The EU Emissions Trading System and Carbon Leakage: Reducing Emissions or Shifting Them Abroad?

Hamid Nejadghorban *†

Abstract

The European Union Emissions Trading System (EU ETS) is central to the EUs efforts to reduce greenhouse gas emissions, yet its impact on carbon and energy flows associated with international trade remains underexplored. This study investigates the causal impact of the first two phases of EU ETS on these measures, addressing gaps in the existing literature. By integrating bilateral import data with carbon and energy intensities for five manufacturing sectors across 32 countries from 1996 to 2012, and by using sector-specific calculations, I capture the nuances of trade-related carbon and energy flows. Utilizing the staggered design of the Synthetic Difference in Differences (SDiD) approach I find that the policy unintentionally increased emissions in non-EU exporting countries due to carbon leakage. Additionally, energy usage embodied in trade rises among these exporters due to the program's effect. These effects are more pronounced for polluting energy sources like fossil fuels. A hypothetical what-if scenario suggests that having similar production technologies to importer countries could prevent significant leakage among unregulated exporters. The results also show that the EU ETS may not effectively reduce global net emissions and could unintentionally increase both net emissions and net energy usage associated with international trade. To mitigate these unintended consequences, policymakers should pursue international coordination, incentivize investment in advanced technologies domestically, promote their adoption abroad, and implement sector-specific interventions, thereby enhancing the EU ETSs effectiveness in contributing to global emissions reductions.

Keywords: Carbon leakage, Energy leakage, Synthetic Difference in Differences, Global emission & energy consumption

JEL Classification: L50, Q54, Q58

*University College London, UK. Email: h.nejadghorban@ucl.ac.uk
†University of Essex, UK. Email: hamid.nejadghorban@essex.ac.uk

1 Introduction

Climate change is a global challenge that requires urgent and coordinated action. Many regions have implemented Emission Trading System (ETS) policies aimed at mitigating its adverse effects.[1] For the past two decades, the European Union (EU) has been at the forefront of efforts to reduce greenhouse gas (GHG) emissions. The EU has committed to significantly reducing GHG emissions as part of its strategy to combat global climate change. Central to this effort is the EU Emissions Trading System (EU ETS), launched in 2005 across 31 countries. However, the absence of a global carbon market, coupled with the fact that many countries have yet to implement a carbon price, has raised policymakers concerns about the potential impacts of unilateral environmental regulations on global carbon emissions reduction (Dechezleprêtre and Sato (2017)).

The unilateral EU environmental regulation raises concerns about carbon leakage. Carbon leakage, an example of the pollution haven effect, refers to shifting domestic pollution-intensive production to regions with less stringent environmental regulations.[2] However, the existing literature indicates that most previous empirical studies have found little to no evidence of carbon embodied in imports (i.e., carbon leakage) due to the EU ETS, and they remain silent on the impact of this unilateral policy on energy embodied in imports (i.e., energy leakage). In this context, *energy leakage* refers to the transfer of energy consumption associated with production from countries with strict environmental regulations to those with lax regulations. Therefore, one of the main objectives of this paper is to investigate the causal impact of the EU ETS on carbon and energy flows associated with international trade. This study also focuses on examining the policy effect on net carbon emissions and energy usage associated with international trade to gain a deeper understanding of the effectiveness of unilateral environmental policies.

The impact of the EU ETS policy on carbon leakage is still questionable, as there is no strong evidence supporting the pollution haven hypothesis (Grether et al. (2012)). Additionally, according to the Porter hypothesis, the negative effects of the EU ETS on firms competitiveness may be mitigated or even offset by improvements in productivity, driven by innovation in low-carbon technologies and products (Porter and Linde (1995); Calel and Dechezleprêtre (2016)). Moreover, although emission costs are typically zero in the EUs trading partner countries, the additional costs imposed by the EU ETS are relatively low. As a result, the emission cost gap between EU ETS-implementing countries and those without such policies is minor compared to the much larger gap in unit labor costs, rendering the impact of emission costs comparatively negligible (Naegele and Zaklan (2019)). Besides, relocating firms outside the EU entails significant opportunity costs, including fixed relocation expenses, a weaker market presence, and diminished bargaining power with foreign policymakers, all of which can reduce the incentive for domestic firms to move opera-

[1] ETSs are now in place in regions such as California, Quebec, the Regional Greenhouse Gas Initiative (RGGI), New Zealand, China, and Switzerland. Currently, 21 operational ETSs worldwide cover 15% of global emissions, with an additional 24 systems planned or under consideration (ICAP (2022)).

[2] According to trade theory, the pollution haven hypothesis suggests that stringent environmental regulations will eventually drive pollution-intensive production to regions with lower environmental abatement costs (e.g., Levinson and Taylor (2008)).

tions abroad. Finally, European firms have been granted substantial free emissions allowances under the EU ETS, which may be sufficient to prevent carbon leakage (Schmidt and Heitzig (2014)).

A substantial body of literature, relying on ex-ante computable general equilibrium (CGE) models, has attempted to estimate the extent of carbon leakage from existing policies (e.g., Branger and Quirion (2014*a*); Gerlagh and Kuik (2014); Carbone and Rivers (2017)). Considerable number of these studies have predicted that unilateral climate policies, such as the EU ETS, could induce carbon leakage. Research by Babiker (2005), Böhringer et al. (2010), and Elliott et al. (2010) forecast substantial leakage, especially, when stringent climate policies are imposed unilaterally and without border adjustments. Furthermore, another strand of the literature focuses on examining the pollution haven effect in the US. These studies generally investigate the relationship between net trade flows and the strictness of pollution regulations, measured by the Pollution Abatement Cost (PAC) using survey data from US manufacturers (e.g., Ederington and Minier (2003); Levinson and Taylor (2008)). However, these approaches often rely on theoretical models and may not capture real-world complexities.

While some ex-post empirical evidence supporting the carbon leakage hypothesis exists, comprehensive support is lacking. One example is Aichele and Felbermayr (2015), who provide evidence that the Kyoto Protocol commitment increased the carbon intensity associated with imports from non-participating countries to participating ones, compared to a scenario where the Kyoto Protocol did not exist.

In the context of the EU ETS, studies by Martin et al. (2014), Dechezleprêtre and Sato (2017), and Naegele and Zaklan (2019), as well as more recent papers by Dechezleprêtre, Fabre, Kruse, Planterose, Chico and Stantcheva (2022), generally find either insignificant or non-robust evidence for carbon leakage. Naegele and Zaklan (2019) used global trade flow data for 66 source regions in 2004, 2007, and 2011. They collected data for 8 sectors subjected to the EU ETS regulations and 17 non-EU ETS sectors. Adapting Aichele and Felbermayr (2015)s methodology, they employed a Difference in Differences (DiD) approach within the gravity model to analyze the impacts of the EU ETS on emissions embodied in traded goods but found no significant effects on carbon leakage during this period. Following a similar empirical approach, Wang and Kuusi (2024) used an extended trade value dataset for 5 sectors targeted by the EU ETS policy and 9 sectors outside this program in 60 countries covering 2000-2018. Their results demonstrate statistically significant and robust reductions in carbon intensity and carbon content for ETS countries. Notably, they found a 6% decrease in CO_2 intensity of exports.

In addition, one strand of the literature focuses on examining carbon leakage within specific sectors. Sartor (2013) for the aluminum sector, Branger et al. (2016) for the cement and steel sectors, and Lin et al. (2019) for pulp and paper found limited evidence of a statistically significant impact of the EU ETS on carbon leakage.[3]

[3] Lin et al. (2019) also demonstrate that the EU ETS has a statistically significantly positive indirect effect on net exports and the prevention of carbon leakage, indicating that the scheme enhances the international competitiveness of the pulp and paper industry by driving firms toward technological innovation.

