How Does Competition Affect Firms' Carbon Performance? Firm-Level Evidence from Tariff Cuts

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Abstract

We examine how changes in competition affect firms' carbon performance. Exploiting reductions in import tariffs as a quasi-natural experiment that increases competitive pressure, we find that stronger competition improves firms' carbon efficiency through lower Scope 1 and 2 emission intensities. These results remain robust to alternative specifications, heterogeneous treatment effects, and placebo tests. Mechanism analyses indicate systematic differences in firms' strategic responses. High-emission-intensity firms tend to adopt visible environmental actions and reallocate resources toward intangible assets, whereas low-emission firms increase investment and internal financing activities. Overall, our results highlight competition as a determinant of corporate decarbonization, suggesting that market forces can complement regulatory approaches to improving firms' environmental performance.

Keywords: Carbon emissions, environmental performance, competition, import tariffs, quasi-natural experiment

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1 Introduction

President Trump's tariff policy following his re-election in 2024 has revived debate about its effects on global competition and corporate implications. While tariffs are often analyzed in terms of efficiency and welfare, their broader environmental impacts remain underexplored. In an era where climate change demands urgent attention and where transition risks increasingly influence firm decisions, understanding how tariff-induced competitive pressures influence carbon performance has never been more critical.

In this paper, we investigate how changes in competition affect firms' carbon performance, focusing on emission intensities. In addition to identifying the average effect, we examine how firms' strategic responses to competition vary according to their initial emission intensities, which may reflect differences in technological flexibility, financial capacity, and reputational exposure.

From a theoretical perspective, the impact of competition on firms' carbon performance is ambiguous. First, low-emission strategies may not always align with shareholder value. In this view, environmental investments can represent agency costs if managers pursue personal interests, such as enhancing their reputation or appeasing stakeholders, rather than maximizing firm value (e.g., Krüger 2015). As competition improves corporate governance and reduces agency costs, managers become less likely to engage in such green investments (e.g., Giroud and Mueller 2010, 2011). Moreover, even when environmental projects are shareholder-value enhancing, competition raises financing frictions by increasing the cost of debt (Valta 2012) and cash flow volatility (Abdoh and Varela 2017), which reduces firms' financial flexibility and may push them to prioritize short-term performance over long-term environmental goals (Asker et al. 2014). Following this reasoning, the relationship between competition and firms' carbon performance is positive, resulting in higher emission intensities.

Second, competition can also provide incentives for firms to improve their environmental performance. Firms facing stronger competitive pressure may pursue differentiation strategies aimed at enhancing brand value through innovation, product features, and quality (Porter 1985), which include environmental improvements (e.g., Flammer 2015).

By lowering their emission intensities, firms may ease competitive pressure by attracting customers and investors, thereby gaining pricing power (e.g., Servaes and Tamayo 2013) and reducing the cost of capital (e.g., Cheng et al. 2014; Barber et al. 2021). Stakeholder-oriented arguments further reinforce this perspective. Growing environmental concerns among customers, investors, and regulators encourage firms to adopt greener practices (e.g., Henriques and Sadorsky 1999; Eesley and Lenox 2006), which strengthen trust and loyalty (e.g., Lins et al. 2017) and matter particularly in competitive markets (Delmas and Toffel 2008). From this perspective, the relationship between competition and firms' carbon performance is negative, implying lower emission intensities.

Third, competition may also encourage firms to engage in more symbolic behavior. In this case, firms respond through greenwashing, for example, by making environmental claims or adopting disclosure-oriented strategies without substantively reducing emissions (Kathan et al. 2025). Such behavior suggests that competition influences communication strategies rather than actual environmental outcomes, adding further ambiguity to how competitive shocks translate into operational carbon performance.

A central challenge in examining the effect of competition is that standard proxies such as the Herfindahl index may not adequately capture its influence on firms' carbon performance, given the multifaceted structure of the underlying mechanisms. To address this concern, we rely on exogenous variation in competition generated by significant reductions in import tariffs. Lower tariffs make foreign goods relatively cheaper than domestic products, thereby intensifying industry-level competitive pressure on domestic firms (e.g., Frésard 2010; Frésard and Valta 2015). This setting provides a quasi-natural experiment that allows us to estimate the causal impact of increasing competition on firms' emission intensities. We identify 19 large import tariff reductions between 2003 and 2023 across industries in the United States, affecting 104 firms within our sample of 2,677 publicly listed firms. Importantly, we do not observe any systematic relationship between tariff cuts and observable industry characteristics, reducing the risk that their timing reflects industry-specific developments.

We find that, on average, sample firms significantly reduce their Scope 1 emission intensity (emissions from firms' own production processes), Scope 2 emission intensity (emissions from purchased energy such as electricity and heat), and combined Scope 1&2 emission intensity following a tariff reduction within their industry. Specifically, we observe a negative average differential change in firms' carbon emission intensities from the pre- to post-treatment period for those firms exposed to tariff cuts, relative to the change in carbon emission intensities in the control group. In terms of magnitude, our findings illustrate economically and environmentally meaningful reductions. The estimated declines in emission intensities are around 23.7% for Scope 1 and 13.1% for Scope 2, corresponding to a 20.7% decline in combined Scope 1&2 emission intensity.

In our main specification, the control group includes both firms that never experienced a tariff cut and treated firms in years without exposure to a tariff reduction (Frésard 2010). Including already treated firms in the control group, however, may contaminate the counterfactual, as their outcomes could already reflect adjustments in emission policy (e.g., Goodman-Bacon 2021). We therefore construct alternative counterfactuals using never-treated firms and treated firms observed only until their first treatment. Further, we complement these tests with nearest-neighbor matching based on pre-treatment firm characteristics, including scope-specific emission intensities, firm size, industry competition level, and state of headquarters. The matched sample shows no statistically significant differences in these characteristics in the pre-treatment period. Across all specifications, the results remain consistent with our baseline estimates.

To address concerns that the results might be driven by omitted industry-year disturbances rather than tariff-induced competitive pressure, we conduct an industry placebo exercise using randomization inference. We preserve the number of treated industries in each year, randomly reshuffle treatment assignment across industries within a year, and re-estimate the baseline model. Across 1,000 random assignments, the placebo coefficients are centered around zero, while the baseline estimates lie in the extreme tails of the placebo distributions, yielding small two-sided randomization-inference p-values. This evidence points to a causal effect of tariff cuts, since estimates of comparable magnitude are rarely observed under placebo reallocations.

In addition, we employ an interaction-weighted event-study difference-in-differences estimator (Sun and Abraham 2021) to test for heterogeneous treatment effects, pre-trends, and dynamic post-treatment responses. The analysis shows that the effects materialize primarily in the period immediately following the tariff cut, with no evidence of differential pre-trends.

To further rule out alternative explanations, we examine whether the results could be driven by positive competitive spillovers or whether efficiency gains from competition are offset by increased production that raises absolute emissions. For both tests, we find no evidence in support of these concerns. Since our results may also depend on the choice of emission data provider, in our case Trucost, and may therefore reflect provider-specific modeling assumptions, we replicate the analysis using emission measures from LSEG. The results remain highly consistent across both datasets, which mitigates concerns that our findings are driven by data-construction choices. Finally, when we define tariff cuts over longer windows (three and six years before and after the event), we continue to find negative effects on emission intensities, but the estimates are smaller and less precisely estimated as the event window expands. However, these longer-horizon estimates are less likely to be causal, as firms may anticipate tariff changes and adjust their behavior prior to implementation, while additional policy and market responses unfold afterward, increasingly confounding the initial tariff-cut shock with endogenous firm adjustments (e.g., Goolsbee and Syverson 2008; Ellison and Ellison 2011).

Building on the baseline findings and the theoretical framework, we evaluate whether firms with different emission intensities respond in distinct ways. Our analysis reveals that firms' strategic responses vary systematically. Firms with particularly high emission intensities, that is, those above the 90^{th} percentile in the respective distribution, tend to adopt visible environmental strategies, such as emissions trading, offering eco-friendly products, or reporting green sites or environmentally friendly buildings, while avoiding more binding commitments, such as environmental partnerships. These actions may reflect symbolic adjustments that are easier to implement and more visible to stakeholders. However, these results are also consistent with underlying technical constraints that limit the scope for immediate substantive abatement. Supporting this interpretation, we do not observe a higher likelihood of emission-related misconduct among these firms, as we would expect under purely symbolic or opportunistic behavior.

For firms with lower emission intensities, that is, those below the sample median of the distribution, competition already leads to an increase in investment activity. This increase also extends to environmental expenditures, indicating that firms have stronger incentives or needs to redirect resources toward environmental improvements as their emission intensities rise. Changes in balance-sheet composition follow a similar gradient. Tangible assets begin to decline at moderate emission intensities (around the sample median), whereas increases in intangible assets emerge only among firms above the 95$^{\text{th}}$ percentile, consistent with reallocations toward process upgrades, technological capabilities, or other non-R&D intangibles.

In terms of financing, we do not detect higher reliance on external capital markets following tariff cuts. Instead, internal liquidity becomes increasingly important as emission intensity rises. This reliance likely reflects the higher external financing costs faced by high-emission firms (e.g., Valta 2012; Chava 2014) as well as the greater flexibility provided by internal funds when competitive pressures require adjustments that cannot easily be deferred (e.g., Frésard 2010). Overall, the results are consistent with firms adapting in ways that enhance their environmental performance and support long-term decarbonization, even if the exact channels cannot be fully identified.

Our paper makes three main contributions. First, we provide causal evidence that tariff-induced increases in competition reduce firms' carbon emission intensities. Thereby, we contribute to a growing literature on competition and environmental performance (e.g., Flammer 2015; Duanmu et al. 2018; Aghion et al. 2023; Pursiainen et al. 2025), with a specific focus on firms' carbon performance.

Second, we show that firms' responses to stronger competition vary systematically with their initial emission profiles. Lower-emission-intensity firms increase investment activity and internal financing, whereas higher-emission-intensity firms reallocate resources away from tangible assets toward intangibles and adopt more visible environmental actions.

Third, we contribute to the literature on how markets influence firms' climate outcomes. While prior work has largely emphasized the pricing of climate risk in financial markets (e.g., Bolton and Kacperczyk 2021; Aswani et al. 2023; Bolton and Kacperczyk 2023; Hsu et al. 2023; Zhang 2025), we show that product-market competition can also discipline firms by strengthening incentives to improve emissions management. This channel is particularly relevant when carbon prices do not fully internalize environmental externalities and climate policies remain incomplete (e.g., Stiglitz 2019). At the same time, this mechanism does not operate uniformly. Only sizable increases in competitive pressure lead to meaningful emission reductions, while smaller changes produce limited effects.

The remainder of the paper proceeds as follows. Section 2 introduces the conceptual framework. Section 3 describes the sample and data, and Section 4 outlines the identification strategy. Section 5 presents the main results, including alternative counterfactuals, dynamic effects, and robustness tests. Section 6 examines firm-level responses to competitive pressure by firms' emissions profiles. Section 7 discusses the role of shock magnitude for competition intensity and our findings. Finally, Section 8 concludes.

2 Conceptual framework: Competition and carbon emission

Competition is a cornerstone of market economies and a central determinant of firm behavior. Extensive research documents effects of competition on both financial and real outcomes, including corporate governance (Giroud and Mueller 2010, 2011), firm performance (Nickell 1996; Bloom and Van Reenen 2007), innovation (Aghion et al. 2005), capital structure (Campello 2003; Xu 2012), stock returns (Hou and Robinson 2006), and investment (Frésard and Valta 2015; Jiang et al. 2015). More recently, attention has shifted to how competition influences firms' social and environmental performance (e.g., Flammer 2015; Duanmu et al. 2018; Aghion et al. 2023; Pursiainen et al. 2025). Building on this literature, we focus on carbon emission intensities as a key dimension of environmental performance that relates to firms' financial and strategic decisions, including resource allocation, investment horizons, and responses to competitive pressure. This section develops the theoretical channels through which competition may influence firms' carbon emission intensities, emphasizing mechanisms that can drive both reductions and increases in emissions.

A first strand of theory suggests that competition may increase firms' carbon emission intensities. Agency theory views Environmental, Social, and Governance (ESG) initiatives as manifestations of managerial discretion that do not necessarily enhance shareholder value (Friedman 1962; Krüger 2015). In this view, managers may pursue social or environmental goals that provide private benefits, such as reputation or prestige, but impose costs on shareholders (Jensen and Meckling 1976). Excessive attention to Corporate Social Responsibility (CSR) can also divert financial and managerial resources away from core business responsibilities (Jensen 2001). In this context, competition acts as a disciplinary mechanism that constrains managerial discretion and reduces agency costs (Giroud and Mueller 2010, 2011). Consequently, when environmental investments are not clearly aligned with shareholder interests, firms under stronger competitive pressure are more likely to scale back or avoid such initiatives. However, this disciplinary role of competition may be less pronounced in firms with stronger governance structures, where environmental initiatives are more likely to align with shareholder interests (Ferrell et al. 2016).

A related mechanism emphasizes that competition exacerbates firms' financial constraints. Intensified product market pressure increases earnings volatility and cash-flow risk (Irvine and Pontiff 2008; Abdoh and Varela 2017), which in turn raises the cost of debt (Valta 2012). For example, Xu (2012) shows that firms rely more on equity issuance after facing an increase in competition. Because green projects are typically capital-intensive and require long-term commitments, tighter financing conditions may crowd out such investments. Under these conditions, firms prioritize liquidity and short-term financial stability over long-term environmental projects with uncertain payoffs (e.g., Asker et al. 2014). This short-term orientation aligns with evidence that stronger product-market competition can shorten firms' strategic planning horizons, as shown by declines in R&D investment and innovation among US firms exposed to Chinese import competition (Autor et al. 2020). In this regard, competitive pressure limits firms' ability to undertake long-term environmental investments. As a result, firms are more likely to delay or forgo investments in cleaner technologies, which in turn can slow the transition to low-carbon production processes and lead to persistently higher emissions.

Consistent with these arguments, empirical evidence supports the view that stronger competition can worsen environmental outcomes. For example, evidence from China indicates that stronger competitive pressure negatively affects firms' environmental performance, particularly when firms adopt a cost-leader strategy (Duanmu et al. 2018).

In contrast, a second line of reasoning emphasizes that competition can enhance firms' carbon performance. According to Porter's theory of competition, firms respond to competitive pressure by either cutting costs or pursuing differentiation strategies (Porter 1985). In advanced economies, exposure to low-cost rivals often renders cost leadership less viable, instead pushing firms toward differentiation based on quality, innovation, and brand reputation (Bernard et al. 2006; Pierce and Schott 2016; Bao and Chen 2018). Environmental performance has become an important dimension of such differentiation, allowing firms to attract environmentally conscious customers and investors, enhance pricing power (Elfenbein and McManus 2010; Servaes and Tamayo 2013; Flammer 2015), and lower the cost of capital (Cheng et al. 2014; Barber et al. 2021; Pedersen et al. 2021). Thus, competition can create financial and strategic incentives for firms to reduce emissions as part of a broader effort to strengthen their competitiveness.

A complementary mechanism is provided by stakeholder theory, which emphasizes the interdependence between firms and their customers, employees, investors, regulators, and local communities (Freeman 1984). Competitive markets amplify the importance of these relationships, as firms risk losing market share, talent, or financing if they fail to meet stakeholder expectations. Growing awareness of climate change increases these pressures, encouraging managers to adopt greener practices (Henriques and Sadorsky 1999; Eesley and Lenox 2006; Delmas and Toffel 2008). Firms with strong CSR profiles benefit from greater stakeholder trust and loyalty (Lins et al. 2017), which can enhance the stability of their cash flows. This also strengthens investor confidence, leading investors to reward credible environmental performance with more favorable financing conditions (Cheng et al. 2014; Barber et al. 2021).

Empirical evidence supports these mechanisms. For example, Flammer (2015) shows that an increase in foreign competition leads US firms to expand their CSR activities in order to differentiate themselves from rivals. Other studies find that firms in more competitive industries are more likely to adopt stronger CSR practices and to innovate more, which also reduces pollution (Fernández-Kranz and Santaló 2010; Aghion et al. 2023). Similarly, Asgharian et al. (2023) find that environmental performance propagates among competitors through competitive pressure and technological spillovers, particularly when a rival improves.

While competition can create incentives for firms to differentiate on environmental performance and respond to stakeholder pressure, these mechanisms are not without limitations. Differentiation may be less effective in industries where emissions are intrinsic to the production process, such as oil and gas, making it difficult for firms to compete credibly on environmental performance (Grinstein and Larkin 2025). In addition, stakeholder pressure relies on accurate and transparent information, yet disclosure quality declines substantially from Scope 1 to Scope 3 emissions, where measurement and verification are highly uncertain (Matsumura et al. 2014; Busch et al. 2022). Such information frictions can weaken the ability of stakeholders and investors to assess firms' true environmental performance, increasing the risk that firms rely on symbolic actions rather than substantive improvements. Firms may therefore engage in "greenwashing" by making environmental claims or adopting disclosure-oriented strategies without meaningful emission reductions (e.g., Lyon and Maxwell 2011; Marquis et al. 2016). As a result, firms' apparent environmental performance may improve even though no substantive operational changes occur (Kathan et al. 2025).

