The Environmental Externalities of the U.S.-China Trade Dispute

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Abstract

We combine U.S. monthly import data, tariff data, and industry-level carbon dioxide (CO_2) emission data to measure the environmental externalities of the tariff surges between the U.S. and China during their trade dispute. We find that U.S. tariffs in general target goods for which Chinese production technology tends to be cleaner than that from the rest of the world (ROW). This reveals an "environmental bias" of U.S. trade policy. We also find that as tariffs increase, the "dirtier" the product, the greater the diversion of trade towards the ROW, deepening the policy bias. At the aggregate level, the average CO_2 emission intensity of U.S. imports (defined as direct and indirect CO_2 emissions of imports divided by the value of imports) has increased, and more so from lower-income countries. In other words, U.S. imports have become "dirtier," suggesting a net negative impact of these trade policies and more so for poorer countries.

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1 Introduction

It is widely recognized that some economies have more stringent environmental policies and employ cleaner production technologies than others. Consequently, the redistribution of productive activities across countries arising from international trade and trade policy changes has environmental implications as pollution emissions change when global value chains shift. While the relationship between international trade and environmental regulation has been studied extensively in the literature (see Antweiler (1996), Frankel and Rose (2005), Lu et al. (2022), Holladay (2016), and Cui et al. (2016)), the impact of man-made trade barriers, i.e. trade policies, on pollution emissions is under-explored. Our paper is the first to empirically investigate the relationship between tariff incidence, U.S. imports, and the emissions inherent in them, within the context of the US-China trade conflict. Specifically, we examine how the US-China trade dispute, one of the largest-scale trade policy interventions in recent years, affected the total emissions contained in, as well as their "dirtiness" or emissions intensity per dollar. This helps shed light on how this trade war affected the global effort to protect the environment due to induced shifts in the global value chain.

In this paper, we first demonstrate the magnitude of trade diversion as a result of the US-China trade war in terms of the volume of U.S. imports from the rest of the world (ROW) using U.S. trade[1] and tariff data.[2] We then combine U.S. trade data with measures of dirtiness of products based on the carbon dioxide emissions generated by production, which Exiobase[3] publishes, to measure the magnitude of the environmental externalities of the U.S.-China trade dispute. Finally, we explore the heterogeneity of trade diversion across products with different levels of dirtiness and across countries at different levels of development.

Our findings uncover clear patterns of trade diversion as we find that the U.S. imports more from other countries, especially developing ones, during the trade dispute with China. Import increases are however heterogeneous across countries and industries. We show that when the tariff on a good coming from China rises, the US tends to substitute Chinese imports with imports from countries using *dirtier* technology. This makes sense as countries with weaker regulations on emissions would have an advantage in producing dirty goods, which given other things, suggests they would be natural candidates to fill the vacuum created by decreasing Chinese exports of such goods. We show that although trade diversion is less likely for dirtier goods, less developed countries export dirtier goods than developed

[1]Sourced from the U.S. Census Bureau's monthly administrative records of imports. Data Source: `https://usatrade.census.gov/`

[2]Provided by the U.S. International Trade Commission `https://www.usitc.gov/`

[3]Data Source: `https://www.exiobase.eu`

countries. While the former decreases the relevance of trade diversion for environmental spillovers, the latter increases it. Our findings highlight the interplay between trade policy, comparative advantage, and environmental considerations, within the context of the U.S.-China trade dispute. Our research adds a significant empirical dimension to this area of study by assessing the potential environmental consequences of trade policy changes.

This paper is related to three main strands of literature. The first is the work on the overall environmental gains or losses from trade. This literature traces its origins back to early studies, such as Antweiler (1996), which creates a "pollution terms of trade" index to quantify a country's environmental gains or losses resulting from international trade. See Copeland and Taylor (2004) for a thorough literature review on this topic. Frankel and Rose (2005) use exogenous determinants of trade as instrumental variables to show that trade tends to reduce three distinct measures of air pollution. This literature provides the context in which to explore the intricate relationship between trade and environmental factors, a key focus of our paper.

Second, our paper contributes to the small but growing body of literature focusing on the interactions between trade policy and the environment. Our work is directly connected to and uses data from Shapiro (2021) which shows that dirtier industries are subject to relatively lower tariffs and non-tariff barriers (NTB), also known as an "environmental bias" of trade policy. He also shows that if the disparity in trade barriers across industries with varying level of dirtiness is eliminated, global CO_2 emissions would go down while global income would be minimally affected.[4]

A few papers in this literature (e.g. Cristea et al. (2013), and Klotz and Sharma (2023) use general equilibrium models to quantify the environmental cost due to the change in trade policy. Cristea et al. (2013) emphasizes the importance of considering transport emissions when designing trade policies. They use general equilibrium trade growth simulations to assess how tariff liberalization and GDP growth influence emissions. Their findings suggest that tariff liberalization can lead to increased transport emissions, resulting in emission growth surpassing trade growth. Klotz and Sharma (2023) develops a comprehensive multi-country, multi-sector general equilibrium framework to quantify the effects of reducing trade barriers and argue that such reductions can lead to higher transportation emissions and wages relative to the prices of other goods. Other papers in this literature, take advantage of data to explore the relationship between trade policies and emissions. For example, Wang et al. (2022) draw on data from 16 industrial sectors in 10 major countries in exploring how

[4]Following Shapiro (2021)'s discussion, Marjit and Mukherjee (2023) presents some theoretical insights into the advantages of lower import tariffs on goods with higher pollution content, particularly when pollution is predominantly generated through domestic production. It delves into the nuanced relationship between trade policy and environmental considerations.

lowering trade barriers can potentially reduce industrial pollution with a focus on energy use intensity and biased technological progress. Cherniwchan (2017) shows that NAFTA played a key role in the clean-up of the U.S. manufacturing sector. Instead of focusing on trade barriers, Shapiro (2016) investigates the impact of shipping costs on CO_2 emissions using panel data from 128 countries. He constructs a model to estimate the welfare effects of trade policies targeting shipping costs and finds that the benefits of trade tend to outweigh its environmental costs in terms of CO_2 emissions.

Third, our paper is also related to the literature on the pollution haven hypothesis, that is, firms will seek to avoid the cost of stringent environmental regulations (and high energy prices) by locating production in countries where environmental norms are laxer. See Kellenberg (2009) and Gill et al. (2018) for a literature review of this area. Our paper finds supporting evidence for this hypothesis, and finds that developing countries (presumably with lax environmental regulations) gain a larger market share of dirty goods in the U.S. market during the U.S.-China trade dispute. For a recent survey on the topic of globalization and the environment, see Copeland et al. (2022).

We begin by motivating our analysis with a few facts. The first documents that CO_2 emission intensity not only varies across industries but for the same industry, it also differs across countries. Chinese emission efficiency is higher than that of the ROW for cleaner products but lower than it for dirty products. The second is that the change in U.S. tariffs in the 2018 wave was higher in products where Chinese emission intensity was lower than that of the ROW. This suggests that these tariff changes could have had an adverse environmental effect globally and particularly on poorer countries.

We then develop an empirical strategy and exploit the U.S.-China trade data using reduced form methods to study the environmental impact of the U.S.-China trade dispute. We believe we are the first to attempt this. We show that Trump tariffs diverted trade towards countries using dirtier production techniques and increased the dirtiness of U.S. imports, and more so, the poorer the country exporting.

The remainder of our paper is organized as follows. Section 2 introduces the datasets used in the analysis. Section 3 presents key statistical facts on the "environmental bias" of U.S. tariffs on Chinese goods. Section 4 studies the pattern of trade diversion of goods with different levels of dirtiness. Section 5 presents the environmental impact of trade diversion i.e. its dirtiness in terms of CO_2 emission across different countries. Section 6 concludes.