Another approach to studying carbon leakage is to examine whether EU companies have relocated production or increased foreign direct investment (FDI) outside of ETS regulation. Several studies have addressed this question but found little to no evidence of such shifts. For example, aus dem Moore et al. (2019), using European firm data from 2002-2012; Dechezleprêtre, Gennaioli, Martin, Muûls and Stoerk (2022), using European firm data from 2007-2014; Koch and Mama (2019), using data from German multinational firms (1999-2013); and Borghesi et al. (2020), using Italian manufacturing firms (2002-2010), all found minimal evidence of production relocation or increased FDI due to the EU ETS.

To the best of my knowledge, this is the first study to apply a reliable causal approach in investigating the carbon leakage effects of the EU ETS. I integrated bilateral import and carbon-energy intensity data to construct a balanced panel dataset spanning the period from 1996 to 2012, encompassing the first and second phases of the EU ETS program. The dataset covers five manufacturing sectors targeted by the EU ETS in 21 countries under the programs regulations, as well as 11 non-EU countries that are not subjected to the policy. I constructed the counterfactual scenario where imports from non-EU countries by countries not affected by the EU ETS policy constitute the control group. Additionally, to construct a control group with a similar trend to the average treatment outcome in the pre-treatment period, I employ the staggered design of the Synthetic Difference in Differences (SDiD) approach. The SDiD method improves upon the traditional DiD approach by allowing for variations in treatment timing and constructing a synthetic control group that better matches the pre-treatment trends of the treated group, enhancing the reliability of causal inference. Hence, the EU ETS treatment dummy is equal to one for countries under the EU ETS regulations that import from non-regulated countries during the period after the programs implementation (2005 for most countries, except for Romania and Bulgaria, where it began in 2007); otherwise, it is set to zero.

The empirical methodologies applied in the literature present various issues related to potential bias. Recent study findings may be biased due to weaknesses in the identification strategy for three major reasons. First, recent studies have considered both sectors targeted by the EU ETS program and those that are not, in their analyses (e.g., (Naegele and Zaklan (2019); Wang and Kuusi (2024)). This could bias the results, as the estimated outcomes may reflect heterogeneity in sector characteristics rather than the effects of the EU ETS treatment. Therefore, unlike the literature, this study focuses solely on the manufacturing sectors under EU ETS regulations. Furthermore, key studies such as Naegele and Zaklan (2019) and Wang and Kuusi (2024) defined the counterfactual scenario such that importers were not under EU ETS regulations. However, these studies did not exclude exporters affected by this program. These exporters are influenced by the EU ETS, which may affect the counterfactual scenario that should represent no implementation of the EU ETS. To address this potential issue in the counterfactual scenario, I considered imports from countries not subjected to the EU ETS regulations for importers outside this policy area in the control group. Finally, the DiD gravity model suggested in the literature relies heavily on the pre-treatment parallel trend assumption, whereas this condition is rarely satisfied in this type of cross-country panel analysis. Therefore, to the best of my knowledge, I employed the staggered design of the SDiD approach for the first time in the literature to construct a synthetic control group with a trend similar to the average treated outcome.

This study presents several compelling findings that significantly contribute to the literature by illuminating the unintended consequences of the EU ETS on carbon emissions and energy consumption associated with international trade. Notably, few studies have empirically assessed the carbon leakage hypothesis within the context of the EU ETS policy (Naegele and Zaklan (2019); Wang and Kuusi (2024)). While existing research largely reports inconclusive evidence of carbon leakage associated with trade as a result of this policy, this study provides robust evidence of increased carbon leakage. This implies that the EU ETS has resulted in a higher carbon content per unit of output in imported goods. This indicates that although the policy may have successfully reduced emissions within the EU, it has inadvertently shifted production and the associated emissions to countries with less stringent environmental regulations.

This paper also contributes to the literature by presenting, to the best of my knowledge, the first precise evaluation of how the EU ETS influences adjusted carbon leakage and energy embodied in imports, unlike many studies that only look at embodied carbon. The findings of this study suggest that the EU ETS has transferred energy usage abroad through trade, as evidenced by the observed increase in energy embodied in imports. This is reflected in the lower adjusted carbon leakage compared to the overall carbon leakage, underscoring that exporters are utilizing energy less efficiently, potentially due to reliance on outdated technologies or less stringent environmental policy. This phenomenon is not solely attributable to higher import volumes but is also linked to the use of less energy-efficient technologies in exporting countries. These findings support a dimension occasionally examined by energy-economic studies that evaluate "upstream" leakage impacts in non-ETS energy markets (e.g., Branger and Quirion (2014*b*); Böhringer et al. (2012)) by pointing to a move towards more pollutant-intensive energy sources outside the EU. Moreover, the leakage effects are more pronounced for polluting energy sources, such as fossil fuels. The higher energy leakage for these sources, combined with a smaller rise in adjusted carbon leakage, suggests a significant decline in the energy efficiency of polluting energy sources among exporters. This implies that the EU ETS may unintentionally contribute to the increased use of less energy-efficient, polluting technologies outside the EU. Therefore, collaborating with trading partners to establish common environmental policies may be necessary to reduce the incentive to outsource production to countries with less stringent environmental standards.

Another contribution of this research to the literature is that I evaluated all the policy impacts on the dependent variables related to carbon and energy flows associated with international trade at the sectoral level. Few studies have analyzed this research question for specific sectors (Sartor (2013); Branger et al. (2016); Lin et al. (2019)), but I have not only found additional evidence for sectors previously examined but also presented new findings for sectors not studied before. These findings are heterogeneous across sectors, with certain industries disproportionately affected. The Non-Metallic Mineral Products (C23) and Metal (C24) industries exhibit more significant leakage effects, highlighting the importance of sector-specific analyses to fully comprehend and address the policys impact. This suggests implementing complementary, sector-specific policies to tackle the unique challenges of each sector, particularly focusing on those with the highest leakage rates.

One potential question that has received less attention in the literature is whether unilateral environmental policies can address international goals of reducing global emissions. This study contributes to the literature by analyzing the what-if scenario, where the production technology of importers is used to calculate the carbon and energy flows associated with trade. It reveals no significant evidence of leakage under this hypothetical condition. This suggests that if production had remained within the EU, or if the production technologies of exporting countries were similar to those in regulated countries, the EU ETS could have effectively prevented significant leakage. This hypothetical analysis underscores the potential effectiveness of stringent domestic environmental policies in reducing emissions when they do not lead to production displacement.

Last but not least, most recent studies evaluate carbon emission reduction due to unilateral environmental policies in countries or within a union. However, this paper contributes to the literature by studying the impact of unilateral environmental policies on global net carbon emissions and net energy usage associated with international trade by comparing the actual leakage with the hypothetical what-if scenario. I highlight how important technological distinctions are in understanding leakage. My approach is consistent with a body of literature in environmental economics that increasingly examines the importance of efficiency gains and technological diffusion (Acemoglu et al. (2012); Fischer and Newell (2008)). I found that the EU ETS has led to an overall increase in net carbon emissions and energy usage embodied in imports. This provides compelling evidence that, in its current form, the EU ETS may not effectively reduce global net carbon emissions and might even unintentionally undermine these efforts by shifting emissions abroad. Therefore, addressing this gap in production processes by investing in advanced technologies domestically and promoting their international adoption appears to be a potential solution for mitigating the elevated carbon and energy flows associated with international trade.