Taken together, the theoretical channels point in opposing directions. Agency and financial-constraint perspectives predict higher emissions by discouraging long-term investments, whereas differentiation and stakeholder perspectives highlight incentives for emission reductions. At the same time, industry constraints, limited disclosure, and greenwashing add further complexity to the issue. Given these competing channels, the effect of competition on firms' emissions remains uncertain. In Section 4, we develop an identification strategy to identify the causal effect of competition on firms' carbon emissions.

3 Data and sample construction

The sample construction starts with the merged Center for Research in Security Prices (CRSP)-Compustat database. We restrict our sample to US public firms with common shares outstanding (CRSP share codes 10 or 11) that are listed on major stock exchanges, specifically the NYSE, NASDAQ, and AMEX. Further, we exclude firms belonging to the financial (i.e., SIC codes 6000–6999) and utility industries (i.e., SIC codes 4900–4999), as well as government entities (i.e., SIC codes $\geq$ 9000). Moreover, we obtain all our firm-specific variables for the sample firms from this database. The sample period covers 2003–2023, reflecting the availability of the emission data used.

To assess firms' carbon performance, we use Scope 1 and Scope 2 emissions data from Trucost Environmental. Trucost provides one of the most comprehensive and methodologically transparent datasets on corporate emissions and is widely used by investors, regulators, and researchers (Aswani et al. 2023; Zhang 2025). Scope 1 measures direct emissions from sources owned or controlled by the firm, such as fuel combustion and industrial processes, while Scope 2 captures indirect emissions from purchased electricity, steam, or cooling.[1] We focus on emission intensity (emissions divided by revenue) rather than absolute emissions, as intensity adjusts for differences in firm scale and operational output and thus better captures carbon efficiency (e.g., Aswani et al. 2023). Absolute emissions are closely tied to firms' production output. If competition leads to a decline in firms' average output, total emissions may fall mechanically even if carbon efficiency remains unchanged or worsens. From an environmental perspective, this distinction is

[1]We do not consider Scope 3 emissions, which occur outside a firm's direct operations, because of their limited data quality and comparability. For example, Busch et al. (2022) show that the consistency of corporate GHG disclosures diminishes progressively from Scope 1 to Scope 3, reflecting the greater uncertainty associated with indirect emissions reporting. Nevertheless, we also report our baseline estimation results for Scope 3 emissions, where Scope 3 upstream covers purchased goods and services and Scope 3 downstream covers product use, transportation, and waste disposal, in Online Appendix B, Table OB1.

crucial because a decline in total emissions, driven by lower output, does not represent genuine improvements in firms' carbon performance or progress toward decarbonization. In contrast, changes in output levels do not directly affect emission intensities, which capture how efficiently firms generate economic value relative to their carbon footprint. For robustness, we also conduct additional analyses using absolute emissions and find no opposing effects that would contradict our main results.

Table 1 reports summary statistics for the main variables used in our analysis. Column "Obs." shows that the sample comprises 21,400 firm-year observations. Although this number may seem small for a sample period of more than 20 years, it reflects Trucost's limited coverage, which expands substantially over time.[2]

Regarding our carbon emission variables, both Scope 1 and Scope 2 emission intensities exhibit pronounced positive skewness, with their mean values exceeding their medians. We also construct Scope 1&2 intensity, defined as the sum of a firm's Scope 1 and Scope 2 emissions divided by its revenues, which provides a consolidated measure of carbon intensity across direct and indirect emissions. Overall, all carbon-emission variables show high standard deviations, indicating considerable variability across firms. To address both skewness and dispersion, we apply natural logarithmic transformations to these variables in the subsequent analysis.

As firm-specific control variables, we employ several characteristics that may influence carbon performance (e.g., Azar et al. 2021), including firm size, valuation, asset structure (net property, plant, and equipment to total assets), leverage, and asset liquidity (cash and short-term investments to total assets). Furthermore, we employ the Herfindahl-Hirschman Index (HHI) as a measure of industry competition.

[Table 1 about here]

4 Identification strategy

Analyzing the impact of competition on firms' carbon performance poses several empirical challenges. For example, employing common competition proxies—such as the HHI or the Lerner Index—in regression models may result in spurious correlations, even when

[2]Coverage increases from 409 firm-years in 2003 to 1,833 firm-years in 2022 in our sample.

incorporating control variables and fixed effects. In this regard, there are at least four potential concerns that can create biased estimates.

First, reverse causality may arise if firms with better carbon performance influence competition levels, rather than competition driving improvements in environmental outcomes. Firms with lower carbon emissions are positively associated with firm valuation and profitability (e.g., Matsumura et al. 2014), which may enhance their market power and change the competitive dynamics within an industry. Second, omitted variable bias may result from unobserved factors that affect both competition and firms' carbon performance. Factors such as shifting consumer preferences or industry-wide shocks could simultaneously influence both, leading to biased coefficients. Third, measurement errors in competition proxies may bias estimates, as indices like the HHI omit non-price dimensions such as low-carbon innovation or competition for climate-oriented investors, and generally exclude private firms due to data limitations. Finally, dynamic feedback effects may occur when competition and carbon performance influence each other over time, creating persistence in both variables, which can cause a misleading relationship.

To address endogeneity concerns, we use a quasi-natural experiment in which tariff cuts introduce random variation in industry competition levels. Because tariff reductions occur at different times across industries, we capture multiple exogenous shocks over time. The underlying mechanism is that a sudden reduction in import tariffs increases competitive pressure by lowering the relative price of foreign products compared to domestic ones (e.g., Frésard 2010).[3]

Following Frésard (2010) and Frésard and Valta (2015), we define tariff rates for an industry-year (three-digit SIC code) as the ratio of duties collected (ad valorem tariff) to the value of imports (free-on-board value). Import tariff data are taken from Schott (2008) and Schott's website[4], and are provided at the product level. Products imported

[3]The variation in tariff rates as a measure of competitive change within an industry has been applied in several studies across different contexts, including cash holdings (Frésard 2010; Alimov 2014), corporate investment (Frésard and Valta 2015; Jiang et al. 2015), plant-level productivity (Lileeva and Trefler 2010), debt (Valta 2012; Xu 2012), corporate social responsibility (Flammer 2015), mergers & acquisitions (Srinivasan 2020), and private equity (Cumming et al. 2022), CEO compensation (Bakke et al. 2022), and workplace safety (Islam et al. 2025).

[4]`https://sompks4.github.io/`

into the US are classified under the Harmonized System (HS) established by the World Customs Organization (WCO), with each product assigned a unique ten-digit HS code. We use the concordance table developed by Pierce and Schott (2012) to map these HS codes to three-digit SIC codes.

Using the constructed industry-year tariff rates, we define a "tariff cut" (TC) as a reduction within an industry-year that is at least twice (or, alternatively, three times) the average negative change in the industry over the sample period. To ensure that these cuts reflect meaningful and persistent increases in the competition level, we exclude those followed by equally large tariff increases within the subsequent three years. We also omit cases where the tariff rate is smaller than 1%. Applying this definition to the available tariff data from 1989 to 2023 identifies 46 tariff cuts. Because environmental data coverage for our variables begins only in 2003, the analysis focuses on the 19 cuts that occurred thereafter. These tariff cuts affected a total of 104 individual firms operating in 11 distinct industries within our sample of 2,677 publicly listed firms.

Figure 1 plots the distribution of tariff cuts over the sample period. The frequency is relatively stable in most years but rises noticeably in 2020 and 2021. This pattern is consistent with recent US trade history; for example, the "Phase One" trade agreement in early 2020 reduced tariffs on approximately $120 billion of Chinese goods[5].

[Figure 1 about here]

Looking more closely at the tariff cuts, most occurred in manufacturing industries, with one exception in the oil industry. For the affected industries, the average tariff rate declined from 6.73% in the year before the cut to 5.77% in the year after, representing a reduction of approximately 14.3%. In comparison, control industries with no tariff cuts over the sample period had average tariff rates of 4.58% in the year before and 4.52% in the year after, when matched to the corresponding years of the treated industries. When focusing on the size of tariff changes in the implementation years, the average cut amounts to 18.13%, with a median of 12.48%.

[5] `https://www.reuters.com/world/whats-us-china-phase-1-trade-deal-signed-2020-2025-01-21/` (last accessed August 11, 2025)

When comparing our empirical setting with other studies in terms of the number and magnitude of tariff cuts, we first note that the 19 tariff cuts identified in our sample are, due to our shorter observation period, reasonable relative to the 91 in Frésard and Valta (2015) (1974–2005) and the 34 in Flammer (2015) (1992–2005). Second, our average tariff rates are higher, while the magnitude of tariff reductions is smaller compared to Frésard and Valta (2015), reflecting the fact that our sample period also includes years characterized by increased protectionism. More specifically, Frésard and Valta (2015) report an almost 50% decrease for treated industries in their sample, from 4.60% to 2.57%. Thus, to assess whether our identified tariff cuts are of substantial magnitude, we follow prior studies that compare them to the Canada-US Free Trade Agreement (FTA), which is commonly regarded as a significant event in trade liberalization. The FTA reduced the average tariff rate for Canadian products from about 4% in 1988 to roughly 3% in 1990, 2% in 1992, and 1% in 1996 (Trefler 2004). In this context, we consider our average tariff cuts of around one percentage point to be substantial.

To further characterize our sample, we compare firms that experienced tariff cuts (treated) and those that were never exposed to any tariff reduction during the sample period, focusing on their carbon performance and firm characteristics. Table 2 reports the mean, median values, and standard deviations of the variables for treated firms (Columns "Treated firms") and never treated firms (Columns "Untreated firms"). For the carbon emission variables, we apply the natural logarithm of one plus the ratio of Scope emissions to firm revenue (tCO_2e per USD 1 million in revenue). Treated firms exhibit higher log-transformed Scope 1, Scope 2, and combined Scope 1&2 emission intensities relative to untreated firms. In terms of firm characteristics, treated firms tend to be larger (Ln(1+Assets)), less profitable (EBITDA-to-assets), have more tangible assets (Net PPE-to-assets), and operate in more competitive industries (HHI).

[Table 2 about here]

Figure 2 incorporates the time dimension to assess the parallel-trends assumption underlying our quasi-natural experiment. Specifically, it plots the evolution of Ln(1+Scope 1 intensity) (Subfigure (a)) and Ln(1+Scope 2 intensity) (Subfigure (b)) on the y-axis for treated firms (solid line) and control firms (dashed line) around tariff cuts.[6] Following Frésard (2010), we define control firms as both never-treated firms and treated firms in years without tariff-cut exposure, which we also adopt in the empirical analysis in the next section.

The graphical analysis reveals two key patterns. First, treated firms exhibit higher intensity levels compared to control firms. Second, only treated firms show a decline in emission intensities around tariff cuts, whereas control firms remain relatively stable, thus supporting the parallel-trends assumption in the pre-treatment period. The graphical illustration indicates that treated firms respond to an exogenous increase in competition from tariff cuts, providing preliminary evidence that stronger competition is associated with improvements in carbon performance.[7]

[Figure 2 about here]

We also note that both analyses reveal differences in the levels of our carbon variables between the groups, which we address in the subsequent empirical analysis by employing a matching approach as an additional component of our identification strategy.

To strengthen our identification strategy and mitigate concerns that our identified tariff cuts are the response of industry-specific developments, such as industry profitability, we regress tariff cuts on the average industry-level values of all control variables introduced in the previous section.[8] Table 3 shows that observable industry characteristics are unrelated to tariff cuts, which equal one in the year of a cut and zero otherwise. In particular, none of the industry-level variables are associated with our identified tariff cuts or predict their occurrence. While this does not rule out the influence of unobserved industry developments, the evidence suggests that tariff cuts are unlikely to be systematically driven by industry trends.

[6] We focus on these two subfigures because the pattern for combined emissions closely mirrors that in Subfigure (a).

[7] Note that the parallel trends assumption in our setting is independent of the functional form of emission intensity, which could otherwise affect the credibility and applicability of our empirical design (Roth and Sant'Anna 2023). This implies that the assumption also holds if we use emission intensity without the log transformation. We provide these figures in Online Appendix A (Figure OA1).

[8] In untabulated results, we replicate the test using median industry-level values and obtain similar results.

[Table 3 about here]

5 The impact of competition on firms' carbon performance

5.1 Baseline estimates

We begin our empirical analysis by estimating the effect of competition on firms' carbon performance using the following baseline difference-in-differences (DiD) specification:

$$y_{i,j,t+1} = \alpha + \beta TCUT_{j,t+1} + \theta X_{i,j,t} + \gamma I_{j,t} + \eta_i + \delta_{t+1} + \varepsilon_{i,j,t+1} \quad (1)$$

where i indexes firm, j indexes industry, and t indexes years. On the left-hand side of Equation (1), $y_{i,j,t+1}$ denotes the carbon performance of firm i, measured by Scope emission intensities. The variable of interest, $TCUT_{j,t+1}$, is a binary variable that equals one for firms in industry j in year $t+1$ if their industry experienced a tariff cut in year t. It is zero in the year before the tariff cut $(t-1)$, while the year of the tariff cut is excluded to isolate the effect better (e.g., Frésard and Valta 2015). It is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. Since tariff cuts occur in different industries at different times, the control group consists of all firms in industries without a tariff cut in year t, even if those industries experienced one earlier or will experience one later. We focus on a short period after a tariff cut to reduce the risk that firms' strategic responses could obscure the effect of the tariff cut (e.g., Goolsbee and Syverson 2008; Ellison and Ellison 2011). Accordingly, β captures the average differential change in carbon performance between treated and control firms from the pre- to the post-cut period (Frésard 2010).

$X_{i,j,t}$ denotes firm-level control variables measusred in year t that capture characteristics potentially influencing the outcome variables. $I_{j,t}$ measures the HHI, which serves as an industry-level control variable to account for the level of competition within an industry at time t. We use firm- and industry-level control variables lagged by one year relative to the dependent variable to mitigate concerns that these characteristics are predetermined with respect to the outcome and to reduce potential simultaneity bias. We include firm fixed effects (η_i) to control for unobserved, time-invariant heterogeneity across firms, and year fixed effects (δ_{t+1}) to account for common macroeconomic developments and regulatory changes, including CO_2 policies. Standard errors are clustered at the industry level because treatment occurs at the industry level, which may lead to correlated residuals within industries.

As a robustness check, we adjust Equation (1) with industry fixed effects in place of firm fixed effects. This specification controls for persistent industry heterogeneity and identifies effects from within-industry variation over time, consistent with prior work on tariff reductions (e.g., Lileeva and Trefler 2010; Cumming et al. 2022). It also mitigates potential concerns in our firm-level panel, where emission data are sometimes sparse due to reliance on disclosure and vendor estimates, raising the risk that firm fixed effects capture data availability rather than true changes in intensities. In these regressions, standard errors are clustered at the firm level.

Table 4 presents the baseline regression results. In Columns (1)–(6), a tariff cut is defined as a reduction in the tariff rate that is at least twice the average negative change in the respective industry (TC 2). The industry-specific averages are computed over the tariff rate sample period from 1989 to 2023. In Columns (7)–(12), we apply a stricter definition, requiring the tariff cut to be at least three times the industry's average negative change (TC 3).

The results show negative and statistically significant coefficients for TCUT across all models. More specifically, treated firms reduce their emission intensities in direct emissions (Scope 1), indirect emissions from energy consumption (Scope 2), and combined emissions, suggesting that stronger competition improves firms' carbon efficiency. Moreover, the results indicate two additional patterns. First, the estimated effects are generally larger in magnitude under the stricter tariff cut definition (TC 2 vs. TC 3). Second, the industry fixed effects regressions produce coefficients on TCUT that remain statistically significant but are smaller in magnitude than in the baseline firm fixed effects specifications.

In terms of economic magnitude, the estimates suggest that firms experiencing a tariff cut reduce their carbon emission intensities by approximately 23.7% for Scope 1 (Column (1)), 13.1% for Scope 2 (Column (2)), and 20.7% for combined Scope 1&2

(Column (3)) from the pre-treatment year ($t-1$) to the post-treatment year ($t+1$), relative to the corresponding change for the control group. These values are illustrative, as the precise magnitudes vary across specifications. Overall, the findings indicate that the effects are both economically meaningful and highly statistically significant and align with differentiation and stakeholder theory (see Section 2).[9]

Turning to the control variables, we find a notable and statistically significant negative relationship between carbon emission intensities and firm size (Ln(1+Assets)) and valuation (M/B ratio), similar to other studies (e.g., Aswani et al. 2023). The lack of significance for the remaining controls reflects the persistence of emission intensities and the fact that firm fixed effects absorb most of the variation, which is also evident in the high adjusted R^2 of our regressions. With industry fixed effects, however, the controls account for more variation, as expected. In this specification, HHI and asset tangibility (Net PPE-to-assets) have positive and statistically significant coefficients, indicating that lower competition and a higher proportion of tangible assets are associated with higher carbon emission intensities. By contrast, these relationships become insignificant when using firm fixed effects. The observed divergence in HHI highlights the sensitivity of competition proxies to specification choices and the underlying sources of variation they capture.

