“Clearing” Customs: Institutional Quality and the Environmental Bias of Carbon Trade Flows

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Abstract

Many countries have enacted policies and targets to lower their GHG emissions. However, the emissions embodied through international trade have been indirectly subsidized through trade policy. I will explore the hypothesis that countries’ institutional quality is related to their carbon-intensive import trade flow through an OLS regression with importer fixed effects using global panel data on trade flow, institutional quality, and direct emissions of products from 2002-2010. Through panel and cross-sectional analysis, I find that legal institutional quality has a negative association with carbon imports both within countries and between countries, while political institutional quality has a positive association with carbon imports between countries. Surprisingly, economic institutional quality’s effects depend on the method of carbon intensity calculation. These findings suggest that international policy-making bodies should take into consideration the differences in institutional qualities of countries when implementing new emissions targets to maximize efficacy.

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1 Introduction

In recent decades, countries have begun to enact policies to limit carbon emissions to prevent the progression of irreversible environmental damage. In an ideal economy, all governments would apply the same optimal policies on carbon emissions within their respective countries. Beyond the preliminary benefits of reducing emissions, this setting would eliminate the presence of carbon leakage: a phenomenon where local producers may be meeting emission targets in their home countries, but instead shift production capacity to an unregulated region, thereby merely relocating carbon emissions to other areas. However, the likelihood of such a global agreement is very small. In fact, global climate agreements like the Kyoto Protocol have only exacerbated the effects of carbon leakage (Aichele and Felbermayr, 2015), implying that current efforts have not properly controlled the carbon footprints of trade. The growth of international trade has also made relocation easier, causing developed countries to generally maintain cleaner emissions, but resulting in 2019 carbon emissions to rise at a rate faster than the previous 10-year average. Without addressing this key issue and the potential forces at play, global efforts to lower emissions may be futile, and could lead to acceleration of environmental damage under the guise of progress.

A potential solution is to implement carbon tariffs appropriately, which levy a charge based on the carbon emissions of imported products. Could this already be the case? In fact, it is not: Shapiro discovered that currently, most countries in the world tend to subsidize the imports of dirty industries (Shapiro, 2020). Additionally, Böhringer et al find that when carbon tariffs are levied, they are likely increase rather than decrease the global cost of emission reduction (Böhringer et al, 2016). They also find that carbon tariffs shift the economic burden of developed-world climate policies to the developing world, which leads to greater inequality. Ideally, all countries should implement carbon policies effectively within their own boundaries, eliminating the need for any sort of carbon trade policy.

The concerning patterns I see in trade leads to questioning of the role that governments play by indirectly affecting the environment through trade policy and trade flows. I hypothesize that developed countries with high institutional quality, and perhaps generally with stringent carbon pricing, may tend to import irresponsibly – this is largely influenced by Shapiro's findings of implicit subsidies in dirty goods in the world economy. In this paper I will explore how an importing country's institutional quality affects their carbon-intensive trade flows by examining panel data from 2002-2010 and applying both a cross-sectional and panel data analysis approach through different lenses of variation. I aim to find a association between a country's institutional quality and their carbon import patterns.

My findings show that the associations between a country's institutional quality and their carbon imports depend on the type of institutional quality, as well as the type of variation (within- or between-countries). Legal institutional quality generally is negatively associated with carbon imports in both variations, whereas political institutional quality is generally positively associated only across countries. This implies that when observing all countries from 2002-2010, countries with higher political institutional strength, including less corruption, greater bureaucratic quality and greater democratic accountability, are associated with importing more carbon-intensive goods. On the other hand, countries with higher legal institutional strength, including stronger property rights, civil liberties, and rule of law, are not associated with importing more dirty goods, which is found in within-country variation as well.

2 Literature Review

The research question is situated at the intersection of trade flow, carbon emissions, and institutional quality, which originate from the fields of trade, environmental and political economics. I will highlight research that draws from the intersections of these fields and then position my work in the existing literature.

A main concern that motivates this paper is the negative repercussions of carbon leakage. Carbon leakage hurts the local economy due to the shifting of production offshore, which results in weakened effectiveness of emission regulation because it diminishes returns from clean technology investments (Huang et al, 2020). Furthermore, there would be additional transportation emissions through the process of transporting the outputs back to the regulated region. After countries began to introduce more climate policy measures after international agreements like the Kyoto Protocol and other global efforts, Aichele and Felbermayr find that many Kyoto countries have indeed adopted more climate policy measures after ratification and have reduced carbon emissions *within* the countries' territories (Aichele and Felbermayr, 2015). However, they found that it has increased committed countries' embodied carbon imports from non-committed countries by 8 percent, and emissions intensity of their imports by about 3 percent. This finding highlights the significance of further investigating the impacts of trade on carbon emissions, as it can potentially contribute to global net losses on GHG emissions despite within-country gains. Given that the Kyoto Protocol is the only international agreement that sets targets for the majority of industrialized countries, exploring the relationship between trade flows and carbon emissions in this paper rather than intra-country emissions would provide useful insights.

Solving carbon leakage may require a degree of institutional quality within countries. Copeland and Taylor propose that restricting imports from countries with poor carbon control policies may actually encourage those countries to adopt even dirtier production, as higher tariffs may lead to cost-cutting for dirty producers (Copeland and Taylor, 2003). In place, they suggest that a good solution for positive environmental outcomes is through capacity-building in developing countries, which is an activity that requires a certain degree of institutional quality (such as low corruption, high rule of law) to implement effectively. Because of this, I believe that investigating institutional quality's relationship to environmental outcomes can generate useful insights for the practicality of such capacity-building initiatives, or other non-tariff solutions to carbon leakage.

Past research has shown that institutional quality has played a role in many environmental outcomes (Azam et al, 2020) (Goel et al, 2013). Empirical evidence has shown that, in the fast-growing developing country of Malaysia from 1984-2008 (a time period partially included within my research question), institutional quality is found to not only affect economic growth directly, but also indirectly via carbon emissions (Lau et al, 2014). This indicates that the quality of institutions plays an important role whereby it helps to reduce environmental degradation in a country even if the country's income is low. The significance of institutional quality is further emphasized through research by Goet et al, who find that more corrupt nations and nations with large shadow sectors have fewer recorded emissions (Goet et al, 2013). However, MENA nations (countries in the Middle East and North Africa) have higher pollution rates despite having lower institutional quality. This implies that different countries across geographical regions have different relationships between institutional quality and carbon emissions, suggesting cross-sectional variation. However, Goet et al focus on degree of corruption and the extent of the shadow sector in a country, which does not fully capture other facets of institutional quality. I aim to see if this association could be due to higher dirty imports, and also expand upon the data by utilizing a data set on institutional quality that measures a country's institutional strength extensively through three categories: economic, political, and legal.

To expand on the relationship between government and emissions, Best et al have found countries with carbon pricing experience a 2 percent decrease in average annual carbon emissions growth rates, but overall contribution of carbon pricing is limited by political infeasibility of implementation in some countries (Best et al, 2020). In fact, in 2019, only 47 countries had a carbon price at either the subnational or national level, which covers approximately 20 percent of global GHG emissions. Interestingly, they emphasize that countries with underdeveloped institutional capabilities have technical challenges in enforcing carbon prices. Levinson and Taylor also note that industries whose abatement costs increased most experienced the largest increases in net imports (Levinson and Taylor, 2008). They find that for the US during this time period, a 1 percent increase in pollution abatement costs resulted in a 0.4 percent increase in net imports from Mexico, implying that richer countries may have greater carbon-intensive trade flows.