These findings emphasize that although the EU ETS has been effective in reducing emissions within the EU, it may have inadvertently contributed to increased net emissions through carbon and energy leakage. This underscores the necessity for policies that consider the interconnected nature of global supply chains and the potential for emissions to shift across borders. Overall, the findings suggest that unilateral environmental policies like the EU ETS must be complemented by comprehensive and collaborative strategies to effectively address global climate change. Policymakers should consider international coordination, technological investments, and sector-specific interventions to ensure that efforts to reduce domestic emissions do not lead to increased emissions elsewhere. Such an integrated approach is essential for achieving meaningful progress toward international climate goals. Implementing the suggested policy measures can mitigate these unintended consequences and enhance the EU ETSs effectiveness in contributing to global emissions reductions.

The remainder of this paper is organized as follows. Section 2 details the data and provides stylized facts. Section 3 identify econometric model. Section 4 presents and discusses the empirical results. Conclusions and policy suggestions follow in Section 5.

2 Data

2.1 Dependent variables

In this study, I collect data from 32 OECD countries and key partners, such as India and Indonesia, covering the period from 1996 to 2012, which includes the first and second phases of the EU ETS program. Table A.1 presents a list of the countries included in the dataset. These countries provide high-quality data, making the panel data more reliable and consistent. The data covers five manufacturing sectors regulated by the EU ETS: Food, Beverages, and Tobacco (ISIC Rev. 4, C10-12); Paper (ISIC Rev. 4, C17); Chemicals (ISIC Rev. 4, C20); Non-Metallic Mineral Products (cement, glass, and ceramic) (ISIC Rev. 4, C23); and Metal (ISIC Rev. 4, C24).[4] Focusing solely on sectors within the EU ETS reduces potential selection bias and minimizes risks associated with fundamental differences between EU ETS and non-EU ETS sectors.

I used three main data sources to create the dependent variables: (1) international manufacturing trade flows, (2) sectoral output levels, and (3) sectoral energy and carbon emissions. Bilateral import values are collected from the UNCTAD-COMTRADE database.[5] Since COMTRADE reports 2-digit bilateral trade values in the ISIC Rev.3 format, I converted them to ISIC Rev.4 using an industry concordance table provided by the World Bank's WITS. Furthermore, to measure economic activity by sector, I collected sectoral gross output data from the World Input-Output Database (WIOD) socio-economic accounts, released in 2016, which categorizes sectors according to ISIC Rev.4. The data, expressed in monetary units of the national currency, were converted to millions of US dollars using market exchange rates. Finally, the data on emission-relevant energy use and the quantity of fossil fuel energy-related carbon dioxide emissions are derived from the WIOD environmental accounts, released in 2016. The data represent carbon dioxide emissions in kilotons (kt) and total fossil fuel energy use in terajoules (TJ).[6]

Table A.5 presents a list of all the dependent variables used in this study, along with a brief description and their respective calculation formulas. I used these key sources to construct the

[4] I used the EUTL Database and the EU ETS Handbook to identify the selected manufacturing sectors. The database includes more than 6,000 installations in the manufacturing sector with opening dates before 2012. First, I categorized the installations based on their activities according to ISIC Rev. 3, then selected manufacturing sectors that represent more than 3% of the total installations. I found that sector C19 (Coke and Refined Petroleum) significantly differs from other sectors, primarily due to a high number of zeros in trade values. Therefore, I excluded sector C19 from the study to mitigate potential bias in the estimates.

[5] Carbon leakage can be effectively measured by the import volume of products, as it removes the effects of price and exchange rate fluctuations. However, there are many missing observations in volume-based datasets, and measurement units vary across products. Therefore, similar to the literature, I utilized bilateral import value data instead of import volume data.

[6] The database includes 13 categories of energy commodities: coal-coke-crude, diesel, electric heat production, fuel oil, gasoline, jet fuel, natural gas, other gas, other petroleum, waste, other sources, liquid gaseous biofuels, and renewable-nuclear.

dependent variables in the main specification (i.e., specification 9). The main variable of interest is the carbon leakage which measures the amount of carbon emissions embedded in imports per unit of output:

$$\mathrm{CL}^s_{ijt} = \mathrm{M}^s_{ijt} \times \frac{\mathrm{C}^s_{jt}}{\mathrm{Q}^s_{jt}} \tag{1}$$

where M^s_{ijt} represents the import value for a specific sector (s) from the origin country (j) to the destination country (i) in a given year (t), and C^s_{jt}/Q^s_{jt} denotes carbon emission per unit of output for a specific sector (s) of the origin country (j) in a given year (t).

I also extended the basic carbon leakage index and constructed the energy-efficiency adjusted carbon leakage as follows:

$$\mathrm{AdjCL}^s_{ijt} = \mathrm{CL}^s_{ijt} \times \frac{\mathrm{Q}^s_{jt}}{\mathrm{E}^s_{jt}} \tag{2}$$

where E^s_{jt} represents total energy or fossil-fuel energy. This extension provides several advantages. First, since energy efficiency varies across regions and sectors, it can be identified which sectors contribute disproportionately to carbon leakage due to low energy efficiency. Second, it captures the variation in the energy transition improvements across sectors and regions. The EU ETS scheme can indirectly motivate firms to invest in renewable energy and energy-efficient technologies that reduce the carbon intensity per unit of energy. Moreover, two producers in different regions with the same carbon emissions might not be equally harmful, as one might use significantly less energy. Therefore, adjusting for energy efficiency in the calculation of carbon leakage provides a more accurate tracking of energy usage progress and helps avoid misleading conclusions about the environmental impact of trade flows and production practices.

Another variable of interest is the energy usage embodied in imports per unit of output (hereafter the energy leakage) which is calculated as follows:

$$\mathrm{EL}^s_{ijt} = \mathrm{M}^s_{ijt} \times \frac{\mathrm{E}^s_{jt}}{\mathrm{Q}^s_{jt}} \tag{3}$$

It captures the implications of the EU ETS on trade flows in terms of energy consumption. Since the EU ETS program targets energy-intensive sectors, energy leakage quantifies how the scheme can shift energy consumption from one region to another due to international trade. This variable is especially crucial when emissions vary among nations due to differences in energy usage efficiency and energy sources, such as fossil fuels versus renewables. Moreover, investigating energy leakage helps track whether the production process has shifted toward adopting cleaner fuels and more efficient energy technologies as a result of the EU ETS program.

I also calculated these variables of interest based on information from the destination countries (importers) to understand how carbon emissions and energy usage would change if these imported goods were produced domestically. I call this the what if scenario, which helps to further explore the impact of the EU ETS policy in shifting carbon and energy flows associated with international trade toward non-EU countries that are not subject to EU ETS regulations.