[Table 4 about here]

Furthermore, our estimates should be interpreted as reduced-form effects of tariff-induced competitive pressure on firms' carbon emission intensities rather than as evidence for a single transmission channel. Prior research shows that tariff reductions and trade liberalization can trigger a range of firm responses, including changes in corporate investment and capital intensity (Frésard and Valta 2015; Jiang et al. 2015), productivity and production adjustment (Lileeva and Trefler 2010), and financing costs and capital

[9] We also report results using level-dependent variables to verify that our findings are not sensitive to the functional form. The coefficients remain negative and statistically significant, indicating that the results are not driven by the log specification; see Online Appendix A, Table OA1. In Panel A of Table OA2 in the Online Appendix A, we further present regressions estimated without control variables, which yield results similar to the baseline and help mitigate concerns that the findings depend on the chosen control set.

structure (Valta 2012; Xu 2012). Consistent with the discussion in Heath et al. (2023), we therefore interpret the coefficient on TCUT as capturing the net effect of increased competition on firms' carbon performance.[10] From an environmental perspective, this reduced-form effect is the relevant object, as it quantifies the overall change in emissions efficiency associated with competitive pressure, irrespective of the specific operational or financial adjustments through which firms achieve it. In Section 6, we further examine which firms adjust and along which margins.

5.2 Alternative counterfactuals and identification robustness

In the previous section, we established a causal link between competition and firms' carbon performance. To test the robustness of this causal interpretation, we next examine whether our results are sensitive to how the control group is defined. In the baseline setting, firms may experience multiple unanticipated tariff reductions over time. However, the current definition of our control group includes both never-treated firms and firms in years when they are not treated. Including firms that have already received a tariff cut in the control group may contaminate the counterfactual, as their outcomes may already reflect changes in firms' emission policy (de Chaisemartin and D'Haultfœuille 2020; Goodman-Bacon 2021). Panel A of Table 5 addresses this concern by redefining the variable TCUT such that the control group consists only of never-treated firms (Columns (1)–(6)) or never-treated firms together with treated firms up to their first tariff cut (Columns (7)–(12)). These definitions are based on tariff cut observations from 1997, five years prior to the start of the sample period.

Using these alternative counterfactuals, we continue to find negative coefficients for the variable TCUT across all models. The magnitudes are broadly similar to those in Table 4, though somewhat less pronounced for Scope 2 emission intensity and slightly weaker in statistical significance.

[10] Nevertheless, we account for multiple hypothesis testing across our three closely related carbon-performance outcomes by reporting Romano-Wolf stepdown adjusted p-values based on 1,000 bootstrap replications (Romano and Wolf 2005; Clarke et al. 2020). The conventional p-values reported in Columns (1)–(3) of Table 4 are 0.0025, 0.0039, and 0.0025, while the corresponding Romano-Wolf adjusted p-values are 0.015, 0.020, and 0.015, respectively.

[Table 5 about here]

To further validate our empirical design, we test whether treated and control firms are comparable. As shown in Table 2, treated firms tend to exhibit higher emission intensities than untreated firms. Such differences may raise questions about the comparability of treated and control firms and, if correlated with outcome dynamics, may bias the estimated treatment effects even when the parallel trends assumption holds and after accounting for control variables and fixed effects. In particular, if these differences reflect temporary fluctuations or unobserved firm characteristics, or if macroeconomic shocks affect the groups differentially, the observed post-treatment changes may partly reflect these factors rather than the tariff cuts themselves (e.g., Blundell and Costa Dias 2000). Therefore, to improve comparability between treated and control firms, Panel B applies nearest-neighbor matching on estimated propensity scores from a logit model. We match firms based on their pre-treatment characteristics measured one year prior to the tariff cut, including Scope specific carbon intensity, firm size (Ln(1+Assets)), industry competition (HHI), year, and the state in which the firm's headquarter is located.

Matching on Scope specific emission intensity helps isolate the effect of the tariff cut from differences in pre-treatment emissions, as firms with varying pre-existing carbon profiles may respond differently to tariff cuts. Firm size is included to mitigate bias due to size-related differences in treatment effects, since larger firms may have more resources, different operational structures, or greater strategic flexibility that could influence both emissions and the response to changes in competition. Industry competition accounts for differences in market pressure, which can influence firm behavior. For example, firms in more concentrated industries may respond differently to tariff changes. Finally, by matching firms based on the states of their headquarters, we consider state-level differences in environmental regulation and policies, such as the presence of emission trading systems. This ensures that the matched control firms resemble treated firms in key attributes before treatment, providing a credible counterfactual for identifying the effect of the tariff cuts and mitigating potential bias from pre-existing differences (e.g., Heckman et al. 1997).

We determine the number of nearest neighbors (k) using two approaches. Since we have a large pool of control firms, we restrict the controls to never-treated firms and apply a strict caliper of 0.01 to ensure very close matches. First, we set $k = 3$ to prioritize high-quality matches for each treated firm, which helps minimize bias while retaining sufficient observations for estimation. Second, we set $k = 7$, corresponding to the average number of firms per industry in our sample, to reflect the typical industry composition in the matched controls. Table A2 in Appendix reports the mean values and standard deviations for treated firms and their matched control firms. We also test whether differences in means are statistically different from zero using two-sided t-tests. Panel A reports results for $k = 3$ and Panel B for $k = 7$. Both panels show that treated and matched firms are closely aligned on the matching variables at pre-treatment, except for HHI in Panel A, where the difference is statistically significant. These findings indicate that the matching procedure achieves a high degree of covariate balance, thereby reducing the risk that observable firm-level heterogeneity biases our estimated effects.

Using these identified matched pairs and restricting the sample to the two-year window before and after each tariff cut (Frésard and Valta 2015), the results in Panel B of Table 5 are mostly consistent with the baseline estimates.[11] As before, the estimated effects are generally smaller in magnitude and slightly less statistically significant.

Another potential concern with our findings is the possibility of heterogeneous treatment effects, which may bias the baseline estimates or mask important dynamics. To test for this and account for the presence of pre-trends or dynamic post-treatment effects, we apply an interaction-weighted event-study estimator (Sun and Abraham 2021), using the same set of fixed effects and control variables as in our main specification. We report the results in Panel A of Table 6 for the event window from $t = -1$ to $t = +1$ with the tariff cut year ($t = 0$) serving as the omitted reference category. This analysis corroborates our findings for Scope 1, Scope 2, and combined emission intensities, with the effect materializing in the year following a tariff cut once appropriate weighting is applied. Importantly, we do not find any significant pre-treatment effects across models relative to the reference

[11] In Online Appendix A, Table OA3, we present results using the matched pairs over the full sample period as well as a narrower window covering one year before and after each tariff cut.

category, consistent with the graphical patterns shown in Figure 2.

[Table 6 about here]

While the event-study evidence mitigates concerns about pre-trends, our findings may still reflect unobserved industry shocks—such as demand fluctuations, regulatory interventions, or technological changes—rather than intensified competition. To assess this possibility, we implement an industry-level placebo test based on randomization inference. Specifically, we keep the number of treated industries per year fixed and randomly reassign treatment status across industries within each year. For each permutation, we re-estimate our baseline specification and obtain a placebo distribution of treatment effects. To avoid contamination from true treatment effects, we exclude the original treatment observations when constructing the placebo samples. If our main estimates were driven by generic industry-year shocks rather than tariff-induced competitive pressure, similarly large effects should arise frequently under these random assignments.

Panel B of Table 6 presents regression results for one illustrative placebo draw. In this example, the placebo treatment is unrelated to the dependent variables across all specifications. In Appendix Table A4, we summarize the distribution of placebo estimates across 1,000 random assignments and report the corresponding two-sided randomization-inference (RI) p-values for our baseline estimates under the null hypothesis of no treatment effect. The placebo coefficients are centered around zero (row "Mean β (TCUT)"). Moreover, the baseline estimates lie in the extreme tails of the placebo distributions, resulting in two-sided RI p-values below 4% (row "RI p-value").

Overall, the evidence from alternative counterfactuals, nearest-neighbor matching, the event-study, and the placebo test strengthens confidence that our baseline results are unlikely to be driven by control-group contamination, pre-treatment differences, heterogeneous treatment effects, or unobserved industry-specific shocks in the DiD framework.

5.3 Alternative mechanism and robustness

While the preceding analyses strengthen the identification of our results, an additional consideration relates to their interpretation and the mechanisms that may underlie them.

The observed reduction in Scope emission intensities does not necessarily imply that firms cut their emissions. Competition may induce firms to operate more efficiently, lowering emissions per unit of output, but at the same time expand production, thereby increasing total emissions. In addition, positive competitive spillovers that raise revenues can also mechanically reduce measured emission intensities, even in the absence of genuine decarbonization.

In Panel A of Table 7, we provide additional tests using the natural logarithm of one plus absolute emissions as the dependent variable, considering Scope 1 (S1 abs), Scope 2 (S2 abs), and combined Scope 1&2 (S1&2 abs).[12] We also examine the natural logarithm of one plus Sales and Sales-Adj, where Sales-Adj deflates sales to 2023 prices to account for the substantial inflation spikes toward the end of our sample period, as well as firms' sales growth (Δ Sales). The results show insignificant coefficients for TCUT across these models, indicating that competition does not increase absolute emissions, nor does it lead to higher sales.[13] This suggests that the negative effects on emission intensities are unlikely to be driven mechanically by sales, but rather reflect genuine improvements in firms' carbon efficiency.

[Table 7 about here]

In Section 3, we highlight the use of the Trucost database and its widespread application. However, a limitation of Trucost is that a large share of firm emissions is modelled at the industry level using its Environmentally Extended Input–Output (EEIO) framework, which assigns industry-specific emissions intensities to firms and scales them by firm-specific economic activity.[14] Even when focusing on emissions intensities as the dependent variable, this approach introduces a strong industry-level structure that may

[12] We report summary statistics for the variables used in this section in Table A3 in the Appendix.

[13] In these regressions, we use contemporaneous control variables to condition on the firm's current size, intentionally netting out the scale effect, because absolute emissions in period t are determined by the firm's production and capacity use in that same period. By contrast, emission intensity already accounts for scale mechanically by dividing emissions by sales, so additional contemporaneous size controls would reintroduce post-treatment scale information. In Online Appendix A, Panel B of Table OA2, we also report estimates without control variables and find similar results.

[14] see `https://www.support.marketplace.spglobal.com/content/dam/spglobal/mi/en/documents/marketplace/datasets/alternative/trucost_environmental/trucost_environmental_data_methodology_guide.pdf` (lastly accessed on Nov 18, 2025).

distort the estimated effect of tariff cuts if tariff exposure is correlated with industry characteristics or industry-specific shocks. In our empirical specifications, we therefore estimate regressions with firm and year fixed effects, which absorb all time-invariant firm heterogeneity, and with industry and year fixed effects, which remove static sector differences embedded in the Trucost model. Since industry-year fixed effects would be collinear with our tariff-cut measure, time-varying industry components of Trucost's modelling remain a potential concern. To ensure that our results are not driven by artefacts of the Trucost framework, we complement our analysis with emissions data from LSEG, whose estimation approach relies more on firm-specific information and therefore exhibits substantially less mechanically imposed industry-time structure. In particular, LSEG prioritizes reported emissions when available and, otherwise, draws on firm-level historical emissions, energy consumption, and other operational characteristics before resorting to industry medians.[15]

Panel B of Table 7 reports the results when using LSEG emission intensities as dependent variables.[16] We find negative and highly statistically significant coefficients for TCUT. Compared with the specifications based on Trucost data, the estimated effects are larger in magnitude, though the sample coverage is considerably lower. Thus, the LSEG-based results reinforce our findings and suggest that they are not an artefact of Trucost's EEIO modeling.

To further strengthen our results, we test robustness along three additional dimensions with regard to our baseline estimates. First, we include state fixed effects to capture heterogeneity across US states, such as differences in carbon pricing, regulation, or economic structure. Second, we re-estimate the models using an alternative industry classification based on four-digit SIC codes. Third, we exclude the post-2019 period to avoid potential distortions from the COVID-19 pandemic; this also addresses the concentration of tariff cuts in 2020 and 2021. In all cases, the results remain consistent with our baseline findings, reinforcing the robustness of our conclusions (see Appendix, Table A5).

[15]see `https://www.lseg.com.cn/content/dam/data-analytics/en_us/documents/fact-sheets/lseg-esg-carbon-data-and-estimate-models.pdf` (lastly accessed on Nov 18, 2025).

[16]We also use CDP data from LSEG and reported emissions from Trucost, and continue to find a significant negative coefficient for TCUT, see Appendix, Table A6.

Finally, we examine the sensitivity of our results to longer event windows by testing whether the effects persist over extended horizons. Defining TCUT over three- and six-year periods around the tariff cut, we continue to find negative effects on emission intensities, but the estimates are smaller and less precisely estimated (see Appendix, Table A7). Because longer windows are more exposed to anticipation effects and concurrent policy and market developments, these estimates are less likely to isolate the causal impact of the tariff cut itself and should therefore be interpreted as descriptive rather than strictly causal (e.g., Goldberg and Pavcnik 2016).

Taken together, these robustness tests indicate that the observed improvements in firms' carbon performance persist across alternative specifications, data sources, and longer event windows, supporting the interpretation that tariff cuts causally improve firms' emission outcomes.

6 Firm-level responses: Emission sensitivity and competitive pressure

The previous section established that large tariff cuts, which exogenously increase competition, lead firms on average to improve their carbon performance. However, this average effect may mask important heterogeneity in how firms respond. Our conceptual framework suggests that firms' adjustments to competitive pressure depend on their initial emission profiles. High-emission firms may find it more difficult to reduce emissions because of technological or structural constraints, but they also face stronger pressures to improve in order to maintain legitimacy and competitiveness. Low-emission firms, by contrast, have less scope for further reductions but may still respond through symbolic actions, enhanced disclosure, or incremental adjustments.

To investigate these heterogeneous responses, we extend our baseline specification by interacting tariff cuts with firms' baseline emission intensities in year t (the tariff-cut year, which is excluded from the outcome regressions).

$$\begin{aligned} y_{i,j,t+1} = \alpha &+ \beta_1 TCUT_{j,t+1} \times Ln(1 + Scope\ 1\&2\ intensity_{i,t}) + \beta_2 TCUT_{j,t+1} \\ &+ \beta_3 Ln(1 + Scope\ 1\&2\ intensity_{i,t}) + \theta X_{i,j,t} + \gamma I_{j,t} + \eta_i + \delta_{t+1} + \varepsilon_{i,j,t+1} \end{aligned} \tag{2}$$

This interaction framework allows us to assess whether the effect of competition systematically varies with firms' initial carbon profiles and to detect potential thresholds where the magnitude or even the direction of the effect shifts. As dependent variables, we focus on firm-level outcomes closely tied to the theoretical channels, including environmental strategies, agency costs, investment, asset structure, and financing choices. The interaction term, β_1, captures whether the sensitivity of these outcomes to tariff cuts varies with firms' emission intensities. In this way, the analysis links heterogeneous firm responses to the conceptual framework, highlighting whether high- and low-emission firms follow different adjustment paths. We report summary statistics for all variables used in this and the following section in Table A3 in the Appendix.

6.1 Environmental strategy and agency costs

We begin our analysis by examining variables that relate more directly to theoretical mechanisms that may hinder genuine reductions in carbon emission intensities or reflect more symbolic adjustments. In this context, we capture firms' potential environmental strategies using a set of binary indicators that track emission-related initiatives: Emission trading, Emission reduction target, and Environmental partnerships. Each of these variables reflects a distinct firm-level approach to addressing greenhouse gas emissions, or at least creating the impression of doing so. In addition, we include Eco-friendly products and Green buildings as dependent variables to assess whether firms are more likely to introduce reusable or energy-efficient products or to report green sites or environmentally friendly buildings following tariff cuts. To evaluate the extent and quality of environmental disclosure, we use Bloomberg's ESG disclosure score, while the Emission score from LSEG provides a measure of firms' commitment and effectiveness in reducing environmental emissions through production and operational processes. We further include firm-level proxies that address the agency cost channel. Specifically, we use the turnover ratio and the expense ratio as indicators of firms' agency costs as well as misconduct cases related to emission accusations. A higher turnover ratio indicates more effective use of assets and therefore implies lower agency costs, whereas an increase in the expense ratio reflects higher operating costs, including nonproductive investments, and thus points to greater agency costs (e.g., Ang et al. 2000). Moreover, the occurrence of misconduct cases related to emissions would indicate that firms engage in symbolic or misleading practices rather than substantive environmental improvements and would also reflect increased agency problems.

Table 8 presents the results based on the TCUT definition of TC 2.[17] Column (1) shows that emission trading activity decreases on average following tariff cuts, as reflected in the negative and statistically significant coefficient on TCUT (−0.1171). However, the positive and significant coefficient on the interaction term TCUT×Ln(1+Scope 1&2 intensity) (0.0157) suggests that this effect reverses for firms with sufficiently high baseline emission intensities. The estimated switching point is approximately 7.11 in Ln(1+Scope 1&2 intensity), which corresponds to roughly the 95$^{\text{th}}$ percentile of the sample distribution. Similarly, we find high switching points for Eco-friendly products (5.36), Green buildings (5.32), and Environmental partnerships (6.00), all of which lie around the 90$^{\text{th}}$ percentile of the distribution. By contrast, the effects on Emission reduction target, Emission score, and ESG disclosure score are statistically insignificant.

