ERASMUS UNIVERSITY ROTTERDAM

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MASTER THESIS INTERNATIONAL ECONOMICS

BIAS OF ANTI-DUMPING TOWARDS EMISSION-INTENSIVE IMPORTS:

THE CASE OF THE U.S.

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ABSTRACT

This paper examines the association of anti-dumping, the most prominent non-tariff globally, to the imports of greenhouse gas emission-intensive industries in times of increasing significance of climate change mitigation strategies. Anti-dumping duties have risen simultaneously with the decrease in tariffs over the past decades and have targeted developing countries that also serve as pollution havens. The developed countries could use anti-dumping to protect domestic interests and level the costs of maintaining strict environmental standards with the developing countries or incentivise emission intensive imports. This paper uses fixed effects regression analysis from 2013 through 2017 in the case of the U.S. and found a significant negative relationship between anti-dumping and emissions until 2016, indicating it is an implicit carbon subsidy on imports of emission-intensive industries.

Keywords: Anti-dumping, U.S., emission-intensive industries, environmental standards

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1. Introduction

The increasing importance of climate change at present signifies the study of the changing atmosphere around international trade and its linkages to the environment through industry emissions. Traditionally, trade policy measures moving towards liberalisation are known to act against the welfare of the environment (Shapiro, 2021; Kono, 2017), with cleaner (less pollution-intensive) industries facing relatively higher tariffs than dirty (high pollution-intensive) industries, where the pollution intensity of an industry is determined by its greenhouse gas emissions.

However, the conventional trade policy measure, i.e., the tariffs, has been decreased as per the regulations and advice over several rounds of talks and agreements by the World Trade Organisation (WTO), then the General Agreement on Tariffs and Trade during the past century. In place of the tariffs, there has been a rise of non-tariff barriers (NTBs) during the past two decades, prominent among them being Anti-Dumping (Zanardi,2004). Anti-dumping is followed by countervailing duties and safeguards measures, among the most used non-tariff barriers.

The use of non-tariff barriers extensively simultaneously with the fall in tariffs indicates that non-tariff barriers as substitutes for tariffs for trade protectionism rather than for legitimate purposes continued the adverse relationship between trade policy measures and environmental welfare (Zanardi, 2004; Shapiro, 2021). Anti-dumping, the most important non-tariff barrier in the case of the United States alone, increased by 55% from 2009 to 2019 in one decade, while the increase in total non-tariff barriers accounted for 77% during the same period (World Bank, 2021).

Anti-dumping is imposed mainly by developed countries like the United States(U.S.) and the European Union on developing nations like China in the guise of protectionism, which is unlike in the case of tariffs, which are imposed without targeting a specific group of countries. On the other hand, developed countries import pollution-intensive industry products from developing countries (Cai et al., 2018). This is mainly due to differences in domestic environmental regulations across broad categories of nations, stringent environmental standards in developed and lax environmental regulations in developing countries (Aichele & Felbermayr, 2012).

The main question addressed in this study is whether developed countries impose Anti-Dumping duties as an alternative to carbon tariffs to level the environmental standards of pollution-intensive exports by developing countries. For this purpose, we form the following research question:

What is the qualitative and quantitative association between Emissions and Anti-dumping?

For this analysis, we use fixed effect regression analysis to observe the effect of emissions on Anti-Dumping. We study the case of the U.S. in this context for two reasons: 1. It is a developed nation that uses Anti-Dumping proactively against developing countries and is the largest importer in the world (World Bank, 2021), and 2. The data on emissions and pollution-intensive industries is widely available at a disaggregated level of industries in the case of the U.S.

The industry classification used in this study is the North American Classification of Industry System (NAICS), and data is available on emissions and tariffs of industries in concentrated manufacturing industries. These manufacturing industries are the major pollution-intensive industries, and this study aims to explore the pollution-intensive industries associated with anti-dumping. The manufacturing industries are the most significant contributor to greenhouse gas emissions by economic sectors in the U.S. (U.S. Environment Protection Agency 2022).

The study would be more exciting if it included the period of the trade war between the U.S. and China as it provides us with real-life aggressive increases of tariffs and non-tariff barriers during the past few years by the U.S. to experiment with the research question (Fajgelbaum & Khandelwal, 2022). However, the data on the specific variables is available sparsely, which constrains our analysis for 2013-2017, whereas the trade war started in 2018.

This paper primarily builds on the "Environmental bias of trade policy" theory by Shapiro (2021). This paper uses a cross-sectional Instrumental Variable Regression to study the association of emissions and tariffs with non-tariff barriers, and a negative relationship was found. This negative relationship is termed as carbon subsidy for pollution-intensive goods; if the relationship were positive, the paper would have termed the relationship as carbon tariff on pollution-intensive goods, these terms carbon subsidy and carbon tariff are also used in this paper in the same context. However, this paper does not consider the anti-dumping duties, the most prominent non-tariff measure we have considered in our analysis. This study finds a negative and significant association of emissions to tariffs and Anti-dumping for the year 2017, indicating implicit carbon tax on imports of greenhouse gas emission-intensive industries by the U.S.

The following parts of this paper are structured: Section 2 provides an overview of the existing literature on which this paper builds further. Section 3 explains the data used in this research study, mainly using publicly available U.S. trade data emissions from the World Trade Organisation (WTO), Temporary Trade Barriers Database (TTBD) and U.S. domestic statistics providers. Section 4 describes the methodology used in this study, which is based on a fixed effects regression analysis. In Section 5, the regression analysis results are presented and discussed. Finally, in Section 6, we conclude with the main findings of this paper, its potential limitations, and possible directions for future research, followed by references and an appendix.

2. Literature review

Tariffs are negatively related to emission-intensive goods, and trade liberalisation and environmental goals do not go hand in hand (Shapiro, 2021; Kono, 2017). In recent decades, trade liberalisation through the efforts of the WTO and tariff agreements has decreased tariffs substantially. However, non-tariff measures have increased to supplement the offsetting effects of reducing tariffs (Ray, 1981).

The various rounds of WTO/GATT(General Agreement on Trade and Tariff) provided the needed push for a decrease in tariff measures for the members and encouraged trade liberalisation. Anti-dumping rose as the most critical non-tariff measure. In the meantime, developed countries have imposed increased anti-dumping measures on developing countries (Zanardi, 2004).

Anti-dumping is used as an excuse for protectionist measures to protect domestic industries rather than their actual intended use (Zanardi, 2004). Among the non-tariff barriers that have risen substantially after strict guidelines from the WTO to decrease tariffs, Anti-Dumping measures are the most prominent ones, and they have increased greatly in number and volume since then (Zanardi, 2004).

There has been a rise in Anti-dumping duties during the recent two decades, mainly by the U.S., E.U. and Australia and a substantial rise in number and amount during the U.S. China trade war and these Anti-dumping duties affect the export trade of a country negatively by volume and increase in export prices (Schiavo et al., 2020; Felbermayr & Sandkamp, 2020).

A part of the literature on Anti-Dumping is about the circumvention of Anti-Dumping duties through third countries to the U.S. and E.U. The increase in Anti-Dumping duties by the U.S., which are used as excuses to protect domestic industries, affects the direct export volume from China but is just rerouted through third countries (Liu & Shi, 2018; Barbaglia et al., 2022). The rise in Anti-Dumping duties increases the productivity of Chinese exporters who survive the increase in duties. This resulting increase in productivity of the exporting country outweighs the benefits to the firms of the country imposing Anti-Dumping (Jabbour et al., 2018).