Last but not least, to measure what is the effect of the EU ETS policy on the net carbon and energy flows associated with international trade I defined the following variables:

$$\mathrm{NetCL}^s_{ijt} = \left(\frac{\mathrm{C}^s_{jt}}{\mathrm{Q}^s_{jt}} - \frac{\mathrm{C}^s_{it}}{\mathrm{Q}^s_{it}}\right) \times \mathrm{M}^s_{ijt} \tag{4}$$

and

$$\mathrm{NetEL}^s_{ijt} = \left(\frac{\mathrm{E}^s_{jt}}{\mathrm{Q}^s_{jt}} - \frac{\mathrm{E}^s_{it}}{\mathrm{Q}^s_{it}}\right) \times \mathrm{M}^s_{ijt} \tag{5}$$

where $\frac{\mathrm{C}^s_{jt}}{\mathrm{Q}^s_{jt}}$ is the carbon intensity of the exporter j at time t in sector s and $\frac{\mathrm{C}^s_{it}}{\mathrm{Q}^s_{it}}$ is the same variable for the importer i. This difference in carbon intensity between the origin (exporter) and destination (importer) countries represents the gap in their production technologies. Hence, when this difference is multiplied by the trade values, it indicates the net carbon leakage associated with international trade. The same explanation applies to the difference between the energy intensity of the exporter and importer countries, $\frac{\mathrm{E}^s_{jt}}{\mathrm{Q}^s_{jt}}$ and $\frac{\mathrm{E}^s_{it}}{\mathrm{Q}^s_{it}}$, respectively, representing the energy leakage embodied in the trade.

This comparison highlights the difference between what has actually occurred in terms of carbon and energy leakage versus the what if scenario, which represents what could happen if the same amount of goods were produced domestically. Estimating the EU ETS effect on these variables reveals the net change in carbon emissions and energy usage resulting from this policy.

2.2 Covariates

The main specifications (i.e., Equation 9) incorporate three groups of covariates. The first group controls for variations between importer-exporter country pairs. GDP per capita (in constant PPP, log-transformed) is commonly used in trade studies to capture differences in economic development and purchasing power. However, relying solely on unilateral dimensions often undermines statistical robustness. To address this, I introduced time-varying country-pair measure of relative size instead of relying on dual unilateral variables. Specifically, I calculated the sectoral similarity index of the GDPs of trading partners (Sim_{ijt}), following the method outlined by Egger (2000):

$$\mathrm{Sim}_{ijt} = \ln\left[1 - \left|\left(\frac{\mathrm{GDP}_{it}}{\mathrm{GDP}_{it} + \mathrm{GDP}_{jt}}\right)^2 - \left(\frac{\mathrm{GDP}_{jt}}{\mathrm{GDP}_{it} + \mathrm{GDP}_{jt}}\right)^2\right|\right] \tag{6}$$

Second, I accounted for time-varying country-level variables for both the exporter and importer countries. I controlled for total trade (% of GDP) and foreign direct investment (% of GDP), as these factors influence trade flows by investing in productive capacity, generating demand for capital goods and intermediate products, promoting industrial expansion, and reflecting trade policies or openness. These variables are collected from the World Development Indicators (WDI) database. I also included the Human Capital Index and Total Factor Productivity (TFP) to account for differences in skill levels and productivity. These data are sourced from the Penn World Table (PWT) database. In addition, the globalization index, sourced from the KOF Swiss Economic Institute, accounts for the effect of the degree of globalization on countries' trade patterns.

The third group of covariates, sourced from the World Input-Output Database (WIOD), controls for variations at the sector-importer-exporter-year level. A measure of the relative sectoral endowment of domestic assets between importers and exporters (endw^s_{ijt}) is approximated by Eq. (7)

$$\text{endw}^s_{ijt} = \left| \ln\left(\frac{\text{Output}^s_{it}}{\text{POP}_{it}}\right) - \ln\left(\frac{\text{Output}^s_{jt}}{\text{POP}_{jt}}\right) \right| \tag{7}$$

I also measure the impact of sector-pair size as given:

$$\text{Mass}^s_{ijt} = ln\left(\text{Output}^s_{it} + \text{Output}^s_{jt}\right) \tag{8}$$

Furthermore, since capital and intermediate inputs directly influence production within a sector, I included these factor inputs (in constant prices) to avoid confounding the observed effects with structural differences. Additionally, I accounted for labor compensation and capital compensation (to value-added) to capture the structural composition of income and effects due to shifts in the relative importance of labor versus capital in production. Moreover, the specification model includes total pollutant energy and clean energy usage to address variations arising from the effect of the price differences between clean energy and fossil fuels and relative energy prices across countries.

Finally, following the literature (e.g., Anderson and Van Wincoop (2004)), I assume that trade costs can be controlled through groups of dummies alongside bilateral distance (Anderson and Van Wincoop (2004)). I used the population-weighted distance between the most populated cities, sourced from the CEPII Gravity Database, and three groups of dummy variables. The first group includes dummy for regional trade agreements sourced from Mario Larchs Regional Trade Agreements Database. The second group includes dummies for countries that share a common official or primary language, countries that are or were in a colonial relationship post-1945, and countries that are current WTO members, sourced from the CEPII Gravity Database. The third group accounts for whether the two countries share a common land border and sea border as well as whether at least one of the two countries is landlocked (no access to the high sea). Table A.4 presents all variables and their data sources. Summary statistics of all variables are available in Table A.3.

3 Stylized Facts

This section presents a set of stylized facts concerning the influence of the EU ETS policy on multiple measures of carbon and energy embodied in imports across five key industrial sectors. These sectors are subject to the EU ETS, and the goal here is to shed light on how policy implementation and subsequent phases of the EU ETS may have affected the carbon and energy content of their traded goods. The variables examinedranging from carbon emissions embodied in imports to net energy flowsare derived from carefully constructed, sector-specific formulas that capture both direct and indirect emissions, as well as the underlying energy use embedded in international trade. The detailed description of these variables, along with their corresponding formulas and concise explanations, is provided in Table A.5.

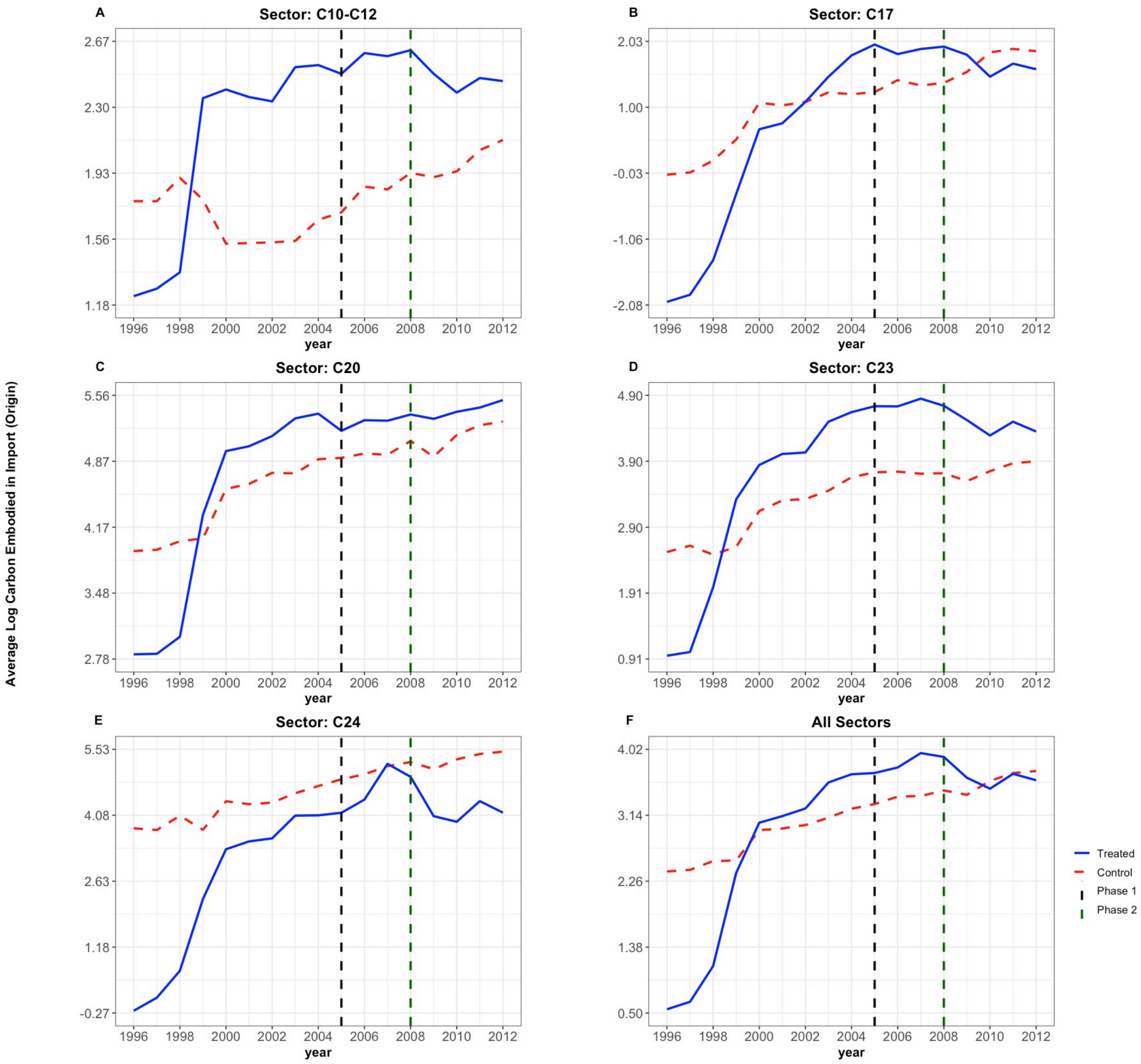
Figure 1 illustrates the evolution of the average log value of carbon embodied in imports under the assumption that goods are produced using the production technology of exporting countries. The figure portrays an upward trajectory for most sectors over the analysis period (1996–2012). Both control (non-EU) and treated (EU ETS-regulated) groups display increasing carbon-embodied imports, suggesting that global trade patterns have, in general, become more emission-intensive over time. Notably, the treated group consistently shows higher levels of carbon leakage relative to the control group.

