



HAL
open science

Carbon Tax and Emissions Transfer: a Spatial Analysis

Sahar Amidi, Rezgar Feizi, Thais Nuñez-Rocha, Isabelle Rabaud

► **To cite this version:**

Sahar Amidi, Rezgar Feizi, Thais Nuñez-Rocha, Isabelle Rabaud. Carbon Tax and Emissions Transfer: a Spatial Analysis. 2022. <hal-04638880>

HAL Id: hal-04638880

<https://univ-orleans.hal.science/hal-04638880v1>

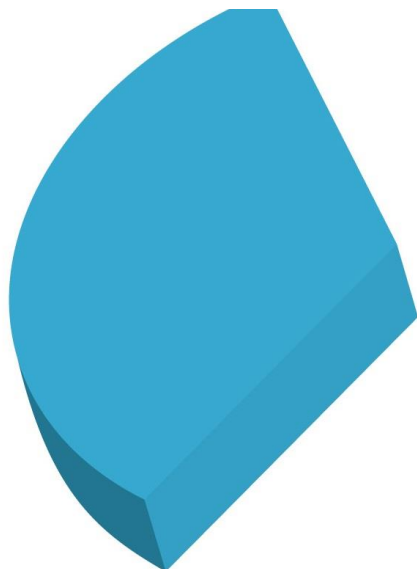
Preprint submitted on 8 Jul 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

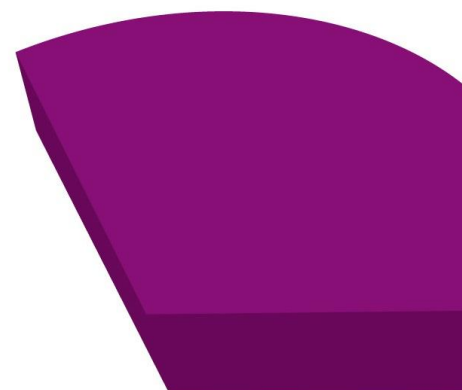
L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



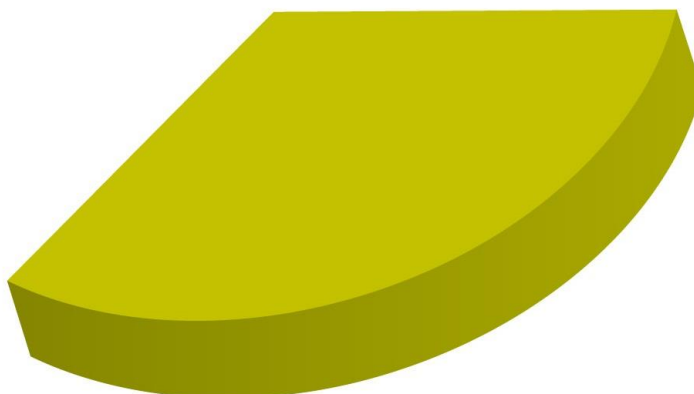
HAL Authorization



**Carbon Tax and Emissions Transfer:
a Spatial Analysis**



**Sahar AMIDI
Rezgar FEIZI
Thais NUNEZ ROCHA
Isabelle RABAUD**



Mise en ligne / Online : 09/12/2022

Carbon Tax and Emissions Transfer a Spatial Analysis

Sahar Amidi, ^{*†} Rezgar Feizi, [‡] Thaís Núñez Rocha, [§] Isabelle Rabaud [¶]

December 7, 2022

Abstract

With the rising role of globalization, assessing the impacts of carbon taxation in emissions embodied in trade becomes a key question. Our contribution consists of examining the effect of the carbon tax on emissions embodied in trade, in the framework of the input-output table. We exploit variation in the economic sector of each country to first, identify the most and fewer contaminated sectors, and second, investigate the spatial correlation due to carbon taxes in the emission embodied in trade using the SDA (structural decomposition analysis), MRIO (multi-regional input-output model), and spatial econometric models, 56 sectors, 43 countries (32 OECD and 11 Non-OECD) from 2000 to 2014. Our findings prove the “Electricity, gas, steam and air conditioning supply” as the highest emitter sector. Also, when carbon tax is imposed in OECD countries, the effect of emissions embodied in exports (EEE) and imports (EEI) increase by 7.4 percent and 83.2 percent respectively, to and from neighboring countries. On the other side for Non-OECD countries, the results are 20.7 percent for exports and 79 percent for imports. Our policy recommendation is to coordinate the level of tax at least by region in order to avoid an increase in emissions embodied in exports.

Keywords: Carbon tax, Trade emission, multi-regional input-output table, Spatial econometric.

JEL codes: C31, Q20, Q43, Q56, R12, R15.

^{*}Corresponding Author, Univ. Orléans, LEO, Rue de Blois-BP 26739, 45067 Orléans Cedex 2, France; ORCID: 0000-0002-8782-8577; sahar.amidi@univ-orleans.fr

[†]For their valuable comments and suggestions, we are grateful to participants in Conférence annuelle de la fédération de recherche (TEPP)2021, PhD Global Tax Symposium 2021, 22nd Global Conference on Environmental Taxation (GCET22)2021, Sustainable macro conference 2021, conferences 8th FAERE 2021 annual conference Grenoble, 1st IAEE Energy, Covid, and Climate Change 2021, 2nd and 3rd International Conference Environmental Economics: A Focus on Natural Resources International Conference 2020 and 2022, Ph.D. workshop Sustainable Development Doctoral Society 2021, 19th International Workshop “spatial Economics and statistics” 2021, as well as in the seminars at university of Orléans 2021.

[‡]University of Luxembourg, Luxembourg, Luxembourg; ORCID: 0000-0001-9293-0149; rezgar.feizi.001@student.uni.lu

[§]Univ. Orléans, LEO, Rue de Blois-BP 26739, 45067 Orléans Cedex 2, France; thais.nunez-rocha@univ-orleans.fr

[¶]Univ. Orléans, LEO, Rue de Blois-BP 26739, 45067 Orléans Cedex 2, France; isabelle.rabaud@univ-orleans.fr

1 Introduction

Carbon Tax is the most recurring tool to decrease the figure of emissions (Kotlikoff et al., 2019). Accordingly, when there is a growth in the carbon tax rate (like the environmental tax), carbon dioxide concentration will theoretically decline (Sundar et al., 2016).¹ Meanwhile, after implementing a carbon tax, countries tend to import carbon intensive goods rather than producing them domestically with clean technology. To reduce trade costs such as fixed and variable costs of production, goods tend to be much more imported from neighboring countries; that is: at low geographical distances and economical perspectives such as strong trade partners (bilateral trade).

Carbon tax can affect the neighborhood nations (spatial impact), whenever there are tax differences between countries, by producing goods and services, countries with lower taxes emit pollution at the national level, then this pollution is transmitted to neighboring countries through emission embodied in exports. Since carbon taxes have increased in OECD and Non-OECD countries we will expect a convergence in terms of emissions embodied in export. While, this is not the case in our result (for further explanation see Figure 1 in stylized fact).

Several studies probe the empirical policy in line with the dwindling rate of CO₂ emissions in trade and link to the international displacement of production.² Some studies believe that offset emission abatement leads to even higher overall emissions,³ while others disagree with this idea.⁴ Some scholars believe that input–output linkages play an important role in explaining the observed volatility of carbon emission embodied in trade (Karnizova (2016), da Silva Freitas et al. (2016), Perobelli et al. (2015)), and Du et al. (2011). This model illustrates the volatility and interaction of direct and indirect emissions between intermediate sectors (for instance “Electricity, gas, steam and air conditioning supply”) and final sectors. There are three reasons for explaining the usage of the input-output model to investigate environmental pollution issues, (Yan et al., 2016): First,

¹In most countries, the carbon tax is known as an environmental tax (Clough, 2016). In the rest of this paper, we will talk about the carbon tax referring to environmental tax.

²e.g. Long et al. (2018); Sakai & Barrett (2016).

³see e.g. McEvoy & McGinty (2018); Asselt & Brewer (2010)

⁴see e.g. Ren et al. (2020); Cao et al. (2019); and Baylis et al. (2013).

ex-ante analysis can be carried out with MRIO table and serve as an effective tool for quantifying key coefficient changes in carbon tax and emission embodied in trade. We have calculated most of our variables using this MRIO table. Second, dependency and proportionality relations between different sectors are analyzed. Finally, the model is very tractable, it clarifies the interactions between intermediate sectors and final sectors.

According to the literature we know that on the one hand, environmental contamination exhibits striking spatial heterogeneity that is important for understanding the effects of policy. Because of the spatial heterogeneity, environmental contamination in one country may have spillovers to their neighboring countries. In the realm of propagation emissions from trade, Chen et al. (2017) demonstrated the spatial dependence of carbon transformations through trade. Currently, within growth in international trade and the widening in geographic separation between production and consumption, regional trade tends to be the core factor in transferring carbon emissions. The industrialized countries become net carbon importers while developing countries become net carbon exporters (Chen et al., 2016).

On the other hand, if in addition to this we have a difference between countries of the carbon tax, the price of intermediate inputs, and final requirements this can make companies to establish manufacturing processes in the area that is the most efficient in terms of costs for them. Hence, pollution is not only transferred from one country to another through trade but also through the difference in the price of intermediate inputs and final requirements in different regions, the difference in the price of pollution for different goods, and the technology that each country uses for producing goods. This technology also affects the level of pollution in the country itself and its neighboring countries.

Ignoring these effects causes biased estimators. Nevertheless, scholars barely discuss the influences of a carbon tax on trading emission embodied behaviors, while carbon taxation influences emitting countries (achieving compliance with commitments to reduce emissions, is still debatable).

Due to this, traditional panel models do not take into account the correlation between economic units and may provide estimated bias and inconsistent results (Elhorst, 2014).

For these reasons, we conduct our analysis while simultaneously taking into account the spatial dependency between economic units utilizing spatial econometric approaches (Anselin, 1988).

Despite the abundance of literature on carbon trading, our study contribute to the existing literature by filling a gap in the spatial effect of the carbon tax through emissions embodied in exports and imports. In this regard, we firstly combine 65 intermediate and final sectors for 43 countries according to their ISIC code in the world input-output database (WIOD). Then, we implement the spatial impact of a direct and an indirect carbon tax on pollution stemming from export and import. The main feature of this study is we examine the way pollution emitted from countries and sectors affects neighboring countries through economical and geographical perspectives.

To know about which sectors emit more pollution through the intermediate and final goods we merged data from 43 countries into 56 intermediate and final sectors. The results are according to the literature (Guo et al. (2018)) pointing "Electricity, gas, steam and air conditioning supply" sector as the one emitting more CO₂ to the environment (see Table 1 of Appendix A). As for the effect of the carbon tax, in OECD countries increase emissions embodied in exports (EEE) and imports (EEI) (7.4 %) and (83.2 %) respectively, to and from neighboring countries and in Non-OECD countries the results are 20.7 percent for emissions embodied in exports (EEE) and 79 percent for and imports (EEI).

The remainder of the paper is structured as follows: section 2 presents the latest work in this filed. Then, the spatial growth model, the spatial weight matrix, and the hypotheses tests, covering both theoretical and empirical issues are explained in section 3. Next, the estimation strategy and data are also shown in section 3. Finally, section 4 discusses the estimated results, and section 5 is about the conclusions and policy recommendations.

2 Literature review

2.1 Theoretical

In the first part of our theoretical model, we will concentrate on the composition effect highlighted by Antweiler et al. (2001). Managi et al. (2009) depicted how the composition of output (i.e., the structure of the intermediate inputs and final requirements) influences emissions, which is determined by the volume of trade and the specialization linked to comparative advantage. Depending on the country's resource affluence and the strength of its environmental regulation, the composition effect could be good or bad. Copeland & Taylor (2013) and Antweiler et al. (2001) highlighted that international trade constructs fairly small changes in pollution concentrations when it alters the composition, and thus the pollution intensity of national output. They also indicated that the composition effect of trade for developing countries makes the environment more pollutant while this effect for developed countries makes them cleaner (Pollution Haven Hypothesis (PHH)). In other words, a country with weak environmental regulations on polluting activities may be more attractive to foreign investors. For example, Mexico has become a pollution haven for the United States battery industry (Rosenthal, 2011).

According to the Porter Hypothesis (PH), which contends that well-designed and stringent environmental regulations can stimulate innovation and benefit polluting countries by increasing firm productivity or the value of their products to consumers (Porter, 1996). Thus, developed countries have a higher income than developing countries, it is easier for developed nations to strengthen the environmental regulation and adapt their production line to low-carbon technologies (technical effect). In the contrary, pollution haven hypothesis claims that trade openness will lead to an influx of polluting corporations into countries with loose environmental standards evidence (Walter & Ugelow, 1979). In other words, developed countries export their pollution to developing countries by importing goods from developing countries. In developing countries, some scholars

consider that trade is environmentally friendly because it makes a balance between both sides of the participants.⁵ In this view, the logical chain that links trade to environmental degradation is broken, and boosts trade on wider economic activity scale. On contrary, some scholars such as Zhang et al. (2020) noted that trade is bad for the environment unless poor countries should prioritize environmental protection, since, poor countries tend to be in developing processes, receiving international investment even for dirty production.

Thus, poor countries lack of strong carbon tax regulations, so rich countries put on targets these countries without striking law (to reduce their costs) to displace their production of dirty goods. In this scenario, the developing country is chosen for the production of high-carbon goods. From this point of view, international trade leads to a greater economic activity scale (e.g. increase in productivity in intermediate inputs, rise in requirement of final goods) and then these economic activities cause environmental degradation (Copeland & Taylor, 2013). In terms of trade parties' contracts, geographical position, and income inequality of countries, some economists considered that trade can be good or bad for the environment Grunewald et al. (2017). This hypothesis illustrates that pollution is being displaced from one country to another, rather than being reduced when regulations, such as taxes, are strengthened (Dinda, 2004). They also assume that increasing environmental regulations in all countries (for example, imposing the same tax for all) raises the overall production cost of high-carbon goods. In this case, the manufacturing firm has to pay a fixed cost for settling the factory and producing processes, also a variable cost for transporting manufactured goods (imports). A carbon tax will increase both the fixed and variable costs of the plant. As a consequence, the comparative advantage of producing dirty goods in neighboring countries is reduced.

The second part of our work is based on the literature of Tobler (1979). According to the first geography law of Tobler, countries are interconnected, but neighboring countries influence each other more than distant countries. Concretely, no country is truly isolated; rather, every country has a dynamic status based on its interactions with other nations. Due to the lack of strong envi-

⁵Kellenberg (2008), Frankel & Rose (2005), Antweiler et al. (2001), and Muradian & Martinez-Alier (2001)

ronmental regulations, some countries try to reduce their production costs by establishing factories in areas with weaker environmental regulations, importing high-carbon products, or exporting low-carbon products, As a result, the interaction between areas with a closer location is pretty relevant. Thus, neglecting the spatial dependency in an econometric analysis when variables are spatially linked will result in econometric estimations that are biased (Anselin & Bera, 1998).