These findings may suggest that firms' responses to intensified competition are selective and may align with evidence of symbolic or strategic environmental actions (e.g., Lyon and Maxwell 2011; Marquis et al. 2016), a concern that may be particularly relevant for firms operating in high-pollution industries (Walker and Wan 2012; Kathan et al. 2025). Specifically, firms with high initial emission intensities are more likely to engage in activities such as emissions trading, launching eco-friendly products, or reporting green-building or sites, which are visible to stakeholders but relatively flexible and less costly to implement. In contrast, more binding commitments such as environmental partnerships show the opposite pattern, suggesting that firms under competitive pressure may avoid long-term cooperative strategies, as these require greater transparency and accountability, which can be unattractive when firms are under intense scrutiny (e.g., Delmas and Burbano 2011).

At the same time, these responses may also reflect actual technological or operational

[17]In Online Appendix B, we also report the results corresponding to this and the following section using TC 3 as the tariff-cut definition, presented in Tables OB2 and OB3.

constraints that limit the scope for immediate, substantive emission reductions. When firms cannot feasibly reduce emissions in the short run, managers may shift toward margins that are more achievable, which can interact with agency considerations. To explore this possibility, Columns (8)–(10) examine agency-related outcomes. We find only a weakly significant negative coefficient on TCUT×Ln(1+Scope 1&2 intensity) for the expense ratio (Column (9)), while the effect on the turnover ratio remains insignificant. The significant result suggests that agency costs decline as firms' emission intensities increase. Furthermore, Column (10), which examines a binary indicator for emission-related misconduct (equal to one in firm-years in which a misconduct case occurs and zero otherwise), shows a negative and statistically significant interaction term. The switching point is 4.54, which lies close to the 75$^{\text{th}}$ percentile of the distribution in Ln(1+Scope 1&2 intensity) and approximates the median emission intensity among treated firms (see Table 2). As a result, firms with higher emission intensity profiles tend to have a lower likelihood of misconduct when facing greater competition. In this regard, intensified competition appears to reduce managerial discretion and the scope for opportunistic behavior, thereby acting as a disciplinary mechanism (e.g., Giroud and Mueller 2010).

[Table 8 about here]

Taken together, our findings point to a multifaceted adjustment process rather than a single dominant mechanism. The evidence on eco-friendly products, green buildings, and other visible actions is consistent with symbolic responses among high-emission firms (e.g., Marquis et al. 2016), particularly where technological constraints may limit the scope for immediate abatement (e.g., Walker and Wan 2012). However, the decline in misconduct among these firms suggests that competitive pressure can tighten managerial discipline, reducing the scope for opportunistic behavior. As these patterns are not mutually exclusive and may operate simultaneously across the emission-intensity distribution, we remain cautious in attributing the results to any single mechanism and therefore turn to the real effects in the next section.

6.2 Investment, asset structure, and financing

Building on the same empirical framework as in the previous section, Table 9 analyzes how firms adjust their investment activity, asset structure, and financing needs in response to an exogenous increase in competition, conditional on their combined Scope 1&2 emission intensities. Whereas the previous analysis focused on variables that may relate to symbolic or strategic responses, this analysis turns to more substantive firm-level decisions that could directly influence firms' carbon emission intensities. Competition influences firms' ability and willingness to invest, restructure assets, or raise external finance (e.g., Xu 2012; Zhang 2023). Conditioning on emission intensities allows us to assess whether high- and low-emission firms differ systematically in these real adjustments when facing stronger competitive pressure.

For investment activity as the dependent variable, we use CAPEX-to-assets, abnormal investments,[18] EnvExp-to-assets (environmental expenditures over total assets), and R&D-to-assets. In Columns (1)–(3), the baseline coefficients on TCUT are negative and significant, indicating that competition reduces investment activity for firms with very low emission intensities. At the same time, the positive and significant interaction terms with Ln(1+Scope 1&2 intensity) suggest that this negative effect weakens as firms' emission intensities increase. The estimated switching points are 2.64 for CAPEX-to-assets, 4.95 for abnormal investment, and 4.00 for EnvExp-to-assets. Compared to the results in Table 8, these switching points are lower, falling below the sample median (3.69) of the emission intensity distribution in the case of CAPEX-to-assets. This suggests that real decisions, such as investment adjustments, respond to competitive pressure at much lower emission levels than strategic environmental actions, which shift around the 90$^{\text{th}}$ percentile of the distribution. In line with the literature, the effect of competition on investment is mixed, with studies documenting both positive impacts (e.g., Jiang et al. 2015) and negative ones (e.g., Frésard and Valta 2015). Our results highlight this ambiguity by showing that the response of firms depends on their emission profiles. Importantly, we also find that environmental expenditures increase with firms' emission intensities when competition

[18] We follow Titman et al. (2004) and Strebulaev and Yang (2013) and define Abnormal investment as the current CAPEX-to-assets scaled by its three-year historical average, minus one.

intensifies. We do not observe any effect on R&D spending (Column (4)).

With regard to firms' asset structure, we observe that TCUT alone is associated with an increase in tangible assets and a decrease in intangible assets (Column (5)–(6)). The interaction terms with Ln(1+Scope 1&2 emission intensity) reveal the opposite pattern, indicating that higher-emission firms reduce tangible assets while increasing intangible assets more strongly in response to competition. The switching points are 3.96 for tangible assets and 5.37 for intangible assets, with the former lying near the sample median (3.89) and the latter close to the 95$^{\text{th}}$ percentile of the overall distribution. This pattern suggests that when competition intensifies, firms shift resources away from physical toward intangible assets; however, given the higher switching point and the insignificant R&D results, this shift appears to occur primarily through non-R&D intangibles, such as technology, process improvements, or intellectual property, rather than through expanded innovation activity.

In the environmental context, such a shift may reflect investments in carbon-efficiency technologies, digital process upgrades, or climate-oriented branding, all of which support differentiation and can strengthen longer-term competitive and regulatory positioning (Porter and van der Linde 1995; Ambec and Lanoie 2008). Consistent with this view, Jiao (2010) shows that investments in stakeholder-related intangibles contribute positively to firm value, underscoring their role as strategic assets in competitive markets. The fact that these effects are more pronounced among high-emission-intensity firms further suggests that such firms rely more heavily on intangible assets to mitigate reputational and regulatory risks as well as to preserve strategic flexibility when adjusting to stronger competition.

Finally, the results also indicate that firms do not issue debt or equity in response to an exogenous shock in competition (Columns (7)–(8)). We therefore turn to internal financing sources in Columns (9)–(10). To do so, we examine changes in cash reserves (ΔCash-to-assets) and cash flows (CF-to-assets). We observe that TCUT reduces cash accumulation for low-emission-intensity firms, as reflected in the negative and significant coefficient on ΔCash-to-assets. The interaction terms, however, are positive and statistically significant, with switching points below the sample average (3.89)—3.80 for ΔCash-to-assets and 2.26 for CF-to-assets—showing that firms with higher emission intensities experience a smaller decline, or even an increase, in internal liquidity when facing stronger competition. This pattern is consistent with the notion that higher-emission-intensity firms rely more heavily on internal funds to support investment and operational adjustments when competition intensifies, either because external financing becomes more expensive for them (e.g., Valta 2012; Chava 2014) or because internal funds provide a more flexible and reliable source of liquidity under tightening competitive pressure (e.g., Frésard 2010).

[Table 9 about here]

Although we cannot directly attribute the observed changes in investment, asset structure, and internal financing to specific low-carbon projects, the evidence elucidates that emission intensity systematically conditions how firms adjust their real and financial decisions in response to competition. These findings are broadly consistent with differentiation strategy and stakeholder theory, as discussed in Section 2, since reallocations toward intangibles and adjustments in financial policy may also serve to reinforce firms' environmental positioning and stakeholder legitimacy.

7 Tariff-cut magnitude and competition intensity

Our empirical setting deliberately adopts a strict definition of tariff cuts, following Frésard and Valta (2015), as our sample period coincides with US trade policy developments increasingly characterized by protectionism. This choice focuses on clearly exogenous and economically meaningful trade liberalization events and reduces the risk that marginal or temporary adjustments in statutory rates are misclassified as genuine tariff reductions. By imposing a stricter threshold, we sharpen the identification of tariff-cut-induced competition shocks and strengthen the interpretability of our estimated treatment effects. Although this approach narrows the number of qualifying events, it enhances internal validity by ensuring that observed firm-level responses are driven by substantive changes in trade policy. As discussed in Section 4, this approach yields a number of tariff cuts comparable to prior studies (e.g., Flammer 2015; Frésard and Valta 2015) and ensures that the identified reductions reflect economically meaningful changes in tariff rates that are plausibly large enough to affect firm behavior (Trefler 2004), that is, tariff cuts of a magnitude sufficient to alter competitive conditions within an industry.

If we redefine tariff cuts using negative industry-median changes rather than negative industry-average changes as the threshold, the number of identified events increases substantially. Specifically, defining tariff cuts as decreases in tariff rates at least twice as large as the industry-median change raises the number of tariff cuts from 19 to 112, affecting 943 firm-year observations. Under this alternative definition, the estimated effects become much smaller in magnitude and less statistically significant. Nonetheless, we continue to find negative and statistically significant impacts on Scope 1 and Scope 1&2 emission intensities (see Appendix, Table A8).

Importantly, this broader definition also implies materially smaller competitive shocks. The average reduction in tariff rates in the cut year declines from 18.13% to 10.21%, implying a roughly 44% smaller change for treated industries. Consistent with this, the effect of increased competition on carbon emission intensities varies with the magnitude of the tariff reduction, suggesting that only sufficiently large cuts generate competitive pressures strong enough to induce meaningful adjustments in firms' emissions. Reassuringly, the qualitative pattern of our baseline results (see Section 5.1) remains unchanged across alternative specifications and control-group constructions (see Section 5.2), indicating that the weaker estimates under the broader, median-based definition primarily reflects small competitive shocks rather than model sensitivity.

These results highlight the importance of the magnitude of the implied competition shock for the estimated effects. This point is also relevant for interpreting related evidence based on broader tariff-change definitions (e.g., Pursiainen et al. 2025). Such broader classifications mechanically capture many smaller adjustments, which may dilute the underlying competitive shock and reduce the estimated effects. Moreover, they are more likely to treat marginal or transitory changes as discrete policy events, increasing measurement error and making it harder to isolate economically meaningful tariff-reduction events that are large enough to induce firm-level responses.

8 Conclusion

Our study shows that large and unexpected tariff cuts, which intensify competition, lead to economically meaningful reductions in firms' Scope 1, Scope 2, and combined emission intensities. A series of identification checks, including alternative counterfactuals, matching, event-study evidence, and placebo tests, supports the interpretation that these reductions arise from competition rather than from pre-trends or industry-specific shocks.

Relating these results to our conceptual framework, we find that firms' responses vary systematically with their initial emission intensities. High-emission-intensity firms pursue visible environmental actions such as emissions trading, eco-friendly products, and green-building initiatives, yet show little engagement in more demanding commitments like environmental partnerships. This evidence points to cases where firms may prioritize symbolic actions, but it is also consistent with technological and operational constraints that limit more substantive abatement. Supporting this interpretation, we also find that competition reduces emission-related misconduct among firms with higher emission intensities, indicating tighter managerial discipline rather than opportunistic behavior.

Real adjustments, by contrast, arise at lower emission intensities. Competition initially reduces investment for low-emission-intensity firms, but the effect turns positive as emission intensity rises. In terms of asset structure, tangible assets begin to decline at moderate emission intensities, whereas increases in intangible assets appear at higher levels, likely driven by non-R&D intangibles. We also find that firms do not increase external financing in response to stronger competition. Instead, they rely more on internal funds, as internal liquidity increases with emission intensity. This reliance is consistent with external financing becoming more costly or harder to access for such firms, making internal funds a more viable source for supporting investment and operational adjustments.

One central implication of our analysis is that the environmental impact of competition is sensitive to the magnitude and credibility of the competitive shock. Focusing on broader event definitions that also incorporate small or marginal tariff changes is unlikely to yield comparable effects, as minor statutory adjustments may not materially alter competitive conditions or firms' investment incentives. Accordingly, competition shocks need to be sufficiently large and economically meaningful to induce measurable improvements in firms' emission intensities.

Although our results indicate that competition improves firms' management of emission intensities at the firm level, aggregate emissions at the national level may still increase due to higher trade volumes or scale effects that lie outside the scope of our analysis. Nevertheless, Shapiro (2016) show that the aggregate gains from international trade outweigh its environmental costs from CO_2 emissions, suggesting that the overall welfare implications of trade-induced competition are not necessarily negative from an environmental perspective. At the same time, the fact that firm-level effects emerge primarily for sufficiently large and credible competitive shocks underscores that drawing definitive policy conclusions about the net environmental impact of increased competition remains complex and warrants further investigation.

In this regard, our findings speak to the broader role of market competition in improving emissions management under incomplete internalization of environmental externalities (e.g., Stiglitz 2019). The evidence suggests that competition can complement carbon pricing by encouraging firms to enhance their carbon efficiency and align more closely with global decarbonization targets.

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Figure 1: Distribution of tariff cuts over sample period

This figure shows the number of tariff cuts by year for the sample firms. Tariff rates at the industry-year level are calculated at the three-digit SIC code as the ratio of duties collected (ad valorem tariff) to the value of imports (free-on-board value). A tariff cut is defined as a reduction in the tariff rate that is at least twice as large as the industry's average negative change.

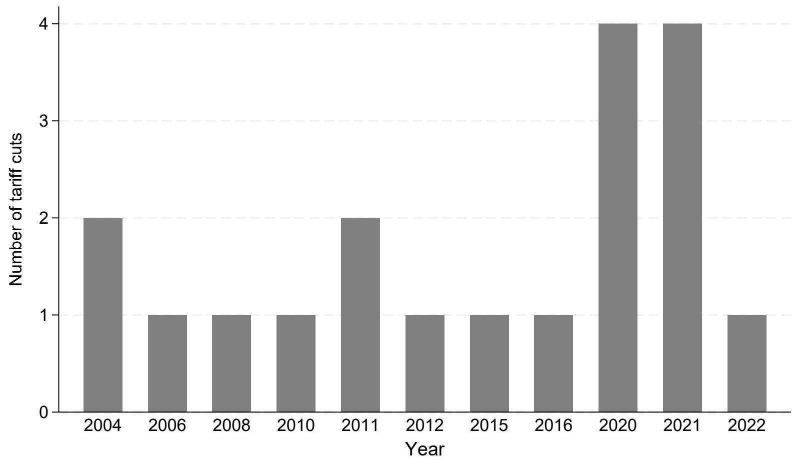
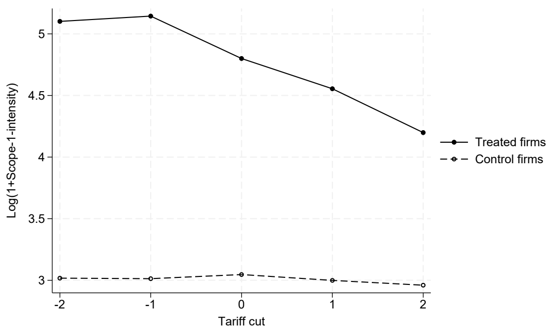
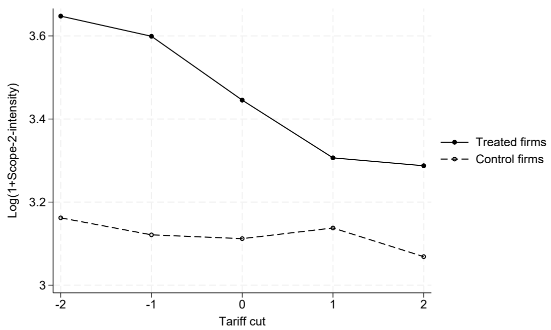


Figure 2: Evolution of Scope 1 and Scope 2 emission intensities around tariff cuts

This figure shows the evolution of firms' Ln(1+Scope 1 emission intensity) and Ln(1+Scope 2 emission intensity) around tariff cuts. A tariff cut is defined as a reduction in the tariff rate at least twice as large as the average negative change in the industry. The y-axis shows the average transformed intensities for treated (solid line) and control firms (dashed line). The x-axis indicates the years relative to a tariff cut, with $t = 0$ denoting the year the cut occurred. Variable definitions and data sources are provided in Table A1.



(a) Scope 1 intensity



(b) Scope 2 intensity

Table 1: Summary statistics of variables

This table presents summary statistics for the firms included in our sample over the period 2003–2023. We exclude firms from the financial industries (SIC codes 6000–6999), utility industries (SIC codes 4900–4999), and government entities (SIC codes $\geq$ 9000). All variables are winsorized at the 1% level in both tails. Variable definitions and data sources are provided in Table A1.

Variable	Obs.	Mean	SD	25%-quantile	Median	75%-quantile
Carbon emission variables						
Scope 1 intensity (tCO_2e/\$ mn rev.)	21,400	96.67	279.94	7.71	16.38	33.82
Scope 2 intensity (tCO_2e/\$ mn rev.)	21,400	33.86	42.75	10.33	19.67	40.89
Scope 1&2 intensity (tCO_2e/\$ mn rev.)	21,400	135.08	322.23	20.34	39.29	81.46
Control variables						
Ln(1+Assets)	21,400	21.50	1.67	20.43	21.59	22.67
M/B ratio	21,400	3.94	6.39	1.48	2.60	4.63
EBITDA-to-assets	21,400	0.09	0.18	0.07	0.12	0.17
Net PPE-to-assets	21,400	0.25	0.22	0.08	0.17	0.36
Book leverage	21,400	0.27	0.22	0.11	0.25	0.39
Cash-to-assets	21,400	0.14	0.15	0.04	0.09	0.18
Herfindahl index	21,400	0.25	0.20	0.10	0.19	0.31

Table 2: Descriptive statistics of treated and untreated firms

This table presents descriptive statistics for treated and untreated firms. The Columns "Treated firms" include all firm-year observations for firms that experienced a tariff cut during the sample period (2003–2023). The Columns "Untreated firms" contain firm-year observations for firms that were never exposed to a tariff cut. A tariff cut is defined as a reduction in the tariff rate that is at least twice the average negative change in the industry. Firms in the financial and utility industries, and government entities, are excluded from the sample. All variables are winsorized at the 1% level in both tails. Variable definitions and data sources are provided in Table A1.

