e., higher environmental scores) should have more significant interests in pushing a climate action agenda.

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

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

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

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

$$\begin{aligned} \mathit{Ln(Scope\ 3)}_{i,t} = \alpha &+ \beta_{SI1} \mathit{Ln(Scope\ 1)}_{i,t} \times \mathit{Ln(Import)}_{i,c,t} \times \mathit{Treat}_{i,t-1} \\ &+ \beta_{SI} \mathit{Ln(Scope\ 1)}_{i,t} \times \mathit{Ln(Import)}_{i,c,t} + \beta_{S1} \mathit{Ln(Scope\ 1)}_{i,t} \times \mathit{Treat}_{i,t-1} \\ &+ \beta_{I1} \mathit{Ln(Import)}_{i,c,t} \times \mathit{Treat}_{i,t-1} + \beta_{S} \mathit{Ln(Scope\ 1)}_{i,t} + \beta_{I} \mathit{Ln(Import)}_{i,c,t} \\ &+ \beta_{1} \mathit{Treat}_{i,t-1} + \beta_{CS}{}' \mathit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned} \tag{2}$$

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

Table 4, Panel A, presents the estimates of Model (2). Column (1) shows the impact of Congress voting score shocks, where *Treat* is 1 for the next five years if the environmental legislative voting score in year $t-1$ increases by more than three times the mean increase in the score over the sample period. Columns (2) and (3) present the effects of close-call election wins by Democratic and Congress members with a lifetime environmental voting score of 60 or above, respectively. *Treat* equals 1 for the next two years (i.e., the length of an election cycle) after the close-call election win in year $t-1$. We find the β_{SI1} coefficients negative and significant across all columns, suggesting a stronger outsourcing effect following an exogenous increase in state-level legislative pressure, intensifying local firms' demand for emission shifting to their foreign suppliers. However, when we replicate the analysis of Column (2) with close wins by Republican members as a placebo test,[20] the reported results in Column (4) yield no strengthening effect on outsourcing.

It is worth noting that while our findings broadly align with those of an earlier study by Bisetti, Lewellen, Sarkar, and Zhao (2023), our emphasis differs. Bisetti, Lewellen, Sarkar, and Zhao find political ideology, especially Republican wins, leads firms to increase pollution and invest less in abatement measures and also a reallocation effect as firms shift emissions away from Democrat-represented areas. Their key mechanism is also increased regulatory inspections and enforcement actions. However, we focus on emission outsourcing along the global supply chain, whereas they investigate a firm's relocation decision. Furthermore, we identify the agency motive of emission outsourcing rather than a firm's economic incentive to optimize production efficiency.

3.2.2 *State-level regulatory stringency*

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

[20]Republican members tend to prioritize environmental issues less compared to their Democratic counterparts (e.g., Di Giuli and Kostovetsky, 2014).

which a state enacts a statutory or executive target to limit carbon output, as recorded in C2ES.

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

Similar to the preceding tests, we investigate the impact of state-level regulatory stringency on firms' carbon emission outsourcing behavior using Model (2), where *Treat* equals 1 for the five years after the state enactment of executive or statutory targets to limit carbon emissions, or alternatively equals 1 for the next five years if the lagged average onsite inspection level per facility increases more than three times the average onsite inspection increase over time. Columns (1) and (2) of Table 4, Panel B, report the results, consistent with the evidence in Panel A. We also conduct falsification tests to rule out the possibilities

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

that our results are spuriously driven. Results in Columns (3) and (4) show no evidence when we estimate the respective models a year before the state-level enactment of emissions reduction targets and onsite inspection spikes.

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

3.3 Directional change in Scope 1 and Scope 3 emissions

Thus far, we have interpreted our key evidence to suggest that when firms reduce Scope 1 but increase imports, their resulting Scope 3 will fall less due to outsourcing. However, one can alternatively interpret that the Scope 1–Scope 3 association mechanically weakens as firms increase imports from foreign suppliers subject to emission policies in their own countries or that firms' imports lead to their Scope 3 increase disproportionally less than their Scope 1. As firms have limited control over their suppliers' emissions, it is unsurprising that the correlation between Scope 1 and Scope 3 would decrease. Under this alternative explanation, the attenuating effect of imports would be found for both increasing and decreasing Scope 1 strategies. To address this empirical challenge, we distinguish between an increase and a decrease in a firm's Scope 1 and replicate Model (1) by replacing the level of emissions with the percentage change. Columns (1) and (2) of Table 5 show subsample results from regressing the percentage change of Scope 3 on the positive ($+\%\Delta$ Scope 1) and negative percentage change in Scope 1 ($-\%\Delta$ Scope 1), respectively, with the control variables and fixed effects included. Column (1) shows a positive coefficient on $\%\Delta$Scope 1 $\times$ Ln(Import) for firms experiencing Scope 1 increases, implying that firms that increase their own emissions also increase their Scope 3, with a larger magnitude for their overseas suppliers. Firms, therefore, place a heavier reliance on supplier carbon production during times of expansions. In contrast, this coefficient is significantly negative in Column (2), indicating that firms that decrease their own emissions would only reduce their upstream Scope 3 overseas to a much smaller extent. This finding is the critical piece of evidence confirming emission outsourcing while ruling out the alternative explanation. To further substantiate this finding, our unreported test finds a statistically significant difference in the %ΔScope 1 $\times$ Ln(Import) coefficient between the two subsamples at the 1% level with an F-statistic of 12.32 (p-value = 0.0005).

Column (3) runs a variant of Model (2) on the entire sample, where *Treat* is replaced with *Indicator* capturing a firm's Scope 1 decrease (Indicator($-\Delta$Scope 1)) from one year to another. We regress Scope 3 on %ΔScope 1, Ln(Import), *Indicator* and the interactions between the variables, together with the same set of control variables employed in Columns (1)-(2). The results show a positive coefficient on %ΔScope 1, indicating that a firm's Scope 3 increases with its Scope 1. Additionally, the coefficient on %ΔScope 1$\times$ Ln(Import) is also positive, albeit statistically insignificant. However, as evidenced by the negative coefficient of %ΔScope 1 $\times$ Indicator($-\Delta$Scope 1), for firms with decreasing Scope 1, their Scope 3 actually increases. Such a negative relationship becomes even stronger with larger imports as reflected by the negative and significant coefficient on the triple-interaction term, reinforcing our outsourcing hypothesis that the attenuating effect of imports is concentrated in firms with decreasing Scope 1.

3.4 Robustness tests

3.4.1 *Placebo tests and subsample analysis*

To further corroborate our main finding, we conduct placebo tests by replacing *Scope 3* in Model (1) separately with downstream Scope 3 and Scope 2 emissions, where neither emission type could be associated with a firm's imports.[22] Columns (1) and (2) of Table 6, Panel A, corroborate our emission outsourcing evidence, as none of the coefficients on *Ln(Scope 1)* $\times$ *Ln(Import)* is significant and negative. While Scope 1 does not correlate with downstream Scope 3, it is positively associated with Scope 2. This finding is intuitive. The more a firm produces locally, the more GHG emissions it will generate from its production (Scope 1) and purchased energies (Scope 2) to support its production activity.

Furthermore, we check whether our baseline results are driven by potential sampling bias. Beginning in 2016 (coinciding with adoption of the 2015 Paris Agreement), Trucost

[22]Note that while S&P Global graciously offers us data on downstream Scope 3, the information is scant. However, we believe analyzing this data would provide some substantiation of our baseline findings.

substantially expanded its coverage, nearly tripling from 2015 to 2016. To ensure that Trucost's expanded coverage of firms does not drive our results, we re-estimate Model (1) on a subsample period from 2006 to 2015. We also repeat our analysis to rule out the size bias by scaling Scope 1 and 3 with total assets. Columns (3) and (4) confirm that our key evidence is robust.

3.4.2 *Alternative explanations*

We also conduct several tests to rule out alternative explanations that our results are due to (i) the Scope 3 measurement issue, (ii) production and not emission outsourcing, and (iii) lower labor costs as opposed to emission outsourcing; (iv) supply chain disruptions; (v) shifts in trade relationships; and (vi) activist investors.

One concern about Scope 3 is that they are challenging to measure, and firms sometimes do not disclose this emission type to CDP. In such a case, Trucost provides its own estimate, which tends to be biased, albeit downwards (Aswani, Raghunandan, and Rajgopal, 2022). To address the potential concern that such biasedness drives our outsourcing effects, we employ a model similar to Model (2), where we replace *Treat* with a binary indicator, *Indicator*, which equals one if Scope 3 is estimated by Trucost and zero if otherwise. Column (1) of Table 6, Panel B, indicates that the coefficient of the triple-interaction term is statistically insignificant, implying no differential impact between estimated and self-disclosed Scope 3.

One may argue that our results can be explained by a firm's production outsourcing rather than emission outsourcing. For example, Li and Zhou (2017) find evidence that U.S. firms shift pollution while outsourcing production to exploit cheaper labor costs, laxer environmental standards, and poorer environmental regulatory quality. However, Esty and Porter (2002) show that firms' outsourcing strategy is driven more by environmental considerations rather than strictly by labor-cost concerns. Admittedly, production and emission outsourcing cannot be mutually exclusive, as firms that outsource their production overseas for cost efficiency will naturally outsource more emissions. Nevertheless, to test whether production outsourcing due to pure cost consideration is the sole explanation for our baseline findings, we use *Indicator* to represent the scale or cost of a firm's production. Specifically, in Column (2) of Panel B, *Indicator* equals one if the firm's capital expenditure (CapEx) is above the industry median and zero otherwise, whereas in Column (3), *Indicator* equals one if the firm's cost of goods sold (COGS) is above the industry median and zero otherwise. Again, the insignificant coefficients of the triple-interaction term suggest that our results are unlikely attributable purely to production outsourcing.

Our results may be potentially explained by the differences in labor costs between the U.S. and the supplier country. Countries with low environmental standards for GHG emissions will likely have lower labor costs and weaker labor protections. To test this, we use the *Indicator* to reflect a supplier country whose average hourly labor cost is below the sample median. The triple-interaction term yields a statistically insignificant coefficient, suggesting that the cross-country difference in labor cost is unlikely to explain our results.

Moreover, our findings cannot be attributed to disruptions in the supply chain. While our untabulated results suggest that the attenuating effect of imports becomes weaker when the supplier country experiences natural disasters disrupting the supply chain, such supply chain disruption effects, which occur sparsely across time, do not undermine our key interpretation based on agency-motivated emission outsourcing. In particular, it does not explain our results on close-call elections and sudden increases in regulatory pressures, which are exogenous to these supply chain disruptions.

Another potential alternative explanation of our results is that firms rationalize their operations by shifting suppliers overseas in response to climate risks and shocks to their supply chain. However, our untabulated results do not indicate a significant change in a firm's number of foreign suppliers after it experiences domestic shocks. Therefore, it is more likely that a firm outsources emissions more to its existing overseas suppliers rather than domestic ones. Furthermore, even if one argues that the firm shifts its carbon footprint to suppliers in countries with less stringent environmental policies in response to domestic regulatory pressures, such shifts in trade relationships can manifest in carbon outsourcing.