In this paper, I will not be exploring the practicality of imposing carbon pricing internationally, but rather exploring the implicit environmental bias of trade flows that are currently already in existence. My empirical approach contrasts Best et al's emphasis on within-country emissions only. Additionally, rather than trying to determine the best solution for solving carbon leakage, I will be exploring a potential existing relationship instead, which would help build upon current findings at the intersections of carbon leakage, institutional quality and trade flows. As institutional quality has been mentioned by Best et al as the key reason for technical challenges in adopting carbon prices, the insights I report would be useful in solving the policy implementation challenge rather than finding a new policy. Furthermore, I extend Shapiro's findings that countries have lower import tariffs and non-tariff barriers (NTBs) on dirty than on clean industries, where dirtiness is measured through carbon emissions per dollar of output (Shapiro, 2020). Shapiro uses cross-sectional data analysis on global tariffs and industry emissions from 2007 to find that if countries applied similar tariffs to clean and dirty goods, global carbon emissions would decrease, suggesting that the current system of tariffs is contributing to emissions. To expand on this, I will be utilizing panel data rather than cross-sectional data on multiple countries from 2002-2010, and changing the outcome variable to trade flow rather than tariffs, which can provide useful insights as it is a direct economic response to trade policy rather than policy itself. I will also focus on institutional quality's explanatory effects, as institutional quality has been shown to impact environmental outcomes.

3 Data

I combine three types of variables: trade flows, direct carbon emissions, and institutional quality[1]. The data represents the time period from 2002-2010 and includes 39 countries, 4519 products and 3 types of institutional quality indicators. The final data set includes 1,534,392 observations, with each row representing a trade flow of a specific product for an importer in a year, as well as the mean carbon emissions of the exporters' production sources involved in the production of the product, and the emissions rate calculated by dividing mean emissions by total imports of that product. The years 2002-2010 were chosen largely due to data availability, but also because this can be viewed as a general period when countries began enacting carbon policies (ex. Canada's first broad-based carbon tax was in 2008), and the future environmental effects of climate change became more apparent globally.

3.1 Data Sources and Gathering

To cover the scope of my research question, I combine three sources of data. Below, I will describe the data sets, how I used them, and the data transformations involved.

3.1.1 EXIOBASE 3: Carbon Emissions

Exiobase covers trade data, input-output tables, and national accounts to construct a global multi-region input-output table (MRIOT) for each year from 1995-2011. It includes 44 countries (28 EU member plus 16 major economies), including five rest of the world regions (which were omitted in my dataset). The data includes 163 industries and 200 products and extends to environmental

[1]Code can be found at `https://github.com/jenny-ll/494thesis`

indicators, including carbon emissions. Exiobase is one of the most extensive MRIOT databases publicly available, and is supported by the European Union. The data is built from a variety of primary data sources including Eurostat, the UN's Comtrade database, and International Energy Agency, including privately licensed data.

I synthesize three MRIOTs per year. MRIOTs describe the sale and purchase relationships between producers and consumers within an economy. Every column and row represents an industry, and each value in the table represents the Euros of output required from the row industry to produce a Euro of output in the column industry. Each year has an MRIOT centred on Industries, and another centred on Products. In a third MRIOT, Exiobase also provides extensions on satellite accounts, including the total direct carbon emissions per million Euros of output for every Country$\times$Industry.

In my analysis, due to calculation constraints, I focus on direction emissions only (ie. emissions required for intermediate industries are not included). I use the Tier 1 method of calculating carbon emissions, as determined by the Intergovernmental Panel on Climate Change. To calculate, I filter the rows for coal extraction, oil extraction and natural gas extraction industries for each column industry in the MRIOT. Using the Python package pymrio, a helpful package for parsing and aggregating Exiobase data created by the creators of Exiobase, I find the carbon emissions per Euro for the coal extraction, oil extraction and natural gas extraction industries in the Satellite MRIOT and multiply those values with the Euros expenditures from the Industries MRIOT. Then, I sum these three values to get the total direct emissions of each Country$\times$Industry. This approach is standard for accounting for pollution. However, because I rely on direct emissions rather than the full carbon-intensity that may be involved with intermediate production in an industry, there is a degree of limitation in my data. To account for intermediate emissions, the Leontief inverse will need to be calculated for the IOT matrix, which may be explored in future research.

After generating the total carbon emissions for each Country$\times$Industry, I use a concordance table provided by Exiobase to map each Product to the Industry that it belongs to. This involves some missing data as there are more Products than Industries, so another limitation in the data is that some Products have identical carbon emissions despite differing in emissions in reality. However, this difference may not be very large, given that these country products originate from the same industry in a given country, so the general level of carbon emissions is captured, though not as precise.

Finally, through Exiobase, I end with data on the total carbon emissions of each product produced by each country in each year from 2002-2010. This will later be mapped and merged onto BACI data, which provides trade flow data.

3.1.2 BACI Database: Trade Flows

BACI is a data set by CEPII that provides yearly data on bilateral trade flows at the product level for more than 5000 products and 200 countries, classified using the Harmonized System (HS) which is the standard nomenclature used in international trade. Up until the 6-digit level, HS codes are standard across all countries. I will be using the BACI version provided for the 2002 HS revision, which includes data for years 2002-2019. The dataset contains variables on Year, Product category (HS 6-digit code), Exporter (ISO 3-digit country code), Importer (ISO 3-digit country code), Value of trade flow (in $1000 USD), and Quantity (in tons). BACI consists of data reported by every country to UN Comtrade, and is freely available on the Internet. CEPII is a leading French centre supported by the French government for research on international trade, macroeconomics and finance.

BACI provides me with my outcome variable, trade flow (in dollars). I proceed to merge BACI with Exiobase through the following. Using a concordance table provided by Exiobase, I firstly map Exiobase product codes to their respective HS-6 code in BACI. Due to the high number of BACI products compared to Exiobase product specifications, there are many different BACI products that have the same carbon emissions associated with them – this results in error, but for the purposes of observing patterns, I believe that the differences in carbon intensity between similar products in the same industry from the same country vary little.

Using the dataframe generated from the earlier Exiobase section, I merge total direct carbon emissions to each product in BACI, indexing on the exporting country of the bilateral flow (as carbon emissions embodied in trade flows are dependent on the country of origin, not the destination country). Then, grouping by year, importer, and HS-6 code, I first sum the total quantity imported, and second take the weighted average (by quantity traded) of carbon emissions of all exporters of that product to that country in that year. **For simplicity, I will refer to this weighted average as Mean Emissions throughout the rest of the paper.**

Lastly, I create a new column called Emissions Rate that is calculated by dividing the weighted mean carbon emissions by the total quantity imported. This emissions rate is a useful metric that controls for between-country differences in absolute trade flows. I use both the Emissions Rate and Mean Emissions in my estimations, which I will elaborate upon through a data visualization as well as in the Results section.

3.1.3 Institutional Quality (IQ) Dataset

The Institutional Quality Dataset, covering up to 197 countries and territories from 1990 to 2010, was created by Aljaz Kuncic, who currently works at the United Nations and previously was faculty at University of Ljubljana. Kuncic utilizes over 30 established institutional indicators and clusters them into three general categories: legal, political and economic. The indicators are obtained from sources such as Freedom House, Fraser Institute, ICRG, and UN sources. Kuncic further clusters countries hierarchically into 5 categories depending on the strength of their institutional quality.

Examples of what each institutional quality indicator measures is in Table 1. I use all three institutional quality indicators in my dataset, through a simple data transformation by mapping them by Year and Country. However, at a glance, some parts of institutional quality seem to be directly irrelevant to international trade, which may potentially bias the results of my empirical strategy – for example, civil liberties and freedom of the press. However, they can still be potentially good proxies for a country's general institutional strength from a holistic perspective. Additionally, the three measures I use are absolute measures, which only reflect internal institutional changes that reflect how countries are doing in time in relation to itself and not other countries. Thus, importer fixed effects can be applied later on.

