How Do Trade Conflicts Affect Corporate Carbon Emissions? Evidence from Global Supply Chain

Zeyun Bei[†]
Ebenezer Effah[‡]
Yaxuan Qi[§]

March 2025

Abstract

This paper examines the effect of trade conflicts on corporate carbon emissions through global supply chains. Exploiting the 2018–2019 U.S.-China tariff hikes as a quasi-natural experiment, we find that U.S. firms subjected to higher import tariffs increased Scope 1 and 2 emissions by 15% and 8%, respectively, compared to minimally affected peers. The effect is amplified for firms reliant on green product imports from China, highlighting supply chain disruptions as a key channel. Financial constraints further exacerbate emissions, as tariff-induced cost pressures reduce green innovation and employment. Cross-sectional tests reveal that firms with weaker climate change ideologies and less diversified supply chains exhibit more pronounced emission increases. Overall, our findings demonstrate that geopolitical trade risks undermine firm-level decarbonization efforts, with implications for policymakers and firms navigating climate goals amid rising protectionism.

Keywords: trade policy, carbon emissions, global supply chains, financial constraints, green innovations.
JEL Classification: F14; F18; Q54; Q55; Q56

[†]City University of Hong Kong. Email: zeyunbei2-c@my.cityu.edu.hk
[‡]City University of Hong Kong. Email: eeffah2-c@my.cityu.edu.hk
[§]City University of Hong Kong. Email: yaxuanqi@cityu.edu.hk

1. Introduction

Firms with cross-border networks are crucial in efforts aimed at addressing climate change (Yu et al., 2023; Zahra, 2024; Allen et al., 2025; Senbet, 2025). This strand of literature aligns with the idea that coordination across national and regional borders is a fundamental strategy for curbing carbon emissions.[1] The effectiveness of such a strategy, however, can be disrupted by trade conflicts (Caliendo et al., 2019; Huang et al., 2023; Allen et al., 2025). Yet, the impact of trade conflicts on firms' decarbonization efforts is unclear. Through the lens of global supply chains, we explore whether and how trade disputes, in the form of import tariff hikes, influence U.S. firms' carbon emissions.

Two arguments underpin our empirical predictions. First, supply chains play a pivotal role in firms' decarbonization efforts and emission incentives. Extant research shows green innovations diffuse through supply chain networks (e.g., Gopalakrishnan et al., 2021; Hege et al., 2024). Import tariff hikes could disrupt this flow, create barriers to adopting cleaner foreign technologies, and consequently increase emissions as firms opt for dirtier alternatives. The second argument is based on the high financial burden induced by import tariff hikes. As Huang et al. (2023) propound, higher tariffs on imported inputs increase production costs and reduce profits. Given that higher financial limitations reduce firms' abatement activities and increase total pollution (Akey and Appel, 2021; Bartram et al., 2022; Kim and Xu, 2022), we expect a rise in import tariffs to reduce affected firms' decarbonization efforts. Taken together, we hypothesize that hikes in import tariffs increase corporate carbon emissions.

To test our hypothesis, we exploit the 2018-2019 U.S.-China tariff hikes as a unique real-world experiment for studying the effects of trade disputes on the carbon emissions of firms linked to global supply chains. Our empirical design employs product-level HS

[1] For example, the United Nations' Sustainable Development Goal 13 (UN SDG 13) requires member nations to "take urgent action to combat climate change and its impacts" (https://www.un.org/sustainabledevelopment/climate-change/). Also, international policymakers, through the Paris Agreement, aim to limit global warming to less than 2 degrees Celsius (https://unfccc.int/process-and-meetings/the-paris-agreement).

code from Panjiva—a global supply chain platform containing import and export data for over 15 million firms and 35 million products—to identify products and, subsequently, U.S. firms subjected to the trade shock. We ensure that both treated and control firms have Chinese suppliers. Our measures of carbon emissions are sourced from the S&P Trucost database. Using a matching-based difference-in-differences (DiD) design, we find that U.S. firms subject to major hikes in Chinese import tariffs during the U.S.-China trade war increased their Scope 1 and 2 emissions by approximately 15% and 8% more than their minimally-affected counterparts, respectively.

Next, we explore the underlying argument that higher tariffs could constrain the trade of green products in the global supply chain, which, in turn, could increase emissions. To the extent that this prediction is true, we expect the documented effect to be stronger for firms that trade more green products in the U.S.-China supply chain. Green products are identified using HS codes from the Organisation for Economic Co-operation and Development (OECD), Asia-Pacific Economic Cooperation (APEC), and World Trade Organization (WTO). We define two binary variables based on whether a firm trades in green products. Then, we interact each binary variable with our independent variable of interest in a heterogeneity test. Consistent with our conjecture, we find that the effect of the trade dispute on carbon emissions is significantly larger for firms that import green products from China.

We also test our financial pressure argument, according to which we expect proxies of financial difficulties to amplify the relationship between the tariff war and corporate carbon emissions. Our measures of financial pressure capture both financial constraint and distress, including the WW index (Whited and Wu, 2006), SA index (Hadlock and Pierce, 2010), COGS/sales, and EBITDA margin. We first show that firms indeed experienced high financial difficulties following the U.S.-China tariff hikes. We then generate a binary variable for high and low financially burdened firms, and interact it with the key DiD covariate in a tripple difference empirical framework. In line with our hypothesis, we find strong evidence that the worsened financial conditions induced by the trade war intensify the impact of the shock on firms' carbon emissions.

To paint a more complete picture of the underlying mechanism, we investigate the operational adjustments that firms make upon experiencing tariff-induced financial problems. Environment-friendly technical changes are widely regarded as a key approach to reducing carbon emissions (Acemoglu et al., 2016a; Aghion et al., 2016). The evidence that firms increase carbon emissions upon hikes in import tariffs motivates our prediction that, faced with tariff-induced financial pressure, firms might have reduced their focus on green-related technologies after the shock. As predicted, we find a significant drop in green innovations, proxied by green patents, following the import tariff hikes during the 2018-2019 U.S.-China trade war. Additionally, the reduction in green innovation moderates the relationship between the trade shock and corporate carbon emissions.

Next, we extend the analysis on operational adjustments to labor employment by investigating the role of environment-related employment in the documented effect. Like the argument about green innovation discussed above, the tariff-induced financial pressure leading to poor carbon emissions performance suggests that firms might have put less priority on environment-related employment after the shock. We demonstrate that affected firms, relative to comparable unaffected firms, indeed reduced both environment-related job positions as well as employees with environmental expertise.

Additionally, we examine whether the operational changes interact with the financial pressure channel. We argue that a firm's green innovation and employment are dependent on the firm's financial resources, and therefore, a rise in financial constraints should reduce green innovation and employment. In support of our conjecture, we find that affected firms with higher financial constraints experience a greater reduction in the scale of green innovation and employment following hikes in import tariffs compared to affected firms with lower financial constraints. These findings help deepen our understanding of how financial resources are important in the operational adjustments forced by higher import tariffs.

Next, we conduct cross-sectional tests based on climate change ideology. Prior research establishes that firms' environmental performance strongly correlates with their stakeholders' climate change perspectives (e.g., Ilhan et al., 2021; Krueger et al., 2024), where weaker climate ideologies typically associate with poorer environmental outcomes. Extending this logic, we hypothesize that tariff-induced financial pressures will lead to greater emission increases among firms with weaker climate ideologies compared to their more environmentally-conscious counterparts. Our empirical tests using multiple climate ideology measures confirm this prediction—the emissions effects of tariff hikes are significantly amplified for firms with lower climate change commitments.

Finally, we study the heterogeneous effects of trade conflicts based on supply chain characteristics, particularly diversification and import specificity. Supply chain diversification, as a risk reduction technique, can mitigate the negative economic effects of supply chain disruptions (Hendricks et al., 2009; Chod et al., 2019). In a similar vein, import specificity should be decreasing in firms' ability to manoeuvre the implications of supply chain disruptions. Our measure of supply chain diversification is based on the Herfindahl-Hirschman Index of the country distribution of suppliers, whereas the proxy for import specificity is based on Product Complexity Index. We find that the effect of the tariff war on firms' carbon emissions is more pronounced for firms with a less diversified supply chain and for those with a high import specificity.

Our study makes several contributions. First, we expand upon the literature that examines carbon emissions along supply chains (e.g., Lin et al., 2019; Waller et al., 2019; Gopalakrishnan et al., 2021; Tian et al., 2022; Song et al., 2023; Hege et al., 2024). For instance, Gopalakrishnan et al. (2021) and Hege et al. (2024) stress that supply chains could facilitate firms' decarbonization efforts. Perhaps closest to our research are Lin et al. (2019) and Tian et al. (2022) both suggesting that when international trade is restricted, global and regional emissions decline. In contrast, we provide microeconomic evidence that trade disputes increase firm-level carbon emissions through the global supply chain.

Second, we extend the recent literature that links financial incentives and corporate environmental outcomes. For example, Forster and Shive (2020) find that short-term pressure for financial performance from outside investors forces public firms to pollute more than private firms. Akey and Appel (2021) also show that subsidiaries increase toxic emissions when parent companies have better liability protection for their subsidiaries' environmental clean-up costs. Similarly, Kim and Xu (2022) find that financial constraints exacerbate pollution by firms due to the costs of waste management. Our research highlights how tariff-induced financial problems reduce firms' green innovation and environment-related employment, subsequently increasing carbon emissions.

Third, we contribute to the literature exploring the effect of trade shocks on firms' operations, including firms' reactions reflected in labor market outcomes (e.g., Autor et al., 2013, 2016; Pierce and Schott, 2016), innovation (Bloom et al., 2016), trade quality (Fieler et al., 2018), markup distortions (Edmond et al., 2015), tax evasion (Fisman et al., 2014), and costs of debt (Valta, 2012). We demonstrate that firms increase carbon emissions as a direct response to trade conflicts.

Finally, our study contributes to the international business and economics literature that focuses on the role of firms as agents of curbing global warming (Yu et al., 2023; Zaheer, 2024; Zahra, 2024; Allen et al., 2025; Senbet, 2025). The conjecture in this group of studies is that firms with international networks have unique features that enable them to play an important role in the fight against climate change. However, such firms could face challenges in thier quest to decarbonize. We show that geopolitical risk in the form of trade conflicts worsens the carbon reduction efforts of such firms.

The rest of the paper is organized as follows. In Section 2, we review the related literature and develop our testable hypothesis. Section 3 provides the institutional background and empirical design. Section 4 describes the data sources and sample construction. In Section 5, we present and discuss our empirical results. Section 6 concludes the paper.

2. Literature Review and Hypothesis

2.1. Carbon Emissions

Climate change has been at the center of academic, practitioner, and political debates as one of the most challenging socioeconomic issues facing humanity in modern times. Its global nature has made it the focus of a growing body of international trade research that highlights firms with footprints across national borders as powerful actors in tackling climate change. For example, Zahra (2024), Allen et al. (2025), and Senbet (2025) argue that the extent to which multinational enterprises (MNEs) can influence the fight against global climate change is dependent on their reach, technological resources, collaborations, and financial resources.