	Treated firms				Untreated firms			
Variable	Obs.	Mean	Median	SD	Obs.	Mean	Median	SD
Carbon emission variables								
Ln(1+Scope 1 intensity)	1,116	4.23	3.88	1.85	20,284	2.99	2.82	1.44
Ln(1+Scope 2 intensity)	1,116	3.47	3.52	0.91	20,284	3.07	2.99	0.92
Ln(1+Scope 1&2 intensity)	1,116	4.80	4.45	1.46	20,284	3.84	3.69	1.20
Control variables								
Ln(1+Assets)	1,116	21.80	21.88	1.82	20,284	21.48	21.57	1.67
M/B ratio	1,116	3.18	2.11	6.15	20,284	3.99	2.63	6.40
EBITDA-to-assets	1,116	0.07	0.13	0.27	20,284	0.09	0.12	0.18
Net PPE-to-assets	1,116	0.44	0.35	0.34	20,284	0.24	0.17	0.21
Book leverage	1,116	0.31	0.27	0.23	20,284	0.27	0.25	0.22
Cash-to-assets	1,116	0.11	0.05	0.16	20,284	0.14	0.09	0.15
Herfindahl index	1,116	0.22	0.11	0.19	20,284	0.25	0.19	0.20

Table 3: Tariff cuts and industry characteristics

This table presents results from fixed-effects regressions in which the dependent variable is TCUT, measured either contemporaneously or as its one-period lead. TCUT equals one for industries exposed to a tariff cut and zero otherwise. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. Control variables represent industry averages at time t. All continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level, and t-values are reported in parentheses.

	TC 2		TC 3	
	TCUT contemporaneous	TCUT one-period-lead	TCUT contemporaneous	TCUT one-period-lead
	(1)	(2)	(3)	(4)
Log(1+Assets)	−0.0010	0.0016	−0.0005	0.0019
	(−0.52)	(0.94)	(−0.21)	(0.99)
M/B ratio	0.0001	0.0002	−0.0001	0.0004
	(0.29)	(1.08)	(−0.24)	(1.06)
EBITDA-to-assets	−0.0054	−0.0156	−0.0097	−0.0133
	(−0.32)	(−1.57)	(−0.58)	(−1.44)
Net PPE-to-assets	−0.0005	0.0006	0.0018	0.0058
	(−0.06)	(0.09)	(0.28)	(0.69)
Book leverage	0.0008	−0.0047	−0.0149	−0.0114
	(0.07)	(−0.47)	(−1.05)	(−0.90)
Cash-to-assets	0.0052	0.0220	−0.0091	0.0408
	(0.39)	(0.90)	(−0.86)	(1.58)
Herfindahl index	0.0003	0.0008	−0.0007	−0.0019
	(0.10)	(0.14)	(−0.27)	(−0.38)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observation	4,564	4,320	4,558	4,315
Adj-R2	0.077	0.087	0.066	0.072

Table 4: Competition and firms' carbon performance

This table presents results from fixed effect regressions, where the dependent variables represent Ln(1+Scope intensities): Scope 1, Scope 2, and combined Scope 1&2. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level for models with firm fixed effects, and at the firm level for models with industry fixed effects. T-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Baseline estimation	DV: Ln(1+Scope intensities)											
	TC 2						TC 3					
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TCUT	-0.2702^{***}	-0.1408^{***}	-0.2321^{***}	-0.2198^{***}	-0.1125^{**}	-0.1744^{***}	-0.2844^{***}	-0.1450^{***}	-0.2405^{***}	-0.2268^{***}	-0.1176^{**}	-0.1788^{***}
	(−3.05)	(−2.91)	(−3.06)	(−3.88)	(−2.21)	(−3.56)	(−3.51)	(−3.07)	(−3.31)	(−4.06)	(−2.28)	(−3.62)
Ln(1+Assets)	-0.0824^{***}	-0.0301^{*}	-0.0526^{***}	-0.0827^{***}	0.0099	-0.0226^{***}	-0.0824^{***}	-0.0300^{*}	-0.0525^{***}	-0.0827^{***}	0.0099	-0.0226^{***}
	(−4.15)	(−1.85)	(−2.91)	(−7.85)	(1.22)	(−2.61)	(−4.16)	(−1.85)	(−2.91)	(−7.85)	(1.21)	(−2.62)
M/B ratio	-0.0026^{**}	-0.0017^{**}	-0.0024^{***}	-0.0067^{***}	-0.0056^{***}	-0.0069^{***}	-0.0026^{**}	-0.0017^{**}	-0.0023^{***}	-0.0068^{***}	-0.0055^{***}	-0.0069^{***}
	(−2.58)	(−2.33)	(−2.67)	(−5.46)	(−5.56)	(−6.58)	(−2.55)	(−2.29)	(−2.63)	(−5.46)	(−5.53)	(−6.56)
EBITDA-to-assets	−0.1153	−0.0274	-0.0890^{*}	−0.0862	−0.0426	−0.0589	−0.1137	−0.0272	-0.0883^{*}	−0.0852	−0.0423	−0.0583
	(−1.58)	(−0.71)	(−1.67)	(−1.52)	(−0.96)	(−1.28)	(−1.56)	(−0.70)	(−1.66)	(−1.50)	(−0.95)	(−1.27)
Net PPE-to-assets	0.2207	0.0581	0.1623	1.2433^{***}	0.8326^{***}	1.2513^{***}	0.2192	0.0566	0.1605	1.2429^{***}	0.8328^{***}	1.2511^{***}
	(1.44)	(0.40)	(1.14)	(9.16)	(9.26)	(11.02)	(1.43)	(0.39)	(1.13)	(9.16)	(9.26)	(11.02)
Book leverage	−0.0048	−0.0334	−0.0245	0.0263	-0.0801^{*}	−0.0407	−0.0051	−0.0339	−0.0249	0.0265	-0.0801^{*}	−0.0406
	(−0.08)	(−0.69)	(−0.49)	(0.50)	(−1.96)	(−0.95)	(−0.09)	(−0.70)	(−0.50)	(0.50)	(−1.96)	(−0.95)
Cash-to-assets	0.0232	−0.0749	−0.0253	-0.2086^{***}	−0.0327	−0.0636	0.0222	−0.0755	−0.0260	-0.2082^{***}	−0.0339	−0.0640
	(0.37)	(−1.57)	(−0.48)	(−2.60)	(−0.52)	(−0.96)	(0.36)	(−1.58)	(−0.49)	(−2.59)	(−0.54)	(−0.96)
Herfindahl index	0.0506	0.0272	−0.0233	0.3876^{***}	0.3097^{***}	0.3818^{***}	0.0506	0.0270	−0.0234	0.3874^{***}	0.3095^{***}	0.3815^{***}
	(0.34)	(0.22)	(−0.18)	(2.88)	(2.83)	(3.39)	(0.34)	(0.22)	(−0.18)	(2.88)	(2.83)	(3.38)
Firm FE	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	No	No	No
Industry FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	21,400	21,400	21,400	21,752	21,752	21,752	21,392	21,392	21,392	21,745	21,745	21,745
Adj-R2	0.894	0.854	0.902	0.747	0.641	0.752	0.894	0.854	0.902	0.747	0.641	0.752

Table 5: Competition and firms' carbon performance: Alternative counterfactuals and matching

This table presents results from fixed effect regressions, where the dependent variables represent Ln(1+Scope intensities): Scope 1, Scope 2, and combined Scope 1&2. In Panel A, the variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms never exposed to a tariff cut (Columns (1)–(6)) or never-treated firms together with treated firms up to their first tariff cut (Columns (7)–(12)). These definitions are based on tariff cut observations from 1997, five years prior to the start of the sample period. In Panel B, the control group is constructed by matching never-treated firms (NT) to treated firms based on pre-treatment characteristics, i.e., one year prior to a tariff cut. Nearest-neighbor matching is performed using propensity scores estimated from a logit model with 0.01 caliper. Covariates include Scope-specific carbon intensity, Ln(1+Assets), HHI, year, and the state in which the firm's headquarters is located. Columns (1)–(6) uses $k = 3$ neighbors, whereas Columns (7)–(12) employs $k = 7$ neighbors. The matching sample covers the years around a tariff cut ($t - 2$ to $t + 2$). In both panels, A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Alt. Ctrf.	DV: Ln(1+Scope intensities)											
	Control group: Never treated						Control group: Until first tariff cut					
	TC 2			TC 3			TC 2			TC 3		
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TCUT	-0.2633^{**}	-0.0887^{**}	-0.2662^{**}	-0.3000^{***}	-0.0974^{**}	-0.2886^{***}	-0.2275^{**}	-0.0910^{**}	-0.2292^{**}	-0.2500^{**}	-0.0975^{**}	-0.2458^{***}
	(−2.07)	(−2.01)	(−2.47)	(−2.81)	(−2.30)	(−2.96)	(−2.01)	(−2.23)	(−2.44)	(−2.39)	(−2.43)	(−2.75)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	20,616	20,616	20,616	20,605	20,605	20,605	20,725	20,725	20,725	20,707	20,707	20,707
Adj-R2	0.889	0.855	0.898	0.890	0.855	0.898	0.890	0.854	0.899	0.890	0.854	0.899

Panel B: Matching (NT)	DV: Ln(1+Scope intensities)											
	N-neighbors: $k = 3$						N-neighbors: $k = 7$					
	TC 2			TC 3			TC 2			TC 3		
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TCUT	-0.1908^{**}	-0.0804^{**}	-0.2110^{***}	-0.2368^{***}	-0.1000^{**}	-0.2547^{***}	-0.2488^{***}	-0.0983^{***}	-0.2343^{***}	-0.2433^{***}	-0.0977^{**}	-0.2584^{***}
	(−2.19)	(−2.29)	(−2.91)	(−2.85)	(−2.59)	(−3.73)	(−3.07)	(−2.67)	(−2.88)	(−3.07)	(−2.59)	(−3.48)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1,427	1,598	1,445	1,344	1,494	1,351	2,323	2,909	2,404	2,178	2,703	2,250
Adj-R2	0.936	0.869	0.932	0.940	0.876	0.951	0.937	0.869	0.936	0.938	0.874	0.946

Table 6: Competition and firms' carbon performance: Heterogeneous treatment (HT) effects and placebo test

This table presents results from event-study estimates using the interaction-weighted (IW) estimator of Sun and Abraham (2021) and from fixed effect regressions. The dependent variables represent Ln(1+Scope intensities): Scope 1, Scope 2, and combined Scope 1&2. In Panel A, coefficients represent event-time effects measured relative to the tariff cut year ($t = 0$, omitted reference category). The control group comprises never-treated firms. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. Panel B reports results for one illustrative draw from an industry-level placebo test based on randomization inference. The number of treated industries per year is held fixed, and treatment is randomly reassigned across industries within each year. The placebo treatment indicator equals one in the placebo post year and zero in the placebo pre year (excluding the placebo event year). Observations from the original treatment window are excluded when constructing the placebo sample. Results for the full set of 1,000 draws and the corresponding two-sided randomization inference p-values for the baseline estimates are reported in Appendix Table A4. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level for models with firm fixed effects, and at the firm level for models with industry fixed effects. T-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: HT effects	DV: Ln(1+Scope intensities)											
	TC 2						TC 3					
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lag 1 year	−0.0193	−0.0727	0.0389	−0.2232	−0.1553	−0.1255	−0.0429	−0.0611	0.0353	−0.2381	−0.1211	−0.1129
	(−0.18)	(−1.29)	(0.39)	(−1.42)	(−1.06)	(−1.02)	(−0.38)	(−1.10)	(0.38)	(−1.58)	(−0.87)	(−0.97)
Lead 1 year	−0.2034***	−0.0731**	−0.1338***	−0.2015***	−0.0671	−0.1234*	−0.2084***	−0.0836***	−0.1403***	−0.1998***	−0.0739	−0.1255*
	(−6.65)	(−2.17)	(−4.19)	(−2.87)	(−0.92)	(−1.88)	(−6.72)	(−2.82)	(−4.65)	(−2.90)	(−1.04)	(−1.95)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	22,990	22,990	22,990	23,316	23,316	23,316	22,990	22,990	22,990	23,316	23,316	23,316
Adj-R2	0.899	0.851	0.904	0.753	0.623	0.755	0.899	0.851	0.904	0.753	0.623	0.755

Panel B: Placebo test	DV: Ln(1+Scope intensities)											
	TC 2						TC 3					
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TCUT	0.0206	−0.0111	0.0258	−0.0450	0.0085	0.0239	−0.0187	−0.1062	−0.0812	−0.0643	−0.0379	−0.0494
	(0.46)	(−0.18)	(0.54)	(−0.79)	(0.17)	(0.51)	(−0.26)	(−1.45)	(−0.85)	(−0.90)	(−0.84)	(−0.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	No	No	No
Industry FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	23,180	23,180	23,180	23,516	23,516	23,516	23,178	23,178	23,178	23,517	23,517	23,517
Adj-R2	0.893	0.851	0.900	0.746	0.632	0.751	0.893	0.851	0.900	0.747	0.632	0.751

Table 7: Absolute emissions, sales, and LSEG emission data

This table presents results from fixed effect regressions. In Panel A, the dependent variables are Ln(1+absolute emissions): Scope 1 (S1 abs), Scope 2 (S2 abs), and combined Scope 1&2 (S1&2 abs), as well as Ln(1+Sales), Ln(1+Sales-Adj), and Δ Sales. Sales-Adj deflates sales to 2023 prices, and control variables are measured contemporaneously. In Panel B, the dependent variables represent Ln(1+Scope intensities): Scope 1, Scope 2, and combined Scope 1&2, using emission data from LSEG, and control variables are measured one year prior to the dependent variable. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. All continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level for models with firm fixed effects, and at the firm level for models with industry fixed effects. T-values are reported in parentheses. *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

Panel A: Absolute emissions & sales	DV: Ln(1+Var)											
	TC 2						TC 3					
Var:	S1 abs	S2 abs	S1&2 abs	Sales	Sales-Adj	Δ Sales	S1 abs	S2 abs	S1&2 abs	Sales	Sales-Adj	Δ Sales
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TCUT	−0.0598	0.0066	−0.0267	0.0968	0.0925	−0.0274	−0.0664	0.0065	−0.0290	0.0906	0.0861	−0.0267
	(−1.33)	(0.21)	(−0.79)	(1.35)	(1.26)	(−1.18)	(−1.59)	(0.20)	(−0.86)	(1.18)	(1.09)	(−1.07)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	21,970	21,970	21,970	21,970	21,970	19,806	21,962	21,962	21,962	21,962	21,962	19,791
Adj-R2	0.932	0.951	0.955	0.970	0.972	0.240	0.932	0.951	0.955	0.970	0.972	0.240

Panel B: LSEG	DV: Ln(1+Scope intensities)											
	TC 2						TC 3					
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TCUT	−0.5631***	−0.3081***	−0.4461***	−0.3622***	−0.3718**	−0.3145***	−0.5710***	−0.3167***	−0.4577***	−0.3601***	−0.3813**	−0.3256***
	(−3.75)	(−4.59)	(−3.70)	(−3.28)	(−2.19)	(−3.00)	(−3.98)	(−5.23)	(−4.10)	(−3.28)	(−2.25)	(−3.14)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	No	No	No
Industry FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	5,750	5,615	5,552	5,936	5,804	5,740	5,747	5,612	5,549	5,932	5,801	5,737
Adj-R2	0.972	0.933	0.965	0.826	0.659	0.789	0.972	0.933	0.965	0.826	0.659	0.789