This gap becomes more pronounced in the later years of the sample period and across most sectors, except for C24, indicating potential sectoral heterogeneity in the policys impact. Moreover, the initiation of Phase I and Phase II of the EU ETS corresponds with observable shifts in the trajectories. During Phase I, most treated sectors exhibit an uptick in carbon leakage, possibly reflecting initial adjustment costs and compliance challenges. As Phase II commences, there is generally a peak (except in C20), followed by a moderate decline, hinting at possible adaptive responses, technological improvements, and other strategic adjustments by regulated firms.

Figure 2 presents trends in the average log value of carbon embodied in imports under the assumption that goods are produced using the production technology of importing countries (the domestic production scenario). The temporal patterns differ from the exporter-technology-based scenario, with some sectors showing stabilization or reductions in carbon leakage during Phase II. The differences between treated and control groups are more pronounced here, revealing that, under domestic production technologies, treated groups tend to exhibit lower relative increases in carbon leakage. By the end of the observation period, carbon leakage is generally lower for the treated group across all sectors, particularly for C24. These observations suggest that the EU ETS may have incentivized cleaner or more efficient domestic production processes, even if the initial years under the policy were marked by adaptation challenges.

Figure 3 extends this descriptive analysis to standardized global net carbon emissions. Here, we consider the difference between carbon embodied in actual imports and the hypothetical emissions that would have occurred if the goods had been produced domestically or produced using the same technology as the importer countries. The sectoral responses vary, with some sectors experiencing a net increase in emissions over time, while others display persistent fluctuations. Crucially, the distinction between Phase I and Phase II is evident across most sectors, except for C17 within the treated group. The positive net emissions observed during Phase I indicate that importing goods may have initially resulted in higher emissions than domestic production would have, elevating net values. Although the gap narrows in Phase II, it remains positive, implying that, while the EU ETS may have promoted greater domestic efficiency and somewhat reduced carbon leakage, its full mitigating effect on net global emissions has not yet fully materialized. This is particularly marked in sectors C20, C23, and C24, as well as all selected sectors at the country level.

Figure 1: Trends in Log Carbon Embodied in Imports (1996-2012) by Sector (Exporter Production Technology)

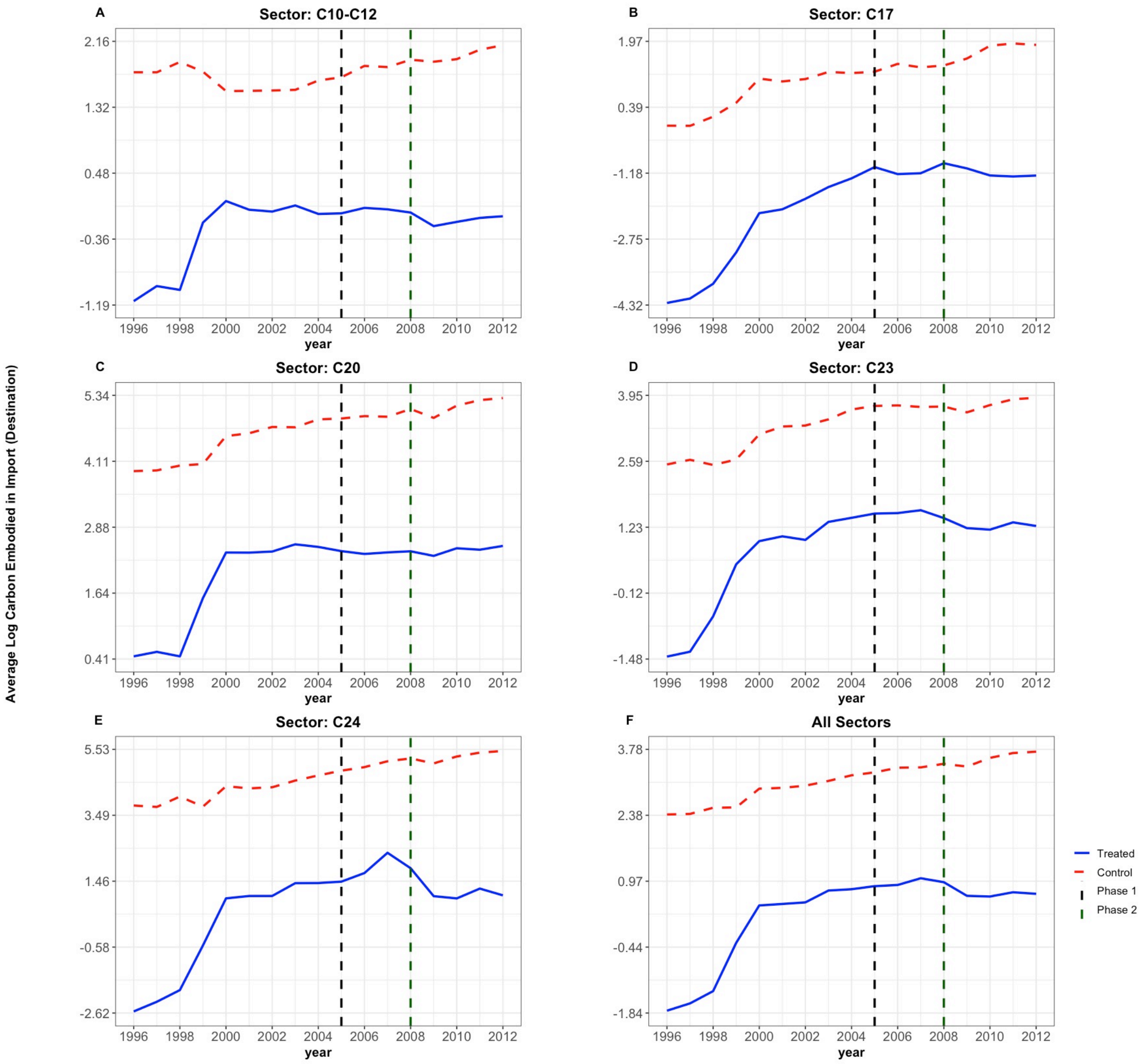


Note: This figure illustrates the changes in the average log carbon embodied in imports across various industrial sectors, comparing the trends between the treatment (blue) and control (red) groups based on the production technology of the exporter countries. Each panel represents a different sector, Panels A-E, alongside an aggregate view of all sectors, Panel F. The vertical dashed lines mark the initiation of Phase 1 (black) and Phase 2 (green) of the EU ETS.