Developing countries like China and ASEAN (Association of South East Asian Nations) are mostly pollution havens for developed countries like the U.S. and E.U. developing countries to relocate dirty industries and also for exporting greenhouse emission-intensive goods (Cai et al., 2018; Salam & Chishti, 2022). Since developing countries are a target for anti-dumping measures imposed by developed countries and exporting emission-intensive goods to developed countries, this paper aims to analyse the gap if anti-dumping is used to make the imports of emission-intensive goods expensive in the case of a developed country like the U.S.

A relatively new branch of Anti-dumping literature examines its relation to emissions. Zheng et al. (2023) provide evidence that Anti-dumping duties are being used to enhance clean production processes/products in developing countries. They go beyond the relation of Anti-Dumping duties and emissions by examining how developed countries transfer the emission reduction burden to developing countries through Anti-Dumping measures.

In this paper, we focus on the U.S., the largest importer of goods (World Integrated Trade Solution, 2024) and its relation to Anti-dumping measures and emissions, this way we analyse if the Anti-Dumping measures, the most prominent of the non-tariff barriers in the recent period, are being used as carbon tariffs or carbon subsidies and thereby realise if the U.S., a developed country in practice is using anti-dumping for or against taxing imports of emission-intensive industries.

Extending the literature to emissions and environmental standard differences informs us of carbon leakage in developing countries. Commitment/adherence to stringent environmental regulations like those of the Kyoto Protocol by just a few countries with status quo environmental regulations in other nations does not help reduce global emissions, as it induces carbon leakage to other countries and increases imported emissions in the committed countries. Finally, the carbon footprint remains the same for the world (Aichele & Felbermayr, 2012).

To add to the literature on global governance on environmental, offshoring and rise in intermediate goods trade makes it challenging for global governmental institutions like WTO to monitor and administer trade policies/problems because of increased inter-country preferences for trade agreements (Antr'as & Staiger, 2012). In the case of offshoring of polluting industries to developing countries by developed countries, it will be harder for global institutions like the WTO to take action and achieve the desired results for the same reason as bilateral agreements trump global environmental regulations.

Pollution transfer through waste trade from developed to developing nations like China, primarily due to weak environmental regulations, contributes significantly to air pollution caused by waste burning (Shi & Zhang, 2023). Though this is just one form of carbon leakage to developing countries, it reiterates the importance of standardising environmental regulations and finding incentives for developing countries to use cleaner production processes.

The paper also builds on the literature of "tariff escalation," i.e., increased tariffs on downstream industries, which are located and organised near consumers and consumer markets, and decreased tariffs on upstream industries, which are often more polluting and offshored to other countries that produce intermediate goods for the downstream industries (Shapiro, 2021; Balassa 1965, Antràs, P., & Gutiérrez, A. 2021).

The Anti-Dumping and Global Value Chain literature provides insights to further look into the role of emissions in Anti-Dumping. The Anti-Dumping measures in the past decade have reduced China's Global Value Chain (GVC) participation in terms of the GVC index and increased China's position in the industry upstream index (Wang et al., 2019). The high upstreamness of an industry is associated with high emissions and a negative relationship between tariffs and emission-intensive goods (Shapiro, 2021). Hence, we must look at the role of anti-dumping in emissions, which has increased prominently in recent times.

Extending this branch of literature is the link between the governments lobbying in favour of domestic interest groups, especially the downstream industries, for lower tariffs on their import of intermediate goods (Grossman & Helpman, 1994; Shapiro, 2021).

Shapiro (2018) found that the decrease in emissions in manufacturing industries while growing the real value of manufacturing output simultaneously in the U.S. is mainly due to adherence to stringent environmental standards rather than a reallocation of industries to other countries like China or Mexico and increased productivity. Levinson (2009) does research for the same period to find out the underlying reasons for the reduction in emissions and growing actual output in manufacturing simultaneously and finds that technological advancements in the face of more stringent environmental laws are the main driving force rather than importing pollution-intensive goods or changing the composition of goods domestically produced.

Foreign-owned firms in developing countries produce lower emissions during trade expansion primarily due to advanced technology, while export firms usually pollute more (Wang, 2021). These findings tell us that poor/developing countries also have a way out of reducing their carbon footprint through technological progress, so the carbon tariffs or substitutes thereof in the form of trade policy would serve as an incentive to decrease manufacturing emissions. Here, we look at whether anti-dumping is a substitute for carbon tax.

A part of the literature on trade and environment focuses on trade policy and emissions linkages, which suggest that environmental aspects must be incorporated into trade policies. The polluting-intensive goods exporting countries would continue to choose to pollute if there were no tariffs, and those that are pollution-intensive goods importing countries would use environmental standards to their advantage as a form of protection (Copeland, 2000). This also leads to carbon leakage from highly regulated countries to countries with low environment regulating standards (Fowlie & Reguant, 2021).

These different environmental standards combined with trade policy without considering emissions will have severe environmental repercussions as, after all, the effects of pollution are global. While some argue that most CO2 emissions from trade are not just from production but amplified with the emissions from shipping, as fossil fuels highly fuel international transit, the gains from international trade in terms of welfare far outweigh them (Copeland & Taylor, 1994; Shapiro 2016). So, the central question is how to tax CO2 emissions or incorporate them in trade policy with substitutes for it as trade policy and environment are interlinked, which is what we investigate in this paper.

A significant part of the literature also focuses on measuring the optimal carbon tariff or the global carbon taxes. If WTO imposes no global carbon tax and if countries with strict regulations and domestic implicit carbon taxes like the U.S. were to impose carbon taxes on their counterparts, i.e., foreign producers from which they import, it would be to prevent leakage and level the playing field primarily and should be allowed by WTO in good faith (Hillman,2013).

The Social Cost of Carbon measured in Pindyck (2019) was \$80 to \$100/M.T., and Shapiro (2021) obtained the optimal carbon tax, which he calls a carbon subsidy, to be \$85 to \$120/M.T. of CO2 emissions, both of which are higher than the U.S. government estimates by IWG of \$40/M.T. of CO2.

The current study also obtained similar results on anti-dumping and emissions for 2013-2016. The rise in anti-dumping duties in recent years, focused on less pollution-intensive exporting industries, serves as carbon subsidies. Studies like Kono (2017) provide strong evidence that there is no issue of reverse causality of tariffs on emissions, which provides a basis for directly inspecting the question at hand with regression analysis.

Most literature examines the effect on a global level and internationally traded goods. Accordingly, it uses Input-Output tables to calculate the emissions embedded in traded goods (Aichele & Felbermayr, 2012; Shapiro, 2021; Zheng et al., 2023) and uses a panel study. Instrumental variables are also popular in the literature as they mostly use indirect emissions from internationally traded goods related to direct emissions and trade barriers. Some papers start with OLS (Ordinary Least Squares) regression analysis with applicable fixed effects and then move to Instrumental Variable (IV) regression because they feel IV is most suitable when using indirect emissions from trade, which is not the case here in this paper (Aichele & Felbermayr, 2012; Kono, 2017; Shapiro, 2021).

This paper essentially builds on the literature on trade policy and environment linkages (Copeland, 2000; Wang, 2021) and carbon leakages from developed countries and tariff and non-tariff barrier/Anti-dumping relation to emissions-intensive imports by developed countries (Kono, 2017; Shapiro, 2021; Zheng et al., 2023). This paper, for the first time, focuses the research on a single developed country, the U.S., and analyses its most important non-tariff measures, Anti-dumping and tariff measures, and links them to emission-intensive imports, thereby bridging the gap in the literature to know whether these measures are used as tools for making emission-intensive goods expensive. We should expect similar results for tariffs to those in the literature. However, in the case of anti-dumping, we are still determining that, on the one hand, they have been used as substitutes for traditional tariffs. On the other hand, they have been targeted in developing countries, which are mostly pollution havens.