Table 1: Examples of Institutional Proxies

Economic IQ	Legal IQ	Political IQ
Financial freedom	Property rights	Democratic accountability
Business freedom	Legal environment	Corruption
Regulatory quality	Civil liberties	Bureaucratic quality
Freedom of the press	Law and order	Internal conflict
Investment profile	Rule of law	Political environment

Note: These are select examples of proxies for institutional quality used by Kuncic.

3.2 Data Analysis (Sources of Variation)

3.2.1 Institutional Quality (IQ)

How much does institutional quality vary over time in countries? The question of what variation exists is important to understand. In Table 2, I create summary statistics of all explanatory variables and the outcome variable, and organize by IQ cluster. There is apparent cross-sectional variation in IQs between countries in different clusters in my data, which can be observed through the different means in each cluster. However by observing the number of observations per cluster, I can see that I have a diverse distribution of IQ levels, but there seems to be more observations among countries in clusters 4 and 5, which is biased towards countries with higher IQ. There is a smaller sample size of lower IQ countries, which may affect the robustness of my cross-sectional analysis between countries. Nonetheless, the diverse distribution of IQs allows me to observe cross-sectional differences between countries.[2]

Beyond cross-sectional variation, it is important to consider panel variation in institutional quality. I consider Table 3, which provides me with the countries with the most variation in IQ from 2002-2010, as well as their general level of IQ through their cluster. Among countries with high variation, there are a variety of clusters represented, which suggests that changes in IQ may be independent of the absolute degree of IQ. This may help me come to a more robust association in my robustness check, as the changes in IQ are slightly more randomized and not biased towards a certain group of countries. Additionally, the smaller standard deviations inform me that the IQ variance within the countries over time is smaller than the variation in means between cross-sectional comparisons. This is expected, as institutional qualities can vary greatly between countries with different histories, political structures, and income, whereas these factors are largely controlled over a period of 9 years within countries.

3.2.2 Measuring Carbon Intensity of Imports: Mean vs. Rate

Looking at Table 2, the Emissions Rate mean and Mean Emissions mean vary across different clusters of IQ. This suggests that there is cross-sectional variation across countries, which suggests

[2]In unreported results, I observe summary statistics of all variables for years 2002, 2006 and 2010 and find that cross-sectional variation in IQ stays consistent.

Table 2: Summary Statistics by IQ of Importer

	Count	Mean	SE of Mean	Std. Dev.
Cluster 1				
Mean Emissions	75936	4.10e+11	3.83e+10	1.05e+13
Emissions Rate	75931	4.18e+07	1128839	3.11e+08
Import Trade Flow	75931	5.599268	.0116877	3.220617
Legal Institutional Quality	75936	.4191467	.0001191	.0328244
Political Institutional Quality	75936	.3894164	.0003687	.1015892
Economic Institutional Quality	75936	.4428006	.0001622	.0447087
Cluster 2				
Mean Emissions	266621	3.38e+11	2.92e+10	1.51e+13
Emissions Rate	266602	3.25e+07	445566.8	2.30e+08
Import Trade Flow	266602	5.07758	.0059434	3.068773
Legal Institutional Quality	266621	.5301264	.0001154	.0595829
Political Institutional Quality	266621	.5652401	.0001819	.093941
Economic Institutional Quality	266621	.548889	.0001542	.0796307
Cluster 4				
Mean Emissions	607836	1.01e+11	1.67e+10	1.30e+13
Emissions Rate	607764	1.84e+07	159778.3	1.25e+08
Import Trade Flow	607764	4.763896	.0042901	3.344552
Legal Institutional Quality	607836	.7149566	.0000846	.0659282
Political Institutional Quality	607836	.7312557	.0000467	.0363988
Economic Institutional Quality	607836	.7166848	.0000662	.051609
Cluster 5				
Mean Emissions	541728	1.46e+11	3.91e+10	2.88e+13
Emissions Rate	541699	2.27e+07	175804.4	1.29e+08
Import Trade Flow	541699	5.5469	.0044134	3.248263
Legal Institutional Quality	541728	.9010721	.0000562	.0413959
Political Institutional Quality	541728	.8566012	.0000554	.0407763
Economic Institutional Quality	541728	.8134843	.0000624	.045953
Total				
Mean Emissions	1492121	1.76e+11	1.67e+10	2.04e+13
Emissions Rate	1491996	2.37e+07	134082.1	1.64e+08
Import Trade Flow	1491996	5.146747	.0026814	3.27524
Legal Institutional Quality	1492121	.7344468	.0001316	.1607344
Political Institutional Quality	1492121	.7297022	.0001152	.1407796
Economic Institutional Quality	1492121	.7079077	.0001011	.1235306

Notes: Cluster 1 represents countries with the lowest IQ and Cluster 5 represents countries with best IQ. Clusters were generated by Kuncic through hierarchical clustering with Euclidean distance and Ward's error sum of squares method. Cluster 3 is missing because the countries in the cluster are not present in my trade and carbon data – there are only 12 countries in Cluster 3.

Table 3: Countries with Top 5 IQ Variation

Country	Std. Dev.	Cluster
Panel A. Economic IQ		
Malta	0.076062	4
Cyprus	0.049432	4
South Korea	0.042191	4
Luxembourg	0.040783	5
Bulgaria	0.038901	2
Panel B. Legal IQ		
Turkey	0.041209	2
India	0.035932	2
Lithuania	0.034875	4
Italy	0.034095	4
Portugal	0.033425	4
Panel C. Political IQ		
Indonesia	0.053884	1
India	0.039375	2
Russia	0.022271	2
France	0.022229	4
Turkey	0.021672	2

Notes: Standard deviation is measured in same unit as IQ. Variation is from 2002-2010.

promise for cross-sectional exploration.

Consider the difference between Mean Emissions and Emissions Rate, two key explanatory variables that represent carbon intensity in different ways. Mean Emissions is a weighted average (by trade quantity) of tons of carbon emitted by all exporters for an imported good, whereas Emissions Rate transforms this into a rate by dividing by quantity imported, giving the mean total tons of carbon emitted per unit of imported good. Countries have larger absolute Mean Emissions, but after dividing by quantity imported, their Emissions Rate is always lower – however, the relative decrease in Emissions Rate is a source of variation between countries, since some countries may not necessarily see as large of a decrease between the two measures as others. For example, they may not import large quantities of dirty goods but if they do, they primarily import from countries with dirty production.

To understand this difference, in Figures 1 and 2, I use hierarchical clustering with the Euclidean distance measure across both rows and columns to plot heat maps with Product Industry on the x-axis and Importer on the y-axis. I first observe Figure 1, which plots the Z-score of Total Mean Emissions of all exporters. It can be observed that there are clear horizontal clusters at the top and bottom of the heat map: the first cluster being China, Canada, India, Australia, Indonesia and the second cluster being the USA, South Korea, Japan, and Mexico. During 2002-2010 many of these countries were among the world's top import partners, despite India and Indonesia being exceptions. Thus, the higher Total Mean Emissions for certain countries can generally be explained by between-country differences in absolute quantity of trade flows, but further investigation will be required.

In Figure 2, the clusters are much less apparent, which suggests that there is variation in the relative decrease after calculating Mean Emissions to Emissions Rate for countries (otherwise, the clusters from the previous heat map would still be largely intact). Countries like Luxembourg and Malta now have relatively higher Emissions Rates represented by darker colours compared to the population mean, despite being far away from the clusters in Figure 1. Interestingly, it was shown earlier in Table 2 that Luxembourg and Malta also had some of the highest variation in IQ. This presents another potential research question, which is whether countries that vary the most in their IQ over time also tend to have dirtier imports.