2 Data

We integrate data from three sources: monthly U.S. trade statistics, information on trade tariffs imposed during the U.S.-China trade conflict, and the Exiobase dataset, which provides estimates of emissions by industry and country.

Monthly U.S. Trade Data We use U.S. trade data sourced from the U.S. Census Bureau's monthly administrative records of imports. The data is publicly available as part of the U.S. Census Bureau's trade database.[5] It provides the values and quantities of monthly trade transactions at the detailed Harmonized System (HS) 10-digit level. We aggregate this data to reduce the computational demands to the HS 8-digit level every month. This serves as the primary level of analysis for our regression models. We do so as this is the level we have good information on U.S. tariffs against Chinese products. The granularity of the data enables a precise examination of trade volume shifts and pattern changes over time, especially during the U.S.-China trade conflict. It offers a detailed view of how the imposition of tariffs and other trade measures impacted trade flows. Our analysis covers the period from January 2015 to December 2019. The period is chosen to avoid distortions caused by the onset of the COVID-19 pandemic in early 2020, which significantly altered global trade patterns.

Tariffs during the Trade Dispute We compile monthly data on the tariffs enacted by the U.S. against China throughout the trade conflict using publicly available tariff schedules provided on the website of the U.S. International Trade Commission (USITC).[6] This includes the timing, rate, and 8-digit HS code of each tariff imposed. 2018 and 2019 saw several rounds of tariff increases, which were part of the U.S.-China trade dispute, and these have been comprehensively documented by the USITC. We define targeted products as those subject to U.S. tariffs on Chinese imports during their trade dispute. Analyses of these tariffs provide insights into the direct regulatory mechanisms of the U.S. and their immediate trade diversion effects.

Exiobase Dataset Exiobase[7] is the primary dataset we use to quantify CO_2 emissions. Exiobase integrates trade data, input-output tables, and national accounts to construct a comprehensive global multi-region input-output table, making it an invaluable resource for our analysis. It provides extensive industry-country-specific estimates of greenhouse gas

[5]Link: `https://usatrade.census.gov/`
[6]Link: `https://www.usitc.gov/`
[7]Link: `https://www.exiobase.eu`

emissions i.e. CO_2. Exiobase covers 163 industries across 44 countries and five remaining regions from 1995 to 2022. Of these industries, 47 are tradable. Exiobase's emissions data are mainly collected from the International Energy Agency (IEA).

Both direct and indirect CO_2 emissions are important when we calculate CO_2 emissions from industries. *Direct emissions* occur during the production process while *indirect emissions* arise from the production of intermediate goods used in various industries. Exiobase provides data on direct CO_2 emissions per million Euros of output for each industry in every country. We use the cleaned Exiobase data created by Shapiro (2021), which incorporates both direct and indirect CO_2 emissions, providing a comprehensive measure of total CO_2 emission intensity, i.e., direct and indirect emissions per dollar at the 6 digit level. From this data package, we obtain measurements of total CO_2 emission intensity for each country at the 6-digit HS code level.

The "dirtiness" of an industry, or "CO_2 emission intensity," is measured as tons of CO_2 emission per dollar of output. A higher level of dirtiness (greater amount of CO_2 emission per dollar of output) indicates a higher level of emission intensity and vice versa. The most disaggregated level where we have information on emission measurement is the 6-digit HS code. As our emissions data is at the 6-digit level, we assign all 8-digit categories in a given HS 6-digit classification the emissions intensity of the 6-digit category.

In addition, the cleaned data package in Shapiro (2021) offers a concordance between Exiobase industry codes and HS-6 digit codes. This permits us to use Shapiro's comprehensive measure of emission intensity along with trade and tariff data to evaluate the broader environmental impact of the U.S.-China trade dispute, including shifts in imports and production across goods and industries with different emissions intensities.

3 The "Environmental Bias" of U.S. Tariffs during the U.S.-China Trade Dispute

In this section, we provide some descriptive analyses that provide insights into the dirtiness of production technology across industries and countries. Specifically, we explore variations in the levels of dirtiness of targeted products from China relative to those from the "rest of the world" (ROW) i.e. all other countries and regions apart from the U.S. and China. Our results provide preliminary evidence of an "environmental bias" in U.S. trade policy, thereby motivating a deeper empirical investigation into the environmental consequences of the trade conflict between the U.S. and China. The analyses are presented as two novel facts below.

Fact 1: CO_2 emission intensity not only varies across industries but for the same industry, it also differs across countries. Chinese emission intensity is higher than that of the ROW for cleaner products but lower than it for dirty products.

Differences in institutions, human capital, and local cultures result in the utilization of different technologies to produce the same products across countries. Consequently, the CO_2 emission for the same product varies by country. Figure 1 presents the distribution of CO_2 emission intensity across countries by industry. Each boxplot represents one industry. The red dot represents the CO_2 emission intensity of Chinese production technology in an industry. The box plot within the figure delineates the median, as well as the 25th and 75th percentiles of CO_2 emission intensity levels for all countries within each industry.[8] Clearly, industries vary in terms of CO_2 emission per dollar of output. Note that the position of Chinese production in terms of CO_2 emission intensity relative to the ROW has a clear pattern. It is not that Chinese production in all industries is more pollution intensive than that of the ROW. Nor is it true that the difference is purely random. Chinese production is more environmentally efficient than that of the ROW for cleaner industries and less environmentally efficient than the ROW for dirtier industries. In other words, high emission intensity industries (but not low emission ones) tend to be produced in a more dirty manner in China.

[8]The horizontal axis ranks industries based on the level of CO_2 emission intensity of Chinese production.

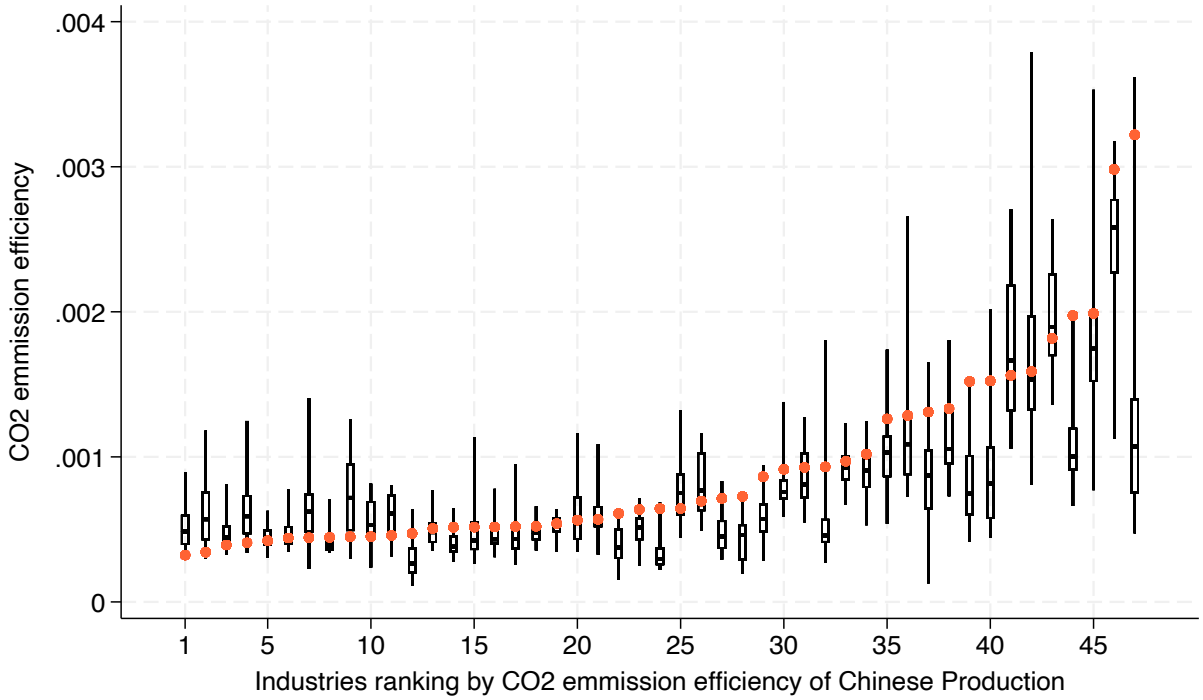


Figure 1: Distribution of CO_2 emission intensity by industry across all countries/regions (ranked by level of CO_2 emission intensity of Chinese production)