Finally, our findings are unlikely the result of being targeted by activist investors who may pressure firms to reduce their domestic emissions. In our sample, the average percentage of hedge fund blockholders is around 2%, and they tend to be highly skewed and concentrate only on a few large companies.[23] Therefore, ownership by hedge funds, which tend to be activist investors, cannot account for the significant cross-firm variations in emission outsourcing.

[23]The average block ownership by green hedge funds is 18% and 62% for the 95th and the 99th percentiles of total observations, respectively.

3.4.3 *Cross-industry and cross-country emission variations*

We test cross-sectional variations in the import interaction effect to help further disentangle emission outsourcing from production outsourcing. If firms actively engage in shifting pollution, their outsourcing activity should be higher in more pollution-intensive industries and countries with laxer regulations. Such evidence also implies that firms have strong intentions to outsource their emission duties beyond the mechanical effect of production outsourcing. Similar to the tests in the preceding subsection, we employ a triple-interaction model to examine these conjectures. Results are shown in Table 7.

In Columns (1), *Indicator* equals one if the firm belongs to Fama-French 30 industries with above-median aggregate Scope 1 scaled by total assets. In Columns (2) and (3), *Indicator* captures countries with below-median enforcement of environmental regulations score (EER) and below-median stringency of the environmental regulation score (SER), respectively.[24] The coefficients of the triple-interaction terms are all negative and statistically significant, indicating that the outsourcing effect is stronger for firms in pollution-intensive sectors and whose suppliers are in less environmentally regulated countries. To further verify that these results are indeed driven by firms with decreasing Scope 1 (such that their Scope 3 is reduced to a less extent as a result of carbon leakage), we interact the triple-interaction term with a binary indicator to capture the firm having a negative change in its Scope 1 and replace Scope 1 (Scope 3) with $\%\Delta$Scope 1 ($\%\Delta$Scope 3). Table IA2 of the Online Appendix shows that the coefficients on the quadruple-interaction terms are negative and significant, reinforcing our above evidence.

4 The Motivations for Emission Outsourcing

Thus far, we have shown the presence of carbon outsourcing by U.S. firms. This section tests two hypotheses that can offer plausible explanations for firms implementing this strategy: (1) the agency cost hypothesis, and (2) the carbon efficiency hypothesis.

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

4.1 The agency cost hypothesis

4.1.1 *Agency motives*

Corporations fearing being labeled as environmentally irresponsible might engage in more aggressive carbon outsourcing.[25] We argue that agency conflicts may drive emission mitigation strategies – firms with greater agency problems are more likely to resort to emission outsourcing. Such conflicts tend to be more severe in firms whose managers care about their firms' social status, are more entrenched, or are incentivized through compensation contracts to improve their firms' ESG ratings rather than the overall carbon reduction.

First, we examine whether corporate insiders have desires to build and maintain a good social status by investigating the association between a firm's social status, measured by its ESG rating, and its direct and indirect emissions. Table 8 reports firm-level regression results based on three popularly adopted ESG ratings provided by Refinitiv, Sustainalytics, and MSCI. We find that only the coefficient on *Ln(Scope 1)* is negative, statistically significant, and robust across different ESG ratings. These ratings do not capture Scope 3 nor Scope 2, thereby leaving room for corporate insiders to game the rating system by "manipulating" Scope 1.

Second, our analysis employs the popularly adopted entrenchment index or E-Index, introduced by Bebchuk, Cohen, and Ferrell (2009), a state-of-the-art measure of governance quality and managerial agency problems, compared with many other governance indicators. We use scores of various governance components from Refinitiv ESG to self-construct the E-index that mimics the original E-index, which only covers the 1990-2006 period. Our E-index contains four entrenchment provisions: staggered boards, poison pills, golden parachutes, and supermajority vote requirement or qualified majority (for amendments of charters and bylaws or lock-in provisions), covering the 2006-2018 sample period. The higher the E-Index, the weaker is a firm's governance quality (i.e., bad governance).

Finally, corporations increasingly link executive pay to ESG goals as more investors, activists, and regulators demand greater accountability of managers for ESG performance. For example, a study by proxy advisory firm Glass Lewis & Co. documents that in 2021, a quarter of U.S. companies included some form of E&S metrics as part of their executive

[25] https://www.cnbc.com/2021/11/11/cop26-fear-of-a-bad-reputation-could-be-what-really-makes-firms-change. html.

incentive plans, compared with 16% in 2019.[26]

We employ a triple-interaction regression model, similar to Model (2), replacing *Treat* with *Agency* indicator to denote different proxies employed in the test. In Table 9, Panel A, we examine agency issues manifested in a firm's emission outsourcing. Columns (1)-(2) of the panel present the test results based on the above E-Index and ESG-linked executive pay. For the latter, we employ a binary indicator to denote the firm that explicitly includes ESG metrics in its executive compensation package. We find emission shifting to occur when managers are more entrenched and executive compensation contracts are linked to their firms' ESG performance, revealing corporate insiders' mounting pressures to improve their firm's ESG rating.

We also investigate whether firms with higher historical ESG ratings are more inclined to subtly outsource emissions to maintain their reputation. As discussed above, a high ESG score offers firms various benefits, and such benefits propel these firms to uphold their domestic social image and environmental standing. Similarly, executives and directors with a pro-environmental image also have reinforcing effects on emission outsourcing.[27] Their reputation is usually tied to their firm's reputation as they take credit for their firm's strong social image and receive private benefits, including better career prospects (Bénabou and Tirole, 2010; Cai, Gao, Garrett, and Xu, 2020). When testing these possible explanations, $Agency_{i,t-1}$ is measured at time $t-1$ and alternately replaced with $Firm\ Greenness_{i,t-1}$, $CEO\ Greenness_{i,t-1}$, and $Board\ Greenness_{i,t-1}$ to capture the established environmental standing of a firm, its CEO, and board of directors. *Firm Greenness* is measured as the decile ranking of firms' ESG scores, defined as a combined score obtained from Refinitiv based on the reported information in the environmental, social and corporate governance pillars with an ESG controversies overlay. We construct $CEO\ Greenness_{i,t-1}$, and $Board\ Greenness_{i,t-1}$ in the following manner. $CEO\ Greenness_{i,t-1}$ is the decile ranking based on CEOs' average ESG scores in $t-5$ to $t-1$, where the average score is taken across all firms in which the CEO has worked during the past five years. A higher ranking denotes a greener CEO for firm i. Similarly, $Board\ Greenness_{i,t-1}$ is the decile ranking based on the average ESG scores of the directors' previously affiliated firms, serving as board members in years $t-5$ to $t-1$.

[26]https://news.bloomberglaw.com/esg/executive-pay-tied-to-esg-goals-grows-as-investors-demand-action.

[27]Previous 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).

Columns (3)-(5) of Panel A present the regression results supporting the agency-motivated outsourcing activity in maintaining an ESG standing.

4.1.2 *Governance mechanism*

Unlike corporate insiders, external stakeholders, such as customers and institutional investors, may have different expectations. These external stakeholders are concerned about their overall climate risk exposures and may care about carbon footprints along the whole value chain. As a result, they have incentives to alleviate agency-motivated outsourcing behavior and reduce any adverse spillover effects on foreign exporters.

Government customers and environmentally-conscious corporate customers should be more concerned about the global community's overall environmental externalities of corporate actions. First, one important role of the government is to act in the public interest and address social issues arising from market failures and negative externalities. As global warming and other environmental issues become increasingly acute and pressing, governments are compelled to reduce firms' overall carbon footprints in the interest of public welfare (Hsu, Liang, and Matos, 2021).[28] Second, climate change constitutes extreme weather events, leading to significant losses for affected firms that propagate through supply chains. Furthermore, corporate customers tend to impose similar socially responsible business behavior on both domestic and foreign suppliers (Dai, Liang, and Ng, 2021). Thus, these customers are more likely to discourage carbon offshoring behavior that would adversely affect their global supply chain and, in turn, their own performance. Lastly, environmentally-conscious institutional investors, who are typically universal owners with international exposures, are also more concerned about the overall ESG performance of their global investment portfolios. They are also more attentive to the systemic climate risks that are impossible to diversify away (Krüeger, Sautner, and Starks, 2020). We contend that these stakeholders act as governance mechanisms to partially correct the agency problem arising from the information inefficiency of ESG ratings and social reputation maintenance. They would focus on reducing a firm's total contribution to global warming rather than the narrowly defined Scope 1.

[28] A government has several tools to achieve its objectives, including taxation and regulations. However, unlike these tools, which often lead to unintended results such as emissions reallocation discussed above and in prior work (Bartram, Hou, and Kim, 2022), we expect that acting as a customer would allow the government to better intervene with its suppliers' corporate decision-making, given its information advantage and bargaining power, to push for the desired course of actions and alleviate carbon outsourcing issues.

We again apply a triple-interaction model to explore these external stakeholders' incentives, where *Indicator* is replaced with *Gov Customer*, *Customer Greenness*, and *Blockholder Greenness*, respectively. *Gov Customer* is defined as the percentage of firm i's sales to its largest government customer identified in the Compustat Segments file. *Customer Greenness* represents the percentage of firm i's sales to its largest corporate customer with the above industry-median Refinitiv ESG score.[29] *Blockholder Greenness* is defined as the percentage of firm i's ownership by greener block institutional investors with half of their portfolio holdings invested in green firms ranked in the top quintile of the Refinitiv ESG score distribution each year.[30] Columns (1)-(3) of Table 9, Panel B, record the impacts of these stakeholders on a firm's carbon footprint management. The coefficient on the triple-interaction term is consistently positive and statistically significant at the 10% level. Thus, in line with our expectations, these stakeholders reduce global environmental externalities by restricting their associated firms from emissions shifting to other countries.

Furthermore, we also test on the quadruple-interaction term by adding a binary indicator for whether the firm experiences Scope 1 decreases ($Indicator(-\Delta Scope\ 1)$) and replacing *Ln(Scope 1)* with $\%\Delta Scope$ 1 and *Ln(Scope 3)* with $\%\Delta Scope$ 3. Table IA3, Panel A, shows the coefficient of the quadruple term to remain mostly negative and statistically significant, except for the E-index as an agency indicator. The implication is that agency problems are a main driver of firms' emission outsourcing behavior. We also conduct similar tests based on the quadruple interaction for the external governance mechanisms. Panel B presents negative and significant coefficients on the triple-interaction, confirming the crucial role of imports in emission outsourcing when firms are decreasing their own Scope 1 output. However, this effect becomes less pronounced with corporate disciplining, as shown by the positive and significant coefficients on all the quadruple interaction terms.

4.2 The carbon efficiency hypothesis

While emission outsourcing can manifest agency problems, it is plausible that a firm implements such a strategy because its foreign suppliers can mitigate the overall carbon emissions

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

[30] A blockholder holds at least 5% of a firm's total shares outstanding.

more efficiently than itself and its domestic suppliers. To explore this alternative interpretation, we test whether a firm's outsourcing activity significantly decreases total carbon emissions.