Therefore, according to these hypotheses, investigation of geographical and trade effects between countries is crucial because it shows that emissions are transferred among countries like a network. In this regard, we have some indicators: emissions embodied in exports and emissions embodied in imports. They are used to calculate the trade-embodied emissions that cause environmental impacts. The core model for estimating the CO₂ emissions embodied in trade is input-output analysis (IOA). This model relies on emissions produced due to energy used in each intermediate consumption and production by sector (Ding et al., 2018). We then matched with the corresponding export and import of goods and services (results are available upon request).

One of the best solutions to decrease greenhouse gases (GHG) emission is imposing tax emissions according to the amount of CO₂ emitted by different sectors. Taxation is also a financial tool that is well considered by most policymakers (Fahimnia et al., 2015). Hence, we can anticipate that an emission tax provides economic motives to reduce pollution from producers that have no intention to conserve the environment.⁶ Due to vast data requirements, and the significant number of countries involved in the management of such a system, there is no worldwide accepted methodology to calculate carbon content (McLure, 2014). In theory, there exist three ways by which levying carbon taxes can equalize countrywide pollution levels (Ding et al., 2018):

1. All countries simply levy the same tax on the carbon content of fossil fuels produced within their borders.
2. The production tax base could be modified to include fuel imports taxes to equalize them

⁶The first country to implement a carbon tax for abatement of the output of greenhouse gases and carbon dioxide is Finland, in 1990, which levy currently stands at 24.39 dollars per ton of carbon. After a year, Sweden and Norway both have implemented their carbon taxes, and Denmark has followed, in 1994.

when production tax is lower in the producing country.

3. Destination-based taxation of emissions is a more complicated solution. To minimize the cost of producing, certain factories have moved closer to the related customers, perhaps in a developed world, and hence it could be very problematic to identify between various taxes which one has led to the choice of a new destination to manufacture goods.

2.2 Empirical

In this section, before assessing the impact of carbon taxes on emissions embodied in trade, we present broad empirical literature.

Aichele & Felbermayr (2015) reported the first empirical "ex-post" evaluation of the Kyoto Protocol using a structural gravity model for the carbon dioxide content of trade. They found that Kyoto's binding commitments have raised committed countries' embodied carbon imports from non-committed countries by roughly 8% and their imports emission intensity by around 3%.

The introduction of carbon taxes and emissions in the trade approach is outlined by Elliott et al. (2010). They explored mitigation techniques for carbon leakages such as border adjustment in carbon policy of neighboring regions, production subsidies on hard-hit industries, and limited adoption of a well reduced (relative to the policy coalition standard) carbon pricing plane in non-coalition regions. Ekins (2009) investigate the carbon taxes and carbon emission permits and take into account the special reference to the revenue-recycling and tax interaction effects. They found that some instruments that raise revenue can be recycled to reduce pre-existing distortionary taxes, so that the latter is significantly less costly than those which cannot be recycled. They also noted that early evaluations of the environmental effects of carbon taxes have been generally positive. Su et al. (2010) analyze the sector aggregation effect of Input-output of CO₂ emissions embodied in trade. They presented a numerical example using the data of 30 industrial sectors of China and for eight Chinese regions in 1997. They show that the results are highly dependent on the degree of spatial aggregation.

Analyses of emission tax without considering interactions between countries were partly carried out by Ren et al. (2020), Guan et al. (2019), Mardones & Flores (2018), McEvoy & McGinty (2018), da Silva Freitas et al. (2016), Karnizova (2016), Marron & Toder (2014), McLure (2014). Thus, as the combination and interaction between the intermediate input and the final requirement framework play an essential role in investigating the effect of global trade emissions, some scholars believe that working at macro level may reduce the capacity of following and calculating links between countries carefully (Perobelli et al., 2015).

In recent years, international trade development allows the emissions to be transferred from one country to another through carbon included in traded goods, so some scholars such as Sakai & Barrett (2016), and Xu & Dietzenbacher (2014) maintain that the emissions embodied in trade is a global issue. To address this effort, one should be focused on the macro level because by considering a group of countries, the interaction between government policies of one country on the production and trade of other countries and the amount of emissions transferred between countries can be seen more obviously. We want to go beyond that and investigate spatial econometric methods to capture this emissions displacement due to differences in carbon tax. More specifically, our specification aims to tackle the effect of carbon taxation on global trade emissions embodied in both the importing country and its neighboring countries. The literature felt like an unfinished puzzle piece about the impact of neighboring countries' carbon taxes on the embodied carbon emissions of export and import. A country's carbon tax is dependent on the carbon tax of its neighbors insofar as that pollution transfers from one country to another.

On the other side we are using this literature, Wang et al. (2020) considered the multi-regional input-output model to estimate the economic benefits and environmental costs of export trade in high- and new-technology industries. They found that the technological progress in China's high- and new-technology industries leads to a decline in emissions embodied in carbon in developed countries whereas rising the pollution in developing countries. Because of the economic efficiency and environmental costs in the exports of these technologies, low economic efficiencies generate

fewer carbon emissions whilst exports of products with high economic efficiencies generate significant carbon emissions. They also concluded that technology improvement in the electrical and optical equipment sector can effectively promote pollution reduction.

Analyzing global emissions embodied in trade from a spatial perspective, Zhong et al. (2018) utilize a multi-regional input-output analytical framework and spatial econometric regression models for 39 countries from 1995 to 2011. They found that the global trade emissions have primarily flown from developing to developed countries and regions. In the light of the results, they concluded that countries endowed with rich natural resources and developed economies such as Canada have become net carbon exporters, when accounting for their trade flows. Furthermore, the energy sector and industrial structure specifically have spatial spillover effects on the emissions embodied in trade changes.

In our empirical application, we combine similar estimation methods to those used by Zhong et al. (2018) and da Silva Freitas et al. (2016) to examine the effectiveness of carbon taxes in lowering emissions embodied in trade in the host country and adjacent areas (in our empirical application). In other words, we use the da Silva Freitas et al. (2016) estimation to calculate the carbon taxes, total emissions when considering tax, and the impact of taxation on the price index. Then we estimate the emissions embodied in export and import using a method of estimation similar to Zhong et al. (2018). The main difference with their strategy is that Zhong et al. (2018) used World Input-Output Tables (WIOT) and underlying data, covering 40 countries, whereas we rely on WIOT and underlying data, covering 43 countries. Their period of study also differs, it spans from 1995-2011 and consider 35 sectors (ISIC ⁷ rev. 3), while we study the period 2000-2024 and 56 sectors (ISIC rev. 4). We also try to find the share of the direct and indirect effects of all 56 sectors and 43 countries.

In the structural decomposition analysis, the case of a carbon tax is discussed, and suggestions are provided to achieve carbon emission reduction through taxation for the countries in the sample

⁷ISIC: International Standard Industrial Classification

(see section 4.2 Spatial Model). In other words, we focus on estimating carbon tax and abatement trade emissions and the share of direct and indirect emissions in different economic sectors over fifteen years. In addition, we investigate the impacts of emissions embodied in trade on the host country and neighboring countries. The latter analysis, to the best of our knowledge, is currently absent in the literature.

Insofar as we consider emissions at the global level, which is the result of the export and import of goods and services for consumption and production, our work contributes to the literature in the following way:

- Calculating carbon emissions embodied in trade, as part of carbon transfer magnitude, to quantify direct or indirect carbon emissions;
- Building a multi-regional input-output model (MRIO) and analyzing the spatial spillover effect of taxation on carbon emissions embodied in trade;
- Considering the magnitude of pollution in different sectors.

3 Empirical Strategy

In this section, we present our data and show summary statistics of them. We analyze 43 countries based on a spatial panel data model. Our data cover the 2000-2014 period.⁸

3.1 Data

Table 1 illustrates the descriptive statistics of the variables, statistical data are gathered for 43 countries (32 OECD and 11 Non-OECD countries).⁹ These countries were chosen to have a

⁸In order to calculate the EEE, EEI, Carbon tax, and other independent variables, we inspire the paper Zhong et al. (2018), and da Silva Freitas et al. (2016). The method calculation of variables meticulously (explanatory and explained variables) is available upon request

⁹The selection of OECD and Non-OECD countries imposed by the availability of the WIOD data, which happen to be the highest pollution emitters per the share of their GDP (see Table 5 of Appendix B)).

comparison between developed and developing economies. The first column describes the short abbreviation of variables according to their definition in column two; column three indicates the united measurement; and the rest of the columns show statistical information. All the data were transformed into the natural log before using them for analyses. Economic data such as intermediate inputs, final demands, and GDP per capita are in 2016 constant prices (US dollars).¹⁰

Table 1: Measurement and Descriptive Statistics of Variables

Variable	Definition	Unit	Mean	Std.Dev.	Min	Max
EEE	Emissions embodied in exports	Mt	3.084312	1.565002	0.1936106	7.440931
E EI	Emissions embodied in imports	Mt	1.902461	0.4997026	0.5171322	2.99465
TAX	carbon tax	Million dollars	12.28591	0.474615	10.42302	13.4406
TEAT	Total emissions with considering tax	mt	9.579304	2.377294	4.020751	15.75208
IPI	The impact of tax on the price index	Million dollar	3.4752	4.176509	-6.906018	16.12223
Clean-energy	The ratio of clean energy to total energy use	%	2.335806	1.175265	-2.438311	4.478425
PGDP	Per capita GDP	Million dollars	9.850114	1.032201	6.198263	11.53506
Intermediate-Local	Intermediate inputs in the local region	Million dollars	12.33394	1.820735	7.795835	16.80984
Final-Local	Final requirements in the local region	Million dollars	12.4209	1.803827	8.209721	16.64163
Intermediate-Other	Intermediate inputs in other regions	Million dollars	11.15688	1.508922	7.028755	14.05075
Final-Other	Final requirements in other regions	Million dollars	10.59018	1.583545	5.804292	14.00776
C-emission	Consumer Emissions	Million dollars	3.403369	1.319361	1.026273	7.452639
P-emission	Producer Emissions	Million dollars	3.654391	1.713101	-0.016084	8.134106
OECD	Belonging to an OECD country	Dummy Variable	0.744186	0.4366564	0	1

Source: Author's calculation based on the dataset.

3.2 Stylized facts

3.2.1 EEE, EEI, and carbon tax

We plotted carbon tax and emissions embodied in exports and imports in Figure 1 because the main question is whether the amount of carbon tax in each country has indeed reduced the amount of emissions embodied in trade in that country and other neighboring countries. In this figure, the carbon tax of both groups of countries shows a positive trend over time and indicates that the carbon tax of OECD countries is higher than that of non-OECD countries. Even though the carbon tax is growing in both OECD and non-OECD countries, our results show no convergence in terms of emissions embodied in exports. It also illustrates that emissions embodied in imports from both groups of countries have experienced a flat pattern over time. Finally, our graph shows that with the increase of the tax, emissions embodied in exports have decreased over time in OECD

¹⁰We have tested cointegration. GDP per capita does not have unit root. The test of the null hypothesis is rejected (H_0 : panels contain unit roots). So GDP per capita is stationary (result is available upon request).

countries, while this trend is slightly increasing in Non-OECD countries. In other words, to know further about the carbon tax changes in the 43 countries under review, as well as the EEE and EEI flow in the two top polluting countries (China and the US) at the beginning (2000) and end of the period (2014), see Appendix B.

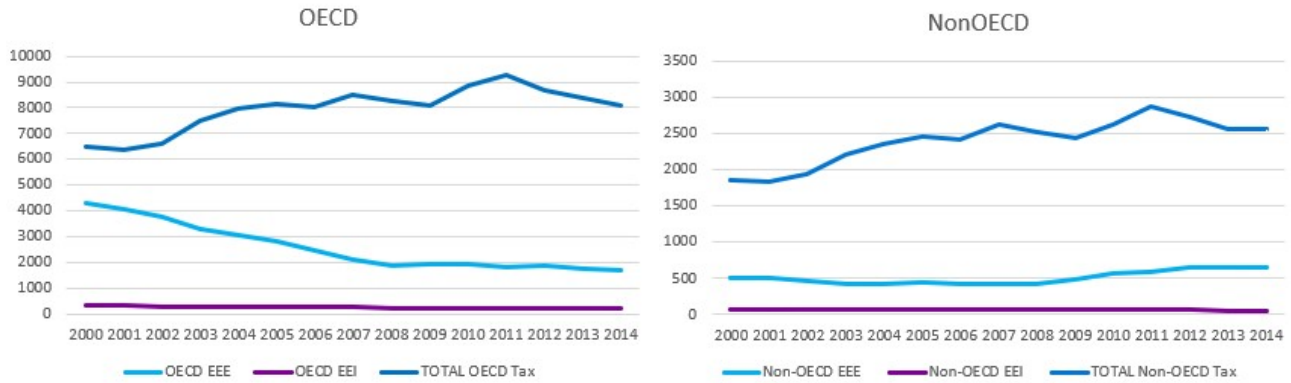


Figure 1: The effect of Carbon tax, EEE and EEI in the OECD and Non-OECD countries

Source: Author's calculation

3.2.2 Coefficient of the Shares of Direct, Indirect and Total Carbon Emissions

SDA (structural decomposition analysis) is based on the input-output model since it gives information regarding the economic structure. Moreover, the SDA has the benefit of apprehending the direct and indirect impact as taken through the Leontief matrix of the input-output models. Besides, the SDA allows evaluating the impacts of the emissions embedded in trade on the economic structure, rather than the unconventional change of each sector. Actually, the transition can be decomposed into many different sections for a systemic decomposition study on the change in carbon emissions integrated with the SDA method of trade. Afterwards impact of these aspects on the carbon emissions embodied in trade will be analyzed. The decomposition form is not specified according to SDA methods, and can normally be overcome with the method of decomposition of polarization or a mean value method. In this section, we propose a structural decomposition analysis for the share of pollution in 56 sectors to assess the amount of emission of each industry. Subsequently, we highlight the higher and less polluting sector for CO₂.¹¹

¹¹We merge the Input-Output tables of the WIOD (World Input-Output Database) 2016 release with CO₂ of Environment Accounts. Therefore, we classified all sectors to 43 countries (31 OECD countries plus 12 major other

Direct effects show how much pollution is produced in each sector. Indirect impacts indicate how much contamination is created by the intermediate products used to produce in each sector. Total effects include all pollution from the production of goods themselves, whether pollution comes from the production of goods or pollution comes from the intermediate goods used in manufacturing.

According to the total CO₂ emissions and the total output of various sectors, the share of direct, indirect, and total carbon emission factors, we decompose all sectors in the Input-Output table into 56 sectors from 2000 to 2014. The results of the calculations are shown in Table 1 of Appendix A. Figure 2 shows the share of direct and indirect emissions of most and fewest polluter sectors.