While Figure 1 highlights the difference in emission intensity, Table 1 displays the percentage difference in CO_2 emission intensity between Chinese production and the ROW. The median and mean values are positive indicating that the CO_2 emissions are on average higher for Chinese industries or that Chinese production is less environmentally efficient compared to that of the ROW. There is also considerable variation across different industries with the coefficient of variation being 0.15. In the median industry, "Coke Oven Coke, Gas Coke, Coal Tar", Chinese production technology emits 7.6% more CO_2 than the ROW per dollar of output. The most significant differences between the production technology of China and that of the ROW are observed in "*Electrical machinery and apparatus*" and "*Cement, lime, and plaster*." In the former, Chinese production technology emits 42.4% more CO_2 per dollar of output compared to the ROW, while in the latter, it emits 119.9% less CO_2 per dollar of output than its ROW counterparts.

Table 1: Percentage Difference between CO_2 emission intensity of Chinese and ROW production

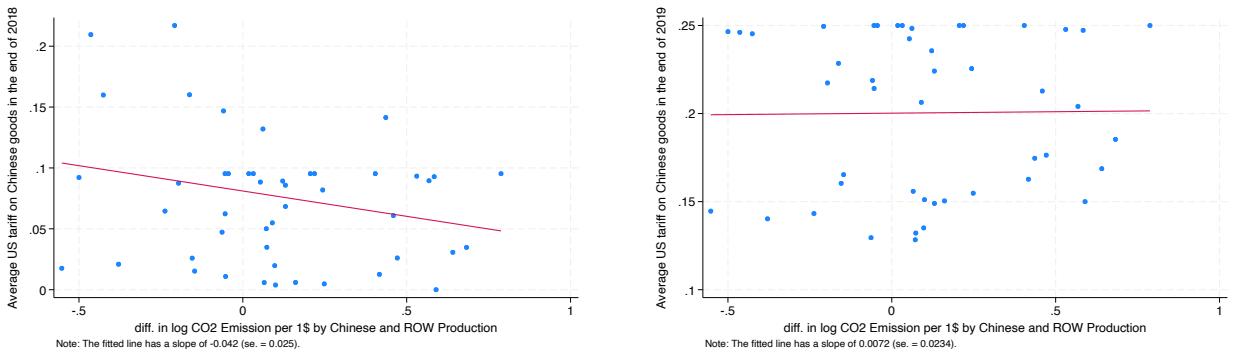
	Percentage Difference
Min	-42.4%
25 percentile	-6.1%
Median	7.6%
75 percentile	49.8%
Max	119.9%
Mean	17.0%
Standard deviation	0.15
Number of Industries	47

Fact 2: Tariffs against Chinese imports in the U.S.-China dispute rose for products where the production technology in China was environmentally friendlier than that of the ROW.

We calculate the relative CO_2 emission intensity of China's and ROW's production for each industry, defined by the logarithm of the ratio of CO_2 emission intensity between China and the ROW $log\left(\frac{CO2_{China}}{CO2_{ROW}}\right)$. A negative value of this logarithm indicates that Chinese production is cleaner than that of the ROW while a positive value indicates the opposite. Then, we compute the weighted change in average U.S. tariffs on Chinese imports at the HS 8-digit level to get the average tariffs at the HS 6-digit level during the U.S.-China trade dispute, using the total import value share in 2016 as weights.[9]

Figure 2 plots the relative CO_2 emission intensity of Chinese and ROW production technologies versus the weighted change in average tariffs on Chinese imports across various industries. As shown in Panel 2a, there is a negative correlation between this change in U.S. tariff rates on Chinese imports in the 2018 wave and the relative CO_2 emission intensity of China's and ROW's production, indicating that U.S. tariffs disproportionately target industries where Chinese production technology is cleaner compared to the ROW's technologies. Such trade policies, if resulting in trade diversion from China to other countries, could lead to increased global CO_2 emissions. This correlation, however, is not evident for the 2019 wave, as depicted by a relatively horizontal line in Panel 2b, suggesting that by 2019, tariffs had been broadened to include nearly all products, diminishing the differential impact on cleaner versus dirtier industries.

[9]The weighted changes in average U.S. tariffs on Chinese imports by the end of 2018 and 2019 are calculated separately to reflect the escalation of tariff increases during the respective years.



(a) The 2018 wave

(b) The 2019 wave

Figure 2: Correlation between $log\left(\frac{CO2_{China}}{CO2_{ROW}}\right)$ and the weighted average tariffs against Chinese imports across different industries

Given the disparities in CO_2 emission intensity levels across different countries' production technologies depicted in Figure 1, trade diversion due to the U.S. tariffs could have significant environmental consequences. If production shifts from China to nations utilizing more polluting technologies for the same products, the consequences would be adverse for the environment while if the reverse is true, it would be beneficial. Since U.S. tariffs rose on goods where China's production technologies tended to be environmentally friendly relative to the ROW, we expect that these tariffs would have an adverse impact on the environment.

4 Trade Diversion and the Dirtiness of Products

4.1 Trade Diversion during the U.S.-China Trade Dispute

Previous research, such as Fajgelbaum et al. (2020), has shown that U.S. tariffs on Chinese imports of targeted goods led to a decrease in imports from China comparing to that from the rest of the world (ROW). We begin by showing that Chinese exports fell while those from the ROW rose in targeted products.

To do so, we utilize a difference-in-differences approach. This method compares changes in imports of targeted products from China and the ROW before and after the tariffs with the trends in non-targeted goods over the same period. Equation (1) outlines our regression specification.

$$\ln Imp_{ckt} = \sum_{\tau=-10,..,0,...10} \beta_\tau^C \mathbb{1}\{TariffEvent_{kt} = \tau\}\mathbb{1}\{c = China\} + \sum_{\tau=-10,..,0,...10} \beta_\tau^R \mathbb{1}\{TariffEvent_{kt} = \tau\}\mathbb{1}\{c = ROW\} + \mu_{ck}^1 + \mu_{ct}^2 + \varepsilon_{ckt} \quad (1)$$

where, $\ln Imp_{ckt}$ is the log of U.S. *import value* of product k at HS 8-digit level from country c at time t (monthly basis). To account for differences in import values across products and countries, we include country-product fixed effects μ_{ck}^1, which allow log imports to have a different intercept for each product and country. Additionally, country-time fixed effects μ_{ct}^2 are incorporated to account for macro-level or aggregate shocks that could affect a country's exports, such as changes in labor costs, currency exchange rates, and other economic conditions. $TariffEvent_{kt}$ generally takes value of 0 or 1. $TariffEvent_{kt} = 1$ if t is the τth month before ($\tau = -10, ..., -1$) or after ($\tau = 1, ..., 10$) the imposition of tariffs. The moment of tariff implementation is represented by $\tau = 0$. To address complications arising from tariffs being enacted mid-month, we rescale the indicator to reflect the portion of the month during which the tariffs were active. Thus, if the tariff is implemented in the middle of the month, the weight is .5.