The above-mentioned factors are consistent with evidence in the large body of single-country domestic studies on climate change. For instance, Acemoglu et al. (2016a), Aghion et al. (2016), and Brown et al. (2022) recognize the importance of firms' technological resources in reducing emission levels. Kim and Xu (2022), Akey and Appel (2021), and Bartram et al. (2022) suggest that firms' financial resources heavily influence decarbonization activities. Regarding reach and collaborations, Waller et al. (2019) observe that greenhouse gas (GHG) emissions from the supply chains of the 2,500 largest global corporations account for more than 20% of global GHG emissions. Similarly, Gopalakrishnan et al. (2021) find that cooperation among firms within supply chains affects GHG emissions.

The existing literature also notes that political and geopolitical frictions could be an obstacle to global coordination and firms' efforts in climate change mitigation (Zahra, 2024; Allen et al., 2025). Our study provides more insights into how geopolitical conflict in the form of tariff wars affects firms' carbon emissions.

2.2. Trade Conflicts

The world has witnessed a significant rise in globalization in recent years. The growing interaction and integration among people, firms, and governments worldwide has greatly benefited the global economy and permitted greater sharing of economic benefits between firms and nations (Acemoglu et al., 2016b). However, events like trade wars have increased uncertainty and sparked debates about the true costs and benefits of globalization (Hong, 2024).

Previous literature documents various effects of trade shocks. There are corporate finance implications of trade shocks. Valta (2012) finds that competition induced by reductions in import tariff rates has a positive effect on the cost of bank debt. Amiti et al. (2020) find significant negative impacts of tariff announcements on U.S. stock prices, returns to capital, and hence aggregate investment. Huang et al. (2023) find that tariff hikes reduce affected firms' market value, with the effect spilling over along the global supply and production chains.

Autor et al. (2013, 2016) examine the labor market implications of trade shocks, showing that rising imports cause higher unemployment, lower labor force participation, and reduced wages in local labor markets that contain import-competing manufacturing industries. Similarly, Pierce and Schott (2016) find that industries that are more exposed to changes in Chinese import tariff experience greater employment loss, increased imports from China, and higher entry by U.S. importers and foreign-owned Chinese exporters.

Bloom et al. (2016) suggest that trade policies that increase import competition are positively associated with innovation and technical change. Fieler et al. (2018) develop a quantitative model that brings together theories linking international trade to quality, technology, and demand for skills. Edmond et al. (2015) find that trade can significantly reduce markup distortions if there is extensive misallocation, and opening to trade exposes hitherto dominant producers to greater competitive pressure. Complementing this literature, we evaluate the effect of trade shocks on corporate emission outcomes.

2.3. Hypothesis Development

This study explores the firm-level response to trade wars through the lens of carbon emissions. There are two plausible reasons to believe that import tariff hikes during trade wars might increase firms' GHG emissions. The first explanation builds on the idea that supply chains are crucial in firms' emission incentives and overall decarbonization efforts (e.g., Gopalakrishnan et al., 2021; Hege et al., 2024). As Hege et al. (2024) find, green innovations flow along supply chain networks. Therefore, we argue that supply chain disruptions, in the form of import tariff hikes, could create significant constraints to the adoption of cleaner technologies from foreign suppliers. This suggests that high import tariffs could disincentivize firms' use of such green technologies, encourage the use of "browner" alternatives, and ultimately raise emission levels.

The second explanation is motivated by evidence that higher import tariffs impose huge financial pressure on firms that deal in the affected products. Building on the general-equilibrium production network model of Dhyne et al. (2021), Huang et al. (2023) theoretically outline various direct and indirect cost consequences of the U.S.-China tariff war. Specifically, import tariff hikes lead to elevated input and production costs for affected U.S. firms. For firms that also depend on domestic inputs, there is an indirect effect arising from escalated domestic input prices, as some suppliers within the home country encounter cost increases directly from the higher tariffs. There is also a potential decline in sales and profits—the higher production costs caused by higher import tariffs are likely to translate into higher prices of finished goods, which could trigger lower demand from customers, decreased sales, and, consequently, lower profits.

Firms' financial resources are fundamental in their carbon emission and pollution abatement performances. For instance, Kim and Xu (2022) show that financial constraints exacerbate toxic pollution by firms due to the costs of waste management. Bartram et al. (2022) also highlight the relevance of financial resources in firms' responses to environmental regulations. If higher financial constraints reduce firms' abatement activities and worsen pollution, then one would expect the higher financial burden levied by import tariff hikes to increase affected firms' carbon emissions relative to unaffected firms. Taken together, the two explanations discussed in this section lead us to the study's main hypothesis that import tariff hikes increase firms' carbon emissions.

3. Institutional Background and Identification

3.1. The U.S.-China Trade War

The relationship between the U.S. and China has evolved dramatically since the normalization of diplomatic ties in the 1970s. In the early years of engagement, trade and investment flows between the two nations increased substantially. China's accession to the World Trade Organization (WTO) in 2001 further integrated the country into the global economy, leading to a rapid expansion of Chinese exports to the U.S. and significant growth in bilateral trade. According to data from the U.S. Census Bureau, China became the U.S.'s principal trading partner in 2015, overtaking Canada.[2]

However, the U.S.-China relationship is politically sensitive to conflicts. Tensions in the bilateral trade reached their peak in 2018 when the Trump administration adopted and quickly expanded the "America First" ideology into Sino–American relations. The administration raised various concerns regarding China, including accusations of currency manipulation, unfair practices against foreign companies, trade imbalance, and the country's "Made in China 2025" initiative. Consequently, the U.S. implemented import tariffs as a strategy to motivate the Chinese government to adopt policies that would better align with U.S. interests.

Starting in 2018, the tariffs on certain products from China experienced a sharp increase.[3] On March 22, 2018, the Trump administration released a presidential memo-

[2] https://www.census.gov/foreign-trade/statistics/highlights/top/index.html

[3] Peterson Institute of International Economics describes the timeline of all events relating to the U.S.-China trade war (https://www.piie.com/blogs/trade-and-investment-policy-watch/trumps-trade-war-timeline-date-guide).

randum in response to findings from a United States Trade Representative (USTR) about China's regulations and practices regarding intellectual property, innovation, and technology (the "Section 301 investigation"). The memo recommended implementing tariffs on nearly $50 billion worth of Chinese imports. President Trump instructed USTR Robert Lighthizer to compile a list of target products within 15 days, focusing particularly on products that China aims to dominate.[4]

On April 3, 2018, the USTR published an initial list of over 1,300 Chinese goods upon which to impose tariffs of up to 25%, totaling approximately $50 billion in U.S. imports from China.[5] Between January 7–9, 2019, trade discussions were held in Beijing between the U.S. and China, resulting in advancements in bridging the gaps between the two nations, along with an agreement to maintain high-level dialogues. On February 14, 2020, the phase one agreement between the Trump administration and China established new US tariffs on imports from China for the foreseeable future. President Biden, taking office in 2021, largely maintained the U.S.-China tariff policies. Tariffs between the two countries remain elevated, becoming the new normal (Bown, 2021).

3.2. Identification Strategy

We employ a difference-in-differences design around the U.S.-China trade war to examine how trade conflicts influence firms' carbon emissions.[6] Specifically, we first calculate the cumulative changes in tariffs for each product imported from China, classified by 6-digit Harmonized System (HS) codes, from 2018 to 2021 relative to the benchmark level at the end of 2017. Second, we categorize goods with a tariff increase exceeding 25% as highly-tariffed, representing the top 20% of products with the largest tariff increases. Conversely, products with a tariff increase below 10% are classified as minimally-tariffed,

[4]In retaliation, the Chinese government announced the next day a list of 128 products that would incur tariffs between 15% and 25% should trade negotiations between the U.S. and China fail.

[5]https://ustr.gov/sites/default/files/files/Press/Releases/301FRN.pdf

[6]The U.S.-China trade war has been the focus of a large body of literature that examines the economic implications of the conflict at both the micro and macroeconomic levels (Amiti et al., 2020, 2021; Fajgelbaum et al., 2020; Huang et al., 2023; Vertinsky et al., 2023).

representing the bottom 20% of tariff increase. Subsequently, We define a firm as "treated" if it imported highly-tariffed products from China within two years prior to the onset of the trade war in 2018. Conversely, "candidate control firms" are those that imported minimally-tariffed products from China and have not engaged in the importation of highly-tariffed Chinese products since 2016. Our goal is to isolate the effects of the U.S.-China trade conflict through the global supply chain rather than broader country-level exposures stemming from differences in market engagement.

We further employ the matching method to control for confounding effects. First, we match control firms by ensuring they operate within the same industry (2-digit SIC code) as the treated firms. Notably, both treated and control firms consist of U.S. firms or multinational companies operating in the U.S. This matching strategy ensures comparable exposure to macroeconomic and industrial factors. Second, we match firms by size within the same tercile to account for how size influences corporate carbon emission. Finally, to further control for two other significant events that disrupted the global supply chain and international trade— the COVID-19 pandemic and the Russia-Ukraine War— we attempt to mirror the supply chain exposure of the treated firms to China in 2020, and to Russia, Ukraine, or Belarus in 2022. For instance, if a treated firm had Chinese suppliers during the COVID-19 pandemic in 2020 or suppliers in Russia, Ukraine, and Belarus in 2022, we match it with control firms that also sourced from China in 2020 or from Russia, Ukraine, or Belarus in 2022, thus subjecting both treated and control firms to similar country-level risks due to COVID-19 and the Russia-Ukraine War.

Our baseline DiD regression model is stated as follows.

$$y_{it} = \beta_1 Treatment_i \times Post_t + \Gamma X_{it} + \mu_i + \mu_t + \epsilon_{it} \tag{1}$$

where $Treatment_i$ equals one if firm i imports goods affected by the import tariff hikes from China before the trade war and zero otherwise. The dependent variable, y, represents our four measures of GHG emissions, including ln(Scope 1), ln(Scope 2), Scope 1 Intensity, and Scope 2 Intensity.[7] Scope 1 is defined as GHG emissions from sources that are owned or controlled by the firm, while Scope 2 captures GHG emissions from the consumption of purchased electricity, heat, or steam. Scope 1 Intensity and Scope 2 Intensity are Scope 1 and Scope 2 emissions scaled by revenue, respectively.

X denotes a set of firm-level control variables, including size (natural logarithm of total assets), leverage (total debt/total assets), cash (cash and cash equivalents/total assets), capital expenditure (capital expenditure/total assets), profitability (ROA), sales growth (the difference between current and previous years' revenue scaled by previous year's revenue), and inventory turnover (cost of goods sold scaled by the average inventory). We also include different combinations of firm fixed effects, year fixed effects, and year-state fixed effects to control for unobserved firm-, time-, and state-time-invariant characteristics that may influence our findings. The coefficient of interest, β_1, represents the difference-in-differences effect of the import tariff hikes between the treated and control firms before and after the shock.

4. Data and Sample

4.1. Data and Sample Construction

First, we obtain firm-level CO_2 emission data from the S&P Trucost database. The Trucost database follows the Greenhouse Gas (GHG) Protocol, which establishes standards for corporate emissions reporting. Carbon emissions are typically grouped into three different categories: Scope 1 emissions include direct emissions from operations that are controlled by the reporting firm, such as fossil fuel use; Scope 2 emissions cover indirect emissions from purchased electricity, heat, steam, or cooling; and Scope 3 emissions capture other indirect emissions not included in Scope 2, like those from the production

[7] S&P Trucost also reports Scope 3, a third proxy for GHG emissions capturing indirect emissions not included in Scope 2. We do not include Scope 3 in our analysis because of evidence of a strong bias in Scope 3 emissions data. Additionally, we lose 60% of our sample if we consider Scope 3).

of purchased materials and product use. There is evidence of a strong bias in Scope 3 emission data (Hege et al., 2024), which is often estimated with less accuracy than Scope 1 and Scope 2 emissions and has many missed data. Therefore, we only use the information on Scope 1 and Scope 2 emissions and exclude Scope 3 emissions.

