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Are the differences in the stringency of domestic environmental regulations affecting the bilateral trade of OECD countries?

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Abstract

The question of whether the stringency of domestic environmental regulations indeed interferes with trade is of growing interest for better policymaking. This paper re-examines the relationship between the stringency of environmental regulations and bilateral trade using a panel dataset consisting of 34 OECD countries over 7 years. Two different types of environmental measures based on energy intensity are constructed, representing 2 sources of differences in environmental regulatory stringency: the absolute difference between 2 countries and a country's relative stringency among 34 countries. Fixed-effects models, mixed-effects models and lagged dependent variable models are employed, respectively accounting for static country heterogeneity, poor variability of policy variables and serial correlation. The findings overall suggest that the differences in the stringency of environmental regulations indeed affect the bilateral trade of OECD countries in some circumstances, although somewhat deviating from the PHH prediction. From a relative perspective, stricter environmental regulations might reduce both exports and imports for the country, and the effect size is growing with GDP per capita. Further, a larger absolute difference in the stringency of environmental regulations between 2 countries is found to be correlated with higher bilateral trade values.

Keywords: Bilateral trade, Environmental regulation, Energy intensity, Gravity model, Panel data

JEL: F14, F18, Q48, Q56

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1 Introduction

Under the framework of Gravity trade model, this paper explores the relationship between the stringency of domestic environmental regulations and bilateral trade flows. More specially this paper intends to investigate: (1) if the stricter domestic environmental regulations would hamper bilateral trade flows as predicted by the *Pollution Haven Effect*; (2) if the effects of interest are uniform across countries or sensitive to the average income level; and (3) if the disparity in environmental regulations is related to the changes in bilateral trade flows. I construct the measures for the environmental regulatory stringency from energy intensity indicators through a ranking system used by Van Beers and Van den Bergh (1997) and Harris et al. (2002). A panel analysis is performed for 7 years from 2010 to 2016, and most OECD members are included in the study.

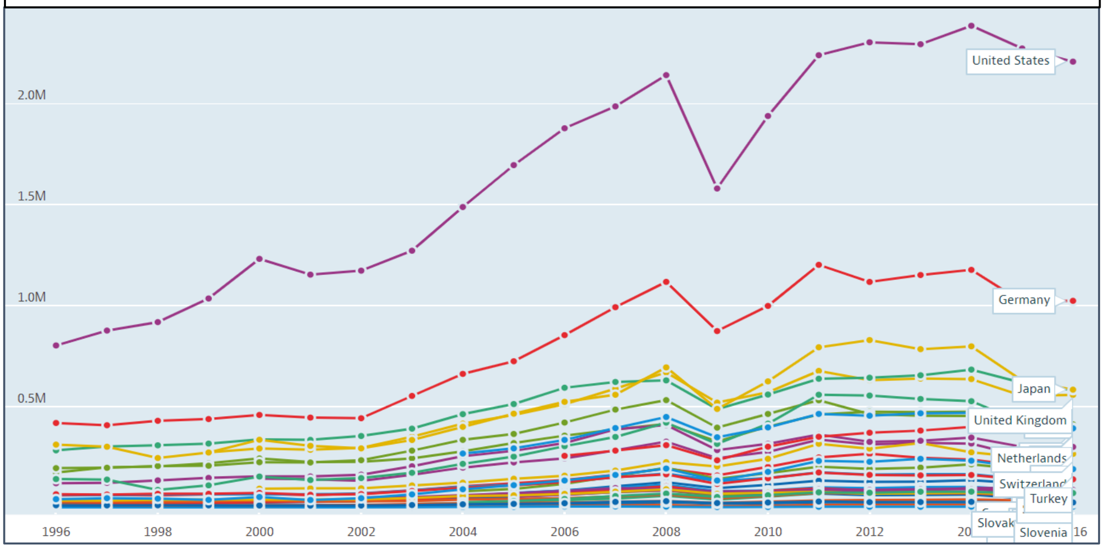
Over the past 2 decades, researchers have been trying to disentangle the relationship between economic development and environmental sustainability. The emphasis has been given to different aspects of the interaction between environmental issues and economic development, with different hypotheses being proposed, developed and examined. Some focus on the mechanism between economic development and environmental performance. For example, the Environmental Kuznets Curve (EKC) which posits that after a certain level of economic growth is attained the environmental situation will improve. Some other study recognizes the role of decreasing trade barriers in this process and points out a possible consequence of high environmental standards imposed on producers, which is that capital-intensive multinational enterprises are moving to undeveloped areas from better-regulated regions thanks to trade liberalization. This hypothesis is known as the Pollution Haven Hypothesis (PHH) and has also been studied extensively, sometimes in conjunction with EKC (Copeland and Taylor 2004) and often relative to Foreign Direct Investment (FDI). In the literature, both directions of the relationship between the environmental regulations and international flows have been largely discussed. The 2 theories listed jointly constitute a substantial piece of the economic-environmental topic. The EKC literature presents the long-lasting investigation of how different stages of economic prosperity feature the environmental quality (see e.g. Magnani 2000; Cole and Elliott 2003a; Copeland and Taylor 2004; Stern 2004), while the PHH addresses the question of how the environment-related costs, no matter in terms of money or opportunities, would affect trade and investment.

Of the two important questions, the latter may be more interesting as understanding how regulations may affect economic activities is directly linked with more efficient policymaking, and if the hypothesis holds, it would also be a candidate explanation for the inverted-U relationship proposed as the EKC (Grossman and Krueger 1995; Cole et al. 1997). Long since the early 1990s, various multinational agreements and international cooperation on environmental policymaking have been brought into play. With more and more international conferences and treaties occurring, environmental regulations and policies are thought to play a more instrumental role than ever. Notwithstanding more and more practices of abating environmental damage with domestic efforts, the concern arises that the increasingly strict environmental inspection and guidance would have associated negative effects on the economic activities, including trade. The Pollution Haven Hypothesis (PHH) has been a starting point for many studies in this narrower field (for instance, Mani and Wheeler 1998; Cole and Eilliot 2003b; Mulatu et al. 2010; Millimet and Roy 2016). In detail, it is proposed that high pollution control costs, or more generally strict environmental regulations within a country would harm domestic firms' comparative advantages and lower their international competitiveness, especially for polluting industries. This situation results in their relocation towards countries with lax environmental regulations for cost-saving reasons, typically from rich countries to poor areas, or North to South as the theory predicts. In a word, strict environmental regulations would lead to unidirectional cross-border investment because the they bring about an invisible disadvantage for firms to compete with other producers in international markets, known as the Pollution Haven Effect. However, the empirical investigation of the Pollution Haven effect doesn't find conclusive evidence in support of the theory. The explanations for empirical failures and shortcomings are widely discussed (for example see Millimet and Roy 2016).

To focus on the basics, a question to answer is if the relative stringency of environmental regulations of a country would indeed change domestic production conditions. In this regard, the impact of relative regulatory strictness on trade is worth studying for two reasons. First, trade is vital nowadays to a country's economy and environmental issues are of global concern. To sort out the environmental impact on bilateral trade helps to put the environmental policymaking in a more connected context. Second, bilateral trade serves as a good tool to aggregate production and consumption for any two countries and display changes, which allows for inference about a country's relative competitiveness in international markets and shed lights on the related topics. Apart from the basic question, it is implied in both EKC and PHH theories that the stringency of environmental regulations increases with income (Dasgupta et al. 1995). It would be also interesting to see whether the average income also plays a role in determining the environment-trade relationship. If the answer is positive, it would be ambiguous if the Pollution Haven Effect is mainly ascribable to the cost advantages associated with lax environmental regulations, or actually a combination of the income gap and lax environmental regulations. The assumption that the impact of environmental regulations on trade is uniform across countries of different income levels is debatable.

Cross-sectional analysis is more frequent in this field (for instance, Van Beers and Van den Bergh 1997; Busse 2004). Panel data have also been largely used in the broader field of trade, but not as popular on this specific topic until fairly recently. An example is that Levinson and Taylor (2008) use a 10-year panel data to study the US's environmental regulatory effects on trade within NAFTA. Also, Kahouli, Omri and Chaibi (2014) study the effects of environmental policies on international trade and FDI with a panel consisting of 14 home countries, 39 host countries and 22 years. Other examples are Xu (2000), Mulatu, Florax and Withagen (2004), Cole (2006) and Costantini and Crespi (2008). More attention now is paid to the potential dynamic effect of environmental policy changes and panel data can provide the dynamics. Serlenga and Shin (2007) argue that it is necessary for researchers to use panel data to answer the question interested. The motivation for employing a panel is twofold. Firstly, the conventional cross sections are unable to handle the bilateral heterogeneity which often involves important determinants of bilateral trade. Panel data allow researchers to make use of more sophisticated econometrical tools and models than OLS. For example, Kahouli et al. (2014) engage several classic panel models including fixed-effects, random-effect, and

Figure 1: Trade in goods (in terms of imports), million US dollars, 1996 – 2016



Data Source: Main Economic database
Indicators: Balance of payments BPM6

Hausman-Talyor regression. Secondly, in the era of globalization, countries are more connected, and the business cycle effects should not be neglected even in bilateral investigations. According to the general trade statistics chart of OECD countries over 20 years in Figure 1, the presence of business cycles is clear. The last reason for focusing merely on panel analysis is in relation to the minor goal of this study, to re-examine the cross-sectionally significant conclusion from Van Beers and Van den Bergh (1997) in the panel setting, bearing in mind the claim made by Harris et al. (2002) that the effects found are owing to the cross-sectional misspecification.

With the panel data available for a large number of countries from 2010 to 2016, I update and extend the work of Harris et al. (2002). I borrow the panel *Model B* from their paper, which includes a time fixed-effects component, as my baseline model. Starting from there, I augment the list of models with random-effect models and lagged dependent variable (LDV) models. Although the usage of LDV model is rather rare in the gravity model literature[1], I defend the appropriateness of some patterns of LDV model in this case. Except for the general effects of environmental regulations on trade, I also investigate the income-contingent effects. The interaction effects of average income level and environmental regulatory stringency on trade provides additional insights into understanding the relationship. A newly derived variable for the measurement of environmental disparity is experimented with as well.

Some interesting findings are obtained. Most importantly, stricter environmental regulations might impede both imports and exports although the effects are weak. It is also found that these effects are not uniform across country but increasing with the average income level of a country. The two findings together suggest that higher level of environmental regulatory strictness in a rich country would lead to decreases in both imports and exports, which may imply a higher level of self-reliance if the domestic demand is unharmed. Besides, some evidence is found to support that a country trades more with another when their environmental regulatory levels differentiate greatly. It is also concluded that serial correlation may be an important source of bias, admitted that the significant impact of domestic environmental regulations on trade is somewhat dependent on the model chosen, mostly confirming the claim of Harris et al. (2002).

[1] Lagged dependent variable approach are sometimes used in gravity setting but usually for the study of other domains of trade. For example, Nath (2009) incorporates LDV model in his paper and study the dynamic influence of trade and foreign direct investment (FDI) on growth of real GDP per capita.

The rest of the paper is structured as follows. In Section 2, the core literature related to this study is presented, and so is the main motivation. The variables are portrayed in Section 3, and together is some information on data. Section 4 introduces the methodology and empirical models used. Section 5 summarizes estimation results, including the discussion of model selection and implication. The limitations and possible extension are discussed in Section 6 and finally, the conclusions are made in Section 7.

2 Literature review and motivation

The possible consequences of environmental costs have caught researchers' eyes for long, though, there's only limited literature within the exact scope of this research if leaving the PHH and EKC theories behind. Whether environmental regulations have a real impact on trade flows remains an empirical question with only indefinite conclusions being made.

Holding an intuitively reasonable hypothesis of stringent environmental regulations dampening trade competitiveness, many fail to observe any significant linkage from early data, typically ranging from the 1970s to 1990s. For instance, Tobey (1990) uses a cross-section Heckscher Ohlin Vanek (HOV) model with the data for 23 countries, and the net exports of 5 different pollution-intensive industries are set to be dependent variable for the year 1975. He finds insignificant evidence for the deviation from the HOV prediction of trade patterns after the introduction of environmental regulatory control. Janicke et al. (1997) and Xu (2000) find no evidence to support a similar hypothesis. Later, Cole and Eilliot (2003a) also utilizes the Heckscher Ohlin Vanek (HOV) model to examine the relationship between green regulations and net imports within pollution-intensive industries for 1995. Similarly, the evidence suggests that neither of their measures of environmental regulations significantly determines net exports of pollution-intensive products, although the intra- and inter-industry shares of trade are found to be influenced by the difference in environmental regulation levels between two countries. On the other hand, it is both directly and indirectly suggested that a significant negative linkage between strict environmental regulations and trade flows could be established in some specific industries, by Kalt (1988), Birdsall and Wheeler (1993), Xing and Kolstad (2000), Wilson et al. (2002) and Jug and Mirza (2005).

A common issue in this field is data availability (Rodríguez and Rodrik 2000). When the data improve, the geographic range of the investigation has enlarged. A large part of previous studies pertains to US trade flows (for example, Kalt 1988; Grossman and Krueger

1993; Osang and Nandy 2000; Levinson and Taylor 2001; Ederington and Minier 2003) and some evidence supports the hypothesis that there is a negative correlation between the compliance costs of environmental regulations and export performance. European literature is also prominent, but there is little robust evidence to support the hypothesized negative impact of tighter regulations on the competitiveness of industrial exports at a country level. The research has been expanded to more countries (for example, Xu 2000; Hao and Liu 2014). A study of the impact on both US and European countries concludes that the effects of the stringency of environmental regulations differ across countries (Mulatu, Florax and Withagen 2004). Meanwhile, the regional study and OECD-focused study become more popular. De Santis (2011) finds that the major Multilateral Environmental Agreements bring a positive overall impact on 14 EU countries' exports. Methodologically, the most used models for these studies are the Heckscher-Ohlin trade model (Tobey 1990; Cole and Eilliot 2003a; Mulatu, Florax and Withagen 2004), the Gravity model (Harris et al. 2002; Costantini and Crespi 2008; Honda 2012) and some variants. Some researchers construct their empirical specifications based on other classic trade frameworks (such as Antweiller 1998). Cole and Eilliot (2003b) draw attention to the caveat of the standard Heckscher-Ohlin-Samuelson (HOS) framework, arguing that it is unable to explain actual trade patterns between similar countries in terms of size and relative factor endowments.

The largest difficulties of investigating this interesting relationship, however, mainly lie with 2 other things, determination of the causation and quality of stringency measures. With much work already done on both the trade impact on the environment and the environmental impact of trade activities, it is reasonable to argue that trade-environmental relationship is two-sided and thus the environmental regulations should not be entirely exogenous. Recent work points out that the endogeneity in the environmental regulations has not been much explored yet, but its existence may have biased downwards the estimates of the impacts of environmental regulation as trade barriers (Ederington and Minier 2003; Millimet and Roy 2016). Trade openness may have some impact on the political determination of environmental regulations (Eliste and Fredriksson 2004). The incentives behind trade-determined environmental policies include that countries may undercut the real international tariffs by relaxing environmental regulations to mollify domestic protectionists, for which point Ederington and Minier (2003) provides some empirical evidence, and that increased imports intensify lobbying for further trade protection through environmental means (Trefler 1993).

How to measure environmental regulations quantitively has always been a crucial question for relevant research. Composite indices based on environmental surveys are one of the most commonly used measures from almost a decade ago. They extensively cover distinct environmental dimensions[2] and sometimes different stages of the policy performance, from awareness of environmental issues to implementation of a policy, as represented by Arrow et al. (1995) and Dasgupta et al. (1995). There are several often-used indicators which, on the other hand, consider exclusively one or few most important aspects of environmental regulations. Examples are the share of environmental tax revenues over GDP, levels of energy consumption and levels of emission. The most explored measures of this type in the literature are emission indicators (see Magnani 2000; Xing and Kolstad 2002; Withagen, Florax and Mulatu 2007; Costantini and Crespi 2008) and abatement costs (see Mulatu et al. 2004; Levinson and Taylor 2008). They are less comprehensive while more relevant for the environmental costs and thus for the production and trade. It's overall accepted now that the environmental costs are too marginal compared to total production costs to noticeably affect the comparative advantage patterns. It is also used as an explanation for the empirical difficulty in observing the effects when abatement costs are used as the environmental measure such as in Levinson and Taylor (2008) and Mulatu, Florax, and Withagen (2004). Van Beers and Van den Bergh (1997) propose another classification of environmental regulatory measures: input-oriented and output-oriented measures. Input-oriented measures concern with the efforts exerted for an environmental goal, mostly in terms of investment expenditures, and output-oriented indicators look at the results of environmental efforts instead of how much a country invests. Public research and development (R&D) expenditures and pollution abatement and control costs are examples of input-oriented measures. The problem with these indicators is that they can't account for the counterbalancing financial assistance, such as import surcharges, and thus exaggerate the real costs the industries undertake to comply with environmental regulations. Van Beers and Van den Bergh (1997) argue that output-oriented measures are a better reflection of environmental regulatory stringency for 2 reasons. First, an output-oriented indicator can reflect the work done for all stages, from how well a policy is designed to how successfully it's implemented, whilst an input-oriented measure can only show the performance of the first stages. Second, it weighs the influence of other opposing policies in the outcome, such as compensating subsidies. So, the output-oriented indicators absorb all the environmental-related effects from both direct environmental regulations and other policies

[2] The environmental dimensions are air, water, land and living resources.

that may be implemented to reduce the side effects of strict environmental regulations, such as subsidies, and reflect the *factual* stringency of environmental regulations. They accordingly form a proxy for environmental regulatory stringency on each country's *change* in energy intensity (energy consumption or energy supply / GDP) over a long time period, together with the *level* of energy intensity in the year of investigation. The method is used also by, for example, Harris et al. (2002) and Cole and Eilliot (2003b).

The thesis is most strongly motivated and inspired by Van Beers and Van den Bergh (1997) and Harris et al. (2002). The former investigates the impact of environmental regulations on bilateral exports of 21 OECD countries in 1992 by the means of gravity models. They construct the measures of environmental regulatory stringency based on a combination of output-oriented indicators as mentioned above, with a focus on the one constructed on the *change* of energy intensity levels between 1991 and 1980, and examine the effects on three different types of bilateral flows: aggregate bilateral trade flows, dirty bilateral trade flow within resource-based industries and non-resource based dirty bilateral trade flows. They conclude that a narrowly defined measure of strictness of environmental regulations (i.e. energy-intensity based measure[3], which is also more directly linked to the Polluter Pays Principle) reveals a significant negative impact on the imports of an OECD country. However, the significant result they obtained is discredited by Harris et al. (2002), who update the study and claim that the finding is due to misspecification. They use OLS panel model, one-way fixed-effects panel model, two-way fixed-effects panel model and in the end three-way fixed-effects panel model[4] on 24 OECD countries for 7 years, from 1990-1996, and find that environmental costs do not have any significant impact on foreign trade as soon as the proper fixed effects are taken into consideration. In both works, narrow output-oriented measures are used.

I follow their path, using the same environmental measures and setting up similar specifications for 3 main reasons. First of all, this design solves the 2 key issues of identifying the relationship. Using the environmental measures based on both the *improvement* and *level* of energy intensity can largely eliminate the concern of measurement error and simultaneity[5].

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[3] Energy intensity refers to energy consumption or energy supply per unit of GDP (sometimes per capita instead). What they use is again a combination of the *level* of energy intensity in a base year and the *change* in energy intensity level over a time period.

[4] One-way fixed effect model here refers to the fixed effect model containing only the importer fixed effects. Two-way fixed-effects model includes also the exporter fixed effects in addition. Three-way fixed effects model comprises time fixed effects, importer and exporter fixed effects.

[5] For details, please refer to Section 3.1.2.3.

Second, I am interested in seeing if the significance of the findings is indeed dependent on specifications, and if the invalidating remark made by Harris et al. (2002) holds when a non-fixed-effects model is used with a different identifying assumption. Finally, both papers use data from the 1990s. The world has largely changed[6], and I want to examine the same relationship with the most updated data and see if the more stabilized inter-situation of main countries helps establish a clearer relationship.