The coefficient share of direct, indirect, and total emissions in the same year of different sectors could differ significantly from an increasing trend. The sector with the largest coefficient of direct, indirect, and total carbon emission for all years is "Electricity, gas, steam and air conditioning supply". Which is use with Guo et al. (2018) say, "*They provide necessary intermediate products or secondary energy to other sectors and emitted more CO₂ in the direct production process. Hence, there is an urgent need to improve their energy use efficiency and emission intensity*". The sector with the smallest coefficient of direct and indirect and total carbon emission for all years is "Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use".

The largest coefficients of the direct, indirect and, total emissions were 37.87 in 2012, 19.83 in 2007, and 42.93 in 2010, respectively, signifying an increasing trend of the inter-sectoral coefficient. The smallest coefficient for direct, indirect and total emission was 0.0058, 0.0026, 0.0058 million ton of CO₂ in 2014, respectively. Thus, the industries have continuously elevated the level of production technology and energy use, and some results of energy-saving and emission reduction were achieved in some sectors because of more attention paid to the environment.

countries). Then we examine the effects of pollution in each sector (see Table 1 of Appendix A.

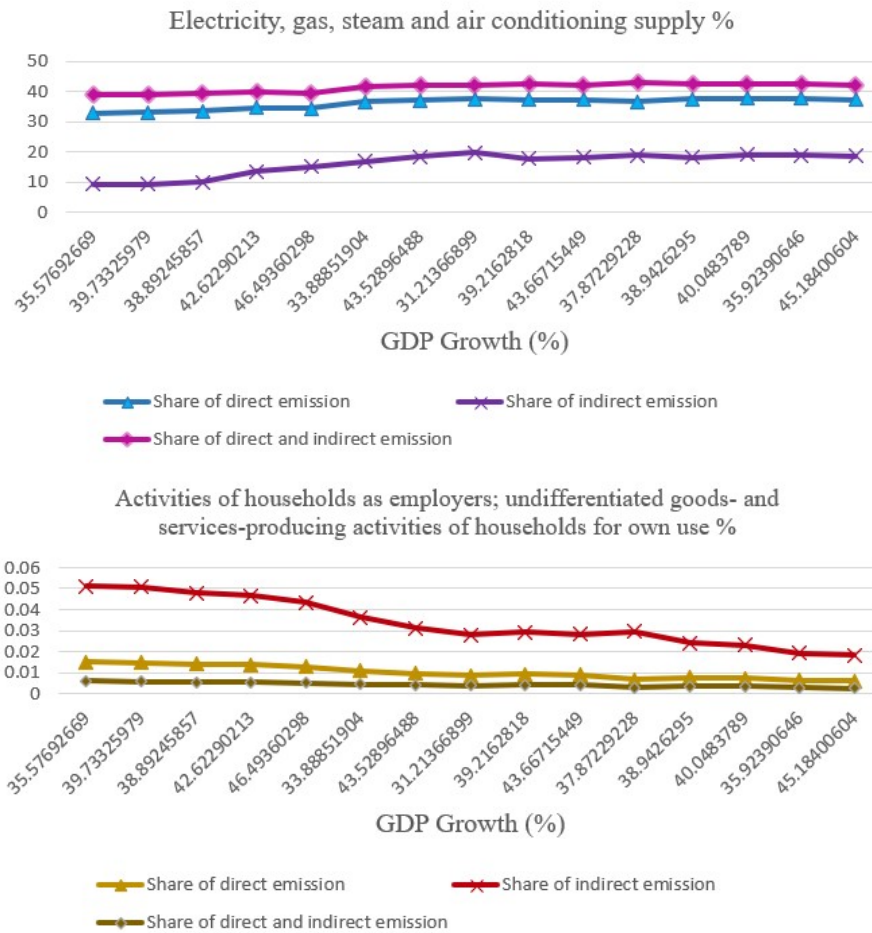


Figure 2: Share of Direct and Indirect Emission in the most and fewer polluter sectors

Source: Author's calculation

3.3 Spatial model

Scholars have used different measurement methods and appropriately introduced other explanatory variables to conduct extensive discussions on the relationship between the emissions embodied in trade and taxation. In conventional regressions, regions are normally considered independently of each other; in the real world, trade breaks down boundaries, facilitates trade interactions,... Therefore, the spatial regression methods are the adapted estimation method. The hypothesis that trade emissions and emission tax have no impact on neighboring regions does not fit the reality of our world. To sum up, in the real world, economic activities in one country affect the economic of neighboring countries. Therefore, ignoring the geographical and trade effects between countries leads us

to biased and inconsistent estimates. In this study, we observe spatial dependency between countries.

Before building the spatial econometric model for the impact of tax on emissions embodied in trade, the existence of the spatial effect must be tested. We use spatial tests to identify whether there is a spatial correlation between the data.¹² In this test, whether or not the non-spatial model can be rejected is determined by the significance of the statistics. We check the log-likelihood function as well. This paper is based on the fact that in this application, both lagged dependent and independent variables are considered. One reason is that not only the value of emissions embodied in trade in a country is related to the value of emissions embodied in trade in neighboring countries, but also the values of independent variables in a country are related to the value of emissions embodied in trade in neighboring countries. SDM (spatial Durbin model) is chosen as a fitted model.¹³ In fact, in the spatial Durbin model, the spatial effect of the explained variable and the explanatory variables are added to the conventional panel model.

Based on the theoretical and empirical literature, the final form of the SDM model can be followed in equation 1 for OECD, on the one hand, and Non-OECD countries, on the other hand:

$$\begin{aligned} LnY_{ijt}^r = & \beta_0 + \rho W_{t-1}^{rs} LnY_{ijt}^r + \beta_1 \mathbf{T}_t^r + \beta_2 LnC_t^r + \beta_3 LnM_{ijt}^r + \\ & \delta_1 W_{t-1}^{rs} LnT_{ijt}^r + \delta_2 W_{t-1}^{rs} LnC_t^r + \delta_3 W_{t-1}^{rs} LnM_{ijt}^r + U_{ijt}^r + \epsilon_{ijt}^r \end{aligned} \quad (1)$$

Our outcome variables indicate both side of trade (imported and exported emissions) so it would be common that we use the same model for both estimations. Where:

- LnY_{ijt}^r is the dependent variable and can take alternatively the values:

– $LnEEE_{ijt}^r$, the emissions embodied in exports of products of sector i from sector j and

¹²The various spatial tests used are: LM (Lagrange multiplier) test, LR (Likelihood Ratio) test, Wald test, Moran MI Error Test.

¹³SAR (Spatial Lag Model), SEM (Spatial Error Model), SDM (Spatial Durbin Model), and SAC (Spatial Autoregressive Model)

country r in year t , i and $j = 1, \dots, 56$, for sectors, $r = 1, \dots, 43$, for countries, and $t = 1, \dots, 15$ for years,

- $LnEEI_{ijt}^r$ the emissions embodied in imports of product from sector i towards sector j and country r in year t ;

Our explanatory variables in this paper are divided into four groups of variables, Tax variables, Control variables, MRIO variables, and Dummy Variable.

- Our first set of explanatory variables called Tax variables. To calculate the carbon tax, total emissions by considering tax, and the impact of tax on price index variables we used da Silva Freitas et al. (2016) paper. This group is our main group of variables, which includes:

$$\beta_1 T_t^r = \beta_1' LnTAX_t^r + \beta_2' LnTEAT_{ijt}^r + \beta_3' LnIPI_{ijt}^r$$

$$\delta_1 W_{t-1}^{rs} LnT_{ijt}^r = \delta_1' W_{t-1}^{rs} LnTAX_t^r + \delta_2' W_{t-1}^{rs} LnTEAT_{ijt}^r + \delta_3' W_{t-1}^{rs} LnIPI_{ijt}^r$$

- $LnTAX_{ijt}^r$ is the rate of total carbon tax of the output in existing sector i from sector j and country r in year t ;
- $LnTEAT_{ijt}^r$ is total emissions before tax in sector i , sector j and country r and year t ;
- $LnIPI_{ijt}^r$ is the impact of tax on industrial price index for sector i and sector j and country r in year t ;
- W_{t-1}^{rs} is the spatial weight matrix between country r and its partner country s , measured by bilateral trade.

- The second set of control variables is as follows:

$$\beta_2 LnC_t^r = \beta_1'' LnClean.engi_t^r + \beta_2'' LnPGDP_t^r$$

$$\delta_2 W_{t-1}^{rs} LnC_t^r = \delta_1'' W_{t-1}^{rs} LnClean.engi_t^r + \delta_2'' W_{t-1}^{rs} LnPGDP_t^r$$

- $\text{LnClean} - \text{engi}_t^r$ is the ratio of clean energy to total energy use country r in year t ;
- LnPGDP_t^r is the GDP per capita country r and year t ¹⁴;
- Third set conventional MRIO variables are variables that we calculate based on the MRIO model. To calculate our dependent variables (emissions embodied in exports, emissions embodied in imports), and some of our independent variables (intermediate inputs in the local region, final requirements in the local region, intermediate inputs in other regions, and final requirements in other regions), we use the MRIO table from the World Input-Output Database (WIOD) (variables were constructed using true numbers). We use Zhong et al. (2018) paper to calculate them and our result is the same as theirs. The calculation of consumer emissions and producer emissions variables is based on Kulionis (2014) paper.

$$\beta_3 \text{Ln}M_t^r = \beta_1''' \text{LnIntermediate.Local}_{ijt}^r + \beta_2''' \text{LnFinal.Local}_{ijt}^r + \beta_3''' \text{LnIntermediate.Other}_{ijt}^r + \beta_4''' \text{LnFinal.Other}_{ijt}^r + \beta_5''' \text{LnC.emission}_{ijt}^r + \beta_6''' \text{LnP.emission}_{ijt}^r$$

$$\delta_3 W_{t-1}^{rs} \text{Ln}M_{ijt}^r = \delta_1''' W_{t-1}^{rs} \text{LnIntermediate.Local}_{ijt}^r + \delta_2''' W_{t-1}^{rs} \text{LnFinal.Local}_{ijt}^r + \delta_3''' W_{t-1}^{rs} \text{LnIntermediate.Other}_{ijt}^r + \delta_4''' W_{t-1}^{rs} \text{LnFinal.Other}_{ijt}^r + \delta_5''' W_{t-1}^{rs} \text{LnC.emission}_{ijt}^r + \delta_6''' W_{t-1}^{rs} \text{LnP.emission}_{ijt}^r$$

- $\text{LnIntermediate} - \text{Local}_{ijt}^r$ is intermediate inputs of sector i to sector j used/produced in local region of country r in year t ;
- $\text{LnFinal} - \text{Local}_{ijt}^r$ is the final demand for products of sector i to sector j in the local region of country r in year t ;
- $\text{LnIntermediate} - \text{Other}_{ijt}^s$ is the intermediate inputs of sector i to sector j produced in other regions of country s in year t ;

¹⁴GDP does not have unit root at level. It rejects the null hypothesis (H0: panels contain unit roots). So Data is stationary at level.

- $LnFinal - Other_{ijt}^s$ is the final demand for products of sector i to sector j in other regions of country s in year t ;
- $LnC - emission_{ijt}^r$ is consumer carbon emissions in sector i and sector j in county r and year t ;
- $LnP - emission_{ijt}^r$ is producer emissions of sector i and sector j in county r and year t .

When it comes to the variables:

- β_K , $K = 1, \dots, 12$ is the parameter of interest to be estimated;
- The spatial auto-regression coefficient would be explained by ρ ;
- β_0 is the constant term over time and fixed-effect to be estimated
- ϵ_{ijt} denotes an independent and identical distribution with zero mean and same variance;
- σ_0^2 ; U_{ijt} is the error term which captures all other omitted country factors, with $E(U_{ijt}) = 0$ for all i, j and t .

A spatial autoregressive term $\sum_{i=1}^n W_{t-1}^{rs} LnY_{ijt}^{rs}$ was included to estimate the spillover effects of carbon emissions of sectors i and j embodied in trade for a given couple of neighbor countries r and s in year t .

The impact of tax on emissions embodied in trade is estimated by four matrices (inverse squared distance, bilateral trade for 2013 (year t-1), export flow for 2013 and import flow for 2013). The geographic and economical matrices can be used to construct an instrument for emissions embodied in trade. This is what we do.

A spatial matrix based on geographical distance (Euclidian distance) in kilometers between centroids of countries i and j is used to illustrate the spatial contiguity, with a zero diagonal and the off diagonal non-zero elements. Often, the off-diagonal elements are scaled so that they add up to unity in each row. Our geographical matrices are $1/d_{ij}^2$, $1/d_{ij}$, Queen, and Rook Contiguity. Two

former geographical matrices were divided by the summation of each horizontal row. When an element of the matrix is larger than the average of the matrix, number one is put in the cell, and in other cases, a zero is used in the cell. In the standard matrix, the final distance matrix is created where the sum of each horizontal row should equal one. Two latter geographical matrices either use distance measurements to identify the proximity of countries or they equal 1 when the countries are adjacent and 0 otherwise. However, the geographical weight matrices might not be a good candidate for this study because most of the 43 countries in our study are spatially isolated. In other words, most of them do not have common borders. This may lead to a poorly fitted spatial regression model.

Due to the fact that carbon emissions of countries inflow or outflow to their important trading partners, carbon emissions embodied in international trade may not only depend on geographic distance but also on the trading partners Liu et al. (2010), Du et al. (2011), and Zhong et al. (2018). We take the bilateral trade matrix as an economic matrix into account in this study. Amidi & Majidi (2020) and Ho et al. (2013) used the bilateral trade flow in the last period to construct the time-varying spatial weights (In this matrix, the trade decisions of one country depend on those of the others) $W_t = [W_{t-1}^{rs}]_{r,s=0}^n$. They also state that the $(r, s)^{th}$ entry of the weight matrix W_t represent the bilateral trade flow of country r and s in year $t - 1$ (nominal millions of US dollar value).¹⁵ trade matrix W_{t-1} is row normalized, and the diagonal elements of W_{t-1} are all zero, and the off-diagonal non-zero (it shows the sum of export and import flows between r and s) elements. The widely used gravity model for international exports and imports between two countries assumes that the unobservable multilateral resistance of each country, which may be correlated with the unobservable in the final equation, might have an impact on exports and imports between two countries Qu et al. (2021).

Conspicuously, due to the simultaneity bias between explained and some explanatory variables

¹⁵In the spatial econometrics literature, the weight matrix is assumed to be exogenous to the dependent variable. In this exercise, we have a geographical and an economic (bilateral trade) distance matrix. When a spatial weights matrix is constructed from a bilateral trade matrix, the spatial weights could be endogenous and also time-varying, while the geographical matrix is usually exogenous and time-invariant. Here, because LnY_{ijt} might affect the trade flow in year t , the trade flow was lagged for one period to form the weight matrices in order to decrease possibility of endogeneity problems Ho et al. (2013).