Figures 4 and 5 provide additional insights by demonstrating energy usage embodied in international trade flows. Figure 4 displays the trends in net energy consumption from all energy sources, whereas Figure 5 focuses specifically on pollutant energy sources. Although the patterns observed in both figures are almost similar to the net carbon emission trends, the trend for the pollutant one parallels the global net emissions trend. This close alignment suggests that pollutant energy sources are likely a key driver of the observed emission trends, particularly during Phase I.

A distinct feature is the difference in patterns between Phase I and Phase II: while there is generally an upward trend in net energy usage approaching the onset of Phase II, a pronounced slowdown or even reversal is evident post-2008. It is essential to note that this deceleration may

Figure 2: Trends in Log Carbon Embodied in Imports (1996-2012) by Sector (Importer Production Technology)

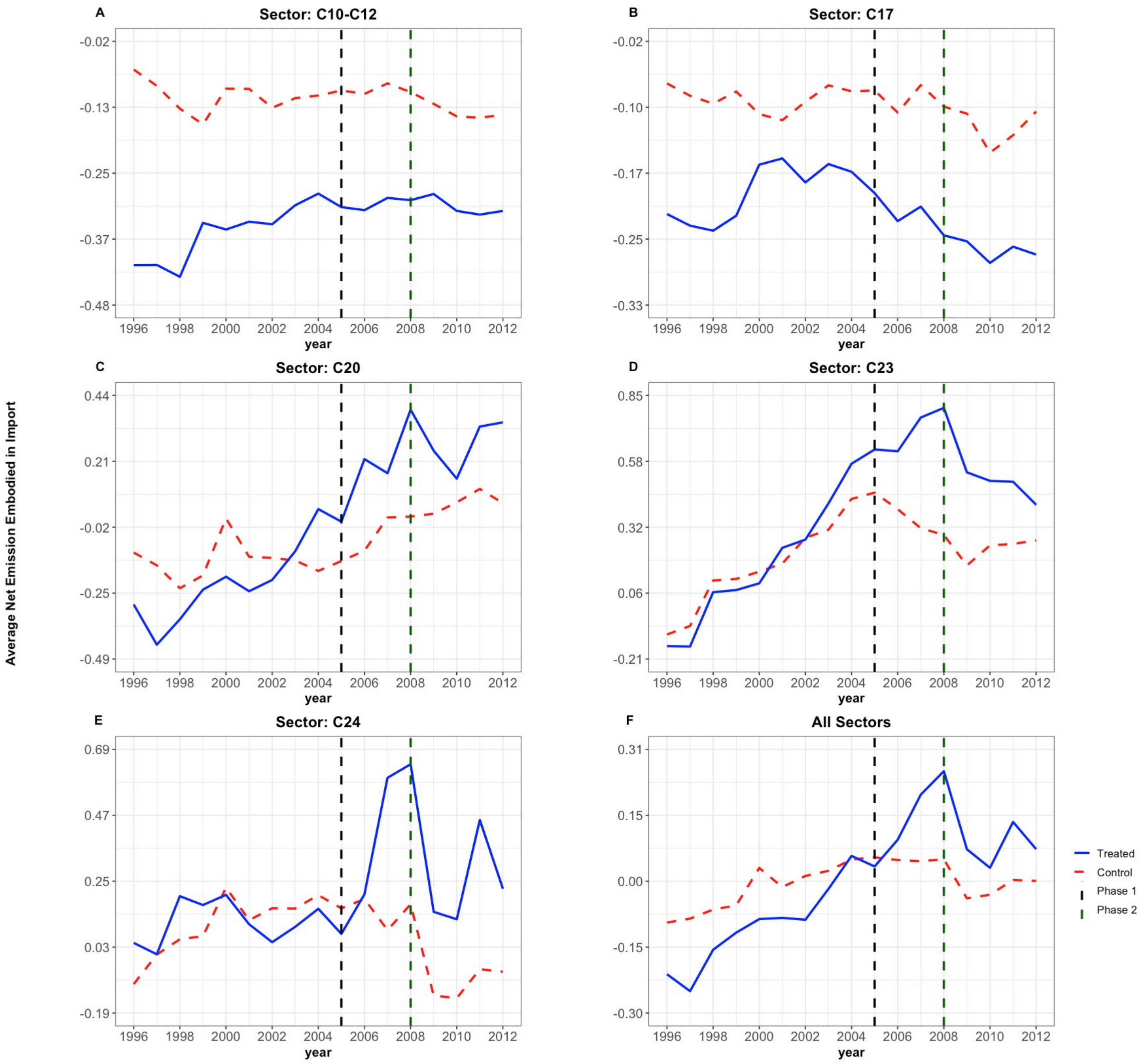


Note: This figure illustrates the changes in the average log carbon embodied in imports across various industrial sectors, comparing the trends between the treatment (blue) and control (red) groups based on the production technology of the importer countries. Each panel represents a different sector, Panels A-E, alongside an aggregate view of all sectors, Panel F. The vertical dashed lines mark the initiation of Phase 1 (black) and Phase 2 (green) of the EU ETS.

be influenced not only by the implementation of Phase 2 but also by the macroeconomic downturn associated with the Great Financial Crisis. This decoupling, could also be attributable to ongoing improvements in production technology, shifts toward cleaner energy inputs, or more stringent environmental policies.

Finally, the different trends observed between Phase I and Phase II may also reflect dynamic adjustment processes within regulated sectors. Firms subject to the EU ETS might have required time to incorporate additional carbon costs into their production structures, potentially losing some international competitiveness in the short run. Over time, however, as firms adapted through innovation, capital investments in cleaner technologies, or improved management practices, they could