This paper contributes to the existing literature in 3 main aspects. To start with, it would be the newest study on this topic. I employ the most recent data, from 2010 to 2016, and re-examine the specifications taking more OECD countries into consideration. If any of the often-referred hypotheses is true, the past 2 decades should have provided the countries with adequate time to diverge more and the conclusion drawn using the new data, if positive, can be more solid support for theoretical groundings. Second, it provides some insights into the well-cited claim of no findings from the panel extension by Harris et al. (2002). The thesis examines the internal validity of their study, in which only fixed-effects specifications are used, and suggests the use of some alternative models including an LDV model. Although LDV models are being explored by more and more researchers, it has not been used yet in the literature of environmental-trade relationship. Last but not least, I establish the interaction between the environmental regulatory stringency and average income through the per-capita variable based on energy intensity and construct a new variable measuring the inequality between 2 countries' environmental regulations. Both the interaction design and inequality index are novel in the literature.

3 Data

Panel data are used. The dataset is newly constructed, comprising bilateral imports data for 34 OECD countries, each country's characteristics and indicators regarding the stringency of environmental regulations. In this section, I introduce all variables involved in the empirical models and provide information for the data series.

[6] The last few decades have been *"characterised by both a steady decrease in global trade barriers and a steady increase in environmental regulation, particularly in the developed world"* (Cole and Eilliot 2003b).

3.1 Variable description

3.1.1 Dependent variable

Imports are chosen in this study to represent bilateral flows[7]. This choice allows exploring the potential effects of environmental regulations on both sides of bilateral trade, because the imports from country i to country j (IMP_{ijt} at time t) are by symmetry the exports from country j to country i in the same time period. I use import values due to the convenience (of using directly the data obtained). It is also a common practice in the literature (for instance, Bergstrand 1985; Deardorff 1998; Carrere 2006) and the values of imports reported by the importing country are known to be more accurate than export values reported by the exporting country (Evenett and Keller 2002). The series of the total imports of goods are in use, under the assumption that environmental regulations would affect physical production more significantly than the trade of services.

3.1.2 Independent variables

The independent variables involved in this study can be categorized into gravity variables, control variables, and policy variables according to their functions in the empirical models.

3.1.2.1 Gravity variables

Gravity variables here refer to the most commonly used variables that are both empirically successful and theoretically important in the Gravity literature, speaking for economics scale, distance and factor endowments[8] in this case.

The economic scale variables are a crucial segment of the gravity model. They represent the aggregate production and country size. A larger country tends to have a greater demand and supply of goods. Under the standard assumption that people enjoy variety, a larger size of production implies more active participation in the trade. Following the common practice in the empirical literature, I include the Gross Domestic Products (mentioned as GDP afterward) for the trading pairs as the first economic scale variables. GDP_i and GDP_j measure respectively the possible demand of the importer, country i, and possible supply of the exporter, country j. Two series of GDP are included in this dataset, of which one is adjusted by constant purchasing

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[7] All of imports, exports and total trade (i.e. exports plus imports) have been explored in the gravity model setting as the dependent variable as every one of them reflects to some extent the gross bilateral trade flows, and there is no definite explanation in the literature why the authors choose one over the others.

[8] The classification of these subcategories is inspired by Baxter and Kouparitsas (2006), but some variables are still differently categorized.

power parities (referred to as GDP1) and the other is adjusted by constant exchange rates (referred to as GDP2). Besides, the populations of trading pairs also enter the model as another economic scale measures. It's straightforward that a country with a greater population would benefit from a larger home market, where there would be more consumption as well as more labour supply within the country, ceteris paribus. Population (POP), supplementing GDP, captures the effects of economies of scale.

The distance variable (DIST) is used as trade cost approximation. The greater the geographic distance is between a pair of trading partners, the higher the trade costs are and the worse the deterioration of the goods may be. Thanks to the development of distance datasets, better measures are now available than the one calculated following Linnemann (1966), which prevailed in the main body of literature before 2000. For this paper, the weighted distances are chosen. These distances are computed through city-level data and based on the assessment of the geographic distribution of population inside each country, providing a more consistent estimation for the border effects[9]. They are called "weighted" as the distances are inter-city distances (the largest cities of two countries) being weighted by the share of the city population in the country's whole population.

The last variables of this group, factor endowments, have been conventionally considered the important determinants of international trade according to the Heckscher-Ohlin theory and they are also commonly included in the empirical gravity models. In this study, all the major factor endowments - capital, labour, and land - are taken into consideration via 2 variables. First, the land areas for the trading countries (LAND) are used as a proxy for land resources, and more generally for natural resources since the larger country often possesses more diverse and richer natural resources. Then following Egger (2002) and Serlenga and Shin (2007), I use 2 countries' GDP per capita to construct a variable representing the difference between these 2 countries' capital-labour ratios. The variable (CE) is constructed according to the following formula:

$$\mathrm{CE}_{\mathrm{ijt}} = \left|\log\left(\frac{GDP_{it}}{POP_{it}}\right) - \log\left(\frac{GDP_{jt}}{POP_{jt}}\right)\right|.$$

This bilateral variable is also useful to avoid collinearity since GDP and population for both importing and exporting countries are already included separately, which function equally as including GDP per capita of two countries respectively.

[9] Any overestimate of the internal/external ratio will yield to a mechanic upward bias in the border effect estimate. (Mayer and Zignago 2011)

3.1.2.2 Control variables

Control variables in this study include some factors that have been asserted to co-determine trade effectively in the empirical work, however, through an unelucidated theoretical mechanism. Common border, cultural distance, and participation in the organizations and agreements are the focus of this group of variables. These variables are also sometimes referred to as trade facilitation variables because they reflect how accessible it is for the home country to trade with a foreign country.

Apart from the geographical distance, sharing a common border or not, in other words, whether contiguous is another source of the trade costs pointed out by the empirical work (see McCallum 1995; Anderson and Van Wincoop 2003). I use a dummy variable to show the land contiguity between two countries (CONTIG), which equals 1 if the 2 countries are contiguous, and 0 otherwise.

Cultural distance is an abstract component of the overall trade resistance and it has been broadly incorporated into the empirical research of gravity models. Cultural differences can obstruct trade in many ways, for instance causing misunderstandings and inefficient negotiation. Language indicator is the most relevant and used measure of this friction. If the trading partners share a common language, the communication friction would be reduced greatly. Hence, I employ a dummy variable reflecting the official languages within trading pairs (COMLANG), which equals 1 if two countries share a common language, and 0 otherwise.

Another important piece of trade facilitation is trade integration and liberalization. In this respect, three variables are added to characterize a country’s level of participation in the trade organizations and agreements. The first one is a variable capturing the joint memberships of the European Union (MEU), equal to 1 if both countries are members of the EU in the given year, and 0 otherwise. There is also a variable describing active preferential trade agreements (PTA), equal to 1 if both countries take part in a preferential trade agreement of any type within a given year, and 0 otherwise. I choose the comprehensive indicator that covers all the preferential trade agreements for trade of goods because the goal is not to study how different types of preferential trade agreements would affect trade differently but to reduce the omitted variable bias and help identify better a fraction of trade that is attributable to the environmental regulations. Noticing that a comprehensive measure may compromise on some specific effects, I add the last variable particularly accounting for the participation in the North American Free

Trade Agreement (NAFTA). It's set to be 1 if both countries are members of NAFTA, and 0 otherwise.

NAFTA has been controversial due to its environmental impacts, and some cooperation work has been done to evaluate the possible loss and push the government to escalate environmental protection. It's also confirmed by Steinberg (1997) that the convergence in trade-environment rules has clustered in 2 geographic regions - represented by the EU and the NAFTA. Admitted that the last two variables may be a little overlapped since NAFTA is one of many PTAs counted in the previous variable, this practice doesn't effectively lead to biased estimation. The main reason is that NAFTA has been a very powerful trade agreement, but the comprehensive indicator skips largely NAFTA's impact as it tries to reflect the effects of all the agreements including many weak ones. Thus, it's reasonable to include both variables in the models, one for the total efforts a country makes for trade integration and another specific for NAFTA's impact.

World Trade Organization (WTO) is very important in the game of trade integration but all those countries within the scope participate in the WTO, so it is not controlled here. Besides, several adjustments have been made compared to the main reference work of Harris et al. (2002), as some of the variables from it are no longer meaningful. For example, the European Community was abolished, and the EU was founded instead. So, I use MEU as a control variable as introduced. I also drop the variable concerning the EFTA. The EFTA becomes much smaller as many previous members are no longer in the organization now. The 4 remaining members of the EFTA are all parts of the EU, and this organization operates in parallel to the EU, so it's plausible that the isolated effects of being a part of the EFTA would be neglectable. The last previously included regressor considers the General Agreement on Tariffs and Trade (GATT), of which Estonia is not a member yet. But this one exception would probably make so few differences that including it in the model doesn't change the result. I thus leave it out.

3.1.2.3 Policy variables

Policy variables are the ones related to environmental regulations, which are of primary interest in this paper.

I use the same narrow output-oriented indicators based on energy intensity, as in Van Beers and Van den Bergh (1997) and Harris et al. (2002). Energy efficiency is one of the most considered aspects of environmental protection and it's important and relevant for understanding the environmental pressures. With quality data available, the indicators are also easily comparable across countries and allow for discussion and comparison of the results with the core literature. Most importantly, it helps mitigate the endogeneity issue, both the potential measurement error and simultaneity[10].

The possible measurement error is due to the existence of financial assistance for trade and production, and it is worried that some environmental measures used could overestimate the real burden on firms resulted from those regulations. These output-oriented environmental measures expand the scope of regulations that are considered as environment-related and take in the effects of the policies that indirectly impact on energy intensity as well. For instance, protective subsidies on production would partially nullify the enforced environmental regulations. If they are not considered as a part of the real stringency of environmental regulations, the environmental costs would be exaggerated in measurement and so mask the real relationship between environmental regulations and trade. The output-oriented measures deem them the factual environmental regulatory laxation and doing so largely reduces the systematic measurement error.

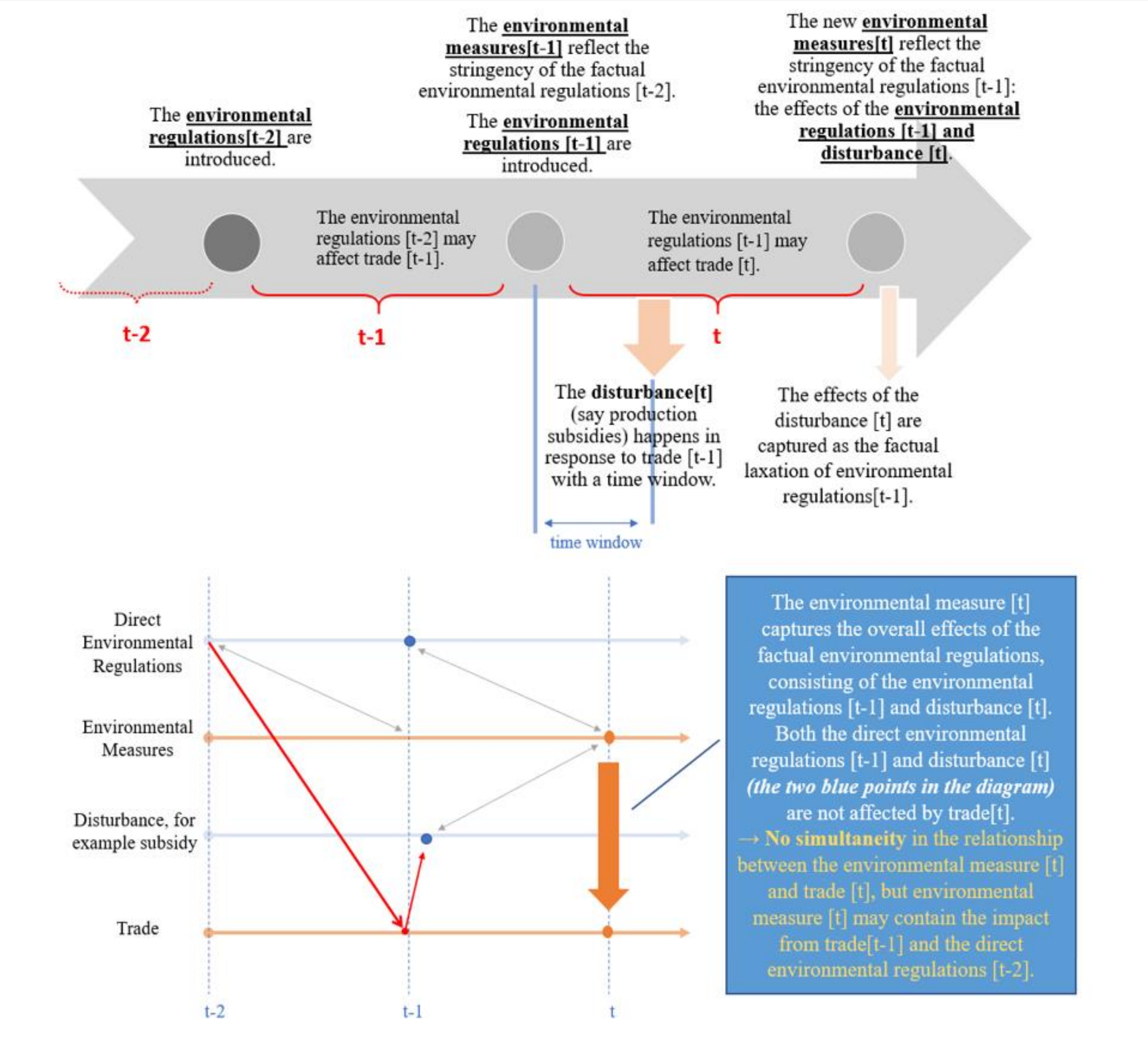
It also significantly mitigates the problem of simultaneity as there exists one period's difference between the measurement and the enactment of environmental regulations and a time window between a potential disturbance[11] and trade outcome. The key assumption here is that, if there is any disturbance interfering with the environmental measures, say a subsidy for production, it would be activated in response to last period's trade performance but not to the expectation of next period's trade performance. It is reasonable because this type of policymaking is known to be evidence-based and it costs time for a policy to be approved. The chain through which they are connected would be: (1) at the end of time t-2 the environmental regulations are intensified; (2) at the end of time t-1, the energy intensity variable measures the strength of environmental regulations of time t-2 and the trade outcome contains these effects from those regulations; (3) at the beginning of time t or shortly after it, the subsidy of production may be placed and it may enter the measurement of environmental regulations at the end of time t. And the measured regulations would be of time period t-1 but not t. So, there is no simultaneity when looking at the relationship between the environmental measure and

[10] Reverse causation is thought to be unlikely because trade cannot be the main reason why a country sets the overall environmental regulations.

[11] For example, financial assistance is transferred to the selected industries facing the strongest competition after the enactment of stricter environmental regulations, and increased imports may even intensify the lobbying activities for more protection. (Trefler 1993)

trade of the same period. The timeline is summarized in Figure 2. Apart from the type of disturbance that is considered factual laxation of regulations, the other protective policies are unlikely to be systematically correlated with the change in energy intensity. The issue is then restrained to be a potential serial correlation between the past and current regulatory stringency.

Figure 2: Reduced simultaneity



I experiment with six unilateral measures of the strictness of the environmental regulations. Three of them are formed based on Total Final Consumption of energy (TFC, Mtoe) and the other three are based on Total Primary Energy Supply (TPES, Mtoe)[12]. Dividing TFC and TPES by 2 different GDP series and populations respectively, I construct these 6 indicators measuring the static relative energy intensity level. Through a ranking procedure (from best to worst, 1 is the best and 34 is the worst), 6 sets of environmental rankings are obtained. The same procedure is repeated to sort in ascending order the difference in the energy intensities between the year of interest and the base year chosen (2000), for measuring the reduction of energy use[13]. Note that the more reduction a country has made, the dynamically stricter the domestic environmental regulations are. The ranking is still ascending in number, with 1 being the best and 34 the worst. I call it the dynamic ranking. In the end, I sum up the static and dynamic ranking and ascendingly arrange them again to obtain their final rankings. In this process, no relative weights are assigned to the two parts as they measure different features and it is difficult to decide which one matters more. An example of final ranks is shown in Table 1 for the year 2016.

Figure 3 and Figure 4 plot the matchability between the rankings and the energy intensity indicators with the former for the static rankings and the latter for the dynamic rankings. As Figure 3 shows, the levels of energy intensity are not perfectly linear and the difference in the level of energy intensity between two countries is not exactly same for every pair, but the rankings are still as meaningful. It’s clearly that those between-country static differences don’t fluctuate too much, except that there are 2 countries doing extremely badly in energy efficiency. The dynamic rankings show a relatively worse matching property than the static ones, featured by the larger intervals for the best and worst countries. But the skewed distribution doesn’t seem to undermine the incentive to use the rankings, because what I try to measure through these countries’ energy usage is the relative stringency. Stringency is a rather abstract concept that doesn’t imply a one-for-one relationship between energy intensity and environmental efforts, and the ranking system is only a tool to put them into a comparative situation which also results in a more reasonable economic interpretation.

[12] Data source is introduced in the next subsection.

[13] Using the absolute values may be a potential flaw in the dynamic measurement, as it is unlikely that energy reduction happens with constant returns to scale. I try to adjust the method by using the relative reduction (as the percentage of indicators for the year 2000) instead of the absolute number and produce another set of dynamic rankings. But the nonparametric test result shows that the newly adjusted rankings are significantly correlated with the full rankings and the coefficients are higher than 0.9 for all 6 measures. Since the new set of dynamic rankings doesn’t significantly change the final rankings, I still go with the original dynamic rankings.

Figure 3: Matching of the rankings for *levels* of energy intensity

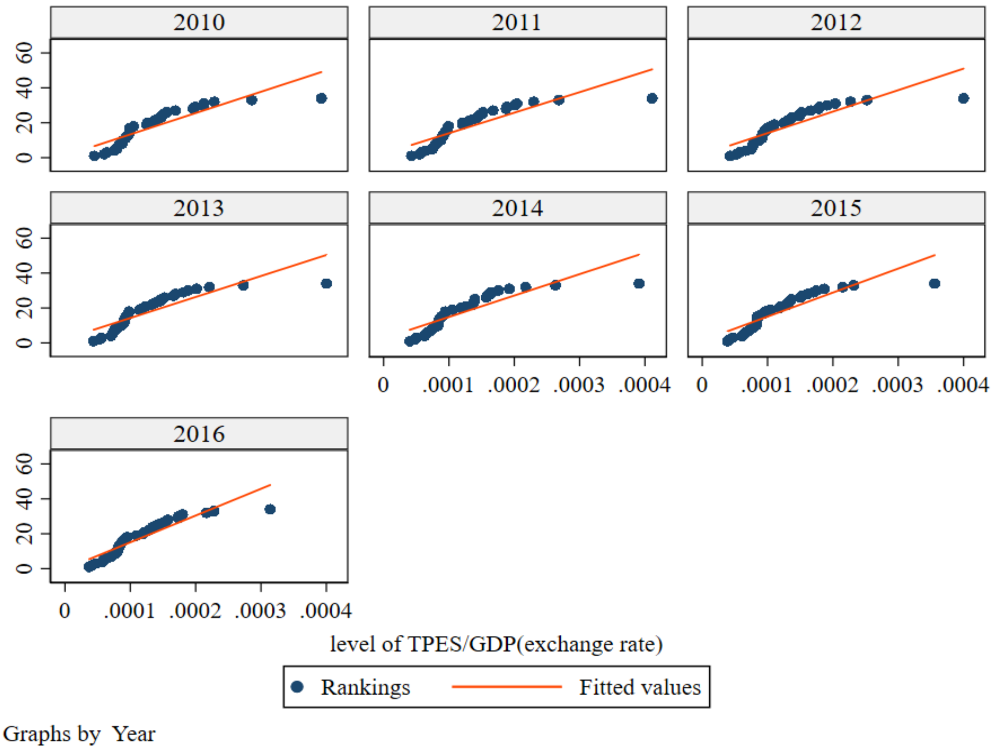


Figure 4: Matching of the rankings for the changes in the energy intensity levels