(distance and trade), the spatial econometric panel models could not be estimated by ordinary least squares (OLS) (Long et al., 2016).

4 Results Spatial Models

4.1 Spatial Autocorrelation Results

In this section, we present our statistics tests and estimation results for 32 OECD countries and 11 Non-OECD countries. Generally, using a pooled panel model to assess the impact of emissions embodied in trade tends to produce a biased decision because such pollution include spatial interaction that has not been nested into standard panel models. To minimize biasing estimates and examine the spatial and spillover impacts of dependent and independent variables, we included the findings of the pool OLS, SAR, SEM, SDM, SAC, and GSPRE models in this study to discover a suitable model.

Spatial autocorrelation represents that the values of a variable correlate to the close locational positions on a two-dimensional surface (Griffith, 1987). Thereafter, neglecting spatial dependency in econometric studies leads to econometric estimates that are biased, since variables have spatial correlation (Anselin, 1988). Following this section, in order to diagnose spatial dependency, we represent the global Moran's indicator as a global-proxy of spatial autocorrelation. We use Moran's I in EEE and EEI models to bold potential spatial associations for 32 OECD countries and 11 Non-OECD countries, taking into account the trade matrix.¹⁶ In Table 2, the positive Moran's I is funded for EEE in OECD countries and EEI in both OECD and Non-OECD countries. The results of the spatial recognition tests demonstrate that zero hypotheses (lack of existence of spatial correlation) are rejected, and there is the spatial auto-correlation in our application. In other words, it indicates the presence of the spatial effects of this group of countries. **This means that positive and strong spatial autocorrelation can be found in these models.** Thus, spatial dependence is observed in these countries. By and large, emissions embodied in trade in one country affect other neighbor-

¹⁶Moran index is sensitive to the matrix selection.

ing countries. Conversely, the result of Moran’s I in the EEE model for Non-OECD is not significant.

To represent the impact of the spatial dependency issue, LeSage & Pace (2009) presented a test that contained spatial lags for dependent variables and independent variables. In order to determine which estimation model (SAR, SEM, SDM, SAC, and GSPRE) should be used. Several tests can be considered to find a more appropriate model:

1. Likelihood ratio (LR) test is based on the log-likelihood function values of the various models.
2. Wald test
3. Lagrange multiplier (LM) tests

The spatial lag model (SAR¹⁷) and spatial error model (SEM¹⁸) are not nested. So Elhorst (2014) suggests that the classic LM-tests proposed by Anselin (1988), or the robust LM-tests proposed by Anselin et al. (1996) can be used to make a better description. Acceptance of the LM (Lagrange multiplier) test shows that the hypothesis of no spatially lagged dependent variable and the hypothesis of no spatially auto-correlated error term are rejected. Also, when a robust LM test is used, the null hypothesis of no spatially auto-correlated error term could not be accepted. Both of the hypotheses, (no spatially lagged dependent variable and no spatially auto-correlated error term) are firmly rejected for these models. The LM-tests in Table 2 illustrates that the SEM model for the EEE model in OECD countries and the EEE model in Non-OECD countries, whileas, the SAR model for EEI in OECD and EEE in Non-OECD are the best models.

Table 2: Spatial autocorrelation tests for Emissions Embodied in Exports and Imports (Dependent variables: EEE and EEI; W: Wtrade2013)

Spatial tests	OECD		Non-OECD	
	EEE (Mt)	EEI (Mt)	EEE (Mt)	EEI (Mt)
Global Moran MI	0.8194***	0.1676***	-0.0065	0.7916***
LM Error (Burrige)	368.3192***	15.4096***	0.0037	54.787***
LM Error (Robust)	432.6812***	1.8727	48.2029***	132.7823***
LM Lag (Anselin)	2.6511	21.7261***	6.1886**	9.3014***
LM Lag (Robust)	67.0131***	8.1892***	54.3878***	87.2967***

¹⁷SAR model contains endogenous interaction effects.

¹⁸SEM model involves the interaction effects among the error terms.

Source: Author's calculation. Note: *p<0.1; **p<0.05; ***p<0.01, respectively. We decide to bring the result of the “trade matrix for the year 2013”

Before choosing the better-fitted model, SDM contains SAR and SEM models, thus we must compare these two models with the SDM model, using the Wald tests. Wald test for SAR model via SDM model test the hypothesis that $\theta = 0$. This means that the null hypothesis in the spatial autocorrelation occurs only if the host country influences the neighboring countries. Wald test for SEM model via SDM model test the hypothesis that $\theta = -\rho\beta$. It can be inferred that spatial autocorrelation occurs only if the error values of a host country has an influence on the error values of neighboring countries. Table 3 rejects these null hypotheses, so the SDM model is accepted. Akaike Information Criterion (AIC) calculates the amount of lost information by a model and the Bayesian information criterion (BIC) maximizes a model's posterior probability given the data (Burnham & Anderson, 2002). The lower amount of AIC must be selected as the better model. Four alternative types of model specifications are examined based on the aforementioned analysis: no fixed effects model, spatial fixed effects model, time-period fixed effects model, and spatial and time fixed effects model. Based on the result of the log-likelihood ratio in these models spatial and time-fixed effects model is chosen for OECD and Non-OECD countries in EEE and EEI.

Table 3: Wald test and Log-likelihood ratio for spatial and time fixed effects model (Dependent variables: EEE and EEI; W: Wtrade2013)

	OECD		Non-OECD	
	EEE (Mt)	EEI (Mt)	EEE (Mt)	EEI (Mt)
AIC	-2412.788	-2632.233	-666.908	-838.5455
BIC	-2312.617	-2532.062	-592.3654	-764.0028
Wald SAR va SDM	33.77***	21.29**	20.1**	70.91***
Wald SEM va SDM	28.18***	18.11**	17.66*	68.23***
Log-likelihood	1230.3939	1340.1166	357.454	443.2728

Source: Author's calculation. Note: *p<0.1; **p<0.05; ***p<0.01, respectively.

We need to know which kinds of spatial weight matrices are suitable to sustain in our application. We calculate log likelihood statistics and corrected R squared statistics to compare the five distinct spatial weight matrices (Queen and rook contiguity, inverse distance, inverse distance square, and trade matrix for the year 2013). In the EEE model, the group of OECD countries has the largest log likelihood value (1279.075) for the inverse distance matrix, but the trade matrix for the year 2013 has the largest corrected R squared of 0.5377. Also, in the EEE model, the group of Non-OECD countries has the largest log likelihood value (373.3158), and the largest corrected R squared of

0.1624 for the inverse distance square matrix.

On the one hand, in the EEI model, the group of OECD countries has the largest log likelihood value (1359.6508) for the rook contiguity matrix, but the Queen contiguity matrix has the largest corrected R squared of 0.7951. Likewise, in the EEI model, the group of Non-OECD countries has the largest log likelihood value (467.4925) for the inverse distance matrix, and the largest corrected R squared of 0.0571.¹⁹ Our result is similar to that of (Zhong et al., 2018), since it is a common stereotype that countries have an influential effect through their mutual border lines. In fact, countries' communications are defined as being in separate spaces, so the use of such matrices does not seem to be an interesting idea. Turning to the other hand, those groups of countries are closely related to each other in terms of international trade rather than in proximity and geographical distance impacts.

To sum up, we decide that the best matrix in this research for EEE and EEI in OECD and Non-OECD countries will be the trade matrix for 2013. It is worth noting that the weight matrices are row-normalized, which means that the elements of each row add up to the unit, making it easier to interpret and compute the magnitude of spatial dependency.

4.2 Spatial Analysis Result

Based on the multi-regional input-output model, average emission embodied export, average emission embodied import, and average environmental tax can be obtained (see Table 5 of Appendix B). Columns (1), (3), (5), and (7) in Table 4 are based on a simple panel pool OLS model. They allow us to see how biased estimation results are if spatial relationships are ignored. Actually, SDM models in Table 4 illustrates the dependencies in the spatial relationships between a dependent variable and independent variables. The dependent variable expresses emissions embodied in export and emissions embodied in import, taking into account bilateral trade in the year t-1 matrices to

¹⁹Results of all models are available upon request.

control spatial autocorrelation (columns (2), (4), (6), and (8)).²⁰

According to Table 4, carbon tax, total emissions after-tax, IPI (impact of tax on price index), intermediate inputs and final requirements in the other regions, and producer emissions concerning trade matrix have a positive, significant effect, and expected sign, while the ratio of clean energy to total energy use, intermediate inputs and final requirements in the local region have a negative, significant effect and expected sign on the emissions embodied in exports in OECD countries. Specifically, carbon tax, GDP per capita, and final requirements in local and other regions, consumer and producer emissions concerning the trade matrix have a positive effect. IPI and intermediate inputs in local and other regions have a negative effect on EEI in OECD countries, respectively.

Carbon tax, the ratio of clean energy to total energy use, and consumer and producer emissions have a positive sign, while intermediate inputs in local and other regions have a negative sign on EEI in Non-OECD countries. We do not have spatial effects in EEE of Non-OECD countries, so we interpret the simple traditional model. In this model, carbon tax, intermediate inputs in other regions, and consumer and producer emissions have a positive effect, but the ratio of clean energy to total energy use, GDP per capita, and intermediate inputs in local regions have a negative effect on EEE in Non-OECD countries.

The effect of the carbon tax on imports is positive. It means that, with an increase in a carbon tax, the output and input prices of products grow, particularly for energy products. Thus, if some sectors reduce the amount of investment, importing goods will become more competitive, and imports will increase. For OECD countries, the amount of tax increases, but for some rich sectors, this amount is not fair enough and cannot be filled with the amount of export, so OECD countries pay the permission of pollution and continue to produce dirty goods, and then export this pollution to the neighboring area. An increase in total emissions after tax due to incorrect environmental policies leads to emissions embodied in exports for OECD countries.

²⁰We estimated the equation for inverse distance matrix, inverse distance square matrix, Queen contiguity matrix, Rook contiguity matrix, and bilateral carbon tax matrix as well. Results are available upon request.

The ratio of clean energy to total energy use (Clean-engi) indicates that using clean technologies is expensive for sectors of OECD and Non-OECD countries, so if they are obliged to use more this technology, their demand will decrease, which will lead to a decline in emissions embodied in exports. These results are in line with Cao et al. (2019), and Zhong et al. (2018), while using clean technologies in Non-OECD countries increases the desire of rich countries to buy clean goods at a low cost, thus increasing emissions embodied in imports.

The magnitude of carbon emissions embodied in trade is influenced by the level of GDP per capita (PGDP) during industrialization. Carbon emissions flow into high-income countries (OECD) and flow out of poor countries (Non-OECD), this leads to confirm the findings of Grunewald et al. (2017), and Xu & Dietzenbacher (2014).

When the local economy produces all the intermediate inputs itself, the pollution from the transportation of these goods through trade (whether through imports or exports) is reduced in the OECD and Non-OECD countries, as found by Zhong et al. (2018), and Xu & Dietzenbacher (2014).

Final requirement in local region (Final-Local, some sectors in input-output table sells some of there output to local consumers) has positive effects on emissions inflows in OECD and Non-OECD, and negative effects on carbon emissions outflows in OECD countries, like in Zhong et al. (2018), and Xu & Dietzenbacher (2014).

As for Zhong et al. (2018), and Xu & Dietzenbacher (2014), Intermediate input in other region (Intermediate-Other, some sectors in input-output table sells some of there output to other sectors in other region) has a negative effect on emissions inflows and a positive effect on carbon emissions outflows.

The coefficient of the Final requirement in other region (Final-Other, some sectors in input-

output table sells some of there output to other region consumers) has a positive impact on emissions inflows in OECD countries and outflows OECD and Non-OECD countries which confirms Zhong et al. (2018) and Xu & Dietzenbacher (2014).

Producer emission indicates that the carbon dioxide emissions calculated from the consumer perspective are significantly higher than producer emission as highlighted by Ren et al. (2020), de Boer et al. (2019), Long et al. (2018), and (Elliott et al., 2010).

The IPI index represents the purchasing power losses for consumers after the implementation of the tax policy. It has a negative effect on emissions embodied in import and positive on export.

Table 4: OLS and SDM spatial and time fixed effects model (Dependent variables: EEE and EEI; W: Wtrade2013)

	OECD				Non-OECD			
	OLS EEE (Mt)	SDM EEE(Mt)	OLS EEI(Mt)	SDM EEI(Mt)	OLS EEE(Mt)	SDM EEE(Mt)	OLS EEI(Mt)	SDM EEI(Mt)
Columns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.672*** (-6.26)		-4.993*** (-30.78)		-1.532** (-2.81)		-6.555*** (-33.21)	
Tax	-0.0110 (-1.16)	0.0738*** (5.84)	0.733*** (50.93)	0.832*** (72.92)	0.207*** (3.38)	-0.0488 (-0.96)	0.911*** (41.13)	0.790*** (23.56)
Teat	0.00202 (0.31)	0.00922** (2.67)	0.00663 (0.69)	-0.00199 (-0.64)	0.00765 (0.32)	0.0171 (1.79)	0.0239** (2.78)	-0.00169 (-0.28)
IPI	0.000110 (0.06)	0.0803*** (4.12)	0.00101 (0.36)	-0.0555** (-3.16)	0.00305 (0.48)	0.247*** (3.65)	0.00468* (2.02)	0.0263 (0.63)
Clean-engi	-0.0168*** (-5.90)	-0.00981* (-2.22)	0.0182*** (4.24)	-0.00333 (-0.83)	-0.100*** (-6.03)	-0.0140 (-1.50)	-0.0158** (-2.63)	0.0183** (3.09)
PGDP	0.0191** (3.03)	-0.00845 (-0.38)	0.00931 (0.98)	0.0712*** (3.53)	-0.126*** (-6.98)	-0.185*** (-3.31)	0.00579 (0.89)	0.0306 (0.88)
Intermediate-Local	0.0409* (2.23)	-0.100*** (-5.85)	-0.441*** (-15.92)	-0.282*** (-18.30)	-0.189** (-3.27)	-0.0808 (-1.16)	-0.332*** (-15.83)	-0.373*** (-8.59)
Final-Local	-0.126*** (-7.29)	-0.134*** (-5.07)	0.130*** (4.97)	0.0966*** (4.07)	-0.0992 (-1.33)	-0.978*** (-10.74)	0.0885** (3.28)	-0.0230 (-0.40)
Intermediate-Other	0.0122 (0.83)	0.0685*** (5.04)	-0.0421 (-1.89)	-0.136*** (-11.10)	0.155*** (3.63)	-0.0430 (-1.10)	-0.0555*** (-3.60)	-0.0889*** (-3.67)
Final-Other	0.0963*** (8.87)	0.0441*** (3.76)	0.0312 (1.90)	0.0423*** (4.02)	0.151*** (5.47)	0.0995** (3.04)	-0.0791*** (-7.94)	0.0311 (1.53)
C-emission	0.454*** (24.16)	-0.0307 (-0.98)	0.282*** (9.92)	0.268*** (9.51)	0.401*** (6.01)	0.148* (2.20)	0.0380 (1.58)	0.245*** (5.58)
P-emission	0.565*** (24.85)	1.072*** (24.05)	0.193*** (5.63)	0.154*** (3.85)	0.630*** (9.02)	1.676*** (14.90)	0.342*** (13.51)	0.290*** (4.16)
W*Tax		0.127 (1.61)		0.132 (1.21)		0.0328 (0.33)		0.0353 (0.42)
W*Teat		0.0155 (1.22)		0.0164 (1.45)		-0.0178 (-0.44)		0.00175 (0.07)
W*IPI		0.0103 (0.13)		0.0192 (0.27)		0.308 (1.58)		0.0919 (0.75)
W*Clean-engi		-0.0333 (-1.55)		-0.0606** (-3.10)		-0.0860 (-1.14)		0.0967* (2.05)
W*PGDP		-0.500*** (-4.44)		-0.0939 (-0.93)		-0.129 (-0.55)		-0.185 (-1.28)
W*Intermediate-Local		-0.116 (-1.16)		-0.243** (-2.65)		0.160 (0.98)		-0.290** (-2.78)
W*Final-Local		0.0350 (0.33)		0.0137 (0.15)		-0.288 (-0.56)		0.213 (0.68)
W*Intermediate-Other		-0.0987 (-1.48)		-0.0737 (-1.20)		-0.0766 (-1.05)		0.0458 (1.02)
W*Final-Other		0.0962 (1.61)		0.0540 (1.00)		0.135 (1.93)		0.0236 (0.54)
W*C-emission		-0.349** (-3.27)		-0.151 (-1.23)		0.0652 (0.22)		-0.0166 (-0.09)
W*P-emission		0.743** (2.97)		0.362* (2.06)		-0.217 (-0.30)		-0.0879 (-0.20)
ρ		-0.205 (-1.63)		-0.0915 (-0.71)		-0.0299 (-0.16)		-0.160 (-1.50)
σ^2		0.000303*** (17.22)		0.000246*** (13.05)		0.000754*** (8.38)		0.000291*** (7.95)
Number of observation	480	480	480	480	165	165	165	165