Figure 3: Trends in Net Carbon Embodied in Imports (1996-2012) by Sector

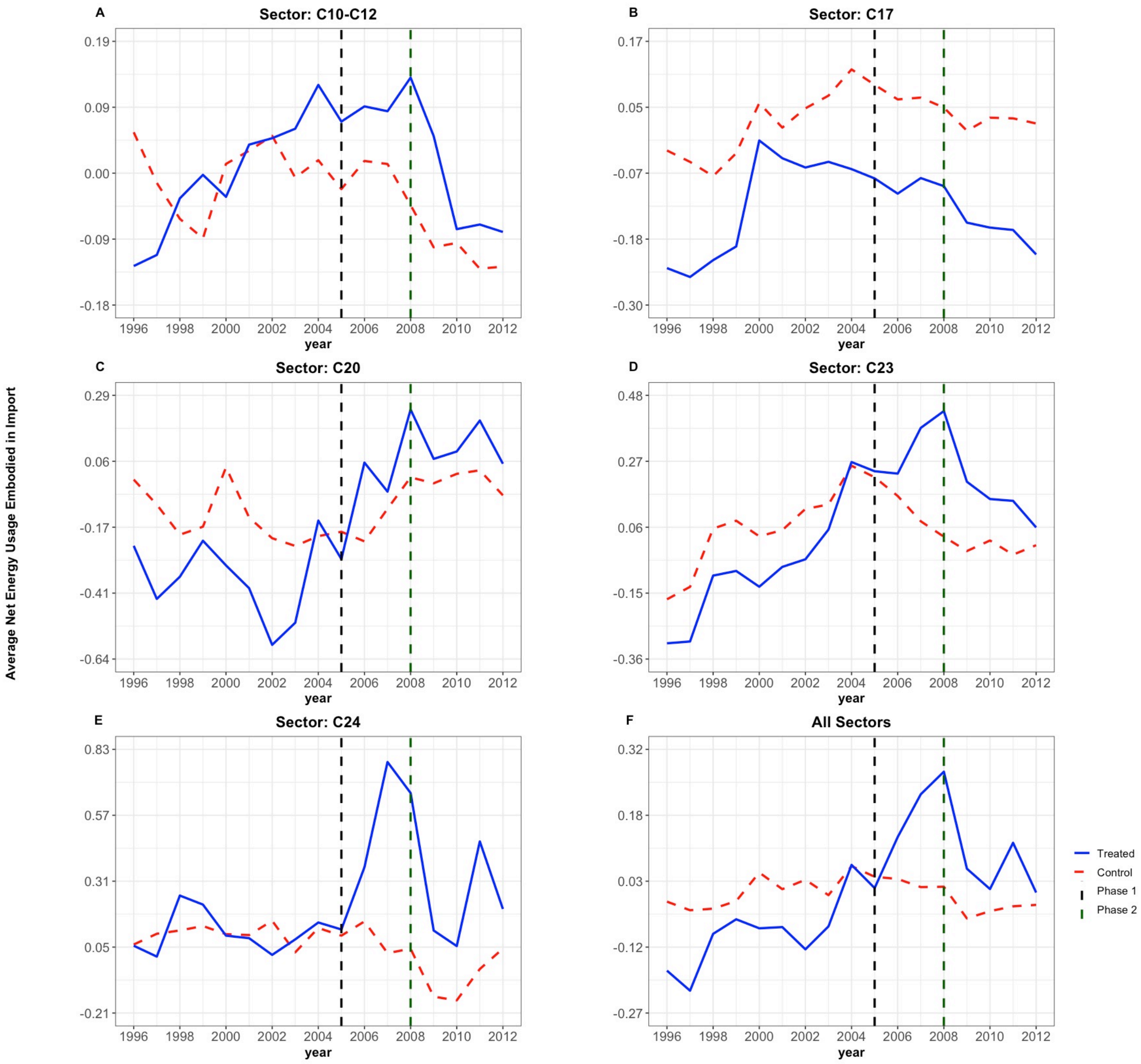


Note: This figure illustrates the changes in net carbon leakage across various industrial sectors, comparing the trends between the treatment (blue) and control (red) groups, based on differences in exporter and importer production technologies. Each panel represents a different sector, Panels A-E, alongside an aggregate view of all sectors, Panel F. The vertical dashed lines mark the initiation of Phase 1 (black) and Phase 2 (green) of the EU ETS.

have partially regained competitiveness while simultaneously reducing carbon and pollutant energy intensities. These patterns reinforce the notion that environmental regulation can induce gradual technological change and improvements in environmental performance, even in the presence of initial compliance challenges.

As these figures reflect raw data, it is important to emphasize that these patterns are descriptive in nature. Hence, it is not possible to conclusively attribute observed changes solely to the EU ETS in this section. The following sections employ rigorous econometric frameworks to formally test these hypotheses and disentangle the direct policy effects of the EU ETS from other potential confounders.

Figure 4: Trends in Net Energy Consumption Embodied in Imports (1996-2012) by Sector

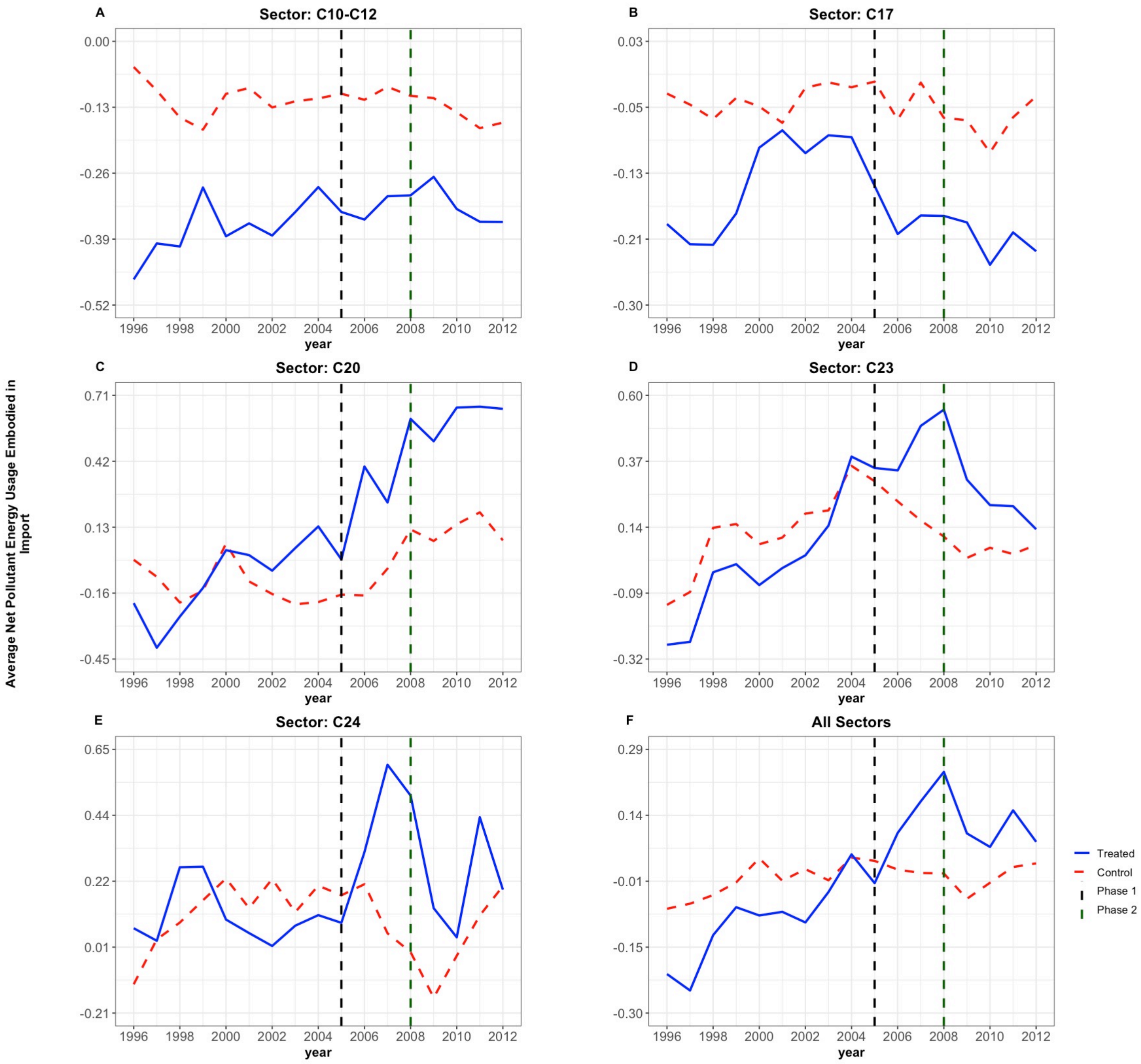


Note: This figure illustrates the changes in net energy use associated with international trade flows from all energy sources across various industrial sectors, comparing the trends between the treatment (blue) and control (red) groups, based on differences in exporter and importer production technologies. Each panel represents a different sector, Panels A-E, alongside an aggregate view of all sectors, Panel F. The vertical dashed lines mark the initiation of Phase 1 (black) and Phase 2 (green) of the EU ETS.