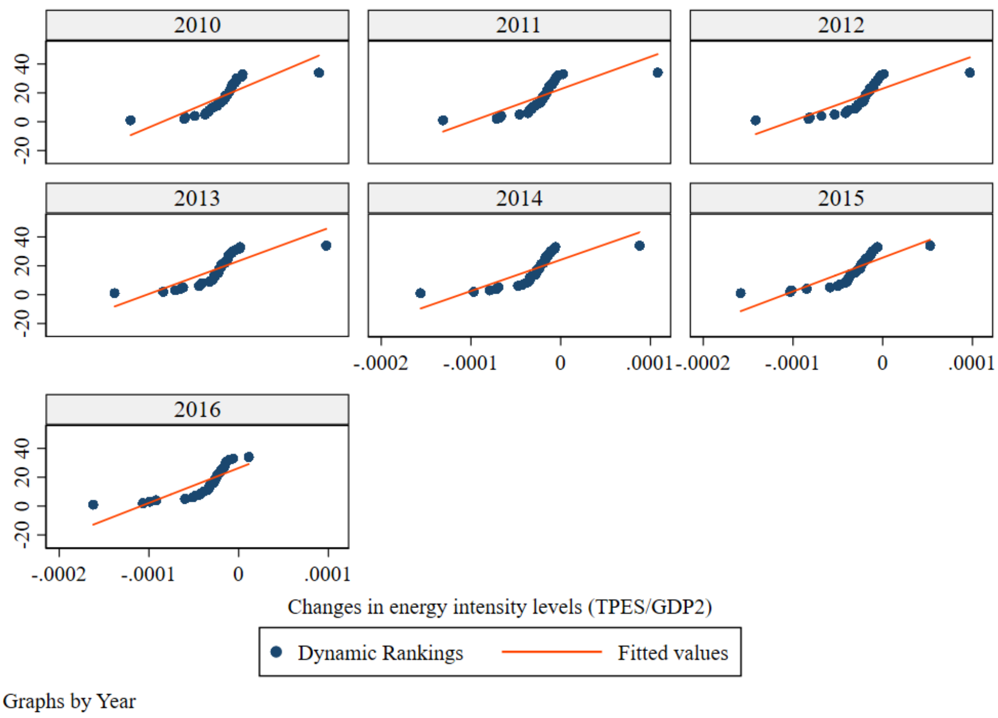


Table 1: Rankings for Environmental regulatory stringency, 2016							
	$R_{\text{TFC,GDP}_1}$	$R_{\text{TFC,GDP2}}$	$\mathrm{R}_{\text{TFC,POP}}$	$\mathrm{R}_{\text{TPES,GDP1}}$	$\mathrm{R}_{\text{TPES,GDP2}}$	$\mathrm{R}_{\text{TPES,POP}}$	Reference,1992
Australia	16	4	23	18	9	28	18
Austria	33	31	31	31	29	29	3
Belgium	31	25	27	23	16	14	15
Canada	19	20	18	27	23	26	17
Chile	7	13	13	26	22	15	/
Czechia	5	12	24	14	18	27	/
Denmark	14	15	21	7	10	8	1
Estonia	9	14	30	15	19	31	/
Finland	32	32	32	33	32	32	/
France	15	18	6	25	25	11	11
Germany	23	22	28	10	8	19	2
Greece	29	30	8	29	31	3	21
Hungary	30	29	26	16	20	21	/
Iceland	34	34	34	34	34	34	22
Ireland	1	1	4	1	1	4	5
Israel	4	6	12	6	5	12	/
Italy	24	28	7	19	27	2	5
Japan	18	16	14	11	3	7	4
Korea	25	26	33	30	26	33	/
Luxembourg	11	7	17	4	4	13	15
Mexico	27	33	10	32	33	10	23
Netherlands	20	24	19	28	24	24	8
New Zealand	21	9	25	22	14	30	24
Norway	26	11	20	21	21	20	7
Poland	12	19	22	5	13	22	/
Portugal	17	23	3	20	30	9	20
Slovakia	3	3	9	3	7	18	/
Slovenia	28	27	29	24	17	25	/
Spain	6	10	2	9	15	6	14
Sweden	8	5	11	12	12	23	12
Switzerland	10	8	5	8	11	5	8
Turkey	13	21	16	17	28	16	19
UK	2	2	1	2	2	1	10
USA	22	17	15	13	6	17	12

Notes:
$\boldsymbol{R_{a,b}}$ denotes the ranks derived from variables a and b, where a is the total energy indicator, chosen between Final Consumption of energy (TFC) and Total Primary Energy Supply (TPES), and b is GDP adjusted by purchasing-power parities (GDP1), GDP adjusted by exchange rates (GDP2) or Population (POP). They are ranked from the best (1) to worst (34). The reference ranking is calculated by TPES and GDP2, from Harris et al. (2002, Table 1, p.10), for the year 1992.

Notable differences are found between the reference rankings and the rankings calculated with the latest data. There are various possible explanations. First, these countries' relative positions regarding their environmental work have changed a lot since 2000, which also strengthens the motivation of an update on this topic. Second, the procedure has some flaws and it produces unstable results. This last critique is not new, but I stick to this choice as this ranking procedure is frequent in the literature (for example, Tobey 1990; Van Beers and Van den Bergh 1997; Harris et al. 2002), which allows for comparison with other results, and the system is easy to manipulate with, given the limited data. Third, the dynamic improvement may dominate the static rankings and distort the results largely, as those ones who have been good at energy efficiency may have more difficulty reducing the energy intensity further. The decomposition of the final rankings of 2016 is shown in Table 2.

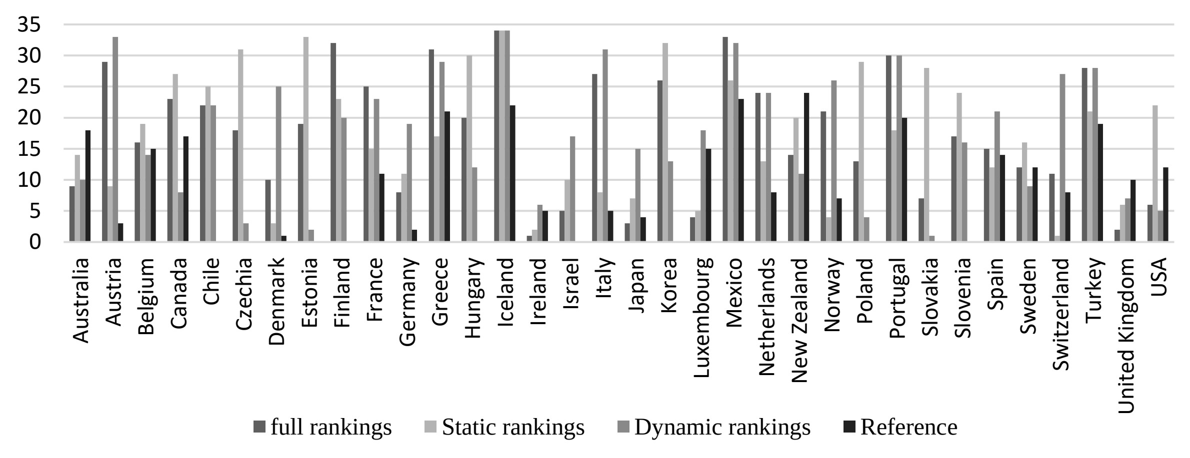
Table 2: Decomposition of the rankings, 2016

	$R_{\text{TFC,GDP}_1}$		$R_{\text{TFC,GDP2}}$		$\mathrm{R}_{\text{TFC,POP}}$		$\mathrm{R}_{\text{TPES,GDP1}}$		$\mathrm{R}_{\text{TPES,GDP2}}$		$\mathrm{R}_{\text{TPES,POP}}$		Reference, 1992
	S	**D**	**S**	**D**	**S**	**D**	**S**	**D**	**S**	**D**	**S**	**D**	
Australia	20	14	8	17	24	16	25	10	14	16	28	18	18
Austria	21	33	16	33	23	28	13	33	9	33	20	28	3
Belgium	30	16	19	18	28	14	26	14	19	14	26	6	15
Canada	33	3	28	7	32	2	33	8	27	11	33	10	17
Chile	17	11	26	6	3	27	19	22	25	13	3	30	/
Czechia	24	2	28	3	19	21	28	3	31	4	21	22	/
Denmark	4	29	3	29	20	17	3	25	3	28	13	8	1
Estonia	26	4	30	2	13	32	30	2	33	2	22	32	/
Finland	32	19	27	24	31	24	32	20	23	23	31	23	/
France	11	22	9	25	14	9	18	23	15	24	18	12	11
Germany	13	24	13	23	21	22	11	19	11	18	19	16	2
Greece	14	31	17	31	4	20	14	29	17	29	4	14	21
Hungary	25	20	32	11	12	29	22	12	30	5	9	27	/
Iceland	34	34	34	34	34	34	34	34	34	34	34	34	22
Ireland	1	5	2	8	17	6	1	6	2	8	14	5	5
Israel	7	18	7	21	7	23	10	17	10	17	10	21	/
Italy	9	30	11	32	10	13	6	31	8	32	6	11	5
Japan	12	23	6	26	16	15	16	15	7	19	17	4	4
Korea	31	10	33	5	27	33	31	13	32	7	28	33	/
Luxembourg	18	13	12	16	33	1	5	18	5	22	30	1	15
Mexico	10	32	23	30	1	26	15	32	26	26	1	24	23
Netherlands	19	17	15	22	26	10	17	24	13	25	23	17	8
New Zealand	29	7	20	9	22	19	28	11	20	12	24	26	24
Norway	16	25	4	27	28	7	12	26	4	31	27	9	7
Poland	22	9	31	4	8	30	20	4	29	3	8	29	/
Portugal	8	26	18	19	5	12	8	30	18	27	5	19	20
Slovakia	15	1	24	1	9	18	21	1	28	1	15	20	/
Slovenia	27	15	25	13	18	25	24	16	24	10	16	25	/
Spain	6	21	10	20	6	11	9	21	12	21	7	13	14
Sweden	23	6	14	12	25	5	23	9	16	15	25	15	12
Switzerland	2	28	1	28	15	8	2	27	1	30	12	7	8
Turkey	5	27	21	15	2	31	7	28	21	20	2	31	19
United	3	12	5	14	11	4	4	7	6	9	11	3	10
USA	28	8	22	10	30	3	27	5	22	6	32	2	12

Notes:
S refers to the static rankings, based on the *levels* of energy intensity for a certain year, and D represents the dynamic rankings, formed upon the *changes* in the levels. They are ranked again from best to worst. The reference is the same as in the Table 1, from Harris et al. (2002, Table 1, p.10).

The static rankings and dynamic rankings show very different results. Figure 5 below is a clear demonstration of the imbalance between static and dynamic rankings, based on the ranking $\mathrm{R}_{\text{TPES,GDP2}}$. Some countries amongst the worst in static rankings such as Slovakia and Estonia are the best in the dynamic rankings, and vice versa (e.g. Denmark). One possibility is that the countries performing worse at first would have a larger room to improve and the dynamics in environmental work naturally lead to the dissimilarity in the final rankings.

Figure 5: Comparison of the full rankings and the 2 components, based on TPES (total primary energy supply) and GDP2 (GDP adjusted on exchange rates) for the year 2016



The unilateral policy variables used in the models are calculated based on these rankings, denoted by EM with an index corresponding to the specific ranking on which it is based, for instance, $\mathrm{EM}_{\mathrm{TPES,GDP_1}}$. The rankings are divided by the number of the countries in the scope (34) and so the scores between 0 and 1 are obtained.[14] The closer a country's score is to 0, the better the country performs within the environmental area and the more stringent its environmental regulations are.

Apart from these unilateral measures discussed above, I also create another set of variables EMD to measure the disparity in the strictness of environmental regulations between a pair of countries that trade with each other. To construct this index of inequality, I first divide the importer country's score by the exporter country's score (either $\mathrm{EM}_{\mathrm{TPES,GDP_2}}$ or $\mathrm{EM}_{\mathrm{TPES,POP}}$), logarithmize it[15], standardize it and then take the absolute value of it.

To illustrate, simply look at the example of constructing EMD for $\mathrm{EM}_{\mathrm{TPES,GDP_2}}$:

$$\mathrm{EMD}_{\mathrm{ijt;TPES,GDP_2}} = \left| \frac{\left[\left(\ln EM_{TPES,GDP_2;it} - \ln EM_{TPES,GDP_2;jt} \right) - mean\left(\ln EM_{TPES,GDP_2} \right) \right]}{SD\left(\ln EM_{TPES,GDP_2} \right)} \right|,$$

where i and j denote 2 different countries and t indexes year. It's worth noting that the environmental measures created are in nature ordinal variables and hence the scores don't

[14] By construction, the value 0 is not in the range of the policy variables but the value 1 is.
[15] Taking the natural logarithm of this quotient first so that it can enter the model directly without log-transformation. Another way to look at it is that I construct an index based on the distance between $\ln EM_i$ and $\ln EM_j$.

represent any quantity or value of anything but a relative position among the 34 OECD countries, and so is the quotient between the scores for 2 countries. Therefore, it is necessary to perform the standardization and take the absolute value so that the variable is no longer ordinal. The new variable describes how far away from each other the 2 countries stand regarding their environmental regulatory stringency. The greater the variable is, the more unequal it is between the two countries' environmental regulatory strictness.

Table 3 provides a summary of all covariates involved in the thesis and introduces the abbreviations used for the rest of the paper.

Table 3: Overview of independent variables

Function of the variable	***Description***	***Type of variable***	***Abbreviation in the model specifications***
Gravity variable, Economics scale	Gross Domestic Products	Unilateral, measurement	GDP
Gravity variable, Economics scale	Population	Unilateral, measurement	POP
Gravity variable, Trade cost	Distance between the 2 countries	Bilateral, measurement	DIST
Gravity variable, Factor endowment	Land area	Unilateral, measurement	LAND
Gravity variable, Factor endowment	Difference in capital endowments	Bilateral, measurement	CE
Control variable, Common border	Contiguity	Bilateral, dummy	CONTIG
Control variable, Cultural distance	Common official language	Bilateral, dummy	COMLANG
Control variable, Participation in the trade	Active preferential trade agreements between 2 countries	Bilateral, dummy	PTA
Control variable, Participation in the trade*	Participation in the North American Free Trade Agreement	Bilateral, dummy	NAFTA
Control variable, Participation in the regional	Joint memberships of the European Union	Bilateral, dummy	MEU
Policy variable of interest	Environmental measurement	Unilateral, ordinal	EM
Policy variable of interest	Differences between environmental regulation indicators in the 2	Bilateral, measurement	EMD

Notes:
A unilateral variable is a variable that is only related to one country, either importer or exporter, whereas a bilateral variable is related to both sides at the same time.
*NAFTA is also an active preferential trade agreement but used as another independent variable in the empirical model for the reason listed in Section 3.1.2.2.

3.2 Data sources

3.2.1 Scope of the study

This study covers a time period of 7 years, from 2010 to 2016. 34 of a total of 36 OECD members are included in the scope of this study. They are: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Israel, Japan, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the United States. Among these countries, Chile, Estonia, Israel, and Slovenia only joined the OECD in 2010, the starting year of the data period. Along with some other earlier joined countries that are also less developed such as Mexico, these relatively new OECD members contribute to the variations across countries regarding environmental work. Latvia and Lithuania are excluded due to the poor data availability and uncertainty of being too new in the OECD.

3.2.2 Data sources for variables

The dataset is constructed from 5 main data sources: UN Comtrade Database, CEPII database, Dynamic Gravity Dataset by United States International Trade Commission, OECD database and the reports released by International Energy Agency.

3.2.2.1 UN Comtrade Database

The bilateral trade data used in the study, the imports, are manually combined from a sequence of country-level data. Due to the technical limitation, the required data are downloaded from the UN Comtrade Database country by country. The standards of data statistics are all compatible in the first place and unchanged. The unit is manually adjusted to millions of US dollars.

3.2.2.2 CEPII database

The data for the weighted distances are obtained from the GeoDist database, provided by Centre d'Études Prospectives et d'Informations Internationales (CEPII). Two series of the weighted distances are included, under the variable DIST, in the database for this study: *distw* and *distwces*[16]. The latter is the focus.

[16] The general formula for calculating the weighed distances is developed by Head and Mayer (2002) and has the following form: $\mathrm{d_{ij}} = [\sum_{k\in i}\left(\frac{pop_k}{pop_i}\right)\sum_{l\in j}\left(\frac{pop_l}{pop_j}\right) d_{kl}^{\theta}]^{\frac{1}{\theta}}$, and the two series are distinguished by the value of the

3.2.2.3 *Dynamic Gravity Dataset*

Except for NAFTA[17], the control variables consisting of CONTIG, COMLANG, and PTA[18] are directly drawn from this dataset, and MEU is derived based on the unilateral variables provided in the dataset.

3.2.2.4 *OECD database*

The GDP data are from the OECD database. Two series of GDP are kept with the study, GDP series with constant prices constant PPP (GDP_1), and GDP series with constant prices constant exchange rates (GDP_2). Both series are adjusted based on the OECD base year 2010, in millions of US dollars. The land area data are also obtained from the OECD database, the area under inland water bodies excluded. The capital endowment variable is calculated on the GDP and population data.

3.2.2.5 *Reports by International Energy Agency*

The data from which I derive the environmental measures are collected from World Energy Balances for the year 2010 – 2017. For TFC and TPES series, each year the World Energy Balance report discloses the detailed data for the past 2 years, and for a same previous year, the reports of two consecutive years give slightly different figures on TFC and TPES. However, the difference is very small, even the largest deviation from each other is less than 2%, so it's almost unlikely for this difference to affect the rankings. I take the relatively more updated figure. For example, for the year 2011, the numbers disclosed in the 2014 report are used eventually instead of the ones from the 2013 report. Both TFC and TPES are in millions of Tonnes of oil equivalent. The population data, in millions, are also collected from World Energy Balances and Energy Balances of OECD countries.

3.3 Summary statistics

3.3.1 Non-environmental variables

Table 4 provides an overview of the gravity variables and the dependent variable in the panel dataset used, before the log-transformation. As the "between" statistics show, the countries in

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parameter θ, 1 for *distw* and -1 for *distwces*. The former is the directly weighted distance while the latter corresponds to the usual coefficient estimated from empirical gravity models.

[17] The data regarding NAFTA are not obtained from any of the data sources listed. NAFTA is a stable agreement with only 3 participants from the beginning, so it is easy to manually add the series into the dataset.

[18] The technical details and the source data of this dataset, including a complete list of the trade agreements recognized, can be found in *The Dynamic Gravity Dataset: Technical Documentation (Gurevich and Herman),* via https://www.usitc.gov/data/gravity/dynamic_gravity_technical_documentation_v1_00_0.html.

the sample differ largely in sizes, in terms of total production, population, and land areas. So do the bilateral trade flows. Except for CE, the natural logarithms of these measurement variables are used in the empirical models.

Table 4: Summary statistics for the important raw data series

Abbr.	*Variable*		*Mean*	*Std. Dev.*	*Min*	*Max*	*No. obs*
IMP	Imports *million USD*	overall	6083.404	19657.19	1.079341	354171.8	N = 7854
		between		19565.39	1,454695	314578.1	n = 1122
		within		1973.138	-40701.68	49712.06	T = 7
GDP	GDP1 (PPP-adjusted) *million USD*	overall	1.360296	2.749445	0.0125871	16.97235	N = 7854
		between		2.747392	0.0136643	15.93754	n = 1122
		within		0.1305833	0.4148094	2.395105	T = 7
GDP	GDP2 (Exchange rate-adjusted) *million USD*	overall	1.38704	2.810893	0.0136837	17.00	N = 7854
		between		2.809044	0.01485479	15.9	n = 1122
		within		0.128131	0.4415538	2.42185	T = 7
POP	Population *million*	overall	37.02966	58.81579	0.3	323.4	N = 7854
		between		58.82455	0.311429	316.6186	n = 1122
		within		1.270214	28.75395	43.81108	T = 7
DIST	Distance (*distw*) km	overall	5466.262	5281.901	160.9283	19539.48	N = 7854
		between		5283.92	160.9283	19539.48	n = 1122
		within		0	5466.262	5466.262	T = 7
DIST	Distance* (*distwce*) km	overall	5422.485	5286.896	141.4463	19537.12	N = 7854
		between		5288.917	141.4463	19537.12	n = 1122
		within		0	5422.485	5422.485	T = 7
LAND	Land Area km^2	overall	1010108	2408625	2430	9147420	N = 7854
		between		2409546	2430	9147420	n = 1122
		within		639.6045	1008720	1018440	T = 7
CE	Capital Endowment (differenced)	overall	0.3963745	0.29662	0.0003003	1.724834	N = 7854
		between		0.2927143	0.009098	1.672018	n = 1122
		within		0.0486541	0.1267426	0.712419	T = 7

Notes:
Overall lines provide the statistics calculated on the entire dataset. *Between* lines summarize the between-group statistics. For the standard deviation, "between" output first estimates the unit-level averages for every unit (trading pair in this case) and then calculate the standard deviation for the group means. *Within* lines concern with the observations per unit over the time period available but are outputted in a special way to make the results also comparable between groups. The statistics are adjusted by the global mean, which may distort the minimum and maximum values to some extent. However, it is not considered an issue here because the within lines still manage to tell about how the variables change within units.
*The explanation about the difference between the 2 distance variables, *distw* and *distwce*, can be found in Section 3.2.2.2 (see *footnote 10*).