3. Data

We consider two main types of variables in this paper: 1. Trade policy 2. Emissions. These are similar to those used in Shapiro (2021), with which we will compare our results. However, instead of a cross-section in this paper, we have the data for 2013-2017 for all variables per their 4 digit-NAICS (North American Industrial Classification System) codes in the case of the United States of America (U.S.). We select the U.S. for analysis because of the wide availability of the emissions data per disaggregated 4-digit NAICS level and its comparability with the reference paper Shapiro (2021).

The data for each variable is available for different periods, and the only overlap of the data for all available variables is the years 2013-2017, which is used here. The 4-digit NAICS industry codes in the final dataset correspond to the production and manufacturing industries, with 11 to 33 codes at the 2-digit NAICS level. The rest of the NAICS codes are for service-oriented industries, which do not have corresponding tariff and non-tariff barriers, though they have emissions. The 11 to 33 NAICS codes include Agriculture-Forestry- Fishing-Hunting, Mining, Utilities, Construction and Manufacturing. There are around 41-44 industries for each year in our analysis.

1. Trade policy

We use the most basic trade barrier, the tariff. The data on the most favoured nation (MFN) tariff and non-most favoured nation applied tariff were available. The non-MFN applied tariff was based on free/bilateral/preferential trade agreements for select countries only for 2022. Hence, we only consider the most favoured nation (MFN) tariffs of the U.S. as it is the most common tariff rate applied per product. The tariff data was available from 2013-2022 from the WTO database. The tariff data was at the 6-digit Harmonised System (H.S.) product level. The 6-digit H.S. codes were converted into 4-digit NAICS industry-level codes to make the same classification for all variables so that they are comparable (As the emissions data was available at the 4-digit NACIS level) and facilitate econometric analysis. For the concordance of H.S. to NAICS codes of trade policy variables, the Pierce and Schott (2012) reference on the data for U.S. imports for the year 2017 NAICS codes is used. The concordances available on U.S. import data are most relevant for aggregating the import tariffs on 4-digit NAICS. The tariff is aggregated at a 4-digit NAICS code by measuring the arithmetic mean/average of all unique 6-digit H.S. codes related to it.

In place of Non-Tariff Barriers, we use the Anti-Dumping duties (A.D.), which make up for most NTBs in recent years and the variable of interest for our research question, as Anti-Dumping was not included in Shapiro 2021 as part of NTBs in their analysis of the relation of NTB's to emissions. The data for Anti-Dumping was available from 1986 -2019. However, the period of data overlap for all variables falls over 2013-2017, which we consider the period for our research. The anti-dumping data was available per case I.D. registered at WTO and collected from the Temporary Trade Barriers Database (TTBD). TTBD provides the concordance for case ID and H.S. code. The H.S. codes are then converted to 4-digit NAICS codes using Pierce Schott (2012). The anti-dumping duties are aggregated at the 4-digit NAICS code by measuring the arithmetic mean/average of all unique 6-digit H.S. codes related to it, similar to tariffs.

2. Emissions

There are two types of emissions: direct and indirect. Direct emissions arise directly from the production process of the good. In contrast, indirect emissions arise from the production of intermediate or input goods used in producing the good. The emissions that are considered here include indirect emissions. Some papers in trade and environment literature also consider the global multi-regional input-output tables to include the emissions embedded from the imported intermediate goods (Shapiro, 2021; Zheng et al., 2023).

Here, for simplicity and because we consider the case of the U.S., we use the domestic emissions (direct+indirect). The emissions data is greenhouse gases, which include all kinds of major polluting gases like carbon dioxide, methane, and nitrous oxide, among twelve other greenhouse gases. All the greenhouse gases are expressed in terms of carbon dioxide equivalents. The emissions are expressed in kg per purchasing price of the product in the U.S.

The emissions data is available from 2010 to 2017 by the classification of the Bureau of Economic Analysis's (BEA) Industry of Economic Account of America for product and industry level where the products and industries have the same code. However, for the year 2017, the BEA adopted a different base year for commodity prices to express emissions and different calculations for emissions, which makes the data on emissions for 2017 different from other years, which is why there is significant use of time-fixed effects here. The Bureau also provides the corresponding 4-digit NAICS codes for industry codes. Hence, this paper aggregates emissions at the industry level for unique 4-digit NAICS industry codes. These NAICS codes provide us with the common I.D. for all the variables for the econometric analysis.

4. Methodology

We use the fixed effects regression analysis to examine our research question, find the quantitative and qualitative association of emissions and anti-dumping, and figure out if developed countries like the U.S. are using anti-dumping as an alternative carbon tariff or carbon subsidy. The main results mainly comprise the manufacturing sector, which contributes most to the emissions, and the analysis focuses on the single case of the U.S. for simplicity and relevance for our study, being a developed country and actively imposing non-tariff barriers, specifically anti-dumping on developing countries.

The relevant literature in this field of study employs Instrumental Variable (IV) regression analysis (Aichele & Felbermayr, 2012; Kono, 2017; Shapiro, 2021). They use IV analysis primarily because of the way the emissions in their data include emissions embedded in traded goods as they collect it from Global Input-Output databases as they focus more on the global level of analysis (Aichele & Felbermayr, 2012; Shapiro, 2021; Zheng et al., 2023), while we include only indirect emissions within the country from each step of production since we single out just the U.S. These papers also use simple Ordinary Least Square (OLS) regression equations to capture the initial relation of emissions and trade policy measure but move on to IV as it is more suitable for their data as indirect emissions and direct emissions might be correlated. For our data structure, the simple fixed effects regression analysis is used for its relevance.

The fixed effects are primarily for time since we perform our analysis for years 2013-2017, and we need to avoid unobserved year-specific characters that bias the results of the analysis. We perform the regression analysis once with tariffs as the dependent variable and another using anti-dumping as the dependent variable, where in both cases, the leading independent variables are the year fixed effects, emissions, interaction term and industry fixed effects. We do this through separate regression analyses, once for tariffs and then for anti-dumping, to be able to compare if tariffs still present the same pattern of being against environmental welfare and if anti-dumping is an alternative to carbon tariff or is also a form of carbon subsidy serving the same purpose as traditional tariff in linkages to environment.

This practice is also used in trade and environment literature, such as Shapiro (2021), but they only perform the analysis for one year, so they do not use the time-fixed effects and do not have the interaction term. However, here in this study, we have access to the dynamic data structure for all variables. The data for each variable for various industries is available for the period of five years, from 2013 to 2017. Hence, the final effect will be measured by the coefficient, which sums up the main effect of emissions and interaction terms, as we want to look at the evolution of the relationship between emissions and trade policy measures over time.