To facilitate this analysis, we construct a measure that estimates the amount of emissions derived from a firm's imported goods, denoted by *Ln(Outsourced Emissions)*, in place of the import volume. This measure quantifies standardized carbon emissions generated along the supply chain from imported products to a firm based on its primary industry and is based on a \$1 million worth of output through the Economic Input-Output Life Cycle Assessment (EIO-LCA) model developed by Carnegie Mellon University.[31] While this measure does not allow us to determine the sources of supplier-induced emissions from different countries the firm imports its goods, it permits us to distinguish Scope 3 from domestic and foreign suppliers. Column (1) of Table 10 presents our firm-level results while controlling for firm-specific characteristics and firm and year fixed effects. Of particular interest is that the coefficient on *Ln(Outsourced Emissions)* is positive but statistically insignificant. This finding indicates that when firms outsource emissions to foreign suppliers, they do not reduce their total emissions, suggesting that firms are not allocating production to increase carbon efficiency.

We proceed to test whether carbon leakage reflects a less risky business strategy for corporate insiders to shirk their environmental responsibilities. If this is the case, we should expect firms to put less effort into local-emission mitigation initiatives as they shift part of their carbon emissions overseas. Therefore, we test whether a firm is more likely to: (i) engage a foreign supplier that it can outsource its emissions, (ii) reduce pollution abatement measures locally, and (iii) invest less in green technology. Columns (2)-(4) present our results. In Column (2), we conduct a linear probability model in which we regress a binary variable, *Foreign Supplier*, on the domestic portion of a firm's Scope 1 emissions as estimated by multiplying the aggregate Scope 1 amount with the ratio of domestic assets to total assets. *Foreign Supplier* is defined as one if the firm has at least one foreign supplier in the following year and zero if otherwise. The coefficient on *Ln(Scope 1)* is shown to be positive and statistically significant. When a firm faces mounting pressure to reduce direct carbon emissions from its domestic production, its likelihood of seeking a foreign supplier to outsource its carbon footprint increases.

[31] Appendix A offers a detailed description of this variable.

Column (3) presents results from estimating a linear probability model in which we regress a binary variable, *Pollution Abatement*, on a firm's Scope 1, Scope 3, and outsourced emissions. Following Akey and Appel (2019), *Pollution Abatement* measures a firm's investment in abatement activities associated with reducing the number of hazardous substances entering the waste stream.[32] *Pollution Abatement* equals one if the firm reports at least one abatement activity in year $t+1$ that reduces a chemical produced in the following activity categories: 1) operating practices, 2) inventory control, 3) spill and leakage, 4) raw material modifications, 5) process modifications, 6) cleaning and degreasing, 7) surface preparation and finishing, or 8) product modifications and zero if otherwise. We find the coefficient of *Ln(Scope 1)* to be positive and statistically significant, whereas that of *Ln(Outsourced Emissions)* to be negative and statistically significant. For more pollution-intensive firms with higher Scope 1, the growing pressure to reduce carbon emissions will increase firms' likelihood of investing in abatement measures in the future. However, this likelihood decreases for those that choose to outsource instead.

Column (4) reports the results from regressing the log of one plus the number of green patents filed by a firm two years ahead ($Ln(Green\ Innovation)_{i,t+2}$), accommodating for the time taken to innovate.[33] We use the International Patent Classifications (IPC) to classify green patents. We focus on those IPCs identified as environmentally sound technologies by the United Nations Framework Convention on Climate Change and obtained from World Intellectual Property (WIPO). This regression model also includes the firm's direct emissions from its own production (*Ln(Scope 1)*) and through its supply chain (*Ln(Scope 3)*). Economic theory suggests that firms may innovate as a differentiation strategy to gain competitive advantages over their rivals (e.g., Aghion et al. 2005). While firms can invest more in green R&Ds gearing toward environmental patents to offset potential adverse regulatory shocks and remain competitive, corporate insiders may consider this strategy riskier. It also demands a longer-term commitment than simply outsourcing emissions abroad. Our results reveal a myopic environmental preference among firms that may have more flexibility to reduce carbon production through outsourcing. *Ln(Outsourced Emissions)* is negatively related to green innovation output, while neither Scope 1 nor Scope 3 bears any significant effect on

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

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

Green Innovation. For example, the estimate of *Ln(Outsourced Emissions)* coefficient is -0.049 ($t-$statistic=-2.44), and the unreported estimate for the 3-year ahead green innovation is -0.063 ($t-$statistic=-2.87). Thus, the greater a firm's import carbon intensity, the less likely it will engage in environmental innovation.

In summary, our results suggest that firms that outsource emissions do not actively pursue carbon efficiency through pollution abatement efforts and clean technology investment. Our analysis potentially reveals the true incentive of these firms: they are unwilling or unable to develop green technology that requires significant capital investments, has long development timelines, and is riskier (e.g., Rugman and Verbeke, 1998; Kolk and Pinkse, 2008).[34]

5 Financial implications

In this section, we evaluate the financial consequences of corporate emission shifting behavior. We ask the following questions. (1) Does emission outsourcing lead to higher operating performance, lower cost of capital, and improved firm valuation? (2) Do investors care about carbon leakage?

5.1 *Operating performance, cost of capital, and valuation*

Outsourcing carbon emissions may enable firms to pass on production and emission costs to their overseas suppliers and, in turn, generate greater operating performance. To investigate this possible outcome, we estimate the following model,

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

where *Performance* alternately represents firm i's operating performance, as proxied by its return on assets (*ROA*), and its components, namely earnings before interest and taxes scaled by sales (*EBIT Margin*), and operating efficiency, as measured by the ratio of sales to assets (*Asset Utilization*). *EBIT Margin* gauges the extent to which prices exceed marginal costs,

[34]These findings are also broadly in line with the work of Cohen, Gurun, and Nguyen (2020), who show that firms from oil, gas, and energy-producing sectors with lower ESG scores are key green innovators in the U.S.

whereas *Asset Utilization* measures how efficiently firms employ their assets to generate sales. *Controls* denotes a vector of variables, including firm size measured by total assets, Tobin's Q, R&D, advertising expenditure, firm leverage, capital expenditure, cash holdings, income volatility, return on equity, and growth in earnings per share (EPS). Columns (1)-(3) of Table 11 highlight estimates of the key coefficients. We find that *ROA* and its components are uncorrelated with *Ln(Scope 1)* and *Ln(Outsourced Emissions)* but positively and significantly related to *Ln(Scope 3)*. The implication is that emission shifting can enhance firms' operating cash flows by adopting a lean production process or utilizing more stakeholder resources (i.e., more production by suppliers).

A natural question that arises is whether the enhanced cash-flow effect is accompanied by a lower cost of equity capital and an improved firm valuation. We test this prediction by reestimating Model (3) with the implied cost of equity capital (*ICC*) and Tobin's Q as alternate dependent variables. Our analysis employs the average of four different estimates for the cost of equity capital implied in share prices and analyst forecasts suggested in the literature (Claus and Thomas, 2001; Gebhardt, Lee, and Swaminathan, 2001; Easton, 2004; Ohlson and Juettner-Nauroth, 2005). We use Tobin's Q, the ratio of the market value of total assets to the book value of total assets, as a proxy for firm value. Columns (4) and (5) indicate that both *Ln(Scope 3)* and *Ln(Outsourced Emissions)* are positive and statistically significantly related to *ICC*, whereas *Ln(Scope 3)* is negative, albeit marginally, associated with *Tobin's Q*. It appears that firms may profit more when they rely heavily on suppliers' emissions, but their carbon leakage presents a greater risk exposure and a higher capital cost, weakening their firm valuation.

5.2 *Outsourcing premium and reputational risk*

In this subsection, we test whether and how financial markets price in the stocks of firms that exploit outsourcing to reduce carbon emissions. Prior research provides evidence that investors attach a larger carbon risk premium to stocks of high-emitting firms (e.g., Bolton and Kacperczyk, 2021). To implement our test, we focus on the relationships between monthly stock returns and different sources of firm-level carbon emissions using the following model,

$$Stock\ Return_{i,m,t+1} = \alpha + \beta_1 Ln(Scope\ 1)_{i,t} + \beta_2 Ln(Scope\ 3)_{i,t} + \beta_3 Ln(Outsourced\ Emissions)_{i,t} + \beta'_{CS} Controls_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \quad (4)$$

where $Stock\ Return_{i,m,t+1}$ is the monthly stock return of firm i in month m of year t+1. Model (4) controls for firm-specific characteristics that are previously shown to predict stock returns, and they include firm-specific *Size*, *BM*, *Leverage*, *PPE*, *CapEx*, *Momentum*, *Volatility*, *Beta*, and *HHI* at year t. It also includes firm and month fixed effects and computes standard errors clustered at the firm level. Results are reported in Columns (1)-(4) of Table 12. We find that carbon emissions are all positive and significantly associated with stock returns when estimated individually, consistent with Bolton and Kacperczyk (2021). However, when these different sources of emissions are estimated jointly, only the coefficients on *Ln(Outsourced Emissions)* and *Ln(Scope 3)* are positive and significant, while the statistical significance of *Ln(Scope 1)* coefficient disappears. The statistically significant carbon risk premium attached to Scope 3 and imported emissions implies that forward-looking investors seek compensation for holding stocks of carbon outsourcers associated with substantial carbon leakage. In other words, the more a firm shifts its carbon emissions abroad, the larger is its outsourcing premium.

We next evaluate whether sources of carbon emissions are linked to one form of climate-related transition risks – 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.[35] Such reputational risk typically affects the "loyalty" of key stakeholders (including customers and suppliers across the global supply chain) to stay with the firm to offset the adverse effect of market-wide systematic shocks;

[35] 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.

thus, it can be considered a source of systematic risk.[36] Therefore, we expect environmentally responsible firms to display a lower ESG-induced reputational risk. That is, firms with less carbon footprint along the global value chain have a lower reputational risk.

We reexamine Model (4) using *RepRisk* β, an estimate of a firm's reputational risk at year t, as the dependent variable, which is estimated as follows. Each year, we rank the firms in our sample based on their reputational risk scores, as provided by RepRisk,[37] and divide them into two portfolios of stocks with high and low reputational risk scores. We compute daily returns on a reputational risk factor by taking the difference in daily returns between the low and high reputational-risk score portfolios. We then regress individual stock returns on the returns of the reputational risk factor and Fama-French-Carhart four factors. The coefficient on the reputational risk factor is our *RepRisk* $\beta_{i,t}$ estimate. We repeat this procedure yearly to obtain annual estimates of each firm's *RepRisk* $\beta_{i,t}$.[38] The results shown in Columns (5)-(8) of Table 12 are broadly consistent with those reported in Columns (1)-(4). That is, the market also attaches a high systematic risk associated with ESG reputation to stocks of carbon outsourcers. *RepRisk* β is positive and significantly related to both *Ln(Outsourced Emissions)* and *Ln(Scope 3)*, while not to *Ln(Scope 1)*. The magnitude and statistical significance of both *Ln(Outsourced Emissions)* and *Ln(Scope 3)* coefficients become even stronger when they are estimated jointly.