From Table 5, it's observed that apart from PTA, the control variables don't change at all over the 7-year period. They are in effect time-invariant, but it's necessary to control them because the trade facilitation conditions vary greatly between country pairs.

Table 5: Summary statistics for the Control variables (dummy variables) by year								
Abbr.	*Control variable*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*
CONTIG	Contiguity	6.60%	6.60%	6.60%	6.60%	6.60%	6.60%	6.60%
COMLANG	Common official language	7.84%	7.84%	7.84%	7.84%	7.84%	7.84%	7.84%
PTA	Preferential trade agreements	71.66%	75.4%	75.58%	75.58%	75.76%	76.29%	76.29%
NAFTA	Participation in NAFTA	0.53%	0.53%	0.53%	0.53%	0.53%	0.53%	0.53%
MEU	Joint EU memberships	37.43%	37.43%	37.43%	37.43%	37.43%	37.43%	37.43%

Notes:
The percentages tell that for a certain year how many trade pairs have the bilateral characteristics of interest (that is how often the corresponding dummy variable takes value 1). For example, for year 2010, 6.6% of the 1122 country pairs share common borders.

3.3.2 Environmental variables

The policy variables measure how strict the environmental regulations are within a country and every country in the scope of this study is given a unique ranking for each year. The 34 unique values from 0 to 1 are repeatedly assigned to the countries and so the mean and standard deviation are identical[19] no matter which one of the 6 constructed environmental measures is calculated upon.

Table 6 displays the strength and direction of the association between the environmental variables and all pairs are significantly correlated at a 0.1% level, with distinguishable levels of correlation. The finding remains valid when grouping by year. It is also found that the pairs constructed with a common component have a larger association and both population-based measures associate with GDP-based measures only to a limited extent. This suggests that the choice of the environmental measure might somewhat alter the estimation results.

Table 6: Rank correlation between the environmental regulatory measures						
	EM1 (TFC,GDP1)	EM2 (TFC,GDP2)	EM3 (TFC,POP)	EM4 (TPES,GDP1)	EM5 (TPES,GDP2)	EM6 (TPES,POP)
EM1 (TFC,GDP1)		0.6484*	0.4168*	0.5658*	0.4036*	0.2774*
EM2 (TFC,GDP2)	0.8222*		0.3432*	0.4629*	0.5426*	0.1729*
EM3 (TFC,POP)	0.5634*	0.4396*		0.3576*	0.2347*	0.6647*
EM4 (TPES,GDP1)	0.7359*	0.6184*	0.4828*		0.6500*	0.4463*
EM5 (TPES,GDP2)	0.5548*	0.7049*	0.3039*	0.8188*		0.3186*
EM6 (TPES,POP)	0.3910*	0.2380*	0.8279*	0.5888*	0.4066*	

Notes:
In the upper triangle is the Kendall's τ_b and the Spearman's ρ coefficients are reported in the lower triangle.
The strongest association is found between the pair using populations as the base, EM3 vs. EM6. The association is the second strongest between the 2 measures whose numerators are the same energy indicator with denominators being one of the two GDP series, namely EM1 vs. EM2, EM4 vs. EM5. Here * indicates significance at the 0.1 percent level.

[19] The mean is 0.5147059 and the standard deviation is 0.2885686 for all 6 measures, with a minimum of 0.0294118 and a maximum of 1.

Table 7: Rank correlation between the updated environmental measures and reference measure						
	EM1 (TFC,GDP1)	EM2 (TFC,GDP2)	EM3 (TFC,POP)	EM4 (TPES,GDP1)	EM5 (TPES,GDP2)	EM6 (TPES,POP)
Reference (TPES,GDP2)	0.0174	0.1068*	-0.1828*	0.2708*	0.3502*	0.0791*
	0.0120	0.0781*	-0.1313*	0.1802*	0.2391*	0.0499*

Notes:
The first row reports the Spearman's ρ coefficients between the means of environmental variables calculated for 34 countries from 2010 to 2016 and the reference measure exemplified for the year 1992 from Harris et al. (2002). The second row tells of Kendall's τ_b for measuring the same association. Here * indicates significance at the 0.1 percent level. P-value of the rank coefficient between the reference measure and EM1 is about 0.19 for both estimates.

Harris et al. (2002) focus on the measure calculated on Total Primary Energy Supply and GDP adjusted by exchange rates ($\mathrm{R}_{\mathrm{TPES,GDP2}}$) because that ranking conforms to the one constructed by Van Beers and Van den Bergh (1997) the most. As displayed in Table 7, $\mathrm{EM}_{\mathrm{TPES,GDP2}}$ is the most similar one to the reference. The result is unsurprising because they are generated with the same data series by the same method, but even the highest correlation coefficient between the constructed rankings and the reference one is around 0.35 only. It implies that none of the indicators shows an adequate level of similarity to the reference one. However, the dissimilarity between the ranks is probably a by-product of the completely different time periods included in the investigation and so plausibly the method is still applicable. I follow Harris et al. (2002) and underscore $\mathrm{R}_{\mathrm{TPES,GDP2}}$ for it allows for comparison.

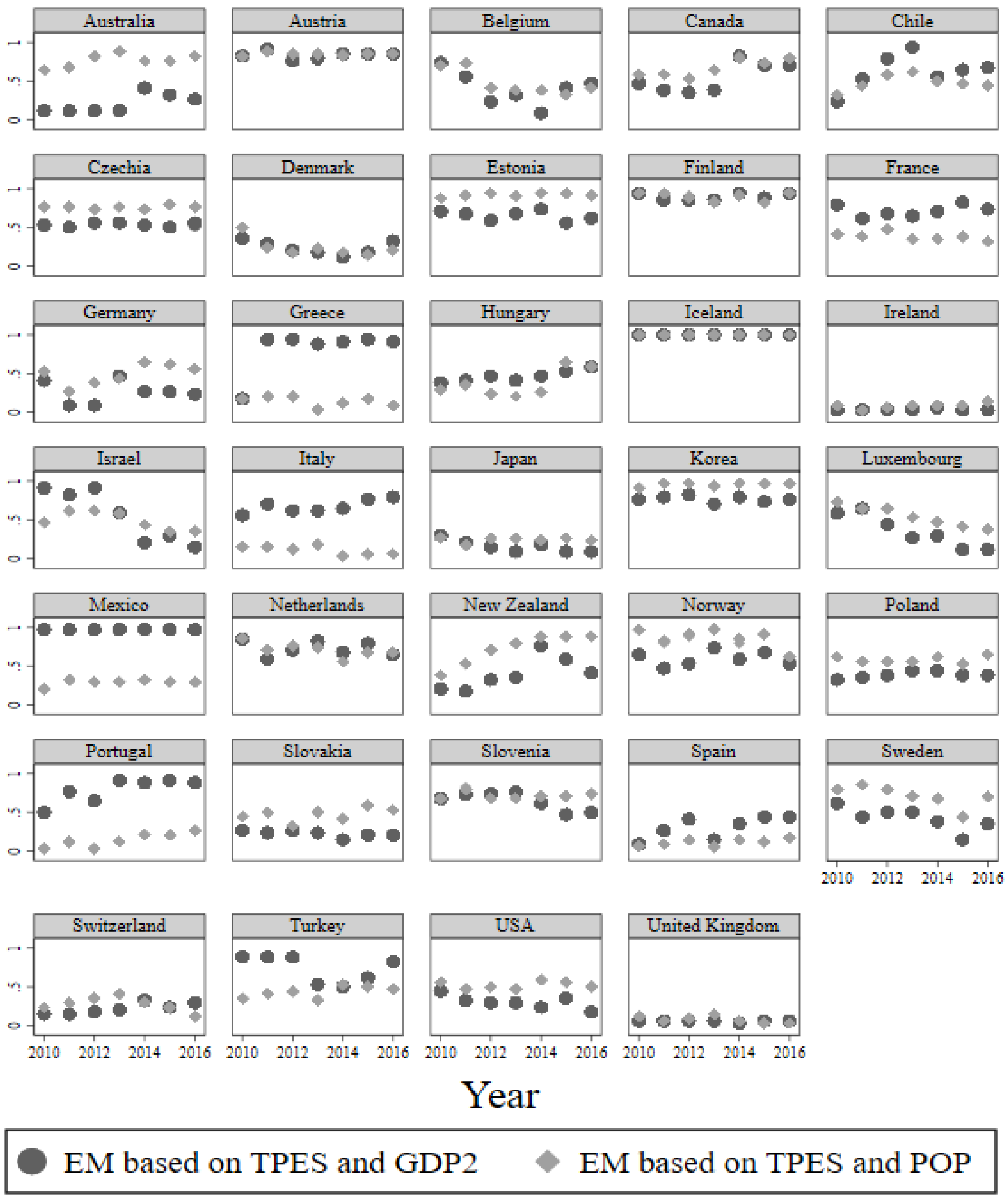
In addition to $\mathrm{EM}_{\mathrm{TPES,GDP2}}$, $\mathrm{EM}_{\mathrm{TPES,POP}}$ is also used in this study as it has an interesting property: theoretically, it is a scaled $\mathrm{EM}_{\mathrm{TPES,GDP2}}$ by the country's average income[20]. Since GDP and population size are both included in the model as independent variables, the "scaler" component is controlled already and $\mathrm{EM}_{\mathrm{TPES,POP}}$ can work as an interaction between $\mathrm{EM}_{\mathrm{TPES,GDP2}}$ and GDP per capita (based on exchange rate). In this way, I investigate whether the strength and direction of the effects of the environmental regulations on trade are dependent on the income level.

Figure 6 plots the yearly environmental measures of focus for all 34 OECD countries. The two measures are akin for most countries in the scope. For Austria, Denmark, Finland, Iceland, Ireland, the Netherlands, and the United Kingdom, they are almost identical.

[20] It can be shown by decomposing the former indicator: $\frac{\mathrm{TPES}}{\mathrm{POP}} = \frac{TPES}{GDP_1} * \frac{GDP_1}{POP}$, where GDP per capita can be viewed as a scaler if holding constant in the analysis.

Nonetheless, the similar traits between the two measures are less present for some other countries. Greece and Mexico are examples in terms of *level* differences. Some small gaps in the dynamic changes of the measures can also be discerned.

Figure 6: Yearly $EM_{TPES,GDP2}$ (based on Total Primary Energy Supply and GDP adjusted on exchange rate and) and $EM_{TPES,POP}$ (based on Total Primary Energy Supply and Population) for 34 OECD countries



Finally, some descriptive information is provided in Table 8 as for EMD variables, exemplified by $EM_{TPES,GDP2}$ and $EM_{TPES,POP}$ because these 2 would be the focus among all 6 measures. Recall that they are standardized and so they indicate how inequal two countries are regarding their environmental regulatory stringency but not the direction. It's shown in Figure

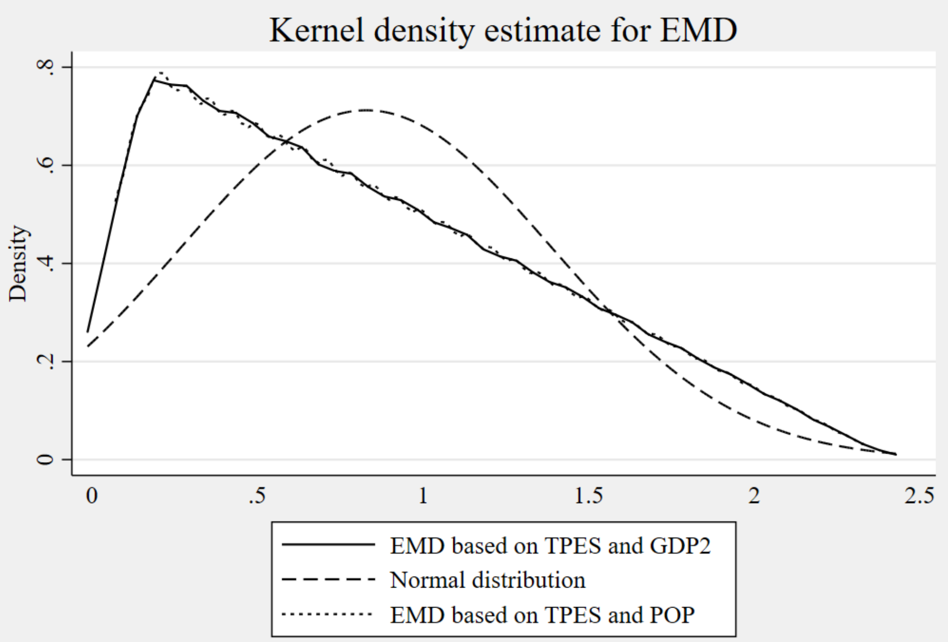
7 that EMD variables are largely skewed to the right. That's partly because this type of variables is established on the EM variables under natural-logarithm transformation and then the absolute value is taken. This skewness wouldn't affect the usage of this variable in the model but gives away that most countries don't suffer from extreme disparities in environmental regulations. In addition, the difference is smaller between the 2 EMD variables in all respects, although the two base variables for calculating the EMD differ substantially from each other. This property of less potential dependence on measure choice may reinforce the rationale of substituting unilateral environmental measures with them.

Table 8: Summary statistics for 2 exemplary EMD variables

	Mean	SD	Max	Min	95%	75%	50%	25%	5%	No.obs
EMD (TPES, GDP2)	0.828	0.560	2.343	0.0710	1.846	1.207	0.710	0.355	0.071	7854
EMD (TPES, POP)	0.828	0.560	2.343	0.0710	1.846	1.207	0.710	0.355	0.071	7854

Notes:
The values are standardized scores, representing how many standard deviations (of the base variable) away they are from their (base variable's) mean. The statistics are produced on the overall sample.

Figure 7: Distribution of 2 exemplary EMD variables



TPES: Total Primary Energy Supply, GDP2: GDP adjusted on exchange rate, POP: population

4 Methodology and the models

4.1 The Gravity setting

This subsection provides some background information for the empirical models modified specifically for the study. All specifications in this study are based on the classic Gravity model as developed by Tinbergen (1962) and Linnemann (1966). The main reason for choosing this model is that focusing on the bilateral flows allows to distinguish the types of trade partners, control more for the heterogeneity of countries and reduce the chance of multiple countries' environmental regulatory differentials cancelling out (as in the HOV models), because multilateral trade is an aggregate of bilateral trade flows (Van Beers and Van den Bergh 1997).

The basic Gravity model has the following form:

$$\mathrm{X_{ij}} = \beta_0 Y_i^{\beta_1} Y_j^{\beta_2} N_i^{\beta_4} N_j^{\beta_4} D_{ij}^{\beta_5} e^{\beta_6 P_{ij}} e^{u_{ij}}$$

with the dependent variable X_{ij} being the trade flows between country i and country j, Y_i and Y_j being the GDP of country i and country j respectively, N_i and N_j being population, D_{ij} representing the distance between 2 countries and P_{ij} assembling all dummy variables that capture other important determinants of trade resistance or aid, such as adjacency and common official language (see CONTIG and COMLANG introduced in Section 3.1.2.2). The log-linear transformation is performed to facilitate the data fitting:

$$\ln X_{ij} = \ln \beta_0 + \beta_1 \ln Y_i + \beta_2 \ln Y_j + \beta_3 \ln N_\mathrm{i} + \beta_4 \ln N_j + \beta_5 \ln D_{ij} + \beta_6 P_{ij} + u_{ij} \tag{1}$$

A caveat for the linear transformation method is that zero trade flow can't be converted into a logarithm. All trade flows involved in this study are positive and so it is applicable here. Coefficients including β_1, β_2, β_3, and β_4 for the factors that facilitate trade are supposed to be positive and those accounting for trade resistance such as β_5 are usually negative.

A large amount of literature has recognized the consistent empirical success of the gravity model in explaining trade flows and consistently high statistical explanatory power (Bergstrand 1985). Admitted that many critics have pointed out an absence of strong theoretical foundations and that all the previous justifications are strongly assumption-inelastic, the validity of gravity trade equations in this paper would be unharmed because the aim for this study is to observe the small fraction of the trade flows that may be significantly linked with environmental regulations, but not to estimate the gravity parameters. The gravity model is empirically sophisticated and a handy tool to discompose bilateral trade and identify a possible residual related to the variables of interest.

4.2 Empirical models

4.2.1 Baseline model

Given the panel data, the cross-sectional gravity model is transformed into a panel gravity model, augmented with a time index. This choice of skipping the cross-sectional model and employing extensively panel models is advantageous in two ways. Firstly, it exploits variation across countries from different years. Secondly, it provides a better environment where many different econometrics tools are eligible and helps reduce the bias resulted from relevant unobservable elements (McPherson et al. 2000).

Baseline model, with time fixed effects, takes the form below:

$$\begin{aligned}\ln IMP_{ijt} = \beta_0 + \lambda_t + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln POP_{it} + \beta_4 \ln POP_{jt} \\ + \beta_5 \ln DIST_{ijt} + \beta_6 CONTIG_{ijt} + \beta_7 COMLANG_{ijt} + \beta_8 PTA_{ijt} \\ + \beta_9 MEU_{ijt} + \beta_{10} NAFTA_{ijt} + \beta_{11} \ln LAND_{it} + \beta_{12} \ln LAND_{jt} + \beta_{13} CE_{ijt} \\ + \beta_{14} \ln EM_{it} + \beta_{15} \ln EM_{jt} + u_{\mathrm{ijt}} \qquad (2)\end{aligned}$$

where β_0 functions the same as $\ln \beta_0$ from the equation (1) for simplicity, λ_t measures the time fixed effects and the other variables have been introduced in detail in Section 3.1.

More complicated than the classic gravity model, it is however the basic model in this study. As a starting point, this panel model provides an overview of how the important covariates are included. It is tailored for the purpose of this study, by introducing the measures of domestic environmental efforts for both countries involved in the bilateral trade respectively, i.e. the policy variables $\mathrm{EM_{it}}$ and $\mathrm{EM_{jt}}$. A country that exerts more efforts in environmental protection has a smaller $\mathrm{EM_t}$, and so if the coefficient β_{14} is found to be positive, it would imply that laxer environmental regulations (from the importer side) would encourage imports on average and if negative, stricter environmental regulations would encourage trade instead. The other environmental coefficient β_{15} delineates the relationship between the exporter's environmental regulatory stringency and its possible ability to export. If it is positive, it would mean that one country is more likely to import from the country with laxer environmental regulations than from a strictly environmentally inspected country; and if negative, then the situation would be the opposite where the country with worse environmental standards may experience a decrease in exports and one country prefers to import from a more environmentally friendly country. Other coefficients $\beta_1, \beta_2, \beta_3, \beta_4, \beta_6, \beta_7, \beta_8, \beta_9, \beta_{10}, \beta_{11}, \beta_{12}$ and β_{13} are expected be positive because these factors aid trade, and β_5 would be negative as it captures trade resistance.

The time fixed-effects term λ_t is meant to capture the time-relevant effects that are not observed already by those independent variables. It can be a global trend in the development of bilateral trades that results from a strengthened international integration, reallocation of resources and better specification of production, a systematic shift of trade towards rising economies such as China, or simply natural fluctuations owing to business cycles.

Unobservable time-related factors being taken care of, though, another concern may arise that the present independent variables are only a subset of all time-invariant factors that affect trade in reality. It implies that there exist possible omitted variables. A common rescue for this issue is to include country-level fixed effects, under the assumption that these unobserved time-invariant effects are grouped within each country. This underlying assumption is innocuous because a country is the basic unit of the international trade and unobservable or non-measurable trade conditions such as the culture, other than the language within a country, are rather homogeneous.