Hence, to answer our research question, we initially estimate the following equations:

$Tariff_{it} = \beta_0 + \beta_1\, delta_t + \beta_2 \text{Emissions}_{it} + \epsilon_{it}$…(1)

$AD_{it} = \beta_0 + \beta_1 delta_t + \beta_2 \text{Emissions}_{it} + \epsilon_{it}$….(2)

$Tariff_{it} = \beta_0 + \beta_1 delta_t + \beta_2 \text{Emissions}_{it} + \beta_3 (delta_t \times Emissions_{it}) + \epsilon_{it}$…(3)

$AD_{it} = \beta_0 + \beta_1 delta_t + \beta_2 \text{Emissions}_{it} + \beta_3 (delta_t \times Emissions_{it}) + \epsilon_{it}$….(4)

We then add industry fixed effects to avoid any unobserved fixed characteristics of industries over time to bias our analysis of results. Some literature, like Shapiro (2021), uses importer fixed effects which is not relevant has importer fixed effects, which is not relevant to our case as we have only one importer, the U.S. Hence, we now estimate including industry fixed effects to the above two same regression equations and see it makes a difference in results.

$$Tariff_{it} = \beta_0 + \beta_2 \text{Emissions}_{it} + \beta_4 industry_i + \epsilon_{it} \ldots(5)$$

$$AD_{it} = \beta_0 + \beta_2 \text{Emissions}_{it} + \beta_4 industry_i + \epsilon_{it} \ldots.(6)$$

$$Tariff_{it} = \beta_0 + \beta_1 delta_t + \beta_2 \text{Emissions}_{it} + 3(delta_t \times Emissions_{it}) + \beta_3 industry_i + \epsilon_{it} \ldots(7)$$

$$AD_{it} = \beta_0 + \beta_1 delta_t + \beta_2 \text{Emissions}_{it} + \beta_3 (delta_t \times Emissions_{it}) + \beta_4 industry_i + \epsilon_{it} \ldots.(8)$$

The explanation of each variable used for estimation is as follows:

Dependent Variable:

Tariff_{it} = Most Favored Nation (MFN) tariff imposed by U.S. yearly specific to each industry

AD_{it} = Anti-Dumping duties imposed by the U.S. yearly specific to each industry

Independent Variable:

Emissions_{it}= Takes value of all emissions aggregated by all years.

$\text{delta}_t \times \text{Emissions}_{it}$= Interaction term provides emissions for all industries aggregated yearly

Control variables:

delta_t= Takes the value of 1 in case of same specific year otherwise 0, time fixed effects

Industry_i= Takes the value of 1 in case of same specific industry otherwise 0

ϵ_{itk} = Error term

In all equations, to measure the final relation, we need to sum up the main effect of emissions and interaction terms for each year, where the year dummy takes 1 for each specific year. This final effect can be interpreted as a carbon tariff/subsidy depending on the sign we observe in the results. This direct interpretation of the final sum as tariff/subsidy is possible because tariff and anti-dumping are measured in percentage of tariff/anti-dumping on the price of an item in an industry, and the emissions are measured in kg tonnes of carbon dioxide equivalent emitted per price of the item in an industry.

The coefficients used to calculate the final effect emissions and interaction term are in the same unit tariff/emissions, making this interpretation possible. For example, we would interpret the equation with the help of the final effect (emissions and interaction terms); if the value of the final sum were "30", then the increase in emissions each year would increase the Anti-Dumping by $30 per additional kg of greenhouse gas emissions produced by the specific industry. The interpretation of tariffs is similar. The standard errors are clustered by industry.

5. Results

5.1 Summary Statistics

Table I describes U.S. manufacturing industries based on emissions by dividing them into two panels: Panel A contains the top 5 cleanest industries, and Panel B contains the top 5 dirtiest industries each for 2017. The data on emissions, tariffs, and anti-dumping for each of these industries is also present in adjacent columns.

The top 5 cleanest industries in 2017 are mainly furniture and electrical equipment manufacturing industries, with average emissions of 0.23 kg of greenhouse gases emitted for the purchasing price of the average product of that industry. The top 5 dirtiest industries in 2017 were mainly plastics, chemicals, cement, pesticide manufacturing industries, and metal ore mining, with average emissions of 1.31 kg of greenhouse gases emitted for the purchasing price of the average product of that industry.

The appendix provides Similar tables for each year, from 2013 to 2016. The composition of top 5 cleanest industries is same for the years 2013-2016 except for 2017. The top 5 cleanest industries during these years comprise general machine, agriculture and related machinery manufacturing and textile mills. However, the composition of the top 5 dirtiest goods remains the same. However, there is a huge difference in mean emissions and mean Anti-Dumping duties for 2017 and the remaining years.

From Table I, for 2017, the cleanest industries faced 6.5 times higher mean tariffs, as the cleanest industries faced a mean tariff of 9.7%, while the dirtiest industries faced 1.5%. In the case of Anti-Dumping, the cleanest industries faced 6.9 times higher mean Anti-Dumping duties than the dirtiest industries. From tables AI in the appendix, we observe that the difference is higher for the remaining years, with the top 5 cleanest industries facing 17 to 22 times higher anti-dumping duties than the top 5 dirtiest industries.

Table I: Cleanest and Dirtiest U.S. Manufacturing Industries in 2017

Industry-2017	Emissions	Tariff	AD
Panel A			
Veneer, Plywood, and Engineered Wood Product Manufacturing	0.22	1.39	58.84
Other Furniture Related Product Manufacturing	0.23	4.30	234.51
Electrical Equipment Manufacturing	0.23	1.81	81.86
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	0.23	0.31	55.62
Other Miscellaneous Manufacturing	0.23	3.39	53.65
Mean of top 5 cleanest industries	0.23	2.24	96.90
Panel B			
Resin, Synthetic Rubber, and Artificial and Synthetic Fibers and Filaments Manufacturing	1.12	4.91	28.53
Cement and Concrete Product Manufacturing	1.13	0.88	65.22
Metal Ore Mining	1.22	0.00	0.00
Basic Chemical Manufacturing	1.38	2.72	117.04
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	1.72	1.30	188.31
Mean of top 5 dirtiest industries	1.31	1.96	79.82

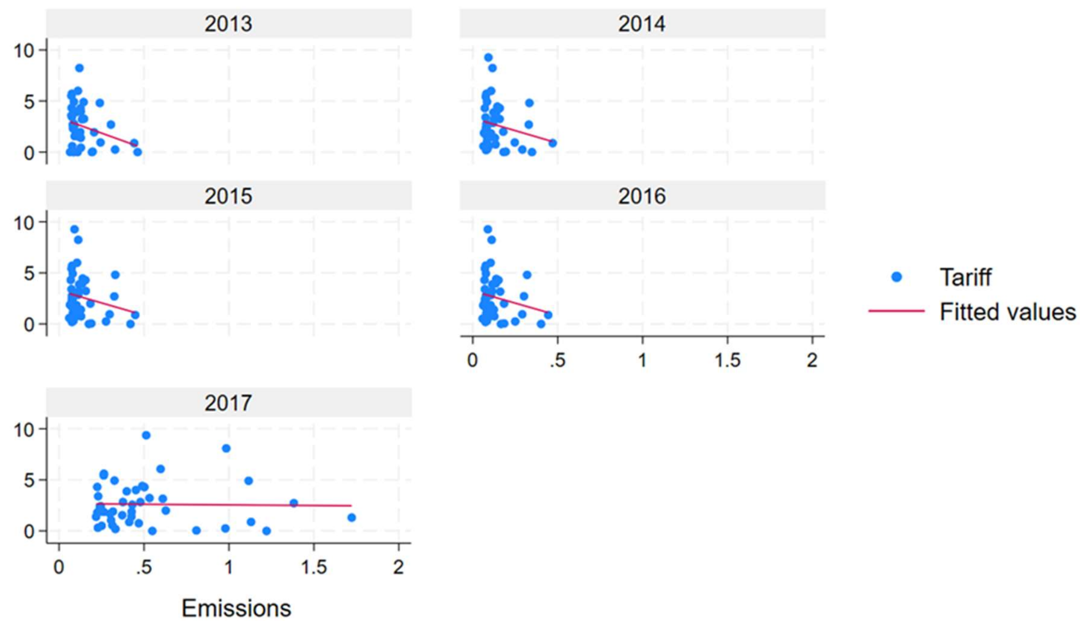
Notes: Emissions are measured in kg per product purchase price. Emissions, Tariff and Anti-Dumping data are collected from the Bureau of Economic Analysis (U.S.), TTBD and WTO databases respectively. For year 2017 there is emissions are calculated using different measure as described in data section 3.