Second, we collect the Product-level U.S.-China tariff data from Bown (2021), which records and dates the tariff actions starting in January 2018. This data includes the tariffs imposed by the U.S. on goods from China, available at the Harmonized System (HS) 10-digit level.

Third, we collect the supply chain data from the S&P Panjiva shipment dataset, a transaction-level supply chain data for the United States. In the United States, the legislation mandates that firms report all physical imports as recorded in the bills of lading to the Federal Customs and Border Protection Agency under the Department of Homeland Security. This dataset includes comprehensive records of all maritime import transactions documented in the bill of lading, a document issued by a carrier to a shipper (supplier) confirming that the goods have been loaded on board for shipment from an origin to a designated destination and consignee (customer). Transaction details also include descriptions of products and quantities. Product categories are defined by the 8-digit or 10-digit HS code. Quantities are measured by shipment weights, as well as the number of containers and shipments.

The Panjiva database includes more than 188 million bills of lading for imports spanning from January 2007 to December 2023. We establish firm-year supply chain networks by defining a customer-supplier relationship between firms in year t if at least one shipping transaction is recorded between them during that year. Notably, the HS codes recorded in Panjiva exhibit an inconsistent structure. To address this, we convert these HS codes into a standardized 6-digit format.[8] We calculate the annual shipment volume by aggregating the shipment weights (in tons) for all transactions recorded for

[8] Different countries implement varying structures of the HS code. The first six digits of HS codes, developed by the World Customs Organization, are internationally consistent in almost every country.

each supplier-customer relationship in a specific year.

One of the significant advantages of Panjiva shipment data is that it is based on actual transaction data. In contrast, other sources of supply chain data, such as FactSet Revere, Compustat, and Bloomberg, rely on publicly available information, which is based on the limited disclosures from listed companies, and are therefore subject to disclosure bias. During political conflicts, firms may be incentivized to omit disclosures of their supply chain relationships with specific entities. Due to the mandatory disclosure requirement, Panjiva provides a more reliable platform for our research. More importantly, Panjiva shipment data also offers product classification information, which is not provided by the aforementioned data sources. We utilize this information to identify which firms import specific products from China. This capability significantly enhances the preciseness of our identification process. Moreover, although Panjiva data primarily contains transactions through marine shipment, it provides sufficient coverage. According to statistics from the United Nations Conference on Trade and Development (UNCTAD), around 80% of the volume of international trade in goods is carried by sea, and this percentage is even higher for most developing countries.[9]

Lastly, Firm-level financial data are obtained from Capital IQ, a database that includes standardized financial statements for a vast array of over 150,000 entities, including both public and privately owned companies on a global scale. Our cross-sectional tests utilize patent data from PatentsView.[10] Data on safety employees and environment-related job postings are obtained from Lightcast (formerly Emsi and Burning Glass Technologies).

We begin our sample construction with the universe of firms covered in the intersection of the S&P Trucost database and the Panjiva dataset. Similar to the adjustments made with Panjiva data, we convert the tariff data from the 10-digit HS code format into a standardized 6-digit HS code format. This conversion involves calculating the averaged

[9] See details in https://unctad.org/topic/transport-and-trade-logistics/review-of-maritime-transport

[10] The support and working team for the PatentsView database comes from the Office of the Chief Economist at the United States Patent and Trademark Office (USPTO).

tariffs for products within each 6-digit HS category. We then integrate the sample with the tariff data based on the 6-digit HS code to further check whether a company imported highly-tariffed or minimally-tariffed Chinese products during the trade war. Through this merger, we identify a total of 1,211 treated firms that imported highly-tariffed products from China within two years prior to the onset of the trade war in 2018 and 3,993 candidate control firms.

Based on these 1,211 treated firms, we search for corresponding control firms following the matching algorithm described in Section 3.2. Online Appendix, Table OA1, presents the en-ante means of the key variables for the treated and control groups, measured one year before the U.S.-China trade war, both before and after matching. We show that the matching algorithm significantly narrows differences in firm carbon emissions and operational performance between groups.

4.2. Summary Statistics

Table 1 presents the summary statistics of the firms we employ in our study. The average GHG emissions from sources that are owned or controlled by our sample firms (i.e., Scope 1) is about 2 million tonnes of carbon dioxide equivalent (tCO_2e), which is approximately four times the average GHG emissions from the consumption of purchased electricity, heat, or steam (i.e., Scope 2). When the emission volumes are log-transformed, however, the averages for the two scopes are similar at approximately 11.57. In terms of intensity, Scope 1 emissions average about 118.6 tCO_2e per million dollars. This is considerably higher than the mean Scope 2 Intensity of 35.55 tCO_2e per million dollars. Our sample firms are fairly large, which is consistent with the fact that we focus on firms with global supply chain networks. Specifically, the average ln(Asset) is 7.637 corresponding to about 2 billion dollars in assets. Firms make about 8 percent profit annually, which is almost equal to the annual growth in sales. Debt and cash represent about 24.7% and 10.6% of total assets, respectively. The mean capital expenditure scaled by total assets is fairly low at 4 percent. In general, the statistics are similar with those of existing studies (e.g., Huang et al., 2023).

[Insert Table 1 about here]

5. Empirical Results

5.1. Baseline Results

Table 2 presents the estimated effect of the import tariff hikes during the U.S.-China trade war on U.S. firm's carbon emissions. In Panel A, we estimate Equation (1). The first four columns focus on Scopes 1 and 2 emissions, whereas the last four columns reports results for the emission intensities. In all columns, the coefficient of interest is significantly positive, suggesting that import tariff hikes worsens affected firms' carbon emissions relative to their comparable unaffected counterparts. In Panel B, we estimate an alternative DiD specification that replaces the binary variable *Treatment* in Equation (1) with the continious variable, *ΔChinese Tariff*, defined as the difference in weighted average import tariff between the pre- and post-event periods. The results presented in panel B are consistent with Panel A.

The documented effect is not only statistically significant but also economically meaningful. To put the economic magnitude into perspective, the estimated magnitudes of 0.144 in Column (1) and 0.075 in Column (3) of Panel A suggest that, *ceteris paribus*, treated firms subject to extreme hikes in Chinese import tariffs during the trade war increased their Scope 1 and 2 emissions by approximately 15% and 8%, respectively, more than the control firms subject to minimally-tariffed importation. We also observe that the magnitudes for Scope 1 and its intensity are generally larger than those for Scope 2, indicating that import tariff hikes affect direct emissions more than indirect emissions.

[Insert Table 2 about here]

Figure 1 plots the dynamic trend of the impact of import tariff hikes on all four proxies of carbon emissions. We also display the 95% confidence interval. The coefficients noticeably increase in magnitude after the trade shock. Moreover, the difference in carbon emissions between the treated and control firms is significantly distinguishable only after the shock. Overall, these graphs help to better establish causality by showing that there is no significant pre-trend effect.

[Insert Figure 1 about here]

5.2. Robustness

In this section, we highlight the robustness of our main finding. Although the exploitation of a matching-based fixed effects DiD design around the 2018-2019 U.S.-China trade shock helps to reduce endogeneity concerns, we further implement alternative methodologies throughout our analyses. First, using multiple proxies of carbon emissions helps mitigate concerns that our results are driven by the definition of the outcome variable. Second, as shown in Panel B of Table 2, the results are robust to using an alternative DiD specification that incorporates a continuous treatment measure instead of a binary measure. Third, our conclusions remain qualitatively unchanged when we include different combinations of fixed-effects in our regressions. The fact that we continue to find a significant positive effect of import tariff hikes on carbon emissions against all these empirical design options suggests that the evidence documented in this study is less likely to be driven by our empirical design choices.

5.3. Underlying Mechanisms

This section investigates the economic justifications for the sharp increase in the GHG emissions of affected U.S. firms following the import tariff hikes arising from the U.S.-China trade war. First, we examine the direct impediments to the trade of green products in the global supply chain. Second, we test how the financial burden created by the tariff hikes could shift firms' priorities away from decarbonization.

5.3.1. Green Products in the Global Supply Chain

In our first channel test, we explore how tariffs directly impact corporate carbon emissions through the disruption of global supply chain for green products. We argue that import tariff hikes could create substantial barriers to the adoption of cleaner and more resource-efficient technologies, including renewable energy equipment acquired from foreign suppliers. By impeding access to and increasing the cost of these green technologies, high import tariffs discourage their use, compelling firms to rely on less environment-friendly alternatives.

Green products are identified using the environmental product list compiled by the APEC, OECD, and WTO based on HS codes.[11] The combined list consists of 248 environmental goods. In our sample, 184 affected customers possess at least one highly tariffed environmental product. More than 78% of these highly tariffed environmental products are utilized in renewable energy plants, 2% are allocated to cleaner or more resource-efficient technologies and products, and 19% are used for wastewater management and potable water treatment.

We define two dummy variables, each of which is interacted with our independent variable of interest in a heterogeneity test. 1{Green Tariff} is equal to one if, prior to the trade war, the firm purchased at least one environmental product affected by the import tariff hikes and zero otherwise. Conversely, 1{No Green Tariff} is equal to one if, in the pre-event period, the firm purchased no environmental product affected by the trade war and zero otherwise. The results are presented in Table 3. We find that the coefficients for firms subject to green tariffs are significantly higher compared to firms without green

[11] Please see the detail at https://www.oecd.org/content/dam/oecd/en/publications/reports/2014/12/the-stringency-of-environmental-regulations-and-trade-in-environmental-goods_g17a2588/5jxrjn7xsnmq-en.pdf

tariffs. The evidence suggests that firms pollute more as the trade war exacerbates barriers to the trade of green products in global supply chains.

5.3.2. Financial Constraints

Next, we test our conjecture that the financial burden levied by high import tariffs is a channel through which the trade war increased firm-level carbon emissions. We first examine the effect of the trade war on two measures of financial constraints, including the WW index (Whited and Wu, 2006) and the SA index (Hadlock and Pierce, 2010), and two measures of financial distress, including COGS/sales, and EBITDA margin. As shown in Panel A of Table 4, the coefficients for WW index, SA index, and COGS/sales are positive, while those for EBITDA margin are negative. This suggests that, upon the commencement of the U.S.-China trade war, affected firms experienced intense financial problems.