Source: Author's calculation. Note: *p<0.1; **p<0.05; ***p<0.01, respectively.

Our model explain the impact of the carbon tax on the emission embodied in export and import. Notably, change in dependent variable related to the main independent variable are important, but pay attention to the alteration value in the neighboring countries and home country it can also be the crucial cause of emission embodied in trade (LeSage & Pace, 2009). In this regard, calculating the marginal effect tends to be the most effective method of accurate explicit. Thus, we

promote our model to calculate the direct, indirect, and total effects as described by (LeSage & Pace, 2009). We are interested in knowing not only the direct effects of a carbon tax on a host country's economy but also the indirect effects on its neighbors. More specifically, direct, indirect, and total effects expressed a change in the dependent variable across all surrounding countries, as a result of a change in the level of emissions embodied in exports from a host country.

Accordingly, based on LeSage & Pace (2009) estimates, in the Table 3, an increase in a country tax, total emissions with considering tax, the impact of tax on price index, intermediate input in other regions, final requirements in other regions, or producer emission are associated with a statistically significant (1% level) increase in its own emissions embodied in export of OECD countries. In opposite, the ratio of clean energy to total energy use, intermediate inputs in the local region, and final requirements in local region decrease own emissions embodied in the export of OECD countries. Also, by increasing the carbon tax, GDP per capita, final requirements in local and other regions, consumer and producer emissions increase, but the impact of tax on price index, and intermediate inputs in local and other regions decreases in their own emissions embodied in import of OECD countries. Concretely, when carbon taxes are implemented, the ratio of clean energy to total energy use, consumer emissions, and producer emissions increase, whereas intermediate inputs in local and other regions decrease in their own emissions embodied in the imports of Non-OECD countries.

In other words, the GDP per capita, and consumer emissions of a host country have negative effects, but producer emissions have a positive effect on emissions embodied in exports of neighboring countries (indirect effect (spillover)) in the OECD countries. An increase of 1% in a ratio of clean energy to total energy use, and 1 million dollars in intermediate input in the local region in the OECD countries cause the decrease of 5.7 and 20.1 percent of these variables, respectively, in neighboring countries. Considering the impact of emissions embodied in imports in Non-OECD countries, an increase of 1 % in the ratio of clean energy to the total energy use of home country causes an increase of 8.5% in the ratio of clean energy in neighboring countries. One million dollars

decreases in the intermediate input in the local region results in a rise of 19.8 percent in the intermediate input in the neighboring region when the impact of emissions embodied in imports in Non-OECD countries are taken into account.

On the whole, concerning the emissions embodied in exports, when the carbon tax, producer emissions, and final requirements in other regions are increased by 1 million US dollars, in OECD countries they are raised by 16.9, 11.7, and 150.5 percent, respectively. In contrast, the ratio of clean energy to total energy use, GDP per capita, intermediate input in the local region, and consumer emissions totally decreases the emissions embodied in exports in OECD countries. Furthermore, an increase of 1 million dollars in the carbon tax and producer emissions of OECD countries leads to growth in 88.8, and 47.8 percent emissions embodied in export, respectively. On the other way, when the ratio of clean energy to total energy use is increased, intermediate inputs in local and other regions will have increased by 5.98, 48.1, and 19.4 percent, respectively. Emissions embodied in imports in OECD countries will decrease. Totally, we find that an increase in trade between countries' independent variables (carbon tax and the ratio of clean energy to total energy use) is associated with a statistically significant (1% level or better) increase in EEI. The total effect is due to the fact that if we increase intermediate input in the local region, it decreases emissions embodied in imports.

Table 5: Direct, Indirect and Total effects (Dependent variables: EEE and EEI; W: Wtrade2013)

Columns Variable	Non-OECD											
	OECD						Non-OECD					
	EEE(Mt)		EEI(Mt)		EEE(Mt)		EEI(Mt)		EEE(Mt)		EEI(Mt)	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
Direct effect	Indirect effect	total effect	Direct effect	Indirect effect	total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	
Tax	0.0723*** (5.55)	0.0965 (1.47)	0.169** (2.58)	0.832*** (70.36)	0.0555 (0.86)	0.888*** (13.45)	-0.0473 (-0.90)	0.0382 (0.36)	-0.00906 (-0.07)	0.795*** (23.43)	-0.0778 (-1.28)	0.717*** (10.41)
Teat	0.00888** (2.62)	0.0112 (1.02)	0.0201 (1.74)	-0.00226 (-0.74)	0.0148 (1.46)	0.0126 (1.17)	0.0169 (1.78)	-0.0196 (-0.50)	-0.00271 (-0.07)	-0.00197 (-0.32)	0.000825 (0.04)	-0.00114 (-0.06)
IPI	0.0822*** (4.49)	-0.00131 (-0.02)	0.0809 (1.08)	-0.0540** (-3.24)	0.0267 (0.39)	-0.0273 (-0.36)	0.254*** (3.79)	0.316 (1.50)	0.371* (2.47)	0.0277 (0.68)	0.0843 (0.77)	0.112 (0.97)
Clean-engi	-0.00939* (-2.16)	-0.0274 (-1.50)	-0.0368* (-2.06)	-0.00292 (-0.76)	-0.0569** (-3.09)	-0.0598** (-3.28)	-0.0137 (-1.34)	-0.0863 (-1.15)	-0.1000 (-1.30)	0.0155** (2.60)	0.0853* (2.03)	0.101* (2.41)
PGDP	-0.000817 (-0.04)	-0.426*** (-3.88)	-0.427*** (-3.74)	0.0720*** (3.70)	-0.0957 (-3.09)	-0.0237 (-0.24)	-0.188*** (-3.35)	-0.136 (-0.54)	-0.324 (-1.22)	0.0359 (1.06)	-0.172 (-1.30)	-0.136 (-1.01)
Intermediate-Local	-0.0985*** (-6.12)	-0.0772 (-1.01)	-0.176* (-2.19)	-0.281*** (-18.95)	-0.201* (-2.34)	-0.481*** (-5.30)	-0.0828 (-1.22)	0.179 (1.13)	0.0963 (0.54)	-0.367*** (-8.71)	-0.198* (-2.16)	-0.565*** (-5.59)
Final-Local	-0.134*** (-4.98)	0.0507 (0.57)	-0.0835 (-0.84)	0.0970*** (3.97)	0.00222 (0.02)	0.992 (0.99)	-0.980*** (-9.85)	-0.268 (-0.47)	-1.248* (-2.04)	-0.0285 (-0.47)	0.205 (0.71)	0.177 (0.59)
Intermediate-Other	0.0698*** (5.26)	-0.0953 (-1.61)	-0.0255 (-0.43)	-0.137*** (-11.48)	-0.0576 (-0.95)	-0.194** (-3.13)	-0.0457 (-1.31)	-0.0810 (-0.99)	-0.127 (-1.30)	-0.0922*** (-4.33)	0.0524 (1.29)	-0.0398 (-0.81)
Final-Other	0.0436*** (3.89)	0.0730 (1.39)	0.117* (2.23)	0.0427*** (4.32)	0.0459 (0.89)	0.0886 (1.71)	0.102*** (3.43)	0.138 (1.75)	0.241** (2.67)	0.0320 (1.77)	0.0184 (0.48)	0.0505 (1.18)
C-emission	-0.0240 (-0.75)	-0.298** (-3.16)	-0.322*** (-3.49)	0.270*** (9.37)	-0.173 (-1.63)	0.0965 (0.90)	0.150* (2.05)	0.0418 (0.14)	0.191 (0.68)	0.248*** (5.08)	-0.0602 (-0.36)	0.188 (1.18)
P-emission	1.060*** (23.56)	0.445** (2.71)	1.505*** (8.91)	0.149*** (3.66)	0.329 (1.81)	0.478* (2.53)	1.673*** (14.21)	-0.270 (-0.35)	1.403 (1.76)	0.289*** (4.17)	-0.136 (-0.34)	0.152 (0.37)

Source: Author's calculation. Note: *p<0.1; **p<0.05; ***p<0.01, respectively.

About the robustness tests, we test the serial correlation (autocorrelation), heteroscedasticity, multicollinearity, and stationarity. We find that in all situations the results remain unchanged and spillovers have a positive effect. Thus all results are fairly robust. Firstly, we check the Structural Break test for the 2008's financial crisis to examine whether our results are robust after splitting our sample in two the period before and after the financial crisis. Following this, we find that there are not any breaks for the EEE and EEI models in OECD and non-OECD groups of countries. Our results are robust to all of these specifications. The models could be affected by GDP per unit of energy consumption country r from county s in year t and GDP growth but it seems these variables are not significant. To consider the unobserved heterogeneity we estimate the time, fixed, time and fixed effect in pool and spatial effects. So we did not bring them in our final results (results of robustness tests are available upon request).

5 Conclusions and Policy Recommendations

5.1 Conclusions

Studies such as this one, on the spatial economics model, for emissions embodied in the trade when there is a carbon tax had been overlooked in the previous literature. Thus, our research provides a preliminary exploration for the analysis of the impact of carbon taxes on emissions embodied in trade. To account for intermediate inputs and final demands for import and export, we match the emissions data to WIOD input-output tables for 43 countries (32 OECD and 11 non-OECD countries) and construct total domestic emissions intensities for each sector in the period 2000-2014. Notably, due to the presence of spatial dependence, OLS will likely lead to biased estimates of the relationships between emissions embodied in trade and carbon tax. At the sector level, the highest direct, total, and indirect emission of CO₂ comes from the sector [Electricity, gas, steam and air conditioning supply], while the lowest direct, indirect and complete emissions of CO₂ occurs in the sector [Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use].

In this study, the rise in price of tax leads to an increase in the amount of CO₂ emitted in exports and imports in OECD and non-OECD countries (Table 4). We highlight the existence of a spillover effect of emissions embodied in exports and imports by considering the distance trade matrix. With the trade matrix (comparative advantage), when we increase the carbon tax by one million US dollars, pollution by import in OECD countries increases by 83.2 percent.²¹ Also, when we increase the carbon tax by one million US dollars, pollution by import in non-OECD countries is increased by 79 percent,²². When we increase the carbon tax by one million US dollars, pollution by export is increased by 7.4 percent in OECD countries.²³ Moreover, when we increase the carbon tax by one million US dollars, pollution by export in non-OECD countries increases by 20.7 percent,²⁴.

These results suggest that when the effects of trade and taxation have been considered in global climate policy, all countries should endure greater emissions' reduction responsibility and increase the production of low carbon goods relatively to that of other goods. We found that not taking into account the spatial effect in environmental tax policy on exports and imports of pollution increases pollution on exports. Considering the large amount of emission embodied in export by the investigated countries, we suggest first to reduce the export flow of local high energy-consuming products. This target can be achieved by raising their prices or reducing the capacity of heavy industry or increasing the taxation of products. These countries/regions should also further increase the price of carbon, in the flow of import of high energy-consuming products, to reduce local energy consumption while strengthening economic ties with the neighboring countries. Moreover, governments set the overall tax policy for the world to try to reduce the considerable energy consumption and the excessively high percentage of heavy industry. Insofar as a high carbon tax rate leads to a considerable disadvantageous impact on the economy and some activity sectors probably experience extremely negative effects, and low tax rate results in some rich companies escaping away from paying attention to environmental regulations and buying pollution licenses

²¹These figures are obtained as $[\exp(0.832)-1]*100$.

²²These figures are obtained as $[\exp(0.790)-1]*100$.

²³These figures are obtained as $[\exp(0.0738)-1]*100$.

²⁴These figures are obtained as $[\exp(0.207)-1]*100$.

pretty easily, the solution should be to calculate the based amount of carbon tax which is fair enough.

5.2 Policy Recommendations

The majority of pollution is contributed to the electricity section. This is a first thing to consider when doing policy to make an efficient and meticulous policy that leads to fewer emissions in sectors where emissions are more authorized or have over polluted than expected levels.

The government should take into account the environmental taxation in their country and their neighbors. Developing countries produce goods that are consumed by developed countries, but carbon emissions are charged to their national accounts. In the end, the consumption price of goods is higher (and can even become prohibitive) in importer countries in comparison with exporter countries. The tendency to make low-carbon goods is also higher in the developed countries than in the developing ones. The best strategy for controlling emissions would be to impose the same carbon tax in all the countries which produce such goods and services and to coordinate their implementation at least by region . In this case, the final cost of producing the good in the neighboring country will be higher than making it in the importing country. If a company wants to produce goods in a neighboring country, in addition to the fixed carbon tax price, it also has to pay a fixed and variable cost of producing the goods.