In general, Figures 1 and 2 show that there is interesting variation in carbon imports. This will be explored further in the Results section.

4 Empirical Strategy

4.1 Econometric Design

I will be using ordinary least squares (OLS) regressions with interactions and importer fixed effects. I will investigate the research question using both cross-sectional and panel variation. Additionally, to extend my findings, I will be utilizing both a dummy variable and a continuous variable

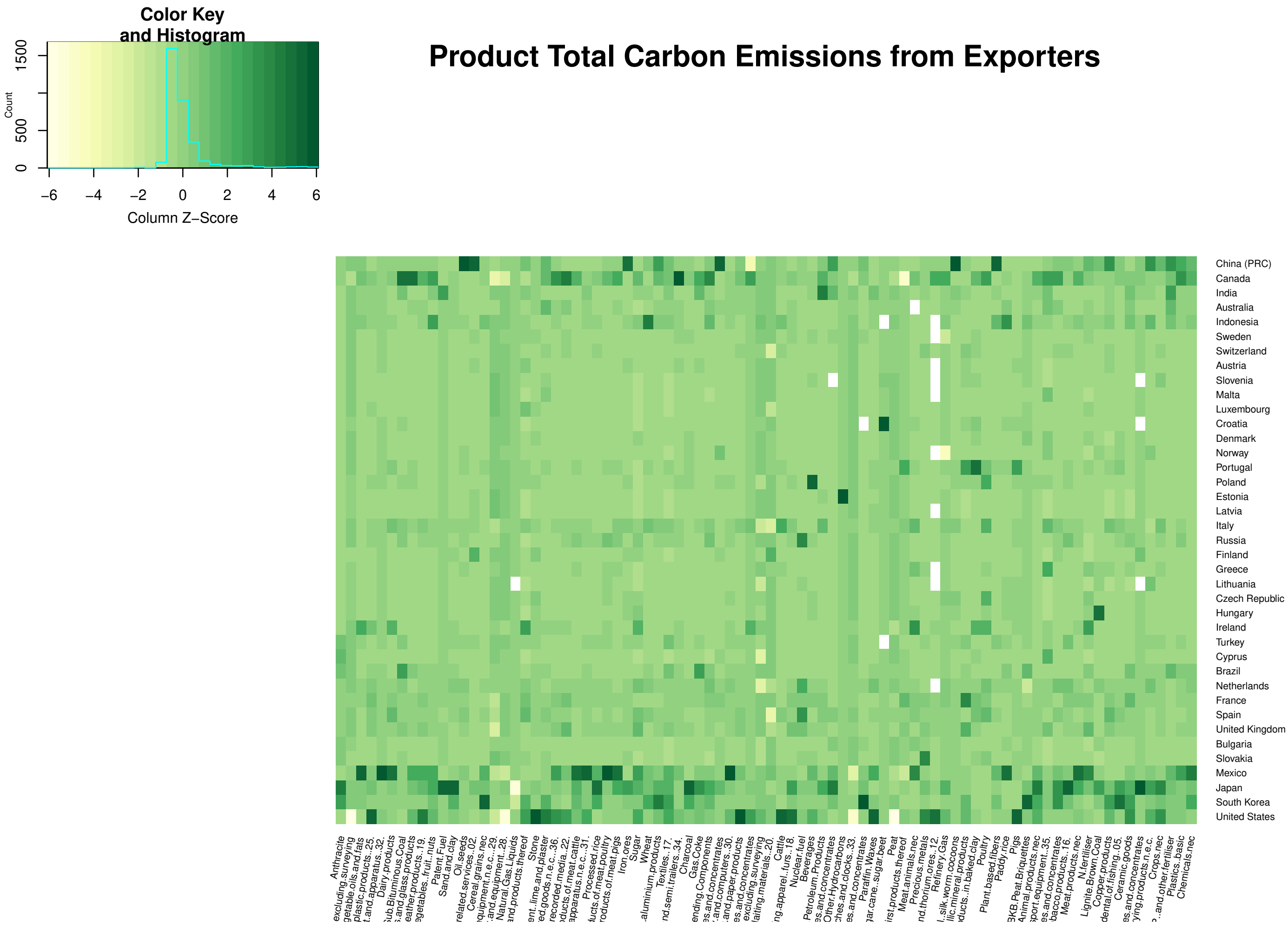

Figure 1: Heat map with each grid representing the Z-score (deviation from the mean) of the total mean carbon emissions of a product imported to a country. Horizontal clusters are found both at the top and bottom of the graph. The clusters mostly include the world's largest importers during 2002-2010 but also a select few outliers, such as India and Indonesia.