Table 8: Environmental strategy and agency costs

This table presents results from fixed effect regressions, where the one-year lead dependent variables capture aspects of firms' environmental strategy and agency costs, including greenhouse gas (GHG)-related misconduct cases. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate at least twice the industry's average negative change. The interaction term is the product of TCUT at $t+1$ and the variable Ln(1+Scope 1&2 intensity) at t. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Emission trading	Emission red. target	Emission score	Eco-friend. products	Green buildings	Environ. partnersh.	ESG Disc.score	Turnover ratio	Expense ratio	GHG misconduct
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TCUT×Ln(1+S1&2 int.)	0.0157**	0.0186	−0.0072	0.0262***	0.0378**	−0.0346***	0.0035	−0.0035	−0.0645*	−0.0607**
	(2.08)	(0.88)	(−0.61)	(3.07)	(2.47)	(−2.84)	(1.54)	(−0.31)	(−1.79)	(−2.15)
TCUT	−0.1117**	−0.0380	0.0215	−0.1405***	−0.2010**	0.2079***	−0.0116	0.0741	0.0635	0.2759
	(−2.40)	(−0.29)	(0.31)	(−2.64)	(−2.10)	(2.84)	(−0.83)	(1.05)	(0.33)	(1.59)
Ln(1+S1&2 int.)	−0.0035	−0.0125	−0.0188***	−0.0251***	−0.0268**	−0.0025	−0.0045	0.0067	−0.0133	0.0034
	(−0.44)	(−0.92)	(−2.83)	(−2.61)	(−2.36)	(−0.22)	(−1.40)	(0.87)	(−0.41)	(0.50)
Ln(1+Assets)	0.0138*	0.0547***	0.0838***	−0.0062	0.1065***	0.0707***	0.0065**	−0.1537***	−0.0541	0.0010
	(1.69)	(5.48)	(9.70)	(−0.60)	(7.30)	(6.42)	(2.26)	(−7.92)	(−1.29)	(0.15)
M/B ratio	0.0004	0.0001	0.0005	−0.0001	0.0008*	−0.0003	0.0000	0.0007	0.0017	0.0001
	(0.96)	(0.09)	(1.38)	(−0.26)	(1.83)	(−0.42)	(0.15)	(1.31)	(0.45)	(0.32)
EBITDA-to-assets	−0.0257	−0.0728	−0.0306	0.0013	0.0199	−0.1049**	0.0023	0.3319***	0.5084	−0.0464*
	(−1.27)	(−1.63)	(−1.63)	(0.06)	(0.47)	(−2.31)	(0.33)	(3.65)	(0.54)	(−1.85)
Net PPE-to-assets	−0.0017	−0.1156	0.0663	0.0243	0.1552*	0.1296	0.0061	−0.0929	−0.1474	0.0901
	(−0.04)	(−1.37)	(1.25)	(0.41)	(1.92)	(1.61)	(0.39)	(−0.97)	(−0.55)	(1.61)
Book leverage	−0.0044	−0.0307	−0.0032	−0.0125	0.0609	−0.0124	−0.0139*	−0.0303	−0.4299	0.0036
	(−0.22)	(−0.89)	(−0.15)	(−0.39)	(1.17)	(−0.26)	(−1.78)	(−0.81)	(−1.25)	(0.13)
Cash-to-assets	0.0215	−0.0676	−0.0008	−0.0250	0.0298	0.0154	−0.0023	−0.1740***	0.0578	0.0119
	(0.75)	(−1.41)	(−0.03)	(−0.56)	(0.68)	(0.34)	(−0.31)	(−3.75)	(0.12)	(0.57)
Herfindahl index	−0.0719	0.0766	0.1370**	0.0110	0.0739	0.1286	0.0115	−0.0331	0.1754*	−0.0329
	(−1.20)	(0.91)	(2.09)	(0.17)	(0.79)	(1.32)	(0.57)	(−0.47)	(1.94)	(−0.30)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	16,743	15,406	16,222	16,984	17,020	17,014	11,823	19,796	19,752	19,804
Adj-R2	0.523	0.648	0.767	0.563	0.612	0.662	0.860	0.904	0.799	0.331

Table 9: Investment, asset structure, and financing

This table presents results from fixed effects regressions, where one-year lead the dependent variables capture firms' investment activity, asset structure, and external financing. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate at least twice the industry's average negative change. The interaction term is the product of TCUT at $t + 1$ and the variable Ln(1+Scope 1&2 intensity) at t. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	CAPEX-to-assets	Abnormal investment	EnvExp-to-assets	R&D-to-assets	Net PPE-to-assets	Intangible-to-assets	Debt issuance	Equity issuance	ΔCash-to-assets	CF-to-assets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TCUT×Ln(1+S1&2 int.)	0.0033***	0.0487***	0.0004***	0.0043	−0.0093***	0.0132***	−0.0008	0.0064	0.0133***	0.0250***
	(6.04)	(3.75)	(3.17)	(1.45)	(−4.26)	(3.94)	(−0.09)	(1.45)	(2.77)	(4.38)
TCUT	−0.0087***	−0.2410***	−0.0016**	−0.0199	0.0368***	−0.0709***	0.0013	−0.0379	−0.0506*	−0.0565
	(−2.74)	(−3.26)	(−2.40)	(−1.44)	(2.78)	(−3.43)	(0.02)	(−1.61)	(−1.75)	(−1.43)
Ln(1+S1&2 int.)	0.0003	0.0368***	−0.0001	−0.0000	0.0016	0.0002	−0.0032	−0.0074***	−0.0020	−0.0009
	(0.32)	(3.01)	(−1.25)	(−0.03)	(0.60)	(0.08)	(−0.92)	(−2.76)	(−0.69)	(−0.43)
Ln(1+Assets)	−0.0042***	0.0008	0.0000	−0.0072***	−0.0025	0.0489***	−0.0667***	−0.0695***	−0.0905***	−0.0235***
	(−4.65)	(0.05)	(0.19)	(−3.49)	(−0.72)	(10.80)	(−10.31)	(−5.56)	(−6.42)	(−6.30)
M/B ratio	0.0002***	0.0029***	0.0000	−0.0001	−0.0002*	0.0000	0.0005*	0.0017**	0.0014**	0.0008**
	(3.74)	(3.09)	(0.30)	(−0.78)	(−1.68)	(0.12)	(1.72)	(2.04)	(2.15)	(2.58)
EBITDA-to-assets	0.0332***	0.5094***	0.0003	−0.0442***	0.0033	−0.0423***	0.0629**	−0.2934***	−0.1695***	0.1922***
	(4.39)	(5.73)	(0.98)	(−3.58)	(0.30)	(−3.13)	(2.26)	(−3.51)	(−2.79)	(3.96)
Net PPE-to-assets	0.0024	−1.7598***	0.0012	0.0318***		−0.4537***	0.0472	0.0279	0.0959***	−0.0596*
	(0.25)	(−10.54)	(0.95)	(3.40)		(−16.45)	(1.35)	(0.94)	(3.55)	(−1.78)
Book leverage	−0.0232***	−0.0417	0.0000	−0.0162**	0.0236**	0.0585***	−0.3693***	0.1339***	−0.0216	0.0190
	(−5.16)	(−0.74)	(0.05)	(−2.13)	(2.20)	(4.73)	(−13.67)	(4.50)	(−0.60)	(1.25)
Cash-to-assets	0.0082*	0.4809***	0.0004	−0.0083	−0.0653***	−0.1647***	−0.0103	−0.0437	−0.3861***	0.0670***
	(1.95)	(4.12)	(0.94)	(−1.05)	(−4.98)	(−8.75)	(−0.60)	(−1.49)	(−12.55)	(2.64)
Herfindahl index	0.0033	0.0541	−0.0006	0.0039	−0.0089	0.0034	0.0112	0.0142	0.0107	0.0088
	(0.31)	(0.70)	(−0.42)	(0.66)	(−0.45)	(0.12)	(0.37)	(0.57)	(0.59)	(0.60)
Constant	0.1315***	0.1940	0.0003	0.2176***	0.3065***	−0.6927***	1.5761***	1.5152***	2.0257***	0.4527***
	(6.29)	(0.53)	(0.22)	(5.11)	(4.03)	(−7.16)	(10.75)	(5.58)	(6.49)	(5.35)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	19,778	18,580	18,893	12,860	19,803	19,567	19,762	18,510	19,799	18,693
Adj-R2	0.726	0.175	0.543	0.875	0.937	0.877	0.173	0.510	0.242	0.655

A Appendix

Table A1: Definition of variables

Variable	Definition	Source
TCUT	TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut (treated group). The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs (control group). A tariff cut TC is defined as a reduction in the tariff rate that is at least twice (or alternatively, three times) as large as the average negative change in the industry.	Schott (2008)
Ln(1+Scope1 intensity)	Ln(1+Scope1 intensity) is calculated as the natural logarithm of one plus a firm's greenhouse gas (GHG) emissions from sources that are owned or controlled by the firm (categorized by the Greenhouse Gas Protocol) divided by the firm's revenue (tCO_2e/USD 1 million revenue).	Trucost
Ln(1+Scope2 intensity)	Ln(1+Scope2 intensity) is calculated as the natural logarithm of one plus a firm's greenhouse gas (GHG) emissions from consumption of purchased electricity, heat or steam by the firm (categorized by the Greenhouse Gas Protocol) divided by the firm's revenue (tCO_2e/USD 1 million revenue).	Trucost
Ln(1+Scope1&2 intensity)	Ln(1+Scope1&2 intensity) is calculated as the natural logarithm of one plus the sum of a firm's Scope 1 and Scope 2 greenhouse gas (GHG) emissions, divided by the firm's revenue (tCO_2e/USD 1 million revenue).	Trucost
Ln(1+Assets)	Ln(1+Assets) is calculated as the natural logarithm of one plus a firm's total assets.	Compustat
M/B ratio	M/B ratio is calculated as the ratio of the market capitalization over book equity.	Compustat
EBITDA-to-assets	EBITDA-to-assets is calculated as operating income over total assets.	Compustat
Net PPE-to-assets	Net PPE-to-assets is calculated as net property, plant, and equipment (PPE) over total assets.	Compustat
Book leverage	Book leverage is calculated as the ratio of total debt to total assets.	Compustat
Ln(1+Scope 1 absolute)	Ln(1+Scope 1 absolute) is calculated as the natural logarithm of one plus a firm's greenhouse gas (GHG) emissions from sources that are owned or controlled by the firm (categorized by the Greenhouse Gas Protocol).	Trucost
Ln(1+Scope 2 absolute)	Ln(1+Scope 2 absolute) is calculated as the natural logarithm of one plus a firm's greenhouse gas (GHG) emissions from consumption of purchased electricity, heat or steam by the firm (categorized by the Greenhouse Gas Protocol).	Trucost
Ln(1+Scope 1&2 absolute)	Ln(1+Scope 1&2 absolute) is calculated as the natural logarithm of one plus the sum of a firm's Scope 1 and Scope 2 greenhouse gas (GHG) emissions.	Trucost
Ln(1+Sales)	Ln(1+Sales) is calculated as the natural logarithm of one plus the firm's sales.	Compustat
Ln(1+Sales-Adj)	Ln(1+Sales-Adj) is calculated as the natural logarithm of one plus the firm's sales, where sales are deflated to 2023 prices.	Compustat
Δ Sales	Δ Sales is calculated as the difference between the natural logarithm of the firm's net sales and the natural logarithm of its lagged net sales.	Compustat
Emission trading	Emission trading equals one if the firm reports on its participation in any emission trading initiative and zero otherwise.	LSEG
Emission reduction target	Emission reduction target equals one if the firm sets targets or objectives to achieve emission reduction and zero otherwise.	LESG

(continued)

Variable	Definition	Source
Emission score	Emission score measures a firm's commitment and effectiveness towards reducing environmental emissions in the production and operational processes. The score ranges from 0 to 1.	LSEG
Eco-friendly product	Eco-friendly product equals one if the firm reports on specific products designed for reuse, recycling, or the reduction of environmental impacts and zero otherwise.	LSEG
Green buildings	Green buildings equals one if the firm reports having environmentally friendly or green sites or offices, and zero otherwise.	LSEG
Environmental partnerships	Environmental partnerships equals one if the firm reports collaborations or initiatives with specialized NGOs, industry associations, or governmental organizations aimed at addressing or improving environmental issues, and zero otherwise	LSEG
ESG disclosure score	ESG disclosure score measures the extent of the firm's disclosure on environmental, social, and governance (ESG) data, incorporating industry-specific weights and relevance adjustments. The score ranges from 0 to 1.	Bloomberg
Turnover ratio	Turnover ratio is calculated as the ratio of a firm's net sales to total assets.	Compustat
Expense ratio	Expense ratio is calculated as the ratio of a firm's operating expenses to net sales.	Compustat
GHG misconduct	GHG misconduct equals one in a given year if the firm is involved in a greenhouse gas (GHG)-related misconduct case, and zero otherwise.	RepRisk
CAPEX-to-assets	CAPEX-to-assets is calculated as the ratio of capital expenditures to total assets.	Compustat
Abnormal investment	Abnormal investment is calculated as the current CAPEX-to-assets scaled by its three-year historical average, minus one (Titman et al. 2004; Strebulaev and Yang 2013).	Compustat
EnvExp-to-assets	EnvExp-to-assets is calculated as the total amount of environmental expenditures to total assets. Environmental expenditures (EnvExp) include all environmental investments and expenditures for environmental protection or to prevent, reduce, or control environmental aspects, impacts, and hazards. It also includes disposal, treatment, sanitation, and clean-up expenditure. The variable is zero when no environmental expenditures are reported.	LSEG
R&D-to-assets	R&D-to-assets is calculated as the ratio of capital expenditures to total assets.	Compustat
Intangible-to-assets	Intangible-to-assets is calculated as the ratio of intangible assets to total assets.	Compustat
Debt issuance	Debt issuance is calculated as the change in total debt (long-term debt plus current debt) from the previous year to the current year, scaled by total assets in the previous year (Leary and Roberts 2014).	Compustat
Equity issuance	Equity issuance is measured as sales of common and preferred stock minus purchases of common and preferred stock in the current year, scaled by lagged total assets (Leary and Roberts 2014).	Compustat
Δ Cash-to-assets	Δ Cash-to-assets is calculated as the change in cash and short-term investments from the previous year to the current year (Riddick and Whited 2009), scaled by lagged total assets.	Compustat
CF-to-assets	CF-to-assets is calculated as income before extraordinary items minus interest expense, taxes, and common dividends (Bates et al. 2009), divided by total assets.	Compustat

Table A2: Descriptive statistics of treated and matched control firms

This table presents descriptive statistics for treated and matched control firms. The Columns "Treated firms" include firm-year observations at pre-treatment, i.e., one year before the tariff cut, for firms that experienced tariff cuts during the sample period from 2003 to 2023. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. The Columns "Control firms" contain firm-year observations for matched firms. The control group is constructed by matching never-treated firms to treated firms based on pre-treatment characteristics measured one year prior to a tariff cut. Nearest-neighbor matching is performed using propensity scores estimated from a logit model with 0.01 caliper. Matching covariates include Scope-specific carbon intensity, Ln(1+Assets), HHI, year, and the state in which the firm's headquarters is located. Panel A uses $k = 3$ neighbors, whereas Panel B employs $k = 7$ neighbors. The Column "Diff. means" reports the differences in mean values between the two groups and tests whether these differences are statistically significant. Firms in the financial and utility industries, and government entities, are excluded from the sample. All variables are winsorized at the 1% level in both tails. Variable definitions and data sources are provided in Table A1. ** indicates statistical significance of a two-sided t-test at the 5% level.

Panel A - N-neighbors: $k = 3$

	Treated firms			Control firms			
Variable	Obs.	Mean	SD	Obs.	Mean	SD	Diff. means
Definition: TC 2							
Ln(1+Scope 1 intensity)	141	5.13	1.76	321	5.16	2.04	−0.03
Ln(1+Scope 2 intensity)	139	3.56	0.90	352	3.61	1.01	−0.05
Ln(1+Scope 1&2 intensity)	141	5.51	1.41	332	5.54	1.66	−0.03
Ln(1+Assets)	141	22.17	1.48	321	21.97	1.58	0.20
Herfindahl index	141	0.23	0.18	321	0.27	0.19	-0.04^{**}
Definition: TC 3							
Ln(1+Scope 1 intensity)	132	5.18	1.71	318	5.16	2.05	0.02
Ln(1+Scope 2 intensity)	135	3.63	0.91	334	3.68	1.01	−0.05
Ln(1+Scope 1&2 intensity)	134	5.58	1.36	312	5.75	1.67	−0.17
Ln(1+Assets)	132	22.08	1.48	320	22.01	1.48	0.07
Herfindahl index	132	0.23	0.17	320	0.23	0.17	0.00

Panel B - N-neighbors: $k = 7$

	Treated firms			Control firms			
Variable	Obs.	Mean	SD	Obs.	Mean	SD	Diff. means
Definition: TC 2							
Ln(1+Scope 1 intensity)	138	5.08	1.76	644	4.86	2.04	0.22
Ln(1+Scope 2 intensity)	139	3.56	0.90	786	3.59	0.99	−0.03
Ln(1+Scope 1&2 intensity)	139	5.49	1.40	678	5.30	1.66	0.19
Ln(1+Assets)	138	22.13	1.47	644	21.97	1.56	0.16
Herfindahl index	138	0.23	0.18	646	0.25	0.19	−0.02
Definition: TC 3							
Ln(1+Scope 1 intensity)	131	5.17	1.71	625	4.90	2.05	0.27
Ln(1+Scope 2 intensity)	134	3.62	0.90	739	3.63	1.00	−0.01
Ln(1+Scope 1&2 intensity)	131	5.54	1.35	634	5.46	1.68	0.09
Ln(1+Assets)	131	22.06	1.47	625	21.86	1.53	0.20
Herfindahl index	131	0.23	0.17	630	0.24	0.18	−0.01

Table A3: Summary statistics of additional analyses

This table presents the summary statistics for all variables used in additional analyses for the firms in our sample, covering the period from 2003 to 2023. We exclude firms from the financial industries (SIC codes 6000–6999), utility industries (SIC codes 4900–4999), and government entities (SIC codes $\geq$ 9000). All variables are winsorized at the 1% level in both tails. Variable definitions and data sources are provided in Table A1.