Converging to the same tax price is beneficial to all countries or regions. More critically, the implementation of an international carbon tax on both production and consumption can be a solution, the reason is that: countries producing more carbon than others, tend to be more reluctant to impose emission prices at the same level as the those that pollute less. If none of the countries accept the carbon tax law and they go on polluting, the transmission of pollution to neighboring countries through trade or poor coordination increases pollution at the global level. The whole world will end up paying a much higher price than taxes paid by each country.

Carbon tax rises emission embodied in export from the country that rise the tax to their neighbors. By and large, our policy recommendation to governments should be not to stop the carbon tax but take into account their effect on neighboring countries and the other way around. We should be cautious when analyzing also the comparative advantage of the countries because this could have an effect increasing EEE and EEI due to dirty specializations. The production of dirty goods should be left to a country with high clean technology.

References

- Aichele, R., & Felbermayr, G. (2015). Kyoto and carbon leakage: An empirical analysis of the carbon content of bilateral trade. *Review of Economics and Statistics*, 97(1), 104--115.
- Amidi, S., & Majidi, A. F. (2020). Geographic proximity, trade and economic growth: a spatial econometrics approach. *Annals of GIS*.
- Anselin, L. (1988). A test for spatial autocorrelation in seemingly unrelated regressions. *Economics Letters*, 28(4).
- Anselin, L., & Bera, A. K. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. *Statistics textbooks and monographs*, 155, 237--290.
- Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional science and urban economics*, 26(1), 77--104.
- Antweiler, W., Copeland, B. R., & Taylor, M. S. (2001). Is free trade good for the environment? *American economic review*, 91(4), 877--908.
- Asselt, H. V., & Brewer, T. (2010). Addressing competitiveness and leakage concerns in climate policy: An analysis of border adjustment measures in the us and the eu. *Energy Policy*, 38(1).
- Baylis, K., Fullerton, D., & Karney, D. H. (2013). Leakage, welfare, and cost-effectiveness of carbon policy. *American Economic Review*, 103(3).
- Burnham, K. P., & Anderson, D. R. (2002). A practical information-theoretic approach. *Model selection and multimodel inference*, 2.
- Cao, J., Ho, M. S., Jorgenson, D. W., & Nielsen, C. P. (2019). China's emissions trading system and an ets-carbon tax hybrid. *Energy Economics*, 81.
- Chen, G., Hadjikakou, M., & Wiedmann, T. (2017). Urban carbon transformations: unravelling spatial and inter-sectoral linkages for key city industries based on multi-region input-output analysis. *Journal of cleaner production*, 163.

- Chen, G., Michalis, H., & Thomas, W. (2016). Urban carbon transformations: unravelling spatial and inter-sectoral linkages for key city industries based on multi-region input–output analysis. *Journal of cleaner production*, 163.
- Clough, S. (2016). Achieving co2 reductions in colombia: effects of carbon taxes and abatement targets. *Rev.Energy Econ*, 56.
- Copeland, B. R., & Taylor, M. S. (2013). *Trade and the environment*. Princeton University Press.
- da Silva Freitas, L. F., de Santana Ribeiro, L. C., Souza, K. B., & DennisHewings, G. J. (2016). The distributional effects of emissions taxation in brazil and their implications for climate policy. *Energy Economics*, 59.
- de Boer, B. F., Rodrigues, J. F., & Tukker, A. (2019). Modeling reductions in the environmental footprints embodied in european union’s imports through source shifting. *Ecological Economics*, 164.
- Dinda, S. (2004). Environmental kuznets curve hypothesis: a survey. *Ecological economics*, 49(4).
- Ding, T., Ning, Y., & Zhang, Y. (2018). The contribution of china’s bilateral trade to global carbon emissions in the context of globalization. *Structural Change and Economic Dynamics*, 46.
- Du, H., Guo, J., Mao, G., M.Smith, A., Wang, X., & Wang, Y. (2011). Co2 emissions embodied in china–us trade: Input–output analysis based on the emergy/dollar ratio. *Energy Policy*, 39(10).
- Ekins, P. (2009). *Carbon taxes and emissions trading: issues and interactions*.
- Elhorst, J. (2014). *Spatial econometrics from cross-sectional data to spatial panels* (Vol. 479).
- Elliott, J., Foster, I., Kortum, S., Munson, T., Cervantes, F. P., & Weisbach, D. (2010). Trade and carbon taxes. *American Economic Review*, 100(2).
- Fahimnia, B., Sarkis, J., Choudhary, A., & Eshragh, A. (2015). Tactical supply chain planning under a carbon tax policy scheme: A case study. *International Journal of Production Economics*, 164.
- Frankel, J. A., & Rose, A. K. (2005). Is trade good or bad for the environment? sorting out the causality. *Review of economics and statistics*, 87(1), 85–91.
- Griffith, D. A. (1987). Spatial autocorrelation. *A Primer* (Washington, DC, Association of American Geographers).
- Grunewald, N., Klasen, S., Martínez-Zarzoso, I., & Muris, C. (2017). The trade-off between income inequality and carbon dioxide emissions. *Ecological Economics*, 142.
- Guan, P., Huang, G., Wang, C. W. L., & Wang, C. L. Y. (2019). Analysis of emission taxes levying on regional electric power structure adjustment with an inexact optimization model—a case study of zibo, china. *Energy Economics*.
- Guo, J., Zhou, L., & Wu, X. (2018). Tendency of embodied carbon change in the export trade of chinese manufacturing industry from 2000 to 2015 and its driving factors. *Sustainability*, 10(6).

- Ho, C.-Y., Wang, W., & Yu, J. (2013). Growth spillover through trade: A spatial dynamic panel data approach. *Economics Letters*, 120(3).
- Karnizova, Y. D. . L. (2016). Emissions cap or emissions tax? a multi-sector business cycle analysis. *Journal of Environmental Economics and Management*, 79.
- Kellenberg, D. K. (2008). A reexamination of the role of income for the trade and environment debate. *Ecological Economics*, 68(1-2), 106--115.
- Kotlikoff, L., Kubler, F., Polbin, A., Sachs, J., & Scheidegger, S. (2019). Making carbon taxation a generational win win. *International Economic Review*.
- Kulionis, V. (2014). *Co2 emissions embodied in international trade of the uk, 1995-2009: A multi-region input-output analysis*. .
- LeSage, J., & Pace, R. K. (2009). *Introduction to spatial econometrics*.
- Liu, X., Ishikawa, M., Wang, C., Dong, Y., & Liu, W. (2010). Analyses of co2 emissions embodied in japan-china trade. *Energy Policy*, 38(3).
- Long, R., Li, J., Chen, H., Zhang, L., & Li, Q. (2018). Embodied carbon dioxide flow in international trade: A comparative analysis based on china and japan. *Journal of environmental management*, 209.
- Long, R., Shao, T., & Chen, H. (2016). Spatial econometric analysis of china's province-level industrial carbon productivity and its influencing factors. *Applied Energy*, 166.
- Managi, S., Hibiki, A., & Tsurumi, T. (2009). Does trade openness improve environmental quality? *Journal of environmental economics and management*, 58(3), 346--363.
- Mardones, C., & Flores, B. (2018). Effectiveness of a co2 tax on industrial emissions. *Energy Economics*, 71.
- Marron, D. B., & Toder, E. J. (2014). Tax policy issues in designing a carbon tax. *American Economic Review*, 104(5).
- McEvoy, D. M., & McGinty, M. (2018). Negotiating a uniform emissions tax in international environmental agreements. *Journal of Environmental Economics and Management*, 90.
- McLure, C. E. J. (2014). Selected international aspects of carbon taxation. *American Economic Review*, 104(5).
- Muradian, R., & Martinez-Alier, J. (2001). Trade and the environment: from a 'southern' perspective. *Ecological Economics*, 36(2), 281--297.
- Perobelli, F. S., Faria, W. R., & de Almeida Vale, V. (2015). The increase in brazilian household income and its impact on co2 emissions: Evidence for 2003 and 2009 from input-output tables. *Energy Economics*, 52.
- Porter, M. (1996). America's green strategy. *Business and the environment: a reader*, 33, 1072.
- Qu, X., Lee, L.-f., & Yang, C. (2021). Estimation of a sar model with endogenous spatial weights constructed by bilateral variables. *Journal of Econometrics*, 221(1), 180--197.

- Ren, J., Chen, X., & Hu, J. (2020). The effect of production- versus consumption-based emission tax under demand uncertainty. *International Journal of Production Economics*, 219.
- Rosenthal, E. (2011). Lead from old us batteries sent to mexico raises risks. *New York: The New York Times*.
- Sakai, M., & Barrett, J. (2016). Border carbon adjustments: Addressing emissions embodied in trade. *Energy Policy*, 92.
- Su, B., H.C.Huang, B.W.Ang, & Zhou, P. (2010). Input–output analysis of co2 emissions embodied in trade: the effects of sector aggregation. *Energy Economics*, 32(1).
- Sundar, S., Mishra, A. K., & Naresh, R. (2016). Effect of environmental tax on carbon dioxide emission: a mathematical model. *American Journal of Applied Mathematics and Statistics*, 4(1).
- Tobler, W. R. (1979). Smooth pycnophylactic interpolation for geographical regions. *Journal of the American Statistical Association*, 74(367), 519--530.
- Walter, I., & Ugelow, J. L. (1979). Environmental policies in developing countries. *Ambio*, 102--109.
- Wang, S., Tang, Y., Du, Z., & Song, M. (2020). Export trade, embodied carbon emissions, and environmental pollution: An empirical analysis of china's high-and new-technology industries. *Journal of Environmental Management*, 276, 111371.
- Xu, Y., & Dietzenbacher, E. (2014). A structural decomposition analysis of the emissions embodied in trade. *Ecological Economics*, 101.
- Yan, J., Zhao, T., & Kang, J. (2016). Sensitivity analysis of technology and supply change for co2 emission intensity of energy-intensive industries based on input–output model. *Applied energy*, 171.
- Zhang, H., Wang, Y., Zhu, X., & Guo, Y. (2020). The impact of energy trade patterns on co2 emissions: An energy and network analysis. *Energy Economics*, 92, 104948.
- Zhong, Z., Jiang, L., & Zhou, P. (2018). Transnational transfer of carbon emissions embodied in trade: Characteristics and determinants from a spatial perspective. *Energy*, 147.

A Appendix A: review of literature and several statistics

Table A1: Average of Share of Direct, Indirect and total Carbon Emission in 56 sectors in period 2000-2014

Sectors (%)	Avg. SDIE	Avg. SDE	Avg. SIE
Accommodation and food service activities	1.0085	1.7829	0.8152
Activities auxiliary to financial services and insurance activities	0.0660	0.1260	0.0512
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	0.0101	0.0338	0.0041
Administrative and support service activities	0.6233	0.9790	0.5344
Advertising and market research	0.0673	0.1274	0.0525
Air transport	2.1608	0.4740	2.5848
Architectural and engineering activities; technical testing and analysis	0.1529	0.2493	0.1289
Computer programming, consultancy and related activities; information service activities	0.1941	0.3540	0.1542
Construction	3.7363	10.9150	1.9514
Crop and animal production, hunting and related service activities	2.0730	2.0882	2.0668
Education	0.7048	1.2010	0.5793
Electricity, gas, steam and air conditioning supply	36.1142	16.0849	41.3520
Financial service activities, except insurance and pension funding	0.3116	0.6422	0.2287
Fishing and aquaculture	0.1353	0.1227	0.1385
Forestry and logging	0.1787	0.1313	0.1905
Human health and social work activities	1.1135	1.7035	0.9678
Insurance, reinsurance and pension funding, except compulsory social security	0.1495	0.2505	0.1243
Land transport and transport via pipelines	3.3623	2.0953	3.6806
Legal and accounting activities; activities of head offices; management consultancy activities	0.3833	0.6894	0.3067
Manufacture of basic metals	7.6422	7.5154	7.7015
Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.2151	0.6819	0.0987
Manufacture of chemicals and chemical products	4.3873	4.7543	4.2878
Manufacture of coke and refined petroleum products	3.2098	3.3799	3.1630
Manufacture of computer, electronic and optical products	0.6531	1.7708	0.3751
Manufacture of electrical equipment	0.6259	1.9187	0.3115
Manufacture of fabricated metal products, except machinery and equipment	1.0465	3.0020	0.5720
Manufacture of food products, beverages and tobacco products	1.8728	3.6333	1.4306
Manufacture of furniture; other manufacturing	0.7956	0.8434	0.7850
Manufacture of machinery and equipment n.e.c.	0.9803	2.5391	0.6000
Manufacture of motor vehicles, trailers and semi-trailers	0.8945	2.4454	0.5148
Manufacture of other non-metallic mineral products	6.5343	3.0331	7.4058
Manufacture of other transport equipment	0.2715	0.6405	0.1821
Manufacture of paper and paper products	0.8162	1.2091	0.7155
Manufacture of rubber and plastic products	1.8628	1.8215	1.8708
Manufacture of textiles, wearing apparel and leather products	0.8583	1.5905	0.6728
Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	0.3128	0.6114	0.2373
Mining and quarrying	3.6344	4.0934	3.5087
Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities	0.0663	0.1793	0.0379
Other professional, scientific and technical activities; veterinary activities	0.1303	0.2195	0.1081
Other service activities	0.8393	1.3060	0.7217
Postal and courier activities	0.1038	0.1718	0.0871
Printing and reproduction of recorded media	0.1773	0.3522	0.1333
Public administration and defence; compulsory social security	2.2297	2.8758	2.0680
Publishing activities	0.0654	0.1879	0.0350
Real estate activities	0.7143	2.0513	0.3788
Repair and installation of machinery and equipment	0.0650	0.1541	0.0433
Retail trade, except of motor vehicles and motorcycles	1.1124	1.8166	0.9346
Scientific research and development	0.1278	0.2191	0.1050
Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services	0.7277	0.4644	0.7937
Telecommunications	0.2495	0.6603	0.1459
Warehousing and support activities for transportation	0.5000	0.8093	0.4259
Water collection, treatment and supply	0.2347	0.5708	0.1504
Water transport	2.0035	0.6625	2.3407
Wholesale and retail trade and repair of motor vehicles and motorcycles	0.2745	0.4648	0.2269
Wholesale trade, except of motor vehicles and motorcycles	1.2199	2.4264	0.9186

source: Author's calculation

Avg. SDIE: Average share of direct and indirect emission, Avg. SDE: Average share of direct emission,