Overall, investors have appropriately factored in the outsourcing premium and reputational risk of outsourced emissions. Thus, firms may maintain their ESG status by engaging in emission shifting strategies but at the expense of higher carbon premiums and larger reputational risks.

[36] Albuquerque, Koskinen, and Zhang (2019) 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.

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

[38] Note that when we regress returns of the reputational risk factor against the returns on the Fama-French-Carhart four factors, the alpha estimate of -3% per annum is statistically significant at the 5% level. The spread between the low and high reputational risk portfolio tends to have an upward trend except for the early stage of the subprime crisis period and 2019. Similar to Edmans (2011), we attribute the reputational risk factor's underperformance to the difficulty of incorporating intangibles into traditional valuation models.

6 Conclusion

Climate change is a real and undeniable global threat, and its effects are already apparent. While companies are firmly committed to reducing their carbon footprints to help combat climate change, there is little evidence to suggest that they follow through on their pledge. Our study, therefore, exploits several newly available firm-level emissions and imports data to conduct an in-depth holistic analysis of firms' climate actions, corporate insider motivations, and financial consequences of such actions. We find robust evidence that U.S. firms play whack-a-mole with carbon pollution, moving carbon emissions from local markets to their suppliers abroad. Such strategies manifest an agency problem. Corporate insiders are incentivized to shift their carbon burden to foreign suppliers when faced with mounting pressures to improve their firm's environmental profile. However, environmentally-conscious stakeholders, such as government, corporate customers, and institutional blockholders, act as governance mechanisms to alleviate such agency-motivated environmental policy. Overall, firms maintain their ESG status by engaging in emission outsourcing strategies at the expense of higher carbon outsourcing premiums and more significant reputational risks.

In summary, our findings suggest that carbon leakage remains a global concern for policymakers and investors and call for more environmental effectiveness of climate policies to avert such economic activity that could undermine international efforts to combat climate change. For example, the European Union's recent enactment of a cross-border adjustment mechanism should deliver a promising set of trade policy tools, including carbon tariffs, fees applied to GHG emissions from imported goods, and among others, to eliminate emission shifting and reduce carbon footprint. The recent SEC's requirement that all public companies disclose Scope 1, 2, and "material" Scope 3 emissions would also provide a valuable first step for market participants and stakeholders to more accurately assess the amount of GHG emissions a firm generates.

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Figure 1:

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

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

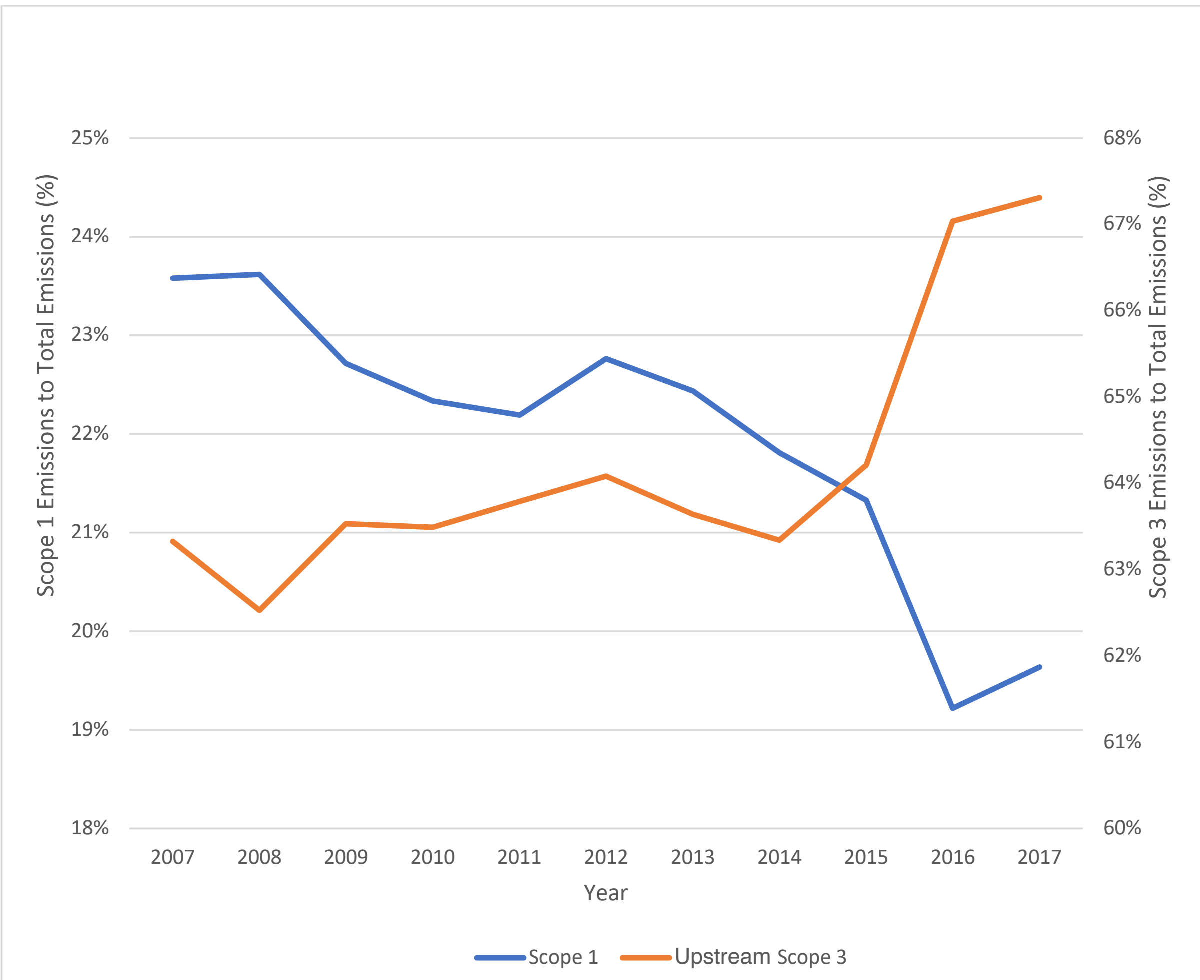

Figure 2:

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

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

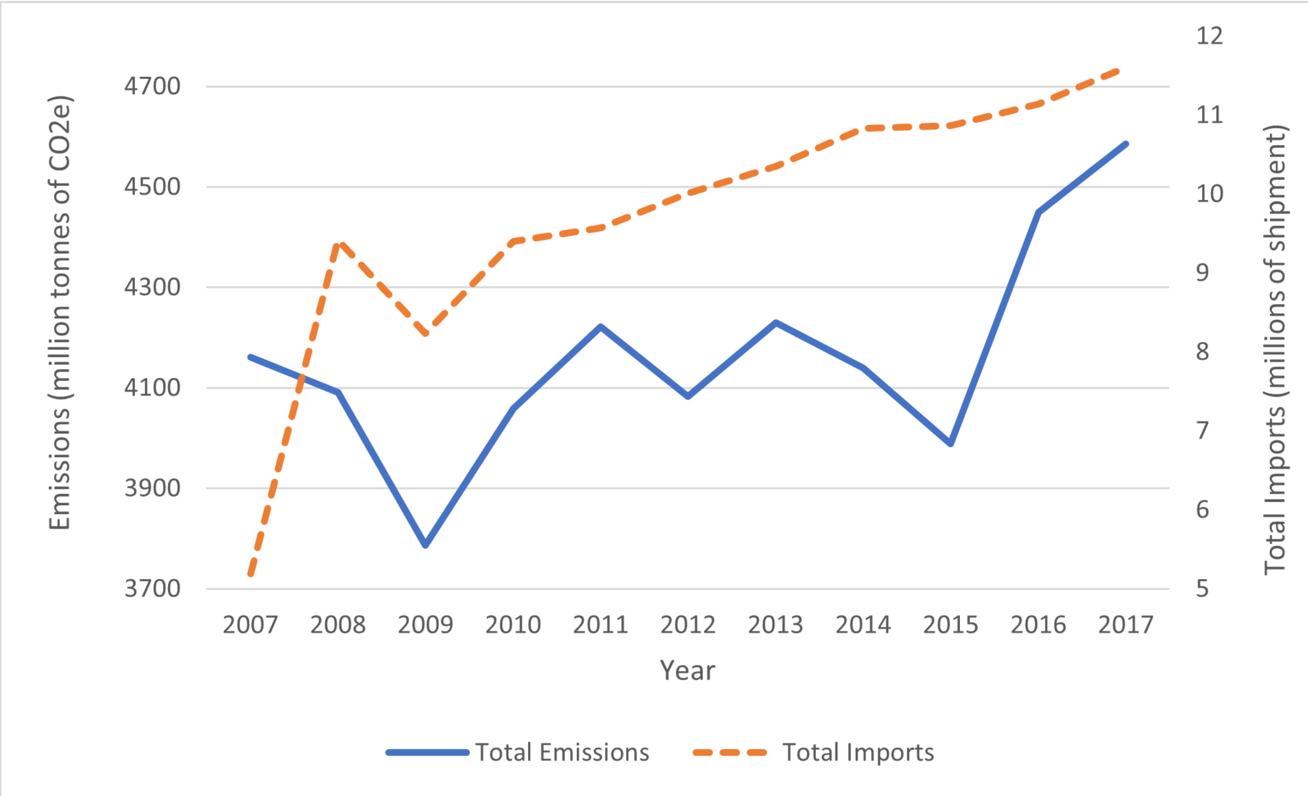

Table 1:
Summary Statistics

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

Variable	Obs	Mean	Stdev	Min	P25	Median	P75	Max
Panel A: Key Variables								
Carbon Emissions								
Scope 1 ('000 tonnes)	76,356	2154.832	4979.683	8.772	47.996	176.987	890.000	19335.910
Scope 3 ('000 tonnes)	76,356	4072.593	6513.327	100.040	418.070	1325.301	4257.182	25775.830
Ln(Scope 1)	76,356	12.397	2.127	9.079	10.779	12.084	13.699	16.777
Ln(Scope 3)	76,356	14.136	1.538	11.513	12.943	14.097	15.264	17.065
Scope 1/Total Emissions	76,356	0.186	0.201	0.018	0.050	0.102	0.236	0.738
Scope 3/Total Emissions	76,356	0.669	0.219	0.170	0.552	0.730	0.857	0.918
%Δ Scope 1	68,007	0.025	0.195	-0.377	-0.075	0.014	0.111	0.484
%Δ Scope 3	68,023	0.048	0.144	-0.230	-0.042	0.041	0.126	0.361
Indicator($-\Delta$ Scope 1)	68,023	0.454	0.498	0.000	0.000	0.000	1.000	1.000
Imports								
Import (Shipment Volume)	76,356	41.474	89.061	0.010	1.000	4.000	26.405	356.150
Import (Firm-Level)	10,422	375.758	823.243	0.000	0.000	8.850	229.510	3208.750
Ln(Import)	76,356	0.037	0.077	0.000	0.001	0.004	0.026	0.305
Ln(Import) (Firm-Level)	10,422	0.215	0.399	0.000	0.000	0.009	0.207	1.437
Panel B: Control Variables (Main)								
Assets	76,356	9.080	1.400	6.718	7.999	8.948	10.143	11.796
Tobin's Q	76,356	1.853	0.826	0.921	1.232	1.614	2.223	4.021
Leverage	76,356	0.261	0.150	0.005	0.152	0.250	0.359	0.571
ROA	76,356	0.108	0.060	0.009	0.064	0.100	0.145	0.235
SalesGrowth	76,356	0.049	0.126	-0.199	-0.023	0.044	0.115	0.321
Tangibility	76,356	0.533	0.320	0.108	0.266	0.460	0.775	1.167
R&D	76,356	0.088	0.131	0.000	0.000	0.018	0.129	0.467