4.2.2 Fixed-effectss models

Model 1 is built upon the baseline panel model with country-specific fixed effects added for both importer and exporter countries with the intention of fixing the issue of omitted variable bias. It has the following form:

$$\begin{aligned}\ln IMP_{ijt} = {} & \alpha_i + \gamma_j + \lambda_t + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln POP_{it} + \beta_4 \ln POP_{jt} \\ & + \beta_5 \ln DIST_{ijt} + \beta_6 CONTIG_{ijt} + \beta_7 COMLANG_{ijt} + \beta_8 PTA_{ijt} \\ & + \beta_9 MEU_{ijt} + \beta_{10} NAFTA_{ijt} + \beta_{11} CE_{ijt} + \beta_{12} \ln EM_{it} + \beta_{13} \ln EM_{jt} \\ & + u_{ijt} \qquad (3)\end{aligned}$$

where the components are almost same as in the equation (2), except that, first, the intercept β_0 can be regarded now absorbed in the fixed effects terms including α_i for the importing side and γ_j for the exporting side[21]; and second, the LAND variables are dropped as suggested by Harris et al. (2002), because they vary merely in the dimension of country. To be precise, there

[21] The fixed effects are in practice one time-invariant intercept per subject. Keeping the original intercept β_0 in the model doesn't really make any difference because the magnitudes of the country-level fixed effects are not the focus of this study. There is thus no need to put any constraint on the sum of panel fixed effects across all observations.

might be some small differences in land areas of a country between the beginning year 2010 and the ending year 2016 due to the geological change, but the differences are too little compared to their magnitudes and can be neglected. Therefore, I take the land areas as time-invariant and consequently their impact would be absorbed into fixed-effects terms.

To understand it better, consider a fixed effect α_i for country i. It would be the average effect of the uncontrolled elements specific to country i on its own imports from all trading partners in the sample. Likewise, γ_j would measure the average effect on country j's exports of it being the trading partner to any country i $(i \neq j)$ in the sample. Mátyás (1997) argues that this three-indexed specification is the most natural gravity specification and it is a direct generalisation of the two-way fixed effects panel data model. Model 1 is therefore just a simplified specification of Model 2 with the unnecessary restriction $\alpha_i = \gamma_j = 0$ imposed for all i and j.

Recall that the environmental measures that are based on Population can alternatively be interpreted as an interaction term, this then gives rise to ***Model 2***:

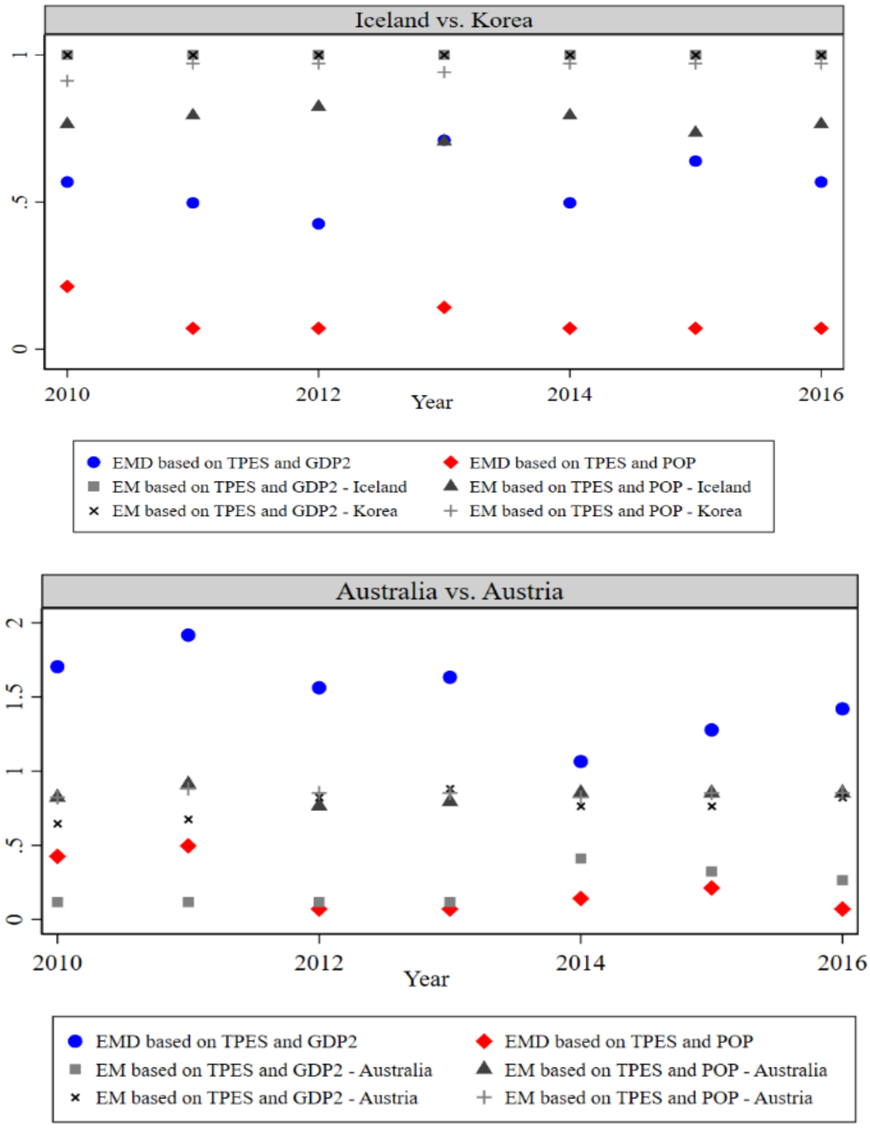
$$\begin{aligned}\ln IMP_{ijt} = {} & \alpha_i + \gamma_j + \lambda_t + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln POP_{it} + \beta_4 \ln POP_{jt} \\ & + \beta_5 \ln DIST_{ijt} + \beta_6 CONTIG_{ijt} + \beta_7 COMLANG_{ijt} + \beta_8 PTA_{ijt} \\ & + \beta_9 MEU_{ijt} + \beta_{10} NAFTA_{ijt} + \beta_{11} CE_{ijt} + \beta_{12} \ln EM_{it} + \beta_{13} \ln EM_{jt} \\ & + \beta_{14} \ln EM_{it} * \ln\left(\frac{GDP_{it}}{POP_{it}}\right) + \beta_{15} \ln EM_{jt} * \ln\left(\frac{GDP_{jt}}{POP_{jt}}\right) + u_{ijt} \qquad (4)\end{aligned}$$

where most variables function in the same way as in Model 1, except that now 2 interaction terms are added. In the regression, they would be performed by $EM_{TPES,POP}$ or $EM_{TFC,POP}$.

Admittedly, including these fixed effects can greatly reduce omitted variable bias, but there is still some doubt related to the implementation of the fixed-effects specification whether it is correct to directly add fixed-effects terms while keeping all the independent variables in the model. By including country-level fixed effects respectively for importers and exporters, all unilateral time-invariant influences that vary only from country to country are captured in fixed-effects terms. However, the variables EM do not technically vary in both dimensions for all subjects, and the within-subject variability is small across time. The policy variables of interest seem "stable" for some countries, Iceland and Korea being great examples with almost constant values of their environmental indicators as seen in Figure 8. Despite the moderate fluctuations extant for some other countries, it remains questionable whether the fixed-effects specification would spoil the estimation by mishandling some of the effects of interest as fixed effects, especially when the magnitudes of the policy variables EM are very small inherently, between 0 and 1.

Regarding the issue, one solution may be to transform the unilateral measures EM into a bilateral measure EMD. This new variable has been introduced detailly in Section 3.1.2.3. In short, this transformation would improve the dynamics, induce more variations and magnify the magnitude of variation both within and across countries, and hence I can exploit more identifying variation. For example, even for the most inert countries in respect of the environmental rankings - Iceland and Korea, the new measure EMD shows a dynamic pattern.

Figure 8: Comparison between exemplary unilateral measures and bilateral measures for environmental regulatory stringency (for trading pairs of Iceland and Korea, Australia and Austria)



It must be explained that the same issue may apply to most dummy variables, namely CONTIG for contiguity, COMLANG for the common language, MEU for joint EU membership and NAFTA, because they don't change over time. They describe a relatively steady status within a trading pair and might be in nature a part of country-specific features. But since the panel estimation is basically repeating at a cross-section level with yearly data and they are not of primary interest to the study, it is harmless to keep these bilateral dummy variables in the model.

Accordingly, ***Model 3*** is formed as:

$$\begin{aligned}\ln IMP_{ijt} = {} & \alpha_{\mathrm{i}} + \gamma_j + \lambda_t + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln POP_{it} + \beta_4 \ln POP_{jt} \\ & + \beta_5 \ln DIST_{ijt} + \beta_6 CONTIG_{ijt} + \beta_7 COMLANG_{ijt} + \beta_8 PTA_{ijt} \\ & + \beta_9 MEU_{ijt} + \beta_{10} NAFTA_{ijt} + \beta_{11} CE_{ijt} + \beta_{12} EMD_{ijt} + u_{\mathrm{ijt}} \qquad (5)\end{aligned}$$

with the previous policy variables $\mathrm{EM_{it}}$ and $\mathrm{EM_{jt}}$ substituted by a single bilateral variable $\mathrm{EMD_{ijt}}$ while other components are unchanged.

As EMD is employed in this specification instead, more attention is paid to the inequality between two countries' environmental efforts and its impact on the imports of country i from country j. This shift of attention does not deviate from the goal of the research because it helps answer the question of whether the absolute difference in environmental regulations affects bilateral trade, even though it is unable to split local and target effect and identify the direction of either effect. If the coefficient β_{12} is significantly negative, it will imply that asymmetry in environmental regulations would hinder trade, and in general these 34 OECD countries prefer trading with the countries that are doing as well as themselves in environmental work. And if positive, the parameter would be a sign that trade happens more when the environmental regulations differentiate a lot between two countries.

4.2.3 Mixed-effects Models

Granted that three-way fixed effects are widely used in the literature, it may still not be able to fully resolve the potential incompatibility between the fixed effects model and one-sided environmental variables. Another possible way to solve it is to view the unobserved country-specific characteristics as randomly distributed and use the random-effect model instead. Indeed, since the countries under investigation are distinct in various respects, the unobserved heterogeneity probably exists. ***Model 4***, a mixed-effects model with exporter and importer random effects as well as the time fixed effects allows for the estimation of explanatory variables which are not time-variant enough, looking like:

$$\begin{aligned}\ln IMP_{ijt} = {} & \alpha_{\mathrm{i}} + \gamma_j + \lambda_t + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln POP_{it} + \beta_4 \ln POP_{jt} \\ & + \beta_5 \ln DIST_{ijt} + \beta_6 CONTIG_{ijt} + \beta_7 COMLANG_{ijt} + \beta_8 PTA_{ijt} \\ & + \beta_9 MEU_{ijt} + \beta_{10} NAFTA_{ijt} + \beta_{11} CE_{ijt} + \beta_{12} \ln EM_{it} + \beta_{13} \ln EM_{jt} \\ & + u_{\mathrm{ijt}}, \end{aligned} \tag{6}$$

and the only difference between Model 1 and Model 4 is the way of treating α_i and γ_j in the estimation.

Another advantage of modelling the unobserved effects as random effects is that it can improve the external validity of this study. The purpose of this study is not to compare the trade performance of the chosen countries, but to understand the general impact of environmental regulatory stringency on trade. The results would be applicable to more countries with similar conditions if the country is treated as randomly drawn from all countries in the world.

To be prudent, EMD is used again as a substitution for the EM variables in this mixed-effects model for answering the last research question and for robustness test. The specification would look the same as Model 3 and so the description is omitted here. Likewise, ***Model 5*** is constructed to test for the interaction effects and it takes exactly the same form as Model 2, therefore the model description is omitted.

4.2.4 Lagged Dependent Variable Models

The last cause of the prospective bias in estimating the environment-related effects may be the dynamics, i.e. serial correlation when using a panel dataset. It can simply be a violation of the assumption that omitted variables are constant over time. The serial correlation may be present in 2 ways. First, there's hysteresis[22] in trade and it is hard to model. The existing economies of scale may evolve to how they are now for some historical reasons. For example, temporary trade policy in place or exchange rate fluctuation may cause foreign firms to establish branch factories overseas (Eichengreen and Irwin 1996). These consequences of past disturbances may continue affecting trade afterward because of the existence of costs associated with shifting a decision for firms. Moreover, it is plausible that there are also first-mover advantages in trade. Consumers may have built trust with certain brands from a foreign country, with which their

[22] Hysteresis here refers to the long-lasting influences of a passing shock.

own country has long trade partnership. And it takes long negotiation and many endeavours to liberalize the trade to a higher extent between 2 countries, which would have provided great opportunities for the exporting incumbents to strengthen their positions in the target market. If so, the longer the two countries have been trading with each other and the larger the trade values are between them, the more likely the trade between them would increase in the future. Second, the impact of a past event on the independent variables including EM needs to be considered too. The worst scenario would be that there're sequential effects between energy-related regulations and trade. As an energy-oriented measure is employed for the investigation, imagine that a company purchases some energy-saving equipment during the time where the country subsidizes this type of environment-improving investment. That environmental policy may have ended shortly after, but the resulted purchase would, however, affect the energy intensity level for a long time, and the effects of past environmental regulations would be measured in the current environmental variable.

The last model I estimate is a lagged dependent variable (LDV) model and it can help to incorporate the probable effects of the autocorrelated factors. ***Model 6*** takes the basic form of the Model 1 with a lagged trade term $\ln IMP_{ij(t-1)}$ added:

$$\begin{aligned}\ln IMP_{ijt} = {} & \beta_0 + \lambda_t + \theta \ln IMP_{ij(t-1)} + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} \\ & + \beta_3 \ln POP_{it} + \beta_4 \ln POP_{jt} + \beta_5 \ln DIST_{ijt} + \beta_6 CONTIG_{ijt} \\ & + \beta_7 COMLANG_{ijt} + \beta_8 PTA_{ijt} + \beta_9 MEU_{ijt} + \beta_{10} NAFTA_{ijt} \\ & + \beta_{11} \ln LAND_{it} + \beta_{12} \ln LAND_{jt} + \beta_{13} CE_{ijt} + \beta_{14} \ln EM_{it} + \beta_{15} \ln EM_{jt} \\ & + u_{\mathrm{ijt}}, \qquad (7)\end{aligned}$$

and only one-period lag is considered as the panel is short, covering merely 7 years.

The advantages of using LDV model in this situation are clear and powerful. First, the assumption that the trade flow at time *t* can be a function of that same type of trade flow at time *t-1* modified by new information doesn't seem odd, and meanwhile the periodic autocorrelation can be interpreted as a theoretical linkage between 2 periods under an LDV model. Second, lagged dependent variable models are theoretically preferable for testing theories that have a dynamic component (Keele and Kelly 2006). As I show earlier, the factual environmental regulations may be adjusted on the past trade flows, which would be the dynamics in policymaking. Although LDV models are being explored by more and more researchers, it has not been used yet in the literature of environmental-trade relationship.

To estimate the specification in a relatively convenient yet effective way with the short panel, a first difference 2SLS estimator is adapted. The ***transformed Model 6*** is as following:

$$\begin{aligned}
\ln IMP_{ijt} - \ln IMP_{ij(t-1)} \\
&= (\lambda_t - \lambda_{t-1}) + \theta\big(\ln IMP_{ij(t-1)} - \ln IMP_{ij(t-2)}\big) + \beta_1(\ln GDP_{it} \\
&- \ln GDP_{i(t-2)}) + \ \beta_2\,(\ln GDP_{jt} - \ln GDP_{j(t-1)}) \\
&+ \beta_3(\ln POP_{it} - \ln POP_{i(t-1)}) + \beta_4\,(\ln POP_{jt} - \ln POP_{j(t-1)}) + \beta_5(CE_{ijt} \\
&- CE_{ij(t-1)})\ + \beta_6(\ln EM_{it} - \ln EM_{i(t-1)}) + \ \beta_7(\ln EM_{jt} - \ln EM_{j(t-1)}) \\
&+ \beta_8(PTA_{ijt} - PTA_{ij(t-1)}) + \big(u_{\mathrm{ijt}} - u_{ij(t-1)}\big) \qquad (8)
\end{aligned}$$

Some of the independent variables don't effectively vary with time, including most dummy variables and distance, and thus are subtracted from the first-difference equation. In practice, the differenced time fixed effects can be assumed to be constant, thus an intercept for the model. After the first-difference transformation, the new dependent variable is now a function of the differenced time-varying independent variables and its own lag. A new issue has arisen here, that this lagged term may still be correlated the new error term $\big(u_{\mathrm{ijt}} - u_{ij(t-1)}\big)$ because the error term contains $u_{ij(t-1)}$ which is perceived as a cause of $\ln IMP_{ij(t-1)}$.

I first adopt an Anderson–Hsiao (AH) estimator to estimate the model, which should work well with a large cross section (1122 country-pairs) over a small time period (T=7). As a generalised solution used, an IV variable $\ln IMP_{ij(t-2)} - \ln IMP_{ij(t-3)}$ can be used for the lagged dependent variable $\ln IMP_{ij(t-1)} - \ln IMP_{ij(t-2)}$. Losing 3 waves of data may cause some problem when the total panel period covers only 7 years. Therefore, I also use the Arellano-Bond estimator, which is also known as difference GMM, to estimate the Model 6 where deeper lags of the dependent variable are used as instruments for differenced lags of the dependent variable. Even though the IV from the first estimator would give a stronger first stage, using the alternative level variable $\ln IMP_{ij(t-2)}$ as the instrumental variable may be a preferred solution in this case because it helps to keep one more wave of data.

In this setting, the dynamics of trade as well as the regulations are captured. The coefficients in front of the differenced environmental measures would be interpreted in a similar way, except that they give more information about the reaction of trade to the changes in the stringency of environmental regulations for this country.

5 Results

5.1 Model comparison

The 6 models implemented in this paper can be summarized into 3 types: fixed-effects model, mixed-effects model, and Lagged Dependent Variable model. Accordingly, the model comparison can take place in 2 pairs: Fixed-effects (FE) Model versus Mixed-effects (ME) Model, and Mixed or Fixed-effects Model versus Lagged Dependent Variable model.

5.1.1 FE Model vs. ME Model

Before the comparison, the poolability of the FE and ME model is checked. The joint F-test result gives a p-value lower than 0.001 for all FE specifications, strongly rejecting the null that fixed-effects intercepts are jointly insignificant and indicating that FE model is preferred to Baseline model. Given that the random-effect (RE) estimator uses the additional orthogonality conditions that the regressors are uncorrelated with the group-specific error, an LM test[23] is performed on the random-effect models. The result of tests suggests the null hypothesis that there is no difference between the pooled regression model and the ME model (or RE model in terms of country-specific effects) is strongly rejected for all ME specifications. Therefore, ME model is preferred to Baseline model.

The question then is whether to model the time-invariant country-specific effects as fixed or random. The differentiation between fixed effects and random effects has been made clear in Section 4.2.3. To briefly explain, the two models have fundamentally different assumptions on (1) the correlation between the group effects and other covariates and (2) the sampling process. Especially random effects require the unobserved elements to be uncorrelated with other observed independent variables throughout the panel. On the one hand, the random effect model is useful in this case, because the variable of interest shows a small variability, which may stimulate the fixed effects to oversoak the effects that are induced by inert country-specific factors, primarily the environmental regulatory measures. Besides, the first assumption should not gainsay the usefulness of random effect model. If this assumption doesn't hold, the most likely violation would be the interaction between regulatory measures and the omitted factors such as climate. But the bias would not be significant because the magnitude of it is determined by the possible correlation size (Clark and Linzer 2015) and it's

[23] Breusch and Pagan Lagrangian multiplier test for random effects.

reasonable to argue that the correlation is trivial. Remember that the measure is constructed equally on static and dynamic rankings. These unobserved time-invariant determinants for bilateral trade may be associated with a country's static ranking but not dynamic ranking. Even between unobserved factors and static rankings, the correlation would be very small because the environmental measures used depend heavily on production and consumption, whereas the omitted variables contributing directly to trade here would be mostly from the elements such as culture and political reasons that don't affect the size of domestic supply or demand (otherwise they would be thought to have been controlled by gravity variables). On the other hand, the random-effect models are not particularly favoured on the second assumption, since 34 out of 36 OECD countries are selected into the study, only 2 left out. They're not so randomly chosen from the population that fixed-effects models would have low external validity. It is hard to choose between the two models just by verifying the assumptions.

Next, I compare the estimates generated with normal standard error for Model 1 and Model 4, trying to discriminate between FE model and ME model, followed by post-estimation Hausman tests. The estimates produced by ME models are larger and more often significant compared to the ones from FE models but with the same signs. The null of the random-effect model (precisely the random-effect components in a ME model) being more consistent and efficient, however, is strongly rejected by Hausman tests. The results are summarized in Table 9 and they suggest that the FE specifications are more trustworthy.