Avg. SIE: Average share of indirect emission

B Appendix B: Sectoral deviation

Table A2: Source of Variables

Short name of Variable	Full Name	Definition	Source
EEE	Emissions embodied in exports		WIOD
EEl	Emissions embodied in imports		WIOD
TAX	Carbon tax	Carbon taxation tries to replace trading as the international system of carbon emissions reduction	OECD
TEBT	Total emissions before tax		WIOD
TEAT	Total emissions after tax	After emission tax is inflicted, the output and input prices of products, particularly energy sector products, will grow	WIOD
IPI	The impact of tax on price index	Implementation of the tax policy could be measured by a general price index that explain the purchasing power losses for consumers	WIOD
GDP-engi	GDP per unit of energy consumption	Unit of energy consumed to generate the amount of GDP in a country	World Bank
Clean-engi	The ratio of clean energy to total energy use	Coal-oil-gas-dominated fossil fuel mix produces a lot of carbon emission in production processes	World Bank
PGDP	Per capita GDP	global trade expands, rapid economic growth is stimulating to speed up global industrial transfer, and thus is influencing carbon emissions embodied in trade all over the world	World Bank
Intermediate-Local	Intermediate inputs in local region	In international trade, foreign capital and energy inflows are the main sources of intermediate inputs, and thus affect carbon emissions flows	WIOD
Final-Local	Final requirements in local region	For one country, each sector in this country would import other regions' final goods and services as final requirements to meet the needs of the local region through international supply chains in the process of globalization	WIOD
Intermediate-Other	Intermediate inputs in other regions		WIOD
Final-Other	Final requirements in other regions		WIOD
C-emission	Consumer Emissions	Carbon dioxide emissions calculated from the consumer perspective are significantly higher than producer emission	WIOD
P-emission	Producer Emissions	Carbon dioxide emissions calculated from the producer	WIOD

Table A3: The abbreviated name

SDA: structural decomposition analysis	NBER: National Bureau of Economic Research
WIOT: input-output tables semi-closed model with eight household groups	FGLS: Feasible Generalized Least Squares
SNA: System of National Accounts	CAS: Chinese Academy of Sciences
SUT: Supply and Use Tables	CEAD: China Emissions Accounts and Datasets
SAM: Social Accounting Matrix	AGEIS: Australian Greenhouse Emissions Information System
SRIO: single region input-output tables	FTA: free trade agreement
BTIO: bilateral trade input-output model	CGER: Center for Global Environmental Research and NIES: National Institute for Environmental Studies
NEEBT: net CO ₂ emissions embodied in bilateral trade	SWIID: Standardized World Income Inequality Database
TEAM: Trade and Environmental Assessment Model	BEA: Bureau of Economic Analysis
LMDI: Logarithmic Mean Divisia Index	NBS: Chinese National Bureau of Statistics
BEETI: net balance of emissions embodied in trade in intermediates and BEETT: total trade	IBGE: Brazilian Institute of Geography and Statistics
	GTAP: Global Trade Analysis Project
	EIA: Energy Information Administration
	NEI: National Emissions Inventory
	EPA: US Environmental Protection Agency
	TATP: terrestrial Air temperature and Precipitation

Table A4: Results of Correlation Between Variables

	eee	eei	tax	teat	ipi	Clean-engi	pgdp
eee	1.0000						
eei	0.5991	1.0000					
tax	0.3965	0.8068	1.0000				
teat	0.8722	0.6431	0.4224	1.0000			
ipi	0.3728	0.1298	0.2325	-0.0445	1.0000		
Clean-engi	-0.0144	-0.0364	0.0263	0.0212	0.0707	1.0000	
pgdp	0.0798	0.1982	0.1939	0.0723	0.0576	-0.2019	1.0000

source: Author's calculation

Table A5: The average of emission embodied in export and import and carbon tax for 2000-2014

Country	code	Avrg. EEE	Avrg. EEI	Avrg. TAX
OECD countries				
Australia	aus	50.79661029	9.100313894	334939.2825
Austria	aut	16.87145772	4.78817513	169857.421
Belgium	bel	26.70316959	6.733997406	227325.7726
Canada	can	77.42223962	9.930795687	328071.7398
Switzerland	che	31.93633507	13.4707526	507579.9839
Czech Republic	cze	11.32190979	9.832361325	382795.4924
Germany	deu	187.2075815	10.22514275	172529.3409
Denmark	dnk	19.83211694	14.60837769	475024.1392
Spain	esp	76.53173737	7.978346119	237446.9336
Estonia	est	1.446026998	3.534826698	128072.2366
Finland	fin	13.47380777	5.939058782	204179.0076
France	fra	145.2721137	10.92329685	294799.9472
United Kingdom	gbr	150.9824349	10.04602783	233780.409
Greece	grc	15.75064801	8.777150406	248781.8225
Croatia	hrV	3.445970831	5.391066601	174672.6566
Hungary	hun	8.5499836	5.075583774	162115.0068
Ireland	irl	14.45984527	4.566584099	161584.4152
Italy	ita	121.8244872	7.458692595	196982.3691
Japan	jpn	341.377003	10.41410861	336847.5793
Korea	kor	61.11263879	5.765567267	220699.6308
Lithuania	ltu	2.755810508	6.499920479	230467.2752
Luxembourg	lux	4.373176512	4.010898099	191516.3626
Latvia	lva	1.446396662	2.941455918	98821.63649
Mexico	mex	67.01969549	13.30514272	362564.6796
Netherlands	nld	44.05544836	8.772824038	266586.7741
Norway	nor	17.61302392	13.16354475	469120.937
Poland	poL	23.05830908	9.020108196	294499.6161
Portugal	prt	13.74342209	7.681996705	244926.1209
Slovak Republic	svk	4.582316301	3.166756661	106778.8683
Slovenia	svn	2.832002482	2.472011484	81544.05095
Sweden	swe	25.14665704	2.700137703	60205.74821
Turkey	tur	32.91277511	6.049291437	197488.8777
United States	usa	967.2983209	15.56530284	322899.9893
Non-OECD countries				
Bulgaria	bgr	2.17809311	3.330447939	129886.802
Brazil	bra	76.60627786	12.10296251	385732.7709
China,P.R.: Mainland	chn	244.280833	5.871437106	242564.4881
Cyprus	cyp	1.973679085	7.927001601	246856.0368
Indonesia	idn	27.78529771	4.881528734	169493.7236
India	ind	71.64263714	6.866056988	220110.5998
Malta	mlt	2.058060405	4.998654184	176644.3062
Romania	rou	7.746212091	8.451783142	290224.5888
Russian Federation	rus	45.43840377	5.360620206	172111.5847
Tanzania	TZA	27.40866477	4.858258195	186566.8085

source: Author's calculation

B.1 EEE, EEI, and Carbon tax

The geo-maps illustrate how much emissions are embodied in exports in top countries like China and the United States emitted to different countries (imports) and also show the changes in carbon tax intensity throughout the 43 countries over the period shown, for 2000 and 2014. Obviously, for both years, the figure of a carbon tax in this group of countries studied increased considerably from 8,334 billion dollars in 2000 to 10,622 billion dollars at the end of the period. In addition, for both the USA and China, they emitted more pollution into Brazil in 2000 than they did into Brazil in 2014, while Mexico for the USA in 2014 and Brazil for China in both 2000 and 2014 being the most contaminated destinations.

As indicated in Figure 3 to Figure 6, for spatial transfer of the EEE in 2000, countries classified by the higher net export of embodied CO₂ emissions are the USA, China, Germany, Japan, the UK, and France, whereas the wealthiest countries, such as Norway, Denmark, Brazil, Mexico, Canada, and Switzerland, had the highest net emissions embodied in import of CO₂ over the period shown.

Figure 4 also depicts the amounts of emissions gap between export and import from 2000 to 2014. It demonstrates that identifying the main emitter of emissions in this study cannot be impossible. We are unable to specify the most emission-importing countries due to the constraint of the input-output table; in other words, the wealthiest importer is not clear to us. Generally, we can say that the countries with the highest CO₂ importers tend to be developing nations.

Specifically, the highest carbon emissions (exceeded from 100 Mt) stem from the USA and China to Brazil in 2000 and Mexico and Brazil in 2014, respectively. Although this figure for the USA went down from 1704.24 to 634.11 between 2000 and 2014, China is the only country that emitted more CO₂ than the 42 other countries from 203.91 to 631.11 over this period. Moreover, in 2000, the top countries which transferred more CO₂ to other countries were the USA, Japan, Germany, the UK, France, and China, whereas the USA, China, Japan, Germany, the UK, and France took the lead in 2014. Countries like the USA, Norway, Mexico, Denmark, and Brazil had

the highest net import of embodied CO₂ emissions in 2000, respectively, while Denmark, the USA, Norway, Brazil, and Mexico were ahead in 2014.