Variable	Obs.	Mean	SD	25%-quantile	Median	75%-quantile
Scope 1 absolute ($MtCO_2e$)	21,970	0.60	2.28	0.01	0.03	0.16
Scope 2 absolute ($MtCO_2e$)	21,970	0.26	0.68	0.01	0.04	0.16
Scope 1&2 absolute ($MtCO_2e$)	21,970	0.88	2.84	0.02	0.08	0.38
Ln(1+Sales)	21,970	21.22	1.96	20.21	21.43	22.51
Ln(1+Sales-Adj)	21,970	21.45	2.00	20.39	21.68	22.79
Δ Sales	19,806	0.08	0.28	−0.01	0.07	0.17
Emission trading	16,743	0.06	0.23	0.00	0.00	0.00
Emission reduction target	15,406	0.30	0.46	0.00	0.00	1.00
Emission score	16,222	0.30	0.31	0.00	0.19	0.54
Eco-friendly product	16,984	0.11	0.32	0.00	0.00	0.00
Green buildings	17,020	0.26	0.44	0.00	0.00	1.00
Environmental partnerships	17,014	0.32	0.47	0.00	0.00	1.00
ESG disclosure score	11,823	0.40	0.11	0.32	0.37	0.47
Turnover ratio	19,796	0.95	0.67	0.50	0.79	1.21
Expense ratio	19,752	1.23	3.56	0.78	0.86	0.93
GHG misconduct	19,804	0.06	0.24	0.00	0.00	0.00
CAPEX-to-assets	19,778	0.04	0.05	0.02	0.03	0.05
Abnormal investment	18,580	0.03	0.63	−0.30	−0.06	0.21
EnvExp-to-assets	18,893	0.001	0.004	0.00	0.00	0.00
R&D-to-assets	12,860	0.06	0.10	0.01	0.02	0.08
Intangible-to-assets	19,567	0.24	0.22	0.05	0.19	0.39
Debt issuance	19,762	0.04	0.16	−0.02	0.00	0.05
Equity issuance	18,510	0.001	0.17	−0.04	0.00	0.00
Δ Cash-to-assets	19,799	0.02	0.16	−0.02	0.00	0.04
CF-to-assets	18,693	−0.04	0.16	−0.04	0.00	0.03

Table A4: Summary statistics of randomized industry placebo tests

This table reports summary statistics from randomized industry placebo tests based on randomization inference. For each draw, the number of treated industries per year is kept fixed, and tariff-cut exposure is randomly reassigned across industries within each year. To avoid contamination from true treatment effects, the original treated industry-year observations are excluded when constructing the placebo samples. The baseline fixed-effects specification is re-estimated, and the resulting placebo coefficients are collected. The table reports the mean, standard deviation (SD), and selected percentiles of the placebo-coefficient distribution across $1,000$ random assignments Randomization inference (RI) p-values refer to the baseline treatment estimates reported in Table 4 (Columns (1)–(3) and (7)–(9)) and equal the fraction of placebo coefficients with absolute value greater than or equal to the actual estimate (two-sided). Variable definitions and data sources are provided in Table A1.

	DV: Ln(1+Scope intensities)					
	TC 2			TC 3		
Statistic (placebo)	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
Mean β (TCUT)	0.005	−0.010	−0.003	0.006	−0.012	−0.004
SD	0.081	0.058	0.066	0.084	0.065	0.070
5th pct.	−0.123	−0.106	−0.110	−0.125	−0.124	−0.118
25th pct.	−0.051	−0.049	−0.048	−0.049	−0.052	−0.046
Median	0.002	−0.010	−0.003	0.003	−0.008	−0.007
75th pct.	0.054	0.031	0.037	0.059	0.028	0.035
95th pct.	0.144	0.085	0.106	0.151	0.097	0.113
RI p-value	0.003	0.013	0.002	0.002	0.036	0.002
Draws	1,000	1,000	1,000	1,000	1,000	1,000

Table A5: Robustness tests

This table presents results from fixed effect regressions, where the dependent variables represent Ln(1+Scope intensities): Scope 1, Scope 2, and combined Scope 1&2. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. Panel A includes state fixed effects and categorizes industries at the three-digit SIC level, whereas Panel B employs the four-digit SIC classification. Panel C again applies the three-digit SIC classification but excludes observations from the year 2020 onward. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the respective industry level, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A - State FE	DV: Ln(1+Scope intensities)					
	TC 2			TC 3		
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)
TCUT	-0.2519^{***}	-0.1345^{***}	-0.2205^{***}	-0.2669^{***}	-0.1390^{***}	-0.2295^{***}
	(-2.94)	(-2.83)	(-2.99)	(-3.43)	(-3.00)	(-3.27)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	21,147	21,147	21,147	21,139	21,139	21,139
Adj-R2	0.894	0.853	0.901	0.894	0.853	0.901

Panel B - SIC 4	DV: Ln(1+Scope intensities)					
	TC 2			TC 3		
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)
TCUT	-0.2210^{*}	-0.1355^{***}	-0.2078^{**}	-0.2923^{***}	-0.1608^{***}	-0.2552^{***}
	(-1.82)	(-2.62)	(-2.27)	(-3.44)	(-4.00)	(-3.65)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	23,171	23,171	23,171	23,117	23,117	23,117
Adj-R2	0.891	0.848	0.898	0.891	0.848	0.898

Panel C - up to 2019	DV: Ln(1+Scope intensities)					
	TC 2			TC 3		
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)
TCUT	-0.3264^{***}	-0.1447^{***}	-0.2783^{***}	-0.3704^{***}	-0.1525^{***}	-0.3035^{***}
	(-4.05)	(-4.54)	(-4.76)	(-7.34)	(-4.96)	(-6.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	14,811	14,811	14,811	14,801	14,801	14,801
Adj-R2	0.915	0.868	0.919	0.915	0.868	0.920

Table A6: Reported emissions by firms

This table presents results from fixed effect regressions, where the dependent variables represent Ln(1+Scope intensities): Scope 1, Scope 2, and combined Scope 1&2. Columns (1)–(3) use emission data from Trucost, categorized as reported, while Columns (4)–(6) employ emission data from CDP as reported in LSEG. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate that is at least twice the industry's average negative change. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the respective industry level, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	DV: Ln(1+Scope intensities)					
	Trucost			LSEG CDP		
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)
TCUT	-0.6901^{**}	-0.2929^{*}	-0.5793^{*}	-0.0791^{*}	-0.2666^{***}	-0.2365^{***}
	(-2.22)	(-1.70)	(-1.84)	(-1.79)	(-2.73)	(-2.69)
Ln(1+Assets)	-0.0146	0.0239	0.0017	-0.1959^{***}	-0.3306^{***}	-0.3480^{***}
	(-0.20)	(0.27)	(0.03)	(-2.78)	(-5.25)	(-5.60)
M/B ratio	0.0003	-0.0007	-0.0000	-0.0007	-0.0059^{**}	-0.0037^{**}
	(0.14)	(-0.42)	(-0.00)	(-0.30)	(-1.98)	(-2.08)
EBITDA-to-assets	0.6389^{**}	0.1560	0.4104^{**}	-0.3027	-0.5198	-0.8153^{***}
	(2.45)	(0.59)	(1.99)	(-0.96)	(-1.53)	(-2.81)
Net PPE-to-assets	0.7076^{**}	1.3352^{***}	1.1787^{***}	-0.0503	-0.4398	-0.0844
	(2.10)	(2.64)	(3.20)	(-0.21)	(-0.85)	(-0.23)
Book leverage	-0.0971	-0.1056	-0.1137	-0.2080	0.2380	-0.0927
	(-0.49)	(-0.48)	(-0.75)	(-1.51)	(0.65)	(-0.54)
Cash-to-assets	-0.0472	-0.0399	0.0588	-0.0087	-0.5120^{**}	-0.2922
	(-0.29)	(-0.19)	(0.28)	(-0.04)	(-2.12)	(-1.36)
Herfindahl index	-0.1658	-0.0051	0.0768	-0.1903	0.0329	-0.1792
	(-0.42)	(-0.02)	(0.25)	(-0.52)	(0.09)	(-0.43)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1,188	1,138	1,113	3,592	3,568	3,557
Adj-R2	0.979	0.960	0.980	0.904	0.862	0.882

Table A7: Competition and firms' long-term carbon performance

This table presents results from fixed effect regressions, where the dependent variables represent Ln(1+Scope intensities): Scope 1, Scope 2, and combined Scope 1&2. The variable TCUT equals one for firms in the three-year or six-year period following a tariff cut (Panels A and B, respectively) and zero in the corresponding pre-treatment window (three or six years before the cut). The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the respective industry level, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A - LT (3 years)	DV: Ln(1+Scope intensities)					
	TC 2			TC 3		
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)
TCUT	-0.1888^{*}	-0.1454^{***}	-0.1810^{**}	-0.2292^{**}	-0.1511^{***}	-0.2083^{***}
	(-1.84)	(-3.06)	(-2.53)	(-2.25)	(-2.86)	(-2.85)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	21,457	21,457	21,457	21,425	21,425	21,425
Adj-R2	0.895	0.854	0.902	0.895	0.854	0.902

Panel B - LT (6 years)	DV: Ln(1+Scope intensities)					
	TC 2			TC 3		
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)
TCUT	-0.1747^{*}	-0.1485^{***}	-0.1652^{**}	-0.2316^{**}	-0.1554^{***}	-0.2036^{***}
	(-1.76)	(-3.11)	(-2.36)	(-2.28)	(-2.74)	(-2.73)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	21,517	21,517	21,517	21,472	21,472	21,472
Adj-R2	0.896	0.854	0.903	0.896	0.854	0.902

Table A8: Carbon performance and alternative tariff cut definition

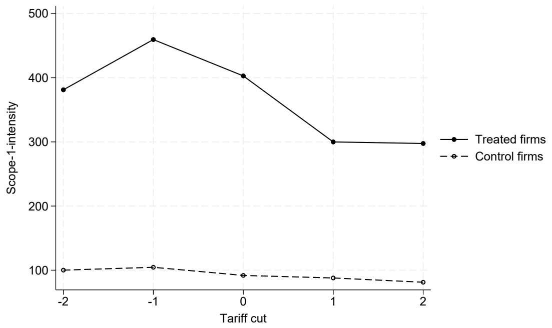
This table presents results from fixed effect regressions, where the dependent variables represent Ln(1+Scope intensities): Scope 1, Scope 2, and combined Scope 1&2. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC median 2) or three times (TC median 3) the industry's median negative change. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the respective industry level, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	DV: Ln(1+Scope intensities)					
	TC median 2			TC median 3		
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)
TCUT	-0.0797^{**}	-0.0186	-0.0563^{*}	-0.0836^{*}	-0.0190	-0.0634^{*}
	(-2.05)	(-0.72)	(-1.80)	(-1.94)	(-0.80)	(-1.89)
Log(1+Assets)	-0.0812^{***}	-0.0300^{*}	-0.0541^{***}	-0.0838^{***}	-0.0276	-0.0539^{***}
	(-4.18)	(-1.74)	(-2.87)	(-4.36)	(-1.60)	(-2.86)
M/B ratio	-0.0020^{**}	-0.0015^{*}	-0.0019^{**}	-0.0019^{*}	-0.0014^{*}	-0.0017^{**}
	(-2.01)	(-1.97)	(-2.13)	(-1.89)	(-1.85)	(-2.01)
EBITDA-to-assets	-0.1155	-0.0302	-0.0946	-0.1145	-0.0352	-0.0969^{*}
	(-1.45)	(-0.74)	(-1.61)	(-1.44)	(-0.87)	(-1.68)
Net PPE-to-assets	0.1784	0.0456	0.1267	0.1581	0.0391	0.1135
	(1.15)	(0.31)	(0.88)	(1.02)	(0.27)	(0.79)
Book leverage	-0.0123	-0.0301	-0.0266	-0.0202	-0.0304	-0.0313
	(-0.22)	(-0.66)	(-0.57)	(-0.35)	(-0.67)	(-0.67)
Cash-to-assets	-0.0180	-0.1020^{**}	-0.0603	-0.0095	-0.0985^{**}	-0.0521
	(-0.35)	(-2.42)	(-1.39)	(-0.18)	(-2.29)	(-1.18)
Herfindahl index	0.0257	0.0349	-0.0367	0.0193	0.0362	-0.0377
	(0.15)	(0.27)	(-0.25)	(0.11)	(0.29)	(-0.25)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	19,499	19,499	19,499	19,336	19,336	19,336
Adj-R2	0.902	0.858	0.906	0.903	0.859	0.907

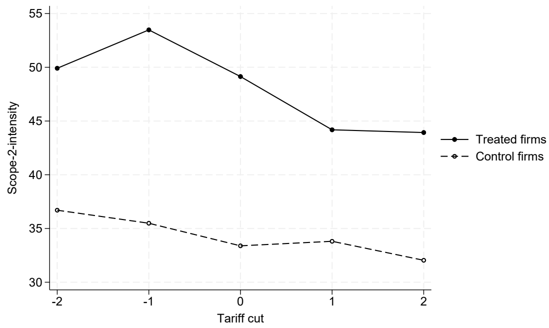
B Online Appendix A

Figure OA1: Evolution of Scope 1 and Scope 2 intensities around tariff cuts

This figure shows the evolution of firms' Scope 1 emission intensity and Scope 2 emission intensity around tariff cuts. A tariff cut is defined as a reduction in the tariff rate at least twice as large as the average negative change in the industry. The y-axis shows the average intensities for treated (solid line) and control firms (dashed line). The x-axis indicates the years relative to a tariff cut, with $t = 0$ denoting the year the cut occurred. Variable definitions and data sources are provided in Table A1.



(a) Scope 1 intensity



(b) Scope 2 intensity

Table OA1: Competition and firms' carbon performance (level)

This table presents results from fixed effect regressions, where the dependent variables represent Scope intensities: Scope 1, Scope 2, and combined Scope 1&2. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level at both ends. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level for models with firm fixed effects, and at the firm level for models with industry fixed effects. T-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	DV: Scope intensities											
	TC 2						TC 3					
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TCUT	-120.8317^{***}	-9.0956^{***}	-139.4395^{***}	-90.1477^{***}	-6.4022^{**}	-103.0576^{***}	-123.4377^{***}	-9.4422^{***}	-142.6142^{***}	-90.5448^{***}	-6.7259^{**}	-103.7718^{***}
	(−3.01)	(−2.84)	(−3.02)	(−4.98)	(−2.45)	(−5.03)	(−3.12)	(−3.07)	(−3.14)	(−4.95)	(−2.54)	(−5.01)
Ln(1+Assets)	0.3304	−0.2400	−0.0945	3.7051	2.1974^{***}	6.9118^{***}	0.3900	−0.2379	−0.0276	3.7044	2.1963^{***}	6.9100^{***}
	(0.09)	(−0.33)	(−0.02)	(1.63)	(5.61)	(2.63)	(0.10)	(−0.33)	(−0.01)	(1.63)	(5.61)	(2.63)
M/B ratio	−0.1277	−0.0438	−0.2047	-0.4296^{***}	-0.1461^{***}	-0.6141^{***}	−0.1228	−0.0433	−0.1992	-0.4273^{***}	-0.1455^{***}	-0.6109^{***}
	(−1.16)	(−1.13)	(−1.48)	(−2.80)	(−3.86)	(−3.23)	(−1.10)	(−1.11)	(−1.43)	(−2.78)	(−3.83)	(−3.21)
EBITDA-to-assets	−16.6132	−1.0335	−23.4321	-23.5646^{**}	-4.6938^{**}	-32.7549^{***}	−16.4523	−1.0291	−23.2546	-23.5241^{**}	-4.6930^{**}	-32.7077^{***}
	(−0.97)	(−0.45)	(−1.17)	(−2.43)	(−2.50)	(−2.92)	(−0.96)	(−0.45)	(−1.16)	(−2.43)	(−2.50)	(−2.91)
Net PPE-to-assets	87.3993^{*}	3.6564	93.5763	212.0348^{***}	42.2366^{***}	281.7123^{***}	86.4886^{*}	3.5964	92.5261	211.8697^{***}	42.2372^{***}	281.5329^{***}
	(1.90)	(0.46)	(1.63)	(6.40)	(7.54)	(6.95)	(1.88)	(0.46)	(1.61)	(6.40)	(7.54)	(6.94)
Book leverage	2.1384	−2.3895	1.2438	−3.1052	-4.0959^{**}	−5.7704	1.8211	−2.4055	0.8858	−3.1804	-4.1069^{**}	−5.8621
	(0.14)	(−0.77)	(0.07)	(−0.30)	(−2.03)	(−0.47)	(0.12)	(−0.78)	(0.05)	(−0.30)	(−2.04)	(−0.48)
Cash-to-assets	1.3868	−2.1799	−1.9727	34.3827^{**}	6.5170^{**}	44.8022^{***}	1.2782	−2.1982	−2.1059	34.3189^{**}	6.4818^{**}	44.6985^{***}
	(0.10)	(−1.03)	(−0.12)	(2.40)	(2.57)	(2.65)	(0.09)	(−1.04)	(−0.13)	(2.39)	(2.56)	(2.64)
Herfindahl index	−24.1425	−0.9538	−28.8552	44.9026	7.9145^{*}	52.1414^{*}	−24.1695	−0.9443	−28.8726	44.6708	7.9317^{*}	51.8928
	(−1.18)	(−0.19)	(−1.26)	(1.57)	(1.73)	(1.65)	(−1.18)	(−0.19)	(−1.26)	(1.56)	(1.72)	(1.64)
Firm FE	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	No	No	No
Industry FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	21,400	21,400	21,400	21,752	21,752	21,752	21,392	21,392	21,392	21,745	21,745	21,745
Adj-R2	0.864	0.831	0.874	0.610	0.560	0.606	0.864	0.831	0.874	0.610	0.560	0.606