Table 2:
The Relationship between Scope 1 and Scope 3 Emissions

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

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

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

	Definition of Dependent Variable, *Scope 3*†					
	Ln(Scope 3)			Scope 3/Total Emissions		
	Firm-Country Level		Firm Level	Firm-Country Level		Firm Level
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Scope 1)	0.084***	0.083***	0.152***			
	(5.66)	(5.49)	(8.66)			
Scope 1/Total Emissions				-0.847***	-0.857***	-0.726***
				(-21.82)	(-21.75)	(-13.17)
Assets	0.705***	0.694***	0.659***	-0.002	-0.002	0.000
	(19.91)	(19.13)	(23.92)	(-0.38)	(-0.37)	(0.06)
Tobin's Q	-0.037**	-0.035**	-0.023**	0.003	0.003	0.000
	(-2.41)	(-2.23)	(-2.56)	(1.12)	(1.11)	(0.23)
Leverage	-0.116*	-0.120**	-0.065	0.012	0.012	-0.002
	(-1.91)	(-1.99)	(-1.07)	(0.71)	(0.67)	(-0.16)
ROA	2.233***	2.138***	1.863***	0.023	0.021	0.035**
	(9.85)	(9.46)	(11.29)	(0.72)	(0.62)	(1.98)
SalesGrowth	0.144***	0.160***	0.027	0.008	0.007	0.007*
	(3.82)	(4.14)	(1.09)	(1.04)	(0.98)	(1.87)
Tangibility	0.446***	0.467***	0.273***	-0.009	-0.008	-0.015
	(4.44)	(4.65)	(2.95)	(-0.60)	(-0.51)	(-1.43)
R&D	0.079	0.063	0.604***	-0.170***	-0.175***	0.008
	(0.27)	(0.21)	(3.49)	(-2.99)	(-2.92)	(0.25)
# Obs	75,886	66,742	10,422	75,886	66,742	10,422
Firm, Country×Year FE	Yes	No		Yes	No	
Firm×Country, Year FE	No	Yes		No	Yes	
Firm, Year FE			Yes			Yes
Adj. R^2	0.989	0.989	0.984	0.979	0.977	0.972

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

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

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

where the vector of *Controls* is as defined in Table 2. † denotes that firm i's emissions are alternately measured in natural log in Columns (1)-(2) and in proportion to total emissions (Scope 1 + Scope 2 + upstream Scope 3) in Columns (3)-(4). Columns (1) and (3) report results at the firm-country level, with the other two columns shown at the firm level. The definition of all variables is detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at the 10%, 5%, and 1% levels, respectively.

	Definition of *Scope 3*†			
	Ln(Scope 3)		Scope 3/Total Emissions	
	Firm-Country Level	Firm Level	Firm-Country Level	Firm Level
Variable	(1)	(2)	(3)	(4)
Ln(Scope 1) × Ln(Import)	-0.019***	-0.040***		
	(-2.82)	(-4.93)		
Ln(Scope 1)	0.085***	0.161***		
	(5.71)	(8.83)		
Scope 1/Total Emissions × Ln(Import)			-0.040**	-0.045***
			(-2.51)	(-2.60)
Scope 1/Total Emissions			-0.846***	-0.718***
			(-21.81)	(-12.63)
Ln(Import)	0.248***	0.518***	0.009***	0.012**
	(3.02)	(5.06)	(2.71)	(2.28)
Assets	0.704***	0.656***	-0.002	0.000
	(19.92)	(23.77)	(-0.39)	(0.07)
Tobin's Q	-0.037**	-0.023**	0.003	0.000
	(-2.42)	(-2.57)	(1.11)	(0.23)
Leverage	-0.117*	-0.072	0.012	-0.002
	(-1.92)	(-1.19)	(0.70)	(-0.25)
ROA	2.233***	1.849***	0.024	0.035**
	(9.85)	(11.24)	(0.72)	(1.97)
SalesGrowth	0.144***	0.027	0.008	0.007*
	(3.81)	(1.11)	(1.04)	(1.86)
Tangibility	0.446***	0.274***	-0.009	-0.014
	(4.44)	(2.98)	(-0.60)	(-1.33)
R&D	0.079	0.605***	-0.170***	0.007
	(0.27)	(3.49)	(-2.99)	(0.24)
# Obs	75,886	10,422	75,886	10,422
Firm, Country×Year FE	Yes	No	Yes	No
Firm, Year FE	No	Yes	No	Yes
Adj. R^2	0.988	0.984	0.979	0.972

Table 4:
Legislative Pressure, State Regulatory Stringency, and Carbon Emissions

This table presents tests of two identification strategies using (i) shocks to Congressional voting scores and close-call elections in Panel A, and (2) shocks to state regulatory stringency in Panel B using the following regression model with triple-interaction effects:

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

where *Treat* is a binary indicator that alternately captures four representations in each panel. For Panel A, we define $Treat$ as follows. In Column (1), *Treat* equals one for five years if the lagged state-average Congress member environmental voting score increases more than three times the mean score increase over time, where the environmental voting score is defined as the number of votes each Congress member made in favor of the environmental bills scaled by the total number of climate change-specific environmental legislations considered in the year; such shock must not revert within the next three years, and changes in firm locations must not drive it. In Columns (2)-(3), a shock to each state depends on the number of close-election wins relative to close-election losses for environmentally-conscious candidates. For each house and senate candidate elected in a state-election year, a close-win (close-loss) is defined as a win (loss), where the difference between the winning and runner-up candidates is 5% or less (i.e., within a 2.5% bandwidth from the 50% threshold for winning elections). Close-wins (close-losses) are summed across all environmentally-conscious candidates, where an environmentally-conscious candidate is a Democrat for Column (2) or has a lifetime environmental voting score of 60 or above for Column (3). *Treat* equals one for the next two years if the number of the close-wins net of close-losses is greater than 0, and 0 otherwise. In Column (4), we repeat the test in Column (2), with Republicans being the close-win candidates. It serves as a placebo test to close-call election analysis. *Ln(Import)* is the import volume measured in the natural log. *Ln(Scope 1)* and *Ln(Scope 3)* are a firm's Scope 1 and upstream Scope 3 emissions, measured in natural log. For Panel B, *Treat* is a binary indicator that alternately captures two representations. In Column (1), a shock at the state level is when a state enacts an executive/statutory target to limit its GHG emissions, and *Treat* equals one for the next five years if the state passes a GHG emission target in year $t-1$. In Column (2), *Treat* equals one for five years if the lagged EPA onsite inspection intensity increases more than three times the average inspection increase in the state; such shock must not revert within the next three years, and changes in firm locations must not drive it. Columns (3) and (4) conduct the tests the year before the state-level statutory/executive target and EPA inspection spike, serving as placebo tests to state-level regulatory stringency shocks. *Ln(Import)* is measured by import volume in the natural log. *Ln(Scope 1)* and *Ln(Scope 3)* are a firm's Scope 1 and upstream Scope 3 emissions, measured in natural log. Both panels employ *Controls* as defined in Table 3. The definition of all variables is detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

Table 4 – Continued
Legislative Pressure, State Regulatory Stringency, and Carbon Emissions

Panel A: Legislative Pressure

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

Panel B: State Regulatory Stringency

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

Table 5:
The Asymmetric Effect of Imports on the Scope 1–Scope 3 Relationship

This table presents results from two tests of the asymmetric effects of a firm's imports on its Scope 1–Scope 3 association. In the first test, the sample is split into two subsamples based on the positive and negative change in Scope 1 emissions, and the subsample analysis of the two subsamples are shown in Columns (1) and (2). In Column (1), we report results from regressing the percentage change in Scope 3 emissions on the positive percentage change in Scope 1 emissions (+%Δ Scope 1), Ln(Import), and their interaction, while controlling for the set of firm-specific variables and fixed effects employed in Table 3. We conduct a similar analysis in Column (2), replacing +%Δ Scope 1 with the negative percentage change in Scope 1 emissions (−%Δ Scope 1). In the second test, we conduct a triple-interaction analysis, regressing the percentage change in Scope 3 emissions on Indicator(−ΔScope 1), Ln(Import), the percentage change in Scope 1 (%ΔScope 1), and their interaction terms, with the same set of control variables in (1) or (2) in place. The definition of all variables is detailed in Appendix A. All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Subsample Analysis		
	+%ΔScope 1	−%ΔScope 1	Entire Sample
Variable	(1)	(2)	(3)
%ΔScope 1 ×Ln(Import) × Indicator(−ΔScope 1)			-0.319**
			(-2.51)
%ΔScope 1 × Indicator(−ΔScope 1)			-0.070**
			(-2.55)
Ln(Import) × Indicator(−ΔScope 1)			0.006
			(0.40)
%ΔScope 1 ×Ln(Import)	0.119*	-0.229***	0.109
	(1.84)	(-3.04)	(1.53)
%ΔScope 1	0.107***	0.044*	0.101***
	(5.27)	(1.82)	(5.69)
Ln(Import)	-0.013	-0.026**	-0.015
	(-1.17)	(-2.47)	(-1.25)
Indicator(−ΔScope 1)			0.003
			(0.56)
# Obs	36,695	30,483	67,551
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Adj. R^2	0.764	0.710	0.740

Table 6:
Robustness Tests

This table presents results from additional analyses of the sample. Panel A reports results from two placebo tests and two subsample analyses using the baseline regression model in Table 3. In Columns (1) and (2), the dependent variable is replaced by downstream Scope 3 and Scope 2 emissions, respectively. In Columns (3) and (4), the main findings are re-evaluated on a shorter sample period between 2006 and 2015. Column (3) reestimates Column (1) of Table 3, whereas Column (4) rescales the key Scope 1 and 3 emissions with a firm's total assets (TA). Panel B explores additional factors that can influence firms' outsourcing behavior. It reports results from triple-interaction model regressions of Scope 3 emissions (*Ln(Scope 3)*) on Scope 1 emissions (*Ln(Scope 1)*), import volume (*Ln(Import)*), and a binary indicator (*Indicator*) that alternately captures four different representations. In Column (1), *Indicator* takes the value of 1 if a third-party data provider estimates Scope 3 emissions, and 0 if firms self-disclose emissions. It alternately indicates firms with above-industry-median (by Fama-French 30 Industry Classification) capital expenditure in Column (2), above-industry-median cost of goods sold in Column (3), and countries with below-median average hourly labor costs in Column (4). The definition of all variables is detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