While this is the case just for the top 5 cleanest and dirtiest industries, we explore further for a comprehensive look through regression estimates, which control for year-fixed effects and industry-fixed effects and are based on all industries.

5.2 Tariffs

Figure I plots graphs of tariffs against emissions for each unique industry, including the regression line fit for each year for the analysis period. The plots for the first four years of the analysis, i.e., for 2013, 2014, 2015 and 2016, have highly similar-looking scattered plots and regression lines. There is a clear negative relationship between tariffs and emissions, with high tariffs on low-emission-intensive industries. However, for the year 2017, it is entirely different; the scattered dots are more dispersed along the axis for emissions. On the surface, there was a substantial increase in emissions in 2017 per industry.

Figure I: Tariff Versus Emissions yearly



Notes: All the graphs plot tariff over emissions for the respective years. The line is a linear trend; in all yearly graphs. line is fitted from regressions including year-fixed effects and standard errors are clustered by industry. For year 2017 there is emissions are calculated using different measure as described in data section 3.

Table II presents regressions for these respective equations in section 4. The initial regressions in columns 1 and 2 yield insignificant results with different signs of coefficients for emissions. Negative for the 1st column, which includes only time-fixed effects in column 1 and positive for the 2nd column, which includes only industry-fixed effects.

For columns 3 and 4, interaction terms are added, and the final effect is presented by Lincom coefficients for each year, which sums up the main effect of emissions and the interaction term effect when the year dummy takes the value of 1. In column 3, which includes only time-fixed effects and interaction terms, the main effect of emissions is found to be negative and highly significant, and the final effect is negative for all years and significant for all years at a 10% level except 2017. The regression equation is comparable to Shapiro (2021) who also finds a significant negative relationship between emissions and tariff. Here, we observe that the final effect coefficient terms are all negative, indicating a carbon subsidy on emissions in the form of import tariffs.

Here, the final effect coefficients (lincom) indicate a carbon subsidy of $4.88, $4.81, and $4.78 per kg greenhouse gas emission per purchasing price of the average product of the specific industry for years 2014, 2015 and 2016, respectively. The magnitude of the coefficients for the final effect(lincom) remained similar, marginally increasing except for the year 2017, where it slightly decreased, and the term was not significant, indicating a marginal increase in carbon subsidy on imports of emission-intensive industries over time.

Column 4 corresponds to a similar regression equation as in column 3 but includes industry-fixed effects. This regression differs from Shapiro(2021), which includes country-fixed effects rather than industry-fixed effects in the main regression. All the terms here are insignificant except for the final effect(lincom) coefficient for 2017, which is marginally positive and significant, unlike just negative when excluding industry-fixed effects. This indicates an implicit carbon tariff of $0.25 for 2017 on imports from emission-intensive industries.

This result for 2013-2016 is quite similar to the literature, which analysed the relationship between tariffs and emissions and found a significant negative association between these two variables, meaning there is a carbon subsidy on imports of emission-intensive industries (Kono, 2017; Shapiro, 2021), though they were for a different period and data structure. However, when we account for industry fixed effects for 2017, which is very recent data, the results were different, presenting a positive relationship/carbon tariff. This difference for 2017, when including industry-fixed effects, needs to be explored further if it influences the rest of the year's estimates, which is explained in robustness checks.

TABLE II
Association of Tariff and Emissions

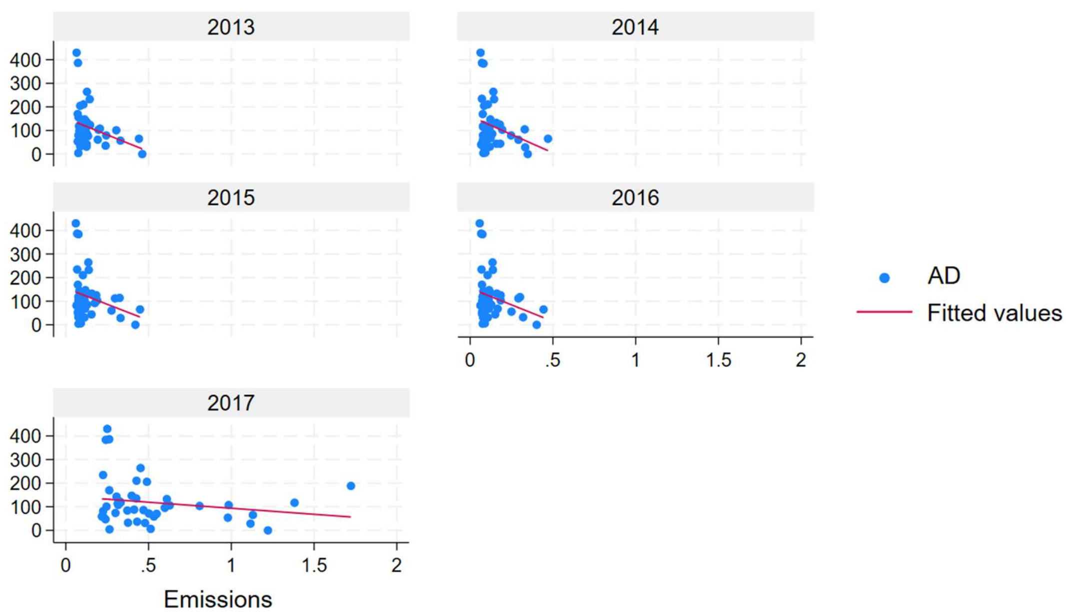
	Tariff (1)		Tariff (2)		Tariff (3)		Tariff (4)	
Year								
2014	0.142				-0.029		-0.249	
	(0.220)				(0.430)		(0.235)	
2015	0.099				-0.088		-0.235	
	(0.208)				(0.399)		(0.233)	
2016	0.088				-0.118		-0.247	
	(0.208)				(0.402)		(0.233)	
2017	0.556				-0.681		-0.293	
	(0.521)				(0.490)		(0.238)	
Emissions	-1.200		0.031		-5.973	***	-0.338	
	(1.163)		(0.058)		(2.110)		(0.645)	
Year # Emissions								
2014					1.092		0.915	
					(1.770)		(0.819)	
2015					1.164		0.862	
					(1.595)		(0.803)	
2016					1.198		0.917	
					(1.676)		(0.813)	
2017					5.851	***	0.584	
					(1.858)		(0.659)	
Intercept	2.674	***	2.598	***	3.353	***	2.750	***
	(0.332)		(0.013)		(0.512)		(0.178)	
N	216		215		216		215	
Lincom								
2014					-4.881	*	0.577	
					(2.884)		(0.479)	
2015					-4.809	*	0.523	
					(2.632)		(0.448)	
2016					-4.775	*	0.579	
					(2.727)		(0.465)	
2017					-0.123		0.246	*
					(0.880)		(0.143)	

Notes: Table presents regression estimates of import tariffs on greenhouse gas emissions. Odd numbered columns do not contain industry fixed effects while even columns do. Except for column 2 every column contains time fixed effects. The main variable for measuring final effect of emissions on anti-dumping s for each year is expressed through lincom coefficients, which sums up the coefficients of emissions and year specific interaction term with emissions. The emissions are aggregated as mean of emissions per industry including both direct and indirect emissions in the U.S. Emissions rates are measured as kg CO_2 *equivalent greenhouse gas emissions per purchasing price of average product for the specific industry. All data are from 2013- 2017. For year 2017 the emissions were calculated using different measure* *as described in data section 3. The standard errors are clustered by industry. The "* " s denotes p-value, *** p<.01, ** p<.05 * , p<.10 .*

5.3 Anti-Dumping

Figure II plots graphs of Anti-dumping against emissions for each unique industry including the regression line fit for each year for the period of analysis. The plot for the first four years of the analysis i.e., for 2013, 2014, 2015 and 2016 have highly similar looking scattered plots and regression lines. It looks like there is a clear negative relationship of anti-dumping and emissions, with high tariffs on low emission intensive industries. Whereas for the year 2017 it's completely different, the scattered dots are more dispersed along the axis for emissions, the same pattern as for tariffs and on the surface, it looks like these is a substantial increase in emissions in 2017 per industry.