We subsequently investigate whether the observed rise in financial problems caused by the trade war plays a significant role in the increase in carbon emissions. Particularly, we employ a triple difference (DDD) analysis to investigate the differential impacts of the trade war on carbon emissions between high and low financial problem firms. We calculate the change in financial burden based on the financial problem proxies after the initiation of the trade war compared to the benchmark values before the shock. Higher financially contrained or distress firms are defined as those in the highest 60% quantile of the proxy increase. Our formal test utilizes the following DDD model.

$$\begin{aligned} y_{it} &= \beta_1 Treatment_i \times Post_t \times 1\{q_{high}(\Delta FC)\}_i + \beta_2 Treatment_i \times Post_t \\ &\quad + \beta_3 Post_t \times 1\{q_{high}(\Delta FC)\}_i + \Gamma X_{it} + \mu_i + \mu_t + \epsilon_{it} \end{aligned} \tag{2}$$

where $1\{q_{high}(\Delta FC)\}_i$ is a binary variable that takes the value of one if firm i's increase in average financial problems from pre- to post-event period exceeds the 60% quantile of the sample. The dependent variables remain the four measures of GHG emissions, including ln(Scope 1), ln(Scope 2), Scope 1 Intensity, and Scope 2 Intensity. All the other variables maintain their original definitions. The coefficient, β_1, represents the differences between the effects of the treatment within the high financial problem firms relative to their low financially burdened counterparts.

Panels B and C of Table 3 present results from estimating Equation (2) using WW index and COGS/sales as the proxies for financial constraint and distress, respectively.[12] We find that the coefficients of the triple interaction terms are consistently positive and significant, suggesting that compared to firms that experienced low financial problems due to the tariff hikes, firms that faced intense tariff-induced financial burden greatly increased carbon emissions after the U.S.-China trade war.

[Insert Table 4 about here]

5.4. The Role of Green Innovations

In this section, we seek to understand the technical changes made by the affected firms after the tariff war that resulted in the higher GHG emissions. The existing literature stresses environment-friendly technical changes as fundamental to firm-level carbon emission reduction. These changes, in turn, highly depends on firms' financial resources. Given the financial problems caused by the tariff war, we expect environment-friendly technical changes to decline upon the import tariff hikes. Our tests explore how the worsened financial conditions caused by the trade war decrease such technical changes and subsequently affect carbon emissions. We capture environment-friendly technical changes by green innovation, defined as the natural logarithm of one plus the number of green patents obtained from the PatentsView database. Patents are classified as "green" according to the OECD green patent classification (Haščič and Migotto, 2015), which is based on Cooperative Patent Classification (CPC) and International Patent Classification (IPC).

In a specification similar to Equation (1), we first examine how the trade war affects firms' green innovation. The dependent variables are the natural logarithm of one plus the

[12] For brevity of presentation, we report results for only WW index and COGS/sales. Our findings are robust to using the other two measures of financial burden.

number of green patent applications and the ratio of green patents to total patent. Panel A of Table 5 displays the results. We find that the treated firms, relative to the control firms, experience a significant decrease in both the number and ratio of green patents.

[Insert Table 5 about here]

Then, we employ the framework of Equation (2) to understand the role of financial constraints in the decline of green innovation. The term $1\{q_{high}(\Delta \text{FC})\}$ equals one if the increase in a firm's WW index exceeds the 60% quantile of the sample. The results are presented in Panel B of Table 5. The coefficients of the triple interaction terms are significantly negative, suggesting that affected firms with financial constraints tend to experience a greater reduction in both the scale and ratio of green patent applications following the trade war compared to affected firms without such constraints.

In Table 6, we investigate the direct role of green innovation in the relationship between import tariff hikes and corporate carbon emissions. We continue to employ the tripple difference regression, utilizing a group variable based on the decline in green patents following the trade war. Specifically, we define $1\{q_{Low}(\Delta \text{Ratio of Green Patents})\}$ as one if the decline in a firm's ratio of green patents exceeds the 60% quantile of the total sample. The change in the ratio of green patents is calculated as the difference between the average ratio of green patents during the trade war and those before the trade war. We observe that affected firms with a greater decline in green patents experience a higher increase in both scope 1 and scope 2 emissions.

[Insert Table 6 about here]

5.5. The Role of Green Employment

Capital and labor make up the core of firms' production function. Therefore, after documenting evidence of a decline in green-focused technical change after the trade war, we extend our investigation to green-focused labor changes. We borrow a similar argument to that of the technical change predictions and hypothesize that the exacerbation of financial conditions by the trade war can potentially decrease firms' investment in environment-related positions and employees. We initially examine how the trade war affects firms' green employment, defined based on a textual analysis of the employment skill requirements from the Lightcast database. To do this, we revisit our baseline regression with the dependent variables replaced with the number of green-related employees and the number of green-related position. The results of our estimations are presented in Table 7, Panel A, which shows that the treated firms experienced a significant decrease in the number of green-related positions and employees relative to the control firms.

[Insert Table 7 about here]

We also decompose the treated sample into financially constrained and unconstrained categories to conduct heterogeneity test.[13] The term $1\{q_{high}(\Delta \text{FC})\}$ equals one if the increase in a firm's WW index exceeds the 60% quantile of the total sample. The dependent variables are the number of green-related employees and the number of green-related positions. The result shown in Panel B of Table 7 shows that the coefficients of the tripple interaction term are negative and significant. This finding suggests that the treated firms with high financial constraints tend to significantly reduce their environment-related employment, whereas those with low financial constraints not show a substantial decline.

5.6. Climate Change Ideology

We also examine the heterogeneous effect of import tariff hikes on carbon emissions based on climate change ideology. Corporate stakeholder perspective on climate change is essential for firms' carbon emission performance (e.g., Ilhan et al., 2021; Krueger et al., 2024). More specifically, this literature suggests that the lower the climate change ideology,

[13]The employment data for our sample is notably limited in terms of the number of observations, especially for the control sample. Consequently, the subcategorization into financially constrained and unconstrained firms in the triple difference regression focuses only on the treated firms.

the worse the environmental performance. Consistent with this argument, we predict that faced with the tariff-induced financial problems, firms with low climate change ideology would increase carbon emissions by a higher magnitude compared with those with high climate change ideoology.

We consider multiple sources of low climate change ideology: (1) the Yale Climate Opinion Maps, (2) presidential elections, (3) state legislation, and (4) firm partisanship. $1\{Low\ Climate\ Ideology\}_s$ equals one when a state has a lower-than-median percentage of the population who think their governor should be doing more/much more to address global warming between 2018 and 2020 and zero otherwise. $1\{Election : REP\}_s$ is one if state s elected a Republican presidential candidate in the 2016 election and zero otherwise. $1\{Legis\ Control : REP\}_s$ is one if state s is under Republican legislative and governmental control from 2017 to 2020, and zero otherwise. $1\{Firm\ Party : REP\}_s$ is one if firm i's political partisanship relatively leans toward the Republican Party in the 2016 and 2020 election cycles and zero otherwise. As presented in Table 8, we find that the implications of high import tariffs for corporate carbon emissions, both in terms of scale and intensities, is more pronounced for firms with low climate change ideology.

[Insert Table 8 about here]

5.7. Supply Chain Characteristics

Finally, we conduct a cross-sectional analysis based on global supply chain features, including diversification and import specificity. Data on supply chain characteristics are gathered from Factset and Panjiva. We first examine the role of global supply chain diversification in the documented relationship. The idea is that diversification could provide risk reduction benefits that can mitigate the negative economic effects of supply chain disruptions caused by the tariff war. For example, a firm with a diversified supply chain can switch to another supply chain if disruption occurs in one part of the supply chain (Hendricks et al., 2009; Chod et al., 2019).

Our measure of supply chain diversification is captured by the Herfindahl-Hirschman Index (HHI) of the country distribution of suppliers, which is the sum of the squares of the proportion of a firm's suppliers in each country relative to its total number of suppliers. A higher (lower) HHI indicates a lower (higher) level of of diversification. We define a dummy variable, $1\{q_{High}HHI_{Country}\}$, as one if HHI is higher than the 60th percentile prior to the trade war in 2017, and zero otherwise. Then, we regress GHG emissions on the interaction term, $Treatment \times Post \times 1\{q_{High}HHI_{Country}\}$. Table 9 presents the results. In Panel A, the positive coefficients indicate that firms with highly concentrated supply chains tend to increase carbon emissions more significantly after the shock, implying that firms with more diversified supply chains experienced less impact. These findings suggest that ex-ante supply chain diversification can mitigate the adverse effects of trade policy risk on corporate carbon emissions.

Additionally, we test the influence of import specificity on carbon emission. We use the Product Complexity Index (PCI) from Hidalgo and Hausmann (2009), which is widely employed in literature (e.g., Jarreau and Poncet, 2012; Tacchella et al., 2013; Maggioni et al., 2016). The Index ranks the specificity and sophistication of the productive know-how required to produce a given product based on the four-digital HS code. Products with a positive PCI value, such as electronics and chemicals, are complex and can only be produced in a few countries. In contrast, products with a negative PCI value, such as raw materials and simple agricultural products, are less complex and can be produced more widely. Firms are likely to face lower switching costs if the input is easy to subsitute (Ersahin et al., 2024).

Utilizing Panjiva shipment data, we match the PCI to imported products by their HS codes. For each firm, we identify Chinese suppliers who provide complex products facing significantly increased tariffs, termed as "Tariffed Specific Suppliers." We calculate the percentage of these suppliers relative to the total number of suppliers, labeled as "%Tariffed Specific Suppliers." A higher percentage suggests that importing firms are dealing with more specific suppliers affected by high tariffs, likely facing higher switching costs. Considering significant industry heterogeneity in input specificity, $1\{q_{High}\%\text{Tariffed Specific Suppliers}\}$ equals one if a firm's percentage of "Tariffed Specific Suppliers" exceeds the 60th industry percentile before the trade war in 2017, and zero otherwise. In Panel B of Table 9, we regress GHG emissions on the interaction term, $Treatment \times Post \times 1\{q_{High}\%\text{Tariffed Specific Suppliers}\}$. The positive coefficients indicate that firms with a higher share of highly tariffed specific suppliers experience increased carbon emissions following the trade war, suggesting that a greater dependency on specific suppliers affected by tariffs contributes to the increased risks and costs associated with switching suppliers, leading to higher carbon emissions.

[Insert Table 9 about here]

6. Conclusion

This paper analyzes the firm-level carbon emission implications of trade shocks. Our identification focuses on U.S. firms that were heavily dependent on Chinese supply chains during the 2018-2019 U.S.-China trade war. Results from our matching-based difference-in-differences design suggest that firms that rely on suppliers from China heavily increased their carbon emissions upon the hikes in import tariffs during the trade war. Subsequent tests reveal two underlying channels: increased barriers to the trade of green products in the global supply chain and tariff-induced financial burden. Firms increase carbon emissions by substantially reducing green innovations and environment-related labor. Stakeholder attention and supply chain characteristics also moderate our findings. Taken together, our research highlights how trade tensions, through the global supply chain, impact environmental outcomes at the microeconomic level.

References

Acemoglu, D., Akcigit, U., Hanley, D., and Kerr, W. (2016a). Transition to Clean Technology. *Journal of Political Economy*, 124(1):52–104.

Acemoglu, D., Johnson, S., Kermani, A., Kwak, J., and Mitton, T. (2016b). The value of connections in turbulent times: Evidence from the United States. *Journal of Financial Economics*, 121(2):368–391.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., and Van Reenen, J. (2016). Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. *Journal of Political Economy*, 124(1):1–51.

Akey, P. and Appel, I. (2021). The Limits of Limited Liability: Evidence from Industrial Pollution. *The Journal of Finance*, 76(1):5–55.

Allen, F., Barbalau, A., Chavez, E., and Zeni, F. (2025). Leveraging the capabilities of multinational firms to address climate change: a finance perspective. *Journal of International Business Studies*.