Panel A: Alternative Scope Measures and Subsample Periods

	Placebo Tests		Subsample: 2006-2015	
	Dependent Variable			
	Ln(Downstream Scope 3)	Ln(Scope 2)	Ln(Scope 3)	Ln(Scope 3/TA)
Variable	(1)	(2)	(3)	(4)
Ln(Scope 1) × Ln(Import)	-0.007	0.015	0.017	-0.264***
	(-1.30)	(1.08)	(-2.39)	(-3.20)
Ln(Scope 1)	-4.988	0.209***	0.077***	0.108***
	(-1.07)	(4.08)	(4.70)	(5.55)
Ln(Import)	0.092	-0.223	0.226**	0.142***
	(1.35)	(-1.28)	(2.54)	(3.10)
# Obs	8,832	75,886	56,017	56,017
Controls	Yes	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.989	0.960	0.989	0.969

Table 6 – Continued
Robustness Tests

Panel B: Alternative Factors

	Definition of Indicator			
	Estimated Scope 3 Emissions	Above Industry Median CapEx	Above Industry Median COGS	Below Country Median Ave Hourly Labor Cost
Variable	(1)	(2)	(3)	(4)
Ln(Scope 1) × Ln(Import) × Indicator	0.017	-0.001	0.015	-0.002
	(1.35)	(-0.05)	(0.95)	(-0.15)
Ln(Scope 1) × Ln(Import)	-0.028***	-0.025**	-0.015**	-0.022*
	(-2.69)	(-2.25)	(-2.45)	(-1.70)
Ln(Scope 1) × Indicator	0.011*	-0.025***	-0.007	0.003
	(1.84)	(-3.15)	(-1.60)	(1.49)
Ln(Import) × Indicator	-0.228	0.070	-0.179	-0.025
	(-1.45)	(0.36)	(-0.94)	(-0.14)
Ln(Scope 1)	0.086***	0.101***	0.105***	0.078***
	(5.66)	(6.83)	(6.45)	(5.29)
Ln(Import)	0.373***	0.294**	0.191**	0.302*
	(2.83)	(2.35)	(2.57)	(1.77)
Indicator	-0.193**	0.312***	0.098**	
	(-2.56)	(3.15)	(2.11)	
# Obs	75,886	75,862	75,886	35,706
Controls	Yes	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.989	0.989	0.989	0.988

Table 7:
Industry Carbon Emissions and Supplier Environmental Regulations

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

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

where *Indicator* is a binary indicator that alternately captures three different representations: (a) above-median emission industries measured based on the Fama-French 30 industries in Column (1), (b) countries with below-median enforcement of the environmental regulatory score (EER) in Column (2), and (c) below-median stringency of the environmental regulatory score (SER) in Column (3). The *Indicator* coefficient is not reported in the last two columns as it is subsumed by country × year fixed effect. *Controls* are as defined in Table 3, with the definition of all variables detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Definition of *Indicator*		
	Above-Median Emissions FF Industries	Country with Below-Median EER	SER
Variable	(1)	(2)	(3)
Ln(Scope 1) × Ln(Import) × Indicator	-0.026**	-0.006*	-0.006**
	(-2.15)	(-1.86)	(-2.00)
Ln(Scope 1) × Ln(Import)	-0.002	-0.004*	-0.004**
	(-0.27)	(-1.93)	(-1.98)
Ln(Scope 1) × Indicator	0.016	0.001	0.002
	(1.40)	(1.03)	(1.18)
Ln(Import) × Indicator	0.329**	0.082*	0.078*
	(2.19)	(1.83)	(1.93)
Ln(Scope 1)	0.075***	0.084***	0.084***
	(4.74)	(5.72)	(5.73)
Ln(Import)	0.038	0.055**	0.057**
	(0.40)	(2.10)	(2.14)
Indicator	-0.164		
	(-1.26)		
# Obs	75,886	72,569	72,569
Controls	Yes	Yes	Yes
Firm, CountryxYear FE	Yes	Yes	Yes
Adj. R^2	0.989	0.989	0.989

Table 8:
ESG Status and Sources of Emissions

This table reports regression results showing the effects of a firm's Scope 1, 2, and 3 emissions on its ESG status,

$$\begin{aligned} \textit{ESG Status}_{i,t+j} &= \alpha + \beta_1 \textit{Ln(Scope 1)}_{i,t} + \beta_2 \textit{Ln(Scope 2)}_{i,t} + \beta_3 \textit{Ln(Scope 3)}_{i,t} \\ &\quad + \beta'_{CS} \textit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t}. \end{aligned}$$

ESG Status is proxied by ESG ratings provided by Refinitiv, Sustainalytics, and MSCI, respectively, and the estimates of the models using these proxies are shown in Columns (1)-(3). *Controls* are as defined in Table 3, with the definition of all variables detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Dependent Variable: ESG Rating by Data Provider		
	Refinitiv	Sustainalytics	MSCI
Ln(Scope 1)	-0.955**	-0.055**	-0.185***
	(-2.47)	(-2.49)	(-2.70)
Ln(Scope 2)	0.006	-0.009	0.086
	(-0.02)	(-0.44)	(1.60)
Ln(Scope 3)	-0.542	0.008	-0.166
	(-0.79)	(0.25)	(-1.42)
# Obs	7,902	5,234	6,935
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Adj. R^2	0.520	0.839	0.416

Table 9:
Testing the Agency Channel

This table reports results from a variety of tests of the agency cost hypothesis based on the following triple-interaction model,

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

where *Ln(Scope 1)*, *Ln(Import)*, and *Ln(Scope 3)* denote a firm's direct emissions, supplier-induced emissions, and import volume, respectively. In Panel A, *Indicator* is denoted by *Agency*, that alternately represents the entrenchment index (E-Index), ESG-linked executive compensation, and the ESG reputation of the firm, CEO, and board levels. Panel B explores different mitigating governance mechanisms through government customers and the historical degree of greenness at the customer and blockholder levels. *Controls* are as defined in Table 3, with the definition of all variables detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

Panel A: Agency Issues

	Definition of *Agency*				
	E-Index	ESG-Linked Exec Pay	Firm Reputation	CEO Reputation	Board Reputation
Variable	(1)	(2)	(3)	(4)	(5)
Ln(Scope 1) × Ln(Import) ×Agency	-0.019***	-0.098**	-0.002**	-0.002*	-0.002*
	(-2.63)	(-1.99)	(-2.02)	(-1.70)	(-1.78)
Ln(Scope 1) × Ln(Import)	0.002	-0.009**	0.004	0.007	0.008
	(0.25)	(-2.51)	(0.94)	(1.37)	(1.47)
Ln(Scope 1) × Agency	0.001	-0.001	-0.002*	-0.009***	-0.009***
	(0.19)	(-0.05)	(-1.78)	(-2.73)	(-2.68)
Ln(Import) × Agency	0.204**	1.295*	0.019*	0.023*	0.023*
	(2.34)	(1.85)	(1.81)	(1.66)	(1.72)
Ln(Scope 1)	0.076***	0.086***	0.021*	0.140***	0.137***
	(4.60)	(5.49)	(1.76)	(4.87)	(4.76)
Ln(Import)	0.043	0.116***	0.101***	-0.084	-0.084
	(0.37)	(2.67)	(4.99)	(-1.25)	(-1.31)
Agency	-0.005	0.016	-0.036	0.115***	0.113***
	(-0.10)	(0.05)	(-0.66)	(2.94)	(2.88)
# Obs	70,956	65,168	65,101	64,034	64,566
Controls	Yes	Yes	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.989	0.987	0.988	0.988	0.988

Table 9 – Continued
Testing the Agency Channel

Panel B: Governance Mechanisms

	Definition of *Governance*		
	Govt Customer	Customer Greenness	Blockholder Greenness
Variable	(1)	(2)	(3)
Ln(Scope 1) × Ln(Import) × Governance	0.002**	0.244*	0.428*
	(2.57)	(1.86)	(1.94)
Ln(Scope 1) × Ln(Import)	-0.030***	-0.058**	-0.072**
	(-2.70)	(-2.56)	(-2.54)
Ln(Scope 1) × Governance	0.000	-0.025	-0.067
	(0.40)	(-0.36)	(-1.58)
Ln(Import) × Governance	-0.024**	-2.596*	-4.841*
	(-2.41)	(-1.78)	(-1.91)
Ln(Scope 1)	0.063***	0.097***	0.096***
	(2.94)	(3.22)	(5.60)
Ln(Import)	0.408***	0.667**	0.859**
	(3.01)	(2.59)	(2.57)
Governance	0.001	0.069	0.765
	(0.13)	(0.09)	(1.50)
# Obs	32,142	14,778	75,715
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Adj. R^2	0.990	0.990	0.989

Table 10:
Testing the Carbon-Efficiency Channel

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

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

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

	Dependent Variable			
	Total Emissions	Foreign Supplier	Pollution Abatement	Green Innovation
Variable	(1)	(2)†	(3)	(4)
Ln(Scope 1)	0.114***	0.006*	0.029**	-0.016
	(8.06)	(1.69)	(2.54)	(-0.64)
Ln(Scope 3)	0.494***		-0.005	-0.014
	(12.99)		(-0.13)	(-0.39)
Ln(Outsourced Emissions)	0.011		-0.019**	-0.049**
	(1.45)		(-1.99)	(-2.44)
# Obs	4,655	7,412	12,837	4,470
Controls	Yes	Yes	Yes	Yes
Firm, Year FE	Yes	Yes	No	Yes
Firm, Chemical, Year FE	No	No	Yes	No
Adj. R^2	0.984	0.826	0.399	0.751

Table 11:
Firm Profitability, Operating Efficiency, and Carbon Emissions

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

$$
\begin{aligned}
Performance_{i,t+1} \quad = \quad & \alpha + \beta_1 \mathit{Ln(Scope\ 1)}_{i,t} + \beta_2\ \mathit{Ln(Scope\ 3)}_{i,t} + \beta_3 \mathit{Ln(Outsourced\ Emissions)}_{i,t} \\
& + \beta'_{CS} \mathit{Controls}_{i,t} + \mathbf{FE} + \epsilon_{i,t},
\end{aligned}
$$

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

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

Table 12:
Outsourcing Premium and Reputational Risk

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

$$\begin{aligned} \textit{Stock Returns}_{i,m,t+1} \textit{ or RepRisk } \beta_{,i,t} &= \alpha + \beta_1 \textit{Ln(Scope 1)}_{i,t} + \beta_2\ \textit{Ln(Scope 3)}_{i,t} + \beta_3 \textit{Ln(Outsourced Emissions)}_{i,t} \\ &\quad + \beta_{CS}' \textit{Controls}^{\dagger}_{i,t} + \mathbf{FE} + \epsilon_{i,t}, \end{aligned}$$