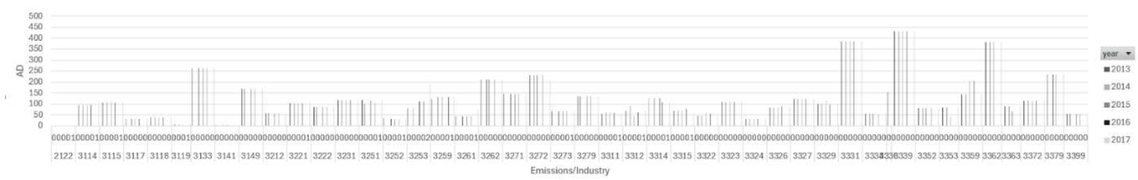
Figure II: Anti-Dumping Versus Emissions yearly



Notes: All the graphs plot Antidumping over Emissions for the respective years. The line is a linear trend; in all yearly graphs. line is fitted from regressions including year-fixed effects and standard errors are clustered by industry. For year 2017 there is emissions are calculated using different measure as described in data section 3.

To observe this more deeply, as Anti-Dumping is the primary variable of interest, we plot a graph to look at the evolution of Anti-Dumping and related emissions for each industry over time in Figure III. The anti-dumping is plotted on the Y-axis per industry with different years as a trend, the industries are plotted on the X-axis, and the emissions per industry for each year are plotted as subgroups per industry on the X-axis. Here, on the surface, we observe little change in the Anti-Dumping of industries over time, but emissions per anti-dumping of industry changed each year. This provides the basis for exploring the association between emissions and anti-dumping changes over time. Individual graphs for Anti-Dumping and Emissions per industry over time are also presented in the appendix in figures A I and A II for clarity.

Figure III: Evolution of Anti-Dumping and emissions over industries over time



Notes: Anti-dumping is plotted on y-axis per industry yearly, emissions are plotted on x-axis as a subgroup per industry on a yearly basis for all years 2013-2017. For year 2017 there is emissions are calculated using different measure as described in data section 3.

Table III presents regressions for these respective equations in section 4. The initial regressions in columns 1 and 2 yield positive and insignificant coefficients for emissions, including only time-fixed effects in column 1 and industry-fixed effects in column 2.

For columns 3 and 4, interaction terms are added, and the final effect is presented by lincom coefficients for each year, which sums up the main effect of emissions and the interaction term effect when the year dummy takes the value of 1. In column 3, which includes only time-fixed effects and interaction terms, the main effect of emissions is found to be negative and highly significant, and the final effect is negative for all years and significant at a 5% level for all years except 2017. Here in this paper, only the anti-dumping measure is used, the most prominent non-tariff barrier, which wasn't included in Shapiro(2021) and found qualitatively similar results for all years except 2017, a significant and substantially larger negative relationship between emissions and anti-dumping/non-tariff measures. Here, we observe that the final effect coefficient terms are all negative with large magnitude, indicating a large carbon subsidy on emissions in the form of anti-dumping. Here the final effect coefficients (lincom) indicate a carbon subsidy of $310.55, $272.25 and $280.10 per kg greenhouse gas emission per purchasing price of the average product of the specific industry for years 2014, 2015 and 2016, respectively.

Column 4 corresponds to a similar regression equation as in column 3 but includes industry-fixed effects. This differs from Shapiro(2021), which includes country-fixed effects rather than industry-fixed ones in the main regression. All the terms here are insignificant except for the final effect(lincom) coefficient for 2017, which is positive and significant, unlike just negative when excluding industry fixed effects. This indicates that there is an implicit carbon tariff of $49.89 for the year 2017 on imports from emission-intensive industries. The magnitude of estimate here is larger than tariffs as it could be because the mean values of Anti-Dumping are higher than tariffs.

This provides strong evidence that anti-dumping is used as a carbon subsidy by the U.S., a developed country, on its imports of greenhouse gas emission-intensive industries. The emissions coefficient is negative and significant until 2016, indicating the importance of including time-fixed effects and interaction terms in the regression equation to calculate the final effect for the correct interpretation of the association of emissions and anti-dumping with the panel data structure. However, when including industry fixed effects, the final effect of 2017 was positive and significant, indicating the need for further study to determine if the different emissions measurements for 2017 were driving these results or if there was a different pattern from 2017. We solve a part of this question by performing a robustness check, removing 2017, and sharing the results in the following paras.

This result is quite similar to the literature that analysed the relationship between non-tariff barriers and emissions and found a significant negative association between these two variables, meaning there is a carbon subsidy on imports of emission-intensive industries (Shapiro, 2021; Zheng et al., 2013). However, those results did not include the anti-dumping in non-tariff barriers, which is the most used non-tariff barrier or used for a different period. Hence, the resulting estimates in this study provide strong evidence of anti-dumping as a carbon subsidy on imports of greenhouse gas emission-intensive industries by the U.S., a developed country, in recent times.

TABLE III
Association of anti-dumping and emissions

	AD (1)	AD (2)	AD (3)	AD (4)
Year				
2014	5.231		8.376	-0.778
	(7.746)		(15.546)	(2.446)
2015	5.274		2.824	-2.452
	(7.575)		(14.534)	(3.435)
2016	4.388		2.308	-3.015
	(7.539)		(14.621)	(3.470)
2017	44.582 *		-7.367	-10.120 *
	(23.605)		(20.970)	(5.270)
Emissions	-101.918	12.881	-282.291 **	103.205
	(61.141)	(11.895)	(105.599)	(71.245)
Year # Emissions				
2014			-28.249	6.823
			(60.625)	(14.015)
2015			10.046	27.555
			(56.359)	(18.661)
2016			2.188	32.010
			(58.789)	(20.311)
2017			231.127 **	-53.317
			(89.811)	(43.059)
Intercept	126.591 ***	113.844 ***	152.240 ***	101.569 ***
	(19.556)	(2.562)	(26.928)	(10.558)
N	216	215	216	215
Lincom				
2014			-310.540 **	110.028
			(127.557)	(75.621)
2015			-272.245 **	130.760
			(112.180)	(79.784)
2016			-280.103 **	135.215
			(118.515)	(82.729)
2017			-51.164	49.889 *
			(45.061)	(29.037)

Notes: Table presents regression estimates of anti-dumping on greenhouse gas emissions. Odd numbered columns do not contain industry fixed effects while even columns do. Except for column 2 every column contains time fixed effects. The main variable for measuring final effect of emissions on anti-dumping s for each year is expressed through lincom coefficients, which sums up the coefficients of emissions and year specific interaction term with emissions. The emissions are aggregated as mean of emissions per industry including both direct and indirect emissions in the U.S. Emissions rates are measured as kg CO_2 *equivalent greenhouse gas emissions per* *purchasing price of average product for the specific industry. All data are from 2013- 2017. For year 2017 there is emissions are calculated using different measure as described in data section 3. The standard errors are clustered by industry. The "* " s denotes p-value, *** p<.01, ** p<.05 * , p<.10*

5.4 Robustness checks:

Though our estimates present strong evidence for implicit carbon subsidy in the form of tariffs and anti-dumping for all years except 2017, it is significant to perform sensitivity analysis and robustness for the validity of the results. We perform the robustness check by removing 2017 from our analysis and performing the same regressions. We do this because, for the year 2017, different measurements were used for calculating emissions, and somehow, though we control for time-fixed effects, it is still essential to check whether this different measurement drives the regression estimates for the remaining years. Tables AII and AIII tabulate the association of tariff and anti-dumping and emissions, respectively, without 2017 emissions data; the results indicate that the coefficients are qualitatively the same for all variables for the remaining years and have almost similar coefficients quantitatively. This proves that the different measurements used for calculating emissions for 2017 were not driving the results for the remaining years. However, to know whether there is a start of a new trend from 2017 is beyond the scope of the present study.