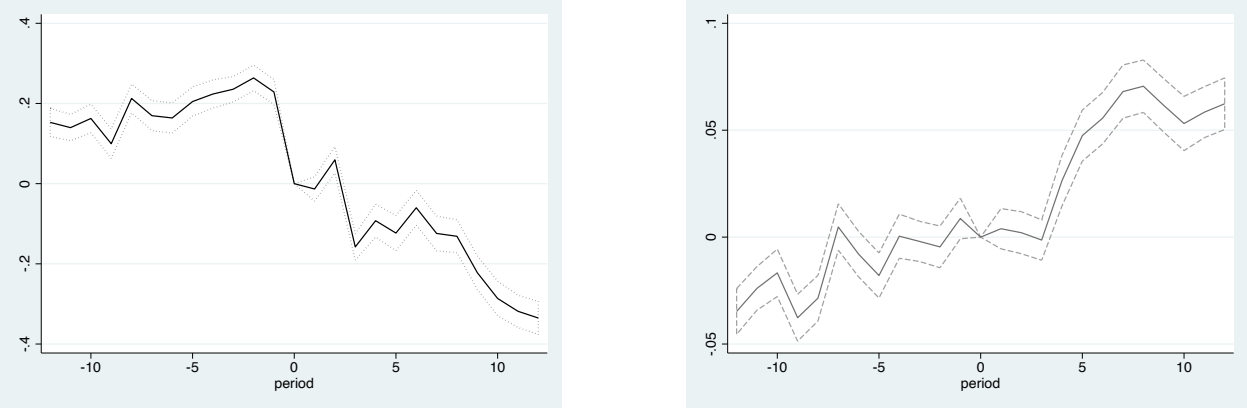
Therefore, β_τ^C identifies the impact of a tariff on U.S. imports from China in the τth month before ($\tau = -10, ..., -1$) or after ($\tau = 1, ..., 10$) the imposition of tariffs, while β_τ^R identifies the impact on U.S. imports from the ROW. These coefficients can be interpreted as the average percentage change in U.S. monthly imports of product k (as logarithmic imports are on the left-hand side of the equation) from China or the ROW before and after the U.S. imposed a tariff increase on Chinese imports.

The panels in Figure 3 provide the estimates for β_τ^C and β_τ^R along with their 95% confidence intervals respectively. Figure 3a is consistent with findings reported by Fajgelbaum et al. (2020) and shows that subsequent to the imposition of tariffs, U.S. imports from China decreased significantly. Figure 3b, on the other hand, shows that imports from the ROW increased substantially. This evidence highlights the trade diversion of U.S. imports away from China and toward the ROW in response to the change in trade policy.

In order to understand the effect of the trade war on emissions, we need to go further and zoom in on the trade diversion effect across countries and products.[10] After this, we are in a position to construct the consequence of trade diversion on emissions.

We classify the Harmonized System (HS) product codes into 18 distinct sections as spec-

[10]Our findings on trade diversion are consistent with Dang et al. (2023), which offers a more detailed examination of the mechanisms shaping trade diversion trends.



(a) China (b) ROW

Figure 3: Trade Diversion after the US-China Trade Dispute

ified in Harmonized Tariff Schedule in the U.S. as presented in Table 2.[11] We identify the top ten trading partners of the U.S., excluding China, to determine which industries these nations have been able to capture a significant portion of the U.S. market, due to trade diversion. To estimate the trade diversion effect across countries and industries, we use the following estimation specification.

$$\ln Imp_{cjkt} = \sum_{c,j} \beta_{c,j} \mathbb{1}\{TariffEvent_{kt} = 1\} \mathbb{1}\{c = Cntry, j = Ind\} + \mu^1_{ck} + \mu^2_{ct} + \varepsilon_{ckt} \quad (2)$$

where, j is the industry of product k, which is defined in Table 2. This specification includes controls for country-product fixed effects μ^1_{ck} and country-time fixed effects μ^2_{ct}. $TariffEvent_{kt}$ associated with $\beta_{c,j}$ is 1 only if a tariff has been imposed by the U.S. on China for product j in industry k. Consequently, the coefficient $\beta_{c,j}$ indicates the average percentage increase in imports from country c in industry j following the imposition of a tariff on any product k within industry j by the U.S. against China.[12] This specification is designed to offer a detailed perspective on the phenomenon of trade diversion, examining how different sectors and geographic areas respond to the imposition of U.S. tariffs on Chinese imports.

Consistent with expectations, the imposition of U.S. tariffs on Chinese goods has led to a decline in Chinese exports to the U.S., as shown in Column (1) of Table 3. Conversely, exports from other regions to the U.S. have generally experienced a positive shift. Among

[11] Notably, the 18th category, "Works of Art, Collectors' Pieces, and Antiques," due to its minimal representation in the dataset, is excluded from our detailed examination.

[12] The readers will notice a similarity between this regression (and its results in Table 3) and Section 3.3 in Dang et al. (2023). The two differ as the current regression includes country-time fixed effects rather than linear time trends for targeted and non-targeted products.

these, the ASEAN countries, Taiwan, India, and Mexico have emerged as the most positively affected. This outcome aligns with these countries' geographical proximity and developmental parallels to China, positioning them well for stepping in the gap left by China. Moreover, the specific industries in which these countries and regions have increased their market share in the U.S. vary, reflecting the diverse comparative advantages of each country/region. This differentiation underscores the complexity of global trade networks and the multifaceted nature of trade diversion.

Assuming that changes in trade follow changes in production from the originating country, and given the various levels of CO_2 emission intensity in production processes across different nations and products, how do these shifts in global trade impact global CO_2 emissions? We attempt to answer this question in the rest of this paper. This restructuring has the potential to either exacerbate or alleviate global CO_2 emission levels. Understanding these dynamics is crucial for assessing the environmental implications of international trade disputes and for informing future policy decisions aimed at minimizing environmental harm while addressing trade imbalances.

Table 2: The Industry List

Industry	**Explanation**
1	Processed Food
2	Mineral Products
3	Products of the Chemical or Allied Industries
4	Raw Hides and Skins, Leather, Furskins and Articles Thereof; Saddlery and Harness; Travel Goods, Handbags and Similar Containers; Articles of Animal Gut (Other Than Silkworm Gut)
5	Plastics and Articles Thereof Rubber and Articles Thereof
6	Wood and Articles of Wood;
7	Textile
8	Apparel and Textile Articles
9	Footwear, Headgear, Umbrellas, Sun Umbrellas, Walking Sticks, Seatsticks, Whips, Riding-Crops and Parts Thereof; Prepared Feathers and Articles Made Therewith; Artificial Flowers; Articles of Human Hair
10	Articles of Stone, Plaster, Cement, Asbestos, Mica or Similar Materials; Ceramic Products; Glass and Glassware; Natural or Cultured Pearls, Precious or Semiprecious Stones, Precious Metals, Metals Clad With Precious Metal, and Articles Thereof; Imitation Jewelry; Coin
11	Base Metals and Articles of Base Metal
12	Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof
13	Electrical machinery and equipment and parts thereof
14	Vehicles, Aircraft, Vessels and Associated Transport Equipment
15	Optical, Photographic, Cinematographic, Measuring, Checking, Precision, Medical or Surgical Instruments and Apparatus; Clocks and Watches; Musical Instruments; Parts and Accessories Thereof
16	Furniture
17	Toys, games and sports requisites; parts and accessories thereof; Miscellaneous manufactured articles
18	Works of Art, Collectors' Pieces and Antiques