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

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

Appendix Table A

Variable Definition and Data Source

Variable	Definition and Data Source
Measures of Firm-level Carbon Emissions and Imports	
Ln(Scope 1)	Ln(1 + Scope 1 emissions), where Scope 1 refers to direct GHG emissions that occur from sources controlled or owned by the firm (e.g., emissions associated with fuel combustion in boilers, furnaces, and vehicles). (Trucost)
Ln(Scope 3)	Ln(1 + upstream Scope 3 emissions), where upstream Scope 3 refers to indirect GHG emissions caused by activities of the firm but occur from the firm's suppliers. (Trucost)
Scope 1/Total Emissions	The ratio of Scope 1 emissions to total emissions (Scope 1 + Scope 2 + Upstream Scope 3), where Scope 2 emissions are indirect emissions from the generation of purchased electricity, steam, heating and cooling consumed by the reporting firm. (Trucost)
Scope 3/Total Emissions	The ratio of upstream Scope 3 emissions to total emissions (Scope 1 + Scope 2 + Upstream Scope 3). (Trucost)
%Δ Scope 1	(Scope 1 in year t − Scope 1 in year $t-1$)/Scope 1 in year $t-1$. (Trucost)
%Δ Scope 3	(Scope 3 in year t − Scope 3 in year $t-1$)/Scope 3 in year $t-1$. (Trucost)
$-\Delta$ Scope 1 Indicator	A binary variable equals 1 if %Δ Scope 1 is negative, and 0 otherwise. (Trucost)
Ln(Import)	Ln(1+the volume of shipment), where the volume of shipment is measured in TEU, scaled by 1,000, from suppliers in each exporting country. (Panjiva)
Ln(Outsourced Emissions)	Ln(1 + the aggregated amount of estimated GHG emissions imported from suppliers overseas). The aggregated amount of GHG emissions is measured as metric tons of CO_2 equivalent in the air from the production of all imported goods (per $1 million economic activity) over all shipment containers (in TEU) in a given year. In particular, we adopt the EIO-LCA GHG emission model from Carnegie Mellon University. We use the industry code corresponding to the imported goods and importer's primary industry codes as input and output industry codes, respectively, to approximate the outsourced carbon emission intensity at the shipment level. The imported good's industry is based on the six-digit HS Code from Panjiva and the HS to NAICS table from Peter K. Schott Website, and the importer's primary industry NAICS code is from Compustat. The EIO-LCA GHG emission model is constructed from the BEA Input-Output model, the IPCC Second Assessment Report, and other resources. (Panjiva & EIO-LCA & Peter K. Schott Website & Compustat)
Identification Variables	
Congress	A binary variable equals 1 for five years if the lagged state-level average Congress member environmental voting score increases more than three times the mean score increase over time (i.e., time-series average of score increase). The score must not revert back within the next three years and nor is driven by changes in firm locations. Congress member environmental voting score is defined as the number of pro-environmental votes each Congress member cast over the total number of climate change-specific environmental bills considered in the year. The average is then taken across each state to proxy for the overall environmental-consciousness of local legislators. (League of Conservation Voters)
Democrat	A binary variable equals 1 for the next two years after the close-call election win by Democratic candidates in year $t-1$ until the next election cycle. (League of Conservation Voters)
Republican	A binary variable equals 1 for the next two years after the close-call election win by Republican candidates in year $t-1$ until the next election cycle. (League of Conservation Voters)
Green Candidate	A binary variable equals 1 for the next two years after the close-call election win by a candidate with a lifetime environmental voting score of at least 60 in year $t-1$ until the next election cycle, where lifetime voting score is defined as the average of all the historical scores recorded for the candidate. (League of Conservation Voters)

Appendix A – Continued
Variable Definition and Data Source

Variable	Definition and Data Source
Identification Variables – Continued	
GHG Target	A binary variable equals 1 for five years starting from one year after the state enactment of executive or statutory targets to limit carbon emissions. (C2ES)
Onsite	A binary variable equals 1 for the next five years if the lagged increase in onsite inspection intensity is more than three times the average inspection increase in the state, where an onsite inspection intensity is defined as the total number of onsite air pollution compliance evaluations conducted by EPA across all facilities located in the state divided by the total number of emitting facilities in that state and year. (ICIS-Air)
Variables in Robustness Tests	
Ln(Import) Firm Level	Ln(1+the volume of shipment), where the volume of shipment is measured in TEU, scaled by 1,000, from all supplying countries to the firm. (Panjiva)
Ln(Downstream Scope 3)	Ln(1 + downstream Scope 3 emissions), where downstream Scope 3 refers to indirect GHG emissions caused by the firm but occur from the firm's customers. (Trucost)
Ln(Scope 2)	Ln(1 + Scope 2 emissions), where Scope 2 emissions are indirect emissions from the generation of purchased electricity, steam, heating, and cooling consumed by the reporting firm. (Trucost)
Ln(Scope 1 / TA)	Ln(1+Scope 1/total assets). (Trucost & Compustat)
Mechanism Variables	
E-Index	The entrenchment index contains four entrenchment provisions: staggered boards, poison pills, golden parachutes, and supermajority requirements for amendments of charters and bylaws and mergers. (Refinitiv ESG and Self-Construction)
ESG-Linked Exec Pay	A dummy indicator equals 1 if the firm has explicit metrics for ESG performances/targets in executive's compensation package and 0 if otherwise. (ISS Incentive Lab)
Firm Reputation	The decile ranking of a firm's ESG score, defined as a combined score based on the reported information in the environmental, social and corporate governance pillars with an ESG controversies overlay. (Refinitiv ESG)
CEO Reputation	The decile ranking of a CEO's previously associated firm ESG scores in the past 5 years, where associated firms are those in which the CEO has worked. For each CEO, an average ESG score is taken across all associated firms over years $t-5$ to $t-1$ and a decile ranking is assigned among all CEOs. (BoardEx & Refinitiv ESG)
Board Reputation	The decile ranking of directors' previously affiliated firm ESG scores in the past 5 years. For each director, an average ESG score is taken across all affiliated firms over years $t-5$ to $t-1$. An average score across all directors of the firm is then taken before a decile ranking is assigned. (BoardEx & Refinitiv ESG)

Appendix A – Continued
Variable Definition and Data Source

Variable	Definition and Data Source
Mechanism Variables – Continued	
Gov Customer	Sum of sales to all major government customers of a firm scaled by the total sales of the firm, where major customers are those accounting for at least 10% of the firm's total revenue. (Compustat Customer Segment)
Customer Greenness	Sum of sales to all major corporate customers with above industry-median ESG score, scaled by the total sales of the firm. (Revere & Refinitiv ESG)
Blockholder Greenness	Percentage of shares owned by blockholders with at least half of their portfolio holdings invested in green firms with above-median ESG scores, where a blockholder owns at least 5% if the firm's total shares outstanding. (FactSet Ownership & Refinitiv ESG)
ESG Score (Sustainalytics)	It is an overall ESG measure that captures a firm's ESG preparedness (an assessment of company management system and policies designed to manage material ESG risks), and ESG performance (evaluated based on quantitative metrics and analysis of controversial incidents that the firm may be involved in). (Sustainalytics)
ESG Score (MSCI)	It is a firm's final ESG rating derived from aggregating the weighted average of the key issue scores. The companies are ranked from best (AAA) to worst (CCC). The score is then is converted from letter grade to numerical scale 1 to 7, with 7 being the best and 1 being the worst. (MSCI)
Pollution Reduction Activities	
Total Emissions	Ln(1+Total Emissions), where Total Emissions is the sum of Scope 1, Scope 2, and upstream Scope 3 emissions. (Trucost)
Foreign Supplier	A binary variable that equals 1 if the firm has at least one foreign supplier in the following year and 0 if otherwise. (Revere)
Pollution Abatement	A binary variable that equals 1 if the firm reports at least one abatement activity in the following year that reduces a chemical production in one of the activity categories: 1) operating practices, 2) inventory control, 3) spill and leakage, 4) raw material modifications, 5) process modifications, 6) cleaning and degreasing, 7) surface preparation and finishing, and 8) product modifications, and 0 if otherwise. (EPA's Pollution Prevention database)
Green Innovation	Two-year ahead log number of green patents filed by the firm, where green patents are those classified as environmentally sound technologies by WIPO based on their IPC patent classes. (PATSTAT & WIPO)
Operating Performance, Reputational Risk, and Stock Returns	
EBIT Margin	Earnings before interest and taxes scaled by sales. (Compustat)
Asset utilization	The ratio of sales to total assets (Compustat).
ICC	Implied cost of equity calculated by taking the average of four different cost of equity estimates following the methodologies outlined in Claus and Thomas (2001), Gebhardt, Lee, and Swaminathan (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005). (IBES)
RepRisk β	The factor loading on the difference between the daily value-weighted return of two portfolios based on firm-level reputational risk score estimated using ESG-related news after controlling Fama-French-Carhart 4 Factors. (RepRisk & CRSP)
Stock Returns	Monthly stock returns. (CRSP)

Appendix A – Continued

Variable Definition and Data Source

Variable	Definition and Data Source
Control Variables (Main)	
Assets	Ln(1+Total Assets). (Compustat)
Tobin's Q	Total Assets plus the market value of equity minus the book value of equity minus deferred taxes divided by total assets. (Compustat)
Leverage	Total debt scaled by total assets. (Compustat)
ROA	Earnings before interest and taxes scaled by total assets. (Compustat)
SalesGrowth	Annual percentage change in sales. (Compustat)
Tangibility	Gross property, plant, and equipment scaled by total assets. (Compustat)
R&D	Cumulative R&D expenditure scaled by total assets over time since 1985 with a decay rate of 15% each year, where missing values for R&D expenditure are replaced by zero. (Compustat)
Control Variables (Implications)	
Age	Ln(1+current fiscal year of a firm − the first year the firm appears in Compustat). (Compustat)
Size	Ln(1+market capitalization). (Compustat)
BM	Book value of equity divided by market value of equity. (Compustat)
PPE	Ln(1+gross property, plant, and equipment). (Compustat)
CapEx	Capital expenditure divided by total assets. (Compustat)
Advertising Expenditure	Advertising expenditure divided by total assets. (Compustat)
Momentum	Cumulative monthly stock return over one-year period. (CRSP)
Return Volatility	Monthly stock return volatility over one-year period. (CSRP)
Beta	CAPM beta calculated over one-year period. (CRSP)
HHI	Herfindahl-Hirschman index measured by the summation of sales-based squared market share of each firm within the same 3-digit SIC industry. (Compustat)
Cash	Cash and marketable securities divided by (total assets − cash and marketable securities). (Compustat)
Income Volatility	Standard deviation of income before extraordinary items per share over the past five years. (Compustat)
ROE	Earnings before interest and taxes scaled by the book value of equity. (Compustat)
EPS Growth	The difference between current year and previous year earnings per share divided by the previous year earnings per share. (Compustat)

Table IA1:
Sample Distribution by Industry

This table reports the distribution of unique firms in our sample across Fama-French 30 industries. It shows the number of unique firms (# Firms) and the percentage of the total number of firms (% Firms) of each industry.