We additionally perform a link test that includes squared emissions in the equation. A similar test was performed in Shapiro (2021), where they tested for sensitivity using non-linear emission specifications. The link test performed for the regression estimates without industry-fixed effects indicates that results are quantitatively similar but lose their significance only by a margin in both cases of tariffs and anti-dumping. In the case of including industry-fixed effects, results remain the same, maintaining their significance.

We also use robust standard errors and cluster them by industry to ensure they are robust to industry-level correlation.

6. Conclusion

6.1 Main findings

In a time of increasing importation to mitigate climate change, this study aims to explore the linkages between trade and the environment, both of which are global phenomena. It asks whether trade policy measures in recent times have evolved as alternatives in the form of implicit carbon tax or carbon subsidies on imports of greenhouse gas emission-intensive industries by developed countries with strict environmental standards like the U.S.

Fixed effects regression analysis with time-fixed effects and later with industry-fixed effects is used for methodology. The resulting estimates of the final effect, including the year and emissions interaction term and the main effect of emissions for each year, were found negative and significant for both tariffs and anti-dumping for all years except 2017 in case of including only time fixed effects. The final effect coefficient in the case of tariff indicates a carbon subsidy of an average of around $4.8, and in the case of anti-dumping, a carbon subsidy of an average of around $288.6. per kg greenhouse gas emission per purchasing price of the average product of the specific industry for all years except 2017. This indicates a very high carbon subsidy and no carbon tax on emissions in the form of the most prominent non-tariff measure: Anti-Dumping.

When industry-fixed effects were included in the cases of both tariffs and anti-dumping, there was a positive relationship for 2017, meaning a carbon tariff that needs to be explored further to spot a trend.

These results are relevant to policymaking. The estimates indicate trade policy measures as potential options for incentivising emission-intensive imports through carbon subsidies. Climate change and other environmental concerns need to be addressed through trade policy, using the trade policy measures as implicit carbon subsidies/tariffs.

6.2 Limitations and scope for further research

Even though the emissions data, which includes direct and indirect emissions in the U.S., is considered in this paper at the NAICS industry level, if data on emissions were available at the product level, it would improve results to be more robust and consistent, than converting the tariff and non-tariff measures, which are already available at a disaggregated product level, to the NAICS industry level through concordances.

This study evaluates the case of a single country, the U.S., regarding tariffs and anti-dumping in recent years. However, for a more comprehensive outlook, more countries need to be studied regarding tariffs and non-tariff barriers. The recent data during the U.S.-China trade war, which is not fully available for all necessary variables, must be included in the future for a more current perspective. Additionally, the qualitative difference in coefficients for 2017 needs to be studied further to check for a change in trend from carbon subsidy to carbon tariff with more recently available data.

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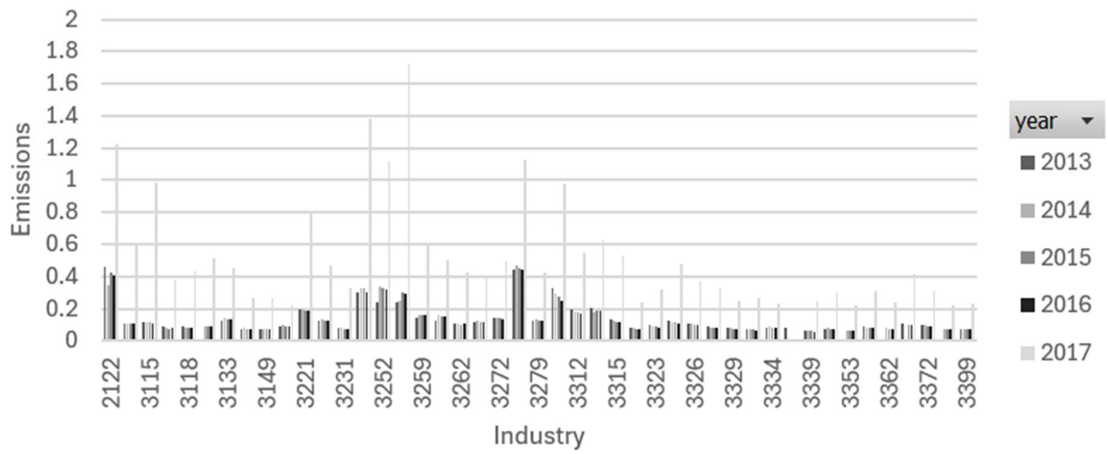
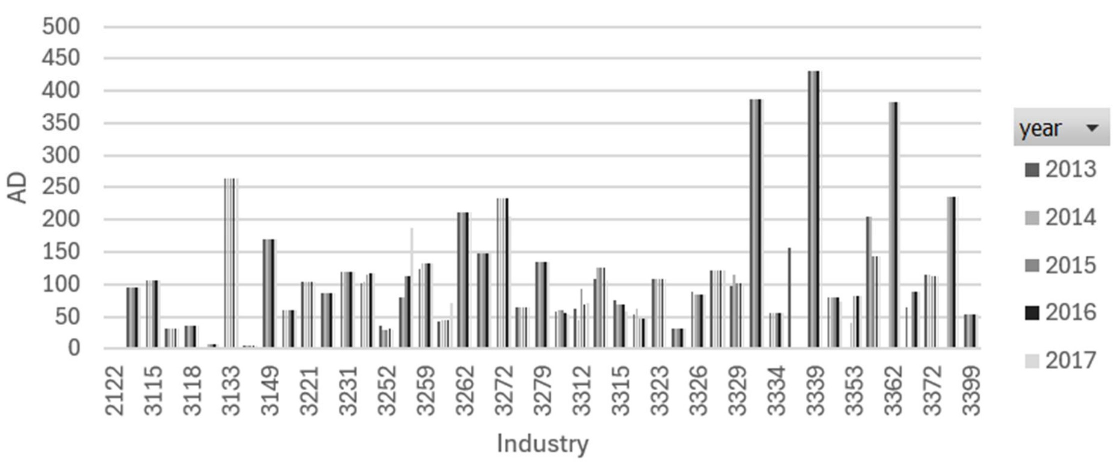
8. APPENDIX

Figure A I : Emissions per industry over time



Notes: Emissions is plotted on y-axis per industry for each year 2013-2017. Emissions rates are measured as kg CO2 equivalent greenhouse gas emissions per purchasing price of average product for the specific industry. The industry classification is 4-digit NAICS level. For year 2017 there is emissions are calculated using different measure as described in data section 3.

Figure A II : Anti-Dumping per industry over time



Notes: Anti-Dumping duties is plotted on y-axis per industry for each year 2013-2017. Anti-dumping duties are aggregated by mean for unique 4-digit NAICS level industry classification.