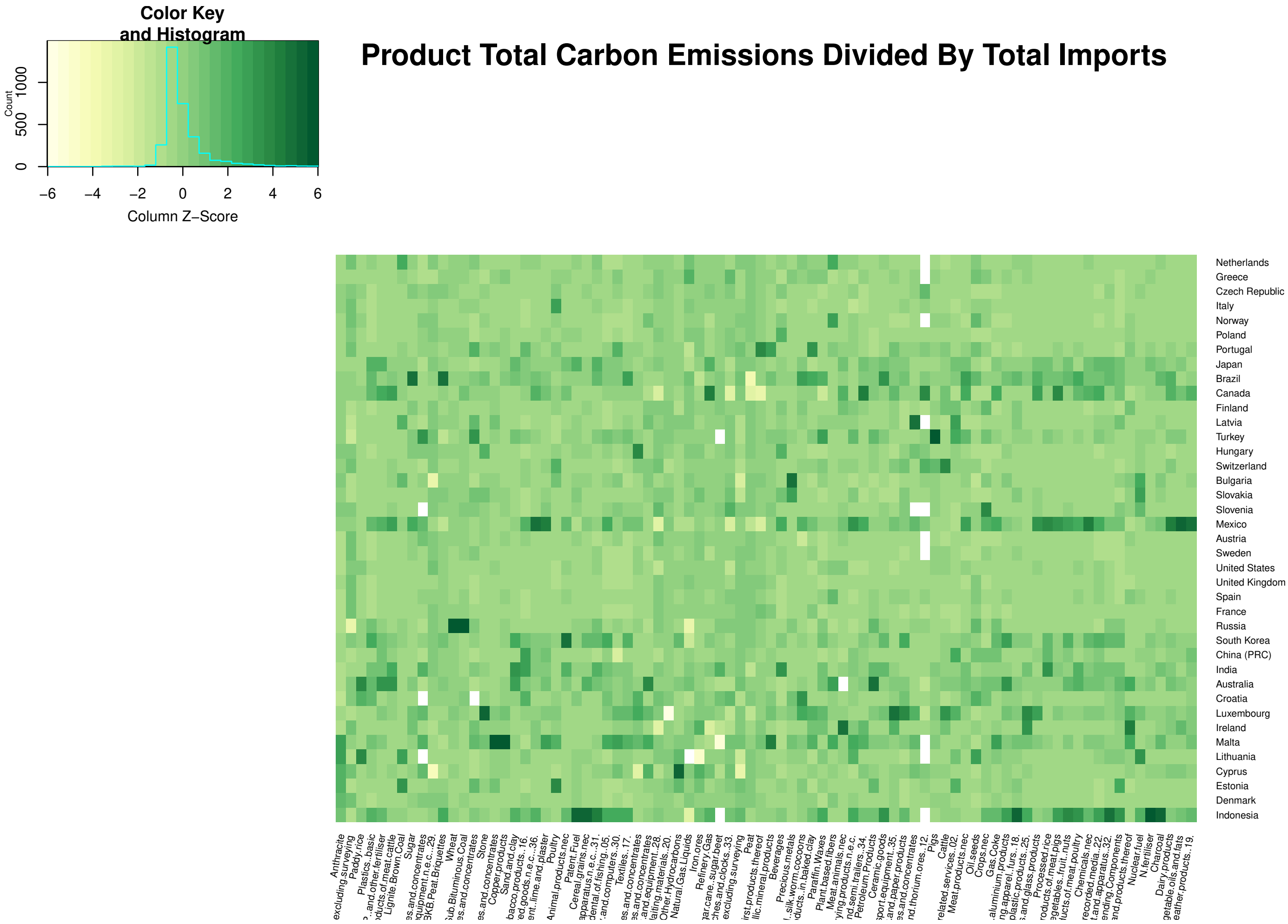

Figure 2: Heat map with each grid representing the Z-score (deviation from the mean) of the emissions rate of a product imported to a country. The horizontal clusters are largely gone and replaced with a more dispersed distribution of dark colours, suggesting that calculating emissions rate from mean carbon emissions “levels the playing field” for countries that simply just have large trade flows. Interestingly, some countries which had lighter colours horizontally in Figure 1 now have darker colours, notably Luxembourg and Malta, who also had among the highest variation in IQ from Table 2.

Table 4: Carbon Intensity of Cleanest and Dirtiest Products in Global Data

HS Code	Product Name	Total Mean Carbon Emissions
	Panel A. Dirtiest products	
270111	Anthracite Coal	1.119×10^{17}
230400	Soya-bean oil-cake and other solid residues	2.354×10^{16}
120810	Flours And Meals Of Soybeans	1.374×10^{16}
310530	Diammonium Hydrogenorthophosphate	1.011×10^{16}
150200	Bovine, sheep and goat fats, raw or rendered	4.697×10^{15}
	Panel B. Cleanest products	
722620	Flat-rolled high-speed steel products	1,062,812.8
722520	Flat-rolled products of other alloy steel	2,062.696
722694	Flat-rolled alloy steel nesoi, plated zinc	102.47949
722693	Flat-rolled alloy steel nesoi, electrolytically plated or zinc coat	78.874539
722910	Wire of high-speed steel	43.570097

Notes: This table can be used for reference in the heat maps. Total Mean Carbon Emissions is calculated as the total sum of all Mean Emissions values of all 39 importers in the data set.

for carbon intensity of imports for separate regressions, and I will also be conducting separate regressions using Mean Emissions and Emissions Rate as explanatory variables.

Before I begin my main estimating equation, I will estimate naïve separate regressions for each institutional quality variable to test which variable has additional explanatory power for carbon-intensive trade flows beyond the other variables. I aim to find whether all three IQ variables move in unison, or have different effects on carbon-intensive trade flow.

Lastly, I will also conduct a robustness check on my panel variation regression by utilizing 12 countries from Table 2 with the highest degree of variation in IQ.

4.2 Estimating Equations

My main estimation will be the following regression:

$$ln(Y_{gi,y}) = \alpha_{ig} + \beta_1 L_{i,y} + \beta_2 E_{i,y} + \beta_3 P_{i,y} + \beta_4 D_{gi,y} + \beta_5 (D_{gi,y} \times L_{i,y}) + \beta_6 (D_{gi,y} \times E_{i,y}) + \beta_7 (D_{gi,y} \times P_{i,y}) + \epsilon_{ig} \quad (1)$$

where $ln(Y_{gi,y})$ = the log-transformed trade flow of good g to a country i in year y. $Y_{gi,y}$ is thus log-normal. This allows us to interpret coefficients as the predicted change in log of $Y_{gi,y}$ with respect to a one-unit increase in an explanatory variable, holding all other variables fixed. $L_{i,y}$ represents the legal institutional quality of that country in year y, $E_{i,y}$ is economic institutional quality, and $P_{i,y}$ is political institutional quality. In a dummy variable regression, $D_{gi,y}$ equals 1 if the imported product to the country is considered carbon-intensive, which means it is in the top quartile of total mean emissions of all products in the data. There are interactions between the carbon intensity dummy and institutional quality indicators, which allows me to consider the effect of institutional quality on trade flow of the goods with the highest carbon intensity.

4.2.1 Continuous Interaction

In separate regressions, $D_{gi,y}$ becomes a continuous variable for either Mean Emissions or Emissions Rate, rather than a dummy variable. This allows for me to observe marginal effects of how IQ on trade flow depends on the carbon intensity of the good, alike to cross partial derivatives.

4.2.2 Importer Fixed Effects

Importer fixed effects are added for panel analysis, but are omitted for cross-sectional analysis. For cross-sectional analysis, "snapshots" of equation (1) will be estimated for each year individually. Additionally, the OLS regression will be estimated without FE to allow for cross-country examination. Sources of variation were mentioned in the previous section.

4.2.3 Naive Regressions

In my naive regressions prior to the main estimating equation, I will be estimating for each individual IQ:

$$ln(Y_{gi,y}) = \alpha_{ig} + \beta_1 L_{i,y} + \beta_2 C_{gi,y} + \beta_3 (C_{gi,y} \times L_{i,y}) + \epsilon_{ig} \tag{2}$$

where $L_{i,y}$ corresponds to either economic, legal or political IQ and $C_{gi,y}$ is a continuous variable for Mean Emissions or Emissions Rate.

4.3 Identification Assumptions

A causal effect can only be claimed in the panel regression, as the cross-sectional regression without importer fixed effects generates omitted variable bias. When importer fixed effects are added, the source of variation in the model is focused on within-country variation over time rather than cross-sectional between-country variation. I assume that there are potential characteristics of countries that may bias the outcome variable, such as general income and country location, which are proven in past research to be correlated to trade flow. Thus, by adding fixed effects, I can make these characteristics time-invariant to focus on the impact of IQ's variation on carbon-intensive imports over time. The identifying assumption of importer FE thus relies on the fact that the characteristics of countries that may impact their carbon trade flows are time-invariant. I would need to assume that in the nine years from 2002-2010, income levels of countries are largely consistent, and country location always stays constant. Secondly, when importer FE are added, it is important to assume that the time-invariant characteristics of each country are unique to the country itself and not correlated to others. If this assumption is satisfied, then it would be more plausible to assume that variation in IQ may be isolated and a causal inference can be made.

However, in this paper, it is difficult to satisfy the identification assumption, as changes in GDP do not stay constant over years, and there is a high likelihood of omitted variable bias even with fixed effects. This includes (but is not limited to) factors such as technology advancement, resource scarcity, and natural weather disasters. In this case, the main goal of the paper would be to form descriptive associations rather than a causal relationship, which would still provide facts that can be beneficial for consideration. I will discuss ways to potentially enhance the likelihood for causal inference in the Conclusion section.

5 Results

This section will begin with naive, panel and cross-sectional regressions using Mean Emissions as the explanatory variable for carbon intensity. Then to extend upon the validity of the findings, Emissions Rate will be used in panel and cross-sectional regressions. Regressions without FE allow for cross-country variation, whereas regressions with FE focus on variation in IQ. Lastly, a robustness check will be performed with the countries that have the highest variation in IQ values.

5.1 Mean Emissions

Mean Emissions is used as the explanatory variable for carbon intensity. A dummy variable is also derived from Mean Emissions to categorize the top 25% of dirty goods by their mean emissions.

5.1.1 Naive Regressions

Table 5 shows separate regressions of each IQ explanation on log import trade flows. This allows me to observe which of the IQ variables most attenuates the estimated coefficient for Mean Carbon Emissions on import trade flows. Due to the presence of OVB, I will not focus on the statistical significance of the coefficients, but rather focus on observing that legal IQ leads to the largest attenuation in the explanatory power of Mean Carbon Emissions.