Table 9: Results for F, LM and Hausman tests for Model 1 and 4

	Results based on $R_{TPES,GDP2}$		Results based on $R_{TPES,POP}$	
	Model 1, FE	Model 4, ME	Model 1, FE	Model 4, ME
EM (log) importer	0.0086168 (0.0077367)	0.009627 (0.0074393)	0.0220447** (0.0087776)	0.0344583*** (0.0084176)
EM (log) exporter	0.0067998 (0.0077367)	0.0231141*** (0.0074393)	0.0290592** (0.0087776)	0.0313163*** (0.0084176)
R^2(overall)	0.9162	0.8406	0.9162	0.8589
F test: time fixed effects = 0	11.95***		11.61***	
F test: country-specific fixed effects=0	71.89***	-	66.25***	-
LM, χ^2	-	19336.03***	-	19052.83***
Hausman, χ^2	253.65***		322.12***	

Notes:
The Model 1 and 4 are respectively estimated with 2 different measures, one based on Total Primary Energy Supply and GDP adjusted by exchange rate and another on Total Primary Energy Supply and population. Normal standard errors are in parentheses. *** indicates p<0.01. The rest of the estimation results are in Appendix (A3).

Heteroskedasticity is a problem in this panel according to both the Breusch-Pagan test and the White test, of which tests the null hypotheses are rejected at a significance level of

0.001. Straightforwardly I perform the clustering at the trading-pair level because it produces more consistent estimates of the standard errors (Drukker 2003). Therefore, the FE estimator is employed in combination with clustered standard errors and the FE estimates are highlighted in the result interpretation.

5.1.2 FE Model vs. Lagged Dependent Variable Model

It is a challenge that most researchers face to choose between the FE and LDV models in a panel setting, and it is often suggested to check the robustness of the findings using alternative identifying assumptions. To explain the main difference between Model 1-5 and the LDV model, Model 6, we can look at their key identifying assumptions:

$$\mathrm{E}\left(\ln IMP_{0ijt} \,|\alpha_\mathrm{i}, \gamma_\mathrm{j}, \lambda_\mathrm{t}, \mathrm{X}, \mathrm{EM}\right) = \mathrm{E}\left(\ln IMP_{0ijt} \,|\alpha_\mathrm{i}, \gamma_\mathrm{j}, \lambda_\mathrm{t}, \mathrm{X}\right) \quad (9)$$

$$\mathrm{E}\left(\ln IMP_{0ijt} \,|\, \ln IMP_{ij(t-1)}, \mathrm{X}, \mathrm{EM}\right) = \mathrm{E}\left(\ln IMP_{0ijt} \,|\, \ln IMP_{ij(t-1)}, \mathrm{X}\right) \quad (10)$$

Remember that the policy variables EM range between 0 (exclusive) and 1 (inclusive) by construction. The EM for the worst performer in the environmental game takes value 1 and so $\ln EM$ equals 0. And Y_{0ijt} in Equation (9) and (10) is the import of a country who has 0 achieved in $\ln EM$. Any country who performs better than this benchmark country has a different negative $\ln EM$ number. Being a benchmark status, Y_{0ijt} is assumed to be unconditional on the environmental differentials that are being investigated. α_i, γ_j and λ_t represent the specific effects on the bilateral trade of country i importing, country j exporting in a certain year t; X is a matrix grouping all the i-unilateral, j-unilateral and bilateral covariates; and EM is the regressor of interest. Equation (9) demonstrates the motivation behind the fixed-effects specifications and all the left deterministic components of the dependent variable are thought to be controlled by the fixed-effects terms (or random-effect terms according to the assumption), if not already controlled by the covariates. Unlike fixed-effects models, LDV models assume that the estimate of EM would not be biased if the other factors, including the lagged dependent variable term, explain for all noises in the dependent variable, as shown in Equation (10). Therefore, the key assumption here to check for choosing between FE model and LDV model is whether the trade flow of time t-1 would interact with the environmental score of time t. And it has been argued in Section 4.2.4 how the past records of trade may affect the environmental measures. Also, because the null hypothesis of no serial correlation is strongly rejected for all FE/ME models by Wooldridge test for autocorrelation, the distinction between the two models matters to answer the research question.

The second consideration is whether the conceived specifications produce efficient and consistent estimates. For the FE models, clustered standard error has been adopted to reduce heteroskedasticity. As for the LDV models, the unit root tests are performed, and the independent variables are found stationary. One important requirement for the Arellano-Bond (AB) estimator to work efficiently is that there be no second-order autocorrelation in the idiosyncratic errors. Correspondingly, I compare the estimates obtained from one-step AB estimator and two-step AB estimator and perform the Arellano-Bond test for validating the assumption[24]. The results are listed in Table 10. The null hypothesis of Arellano-Bond test that there is zero autocorrelation is all unrejected at order 2, and so there is no strong reason against using AB estimator. And the significant estimates from the two AB estimators are fairly similar, so there is no great need to switch from one-step estimator to two-step one. Compared with another estimator involved, the AB estimator reduces the number of lost waves of data by 1, so it is expected that AB one-step estimator performs better than Anderson–Hsiao (AH) estimator. AH results are used for robustness check.

Overall there is no strong reason to refute the usage of Lagged Dependent Variable model. Fixed-effects models and Lagged Dependent Variable models are therefore both extensively estimated, and the bracketing property may give the information needed.

Table 10: Comparison between one-step and two-step AB estimates

	AB estimator (one-step), robust	AB estimator (two-step), robust[25]
EM5(log) importer	-0.0019838 (0.0090334)	0.0094769 (0.0111539)

[24] Sargan Test of overidentifying restrictions may also be informative, but it is not performed in this study because it is found to overreject in the presence of heteroskedasticity when performed after one-step estimation and underreject with two-step estimation (Arellano and Bond, 1991). And it is not applicable when robust standard errors are computed.

[25] Windmeijer bias-corrected robust VCE is used.

EM5(log) exporter	-0.0193725*	-0.03366***
	(0.007519)	(0.009465)
EM6(log) importer	0.0410136***	0.0393656**
	(0.0099544)	(0.0133306)
EM6(log) exporter	0.0160086**	0.0097694
	(0.0080543)	(0.0110175)
EMD(based on EM5)	0.0298462***	0.0034427
	(0.0107549)	(0.0135272)
EMD(based on EM6)	0.0049087	-0.0050816
	(0.011293)	(0.015341)
Arellano-Bond Test for autocorrelation of order 2	H_0 rejected at order 1 but unrejected at order 2 for all specifications	H_0 rejected at order 1 but unrejected at order 2 for all specifications

Notes:
The results are combined from 8 specifications in total, 4 with AB one-step estimator and 4 with AB two-step estimator. Only the estimated coefficients of interest are kept here. In order to perform the Arellano-Bond Test, all the time-invariant variables are dropped from specification in the estimation. As a result, the coefficients obtained from one-step AB estimator are slightly different from the reported ones in the next subsection. The results shown here are only for comparison and selection of model.
*p<0.1, **p<0.05, ***p<0.01.

5.2 Estimation results

Several remarks need to be made before reporting the estimation results that: (1) clustered standard errors are computed for the fixed-effects models and the cluster is performed on trading pairs, while mixed-effects models are estimated with normal standard errors; (2) robust standard errors are computed for LDV models. Table 11 and Table 12 aggregate the estimated coefficients for the variables of primary interest, covering the results from all the models. Results from the baseline model are not interpreted but still included in Table 11 for the purpose of robustness check and comparison.

5.2.1 Estimation with unilateral environmental measure EM

Specifications reported under (1), (3), (5), (7) and (8) in Table 11 are based on the unilateral measure of $EM_{TPES,GPD2}$.

Significant parameter estimates are obtained for $EM_{TPES,GPD2}$ only in the LDV specification (7) and (8), and only for the exporter. By the means of Arellano-Bond estimator, a coefficient of -2.1% is found at a significance level of 0.05, and AH estimator finds an estimate of -1.27% at the 10% significance level. It implies that a country imports more from the exporter country with stricter environmental regulations. That is, stricter environmental regulations may do good to a country's exports, even though the effect size is small under the assumption that the past trade affects the unilateral measures importantly.

However, this result is confounded by the fact that both fixed-effects specification (3) and mixed-effects specification (5) find insignificant but positive coefficients on both sides of trade, which indicates a positive correlation between lax environmental regulations and one country's trade flows and implies that stricter environmental regulations would impede both imports and exports.

None of the specifications manages to detect a significant correlation between home country's $\mathrm{EM}_{\mathrm{TPES,GPD2}}$ and its own imports. If this is the case, it would signal that a country's environmental consideration does not affect its decision to import from others.

The findings from unilateral measures are therefore inconclusive.

5.2.2 Estimation with Interaction terms

Parameters for interaction terms are estimated in Model 2 and 5 and reported under specification (4) and (6), and the Baseline estimation is reported under specification (2) in Table 11.

Some significantly positive estimates are obtained for the interaction terms $\mathrm{EM}_{\mathrm{TPES,POP,i}}$ and $\mathrm{EM}_{\mathrm{TPES,POP,j}}$ in Model 2. The magnitude of the $\mathrm{EM}_{\mathrm{TPES,POP,i}}$ estimate is 2.2%, significant at the 5% level, and the other estimated coefficient is 2.9% at the 0.1% significance level[26]. The mixed-effects model gives similar coefficients but not significant. As the FE models has been shown to be preferred, I focus on the estimates from specification (4), Model 2. Although the estimates for the "pure" environmental measures $\mathrm{EM}_{\mathrm{TPES,GDP2,i}}$ and $\mathrm{EM}_{\mathrm{TPES,GDP2,i}}$ are not significantly different from 0, combining the effects from unilateral EM terms and interaction terms, the result implies that the effects of environmental regulations on trade are indeed contingent on the average income levels. When the income level for a country is higher than the sample average, the stricter environmental regulations may cause a larger decrease in the values of bilateral trade flows for this country. The composite correlation between stricter environmental regulations and trade is found to be negative[27].

Table 11: Selected estimation results for Models using unilateral environmental measures

	Dependent variable:						
	Imports of goods(log)						
	Baseline Model	***Fixed-effects Model***		***Mixed-effects Model***		***LDV-AB estimator***	***LDV-AH estimator***
		Model 1	**Model 2**	**Model 4**	**Model 5**		**Model 6**

[26] In Table 11, it is marked with 1% significance level. But it is in fact significant even at 0.1% level. Moreover, directly regressing on GDP per capita doesn't change the result. This result is not included in the paper but is available upon request.

[27] Remember that the worse a country performs in terms of environmental regulations, the greater in value the environmental measure is in this study. A positive coefficient thus represents the negative correlation: worse environmental performance may lead to higher imports value.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)		(8)
Lagged IMP							0.235***	Lagged differenced IMP	0.0417
							(0.053)		(0.129)
EM5(log) importer	0.016	-0.072***	0.007	0.0002	0.004	-0.006	-0.00251	Differenced EM5 importer	-0.00125
	(0.025)	(0.027)	(0.011)	(0.011)	(0.020)	(0.021)	(0.009)		(0.009)
EM5(log) exporter	-0.036	-0.126***	0.005	-0.004	0.022	0.013	-0.0210**	Differenced EM5 exporter	-0.0127*
	(0.025)	(0.027)	(0.011)	(0.011)	(0.020)	(0.021)	(0.008)		(0.007)
EM6(log) importer		0.177***		0.022**		0.032		Differenced EM6 importer	
		(0.027)		(0.011)		(0.024)			
EM6(log) exporter		0.179***		0.031***		0.029		Differenced EM6 exporter	
		(0.026)		(0.009)		(0.024)			
GDP1(log) importer	1.289***	1.213***	1.274***	1.222***	1.248***	1.201***	0.0158	Differenced GDP1 importer	0.1065
	(0.079)	(0.077)	(0.123)	(0.130)	(0.144)	(0.147)	(0.111)		(0.230)
GDP1(log) exporter	1.475***	1.398***	0.552***	0.478***	1.005***	0.960***	-0.272**	Differenced GDP1 exporter	-0.0389
	(0.079)	(0.079)	(0.117)	(0.122)	(0.149)	(0.154)	(0.118)		(0.161)
POP (log) importer	-0.415***	-0.306***	-0.157	-0.095	-0.382**	-0.329**	-0.439	Differenced POP importer	-0.3474
	(0.075)	(0.076)	(0.319)	(0.325)	(0.147)	(0.151)	(0.286)		(0.301)
POP (log) exporter	-0.533***	-0.423***	-1.303***	-1.216***	-0.140	-0.090	-0.634*	Differenced POP exporter	-0.638
	(0.078)	(0.078)	(0.330)	(0.336)	(0.154)	(0.160)	(0.358)		(0.444)
DIST (log)	-0.734***	-0.724***	-0.991***	-0.991***	-0.986***	-0.986***	-15.12***		
	(0.041)	(0.040)	(0.053)	(0.053)	(0.017)	(0.017)	(3.561)		
Observations	7,854	7,854	7,854	7,854	7,854	7,854	5610	Observations	4488
R^2	0.869	0.875	0.916	0.916				R^2 overall	0.0506
Adjusted R^2	0.869	0.874	0.915	0.915				F	1.87**
Log Likelihood					-7,750.719	-7,754.794	351.02***	χ^2	
Akaike Inf. Crit.					15,551.440	15,563.590			
Bayesian Inf.					15,725.660	15,751.750			
Residual Std. Error	0.786(df = 7832)	0.769(df = 7830)	0.631(df = 7768)	0.631(df = 7764)					

Notes:
*p<0.1; **p<0.05; ***p<0.01. Robust standard deviation is in parentheses. See Appendix – A3 for complete estimation results.
All parameter estimates for unimportant variables and fixed/random effect terms are not included in the table due to lack of interest. GDP1 refers to Gross Domestic Production adjusted on Purchasing Power Parity. POP stands for Population. DIST is the distance variable. LAND and CE respectively proxy the land and the difference in capital-labour ratio endowment. EM represents Environmental regulatory measures and they are built up energy intensity in this paper. EM5 is an ordinal variable built on primary energy supply per unit of GDP adjusted on exchange rate and EM6 is built on primary energy supply per capita. The detailed explanation of variables and data source can be found in Section 3.1.

5.2.3 Estimation with bilateral environmental measure EMD

Specifications numbered from (9) to (12) estimate the parameters for the bilateral measure EMD built upon $\mathrm{EM_{TPES,GPD2}}$. The results are reported in Table 12.

The specification (9) and (10), which don't include a lagged term, obtain completely different results from the LDV specification (11) and (12). The estimation of the FE Model (Model 3) and the ME Model (Model 4) yields negative estimates for the EMD constructed on $\mathrm{EM_{TPES,GDP2}}$, but the coefficients are not significantly different from 0. The LDV specifications, on the contrary, claim that both parameters are positive. The magnitude of Arellano-Bond estimate is 3.07% at a significance level of 0.01. Anderson–Hsiao (AH) estimator generates an estimated coefficient of 2.09% with a significance level of 0.05.

Table 12: Selected estimation results for Models using bilateral environmental measures					
	Dependent variable:				
	Imports of goods(log)				
	FE Model	***ME Model***	***LDV-AB estimator***		***LDV-AH estimator***
	Model 3	**Model 4**	**Model 6**		
	(9)	(10)	(11)		(12)
EMD (based on EM5)	-0.016 (0.030)	-0.013 (0.014)	0.0307*** (0.011)	Differenced EMD (based on EM5)	0.0209** (0.103)
GDP1 (log) importer	1.259*** (0.122)	1.241*** (0.143)	-0.00989 (0.110)	Differenced GDP1(log) importer	0.118 (0.227)
GDP1 (log) exporter	0.539*** (0.116)	0.982*** (0.148)	-0.268** (0.117)	Differenced GDP1(log) exporter	-0.0010 (0.160)
POP (log) importer	-0.180 (0.317)	-0.377** (0.146)	-0.386 (0.286)	Differenced POP (log) importer	-0.3314 (0.298)
POP (log) exporter	-1.320*** (0.323)	-0.124 (0.153)	-0.592* (0.357)	Differenced POP (log) exporter	-0.627 (0.442)
DIST (log)	-0.991*** (0.053)	-0.986*** (0.017)	-15.03*** (3.556)	Differenced DIST (log)	-
Lagged IMP			0.236*** (0.053)	Lagged Differenced IMP	0.038 (0.128)
Observations	7854	7854	5610		4488
R^2	0.916			R^2 overall	0.0518
Adjusted R^2	0.915			F	1.86**
Residual Std. Error (df = 7769)	0.631		69.95***	χ^2	

Notes:
*p<0.1; **p<0.05; ***p<0.01. Robust standard deviation is in parentheses. See Appendix – A3 for complete estimation results.
All parameter estimates for unimportant variables and fixed/random effect terms are not included in the table due to lack of interest. GDP1 refers to Gross Domestic Production adjusted on Purchasing Power Parity. POP stands for Population. DIST is the distance variable. LAND and CE respectively proxy the land and the difference in capital-labour ratio endowment. EMD is a standardized score of the disparity between 2 countries in terms of environmental efforts, transformed based on EM5 in the reported estimation. And EM5 is ordinal variable built on primary energy supply per unit of GDP adjusted on exchange rate. The detailed explanation of variables and data source can be found in Section 3.1.

The contradicting results are again rooted in different underlying assumptions. In the construction of EMD, the potential serial correlation between past trade flows and current environmental measure is not dealt with and remains an issue. It may be the reason why the LDV model suggests a distant coefficient. Within the LDV models, the influence of past trade flows is controlled, so the resulted findings are supposed to be more consistent if the underlying assumption that there is serious serial correlation is true.

5.3 Discussion

If looking at each environmental variable used separately, the results vary with the choice of environment-related variables and specifications. It supports the claim by Harris et al. (2002)

that some significant empirical results are dependent on the specifications. However, since they neglect the possible serial correlation, the specifications they used may also be imperfect.

As discussed in Section 5.1.2, whether existing significant serial correlation between the past trade and current EM is the key to determine which estimates, FE or LDV, are more consistent. Plausibly, if the issue of serial correlation exists, it should occur in all 34 countries. Since the unilateral measures are ordinal, the ranking system would not recognize the historical influence within a country if there is no change in the country's relative position. It suggests that the LDV models may overestimate the serial correlation in the specifications where the unilateral measures are used. However, the LDV estimates may be more reliable with respect to EMD because the bilateral environmental measures embody more dynamics and are more vulnerable to the serial correlation than the unilateral ones.

As emphasized, a country's EM is determined by the other countries' performance in the same period. It means that they are unable to capture the association between a country's historical performance and current performance. A higher EM doesn't mean that the environmental regulations in this country are more stringent than how they were last year. However, the bilateral measures are built to compare the environmental regulatory stringency within a pair of countries only and allow for the intertemporal comparison. A higher EMD_{ijt} certainly indicates that the environmental status become more inequal between country i and country j at time *t* than at time *t-1*. Accordingly, it can be concluded that only weak and insignificant evidence is found to support that stricter environmental regulations may hamper bilateral trade, both imports and exports, but the disparity between 2 countries' environmental regulations is significantly and positively associated with imports.

Consolidating the findings from the preferred models reveals that: (1) the trade of a country may be hardly reduced in reaction to stricter environmental regulations in general; (2) but when a country is richer, the imports and exports respond more strongly to the changes in environmental regulations; (3) trade happens more between 2 countries whose environmental regulatory stringencies are more distant.

The first two findings from the exporter part, although with tiny effect size, are in support of the claim that increasing environmental regulations can form a new trade barrier and hinder trade, yet caution that this claimed consequence may mainly apply to the richest countries. On the other hand, importer-side effects contradict the trade-environmental prediction of the Pollution Haven Effect. The theory often suggests that stricter environmental regulations would increase imports because of the suppressed domestic production, which is not the case here.

There might be various effects interacting and codetermining the outcomes. One of the effects can attribute to unobserved domestic industry protection. One country may set higher importing standards for some commodities, constraining the foreign supply available within the country, which would be the case suggested by Ederington and Minier (2003) and Eliste and Fredriksson (2004). When cheap substitute goods are no longer available due to their dissatisfying production standards, consumers would have to accept a higher price and maintain or even increase the demand of domestic goods. It can be a limitation of the study because doing so wouldn't be reflected by this country's own environmental output-oriented indicator and it can be further investigated. It's also a possibility that some unknown subsidies compensating for greater environmental control may lead to neutralisation of environmental regulatory effects on output and trade flows, partly in agreement with Eliste and Fredriksson (2002). Since the environmental measures employed in this study are output-oriented, they would take in the effects related to production-encouraging subsidies and reflect them in the outcomes, and so those production subsidies would not be the ones contributing to the interesting finding here. A possible example is the R&D-related subsidies from the government in order to improve green technology, accelerate innovation and improve production efficiency, in line with the Porter hypothesis (see Porter and Van Der Linde 1995).