Table 3: Trade Diversion by Country and Industry

Industry	(1) China	(2) ASEAN	(3) Europe	(4) Mexico	(5) Canada	(6) Japan	(7) Korea	(8) India	(9) Taiwan	(10) Brazil	(11) Switzerland	(12) Others
1	-0.361	-0.066	0.023	0.096	0.102	0.171	0.123	0.007	0.196	0.144	0.008	0.003
	(0.042)***	(0.032)*	(0.020)	(0.052)	(0.042)*	(0.042)***	(0.040)**	(0.052)	(0.048)***	(0.060)*	(0.057)	(0.017)
2	-0.322	-0.224	-0.028	0.239	0.209	0.193	0.252	0.105	-0.011	0.324	-0.028	0.107
	(0.094)***	(0.122)	(0.042)	(0.104)*	(0.065)**	(0.090)*	(0.095)**	(0.127)	(0.204)	(0.159)*	(0.153)	(0.046)*
3	-0.259	-0.029	-0.024	0.077	0.028	0.082	0.153	0.102	0.114	0.023	-0.021	0.014
	(0.027)***	(0.038)	(0.014)	(0.040)	(0.031)	(0.029)**	(0.042)***	(0.032)**	(0.044)*	(0.053)	(0.048)	(0.020)
4	-0.318	0.112	-0.013	0.061	0.076	0.039	0.142	0.264	0.094	0.028	0.072	0.045
	(0.050)***	(0.040)**	(0.018)	(0.065)	(0.042)	(0.039)	(0.052)**	(0.057)***	(0.050)	(0.076)	(0.066)	(0.026)
5	-0.365	0.385	-0.021	-0.025	0.024	0.095	-0.024	0.047	0.074	-0.144	-0.209	-0.058
	(0.050)***	(0.073)***	(0.028)	(0.086)	(0.060)	(0.063)	(0.100)	(0.069)	(0.122)	(0.124)	(0.120)	(0.029)
6	-0.253	0.128	0.030	0.094	0.022	-0.019	0.047	0.196	0.257	0.077	-0.032	0.016
	(0.035)***	(0.041)**	(0.021)	(0.065)	(0.042)	(0.051)	(0.084)	(0.053)***	(0.059)***	(0.078)	(0.068)	(0.025)
7	-0.423	-0.053	0.006	-0.003	0.051	-0.067	-0.038	-0.029	-0.032	-0.048	-0.103	-0.050
	(0.030)***	(0.040)	(0.016)	(0.060)	(0.048)	(0.037)	(0.055)	(0.036)	(0.042)	(0.079)	(0.050)*	(0.024)*
8	-0.019	-0.138	0.034	-0.160	-0.039	0.118	0.077	-0.041	-0.108	0.163	-0.188	-0.063
	(0.032)	(0.035)***	(0.017)*	(0.053)**	(0.042)	(0.041)**	(0.057)	(0.039)	(0.068)	(0.072)*	(0.071)**	(0.017)***
9	-0.182	0.087	0.117	0.017	0.092	0.235	0.144	-0.047	-0.340	-0.088	0.068	-0.088
	(0.054)***	(0.060)	(0.036)**	(0.107)	(0.102)	(0.090)**	(0.129)	(0.085)	(0.106)**	(0.118)	(0.145)	(0.034)**
10	-0.254	0.011	-0.036	0.094	0.038	0.065	-0.006	0.133	0.164	-0.119	0.024	-0.039
	(0.044)***	(0.051)	(0.022)	(0.060)	(0.062)	(0.054)	(0.078)	(0.053)*	(0.071)*	(0.092)	(0.071)	(0.026)
11	-0.204	0.064	0.003	0.119	0.084	0.026	0.116	0.085	0.108	-0.097	-0.008	-0.024
	(0.026)***	(0.030)*	(0.013)	(0.036)***	(0.031)**	(0.031)	(0.039)**	(0.037)*	(0.034)**	(0.055)	(0.038)	(0.020)
12	-0.306	-0.028	0.027	0.113	0.146	0.006	0.038	0.139	0.169	0.141	0.072	-0.063
	(0.031)***	(0.029)	(0.012)*	(0.038)**	(0.029)***	(0.029)	(0.038)	(0.036)***	(0.029)***	(0.053)**	(0.036)*	(0.017)***
13	-0.427	0.000	0.015	0.041	0.069	-0.024	0.081	0.045	0.137	0.077	0.044	-0.005
	(0.035)***	(0.031)	(0.014)	(0.048)	(0.034)*	(0.035)	(0.047)	(0.050)	(0.040)***	(0.057)	(0.048)	(0.020)
14	-0.126	0.041	0.018	0.201	0.099	-0.056	-0.090	0.276	0.137	0.058	0.046	-0.044
	(0.062)*	(0.059)	(0.026)	(0.065)**	(0.054)	(0.045)	(0.077)	(0.070)***	(0.054)*	(0.103)	(0.124)	(0.036)
15	-0.290	-0.017	0.034	0.214	0.146	0.046	0.018	0.047	0.247	-0.082	0.089	0.030
	(0.040)***	(0.042)	(0.019)	(0.077)**	(0.042)***	(0.035)	(0.056)	(0.075)	(0.051)***	(0.063)	(0.049)	(0.029)
16	-0.325	0.153	0.037	0.029	0.177	0.061	-0.179	0.065	-0.111	0.440	0.063	-0.028
	(0.060)***	(0.085)	(0.027)	(0.080)	(0.059)**	(0.086)	(0.100)	(0.056)	(0.100)	(0.102)***	(0.094)	(0.034)
17	-0.084	-0.107	0.009	-0.248	-0.026	0.078	0.010	0.055	0.112	0.000	0.075	-0.045
	(0.056)	(0.077)	(0.036)	(0.101)*	(0.098)	(0.092)	(0.101)	(0.112)	(0.071)	(0.165)	(0.105)	(0.048)
18	-1.005	-0.286	0.026	0.234	0.372	0.039	0.645	0.069	-1.296	-0.142	-0.242	0.057
	(0.409)*	(0.273)	(0.086)	(0.227)	(0.253)	(0.137)	(0.329)*	(0.228)	(0.326)***	(0.257)	(0.307)	(0.072)

4.2 The "Environmental Bias" of Trade: Patterns

In this section, we utilize data from Exiobase on the level of CO_2 emission intensity of production across countries and products. We have two new empirical facts presented below.

Fact 3: The U.S. increases its imports in "dirtier" industries as a substitute for Chinese imports more so than in industries associated with "cleaner" goods. Moreover, the replacement of Chinese imports in these dirtier industries tends to come from countries with lower per capita incomes.