FFI 30 Code	Fama-French 30 Industry Classification	# Firms	% Firms
1	Food Products	44	2.99%
2	Beer & Liquor	7	0.48%
3	Tobacco Products	1	0.07%
4	Recreation	34	2.31%
5	Printing and Publishing	17	1.16%
6	Consumer Goods	26	1.77%
7	Apparel	24	1.63%
8	Healthcare, Medical Equipment, Pharmaceutical Products	138	9.39%
9	Chemicals	55	3.74%
10	Textiles	5	0.34%
11	Construction and Construction Materials	73	4.97%
12	Steel Works Etc	23	1.56%
13	Fabricated Products and Machinery	73	4.97%
14	Electrical Equipment	28	1.90%
15	Automobiles and Trucks	43	2.93%
16	Aircraft, ships, and railroad equipment	21	1.43%
17	Precious Metals, Non-Metallic, and Industrial Metal Mining	11	0.75%
18	Coal	9	0.61%
19	Petroleum and Natural Gas	66	4.49%
20	Utilities	61	4.15%
21	Communication	36	2.45%
22	Personal and Business Services	171	11.63%
23	Business Equipment	172	11.70%
24	Business Supplies and Shipping Containers	32	2.18%
25	Transportation	55	3.74%
26	Wholesale	68	4.63%
27	Retail	110	7.48%
28	Restaraunts, Hotels, Motels	26	1.77%
30	Everything Else	41	2.79%
Total		1470	100.00%

Table IA2:
Industry Carbon Emissions and Supplier Environmental Regulations

This table reports results using the quadruple-interaction model regression of the percentage change in Scope 3 emissions on the percentage change in Scope 1 emissions (*%ΔScope 1*), import volume (*Ln(Import)*), a binary indicator capturing the firm's industry emission level and its outsourcing-country environmental regulatory stringency, a binary indicator of decreasing Scope 1 emissions (*Indicator(−ΔScope 1)*), and their interaction terms. *Indicator* alternately captures three different representations: (1) above-median emission industries measured based on the Fama-French 30 industries in Column (1), (2) countries with below-median enforcement of the environmental regulatory score (EER) in Column (2), and (3) below-median stringency of the environmental regulatory score (SER) in Column (3). The *Indicator* coefficient is not reported in the last two columns as it is subsumed by country × year fixed effect. *Controls* are as defined in Table 3, with the definition of all variables detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Definition of *Indicator*		
	Above-Median Emissions FF Industries	Country with Below-Median EER	SER
Variable	(1)	(2)	(3)
%ΔScope 1 × Ln(Import) × Indicator × Indicator(−ΔScope 1)	-0.492**	-0.399**	-0.556***
	(-2.29)	(-2.15)	(-2.77)
%ΔScope 1 × Ln(Import) × Indicator	0.037	0.217*	0.228*
	(0.22)	(1.73)	(1.83)
%ΔScope 1 × Ln(Import) × Indicator(−ΔScope 1)	0.147	-0.245**	-0.235**
	(0.93)	(-2.19)	(-2.07)
%ΔScope 1 × Ln(Import)	-0.012	0.071	0.075
	(-0.09)	(1.18)	(1.21)
%ΔScope 1 × Indicator × Indicator(−ΔScope 1)	0.145***	0.004	0.006
	(3.01)	(0.26)	(0.36)
%ΔScope 1 × Indicator	-0.103***	0.003	0.001
	(-3.21)	(0.36)	(0.12)
%ΔScope 1 × Indicator(−ΔScope 1)	-0.156***	-0.070***	-0.070***
	(-4.31)	(-2.69)	(-2.67)
%ΔScope 1	0.176***	0.098***	0.098***
	(6.32)	(5.87)	(5.83)
Ln(Import) × Indicator × Indicator(−ΔScope 1)	-0.030	0.014	0.003
	(-0.47)	(0.43)	(0.12)
Ln(Import) × Indicator	-0.014	-0.030	-0.034
	(-0.35)	(-1.27)	(-1.40)
Ln(Import) × Indicator(−ΔScope 1)	0.015	0.004	0.006
	(0.27)	(0.29)	(0.42)
Ln(Import)	0.007	-0.008	-0.009
	(0.21)	(-0.83)	(-0.85)
Indicator(−ΔScope 1)	0.010	0.003	0.003
	(1.52)	(0.59)	(0.59)
Indicator	-0.008		
	(-1.19)		
# Obs	67,551	64,613	64,613
Controls	Yes	Yes	Yes
Firm, Country×Year FE	Yes	Yes	Yes
Adj. R^2	0.710	0.741	0.741

Table IA3: Mechanisms

This table reports results showing the various mechanisms through which changes in a firm's direct Scope 1 emissions asymmetrically affect its suppliers' emissions as captured in Scope 3. Panels A and B of this table employ the quadruple-interaction model regression of the percentage change in Scope 3 emissions on the percentage change in Scope 1 emissions (*%ΔScope 1*), import volume (*Ln(Import)*), a continuous measure capturing the various mechanisms driving the outsourcing behavior, and a binary indicator of decreasing Scope 1 emissions (*Indicator($-\Delta$Scope 1)*), and their interaction terms. Panel A presents results from tests of whether emission outsourcing is a manifestation of agency conflicts. The quadruple-interaction model incorporates a variable, *Agency*, that alternately represents the entrenchment index (E-Index), ESG-linked executive compensation, and the ESG reputation of the firm, CEO, and board levels. Panel B explores different mitigating governance mechanisms (*Governance*) through government customers and the historical degree of greenness at the customer and blockholder levels. *Controls* are as defined in Table 3, with the definition of all variables detailed in Appendix A. The regression model includes firm and country×year fixed effects (**FE**). All $t-$statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. *, **, *** are significance levels denoted at 10%, 5%, and 1% levels, respectively.

	Definition of *Agency*				
	E-Index	ESG-Linked Exec Pay	Firm Reputation	CEO Reputation	Board Reputation
Variable	(1)	(2)	(3)	(4)	(5)
	Panel A: Agency Issues				
%ΔScope 1 × Ln(Import) × Agency × Indicator(−ΔScope 1)	-0.005	-2.550*	-0.048*	-0.075*	-0.077*
	(-0.03)	(-1.67)	(-1.67)	(-1.65)	(-1.70)
%ΔScope 1 × Ln(Import) × Agency	0.264**	1.712	0.023	0.037	0.035
	(2.18)	(1.56)	(1.39)	(1.64)	(1.51)
%ΔScope 1 × Ln(Import) × Indicator(−ΔScope 1)	-0.263	-0.240	0.277	0.428	0.449
	(-0.72)	(-1.21)	(1.34)	(1.28)	(1.34)
%ΔScope 1 × Ln(Import)	-0.449**	-0.065	-0.157	-0.212	-0.207
	(-2.04)	(-0.57)	(-1.33)	(-1.34)	(-1.28)
%ΔScope 1 × Agency × Indicator(−ΔScope 1)	0.007	0.292**	0.003	0.021**	0.022**
	-0.27	(2.12)	(0.38)	(2.19)	(2.19)
%ΔScope 1 × Agency	-0.007	-0.215***	-0.009*	-0.024***	-0.024***
	(-0.45)	(-2.59)	(-1.81)	(-3.92)	(-3.97)
%ΔScope 1 × Indicator(−ΔScope 1)	-0.090*	-0.088***	-0.137**	-0.234***	-0.233***
	(-1.73)	(-3.31)	(-2.14)	(-3.47)	(-3.49)
%ΔScope 1	0.141***	0.136***	0.181***	0.253***	0.257***
	(4.38)	(7.94)	(5.07)	(6.23)	(6.21)
Ln(Import) × Agency × Indicator(−ΔScope 1)	-0.001	0.044*	0.005	-0.005	-0.006
	(-0.31)	(1.83)	(0.64)	(-0.54)	(-0.61)
Ln(Import) × Agency	0.073	-0.188	-0.007	-0.005	-0.005
	(1.08)	(-0.53)	(-1.41)	(-0.93)	(-0.86)
Ln(Import) × Indicator(−ΔScope 1)	-0.039	-0.125	-0.030	0.043	0.045
	(-1.09)	(-0.49)	(-0.55)	(0.65)	(0.68)
Indicator(−ΔScope 1)	0.011*	0.013**	0.005	0.000	0.000
	(1.74)	(1.99)	(0.84)	(0.06)	(0.01)
Ln(Import)	-0.119	0.021	0.048	0.030	0.029
	(-0.97)	(0.52)	(1.47)	(0.81)	(0.78)
Agency	0.063	-0.003	-0.001	-0.003	-0.002
	(0.88)	(-0.11)	(-0.89)	(-1.20)	(-1.09)
# Obs	63,506	60,721	59,705	58,344	58,849
Controls	Yes	Yes	Yes	Yes	Yes
Firm, Country × Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.686	0.685	0.728	0.724	0.722

Table IA3 Mechanisms – Continued

	Definition of *Governance*		
	Govt Customer	Customer Greenness	Blockholder Greenness
Variable	(1)	(2)	(3)
	Panel B: Governance Mechanisms		
%ΔScope 1 × Ln(Import) × Governance × Indicator(−ΔScope 1)	0.047**	1.181**	0.971*
	(2.46)	(2.26)	(1.72)
%ΔScope 1 × Ln(Import) × Governance	-0.025**	-0.835*	-0.680
	(-2.10)	(-1.97)	(-1.54)
%ΔScope 1 × Ln(Import) × Indicator(−ΔScope 1)	-0.463***	-0.329***	-0.288**
	(-2.93)	(-3.26)	(-2.33)
%ΔScope 1 × Ln(Import)	0.169	0.105	0.161*
	(1.64)	(1.48)	(1.70)
%ΔScope 1 × Governance × Indicator(−ΔScope 1)	-0.008*	-0.186	0.302
	(-1.94)	(-0.58)	(1.20)
%ΔScope 1 × Governance	0.004**	0.250	0.034
	(1.99)	(1.39)	(0.21)
%ΔScope 1 × Indicator(−ΔScope	-0.046	-0.039	-0.108**
	(-1.47)	(-0.60)	(-2.13)
%ΔScope 1	0.083***	0.100***	0.057*
	(3.62)	(3.09)	(1.74)
Ln(Import) × Governance × Indicator(−ΔScope 1)	-0.003	-0.078	-0.030
	(-0.93)	(-0.55)	(-0.25)
Ln(Import) × Governance	0.005***	0.153	0.093
	(3.14)	(1.52)	(1.43)
Ln(Import) × Indicator(−ΔScope 1)	-0.003	-0.020	0.014
	(-0.13)	(-0.75)	(0.66)
Indicator(−ΔScope 1)	0.002	0.012	-0.014***
	(0.36)	(1.17)	(-2.96)
Ln(Import)	-0.023	-0.017	-0.025*
	(-1.42)	(-1.07)	(-1.71)
Governance	-0.001	0.003	0.021
	(-1.38)	(0.03)	(0.88)
# Obs	31,644	14,667	67,422
Controls	Yes	Yes	Yes
Firm, Country × Year FE	Yes	Yes	Yes
Adj. R^2	0.798	0.763	0.729

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