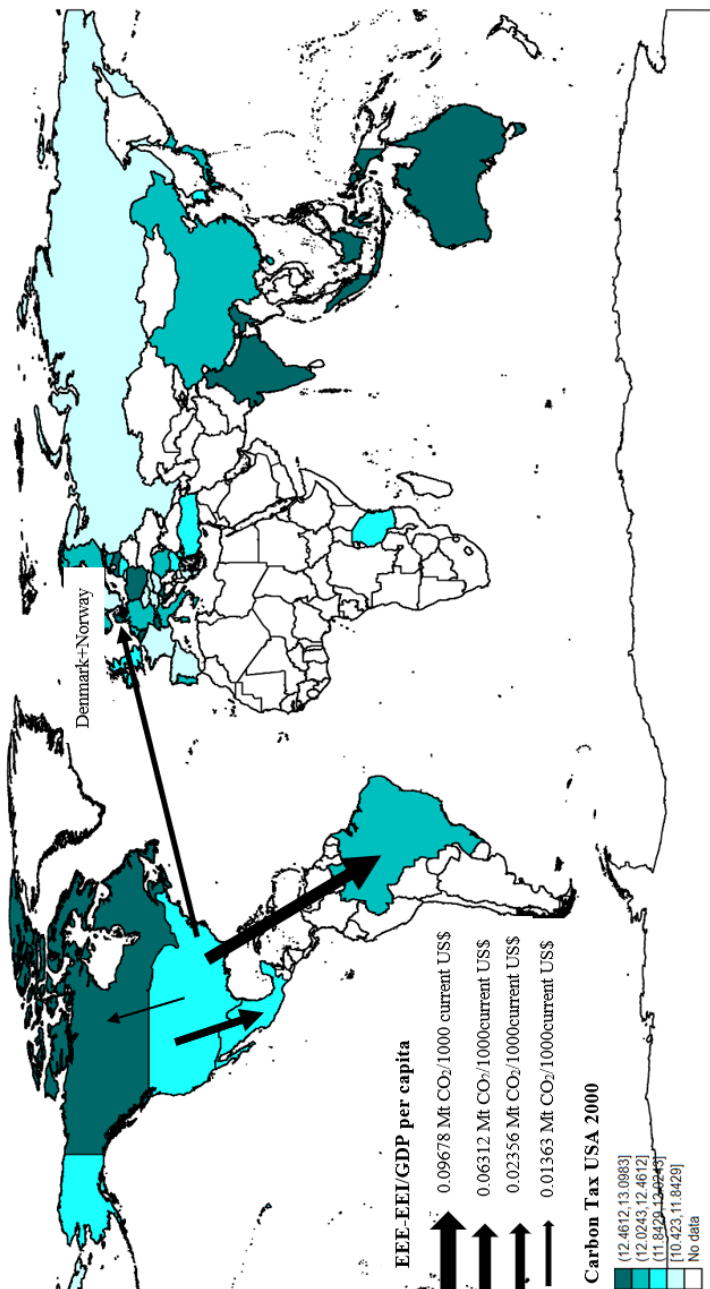


Figure 3: The effect of Carbon tax, EEE and EEI in the USA 2000

Source: Author's calculation

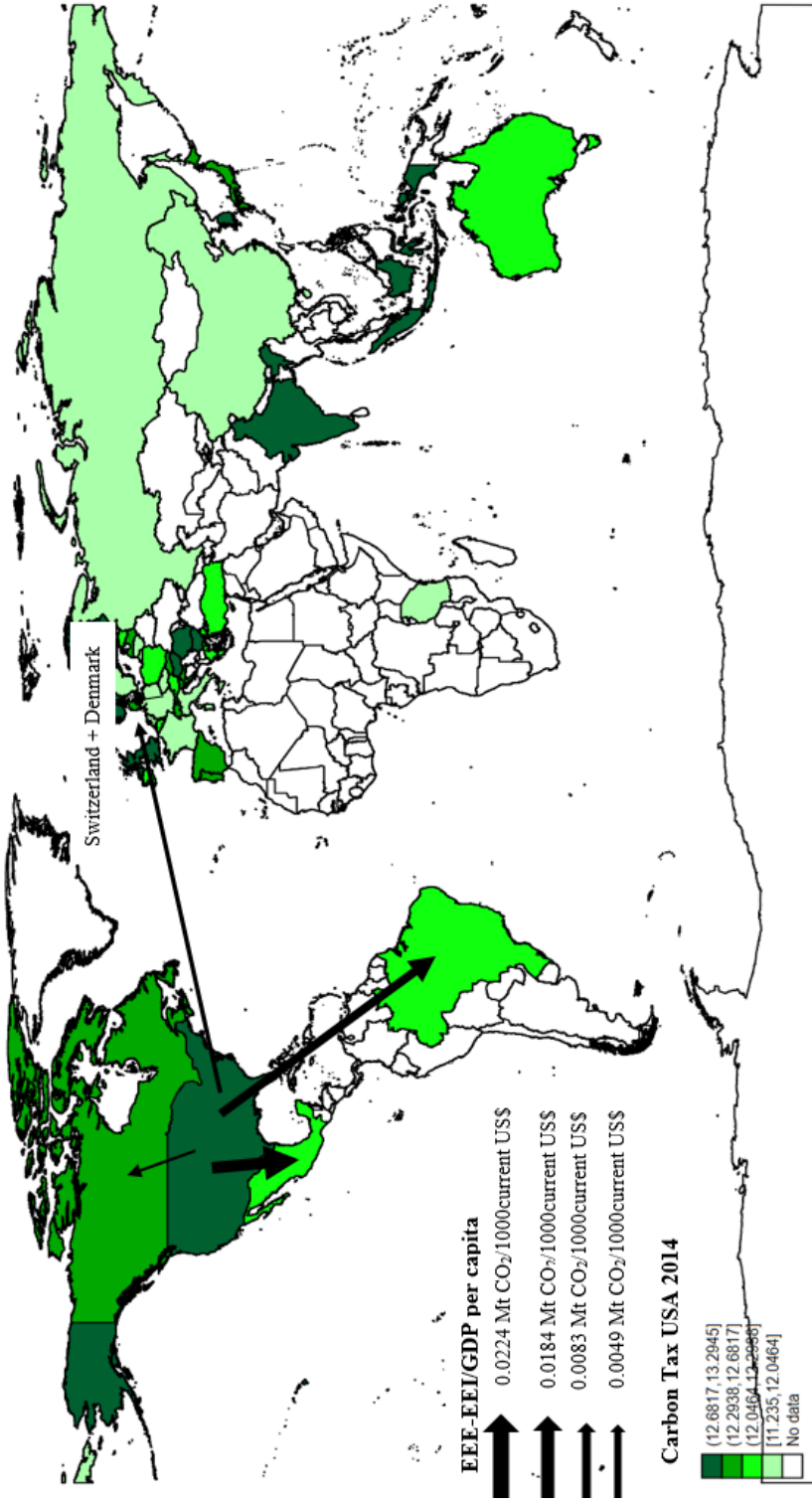


Figure 4: The effect of Carbon tax, EEE and EEI in the USA 2014

Source: Author's calculation

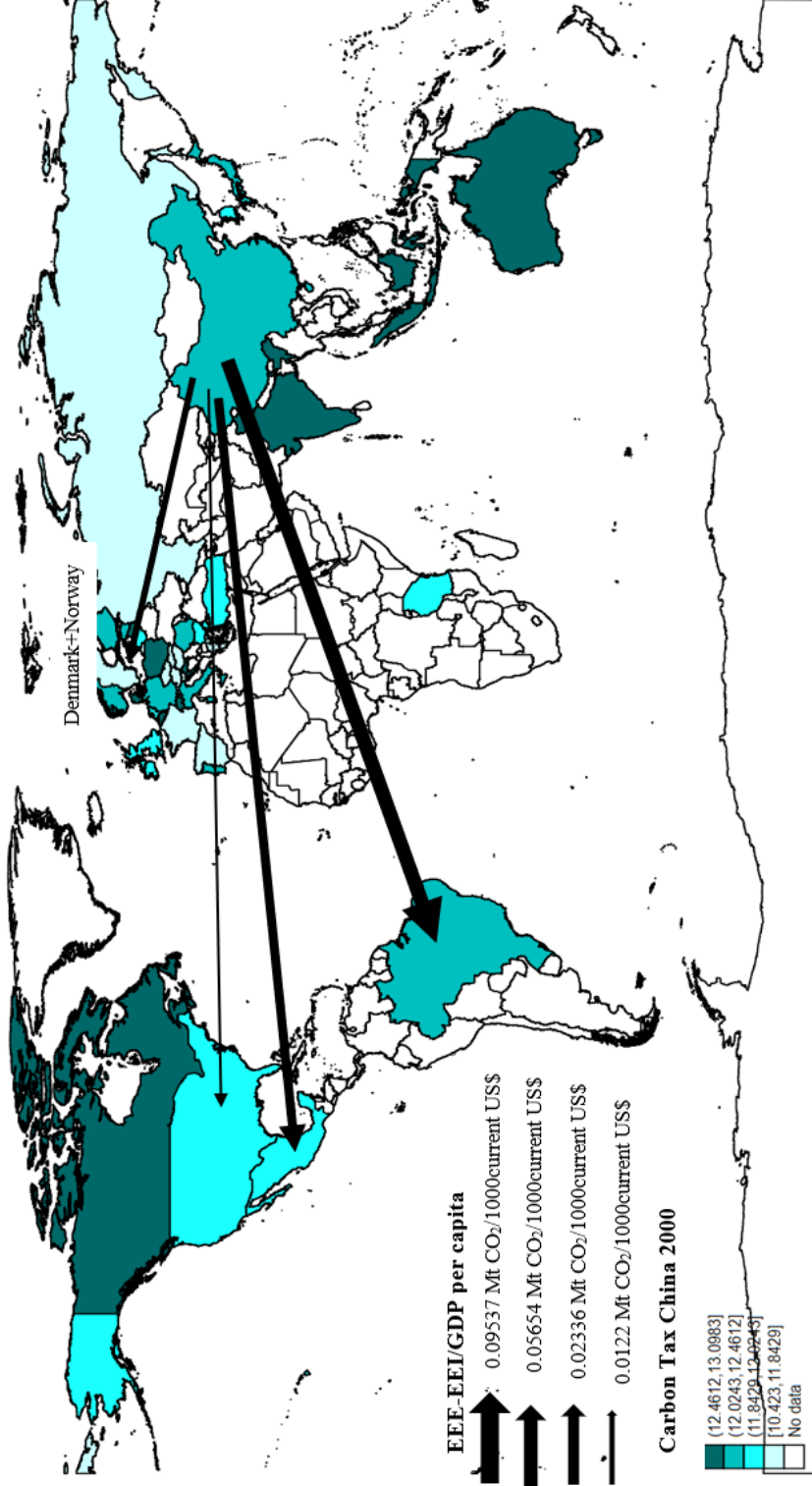


Figure 5: The effect of Carbon tax, EEE and EEI in China 2000

Source: Author's calculation

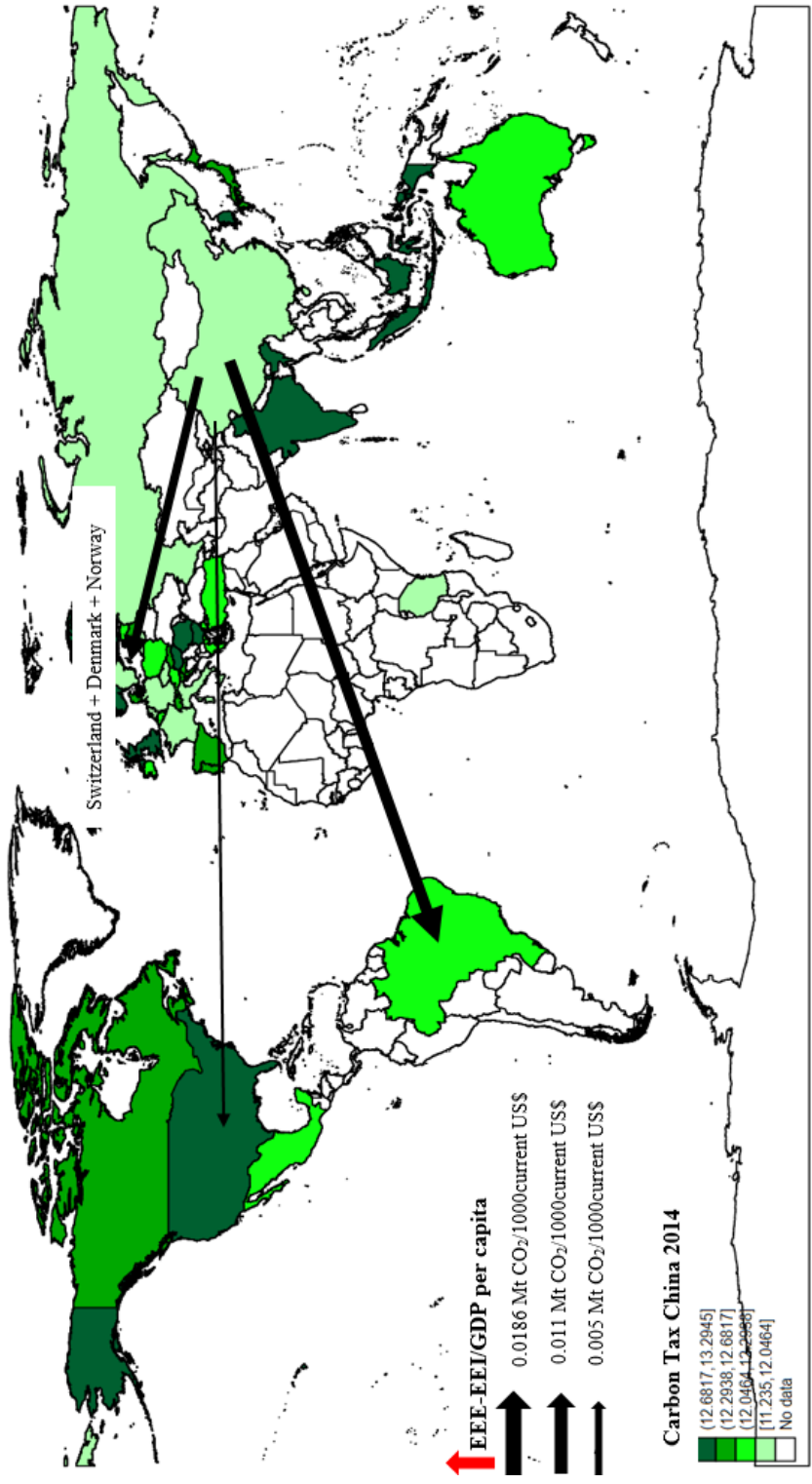


Figure 6: The effect of Carbon tax, EEE and EEI in China 2014

Source: Author's calculation

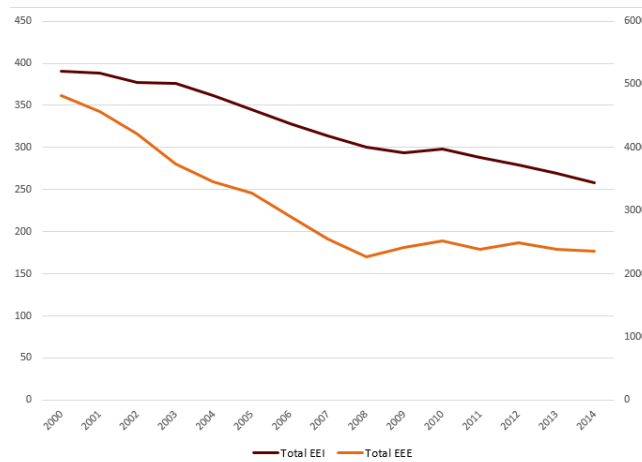


Figure 7: GAPS Between EEE and EEI

Source: Author's calculation

The line graphs in Figure 5, compare the amounts of total estimated tax for both OECD and Non-OECD countries with emission embodied in export and import from 2000 to 2014. Overall, the figure of estimated tax for both countries have upward trend between 2000 and 2014. Except for EEE of Non-OECD countries others line (EEE and EEI) have downward trend over the period shown. Total tax emissions for OECD countries increased steadily from 700 in 2000 to just over 900 in 2010 before declining significantly to 800 at the end of the period, while at the beginning, EEE declined from just under 450 to 170 in 2007 and then maintained the same level until 2014. In comparison, EEI moderately go down during the next 15 years. In 2000, for Non-OECD countries EEE decrease from 260 to somewhere in vicinity of 200 in 2002, then don't changes between 2003 and 2007. Following this, there is a dramatic growth to 650 in 2014. By contrast, EEI experience slightly decline during this period.

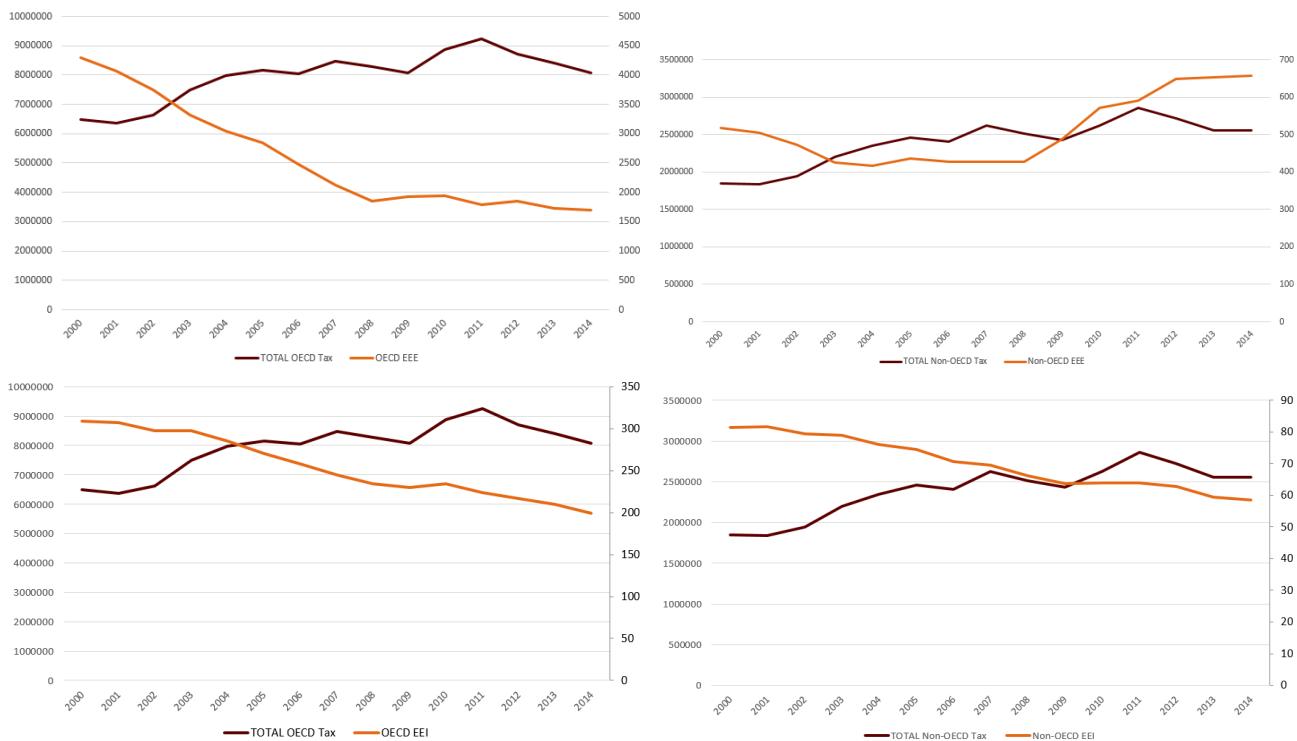


Figure 8: The effect of Carbon tax, EEE and EEI in the countries under study

Source: Author's calculation

The gap tax between total real tax and estimated tax in this study comes from the usage of equation 14. In this function, environment carbon tax is equal to the inverse of output matrix which multiplied emission coefficient for each sector in each country by carbon tax coming from activity sector, this indicate the amount of emission tax from each sectors in each countries.

The Figure 6 shows the gap between estimated tax and real tax from 2000 to 2014. Overall, the figure for a gap between estimated tax and real tax was initially almost as high as real tax (around 1,000 billion dollars). However, while both increased between 2000 and 2004, the former despite moderate fluctuation maintained the same level until 2014, the latter increased slightly until hitting a peak of 12,000 billion dollars in 2011 and then unchanged through the remained period.

Total estimated tax during the whole of the period as much higher than, and has a striking resemblance in movement with the figure for the gap between estimated tax and real tax.

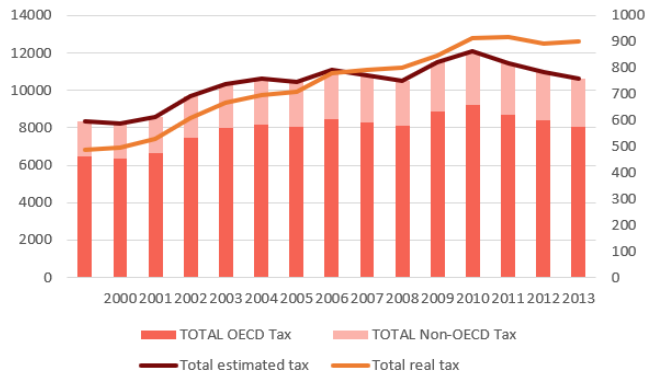


Figure 9: GAPS Between estimated Carbon tax and real tax (billion dollars)

Source: Author's calculation