To explore the impact of the U.S. trade policy on trade diversion across various industries, particularly in relation to their environmental impact, we use the following regression specification.

$$\begin{aligned}\ln y_{ckjt} &= \beta_1^C Tariff_{kt} \times \mathbb{1}\{c = China\} + \beta_2^C Tariff_{kt} \times \mathbb{1}\{c = China\} \times CO2Int_k \\ &+\beta_1^R Tariff_{kt} \times \mathbb{1}\{c = ROW\} + \beta_2^R Tariff_{kt} \times \mathbb{1}\{c = ROW\} \times CO2Int_k \\ &+\mu_{ck}^1 + \mu_{ct}^2 + \mu_{jt}^3 + \varepsilon_{ckjt}\end{aligned}$$

where, y_{ckjt} represents U.S. imports (by value or quantity) of product k at the HS 8-digit code level from country c at time t (on a monthly basis), with j denoting the HS 2-digit code of product k. $Tariff_{kt}$ is the tariff rate imposed by the U.S. on Chinese imports during the trade dispute at time t for product k. The coefficients β_1^C and β_1^R then identify the change in U.S. imports in response to the U.S. tariffs on Chinese imports, from China and the ROW respectively. The interaction terms between tariff incidence and the average CO_2 emission intensity of product, $Tariff_{kt} \times \mathbb{1}\{c = China\} \times CO2Int_k$ and $Tariff_{kt} \times \mathbb{1}\{c = ROW\} \times CO2Int_k$, introduce the dimension of environmental impact. $CO2Int_k$ assesses the average environmental footprint of product k. Thus, β_2^C and β_2^R capture the heterogeneous effects of trade diversion for products with varying levels of environmental impact. For example, if β_1^R is positive (so that a tariff on China increases US imports from the ROW) and β_2^R is also positive, it means the increase in imports is greater when the production of the good induces more emissions i.e. it is dirtier.

The regression controls include product-country fixed effects μ_{ck}^1 to account for time-invariant demand characteristics specific to each product-country pairing, country-time fixed effects, μ_{ct}^2 to adjust for macro-level shocks affecting a country's exports, and HS 2-digit code-time fixed effects μ_{jt}^3 to control for time-variant industry-level demand shifts.

The findings with log import value and quantity as the dependent variable are presented in Columns (1) and (4) of Table 4. The coefficient of $Tariff_{kt} \times \mathbb{1}\{c = China\}$ is negative,

indicating a decline in U.S. imports from China following the tariff imposition. Conversely, the coefficient of $Tariff_{kt} \times \mathbb{1}\{c = ROW\}$ is positive, suggesting an increase in U.S. imports from the ROW as a replacement for Chinese goods. In addition, the positive coefficient of $Tariff_{kt} \times \mathbb{1}\{c = ROW\} \times CO2Int_k$ implies that the U.S. has shifted its imports to "dirtier" products from the ROW, thereby indicating larger trade diversion for environmentally less efficient goods during the U.S.-China trade dispute.

We then further explore the sources of dirtier goods imported by the U.S. as alternatives to Chinese products by categorizing countries into high- and low- income groups based on the median of per capita GDP in 2015. Countries with a per capita GDP above the median are categorized as high-income, while those with per capita GDP below it are considered low-income. The analysis, as detailed in Columns (2) and (3) using log U.S. import value as dependent variable, applies the same regression framework as that represented in Column (1) but segments the data into that for the two income groups separately. The findings show that the coefficients of $Tariff_{kt} \times \mathbb{1}\{c = ROW\}$ are positive for both income groups, indicating an overall increase in U.S. imports from the ROW amidst the trade dispute. Notably, the magnitude of this coefficient is 3 to 4 times larger for low-income countries, suggesting a greater shift towards sourcing from these nations.

Furthermore, the coefficient on the interaction term $Tariff_{kt} \times \mathbb{1}\{c = ROW\} \times CO2Int_k$, which indicates the relationship between the trade diversion patterns and the dirtiness of goods, is positive for both high and low-income countries. However, this coefficient is significantly larger for low-income countries, indicating a substantial increase in the U.S. import activity of dirtier goods from these countries. While the volume of U.S. imports from high-income countries has also elevated, the increase does not disproportionately favor dirtier goods as β_2^R in this case is not significant. All these results are robust when we use U.S. import quantity as our dependent variable as shown in Columns (5) and (6) of Table 4.

These results indicate that during the U.S.-China trade dispute, the U.S. has leaned towards importing from low-income countries, particularly in terms of dirtier products. This trend not only reflects the trade diversion effects but also highlights the environmental implications of shifting trade patterns. This result is consistent with the pollution haven hypothesis in the literature, see for example Levinson (2023), Kellenberg (2009), and Gill et al. (2018), which study suggests that low-income countries, potentially due to less stringent environmental regulations or lower production costs in pollution-intensive industries, have become significant suppliers of dirtier goods to the U.S. market, posing challenges to the global environmental sustainability efforts.

Table 4: Trade Diversion and the Dirtiness of Production Technology

	(1)	(2)	(3)	(4)	(5)	(6)
	log(Import Value)			log(Import Quantity)		
	All	Low Income	High Income	All	Low Income	High Income
$Tariff_{kt} \times \mathbb{1}\{c = China\}$	-1.839			-4.380		
	(0.794)*			(1.176)***		
$Tariff_{kt} \times \mathbb{1}\{c = China\} \times CO2Int_k$	-0.017			-0.328		
	(0.108)			(0.161)*		
$Tariff_{kt} \times \mathbb{1}\{c = ROW\}$	1.479	5.370	0.807*	2.153	7.285	0.602
	(0.398)***	(1.244)***	(0.436)	(0.625)***	(1.809)***	(0.695)
$Tariff_{kt} \times \mathbb{1}\{c = ROW\} \times CO2Int_k$	0.181	0.723	0.087	0.283	0.994	0.072
	(0.054)***	(0.169)***	(0.059)	(0.085)***	(0.246)***	(0.094)
HS8-Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HS2-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5044840	759516	3959958	4175403	648260	3244336
R-sq	0.839	0.816	0.832	0.864	0.855	0.856

Fact 4: The U.S. substitutes Chinese imports of a product with imports from countries with either the highest or lowest CO_2 emission intensity in the production of that product.

Given the diversity in production technologies among countries in terms of their emissions intensities documented in Figure **??**, it is important to see if the U.S. is replacing Chinese imports with goods from countries using either less or more environmentally harmful technologies. To study the environmental implications of trade shifts, we categorize countries into four quartiles based on their CO_2 emissions per dollar of output for each HS 8-digit product. The first quartile represents countries that have the cleanest production technology for product k, while the countries with the dirtiest production technology are in the fourth quartile. We introduce dummy variables Qth Quartile of $\text{CO2Int}_{ck} = 1$ to indicate whether a country c's production technology for producing product k falls within a specific Qth quartile regarding CO_2 emission intensity. Our analysis employs the following regression model:

$$\begin{aligned}\ln y_{ckt} \quad = \quad & \sum_{Q=2,3,4} \beta_Q Tariff_{kt} \times \mathbb{1}\{c = ROW\} \times \mathbb{1}\{Q\text{th Quartile of CO2Int}_{ck}\} \\ & + \mu^1_{ck} + \mu^2_{ct} + \mu^3_{kt} + \varepsilon_{ckt}\end{aligned}$$

where, y_{ckt} represents U.S. imports (value or quantity) of product k at the HS 8-digit code level from country c at time t (on a monthly basis).[13] We interact the U.S. tariff rate of product k on Chinese imports at time t ($Tariff_{kt} \times \mathbb{1}\{c = ROW\}$), with the CO_2 intensity quartile dummy of country c's production technology of product k ($\mathbb{1}\{Q\text{th Quartile of CO2Int}_{ck}\}$), with the first quartile being the base group. The interaction term's coefficient, β_Q, captures the differential impact of U.S. tariffs on imports from countries across different CO_2 emission intensity levels.

The regression controls include product-country fixed effects μ^1_{ck} to account for time-invariant demand characteristics specific to each product-country pairing, country-time fixed effects, μ^2_{ct} to adjust for macro-level shocks affecting a country's exports, and the HS 8-digit-time fixed effects μ^3_{kt} to account for the average increase in U.S. imports from non-targeted countries during the trade dispute with China by product. The HS 8-digit-time fixed effects μ^3_{kt} are co-linear with $Tariff_{kt} \times \mathbb{1}\{c = ROW\}$ (which is why this term is omitted) and capture the average increase of the U.S. imports from bystander countries during the U.S.-China trade dispute. As the omitted quartile is the first one, all the β_Q coefficients are relative to it.