It can also be inferred from the second finding that this richer and more environmentally responsible country may satisfy more of the domestic demand with domestic supply, if the aggregate demand doesn't change with environmental regulatory stringency. For a country to do that, the composition of trade may change largely. For some small rich countries without conditions or resources to produce some necessary goods, they must rely on imports for these things. For example, food imports including vegetables are a necessity for Sweden. If Sweden experiences this increase in the level of self-reliance, it would be because they reduce the imports of high-value goods, such as cars and high-tech products, when maintaining the necessary imports. This could be further studied. An interesting implication follows that once a clear one-way relationship is established, environmental regulations could be used in the future, for the economically strong country that is rich in resource, to protect and even drive their own economic growth.

Interpreting the results from environmental inequality measures completes the story by revealing the possible preference of consumers. The positive coefficients found through the LDV models suggest that consumers prefer products from a foreign country that is very different in the environmental agenda, and it can be possibly interpreted in both directions. Consumers may prefer goods produced in a better-regulated country, featured by environmentally friendly products like Tesla cars. Alternatively, consumers may purchase often foreign goods from the country with very worse environmental protection, maybe because the products are cheaper. Or both effects exist, if two countries mainly export fundamentally different types of commodities. For example, a country with worse environmental regulations exports the commodities that are widely used in daily life but with low mark-up and high energy consumption in production to another rich but small country, and the latter exports goods with higher mark-ups, produced with newer and cleaner technology. It is hard to identify which way the effects flow, and this ambiguity also gives rise to the possible extension of this paper. This last finding in principle contradicts the claim of Eliste and Fredriksson (2004) that open trade may induce a trade partner to upgrade their lax environmental regulations and consequently the environmental regulations in two countries having close trade relations tend to converge.

6 Limitation and possible extension

In addition to the ambiguity mentioned above, two more sources of limitation should be cautioned, and they provide some reflections and directions for further research.

First, using energy intensity to construct the environmental measures indeed has its weakness, like any other existing environmental measures. It may not be informative if a country mostly uses renewable energy sources and it's also largely dependent on the types of industries which drive a country's economic growth. Besides, when the relevant regulations are not reflected in the reduced production, the measure fails to fully capture the effects of environmental regulation that does not pertain energy use. For example, the emission quotas are sometimes used to limit toxic emissions including sulphur dioxide and nitrogen oxide and they are certainly an important part of environmental regulations. But the measures based on energy intensity can only capture their impact through reduced production and fail to capture if there is any technological development for direct emission reduction. Accordingly, future research could explore a composite environmental measure that considers both energy use and emissions. It would be interesting because the energy structure can also be reflected through composition and amount of emission.

Second, studying the relationship with the total imports of goods for a country may be insufficient to unveil the real effects of strict environmental regulations on trade. As the Pollution Haven Effect predicts, the stricter environmental regulations may affect the pollution-intensive industries the most. The methodology and models can be applied to industrial data, such as pollution-intensive industries (Cole and Eilliot 2003b) and the agricultural industry. If the relationship between environmental regulatory disparity and trade is found more evident within the former industries, it would supplement and further develop the PHH. The latter is interesting to research on because it is one of the most important and stable components of trade where serial correlation is supposed to be serious. Past trade flows are thought to have some impact on the political determination of relevant environmental regulations since *"agricultural sector is resourced based, lower environmental regulations may therefore not induce capital movements thus lowering the incentives for strategic behaviour"* (Eliste and Fredriksson 2004). It would help examine the findings.

It should also be addressed that for selecting the most successful model, especially between the fixed-effects and lagged dependent variable model, more insights are needed. More studies can be conducted on understanding the dynamics in environmental policymaking, and a better criterion can be developed.

7 Conclusion

This paper focuses on the relationship between the strictness of environmental regulation and bilateral trade. The study is based on a panel dataset consisting of 34 OECD countries, each of them being both importer and exporter to the others for 7 years, from 2010 to 2016. Three main types of models are involved, fixed-effects models, mixed-effects models and lagged dependent variable models respectively accounting for static country heterogeneity, poor variability of policy variables and serial correlation. Fixed-effects models with clustered standard errors tend to perform better and lagged dependent variable models, especially when Arellano-Bond estimator is used, indeed provide some evidence for dynamic effects.

Two types of environmental variables are used. A total of 6 unilateral environmental regulatory measures are constructed with a ranking system, and based on them, bilateral measures are created in order to measure how different the countries are in terms of environmental management. The unilateral measures EM are the approximation of the stringency of factual environmental regulations, including all the effects of the indirectly environment-affecting policies that may undermine the effectiveness of the direct environmental policies. They represent the relative status of a country regarding the environmental-protection outcome internationally. The bilateral measures EMD are the absolute terms of inequality between 2 countries in environmental progress. Therefore, a country with a good relative status doesn't carry this property into the degree of disparity with another country, and the two measures can complement each other in revealing how the differences in environmental regulatory stringency may affect bilateral trade. The per-capita environmental measures are also involved in the study. They function as interaction terms that describe an impact attributable to both environmental regulation and GDP per capita. If holding the environmental measure constant, the impact would be like a function increasing in the average income of the country.

The conclusions of this study are threefold. First, there is only weak evidence of a "pure" environmental regulatory effect on trade, and it accords with the direction of the Pollution Haven Effect only for exporter side. Second, there is strong evidence that the environmental regulations may have different effects on countries with different levels of income. Richer countries tend to be more affected by the stringency of environmental regulations in trade and the stricter environmental regulations would reduce exports as well as imports. It is a new observation. The inference follows that strictly environmentally regulated countries may be more self-reliant. Lastly, a remark can be added that a country may trade more with the very environmentally friendly trading partner or the worst environmental player, but less with the countries sharing a similar regulatory status in environmental work.

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Appendices

A1. The experiment with per-capita environmental measure

1. Motivation and description

I focus on one more indicator from the six alternatives, $\mathrm{EM}_{\mathrm{TPES,POP}}$, in addition to $\mathrm{EM}_{\mathrm{TPES,GDP2}}$ that is extensively explored in the paper. The purpose is to (1) examine how much the relationship found is dependent on the choice of environmental measure, (2) examine whether the per-capita environmental measures are a better proxy for environmental regulatory stringency.

How much primary energy on average one citizen has at his disposal should be the most direct and fundamental indicator for a country's environmental pressures because it reveals both how many materials a citizen takes from nature and how many pollutants and emissions he produces and imposes on nature, when all environmental pressures come from human activities. For example, the concept of carbon footprint is omnipresent in daily life and it is used mostly with individual units. The rationale behind the indicator $\mathrm{EM}_{\mathrm{TPES,POP}}$ also being a good measure for the strictness of environmental regulations is that not only is it a result of the production-related environmental regulations but also gives away the level of general environmental awareness in the society and the outcome of the relevant education, which is also a part of the environmental regulations and policies.

The motivation of using $\mathrm{EM}_{\mathrm{TPES,POP}}$ along with $\mathrm{EM}_{\mathrm{TPES,GDP2}}$ in this study is twofold. First, from an economic perspective, since OECD countries are overall rich[28] now, especially when compared to how they were in the 1990s, the relative primary energy supply per capita may help unveil the real environmental performance of a country, mitigating the impacts from the first-mover advantages in technology and systematic differences among the countries that are a facet of history, such as the gap in their industrial structures. In Figure 9, a general tendency of decline in the correlation coefficient between these 2 measures is observed over the investigated time period, which hints that these 2 measures may carry increasingly different information about the environmental performance with the relative economic development

[28] All the countries in the scope of investigation hold a GDP per capita higher than the world average for the time period 2010-2016, although Mexico and Turkey are not classified as the OECD high-income countries. It's reasonable to argue that the countries are overall rich in the sense that people in these countries have a relatively good standard of living.

being more stabilized. Second, $EM_{TPES,POP}$ can also function as an interaction between $EM_{TPES,GDP2}$ and GDP per capita based on exchange rate as I have shown in the paper. Comparing the results relative to both $EM_{TPES,GDP2}$ and $EM_{TPES,POP}$ would give a more complete picture of the interaction between trade and environmental regulations.

Figure 9:Changes in the correlation coefficients of 2 types - Spearman's ρ and Kendall's τ - between EM5 (calculated on Total primary energy supply, GDP adjusted on exchange rate) and EM6 (calculated on Total primary energy supply, Population) from 2010 to 2016

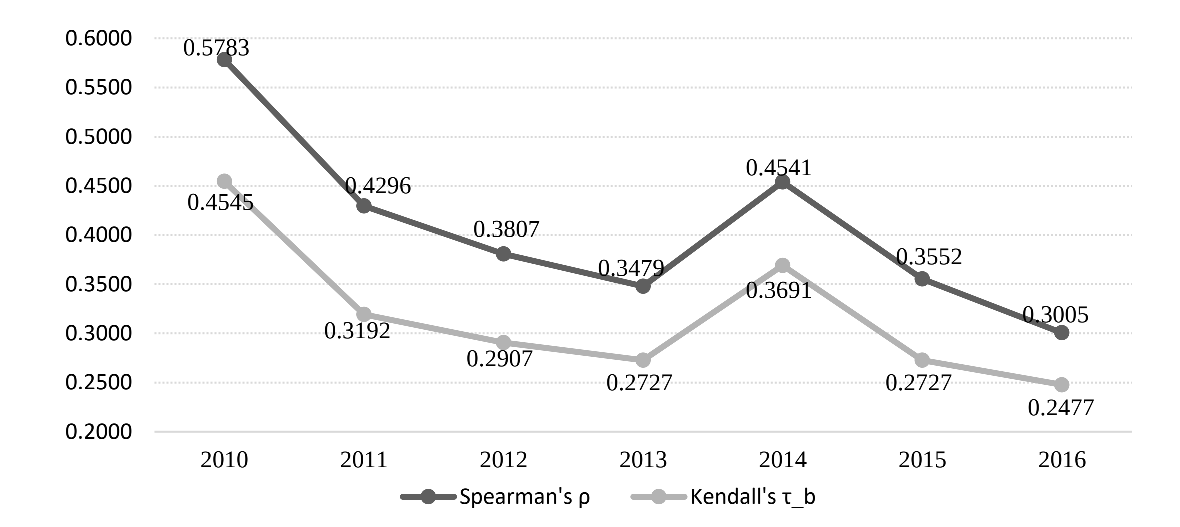
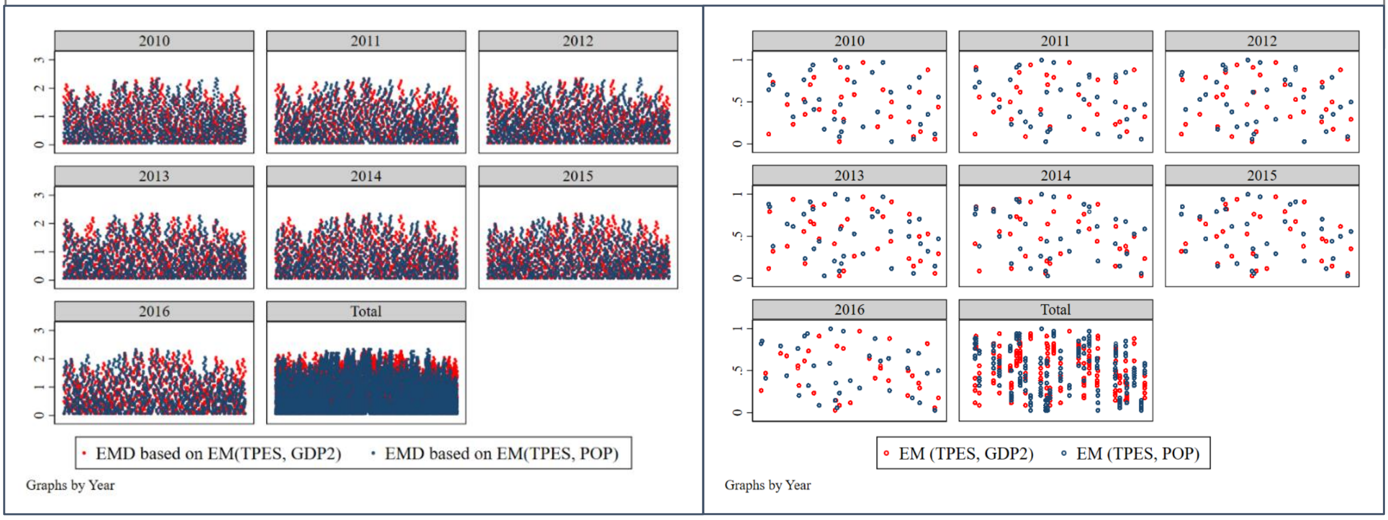


Figure 10 provides basic comparative statistics for the GDP-based environmental measures and the population-based ones. It is shown that different measures do provide different evaluation outcomes.

Figure 10: Comparative statistics for GDP-based environmental variable and Population-based variable



2. Result and comparison

Table 13 aggregates the estimation results of all the environmental variables and all the models involved. The results under specification (5), (8), (11) and (13) in Table 13 are estimated with the unilateral measure of $\mathrm{EM}_{\mathrm{TPES,POP}}$. Resorting to $\mathrm{EM}_{\mathrm{TPES,POP}}$ yields different results from the ones estimated for $\mathrm{EM}_{\mathrm{TPES,GDP2}}$[29]. Regardless of significance, the estimated coefficients appear to be universally positive, basically in line with the earlier findings when $\mathrm{EM}_{\mathrm{TPES,GDP2}}$ is estimated with. Among all, specifications (5) and (11) exhibit strong evidence towards a positive correlation between lax environmental regulations and both imports and exports. In specification (5), a coefficient of 2.2% for importer environmental parameter is obtained, statistically significant at the level of 0.05, and a coefficient of 2.9% for exporter environmental parameter, significant at the level of 0.01. With LDV model, the magnitude of importer side effects is enlarged to 4% at 1% significance level. The exporter side effects are weaker, 1.52% at only 10% significance level. The estimates for population-based EM advocate for the Pollution Haven Hypothesis that lax environmental regulations provide better conditions for exports but also contradicts the theorical prediction regarding the imports.

Results from specification (4), (5), (7), (8), (11) and (13) are of the same direction suggesting that the laxer the environmental regulations are for either trading side, the greater the import values are between them, although this finding contradicts the prediction of specification (10) and (12). It the population-based environmental measure is also a good proxy, the evidence supporting positive correlation would outweigh the rest. It also strengthens the argument that the estimates for the unilateral environmental measures produced by LDV models may be biased because the serial autocorrelation is overestimated.

As for the bilateral measure EMD, specifications (15), (17), (19) and (21) give the estimation results for the one based on $\mathrm{EM}_{\mathrm{TPES,POP}}$. The estimation for FE model and ME model yields negative estimates for EMD constructed on $\mathrm{EM}_{\mathrm{TPES,POP}}$ that are similar to the results for the EMD based on $\mathrm{EM}_{\mathrm{TPES,GDP2}}$. A consistent coefficient of -6.2% is estimated for the EMD measuring the difference in energy intensities per capita, at 10% significance level from the fixed-effects specification and 1% signification level from the mixed-effects specification. The results from LDV models are, however, both positive but insignificant, contradicting the earlier findings.

[29] See Section 5.2.

This mixed evidence may belie the correlation established earlier between the degree of inequality in environmental regulatory stringency and trade, but it's most likely because EMD built upon $EM_{TPES,POP}$ absorbs other elements in the measurement, which contaminate the result. If so, the positive estimates with respect to GDP-based EMD are more justified, which suggesting that one country trades more with the partners with much stricter or laxer environmental regulations. On the other hand, since $EM_{TPES,POP}$ is theoretically income-adjusted $EM_{TPES,GDP2}$, it is also reasonable to assume that the result changes with the level of average incomes. It may be that the richer a country is, the more it prefers to trade with similar countries in terms of environmental progress. Therefore, it is important to check the specifications with interaction terms to determine which case is more plausible.

However, by comparing the results from specification (5) and (6)[30], it's found the estimates for per-capita EM don't change much, which could invalidate the usage of per-capita EM for measuring the relative position regarding environmental work[31] and indicate that the effects may strongly depend on the income levels.

In sum, the population-based measure may not serve well for approximating the stringency of environmental regulations on its own, but it overall provides more evidences in support of the conclusions drawn with the use of GDP-based environmental measures.

[30] The result of comparison is similar also between (8) and (9).
[31] If per-capita variables work well for approximating the environmental regulatory strictness, the estimates built on 2 different assumptions should be more distinguishable.

Table 13: Main estimation Results for the empirical models

Panel A reports the estimation results that investigate the relationship between bilateral trade flows and the level of environmental regulations using the proposed empirical model 1, 2, 4 and 5 using unilateral environmental variables: respectively, the three-way fixed effects model including importer fixed effects, exporter fixed effects and time fixed effects and the mixed-effects model with time fixed-effects and country-specific mixed effects, with and without interaction terms. Baseline model estimates are provided too for robustness check.
Panel B provides information on the results of estimation using Lagged Dependent Variable models, Model 6, regarding the unilateral measures. The Arellano-Bond (AB) estimator and Anderson–Hsiao (AH) estimator are engaged in estimating the models sequentially.
Panel C depicts the estimates produced from the estimation of the models with bilateral environmental index, first the three-way fixed-effects model and then the mixed-effects model considering importer random effects, exporter random effects and time fixed effects, followed by LDV models in the end.

Panel A: Selected estimation results for Models using unilateral environmental measures

	Dependent variable:								
	Imports of goods(log)								
	Baseline Model			*Three-way fixed-effects Model*			*Mixed-effects Model*		
				Model 1		Model 2	Model 4		Model 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EM5(log) importer	0.016		-0.072***	0.007		0.0002	0.004		-0.006
	(0.025)		(0.027)	(0.011)		(0.011)	(0.020)		(0.021)
EM5(log) exporter	-0.036		-0.126***	0.005		-0.004	0.022		0.013
	(0.025)		(0.027)	(0.011)		(0.011)	(0.020)		(0.021)
EM6(log) importer		0.142***	0.177***		0.022**	0.022**		0.029	0.032
		(0.024)	(0.027)		(0.011)	(0.011)		(0.023)	(0.024)
EM6(log) exporter		0.118***	0.179***		0.029***	0.031***		0.034	0.029
		(0.025)	(0.026)		(0.009)	(0.009)		(0.023)	(0.024)
GDP1(log) importer	1.289***	1.264***	1.213***	1.274***	1.221***	1.222***	1.248***	1.210***	1.201***
	(0.079)	(0.073)	(0.077)	(0.123)	(0.125)	(0.130)	(0.144)	(0.144)	(0.147)
GDP1(log) exporter	1.475***	1.502***	1.398***	0.552***	0.487***	0.478***	1.005***	0.942***	0.960***
	(0.079)	(0.076)	(0.079)	(0.117)	(0.119)	(0.122)	(0.149)	(0.151)	(0.154)
POP (log) importer	-0.415***	-0.355***	-0.306***	-0.157	-0.095	-0.095	-0.382**	-0.337**	-0.329**
	(0.075)	(0.071)	(0.076)	(0.319)	(0.325)	(0.325)	(0.147)	(0.150)	(0.151)
POP (log) exporter	-0.533***	-0.522***	-0.423***	-1.303***	-1.208***	-1.216***	-0.140	-0.074	-0.090
	(0.078)	(0.076)	(0.078)	(0.330)	(0.333)	(0.336)	(0.154)	(0.157)	(0.160)
DIST	-0.734***	-0.725***	-0.724***	-0.991***	-0.991***	-0.991***	-0.986***	-0.986***	-0.986***
	(0.041)	(0.040)	(0.040)	(0.053)	(0.053)	(0.053)	(0.017)	(0.017)	(0.017)
Observations	7,854	7,854	7,854	7,854	7,854	7,854	7,854	7,854	7,854
R2	0.869	0.873	0.875	0.916	0.916	0.916			
Adjusted R2	0.869	0.872	0.874	0.915	0.915	0.915			
Log Likelihood							-7,750.719	-7,749.165	-7,754.794
AIC							15,551.440	15,548.330	15,563.59
BIC							15,725.660	15,722.550	15,751.75
Residual Std. Error	0.786 (df = 7832)	0.775 (df = 7832)	0.769 (df = 7830)	0.631 (df = 7768)	0.631 (df = 7768)	0.631 (df = 7764)			