Tables A I: Cleanest and Dirtiest U.S. Manufacturing Industries

Industry-2013	Emission	Tariff	AD
Panel A			
Other General Purpose Machinery Manufacturing	0.07	0.00	429.95
Other Miscellaneous Manufacturing	0.07	3.59	53.65
Other Textile Product Mills	0.07	5.51	169.69
Agriculture, Construction, and Mining Machinery Manufacturing	0.07	4.33	386.28
Textile Furnishings Mills	0.08	5.71	4.37
Mean of top 5 cleanest industries	0.07	3.83	208.79
Panel B			
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	0.24	0.94	79.20
Basic Chemical Manufacturing	0.31	2.69	100.93
Iron and Steel Mills and Ferroalloy Manufacturing	0.33	0.25	57.00
Cement and Concrete Product Manufacturing	0.44	0.88	65.22
Metal Ore Mining	0.46	0.00	0.00
Mean of top 5 dirtiest industries	0.36	0.95	60.47

Industry-2014	Emission	Tariff	AD
Panel A			
Other General Purpose Machinery Manufacturing	0.06	0.58	429.95
Electrical Equipment Manufacturing	0.07	1.87	40.27
Agriculture, Construction, and Mining Machinery Manufacturing	0.07	1.97	386.28
Other Furniture Related Product Manufacturing	0.07	4.30	234.51
Other Miscellaneous Manufacturing	0.08	3.40	53.65
Mean of top 5 cleanest industries	0.07	2.42	228.93
Panel B			
Iron and Steel Mills and Ferroalloy Manufacturing	0.29	0.25	60.73
Basic Chemical Manufacturing	0.33	2.69	104.71
Resin, Synthetic Rubber, and Artificial and Synthetic Fibers and Filaments Manufacturing	0.33	4.81	28.65
Metal Ore Mining	0.35	0.00	0.00
Cement and Concrete Product Manufacturing	0.47	0.88	65.22
Mean of top 5 dirtiest industries	0.35	1.73	51.86

Industry-2015	Emission	Tariff	AD
Panel A			
Other General Purpose Machinery Manufacturing	0.06	0.58	429.95
Electrical Equipment Manufacturing	0.06	1.87	81.86
Agriculture, Construction, and Mining Machinery Manufacturing	0.07	1.97	386.28
Other Furniture Related Product Manufacturing	0.07	4.30	234.51
Other Miscellaneous Manufacturing	0.07	3.40	53.65
Mean of top 5 cleanest industries	0.07	2.42	237.25
Panel B			
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	0.30	0.94	112.03
Basic Chemical Manufacturing	0.32	2.70	113.95
Resin, Synthetic Rubber, and Artificial and Synthetic Fibers and Filaments Manufacturing	0.33	4.81	28.65
Metal Ore Mining	0.42	0.00	0.00
Cement and Concrete Product Manufacturing	0.45	0.88	65.22
Mean of top 5 dirtiest industries	0.36	1.87	63.97

Industry-2016	Emission	Tariff	AD
Panel A			
Other General Purpose Machinery Manufacturing	0.06	0.52	429.95
Electrical Equipment Manufacturing	0.06	1.81	81.86
Agriculture, Construction, and Mining Machinery Manufacturing	0.07	1.97	386.28
Other Furniture Related Product Manufacturing	0.07	4.30	234.51
Cutlery and Handtool Manufacturing	0.07	2.37	46.86
Mean of top 5 cleanest industries	0.07	2.19	235.89
Panel B			
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	0.29	0.94	112.03
Basic Chemical Manufacturing	0.30	2.71	117.48
Resin, Synthetic Rubber, and Artificial and Synthetic Fibers and Filaments Manufacturing	0.32	4.81	31.85
Metal Ore Mining	0.40	0.00	0.00
Cement and Concrete Product Manufacturing	0.44	0.88	65.22
Mean of top 5 dirtiest industries	0.35	1.87	65.32

Notes: Emissions are measured in kg per product purchase price. Emissions, Tariff and Anti-Dumping data are collected from the Bureau of Economic Analysis (U.S.), TTBD and WTO databases respectively for the specific years.

TABLE AII

Association of tariff and emissions without 2017

	Tariff (1)		Tariff (2)		Tariff (3)		Tariff (4)	
Year								
2014	0.126				-0.029		-0.248	
	(0.219)				(0.430)		(0.238)	
2015	0.076				-0.088		-0.234	
	(0.206)				(0.399)		(0.232)	
2016	0.049				-0.118		-0.246	
	(0.206)				(0.401)		(0.232)	
Emissions	-5.106	*	0.305		-5.973	**	-0.535	
	(2.493)		(0.936)		(2.109)		(0.632)	
Year # Emissions								
2014					1.092		0.910	
					(1.769)		(0.840)	
2015					1.164		0.860	
					(1.594)		(0.801)	
2016					1.198		0.909	
					(1.676)		(0.831)	
Intercept	3.229	**	2.562	**	3.353	**	2.771	**
	(0.500)		(0.129)		(0.512)		(0.120)	
N	172		171		172		171	
Lincom								
2014					-4.881	*	0.374	
					(2.883)		(1.029)	
2015					-4.809	*	0.324	

			(2.631)	(0.979)
2016			-4.774 *	0.373
			(2.725)	(1.018)

Notes: Table presents regression estimates of tariffs on greenhouse gas emissions. Odd numbered columns do not contain industry fixed effects while even columns do. Except for column 2 every column contains time fixed effects. The main variable for measuring final effect of emissions on anti-dumping s for each year is expressed through lincom coefficients, which sums up the coefficients of emissions and year specific interaction term with emissions. The emissions are aggregated as mean of emissions per industry including both direct and indirect emissions in the U.S. Emissions rates are measured as kg CO_2 *equivalent greenhouse gas emissions per purchasing price of average product for the specific industry. All data are from 2013- 2016. The standard errors are clustered by industry. The "* " s denotes p-value, *** p<.01, ** p<.05 * , p<.10*

TABLE AIII

Association of anti-dumping and emissions without 2017

	AD (1)		AD (2)		AD (3)		AD (4)	
Year								
2014	4.462				8.376		-0.296	
	(7.637)				(15.539)		(2.084)	
2015	4.171				2.824		-2.569	
	(7.358)				(14.527)		(3.505)	
2016	2.562				2.308		-3.071	
	(7.331)				(14.614)		(3.538)	
Emissions	-285.879	*	44.883		-282.291	*	34.193	
	(111.369)		(78.957)		(105.548)		(74.289)	
Year # Emissions								
2014					-28.249		3.824	
					(60.595)		(10.311)	
2015					10.046		28.709	
					(56.332)		(19.566)	
2016					2.188		30.690	
					(58.761)		(21.494)	
Intercept	152.750	**	110.002	**	152.240	**	110.814	**
	(26.674)		(10.851)		(26.915)		(10.686)	
N	172		171		172		171	
Lincom								
2014					-310.540	**	38.017	
					(127.495)		(79.193)	
2015					-272.245	**	62.902	
					(112.126)		(85.045)	
2016					-280.103		64.884	

	(118.458)	(87.661)

Notes: Table presents regression estimates of anti-dumping on greenhouse gas emissions. Odd numbered columns do not contain industry fixed effects while even columns do. Except for column 2 every column contains time fixed effects. The main variable for measuring final effect of emissions on anti-dumping s for each year is expressed through lincom coefficients, which sums up the coefficients of emissions and year specific interaction term with emissions. The emissions are aggregated as mean of emissions per industry including both direct and indirect emissions in the U.S. Emissions rates are measured as kg CO_2 *equivalent greenhouse gas emissions per purchasing price of average product for the specific industry. All data are from 2013- 2016. The standard errors are clustered by industry. The "* " s denotes p-value, *** p<.01, ** p<.05 *, p<.10*