Table OA2: Competition and firms' carbon performance without control variables

This table presents results from fixed effect regressions. Panel A reports estimates using Ln(1+Scope intensities), including Scope 1, Scope 2, and combined Scope 1&2. Panel B reports results for Ln(1+absolute emissions)—Scope 1 (S1 abs), Scope 2 (S2 abs), and combined Scope 1&2 (S1&2 abs)—as well as Ln(1+Sales), Ln(1+Sales-Adj), and Δ Sales. Sales-Adj deflates sales to 2023 prices. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. All continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level for models with firm fixed effects, and at the firm level for models with industry fixed effects. T-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A	DV: Ln(1+Scope intensities)											
	TC 2						TC 3					
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TCUT	-0.2628^{***}	-0.1259^{**}	-0.2250^{***}	-0.2143^{***}	-0.1122^{**}	-0.1761^{***}	-0.2790^{***}	-0.1306^{***}	-0.2349^{***}	-0.2271^{***}	-0.1215^{**}	-0.1864^{***}
	(-3.02)	(-2.56)	(-2.93)	(-4.21)	(-2.33)	(-3.98)	(-3.57)	(-2.74)	(-3.23)	(-4.56)	(-2.50)	(-4.21)
Firm FE	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	No	No	No
Industry FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	22,425	22,425	22,425	22,724	22,724	22,724	22,417	22,417	22,417	22,717	22,717	22,717
Adj-R2	0.892	0.853	0.900	0.728	0.626	0.733	0.892	0.853	0.900	0.728	0.626	0.733

Panel B	DV: Ln(1+Var)											
	TC 2						TC 3					
Var:	S1 abs	S2 abs	S1&2 abs	Sales	Sales-Adj	Δ Sales	S1 abs	S2 abs	S1&2 abs	Sales	Sales-Adj	Δ Sales
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TCUT	-0.0025	0.0743	0.0302	0.1549	0.1534	-0.0734^{***}	-0.0005	0.0840^{*}	0.0370	0.1590	0.1572	-0.0756^{***}
	(-0.07)	(1.62)	(0.87)	(1.48)	(1.43)	(-3.50)	(-0.02)	(1.93)	(1.11)	(1.50)	(1.45)	(-3.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	22,425	22,425	22,425	22,407	22,407	20,200	22,417	22,417	22,417	22,399	22,399	20,185
Adj-R2	0.922	0.937	0.943	0.948	0.951	0.205	0.922	0.937	0.943	0.948	0.951	0.205

Table OA3: Competition and firms' carbon performance: Matching with different periods around tariff cuts

This table presents results from fixed effect regressions, where the dependent variables represent Ln(1+Scope intensities): Scope 1, Scope 2, and combined Scope 1&2. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is zero for the control group, which is constructed by matching never-treated firms (NT) to treated firms based on pre-treatment characteristics, i.e., one year prior to a tariff cut. Nearest-neighbor matching is performed using propensity scores estimated from a logit model with 0.01 caliper. Covariates include Scope-specific carbon intensity, Ln(1+Assets), HHI, year, and the state in which the firm's headquarters is located. Columns (1)–(6) uses $k = 3$ neighbors, whereas Columns (7)–(12) employs $k = 7$ neighbors. The matching sample encompasses firm-years for both treated and matched firms over the full sample in Panel A, and firm-years from $t-1$ to $t+1$ around a tariff cut in Panel B. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A - Whole sample	DV: Ln(1+Scope intensities)											
	N-neighbors: $k=3$						N-neighbors: $k=7$					
	TC 2			TC 3			TC 2			TC 3		
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TCUT	-0.2724^{***}	-0.1273^{**}	-0.2290^{***}	-0.2554^{***}	-0.1326^{***}	-0.2589^{***}	-0.2687^{***}	-0.1337^{**}	-0.2129^{***}	-0.2420^{***}	-0.1389^{**}	-0.2505^{***}
	(−3.25)	(−2.20)	(−2.84)	(−3.07)	(−2.82)	(−3.68)	(−3.20)	(−2.04)	(−2.62)	(−2.86)	(−2.49)	(−3.42)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	3,672	4,654	3,893	3,527	4,300	3,624	5,873	7,522	6,117	5,495	6,856	5,611
Adj-R2	0.912	0.838	0.914	0.904	0.840	0.915	0.910	0.825	0.906	0.909	0.837	0.911

Panel B - $t-1$ to $t+1$	DV: Ln(1+Scope intensities)											
	N-neighbors: $k=3$						N-neighbors: $k=7$					
	TC 2			TC 3			TC 2			TC 3		
	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2	Scope 1	Scope 2	Scope 1&2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TCUT	-0.1303	-0.0787^{*}	-0.2073^{**}	-0.2113^{**}	-0.1036^{**}	-0.2490^{***}	-0.2028^{*}	-0.1029^{**}	-0.2399^{**}	-0.2387^{**}	-0.0828^{*}	-0.2818^{***}
	(−1.09)	(−1.83)	(−2.09)	(−2.15)	(−2.21)	(−2.98)	(−1.82)	(−2.42)	(−2.30)	(−2.22)	(−1.76)	(−2.99)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	834	893	855	797	850	787	1,382	1,640	1,444	1,274	1,540	1,314
Adj-R2	0.937	0.870	0.933	0.941	0.869	0.957	0.938	0.875	0.941	0.940	0.865	0.953

C Online Appendix B

Table OB1: Competition and firms' carbon performance (Scope 3 emissions)

This table presents results from fixed effect regressions, where the dependent variables represent Ln(1+Scope intensities): Scope 3 US (upstream) and Scope 3 DS (downstream). The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate that is at least twice (TC 2) or three times (TC 3) the industry's average negative change. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level for models with firm fixed effects, and at the firm level for models with industry fixed effects. T-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Scope 3 emissions	DV: Ln(1+Scope intensities)							
	TC 2				TC 3			
	Scope 3US	Scope 3DS	Scope 3US	Scope 3DS	Scope 3US	Scope 3DS	Scope 3US	Scope 3DS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TCUT	0.0040	−0.6845*	−0.0021	−0.7722***	−0.0008	−0.7545**	−0.0036	−0.8608***
	(0.26)	(−1.77)	(−0.10)	(−7.03)	(−0.04)	(−2.10)	(−0.16)	(−8.15)
Ln(1+Assets)	0.0063	−0.0572	0.0090*	−0.1043***	0.0063	−0.0569	0.0090*	−0.1044***
	(0.96)	(−0.84)	(1.89)	(−5.22)	(0.97)	(−0.84)	(1.89)	(−5.23)
M/B ratio	−0.0001	−0.0015	−0.0014**	−0.0025	−0.0001	−0.0015	−0.0014**	−0.0025
	(−0.19)	(−0.72)	(−2.28)	(−0.82)	(−0.21)	(−0.74)	(−2.27)	(−0.83)
EBITDA-to-assets	−0.0296	0.0177	0.0539	0.2720**	−0.0300	0.0278	0.0538	0.2760**
	(−1.54)	(0.15)	(1.54)	(2.20)	(−1.56)	(0.23)	(1.53)	(2.23)
Net PPE-to-assets	0.0218	0.3058	0.2395***	0.3081*	0.0219	0.2887	0.2396***	0.3050
	(0.37)	(0.87)	(4.36)	(1.66)	(0.38)	(0.82)	(4.36)	(1.64)
Book leverage	0.0168	0.2751	−0.0352	−0.1585	0.0168	0.2739	−0.0351	−0.1587
	(0.63)	(1.41)	(−1.15)	(−1.43)	(0.63)	(1.40)	(−1.14)	(−1.43)
Cash-to-assets	−0.0103	0.3939**	−0.1140**	0.2733*	−0.0104	0.3861**	−0.1148**	0.2737*
	(−0.40)	(2.56)	(−2.48)	(1.83)	(−0.41)	(2.52)	(−2.50)	(1.83)
Herfindahl index	0.0986*	−0.2990	0.1338**	−0.5435	0.0995*	−0.2840	0.1357**	−0.5194
	(1.94)	(−0.75)	(2.00)	(−1.50)	(1.95)	(−0.71)	(2.03)	(−1.43)
Firm FE	Yes	Yes	No	No	Yes	Yes	No	No
Industry FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	21,400	10,411	21,752	10,803	21,392	10,409	21,745	10,800
Adj-R2	0.964	0.862	0.842	0.674	0.964	0.862	0.842	0.674

Table OB2: Environmental strategy and agency costs (TC 3)

This table presents results from fixed effect regressions, where the one-year lead dependent variables capture aspects of firms' environmental strategy and agency costs, including greenhouse gas (GHG)-related misconduct cases. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate at least three times the industry's average negative change. The interaction term is the product of TCUT at $t+1$ and the variable Ln(1+Scope 1&2 intensity) at t. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Emission trading	Emission red. target	Emission score	Eco-friend. products	Green buildings	Environ. partnersh.	ESG Disc.score	Turnover ratio	Expense ratio	GHG misconduct
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TCUT×Ln(1+S1&2 int.)	0.0172**	0.0207	−0.0144	0.0301***	0.0331**	−0.0397***	0.0056**	0.0063	−0.0634*	−0.0545*
	(2.22)	(0.93)	(−1.07)	(2.79)	(1.98)	(−3.38)	(2.07)	(0.43)	(−1.77)	(−1.85)
TCUT	−0.1216**	−0.0506	0.0667	−0.1632**	−0.1724	0.2385***	−0.0236	0.0105	0.0584	0.2353
	(−2.52)	(−0.37)	(0.82)	(−2.39)	(−1.64)	(3.37)	(−1.45)	(0.11)	(0.29)	(1.30)
Ln(1+S1&2 int.)	−0.0035	−0.0125	−0.0189***	−0.0251***	−0.0268**	−0.0024	−0.0046	0.0067	−0.0133	0.0032
	(−0.45)	(−0.92)	(−2.83)	(−2.60)	(−2.36)	(−0.21)	(−1.42)	(0.87)	(−0.41)	(0.48)
Ln(1+Assets)	0.0138*	0.0548***	0.0837***	−0.0059	0.1064***	0.0704***	0.0065**	−0.1536***	−0.0540	0.0007
	(1.70)	(5.49)	(9.68)	(−0.58)	(7.29)	(6.41)	(2.27)	(−7.92)	(−1.29)	(0.11)
M/B ratio	0.0004	0.0000	0.0005	−0.0001	0.0008*	−0.0003	0.0000	0.0007	0.0017	0.0001
	(0.96)	(0.07)	(1.38)	(−0.16)	(1.83)	(−0.43)	(0.30)	(1.31)	(0.45)	(0.37)
EBITDA-to-assets	−0.0257	−0.0726	−0.0302	0.0022	0.0197	−0.1048**	0.0022	0.3309***	0.5083	−0.0453*
	(−1.27)	(−1.62)	(−1.61)	(0.10)	(0.46)	(−2.31)	(0.31)	(3.65)	(0.53)	(−1.81)
Net PPE-to-assets	−0.0015	−0.1148	0.0661	0.0234	0.1553*	0.1298	0.0062	−0.0951	−0.1470	0.0902
	(−0.03)	(−1.37)	(1.25)	(0.39)	(1.92)	(1.61)	(0.39)	(−0.99)	(−0.55)	(1.61)
Book leverage	−0.0048	−0.0307	−0.0030	−0.0131	0.0607	−0.0118	−0.0139*	−0.0298	−0.4305	0.0040
	(−0.24)	(−0.88)	(−0.14)	(−0.40)	(1.17)	(−0.25)	(−1.79)	(−0.80)	(−1.25)	(0.15)
Cash-to-assets	0.0214	−0.0669	−0.0009	−0.0266	0.0301	0.0151	−0.0025	−0.1759***	0.0576	0.0120
	(0.75)	(−1.40)	(−0.04)	(−0.60)	(0.68)	(0.33)	(−0.33)	(−3.77)	(0.12)	(0.58)
Herfindahl index	−0.0709	0.0793	0.1372**	0.0114	0.0723	0.1271	0.0112	−0.0338	0.1751*	−0.0320
	(−1.19)	(0.94)	(2.10)	(0.17)	(0.77)	(1.30)	(0.55)	(−0.48)	(1.94)	(−0.30)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	16,734	15,398	16,212	16,975	17,011	17,005	11,816	19,788	19,744	19,796
Adj-R2	0.522	0.648	0.766	0.563	0.611	0.662	0.860	0.904	0.799	0.331

Table OB3: Investment, asset structure, and financing (TC 3)

This table presents results from fixed effects regressions, where one-year lead the dependent variables capture firms' investment activity, asset structure, and external financing. The variable TCUT equals one for firms in the year following a tariff cut and zero for the year before the tariff cut. The year of the tariff cut is excluded. This variable is also zero for firms that never experienced a tariff cut and for treated firms when no tariff cut occurs. A tariff cut is defined as a reduction in the tariff rate at least three times the industry's average negative change. The interaction term is the product of TCUT at $t+1$ and the variable Ln(1+Scope 1&2 intensity) at t. Control variables are measured one year prior to the dependent variable, and all continuous variables are winsorized at the 1% level in both tails. All regressions include a constant, which is omitted from the table for brevity. Variable definitions and data sources are provided in Table A1. Standard errors are clustered at the industry level, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	CAPEX-to-assets	Abnormal investment	EnvExp-to-assets	R&D-to-assets	Net PPE-to-assets	Intangible-to-assets	Debt issuance	Equity issuance	ΔCash-to-assets	CF-to-assets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TCUT×Ln(1+S1&2 int.)	0.0024***	0.0302	0.0004***	0.0046	−0.0098***	0.0135***	−0.0013	0.0028	0.0141**	0.0241***
	(3.10)	(1.57)	(3.18)	(1.59)	(−4.27)	(3.45)	(−0.15)	(0.59)	(2.58)	(4.26)
TCUT	−0.0036	−0.1239	−0.0017**	−0.0214	0.0396***	−0.0727***	0.0049	−0.0144	−0.0562*	−0.0512
	(−0.81)	(−1.18)	(−2.44)	(−1.60)	(2.82)	(−3.01)	(0.09)	(−0.55)	(−1.66)	(−1.29)
Ln(1+S1&2 int.)	0.0003	0.0361***	−0.0001	−0.0000	0.0016	0.0002	−0.0032	−0.0074***	−0.0021	−0.0008
	(0.29)	(2.95)	(−1.26)	(−0.03)	(0.59)	(0.09)	(−0.92)	(−2.77)	(−0.70)	(−0.41)
Ln(1+Assets)	−0.0042***	−0.0001	0.0000	−0.0072***	−0.0025	0.0489***	−0.0667***	−0.0696***	−0.0906***	−0.0235***
	(−4.67)	(−0.01)	(0.19)	(−3.49)	(−0.73)	(10.81)	(−10.33)	(−5.58)	(−6.44)	(−6.30)
M/B ratio	0.0002***	0.0028***	0.0000	−0.0001	−0.0002*	0.0000	0.0005*	0.0017**	0.0014**	0.0008**
	(3.75)	(3.06)	(0.31)	(−0.78)	(−1.70)	(0.04)	(1.70)	(2.05)	(2.14)	(2.56)
EBITDA-to-assets	0.0333***	0.5118***	0.0003	−0.0443***	0.0034	−0.0424***	0.0636**	−0.2930***	−0.1693***	0.1912***
	(4.39)	(5.73)	(0.97)	(−3.58)	(0.30)	(−3.15)	(2.28)	(−3.51)	(−2.79)	(3.95)
Net PPE-to-assets	0.0026	−1.7552***	0.0012	0.0318***		−0.4537***	0.0471	0.0288	0.0958***	−0.0610*
	(0.27)	(−10.50)	(0.95)	(3.40)		(−16.45)	(1.35)	(0.97)	(3.55)	(−1.83)
Book leverage	−0.0233***	−0.0441	0.0000	−0.0163**	0.0235**	0.0583***	−0.3691***	0.1336***	−0.0214	0.0194
	(−5.18)	(−0.78)	(0.04)	(−2.14)	(2.20)	(4.72)	(−13.64)	(4.49)	(−0.60)	(1.27)
Cash-to-assets	0.0083**	0.4865***	0.0004	−0.0083	−0.0652***	−0.1648***	−0.0103	−0.0428	−0.3859***	0.0658**
	(1.98)	(4.15)	(0.94)	(−1.05)	(−4.98)	(−8.75)	(−0.60)	(−1.45)	(−12.55)	(2.59)
Herfindahl index	0.0031	0.0493	−0.0006	0.0038	−0.0089	0.0039	0.0114	0.0139	0.0110	0.0086
	(0.30)	(0.63)	(−0.42)	(0.64)	(−0.45)	(0.14)	(0.37)	(0.56)	(0.60)	(0.59)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	19,770	18,572	18,886	12,855	19,795	19,559	19,754	18,502	19,791	18,685
Adj-R2	0.725	0.176	0.543	0.875	0.937	0.877	0.173	0.509	0.241	0.655