Amiti, M., Gomez, M., Kong, S. H., and Weinstein, D. (2021). Trade Protection, Stock-Market Returns, and Welfare. *NBER Working Paper*.

Amiti, M., Kong, S. H., and Weinstein, D. (2020). The Effect of the U.S.-China Trade War on U.S. Investment. *NBER Working Paper*.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6):2121–2168.

Autor, D. H., Dorn, D., and Hanson, G. H. (2016). The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade. *Annual Review of Economics*, 8(Volume 8, 2016):205–240.

Bartram, S. M., Hou, K., and Kim, S. (2022). Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics*, 143(2):668–696.

Bloom, N., Draca, M., and Van Reenen, J. (2016). Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. *The Review of Economic Studies*, 83(1):87–117.

Bown, C. P. (2021). The US–China trade war and Phase One agreement. *Journal of Policy Modeling*, 43(4):805–843.

Brown, J. R., Martinsson, G., and Thomann, C. (2022). Can Environmental Policy Encourage Technical Change? Emissions Taxes and R&D Investment in Polluting Firms. *The Review of Financial Studies*, 35(10):4518–4560.

Caliendo, L., Dvorkin, M., and Parro, F. (2019). Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock. *Econometrica*, 87(3):741–835.

Chod, J., Trichakis, N., and Tsoukalas, G. (2019). Supplier Diversification Under Buyer Risk. *Management Science*, 65(7):3150–3173.

Dhyne, E., Kikkawa, A. K., Mogstad, M., and Tintelnot, F. (2021). Trade and Domestic Production Networks. *The Review of Economic Studies*, 88(2):643–668.

Edmond, C., Midrigan, V., and Xu, D. Y. (2015). Competition, Markups, and the Gains from International Trade. *American Economic Review*, 105(10):3183–3221.

Ersahin, N., Giannetti, M., and Huang, R. (2024). Trade credit and the stability of supply chains. *Journal of Financial Economics*, 155:103830.

Fajgelbaum, P. D., Goldberg, P. K., Kennedy, P. J., and Khandelwal, A. K. (2020). The Return to Protectionism. *The Quarterly Journal of Economics*, 135(1):1–55.

Fieler, A. C., Eslava, M., and Xu, D. Y. (2018). Trade, Quality Upgrading, and Input Linkages: Theory and Evidence from Colombia. *American Economic Review*, 108(1):109–146.

Fisman, R., Hamao, Y., and Wang, Y. (2014). Nationalism and Economic Exchange: Evidence from Shocks to Sino-Japanese Relations. *The Review of Financial Studies*, 27(9):2626–2660.

Forster, M. M. and Shive, S. A. (2020). Corporate Governance and Pollution Externalities of Public and Private Firms. *The Review of Financial Studies*, 33(3):1296–1330.

Gopalakrishnan, S., Granot, D., Granot, F., Sošić, G., and Cui, H. (2021). Incentives and Emission Responsibility Allocation in Supply Chains. *Management Science*, 67(7):4172–4190.

Hadlock, C. J. and Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, 23(5):1909–1940.

Haščič, I. and Migotto, M. (2015). Measuring environmental innovation using patent data. *OECD Working Paper*.

Hege, U., Li, K., and Zhang, Y. (2024). Climate Innovation and Carbon Emissions: Evidence from Supply Chain Networks. *SSRN Working Paper*.

Hendricks, K. B., Singhal, V. R., and Zhang, R. (2009). The effect of operational slack, diversification, and vertical relatedness on the stock market reaction to supply chain disruptions. *Journal of Operations Management*, 27(3):233–246.

Hidalgo, C. A. and Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, 106(26):10570–10575.

Hong, J. (2024). Globalization and stock price crash risk: evidence from the US granting permanent normal trade relations to China. *Journal of International Business Studies*, 55(8):997–1019.

Howe, P. D., Mildenberger, M., Marlon, J. R., and Leiserowitz, A. (2015). Geographic variation in opinions on climate change at state and local scales in the USA. *Nature Climate Change*, 5(6):596–603.

Huang, Y., Lin, C., Liu, S., and Tang, H. (2023). Trade networks and firm value: Evidence from the U.S.-China trade war. *Journal of International Economics*, 145:103811.

Ilhan, E., Sautner, Z., and Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies*, 34(3):1540–1571.

Jarreau, J. and Poncet, S. (2012). Export sophistication and economic growth: Evidence from China. *Journal of Development Economics*, 97(2):281–292.

Kim, T. and Xu, Q. (2022). Financial constraints and corporate environmental policies. *The Review of Financial Studies*, 35(2):576–635.

Krueger, P., Sautner, Z., Tang, D. Y., and Zhong, R. (2024). The effects of mandatory ESG disclosure around the world. *Journal of Accounting Research*, 62(5):1795–1847.

Lin, J., Du, M., Chen, L., Feng, K., Liu, Y., V. Martin, R., Wang, J., Ni, R., Zhao, Y., Kong, H., Weng, H., Liu, M., van Donkelaar, A., Liu, Q., and Hubacek, K. (2019). Carbon and health implications of trade restrictions. *Nature Communications*, 10(1):4947.

Maggioni, D., Lo Turco, A., and Gallegati, M. (2016). Does product complexity matter for firms' output volatility? *Journal of Development Economics*, 121:94–109.

Pierce, J. R. and Schott, P. K. (2016). The Surprisingly Swift Decline of US Manufacturing Employment. *American Economic Review*, 106(7):1632–1662.

Senbet, L. W. (2025). Multinational enterprises and climate action: a low-income perspective with Africa focus. *Journal of International Business Studies*.

Song, S., Dong, Y., Kull, T., Carter, C., and Xu, K. (2023). Supply chain leakage of greenhouse gas emissions and supplier innovation. *Production and Operations Management*, 32(3):882–903.

Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A., and Pietronero, L. (2013). Economic complexity: Conceptual grounding of a new metrics for global competitiveness. *Journal of Economic Dynamics and Control*, 37(8):1683–1691.

Tian, K., Zhang, Y., Li, Y., Ming, X., Jiang, S., Duan, H., Yang, C., and Wang, S. (2022). Regional trade agreement burdens global carbon emissions mitigation. *Nature Communications*, 13(1):408.

Valta, P. (2012). Competition and the cost of debt. *Journal of Financial Economics*, 105(3):661–682.

Vertinsky, I., Kuang, Y., Zhou, D., and Cui, V. (2023). The political economy and dynamics of bifurcated world governance and the decoupling of value chains: An alternative perspective. *Journal of International Business Studies*, 54(7):1351–1377.

Waller, M. A., Hoek, R. v., Davletshin, M., and Fugate, B. (2019). *Integrating Blockchain into Supply Chain Management: A Toolkit for Practical Implementation*. Kogan Page Publishers.

Whited, T. M. and Wu, G. (2006). Financial constraints risk. *The Review of Financial Studies*, 19(2):531–559.

Yu, H., Bansal, P., and Arjaliès, D.-L. (2023). International business is contributing to environmental crises. *Journal of International Business Studies*, 54(6):1151–1169.

Zaheer, S. (2024). The sustainability of MNE sustainability initiatives. *Journal of International Business Studies*.

Zahra, S. A. (2024). MNEs and financing climate change transitions: the challenge of collective action. *Journal of International Business Studies*.

Appendix A: Variable Definitions

This table presents the definitions and data sources of the study's variables.

Variable name	Definition	Data Source
Carbon Emissions		
Scope $1_{i,t}$	Greenhouse gas (GHG) emissions from sources that are owned or controlled by firm i in year t (in tCO2e).	S&P Trucost
Scope $2_{i,t}$	Greenhouse gas (GHG) emissions from the consumption of purchased electricity, heat, or steam by firm i in year t (in tCO2e).	S&P Trucost
Scope 1 $\text{Intensity}_{i,t}$	Greenhouse gas (GHG) emissions from sources that are owned or controlled by the firm i relative to firm i's revenue in year t (in tonnes/$M).	S&P Trucost
Scope 2 $\text{Intensity}_{i,t}$	Greenhouse gas (GHG) emissions from the consumption of purchased electricity, heat, or steam by firm i, relative to firm i's revenue in year t. (in tonnes/$M).	S&P Trucost
U.S.-China Trade War		
Treatment	A dummy variable set to one if a firm imported goods subjected to substantial tariff increases (over 25%) from China within the two years preceding the US-China trade war, and zero otherwise.	S&P Panjiva
Post	A dummy variable set to one after 2017, and zero otherwise	Constructed
ΔChinese Tariff	The weighted average of tariff changes on Chinese imports, using the import volume of each Chinese product before the trade war as the weight.	S&P Panjiva
Firm Characteristics		
$\text{Asset}_{i,t}$	Total assets (in millions of USD) for firm i in year t.	S&P Capital IQ
$\text{LER}_{i,t}$	Total debt scaled by total assets for firm i in year t.	S&P Capital IQ
$\text{Cash/Asset}_{i,t}$	Cash and equivalents scaled by total assets for firm i in year t.	S&P Capital IQ
$\text{CAPEX/Asset}_{i,t}$	Capital expenditures scaled by total assets for firm i in year t.	S&P Capital IQ

Inventory Turnover$_{i,t}$	Cost of goods sold scaled by the average value of the inventory for firm i in year t, indicating how often the business inventory turns over during the year t.	S&P Capital IQ
Sale Growth$_{i,t}$	The annual growth rate of total revenue for firm i in year t.	S&P Capital IQ
COGS/Sale$_{i,t}$	Cost of goods sold scaled by the total revenue for firm i in year t.	S&P Capital IQ
EBITDA Margin$_{i,t}$	EBITDA scaled by total revenue for firm i in year t.	S&P Capital IQ
Short-term Debt/Asset$_{i,t}$	Short-term debt (usually with interest, within one year) scaled by total asset for firm i in year t.	S&P Capital IQ
1{Green Tariff}	A dummy variable set to one if, prior to the trade war, the firm purchased at least one environmental product affected by the import tariff hikes and zero otherwise. Environmental products are identified using the environmental product list compiled by the Asia-Pacific Economic Cooperation (APEC), Organisation for Economic Co-operation and Development (OECD), and World Trade Organization (WTO) based on HS codes.	S&P Panjiva, APEC, OECD, and WTO
1{No Green Tariff}	A dummy variable set to one if, in the pre-event period, the firm purchased no environmental product affected by the trade war and zero otherwise. Environmental products are identified using the environmental product list compiled by the Asia-Pacific Economic Cooperation (APEC), Organisation for Economic Co-operation and Development (OECD), and World Trade Organization (WTO) based on HS codes.	S&P Panjiva, APEC, OECD, and WTO