[13] Here, we only use the data of US imports from the ROW.

Columns (1) and (3) in Table 5 present the estimation results with the U.S. import value and quantity as the dependent variables, respectively. As shown in column (1), the coefficients of the interaction terms with the second and third quartiles are significantly negative, while the coefficient of the interaction terms with the fourth quartile is less negative and not significant. This implies that U.S. imports of a HS 8-digit product from countries with either the least or most CO_2 emission efficient technology increase more than those from countries with the mid-range CO_2 emission efficient technology. As shown in column (3), the result is robust when we use import quantity as the dependent variable.

As a robustness check, we further control for $ROW \times Tariff_{kt} \times \log(GDPpercapita)$ and $ROW \times Tariff_{kt} \times CO2Int_{kt} \times \log(GDPpercapita)$, which capture the heterogeneous trade diversion effects studied in Fact 3, the results as shown in Column (2) and (4) in Table 5 are similar.

Table 5: Trade Diversion and the Dirtiness of Production Technology

	(1)	(2)	(3)	(4)
	log(Import Value)		log(Import Quantity)	
$ROW \times Tariff_{kt} \times$ 2nd Quartile of CO2Int	-0.078	-0.086	-0.094	-0.105
	(0.039)*	(0.039)*	(0.065)	(0.065)
$ROW \times Tariff_{kt} \times$ 3rd Quartile of CO2Int	-0.096	-0.114	-0.181	-0.209
	(0.044)*	(0.044)**	(0.069)**	(0.070)**
$ROW \times Tariff_{kt} \times$ 4rd Quartile of CO2Int	-0.045	-0.066	-0.053	-0.085
	(0.043)	(0.043)	(0.069)	(0.069)
$ROW \times Tariff_{kt} \times$ log(GDP per capita)		-0.544		-1.029
		(0.315)		(0.474)*
$ROW \times Tariff_{kt} \times CO2Int_k \times log(GDPpercapita)$		-0.059		-0.118
		(0.043)		(0.065)
HS8-Country FE	Yes	Yes	Yes	Yes
Country-Time FE	Yes	Yes	Yes	Yes
HS8-Time FE	Yes	Yes	Yes	Yes
N	4678520	4675331	3853140	3850381
R-sq	0.846	0.846	0.872	0.872

To summarize, Facts 1-4 demonstrate that CO_2 emission rates not only differ by industry but also by country, reflecting the varied production technologies used within the same sectors. U.S. tariffs on Chinese goods (especially in the first wave) tend to target products for which China's production is comparatively cleaner than that of the ROW, suggesting that the U.S. might substitute Chinese imports with products from countries that have lower CO_2 emission efficiencies. Our analysis further reveals diverse trade diversion effects, both across different products and within the same product across countries. Notably, the U.S. tends to increase its imports from industries with higher emissions when replacing Chinese goods, suggesting a preference for dirtier industries in the trade diversion process. Additionally, imports of these dirtier goods from China are more likely to be substituted with goods from lower-income countries. This is bad for the environment as production in these nations may lean towards being more emission-intensive, given their export composition to the U.S.

Moreover, our research shows that for the same products, the U.S. opts for imports from countries at either the spectrum's end in terms of CO_2 emission intensity. This substitution pattern indicates a complex, non-linear effect on global emissions, as the overall impact of this trade diversion on global CO_2 emissions remains ambiguous. Given these intricate dynamics of trade diversion, we explore the consequences of the U.S.-China trade dispute on global CO_2 emissions in Section 5, providing further insights into the broader environmental implications of these economic policies.

5 CO_2 Emission during the US-China Trade Dispute

In this analysis, we investigate the impact of trade diversions during the US-China trade conflict on global CO_2 emissions and emission intensity. We calculate the level of CO_2 emissions embedded in the values of U.S. imports from each country. We do so by using data from Shapiro 2016. We multiply the CO_2 emission intensity by the dollar value of U.S. imports for each specific product-country pair.

5.1 CO_2 Emission by Product

We first explore the effects of trade diversion on the cleanliness of U.S. imports. To quantify the change in CO_2 emissions from imports due to the U.S.-China trade dispute, we multiply the CO_2 emission intensity with the value of U.S. imports at HS 8-digit level. This gives us CO_2 emissions of imports for each product category every month. We then analyze the difference before and after the implementation of tariffs, as well as between targeted and non-targeted products, with targeted products being those subject to U.S. tariffs on China.

Employing a difference-in-differences approach, we aim to understand how the U.S.-China trade dispute has influenced the environmental footprint of U.S. imports at the product level through the following regression specification:

$$y_{kt} = \beta Tariff_{kt} + \mu_t^1 + \mu_k^2 + \varepsilon_{kt} \tag{3}$$

where, y_{kt} represents our dependent variables of interest i.e. log of U.S. import value, log of total CO_2 emissions embedded in imports, and log CO_2 emission intensity of product k at time t. We evaluate y_{kt} for imports exclusively from China, exclusively from the ROW excluding China, and from all countries globally respectively to analyze the impact of U.S. tariffs on changes in CO_2 emissions and emission intensity from different groups.

$Tariff_{kt}$ denotes the U.S. tariffs on Chinese imports for product k at time t, with an increase post-July 2018 for targeted products and remaining constant for non-targeted products. Time and product fixed effects (μ_t^1 and μ_k^2) are included to control for aggregate demand shocks in the U.S. and product-specific characteristics respectively.

The regression results, presented in Table 6, show a decrease in U.S. imports from China and overall as the tariffs rose but an increase in imports from the ROW, in line with the results in Figure 3a. Column (4) shows that the level of CO_2 emission in U.S. imports from China decreased (as expected given the decrease in the imports from China in column 1) while column (5) shows that the level of CO_2 emission of the U.S. imports from the ROW increased (in line with the increase in imports from the ROW in Column 2). Overall, as shown in Column (6), the total level of CO_2 emissions of U.S. imports decreased (in line with the decreases in U.S. import value in Column 3). However, we should view these results with some caution. We do not account for changes in emissions coming from changes in U.S. production. We are only looking at those coming from changes in U.S. trade.

With this caution in mind, it makes sense to look at the CO_2 emission intensity (tons of CO_2 emission per dollar value) of U.S. imports. Columns (7) - (9) report the value of β in Equation 3 when the CO_2 emission intensity of U.S. imports is on the left hand side. β can be interpreted as the average effect of U.S. tariffs on the CO_2 emission intensity of the production of targeted products during the U.S.-China trade dispute. Note that the time and product fixed effects pick up the average CO_2 emission intensity at any time and for any product. Columns (7) and (8) show that the CO_2 emission intensity of U.S. imports from China and the ROW does not change before and after the tariff changes in 2018, which is not surprising as the CO_2 emission intensity in Exiobase is not time variant. However, as shown in Column (9), the CO_2 emission per dollar of U.S. aggregate imports has increased.

This comes from the trade diversion from China to the ROW. In other words, U.S. imports overall have become more emissions-intensive. This result is also consistent with Fact 2 in Section 4.1, that is, U.S. tariffs on Chinese imports generally target the products where the Chinese production technology is cleaner than that of the ROW. The estimates in Column (9) indicate that CO_2 emission per dollar of U.S. imports increases by 0.4%[14] on average for products subject to a 25% tariff during the U.S.-China trade dispute.