5.1.2 Panel Regressions with OLS and FE

Table 6 estimates four regressions: (1) OLS with Mean Emissions, (2) OLS with Carbon Dummy, (3) OLS with Mean Emissions and Fixed Effects, and (4) OLS with Carbon Dummy and Fixed Effects. Columns (3) and (4) focus on within-country variation, whereas columns (1) and (2) are focused on cross-sectional variation. By comparing regressions with interactions on either a dummy or continuous variable, I can distinguish between countries' effects towards the dirtiest goods only, versus countries' general effects towards carbon imports. The interactions represent the additional effect of carbon emissions on import trade flow for three different IQs.

In column (1) and (3), the interpretation of the interaction estimates are different from column (2) and (4). Because column (1) uses a continuous $\times$ continuous interaction term, the interpretation is similar to considering cross partial derivatives: the marginal effect of IQ on import trade flow depends on the carbon intensity of the good. For instance, in the economic IQ interaction of column (1), the effect of economic IQ on import trade flow is negatively dependent on mean carbon emissions, which implies that the effect of economic IQ will be lower when mean carbon emissions is higher. Thus, the effect of economic IQ on the outcome variable decreases at a statistically significant rate at the 5% level if mean carbon emissions is high. In both columns (1) and (3), with and without

Table 5: Institutional Quality Explanations for Carbon-Intensive Imports

	(1)	(2)	(3)
Mean Carbon Emissions	3.03e-14***	2.96e-14***	3.04e-14***
	(5.92e-15)	(4.10e-15)	(4.57e-15)
Economic Institutional Quality	0.387***		
	(0.0215)		
Mean Carbon Emissions × Economic Institutional Quality	-3.54e-14***		
	(7.38e-15)		
Legal Institutional Quality		0.286***	
		(0.0163)	
Mean Carbon Emissions × Legal Institutional Quality		-3.35e-14***	
		(5.53e-15)	
Political Institutional Quality			-0.696***
			(0.0184)
Mean Carbon Emissions × Political Institutional Quality			-3.64e-14***
			(6.46e-15)
Constant	4.872***	4.935***	5.653***
	(0.0153)	(0.0122)	(0.0136)
Observations	1491996	1491996	1491996

Notes: Dependent variable in all regressions is total imports of a good in a country in a year. Robust standard errors. Standard errors in parentheses.
* $p < .10$, ** $p < .05$, *** $p < .01$

fixed effects, when countries generally import a cleaner good the effect of economic IQ increases the import trade flow of the good. Since this continuous $\times$ continuous interaction is statistically significant in both columns, it can be inferred that in both cross-sectional and panel variation, there is a negative association between economic IQ and carbon-intensive trade flows.

The interaction estimates in column (2) provide me with the differential effect of IQs for only products that are very dirty (have mean emissions in the top quartile of all products in the data set). When goods are dirty, the effect of legal IQ predicts an expected change of -1.58 in log import trade flow, which implies that legal IQ has a negative association with the outcome and lowers trade flow of the dirtiest goods. On the other hand, for both political and economic IQ, there is a positive association with carbon-intensive trade flow. Due to OVB, it is unlikely that these are causal inferences, as the variation is dependent on cross-sectional variation without FE.

When looking at within-country variation in columns (3) and (4), the estimates are only significant for interaction effects of economic IQ for goods of all carbon intensities, which implies that the effect of economic IQ on carbon imports will be lower when mean carbon emissions is higher. However, the estimates are all significant for interaction effects of all IQs when observing the dummy interaction effects on the most dirtiest imported goods in column (4), with legal IQ having a negative effect and political IQ having a positive association with carbon-intensive goods.

In summary, in both within-country and between-country variations, economic IQ seems to have a significant negative association with imports that have greater mean emissions. Within countries, political IQ has a significant positive association with the dirtiest imports only, and legal IQ has a significant negative association with the dirtiest imports only. Across countries, this pattern is identical. All values for political and legal IQ are significant at the 1% level.

5.1.3 Cross-sectional Regressions by Year

How does IQ of different countries impact carbon trade flows in each year individually, and is it consistent? To make the cross-sectional analysis more granular, I estimate the regressions without FE for each year separately to observe the consistency of both the continuous and dummy interaction terms for each IQ over time. The interaction estimates in Table 7 and 8 show different results. Table 7 shows values of continuous $\times$ continuous interaction estimates using Mean Emissions, which were

Table 6: Association of Imports and Carbon Emissions with IQ, 2002-2010

	OLS		FE	
	(1)	(2)	(3)	(4)
Mean Carbon Emissions	2.85e-14***	1.548***	2.75e-14***	2.018***
	(4.69e-15)	(0.0287)	(4.59e-15)	(0.0284)
Economic Institutional Quality	3.071***	2.045***	0.700***	0.604***
	(0.0448)	(0.0628)	(0.0966)	(0.0966)
Legal Institutional Quality	5.003***	4.600***	1.869***	2.552***
	(0.0433)	(0.0622)	(0.118)	(0.116)
Political Institutional Quality	-8.307***	-7.635***	0.975***	-0.852***
	(0.0527)	(0.0794)	(0.163)	(0.160)
Legal Institutional Quality × Mean Carbon Emissions	-2.11e-14	-1.584***	-1.53e-14	-2.335***
	(1.55e-14)	(0.0770)	(1.46e-14)	(0.0758)
Political Institutional Quality × Mean Carbon Emissions	1.94e-14	2.006***	1.07e-14	3.755***
	(1.44e-14)	(0.0964)	(1.33e-14)	(0.0944)
Economic Institutional Quality × Mean Carbon Emissions	-3.03e-14**	1.585***	-2.69e-14**	-0.715***
	(1.38e-14)	(0.0780)	(1.28e-14)	(0.0758)
Constant	5.358***	4.406***	2.383***	1.929***
	(0.0152)	(0.0241)	(0.153)	(0.141)
Observations	1491996	1491996	1491996	1491996

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: FE columns represent an OLS regression with importer (country) fixed effects. The left column represents the explanatory carbon intensity variable as a continuous variable (Mean Carbon Emissions), and the right column represents the variable as a dummy variable that equals 1 when Mean Carbon Emissions are in the top quartile of the data.

interpreted previously in Table 6. Of note in Table 7 is that for most years, the economic IQ interaction is statistically significant, whereas this is not true for political nor legal IQ. Although the sign of the estimate changes over time, the statistical significance suggests that when analyzing countries in a cross-section, economic IQ has a greater marginal effect on impacting carbon-intensive trade flows in terms of mean emissions of the good. For most years, this interaction effect seems to be negative.

On the other hand, for Table 8, which features dummy $\times$ continuous interaction estimates using Carbon Dummy and focuses solely on goods that have the highest mean emissions, the values for the economic IQ interaction are statistically significant and positive, suggesting that when analyzing countries in a cross-section, economic IQ increases the prediction of importing the dirtiest goods. Additionally, for legal and political IQ interactions, the estimates are not consistently significant across years. This could be due to confounding effects of year variation, causing endogeneity. Interestingly, the legal IQ interaction estimates are statistically significantly negative, or are insignificant, implying that for the dirtiest good import trade flows, legal IQ tends to predict a negative additional effect. The political IQ interaction estimates are often insignificant, and are usually insignificant in years when legal IQ is insignificant as well. This suggests potential collinearity between the variables, but it is nonetheless still important to include both variables for explanatory reasons, and the collinearity is not severe since there are years where political and legal IQ have different significance levels.