WW Index	Whited and Wu (2006) financial constraint index: - 0.091×CF - 0.062×DIVPOS + 0.021×TLTD - 0.044×LNTA + 0.102×ISG - 0.035×SG, where TLTD is the ratio of the long-term debt to total assets; DIVPOS is an indicator that takes the value of one if the firm pays cash dividends; SG is firm sales growth; LNTA is the natural log of total assets; ISG is the firm's three-digit industry sales growth; CASH is the ratio of liquid assets to total assets; CF is the ratio of cash flow to total assets	S&P Capital IQ and Compustat
SA Index	Hadlock and Pierce (2010) financial constraint index: – 0.737×Firm Size + 0.043×Firm Size^2 – 0.040×Age	S&P Capital IQ and Compustat
#GreenPatents:CPC	The logarithm of one plus the number of green patent applications (Tag a patent as "green" using Cooperative Patent Classification (CPC))	The U.S. Patent and Trademark Office (USPTO)
#GreenPatents:IPC	The logarithm of one plus the number of green patent applications (Tag a patent as "green" using International Patent Classification (IPC))	USPTO
Ratio of Green Patents:CPC	The ratio of green patent applications over the total number of patent applications (Tag a patent as "green" using Cooperative Patent Classification (CPC))	USPTO
Ratio of Green Patents:IPC	The ratio of green patent applications over the total number of patent applications (Tag a patent as "green" using International Patent Classification (IPC))	USPTO
#Environment-related Positions	The logarithm of one plus the number of environment-related positions available.	EMSI employment data
#Environment-related Employees	The logarithm of one plus the number of environment-related employees.	EMSI employment data

$1\{q_{High}(\Delta \text{COGS/Sale})\}_i$	A dummy variable set to one if the increase in firm i's COGS-to-sale ratio, defined as the difference between the average COGS-to-sale ratio during the US-China trade war and the benchmark level before the trade war, exceeds the 60th percentile of the total sample, and zero otherwise.	Constructed
$1\{q_{Low}(\Delta \text{EBITDA Margin})\}_i$	A dummy variable set to one if the decrease in firm i's EBITDA margin, calculated as the difference between the benchmark level of EBITDA margin before the trade war and the average EBITDA margin during the trade war (2018-2021), exceeds the 60th percentile of the total sample, and zero otherwise.	Constructed
$1\{q_{High}(\Delta \text{WW Index})\}_i$	A dummy variable set to one if the increase in firm i's WW index, defined as the difference between the average WW index during the US-China trade war and the benchmark level before the trade war, exceeds the 60th percentile of the total sample, and zero otherwise.	Constructed
$1\{q_{High}(\Delta \text{SA Index})\}_i$	A dummy variable set to one if the increase in firm i's SA index, defined as the difference between the average SA index during the US-China trade war and the benchmark level before the trade war, exceeds the 60th percentile of the total sample, and zero otherwise.	Constructed
$1\{q_{Low}(\Delta \text{Ratio of Green Patents})\}_i$	A dummy variable set to one if the decrease in firm i's ratio of green patents, calculated as the difference between the benchmark ratio of green patents before the trade war and the average ratio during the trade war, exceeds the 60th percentile of the total sample, and zero otherwise.	Constructed
$1\{\text{LowClimateIdeology}\}_i$	A dummy variable set to one if firm i's operations are located in a state where a relatively low percentage of people believe that protecting the environment is more important than economic growth (the percentage being lower than the national median level), and zero otherwise.	Howe et al. (2015)

$1\{\text{Election:REP}\}_i$	A dummy variable set to one if firm i is located in a state that voted for a Republican presidential candidate in the 2016 election, and zero otherwise.	
$1\{\text{LegisControl:REP}\}_i$	A dummy variable set to one if firm i is located in a state whose legislature was controlled by Republicans during the trade war, and zero otherwise.	
$1\{\text{FirmParty:REP}\}_i$	A dummy variable set to one if firm i's political partisanship relatively leans toward the Republican Party in the 2016 and 2020 election cycles, and is set to zero otherwise. The partisanship measure is calculated as the ratio of the cumulative dollar contributions made by the executive to the Republican Party over those made to the Democratic Party during the 2016 and 2020 election cycles. A firm is defined as a Republican Party firm if its partisanship measure exceeds the 60th percentile of the total sample.	S&P Capital IQ and DIME database
$1\{q_{High} HHI_{Country}\}$	A dummy variable set to one if HHI is higher than the 60th percentile prior to the trade war and zero otherwise. HHI is the Herfindahl-Hirschman Index of the country distribution of suppliers, which is the sum of the squares of the proportion of a firm's suppliers in each country relative to its total number of suppliers.	Factset and S&P Panjiva
$1\{q_{High}$%Tariffed Specific Suppliers$\}$	A dummy variable set to one if a firm's percentage of Tariffed Specific Suppliers exceeds the 60th industry percentile before the trade war and zero otherwise. Tariffed Specific Suppliers are Chinese suppliers who provide complex products facing significantly increased tariffs, where product complexity is defined based on the Product Complexity Index (PCI)	Factset and S&P Panjiva

Table 1: Summary Statistics

Note: This table shows the summary statistics for our sample firms, including the absolute emission of greenhouse gases, emission intensity, and other firm characteristics. The table reports the mean, standard deviation, median, minimum, and maximum. Detailed variable definitions are provided in Appendix A.

Variable	Mean	Stdev	Min	Q25	Median	Q75	Max	# Obs
Scope 1	2014600.774	9752302.251	0.000	24072.247	92808.568	402220.443	178618709.922	12432
Scope 2	532157.115	1430230.127	0.000	31267.375	113814.699	409633.656	23773921.178	12432
ln(Scope 1)	11.570	2.381	0.000	10.089	11.438	12.905	19.001	12432
ln(Scope 2)	11.568	2.023	0.000	10.350	11.642	12.923	16.984	12432
Scope 1 Intensity	118.613	387.696	0.260	9.223	18.429	45.151	4921.558	12432
Scope 2 Intensity	35.550	40.435	0.548	12.539	22.345	41.735	279.767	12432
ln(Asset)	7.637	2.362	0.002	6.276	7.755	9.065	15.170	19911
ROA	0.084	0.071	-0.110	0.042	0.076	0.121	0.321	18285
LER	0.247	0.173	0.000	0.109	0.236	0.359	0.753	18513
Sale Growth	0.086	0.186	-0.432	-0.011	0.063	0.153	1.091	19128
CAPEX/Asset	0.040	0.032	0.000	0.017	0.032	0.054	0.182	17454
Cash/Asset	0.106	0.095	0.002	0.035	0.077	0.148	0.441	19858
Inventory Turnover	0.123	0.265	0.012	0.034	0.050	0.083	2.302	17553

Table 2: Import Tariff Hikes and Corporate Carbon Emissions

Note: This table presents the baseline regression results. Dependent variables include the logarithm of one plus the absolute value of Scope 1 and Scope 2 emissions, and the intensities of both Scope 1 and Scope 2. Treatment is an indicator variable set to one if a firm imported goods subjected to substantial tariff increases (over 25%) from China within the two years preceding the US-China trade war and zero otherwise. Post is set to one after 2017 and zero otherwise. Panel B presents the robustness results using a continuous treatment variable, ΔChinese Tariff, calculated as the weighted average of tariff changes on Chinese imports, using the import volume of each Chinese product before the trade war as the weight. Reported are the regression coefficients, standard errors (in parentheses), and R^2 values. Significance levels are denoted by *, **, and *** for 10%, 5%, and 1%, respectively. All variable definitions are provided in Appendix A.

	ln(Scope 1)		ln(Scope 2)		Scope 1 Intensity		Scope 2 Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Results for Standard DID Regression								
Treatment×Post	0.144***	0.109***	0.075***	0.067**	44.321***	58.184***	4.381***	3.571***
	(0.029)	(0.031)	(0.026)	(0.027)	(9.227)	(9.835)	(0.944)	(1.008)
Adjusted R^2	0.911	0.914	0.901	0.903	0.729	0.731	0.742	0.744
Panel B: Robustness Results Using the Weighted Average of Tariff Changes on Chinese Imports								
ΔChinese Tariff×Post	0.008***	0.006***	0.007***	0.006***	1.517***	2.192***	0.249***	0.212***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.427)	(0.457)	(0.044)	(0.047)
Adjusted R^2	0.911	0.914	0.901	0.904	0.728	0.731	0.742	0.744
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓		✓	
Year-State FE		✓		✓		✓		✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	11,046	11,046	11,046	11,046	11,046	11,046	11,046	11,046

Figure 1: Parallel Trend Graphs

Note: This figure shows the parallel trend test of baseline regression. Dependent variables include the logarithm of one plus the absolute value of Scope 1 and Scope 2 emissions, and the intensities of both Scope 1 and Scope 2. Control variables for all regressions are the same as in the baseline regression. The year 0 represents the first year of the trade war in 2017. The vertical line around each plotted coefficient indicates the 95% confidence interval. All variable definitions are provided in Appendix A.

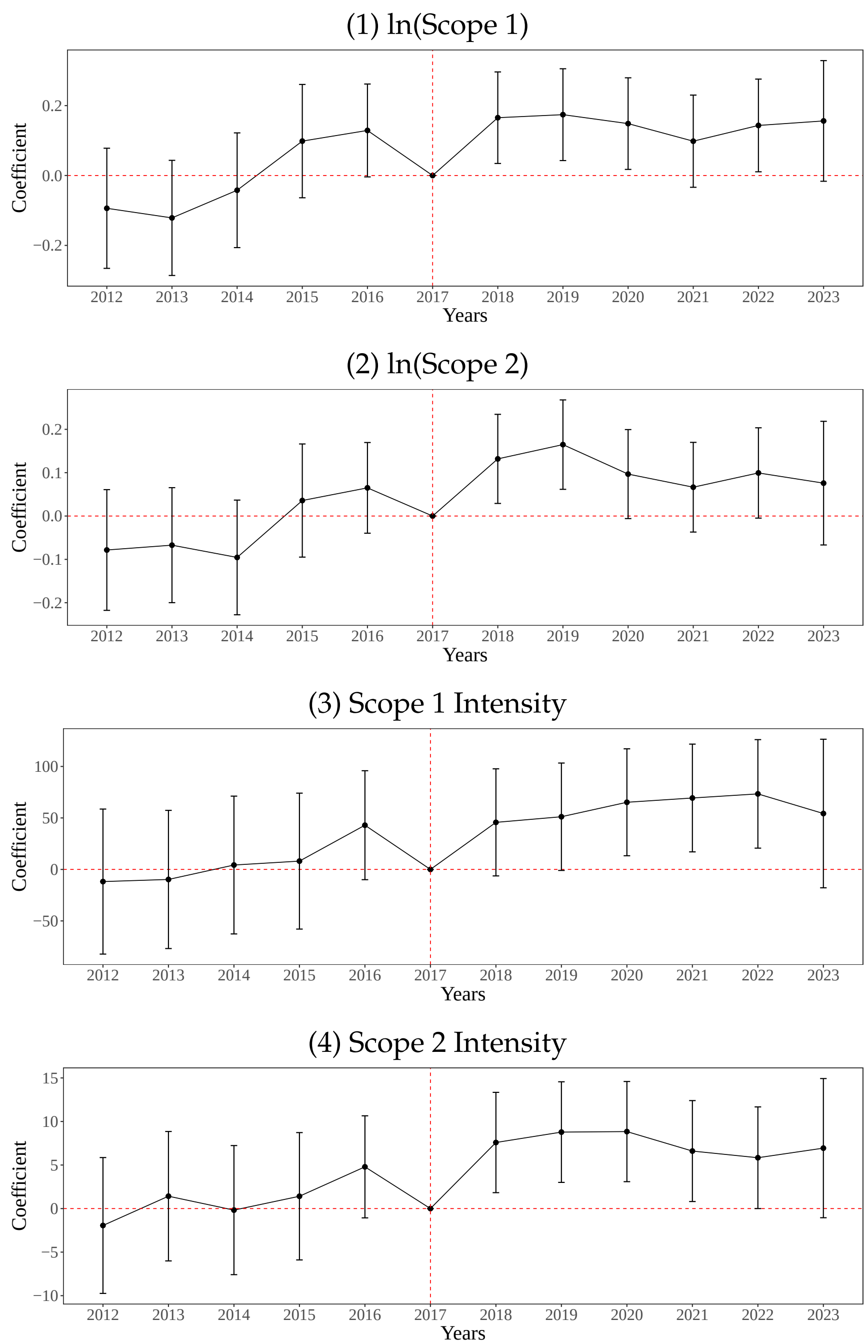

Table 3: Environmental Tariffs as an Underlying Mechanism

Note: This table presents the role of disruptions to green products trade as a channel through which the U.S.-China trade war affects corporate carbon emissions. The dependent variables include the logarithm of one plus the absolute value of Scope 1 and Scope 2, and the Scope 1 and Scope 2 intensities. Treatment is an indicator variable set to one if a firm imported goods subjected to substantial tariff increases (over 25%) from China within the two years preceding the US-China trade war and zero otherwise. Post is set to one after 2017 and zero otherwise. 1{Green Tariff} is equal to one if, prior to the trade war, the firm purchased at least one environmental product affected by the import tariff hikes and zero otherwise. 1{No Green Tariff} is equal to one if, in the pre-event period, the firm purchased no environmental product affected by the trade war and zero otherwise. Reported are the regression slopes, standard errors in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All the other variable definitions are presented in Appendix A.