Panel B: Selected Estimation results for Model 6

	Dependent variable:				
	Imports of goods(log)				
	Arellano-Bond estimator			*Anderson–Hsiao (AH) estimator*	
	(10)	(11)		(12)	(13)
Lagged IMP	0.235***	0.223***	L. Differenced IMP	0.0417	0.0452
	(0.053)	(0.053)		(0.129)	(0.129)
EM5(log) importer	-0.00251		Differenced EM5 importer	-0.00125	
	(0.009)			(0.009)	
EM5(log) exporter	-0.0210**		Differenced EM5 exporter	-0.0127*	
	(0.008)			(0.007)	
EM6(log) importer		0.0407***	Differenced EM6 importer		0.0148
		(0.010)			(0.010)
EM6(log) exporter		0.0152*	Differenced EM6 exporter		0.0116
		(0.008)			(0.008)
GDP1(log) importer	0.0158	-0.0664	Differenced GDP1 importer	0.1065	0.0747
	(0.111)	(0.112)		(0.230)	(0.229)
GDP1(log) exporter	-0.272**	-0.273**	Differenced GDP1 exporter	-0.0389	-0.0341
	(0.118)	(0.120)		(0.161)	(0.160)
POP(log) importer	-0.439	-0.236	Differenced POP importer	-0.3474	-0.2848
	(0.286)	(0.290)		(0.301)	(0.305)
POP(log) exporter	-0.634*	-0.520	Differenced POP exporter	-0.638	-0.5854
	(0.358)	(0.359)		(0.444)	(0.449)
DIST	-15.12***	-14.92***			
	(3.561)	(3.56)			
Observations	5610	5610		4488	4488
R^2 overall				0.0506	0.0544
F				1.87**	2.42***
χ^2	351.02***	377.57***			

Panel C: Selected estimation results for Models using bilateral environmental measures

	Dependent variable:								
	Imports of goods(log)								
	Fixed-effects Model		*Mixed-effects Model*		*LDV-AB estimator*			*LDV-AH estimator*	
	Model 3		Model 4		Model 6				
	(14)	(15)	(16)	(17)	(18)	(19)		(20)	(21)
EMD(based on EM5)	-0.016		-0.013		0.0307***		D. EMD (based on EM5)	0.0209**	
	(0.030)		(0.014)		(0.011)			(0.103)	
EMD(based on EM6)		-0.062*		-0.062***		0.00589	D. EMD (based on EM6)		0.0075
		(0.033)		(0.014)		(0.011)			(0.011)
GDP1(log) importer	1.259***	1.260***	1.241***	1.241***	-0.00989	-0.00953	D. GDP1(log) importer	0.118	0.1085
	(0.122)	(0.122)	(0.143)	(0.143)	(0.110)	(0.11)		(0.227)	(0.228)
GDP1(log) exporter	0.539***	0.540***	0.982***	0.979***	-0.268**	-0.264**	D. GDP1(log) exporter	-0.0010	-0.0080
	(0.116)	(0.116)	(0.148)	(0.149)	(0.117)	(0.117)		(0.160)	(0.161)
POP(log) importer	-0.180	-0.167	-0.377**	-0.377**	-0.386	-0.399	D. POP (log) importer	-0.3314	-0.3519
	(0.317)	(0.319)	(0.146)	(0.147)	(0.286)	(0.288)		(0.298)	(0.300)
POP(log) exporter	-1.320***	-1.306***	-0.124	-0.122	-0.592*	-0.600*	D. POP (log) exporter	-0.627	-0.643
	(0.323)	(0.323)	(0.153)	(0.154)	(0.357)	(0.359)		(0.442)	(0.445)
DIST	-0.991***	-0.988***	-0.986***	-0.982***	-15.03***	-14.98***	D. DIST	-	-
	(0.053)	(0.052)	(0.017)	(0.017)	(3.556)	(3.566)			
L. IMP					0.236***	0.238***	L.D. IMP	0.038	0.0418
					(0.053)	(0.053)		(0.128)	(0.129)
Observations	7854	7854	7854	7854	5610	5610		4488	4488
R^2	0.916	0.916					R^2 overall	0.0518	0.0529
Adjusted R^2	0.915	0.915							
Log Likelihood			-7,748.285	-7,739.282			F	1.86**	2.14
AIC			15,544.570	15,526.560					
BIC			15,711.820	15,693.810	69.95***	353.35***	χ^2		
Residual Std.	0.631	0.631							

Notes:
*p<0.1; **p<0.05; ***p<0.01. Robust standard deviation is in parentheses. See Appendix – A3 for complete estimation results.
All parameter estimates for unimportant variables and fixed/random effect terms are not included in the table due to lack of interest. GDP1 refers to Gross Domestic Production adjusted on Purchasing Power Parity. POP stands for Population. DIST is the distance variable. LAND and CE respectively proxy the land and the difference in capital-labour ratio endowment. EM represents Environmental regulatory measures. EM5 is an ordinal variable built on primary energy supply per unit of GDP adjusted on exchange rate and EM6 is built on primary energy supply per capita. EMD is a standardized score of the disparity between 2 countries in terms of environmental efforts, transformed based on EM, specifically on EM5 and EM6 in the reported estimation. The detailed explanation of variables and data source can be found in Section 3.1.

A2. Derivation of the First-difference version of Model 5

First-Difference models look at the difference between the dependent variable and the lagged dependent variable, and substituting the equation of time *t-1* into the lagged dependent variable in the righthand side gives:

$$
\begin{aligned}
&\ln IMP_{ijt} - \ln IMP_{ij(t-1)} \\
&\quad = \beta_0 + \lambda_t + \theta \ln IMP_{ij(t-1)} + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} \\
&\quad + \beta_3 \ln POP_{it} + \beta_4 \ln POP_{jt} + \beta_5 \ln DIST_{ijt} + \beta_6 CONTIG_{ijt} \\
&\quad + \beta_7 COMLANG_{ijt} + \beta_8 PTA_{ijt} + \beta_9 MEU_{ijt} + \beta_{10} NAFTA_{ijt} \\
&\quad + \beta_{11} \ln LAND_{it} + \beta_{12} \ln LAND_{jt} + \beta_{13} CE_{ijt} + \beta_{14} \ln EM_{it} + \beta_{15} \ln EM_{jt} \\
&\quad + u_{\mathrm{ijt}} - (\beta_0 + \lambda_{t-1} + \theta_1 \ln IMP_{ij(t-2)} + \beta_1 \ln GDP_{i(t-1)} + \beta_2 \ln GDP_{j(t-1)} \\
&\quad + \beta_3 \ln POP_{i(t-1)} + \beta_4 \ln POP_{j(t-1)} + \beta_5 \ln DIST_{ij(t-1)} + \beta_6 CONTIG_{ij(t-1)} \\
&\quad + \beta_7 COMLANG_{ij(t-1)} + \beta_8 PTA_{ij(t-1)} + \beta_9 MEU_{ij(t-1)} + \beta_{10} NAFTA_{ij(t-1)} \\
&\quad + \beta_{11} \ln LAND_{i(t-1)} + \beta_{12} \ln LAND_{j(t-1)} + \beta_{13} CE_{ij(t-1)} + \beta_{14} \ln EM_{i(t-1)} \\
&\quad + \beta_{15} \ln EM_{j(t-1)} + u_{\mathrm{ij(t-1)}})
\end{aligned}
$$

Rearranging it:

$$
\begin{aligned}
&\ln IMP_{ijt} - \ln IMP_{ij(t-1)} \\
&\quad = (\lambda_t - \lambda_{t-1}) + \theta\big(\ln IMP_{ij(t-1)} - \ln IMP_{ij(t-2)}\big) + \beta_1(\ln GDP_{it} \\
&\quad - \ln GDP_{i(t-2)}) + \beta_2 (\ln GDP_{jt} - \ln GDP_{j(t-1)}) \\
&\quad + \beta_3(\ln POP_{it} - \ln POP_{i(t-1)}) + \beta_4 (\ln POP_{jt} - \ln POP_{j(t-1)}) \\
&\quad + \beta_5(\ln DIST_{ijt} - \ln DIST_{ij(t-1)}) + \beta_6(CONTIG_{ijt} - CONTIG_{ij(t-1)}) \\
&\quad + \beta_7(COMLANG_{ijt} - COMLANG_{ij(t-1)}) + \beta_8(PTA_{ijt} - PTA_{ij(t-1)}) \\
&\quad + \beta_9(MEU_{ijt} - MEU_{ij(t-1)}) + \beta_{10}(NAFTA_{ijt} - NAFTA_{ij(t-1)}) \\
&\quad + \beta_{11} (\ln LAND_{it} - \ln LAND_{i(t-1)}) + \beta_{12} (\ln LAND_{jt} - \ln LAND_{j(t-1)}) \\
&\quad + \beta_{13}(CE_{ijt} - CE_{ij(t-1)}) + \beta_{14}(\ln EM_{it} - \ln EM_{i(t-1)}) \\
&\quad + \beta_{15}(\ln EM_{jt} - \ln EM_{j(t-1)}) + (u_{\mathrm{ijt}} - u_{ij(t-1)})
\end{aligned}
$$

The variables CONTIG, COMLANG, MEU and NAFTA are dummy variables whose values don’t alter, measuring some persistent status of countries. They are mostly unlikely to be altering in a short panel, which is also confirmed by the summary statistics. Besides, the variable DIST is almost time invariant as well because of its nature. Although the weighted distance is employed which may imply some fluctuation in the distance value as a consequence of population distribution changes, the fluctuation is insignificant in comparison to the large scale and could be neglected. Finally, the land areas of the countries, represented by LAND variables, are also often considered stagnant. The final model is transformed into the equation (8), as shown below:

$$
\begin{aligned}
\ln IMP_{ijt} - \ln IMP_{ij(t-1)} \\
&= (\lambda_t - \lambda_{t-1}) + \theta\big(\ln IMP_{ij(t-1)} - \ln IMP_{ij(t-2)}\big) + \beta_1(\ln GDP_{it} \\
&- \ln GDP_{i(t-2)}) + \beta_2 (\ln GDP_{jt} - \ln GDP_{j(t-1)}) \\
&+ \beta_3(\ln POP_{it} - \ln POP_{i(t-1)}) + \beta_4 (\ln POP_{jt} - \ln POP_{j(t-1)}) + \beta_5(CE_{ijt} \\
&- CE_{ij(t-1)}) + \beta_6(\ln EM_{it} - \ln EM_{i(t-1)}) + \beta_7(\ln EM_{jt} - \ln EM_{j(t-1)}) \\
&+ \beta_8(PTA_{ijt} - PTA_{ij(t-1)}) + \big(u_{\mathrm{ijt}} - u_{ij(t-1)}\big)
\end{aligned}
$$

A3. Complete Regression Results

Table 14: Complete Regression Results for all empirical models in this paper

Panel A provides complete estimations results for Model 1-5 and Panel B provides complete estimation results for Model 6, estimated with respectively Arellano-Bond (AB) estimator and Anderson–Hsiao (AH) estimator.

Panel A: Estimation Results for Model 1-5

	Dependent variable:									
	Imports of goods(log)									
	Fixed-effects Model					*Mixed-effects Model*				
	Model 1		Model 2	Model 3		Model 4		Model 3-mixed effects		Model 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EM5(log) importer	0.007		0.0002			0.004				-0.006
	(0.011)		(0.011)			(0.020)				(0.021)
EM5(log) exporter	0.005		-0.004			0.022				0.013
	(0.011)		(0.011)			(0.020)				(0.021)
EM6(log) importer		0.022**	0.022*				0.029			0.032
		(0.011)	(0.011)				(0.023)			(0.024)
EM6(log) exporter		0.029***	0.031***				0.034			0.029
		(0.009)	(0.009)				(0.023)			(0.024)
EMD(based on EM5)				-0.016				-0.015		
				(0.030)				(0.014)		
EMD(based on EM6)					-0.062*				-0.062***	
					(0.033)				(0.014)	
GDP1(log) importer	1.274***	1.221***	1.222***	1.259***	1.260***	1.248***	1.210***	1.241***	1.242***	1.201***
	(0.123)	(0.125)	(0.129)	(0.122)	(0.122)	(0.144)	(0.144)	(0.142)	(0.142)	(0.147)
GDP1(log) exporter	0.552***	0.487***	0.478***	0.539***	0.540***	1.005***	0.942***	0.982***	0.982***	0.960***
	(0.117)	(0.119)	(0.122)	(0.116)	(0.116)	(0.149)	(0.151)	(0.148)	(0.148)	(0.154)
POP(log) importer	-0.157	-0.095	-0.095	-0.180	-0.167	-0.382***	-0.337**	-0.377**	-0.379***	-0.329**
	(0.319)	(0.325)	(0.325)	(0.317)	(0.319)	(0.147)	(0.149)	(0.146)	(0.146)	(0.151)
POP(log) exporter	-1.303***	-1.208***	-1.216***	-1.320***	-1.306***	-0.140	-0.074	-0.124	-0.126	-0.090

	(0.330)	(0.333)	(0.336)	(0.323)	(0.323)	(0.154)	(0.157)	(0.153)	(0.153)	(0.160)
DIST(log)	-0.991***	-0.991***	-0.991***	-0.991***	-0.988***	-0.986***	-0.986***	-0.986***	-0.982***	-0.986***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.052)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
LAND(log) importer						0.157***	0.152***	0.158***	0.157***	0.152***
						(0.054)	(0.053)	(0.054)	(0.053)	(0.053)
LAND(log) exporter						0.039	0.035	0.042	0.042	0.034
						(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
CE	-0.087	-0.087	-0.087	-0.084	-0.088	-0.095***	-0.095***	-0.092***	-0.096***	-0.095***
	(0.087)	(0.087)	(0.087)	(0.088)	(0.087)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
COMLANG	0.268***	0.268***	0.268***	0.267***	0.273***	0.274***	0.274***	0.273***	0.278***	0.274***
	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
CONTIG	0.199**	0.199**	0.199**	0.199**	0.189*	0.203***	0.203***	0.203***	0.193***	0.203***
	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
PTA	0.412***	0.412***	0.413***	0.410***	0.409***	0.403***	0.403***	0.402***	0.401***	0.403***
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
MEU	0.165*	0.165*	0.165*	0.166*	0.167*	0.162***	0.162***	0.163***	0.165***	0.162***
	(0.096)	(0.096)	(0.096)	(0.097)	(0.096)	(0.036)	(0.036)	(0.036)	(0.035)	(0.036)
NAFTA	0.194	0.194	0.194	0.197	0.216	0.214*	0.215*	0.217*	0.236**	0.215*
	(0.321)	(0.321)	(0.321)	(0.321)	(0.323)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)
Year = 2011	0.109***	0.111***	0.111***	0.110***	0.110***	0.094***	0.096***	0.095***	0.095***	0.096***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Year = 2012	0.068***	0.069***	0.070***	0.069***	0.069***	0.045*	0.047*	0.046*	0.046*	0.047*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Year = 2013	0.091***	0.093***	0.093***	0.092***	0.092***	0.057**	0.059**	0.058**	0.058**	0.059**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Year = 2014	0.082***	0.087***	0.087***	0.085***	0.085***	0.034	0.039	0.036	0.036	0.038
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)
Year = 2015	-0.068***	-0.061***	-0.060***	-0.064***	-0.065***	-0.134***	-0.128***	-0.132***	-0.132***	-0.128***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Year = 2016	-0.082***	-0.073***	-0.072***	-0.077***	-0.079***	-0.165***	-0.156***	-0.162***	-0.162***	-0.157***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Constant						14.973***	14.749***	14.834***	14.877***	14.783***

						(1.092)	(1.075)	(1.080)	(1.079)	(1.091)
Observations	7,854	7,854	7,854	7,854	7,854	7,854	7,854	7,854	7,854	7,854
R^2	0.916	0.916	0.916	0.916	0.916					
Adjusted R^2	0.915	0.915	0.915	0.915	0.915					
Log Likelihood						-7,739.365	-7,737.807	-7,736.786	-7,727.610	-7,743.441
Akaike Inf. Crit.						15,528.730	15,525.610	15,521.570	15,503.220	15,540.880
Bayesian Inf. Crit.						15,702.950	15,699.830	15,688.820	15,670.470	15,729.040
Residual Std. Error	0.631 (df = 7768)	0.631 (df = 7768)	0.631 (df = 7766)	0.631 (df = 7769)	0.631 (df = 7769)					

Note:

For fixed-effects models, clustered standard errors are in parentheses; for mixed-effects models, standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.
For detailed variable description, please see Section 3.1. For model description, please see Section 4.2.

Panel B: Selected Estimation results for Model 6									
	Dependent variable:								
	Imports of goods(log)								
	Arellano-Bond estimator					*Anderson–Hsiao (AH) estimator*			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Lagged IMP	0.2354***	0.2233***	0.2359***	0.2380***	Lagged Differenced IMP	0.0417	0.0452	0.0384	0.0418
	(0.053)	(0.053)	(0.053)	(0.053)		(0.129)	(0.129)	(0.128)	(0.129)
EM5(log) importer	-0.0025				Differenced EM5(log) importer	-0.0013			
	(0.009)					(0.009)			
EM5(log) exporter	-0.0210**				Differenced EM5(log) exporter	-0.0127			
	(0.008)					(0.007)			
EM6(log) importer		0.0407***			Differenced EM6(log) importer		0.0148		
		(0.010)					(0.010)		
EM6(log) exporter		0.0152			Differenced EM6(log) exporter		0.0116		
		(0.008)					(0.008)		
EMD(based on EM5)			0.0307**		Differenced EMD(based on EM5)			0.0209*	
			(0.011)					(0.0103)	
EMD(based on EM6)				0.0059	Differenced EMD(based on EM6)				0.0075
				(0.011)					(0.011)
GDP1(log) importer	0.0158	-0.0664	-0.0099	-0.0095	Differenced GDP1(log) importer	0.1065	0.0747	0.1180	0.1085
	(0.111)	(0.112)	(0.110)	(0.110)		(0.230)	(0.229)	(0.227)	(0.228)
GDP1(log) exporter	-0.2718*	-0.2734*	-0.2684*	-0.2639*	Differenced GDP1(log) exporter	-0.0389	-0.0341	-0.0010	-0.0080
	(0.118)	(0.120)	(0.117)	(0.117)		(0.161)	(0.160)	(0.160)	(0.161)
POP(log) importer	-0.4390	-0.2355	-0.3863	-0.3987	Differenced POP(log) importer	-0.3474	-0.2848	-0.3314	-0.3519
	(0.286)	(0.290)	(0.286)	(0.288)		(0.301)	(0.305)	(0.298)	(0.300)
POP(log) exporter	-0.6335	-0.5198	-0.5916	-0.6002	Differenced POP(log) exporter	-0.6376	-0.5854	-0.6271	-0.6434
	(0.358)	(0.359)	(0.357)	(0.359)		(0.444)	(0.449)	(0.442)	(0.445)
DIST(log)	-15.1167***	-14.9187***	-15.0862***	-14.9678***	Differenced DIST(log)	0.0000	0.0000	0.0000	0.0000
	(3.561)	(3.557)	(3.570)	(3.566)		(.)	(.)	(.)	(.)
LAND(log) importer	3.9805**	3.9595**	4.0525**	4.0149**	Differenced LAND(log) importer	2.3803	2.4193	2.3661	2.4042
	(1.382)	(1.389)	(1.388)	(1.387)		(1.477)	(1.493)	(1.486)	(1.479)
LAND(log) exporter	6.6559***	6.4846***	6.5418***	6.5064***	Differenced LAND(log) exporter	4.3340*	4.2805*	4.2335*	4.2732*
	(1.884)	(1.867)	(1.895)	(1.888)		(2.131)	(2.123)	(2.138)	(2.131)
CE	0.0500	0.0660	0.0404	0.0493	Differenced CE	-0.0029	0.0164	-0.0160	-0.0044
	(0.103)	(0.103)	(0.104)	(0.104)		(0.120)	(0.119)	(0.121)	(0.120)
PTA	-0.1354*	-0.1380*	-0.1402*	-0.1401*	Differenced PTA	-0.1369*	-0.1369*	-0.1359*	-0.1375*
	(0.057)	(0.056)	(0.058)	(0.056)		(0.061)	(0.060)	(0.061)	(0.060)
Constant	0.0000	0.0000	0.0000	0.0000	Constant	0.0011	0.0012	-0.0002	0.0004
	(.)	(.)	(.)	(.)		(0.010)	(0.010)	(0.010)	(0.010)
N	5610	5610	5610	5610		4488	4488	4488	4488
					F(10, 1121)	1.8739*	2.4175**	2.1373*	1.8615*

Notes:
Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
For detailed variable description, please see Section 3.1. For model description, please see Section 4.2.