Table 7: Association of Imports and Carbon Emissions with IQ, by year

	(1) 2002	(2) 2003	(3) 2004	(4) 2005	(5) 2006	(6) 2007	(7) 2008	(8) 2009	(9) 2010
Legal IQ	7.357***	5.892***	9.450***	6.437***	5.150***	2.630***	1.668***	2.596***	4.466***
	(0.129)	(0.123)	(0.125)	(0.144)	(0.132)	(0.130)	(0.129)	(0.132)	(0.139)
Political IQ	-11.78***	-12.07***	-12.64***	-8.094***	-8.751***	-5.008***	-4.358***	-5.055***	-7.522***
	(0.149)	(0.155)	(0.181)	(0.184)	(0.163)	(0.151)	(0.158)	(0.153)	(0.153)
Economic IQ	5.794***	7.033***	2.082***	0.931***	3.221***	1.626***	1.926***	1.765***	2.179***
	(0.134)	(0.118)	(0.141)	(0.138)	(0.130)	(0.133)	(0.135)	(0.147)	(0.143)
Mean CE	-1.33e-14	2.63e-14***	2.37e-14***	2.65e-14***	4.74e-14***	7.25e-14***	1.06e-13***	4.93e-14**	7.16e-14***
	(1.56e-14)	(7.09e-15)	(6.90e-15)	(7.07e-15)	(9.94e-15)	(1.69e-14)	(1.89e-14)	(1.94e-14)	(2.11e-14)
Legal IQ × CE	2.18e-14	-2.91e-14	-1.54e-14	-1.92e-14	4.20e-14	1.79e-14	1.45e-14	-6.80e-14	-2.02e-13***
	(2.95e-14)	(4.35e-14)	(2.41e-14)	(3.14e-14)	(2.59e-14)	(3.14e-14)	(3.27e-14)	(5.76e-14)	(5.26e-14)
Political IQ × CE	-9.35e-14*	-6.66e-15	2.14e-14	5.93e-14**	-2.97e-14	5.50e-14	5.26e-14	9.34e-14	1.69e-13***
	(5.21e-14)	(4.22e-14)	(2.77e-14)	(2.88e-14)	(3.15e-14)	(6.10e-14)	(7.95e-14)	(7.44e-14)	(6.34e-14)
Economic IQ × CE	1.03e-13**	4.94e-15	-3.21e-14	-6.75e-14***	-7.24e-14***	-1.62e-13***	-1.96e-13***	-6.00e-14	-3.80e-14
	(5.23e-14)	(2.94e-14)	(2.21e-14)	(2.33e-14)	(1.56e-14)	(4.80e-14)	(5.95e-14)	(8.57e-14)	(6.76e-14)
Constant	4.116***	4.593***	5.899***	5.500***	5.416***	5.855***	5.952***	5.716***	6.003***
	(0.0430)	(0.0429)	(0.0425)	(0.0449)	(0.0450)	(0.0486)	(0.0463)	(0.0500)	(0.0498)
Observations	168977	169423	169911	169688	169891	162690	161198	159838	160380

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: Association of Imports and Carbon Emissions with IQ, by year

	(1) 2002	(2) 2003	(3) 2004	(4) 2005	(5) 2006	(6) 2007	(7) 2008	(8) 2009	(9) 2010
Legal IQ	6.470***	5.525***	8.386***	5.811***	5.507***	2.473***	1.461***	2.060***	4.153***
	(0.180)	(0.174)	(0.176)	(0.207)	(0.200)	(0.193)	(0.197)	(0.189)	(0.202)
Political IQ	-10.49***	-11.18***	-10.91***	-6.867***	-8.802***	-4.449***	-3.865***	-4.417***	-7.351***
	(0.217)	(0.228)	(0.270)	(0.274)	(0.259)	(0.234)	(0.253)	(0.232)	(0.233)
Economic IQ	4.700***	5.917***	0.816***	-0.564***	2.054***	0.231	0.585***	0.963***	1.319***
	(0.174)	(0.151)	(0.200)	(0.195)	(0.189)	(0.195)	(0.205)	(0.216)	(0.214)
Carbon Intensity Dummy	1.878***	1.788***	1.327***	1.289***	1.484***	1.139***	1.189***	1.520***	1.278***
	(0.0778)	(0.0796)	(0.0804)	(0.0843)	(0.0863)	(0.0947)	(0.0927)	(0.0967)	(0.0970)
Legal IQ × Dummy	-2.493***	-2.586***	-3.102***	-1.882***	-2.776***	-0.558**	0.244	0.296	-0.833***
	(0.229)	(0.218)	(0.221)	(0.256)	(0.241)	(0.235)	(0.237)	(0.235)	(0.248)
Political IQ × Dummy	2.992***	3.938***	2.110***	0.455	3.254***	0.410	0.00709	0.385	2.191***
	(0.270)	(0.282)	(0.331)	(0.334)	(0.307)	(0.280)	(0.299)	(0.281)	(0.281)
Economic IQ × Dummy	0.846***	-0.0277	3.208***	3.952***	1.744***	2.727***	2.232***	1.439***	1.119***
	(0.225)	(0.200)	(0.248)	(0.241)	(0.231)	(0.238)	(0.246)	(0.263)	(0.259)
Constant	3.258***	3.670***	4.902***	4.651***	4.483***	5.043***	5.134***	4.686***	5.125***
	(0.0633)	(0.0655)	(0.0672)	(0.0704)	(0.0729)	(0.0806)	(0.0796)	(0.0818)	(0.0825)
Observations	168977	169423	169911	169688	169891	162690	161198	159838	160380

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

5.2 Emissions Rate

Emissions Rate is used as another explanatory variable for carbon intensity: the amount of carbon emitted per unit of imported good, which helps to control for between-country discrepancies in total trade flow. I believe that Emissions Rate may be a more robust explanatory variable for carbon intensity rather than Mean Emissions, because it provides a relative measure of a country's import carbon intensity to the amount they imported.

5.2.1 Panel Regressions with OLS and FE

Table 9 shows estimates for IQ interactions with Emissions Rate, with column (1) consisting of variation between countries and column (2) consisting of variation within countries. In column (1) it can be seen that all interaction terms are statistically significant. Due to the nature of a continuous $\times$ continuous interaction term, the marginal effect of IQ depends on the carbon intensity of the good, and I cannot interpret the estimate as the differential effect of IQ on carbon-intensive goods. For legal IQ in both columns (1) and (2), the interaction estimates are statistically significant and negative at the 1% level, suggesting that legal IQ's effect on import trade flow is negatively dependent on the emission rate of the good regardless of comparing legal IQ across countries (OLS) or variation of legal IQ within countries (FE).

In Table 9, political IQ's interaction effect is positive in column (1) which suggests that political IQ's effect on import trade flow is positively dependent on the emission rate of the good. Thus, in a cross-sectional analysis between countries, this estimate suggests that generally, countries with greater political IQ are more likely to increase imports of goods with higher emissions rates. However, in column (2), the political interaction term estimate is insignificant, which suggests that with regard to within-country variation, political IQ does not have any additional effect on imports when the emissions rate of the good is higher.

In Table 9, economic IQ's interaction effect is marginally statistically significant and positive in column (1), suggesting that between countries, economic IQ's effect on import trade flow is positively dependent on the emission rate. In column (2), the interaction effect is statistically significant and positive again, but instead suggests that within countries, an increase in economic IQ tends to positively affect the import of carbon-intensive goods measured through high emission rates.