[14]The increase of CO_2 emission per dollar of US imports $= (exp(0.019 * 0.25) - 1) * 100\%$, where 0.25 is the tariff increase for most products during the US-China trade dispute.

Table 6: CO2 Emission of the US Imports by Products

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	log(Import Value)			log(CO2 Emission)			log(CO2 Emisssion Intensity)		
	China	ROW	All	China	ROW	All	China	ROW	All
$Tariff_{kt}$	-1.704	0.115	-0.308	-1.636	0.045	-0.302	0.000	0.002	0.019
	(0.033)***	(0.025)***	(0.024)***	(0.035)***	(0.026)	(0.025)***	(0.000)	(0.003)	(0.003)***
HS8 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	382399	491990	505202	325304	407813	416920	325304	407813	416920
R-sq	0.877	0.918	0.924	0.880	0.924	0.928	1.000	0.977	0.979

5.2 CO_2 Emission by Country

The trade diversion resulting from the U.S.-China trade dispute has led to shifts in the composition of products exported by bystander countries. As highlighted in Fact 3 in Section 4 on the environmental impact of trade diversion, the U.S. has significantly increased its imports of products with higher CO_2 emissions from lower-income countries.

To investigate how trade diversion during the U.S.-China trade dispute has altered the environmental contents of various countries' exports to the U.S., we restrict our analysis to imports from the ROW only. We categorize all HS 8-digit products into two groups indicated by $Target_k$: targeted ($Target_k = 1$) and non-targeted ($Target_k = 0$) products, based on whether they were subjected to U.S. tariffs against China as defined in Section 2. Targeted products are those directly impacted by tariffs, while non-targeted products serve as a comparative baseline. This distinction allows for a comparison of how tariffs have influenced CO_2 emissions of targeted and non-targeted goods associated with U.S. imports from different countries, particularly focusing on whether these imports have become "dirtier" in terms of CO_2 emissions.

To analyze shifts since the tariff imposition in July 2018, we introduce a binary indicator $\mathbb{1}\{t >= 2018.7\}$ to distinguish between the periods before and after tariffs. Figure 2b shows that within products targeted in 2019, there is no correlation between the the level of CO_2 emission intensity in China relative to the ROW and the tariffs, while such a correlation exists within products targeted in 2018. For this reason, we focus our attention only on products targeted in 2018. Our methodology employs a difference-in-differences approach, comparing emission intensity before and after the tariff changes in 2018, and between targeted and non-targeted products.

The regression model used for this analysis is as follows:

$$y_{knt} = \beta_1 Target_k \times \mathbb{1}\{t >= 2018.7\} + \mu^1_{nk} + \mu^2_{nt} + \varepsilon_{kt}$$

where, $Target_k$ indicates targeted or non-targeted products. y_{knt} is the variable of interest, i.e., log of CO_2 emissions in imports and log CO_2 emission intensity of product k from country n at time t. The interaction term $Target_k \times \mathbb{1}\{t >= 2018.7\}$ captures the average effect of the U.S.-China trade dispute of 2018 on the variable in question. The inclusion of country-product fixed effects (μ^1_{nk}) and country-time fixed effects (μ^2_{nt}) allows us to control for specific attributes of each country-product combination and macroeconomic or aggregate shocks affecting a country's exports.

We further interact $Target_k \times \mathbb{1}\{t >= 2018.7\}$ with log of GDP per capita, $\log(pcGPDP)$, to explore the heterogeneous impact of the tariff surges on countries with different level of

income.

Table 7 reports the regression results. Column (1) shows that the level of CO_2 emissions of exports to the U.S. from bystander countries on average have decreased. However, it is worth noting that the effect varies substantially across countries by their level of income and that the level of CO_2 emissions from the imports of poor countries have been rising. In Column (2), the coefficient of $Target_k \times \mathbb{1}\{t >= 2018.7\}$ is positive, indicating larger CO_2 emission of exports to the U.S., while the coefficient of the interaction term $Target_k \times \mathbb{1}\{t >= 2018.7\} \times \log(pcGDP))$ is significantly negative indicating that the increase in CO_2 emission happens for exporting countries with lower income levels. The estimates in Column (2) indicate that the country with the lowest income country increases CO_2 emission in its exports to the US by 6.48%, while the country with the highest income country decreases CO_2 emission in its exports to the US by 64% as a result of the change in the composition of its exports.

Columns (3) and (4) in Table 7 further explore the CO_2 emission intensity of exports to the U.S. from bystander countries. Although the average CO_2 emission intensity decreases slightly (but not significantly) as shown in Column (3), there is a lot of heterogeneity across countries. In Column (4), we add the interaction term $Target_k \times \mathbb{1}\{t >= 2018.7\}$, and find that its coefficient is significantly positive. This indicates an increase in the level of CO_2 emission intensity, while the coefficient of the interaction term $Target_k \times \mathbb{1}\{t >= 2018.7\} \times \log(pcGDP))$ is significantly negative, indicating that it is less so for countries with lower per capita income. The estimates in Column (4) show that the country with the least income increases its CO_2 intensity of its exports to the US by 31%, while the country with the highest income decreases it by 34%. This of course occurs due to the changes in the composition of exports.

These findings underscore the significant redistributive effect of the U.S.-China trade dispute on CO_2 emissions in U.S. imports. The U.S. shifts towards importing more emission-intensive goods from lower-income countries, most likely making them face greater environmental degradation. Thus, even though their exports rise, they likely pay a cost in terms of the environment. Our results highlight the environmental costs associated with additional exports/production in these countries.

Table 7: CO2 Emission of the US Imports by Country (the ROW)

	(1)	(2)	(3)	(4)
	log(CO_2 Emission)		log(CO_2 Emission Intensity)	
$Target_k \times \mathbb{1}\{t >= 2018.7\}$	-0.269	1.047	-0.059	1.270
	(0.055)***	(0.614)*	(0.043)	(0.439)***
$Target_k \times \mathbb{1}\{t >= 2018.7\} \times \log(pcGDP)$		-0.133		-0.135
		(0.062)**		(0.045)***
Country-Target$_k$ FE	YES	YES	YES	YES
Country-Time FE	YES	YES	YES	YES
N	10284	10236	10284	10236
R-sq	0.985	0.985	0.876	0.877

6 Conclusion

In this paper, we unpack and analyze the environmental impact of the trade diversion that happens as a result of the U.S.-China trade dispute from comprehensive angles. We first show descriptive evidence of the existence of the "environmental bias" of U.S. trade policy, which is embodied in the fact that U.S. tariffs disproportionately target products for which China has relatively cleaner production technologies than the ROW. Then, we empirically show evidence of the overall trade diversion, i.e. U.S. switching to import more from bystander countries in place of China as a consequence of the tariff surges on Chinese products. We then examine the heterogeneity of the trade diversion effects in terms of CO_2 emissions across products and across source countries. While we find that the U.S. has increased its imports more in dirtier industries and more from countries with lower per capita income, the substitution patterns are less conclusive in terms of pollution emissions: our analyses suggest that the U.S. replaces the same products of Chinese imports with those from countries of either highest or lowest CO_2 emission intensity.

For this reason we try to quantify the impact of the trade dispute on global CO_2 emissions coming from US imports. Our results indicate that U.S. imports have become overall dirtier in terms of CO_2 emissions - this is consistent with the intuition that lower income countries have been able to step into the gap left by China as they have comparative advantage in the production of dirty goods and thus could take advantage of the "environmental bias" of U.S. trade policy. As these countries reap gains from the U.S.-China trade dispute in terms of their exports, there would be a cost associated with this if their production of these goods also rises with their exports as these exports are dirty.

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