	ln(Scope 1)		ln(Scope 2)		Scope 1 Intensity		Scope 2 Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Effects of Pre-Event Tariffed Environmental Products on Carbon Emissions								
Treatment×Post×1{Green Tariff}	0.230***	0.186***	0.114***	0.088**	51.103***	68.747***	5.517***	4.051***
	(0.037)	(0.039)	(0.033)	(0.034)	(11.619)	(12.289)	(1.189)	(1.260)
Treatment×Post× 1{No Green Tariff}	0.090***	0.059*	0.050*	0.054*	40.074***	51.434***	3.669***	3.264***
	(0.033)	(0.034)	(0.029)	(0.030)	(10.232)	(10.904)	(1.047)	(1.118)
$\Delta Slope$	[0.140***]	[0.127***]	[0.063**]	[0.035]	[11.030]	[17.313]	[1.848]	[0.787]
Control	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓		✓	
Year-State FE		✓		✓		✓		✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	11,046	11,046	11,046	11,046	11,046	11,046	11,046	11,046
Adjusted R^2	0.911	0.914	0.901	0.903	0.729	0.731	0.742	0.744

Table 4: Financial Pressure as an Underlying Mechanism

Note: This table presents the role of financial pressure as a channel through which the U.S.-China trade war affects corporate carbon emissions. Panel A tests the consequences of the trade war on financial constraints and distress. Dependent variables include the Whited-Wu (WW) index (Whited and Wu, 2006), the SA index (Hadlock and Pierce, 2010), COGS-to-sales ratio, and EBITDA margin. Treatment is an indicator variable set to one if a firm imported goods subjected to substantial tariff increases (over 25%) from China within the two years preceding the US-China trade war and zero otherwise. Post is set to one after 2017 and zero otherwise. Panels B and C explore the impacts of increased WW index and COGS-to-sales ratio on firms' carbon emissions during the trade war, respectively. The dependent variables include the logarithm of one plus the absolute value of Scope 1 and Scope 2 emissions, as well as the intensities of both Scope 1 and Scope 2. The financial pressure proxy is classified as one if the increase exceeds the 60th percentile of the total sample and zero otherwise. Reported are the regression coefficients, standard errors (in parentheses), and R^2 values. Significance levels are denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively. All variable definitions are provided in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Effect of Trade war on Financial Constraints and Distress								
	WW Index		SA Index		COGS/Sales		EBITDA Margin	
Treatment×Post	0.003**	0.003**	0.050***	0.036***	0.430***	0.394**	−0.227**	−0.615***
	(0.001)	(0.002)	(0.005)	(0.006)	(0.162)	(0.183)	(0.098)	(0.117)
Observations	11,332	7,920	11,231	7,946	16,083	11,052	16,079	11,052
Adjusted R^2	0.896	0.908	0.943	0.957	0.931	0.949	0.907	0.927
Panel B: Role of Financial Constraints on Carbon Emission: WW Index								
	ln(Scope 1)		ln(Scope 2)		Scope 1 Intensity		Scope 2 Intensity	
Treatment×Post× $1\{q_{High}(\Delta \text{WW Index})\}$	0.274***	0.269***	0.123**	0.117*	57.009***	55.123**	4.550**	8.351***
	(0.065)	(0.071)	(0.058)	(0.065)	(20.902)	(23.502)	(2.149)	(2.421)
Observations	10,344	10,344	10,344	10,344	10,344	10,344	10,344	10,344
Adjusted R^2	0.917	0.921	0.903	0.906	0.747	0.750	0.747	0.749
Panel C: Role of Increased Cost of Input on Carbon Emission								

	ln(Scope 1)		ln(Scope 2)		Scope 1 Intensity		Scope 2 Intensity	
Treatment×Post× $1\{q_{High}(\Delta\text{COGS/Sale})\}$	0.199***	0.123**	0.055	0.059	63.042***	70.954***	4.456	4.747
	(0.060)	(0.061)	(0.053)	(0.054)	(18.769)	(19.443)	(2.999)	(3.044)
Observations	11,044	11,044	11,044	11,044	11,044	11,044	11,044	11,044
Adjusted R^2	0.911	0.914	0.901	0.903	0.729	0.732	0.786	0.797
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓		✓	
Year-State FE		✓		✓		✓		✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 5: The Impact of the Tariff War on Green Innovation

Note: Panel A of this table examines the impact of the trade war on firms' green innovation. Panel B explores the impacts of increased financial constraints on firms' green innovation during the trade war. Treatment is one if a firm imported goods subjected to substantial tariff increases (over 25%) from China within the two years preceding the trade war and zero otherwise. Post is one after 2017 and zero otherwise. The indicators $1\{q_{\text{High}}(\Delta\text{FC})\}$ is set to one if the increase in WW index during the trade war exceeds the 60th percentile of the total sample and zero otherwise. Dependent variables in both panels include the logarithm of one plus the number of green patents and the ratio of green patents to the total number of patents. Patents are classified as "green" using the International Patent Classification (IPC) and Cooperative Patent Classification (CPC). Reported are the regression coefficients, standard errors (in parentheses), and R^2 values. Significance levels are denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively. Variable definitions are provided in Appendix A.

	#Green Pat.: CPC		#Green Pat.: IPC		Gr. Pat. Ratio: CPC		Gr. Pat. Ratio: IPC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Effect of Trade war on Green Innovation								
Treatment×Post	−0.025	−0.067***	−0.115***	−0.204***	−0.578*	−0.940**	−0.423	−1.620
	(0.017)	(0.024)	(0.031)	(0.041)	(0.330)	(0.435)	(0.874)	(1.068)
Observations	7,809	5,907	7,809	5,907	7,809	5,907	7,809	5,907
Adjusted R^2	0.786	0.789	0.799	0.816	0.454	0.490	0.444	0.494
Panel B: Role of Financial Constraints on Green Innovation								
Treatment×Post×$1\{q_{high}(\Delta\text{FC})\}$	−0.129***	−0.115*	−0.375***	−0.278***	−1.484*	−3.003***	−2.960	−6.124**
	(0.042)	(0.063)	(0.077)	(0.106)	(0.819)	(1.162)	(2.192)	(2.779)
Observations	7,157	5,276	7,157	5,276	7,157	5,276	7,157	5,276
Adjusted R^2	0.804	0.811	0.813	0.836	0.485	0.523	0.456	0.526
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓		✓	
Year-State FE		✓		✓		✓		✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 6: The Role of Green Innovation

Note: This table presents the impacts of decreased green innovation on firms' carbon emissions during the trade war. Dependent variables include the logarithm of one plus the absolute value of Scope 1 and Scope 2 emissions, and the intensities of both Scope 1 and Scope 2. Treatment is one if a firm imported goods subjected to substantial tariff increases (over 25%) from China within the two years preceding the trade war and zero otherwise. Post is one after 2017 and zero otherwise. $1\{q_{\text{Low}}(\Delta\text{Ratio of Green Patents})\}$ is one if the decrease in Ratio of Green Patents exceeds the 60th percentile of the total sample and zero otherwise. Panels A and B focus on when patents are classified as "green" using the IPC and CPC, respectively. Reported are the regression coefficients, standard errors (in parentheses), and R^2 values. Significance levels are denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively. All variable definitions are provided in Appendix A.

	ln(Scope 1)		ln(Scope 2)		Scope 1 Intensity		Scope 2 Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Results Based on CPC Green Codes								
Treatment×Post×$1\{q_{Low}(\Delta$Ratio of Green Patents$)\}$	0.335***	0.364***	0.312***	0.279***	59.501**	31.394	7.488**	5.663*
	(0.097)	(0.096)	(0.085)	(0.086)	(29.968)	(30.463)	(3.190)	(3.250)
Observations	10,582	10,582	10,582	10,582	10,582	10,582	10,582	10,582
Adjusted R^2	0.914	0.918	0.904	0.906	0.753	0.755	0.743	0.744
Panel B: Results Based on IPC Green Codes								
Treatment×Post×$1\{q_{Low}(\Delta$Ratio of Green Patents$)\}$	0.184**	0.175**	0.127*	0.230***	196.50***	185.61***	7.151***	9.509***
	(0.082)	(0.084)	(0.072)	(0.075)	(25.414)	(26.397)	(2.712)	(2.822)
Observations	10,582	10,582	10,582	10,582	10,582	10,582	10,582	10,582
Adjusted R^2	0.913	0.918	0.904	0.906	0.754	0.756	0.743	0.745
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓		✓	
Year-State FE		✓		✓		✓		✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 7: The Impact of the Tariff War on Environment-related Employment

Note: Panel A of this table examines the impact of the trade war on firms' environment-related employment. Panel B explores the impacts of increased financial constraints on firms' environment-related employment during the trade war. Treatment is an indicator variable set to one if a firm imported goods subjected to substantial tariff increases (over 25%) from China within the two years preceding the US-China trade war and zero otherwise. Post is set to one after 2017 and zero otherwise. $1\{q_{\text{High}}(\Delta\text{FC})\}$ is set to one if the increase in a firm's financial constraints (measured by the WW index) during the trade war exceeds the 60th percentile of the total sample, and zero otherwise. Dependent variables in both panels include the logarithm of one plus the number of environment-related positions available and the number of environment-related employees. Reported are the regression coefficients, standard errors (in parentheses), and R^2 values. Significance levels are denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.Variable definitions are provided in in Appendix A.