Lastly, in Table 10, I observe the granularity of the cross-sectional regressions which allows me to view the statistical significance and direction of the estimates across years. The interaction estimates for legal IQ are statistically significant for all years except for 2010, and are all negative. This suggests that consistently through each year and across countries, legal IQ's effect on trade flow is negatively dependent on the emission rate of goods, implying that legal IQ is negatively associated with carbon-intensive goods as measured by emission rates. Additionally, economic IQ and political IQ interaction estimates are often insignificant in most years, suggesting that there is not a strong association between countries with high economic and political IQ and their carbon-intensive trade flow of imports.

Table 9: Association of Imports and Carbon Emission Rates with IQ

	(1) OLS	(2) FE
Emissions Rate	1.03e-10	-2.12e-10
	(1.81e-10)	(2.05e-10)
Economic Institutional Quality	2.993***	0.700***
	(0.0481)	(0.0987)
Legal Institutional Quality	5.159***	1.954***
	(0.0458)	(0.118)
Political Institutional Quality	-8.380***	0.941***
	(0.0549)	(0.164)
Legal Institutional Quality × Emissions Rate	-5.96e-09***	-4.11e-09***
	(7.38e-10)	(8.31e-10)
Political Institutional Quality × Emissions Rate	2.27e-09***	7.21e-10
	(8.10e-10)	(9.09e-10)
Economic Institutional Quality × Emissions Rate	1.53e-09*	1.81e-09**
	(8.26e-10)	(8.24e-10)
Constant	5.390***	2.404***
	(0.0160)	(0.153)
Observations	1491996	1491996

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 10: Association of Imports and Carbon Emission Rates with IQ, by year

	(1) 2002	(2) 2003	(3) 2004	(4) 2005	(5) 2006	(6) 2007	(7) 2008	(8) 2009	(9) 2010
Legal IQ	7.441***	6.017***	9.569***	6.593***	5.309***	2.961***	1.831***	2.738***	4.544***
	(0.135)	(0.126)	(0.127)	(0.145)	(0.136)	(0.139)	(0.133)	(0.134)	(0.142)
Political IQ	-11.86***	-12.16***	-12.61***	-8.186***	-8.835***	-5.168***	-4.459***	-5.039***	-7.465***
	(0.152)	(0.158)	(0.184)	(0.186)	(0.166)	(0.156)	(0.164)	(0.156)	(0.156)
Economic IQ	5.778***	6.987***	1.959***	0.880***	3.117***	1.415***	1.818***	1.585***	2.021***
	(0.139)	(0.122)	(0.147)	(0.142)	(0.137)	(0.138)	(0.143)	(0.151)	(0.150)
ER	-1.71e-10	-2.50e-10	8.03e-10***	1.62e-10	-6.83e-10	-8.96e-10	-4.37e-10	3.93e-10	4.31e-10
	(3.48e-10)	(3.71e-10)	(2.80e-10)	(4.86e-10)	(5.76e-10)	(7.36e-10)	(5.53e-10)	(5.02e-10)	(7.56e-10)
Legal IQ × ER	-3.60e-09*	-5.01e-09***	-4.16e-09***	-6.83e-09***	-6.22e-09***	-1.20e-08***	-4.69e-09***	-5.95e-09***	-9.32e-10
	(2.06e-09)	(1.66e-09)	(1.48e-09)	(1.16e-09)	(1.41e-09)	(2.18e-09)	(1.58e-09)	(1.38e-09)	(1.83e-09)
Political IQ × ER	3.30e-09*	3.08e-09*	-2.77e-09	3.16e-09	2.57e-09	4.91e-09**	2.64e-09	-1.02e-10	-5.07e-09***
	(1.88e-09)	(1.84e-09)	(2.17e-09)	(1.99e-09)	(1.87e-09)	(2.19e-09)	(2.20e-09)	(1.69e-09)	(1.86e-09)
Economic IQ × ER	-8.59e-10	-4.78e-11	3.87e-09	1.81e-09	2.34e-09	6.02e-09***	9.71e-10	2.42e-09	2.29e-09
	(1.58e-09)	(1.42e-09)	(2.60e-09)	(2.01e-09)	(2.04e-09)	(1.98e-09)	(2.05e-09)	(1.78e-09)	(2.02e-09)
Constant	4.145***	4.634***	5.910***	5.519***	5.476***	5.925***	6.020***	5.780***	6.073***
	(0.0438)	(0.0439)	(0.0429)	(0.0463)	(0.0473)	(0.0521)	(0.0493)	(0.0511)	(0.0529)
Observations	168977	169423	169911	169688	169891	162690	161198	159838	160380

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

5.3 Robustness Check

To determine the strength of a potential causality effect, in Table 11 I conduct a robustness check by estimating the OLS and FE regressions on the countries with the highest degree of IQ variation (Table 2). There are 12 countries included in this sample. Due to the small sample size and potential endogeneity caused by omitted variables, it is difficult to conclude any kind of causal effect that institutional quality may have on carbon-intensive imports. However, the robustness check has asserted that the legal IQ interaction estimate remains negative and statistically significant in both cross-country and within-country variations, which suggests that although it is difficult to claim causality, there is still an additional negative interaction effect between legal IQ and carbon-intensive trade flow. Political and economic IQ interaction estimates are now also statistically significant, but due to the smaller sample size, it is difficult to assert that this is an improved estimate over Table 9.

Table 11: Association of Imports and Carbon Emission Rates with Highest IQ Variation

	(1) OLS	(2) FE
Emissions Rate	-6.05e-10	-1.25e-09***
	(4.39e-10)	(4.25e-10)
Economic Institutional Quality	1.515***	2.323***
	(0.0750)	(0.126)
Legal Institutional Quality	1.203***	0.561***
	(0.0846)	(0.177)
Political Institutional Quality	-6.634***	2.152***
	(0.112)	(0.216)
Legal Institutional Quality $\times$ Emissions Rate	-5.16e-09***	-4.19e-09***
	(1.51e-09)	(1.34e-09)
Political Institutional Quality $\times$ Emissions Rate	7.40e-09***	6.05e-09***
	(2.21e-09)	(1.94e-09)
Economic Institutional Quality $\times$ Emissions Rate	-3.61e-09***	-1.64e-09*
	(1.03e-09)	(8.89e-10)
Constant	7.428***	0.798***
	(0.0295)	(0.148)
Observations	488123	488123

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

6 Conclusion

How does institutional quality of an importing country affect the environmental bias of trade? Legal institutional quality and political institutional quality generally have negative and positive associations respectively with dirty good imports across both emission rates and mean emissions, but economic institutional quality has opposite effects. This is surprising, as mean emissions and emission rates are closely related and should largely differ by magnitude, but not direction. An idea is that this could be because economic institutional quality is more closely related to trade, and some proxies for economic IQ are directly related to trade quantity. I believe that the model using emission rate is stronger, as the rate controls for relative trade quantity, which leads to the likelihood that economic institutional quality has a positive association with dirty good imports.

I find that legal institutional quality generally has a negative association with dirty good imports both within and across countries, and passes my robustness check. I also find that across countries, political institutional quality generally has a positive association with dirty good imports, but that association is not present in within-country variation. Lastly, economic institutional quality's effects on dirty trade flow differ depending on how mean carbon emissions are calculated, which requires more future research to understand. More research is also required to investigate the distribution of dirtiness of imports, such as through a categorical variable, because there may be potential evidence that countries may not be importing the dirtiest goods, but are importing goods that are in the mid-to-high range of emissions that are not captured. The limitations of a dummy variable interaction do not allow for this sensitivity analysis. To improve my estimation and work towards a causal inference, adding more controls such as GDP may help to reduce OVB. Possible avenues for future research include adding indirect carbon emissions to direct emissions, as well as adding the emissions of additional GHGs such as nitride oxide or methane, which have a much larger environmental footprint than carbon dioxide and are important to consider as well.

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