	#Env.-related Positions		#Env.-related Employees	
	(1)	(2)	(3)	(4)
Panel A: Effect of Trade war on Green Employments				
Treatment×Post	−0.083**	−0.113**	−0.116***	−0.135**
	(0.038)	(0.052)	(0.044)	(0.061)
Observations	1,738	1,394	1,738	1,394
Adjusted R^2	0.652	0.701	0.632	0.669
Panel B: Role of Financial Constraints on Green Employment				
Treatment×Post×$1\{q_{high}(\Delta$ FC$)\}$	−0.106**	−0.131**	−0.137***	−0.206***
	(0.044)	(0.055)	(0.051)	(0.065)
Observations	1,789	1,416	1,789	1,416
Adjusted R^2	0.663	0.707	0.643	0.678
Controls	✓	✓	✓	✓
Year FE	✓		✓	
Year-State FE		✓		✓
Firm FE	✓	✓	✓	✓

Table 8: The Moderating Role of Climate Ideology

Note: This table presents the impact of climate ideology on firms' carbon emissions during the tariff war. The dependent variables in Panel A include the logarithm of one plus the absolute values of Scope 1 and Scope 2 emissions; those in Panel B include the intensities of Scope 1 and Scope 2 emissions. Treatment is an indicator variable set to one if a firm imported goods subjected to substantial tariff increases (over 25%) from China within the two years preceding the US-China trade war and zero otherwise. Post is set to one after 2017 and zero otherwise. 1{LowClimateIdeology} is set to one if a firm is located in a state with a lower-than-national median percentage of people who consider environmental issues important and zero otherwise. 1{Election:REP} is set to one if a firm is located in a state that voted for a Republican presidential candidate in the 2016 election and zero otherwise. 1{LegisControl:REP} is set to one if a firm is located in a state whose legislature was controlled by Republicans during the trade war and zero otherwise. 1{FirmParty:REP} is set to one if firm i's political partisanship relatively leans toward the Republican Party in the 2016 and 2020 election cycles and zero otherwise. Reported are the regression coefficients, standard errors (in parentheses), and R^2 values. Significance levels are denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively. Variable definitions are in Appendix A.

Moderator	1{LowClimateIdeology}		1{Election:REP}		1{LegisControl:REP}		1{FirmParty:REP}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Results for Absolute Emissions								
	ln(Scope1)	ln(Scope2)	ln(Scope1)	ln(Scope2)	ln(Scope1)	ln(Scope2)	ln(Scope1)	ln(Scope2)
Treatment×Post× Moderator	0.212***	0.164**	0.171**	0.291***	0.176**	0.285***	0.159*	0.170**
	(0.081)	(0.074)	(0.080)	(0.074)	(0.081)	(0.074)	(0.082)	(0.075)
Observations	9,416	9,416	9,416	9,416	10,165	10,165	9,246	9,246
Adjusted R^2	0.922	0.905	0.922	0.905	0.920	0.905	0.922	0.905
Panel B: Results for Emission Intensity								
	Scope 1 Intensity	Scope 2 Intensity	Scope 1 Intensity	Scope 2 Intensity	Scope 1 Intensity	Scope 2 Intensity	Scope 1 Intensity	Scope 2 Intensity

Treatment×Post× Moderator	200.22***	11.237***	130.96***	7.644***	134.16***	7.600***	165.90***	14.223***
	(26.846)	(2.740)	(26.714)	(2.722)	(26.360)	(2.758)	(27.128)	(2.802)
Adjusted R^2	0.769	0.761	0.768	0.760	0.759	0.749	0.775	0.760
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-State FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	9,416	9,416	9,416	9,416	10,165	10,165	9,246	9,246

Table 9: The Moderating Role of Supply Chain Characterisitics

Note: This table presents the heterogeneous effect of the trade war on corporate carbon based on supply chain characteristics. The dependent variables include the logarithm of one plus the absolute value of Scope 1 and Scope 2, and the Scope 1 and Scope 2 intensities. Treatment is an indicator variable set to one if a firm imported goods subjected to substantial tariff increases (over 25%) from China within the two years preceding the US-China trade war and zero otherwise. Post is set to one after 2017 and zero otherwise. $1\{q_{High}HHI_{Country}\}$ is a dummy variable set to one if the Herfindahl-Hirschman Index of the country distribution of suppliers is higher than the 60th percentile prior to the trade war and zero otherwise. $1\{q_{High}\%\text{Tariffed Specific Suppliers}\}$ is a dummy variable set to one if a firm's percentage of Tariffed Specific Suppliers exceeds the 60th industry percentile before the trade war and zero otherwise. Tariffed Specific Suppliers are Chinese suppliers who provide complex products facing significantly increased tariffs, where product complexity is defined based on the Product Complexity Index (PCI). Reported are the regression slopes, standard errors in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All the other variable definitions are presented in Appendix A.

	ln(Scope 1)		ln(Scope 2)		Scope 1 Intensity		Scope 2 Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Results Based on Pre-Event Supply Chain Diversification								
Treatment×Post× $1\{q_{High}(HHI_{Country})\}$	0.195***	0.172***	0.147***	0.100***	24.711	36.280*	14.171***	14.493***
	(0.042)	(0.044)	(0.037)	(0.039)	(18.649)	(19.602)	(2.119)	(2.167)
Observations	11,046	11,046	11,046	11,046	11,046	11,046	11,046	11,046
Adjusted R^2	0.911	0.914	0.901	0.903	0.829	0.828	0.787	0.798
Panel B: Results Based on the Input Specificity								
Treatment×Post× $1\{q_{High}(\%\text{Tariffed Specific Suppliers})\}$	0.075**	0.105***	0.057*	0.099***	15.450	12.472	1.988*	3.513***
	(0.037)	(0.039)	(0.033)	(0.034)	(11.693)	(12.259)	(1.197)	(1.256)
Observations	11,046	11,046	11,046	11,046	11,046	11,046	11,046	11,046

Adjusted R^2	0.911	0.914	0.901	0.903	0.729	0.731	0.742	0.744
Control	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓		✓		✓		✓	
Year-State FE		✓		✓		✓		✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓

ONLINE APPENDIX

How Do Trade Conflicts Affect Corporate Carbon Emissions? Evidence from Global Supply Chain

Table of Contents

Table OA1: Ex-ante Covariates Statistic of Affected Customers

Note: This table presents the mean values of key variables for both treated and control firms in the years preceding the event, analyzed both before and after matching. Additionally, we report the T-statistic to test for equality of means between the groups. The treated firms are those that imported goods subjected to substantial tariff increases (over 25%) from China within the two years prior to 2018. In contrast, the control firms are characterized by imports of goods with minor tariff increases (less than 10%) from China during the same period, with no imports of highly-increased-tariffed goods post-2016. We employ a matching algorithm ensuring that control firms match the treated firms in the same industry and size terciles. Variable definitions are detailed in Appendix A.

Variable	Matching Algorithm	Mean (Treated)	Mean (Control)	T-stat
ln(Scope 1)	Unmatched	11.560	10.914	4.433
	matched	11.505	10.992	3.384
ln(Scope 2)	Unmatched	11.745	11.008	6.204
	matched	11.714	11.052	5.329
Scope 1 Intensity	Unmatched	123.57	137.95	-0.443
	matched	115.71	154.71	-0.995
Scope 2 Intensity	Unmatched	41.696	42.222	-0.120
	matched	42.468	44.569	-0.431
ln(Asset)	Unmatched	8.173	5.823	16.596
	matched	8.177	6.875	8.679
LER	Unmatched	0.264	0.298	-1.115
	matched	0.258	0.250	0.651
Sale Growth	Unmatched	0.131	3105	-1.001
	matched	0.077	0.085	-0.793
ROA	Unmatched	0.119	-1.814	1.014
	matched	0.080	0.076	0.690

Table OA2: Industry Distribution and Summary of Carbon Emissions

Note: This table reports the industry distribution of our treated sample.

Rank	Industry Name	# of Firms	Mean (Scope 1)	Rank (Scope 1)	Mean (Scope 2)	Rank (Scope2)
1	Machinery	76	99985	33	148269	31
2	Trading Companies and Distributors	29	1239746	11	427692	19
3	Electronic Equipment, Instruments and Components	28	189189	27	606970	13
4	Automobile Components	27	218533	25	451646	16
5	Electrical Equipment	26	96944	35	182118	30
6	Chemicals	25	4006619	5	1800071	4
7	Metals and Mining	20	14479505	2	1747465	5
8	Specialty Retail	20	153568	31	483947	14
9	Household Durables	19	214348	26	370474	22
10	Building Products	15	521876	20	480569	15
11	Consumer Staples Distribution and Retail	15	1411596	9	3020057	1
12	Banks	13	46167	41	355395	23
13	Broadline Retail	12	923059	13	1418368	7
14	Automobiles	11	759398	16	1891886	3
15	Health Care Equipment and Supplies	10	45251	42	77212	39
16	Technology Hardware, Storage and Peripherals	10	471613	22	1442395	6

Table OA3: Supply Chain Adjustments: Suppliers' Emission

Note: This table presents the effect of the trade war on suppliers' GHG emissions. Treatment is an indicator variable set to one if a firm imported goods subjected to substantial tariff increases (over 25%) from China within the two years preceding the US-China trade war and zero otherwise. Post is set to one after 2017 and zero otherwise. Reported are the regression slopes, standard errors in the parentheses, and R^2s. The differences in coefficients between subsamples ($\Delta Slope$) are shown in the square brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All the other variable definitions are presented in Appendix A.

	New Suppliers' Averaged Scope1 Emission		New Suppliers' Averaged Scope2 Emission		Total Suppliers' Averaged Scope1 Emission		Total Suppliers' Averaged Scope2 Emission	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	−0.873***	−0.508***	−0.828***	−0.485***	−0.723***	−0.230**	−0.673***	−0.178**
	(0.153)	(0.176)	(0.144)	(0.164)	(0.110)	(0.092)	(0.101)	(0.080)
ln(Asset)	0.353***	0.256**	0.308***	0.232**	0.246***	0.153***	0.229***	0.156***
	(0.077)	(0.112)	(0.072)	(0.104)	(0.055)	(0.058)	(0.051)	(0.051)
ROA	−0.414	0.687	0.132	1.551	−0.761	0.193	−0.131	1.036**
	(0.808)	(1.036)	(0.760)	(0.964)	(0.581)	(0.540)	(0.533)	(0.468)
Leverage	0.203	−0.346	0.232	−0.261	−0.246	−0.214	−0.111	0.090
	(0.351)	(0.460)	(0.330)	(0.429)	(0.252)	(0.240)	(0.231)	(0.208)
CAPEX/Assets	2.019	−0.424	1.858	−1.413	−0.303	−1.644	0.146	−2.079**
	(1.799)	(2.284)	(1.692)	(2.126)	(1.292)	(1.190)	(1.185)	(1.031)
Cash flow/Asset	−1.212*	−1.804**	−1.040*	−1.457**	−0.550	−1.362***	−0.331	−0.974***
	(0.625)	(0.789)	(0.588)	(0.735)	(0.449)	(0.411)	(0.412)	(0.356)
Inventory Turnover	0.307	−0.497	0.476	−0.214	0.622*	0.041	0.666**	0.156
	(0.503)	(0.638)	(0.473)	(0.594)	(0.361)	(0.333)	(0.331)	(0.288)
Sale Growth	−0.302	−0.246	−0.277	−0.233	−0.512***	−0.452***	−0.481***	−0.351***

	(0.231)	(0.282)	(0.217)	(0.262)	(0.166)	(0.147)	(0.152)	(0.127)
Year FE	✓		✓		✓		✓	
Year-State FE		✓		✓		✓		✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	16,083	11,052	16,083	11,052	16,083	11,052	16,083	11,052
Adjusted R^2	0.601	0.692	0.607	0.700	0.798	0.913	0.806	0.925