4 Methodology

The DiD Gravity model that is broadly used and suggested by the literature (Aichele and Felbermayr (2015), Naegele and Zaklan (2019), Wang and Kuusi (2024)) may result in a biased estimator. The main issue with this approach is that the pre-treatment parallel trend assumption among the treatment and control units is hardly satisfied in this type of cross-country panel analysis. The average trend of the main outcome (carbon leakage) for the treatment and control groups at the sectoral level and the country level for all five regulated manufacturing sectors is illustrated in Figure 1, Figure 2, and Figure 3 for the carbon leakage based on the exporter production technology, importer

Figure 5: Trends in Net Pollutant Energy Consumption Embodied in Imports (1996-2012) by Sector



Note: This figure illustrates the changes in net energy use associated with international trade flows from pollutant energy sources across various industrial sectors, comparing the trends between the treatment (blue) and control (red) groups, based on differences in exporter and importer production technologies. Each panel represents a different sector, Panels A-E, alongside an aggregate view of all sectors, Panel F. The vertical dashed lines mark the initiation of Phase 1 (black) and Phase 2 (green) of the EU ETS.

production technology, and net carbon emissions associated with international trade, respectively. One can see that the parallel trend assumption in the pre-treatment period could be violated even for the average values with less fluctuation. Hence I suggest employing the the staggered design of the Synthetic Difference in Differences (SDiD) which constructs a synthetic control group with a similar trend to the average outcome for the treatment group to evaluate the causal impacts of the EU ETS policy on carbon and energy flows associated with international trade.

The SDiD method is introduced to merge the advantages of the Difference-in-Differences (DiD) and the Synthetic Control Method (SCM) in causal inference with panel data (Arkhangelsky et al.

(2021)). This approach offers flexibility in estimating treatment effects, especially when the parallel trends assumption may not hold across all units, by employing data-driven weighting to construct more credible comparison groups.

Arkhangelsky et al. (2021) reformulate the SCM as a weighted least squares estimator incorporating unit-specific weights and time fixed effects. By extending this specification to include unit fixed effects (e.g., importer-exporter pairs) and time weights, they derive the SDiD estimator. Including unit fixed effects introduces flexibility, while adding time weights ensures that weighted periods align more closely with those relevant for constructing the counterfactual. Consequently, the SDiD method can be perceived as a doubly weighted extension of DiD, capable of incorporating both time-invariant and time-varying covariates.

To address potential estimation issues in the DiD gravity model, I utilize the staggered design of the SDiD approachapplied here for the first time in the literature, to the best of my knowledge, with the following specification:

$$Y_{pt} = \mu + \tau W_{pt} + X'_{pt}\beta + \alpha_p + \delta_t + \varepsilon_{pt} \tag{9}$$

Here, the index p refers to the pair consisting of importer i and exporter j, totalling $N = 341$ units, while t represents time across $T = 17$ years, from 1996 to 2012. Y_{pt} is the dependent variable for pair p at time t from the list of dependent variables that can be found in Table A.5. The treatment indicator $W_{pt} \in \{0, 1\}$ equal to one for countries under the EU ETS regulations that import from non-regulated countries during the period after the programs implementation (2005 for most countries, except for Romania and Bulgaria, where it began in 2007); otherwise, it is set to zero. The primary parameter of interest is the SDiD estimator τ, representing the causal effect of the EU ETS policy on carbon and energy flows associated with international trade. X_{pt} is a vector of covariates detailed in Section 2.2 and β is a vector of coefficients corresponding to it. α_p denotes the pair of importer-exporter fixed effects, capturing unobserved heterogeneity between country pairs. δ_t captures the year-fixed effect, controlling for global shocks affecting all output variables equally in a given year. ϵ_{pt} is the error term, assumed to be independently and identically distributed.

In line with Arkhangelsky et al. (2021) and Kranz (2022), I outline the SDiD estimation via the following optimization process :

First, as per Kranz (2022), I estimate the fixed-effects regression:

$$Y_{pt} = \mu + X'_{pt}\beta + \alpha_p + \delta_t + e_{pt} \tag{10}$$

I then compute the adjusted outcome variable using:

$$Y_{pt}^{\text{adj}} = Y_{pt} - X'_{pt}\hat{\beta} \tag{11}$$

Next, following Arkhangelsky et al. (2021), I determine the optimal weights ω_p and λ_t that balance pre-treatment outcomes and trends between treated and control units. This is achieved by minimizing the difference between the weighted average of control outcomes and the simple average of treated outcomes before treatment adoption. Finally, utilizing these weights, I perform a weighted two-way fixed effects regression of Y_{pt}^{adj} on W_{pt} to estimate τ, with the weights enhancing the credibility of the control comparisons:

$$\left(\hat{\mu}, \hat{\alpha}, \hat{\delta}, \hat{\tau}^{\text{sdid}}\right) = \arg\min_{\mu,\alpha,\delta,\tau} \sum_{p=1}^{N} \sum_{t=1}^{T} \left(Y_{pt}^{\text{adj}} - \mu - \alpha_p - \delta_t - W_{pt}\tau\right)^2 \hat{\omega}_p \hat{\lambda}_t \tag{12}$$

Essentially, the SDiD estimator integrates unit and time fixed effects alongside the weights. Time weights (λ_t) are selected to ensure that, within each unit, the weighted average outcomes over time closely approximate the target period. Overall, SDiD extends DiD by incorporating unit and time weights, and differs from SCM by including unit fixed effects and permitting time weights. This approach enhances the standard DiD estimator by introducing data-driven weights, while still differencing out fixed effects α_p and δ_t as in traditional DiD. It contrasts with the SCM estimator by incorporating these fixed effects, which account for level differences across units.

After estimating the average treatment effect, I assess statistical significance using conventional inferential methods, rather than the placebo tests typically employed in SCM, using Jackknife, which omits one unit at a time to estimate variance. The deterministic process of this approach ensures that results are reproducible without the need to set a random seed.

When investigating the impact of the EU ETS policy on carbon leakage, adjusted carbon leakage, and energy embodied in imports for both actual and hypothetical scenarios, the dependent and independent variables in Specification 9 (except for W_{pt} and the binary variables) are in logarithmic terms. This means the effect of the EU ETS on these variables can be calculated using the estimated value of $\hat{\tau}$ as follows: $[\exp(\hat{\tau}) - 1] \times 100\%$. However, because net values can include a range of values, including negatives, using a logarithmic transformation is challenging. Therefore, when examining the programs effect on net global carbon emissions and energy usage associated with international trade, I use standardized values for all dependent and independent variables (except for W_{pt} and the binary variables) in this specification. To interpret the estimated coefficient of the policy effect, the estimated effect can be expressed in the original units of Y_{pt} as follows: $\hat{\tau} \times \sigma_Y$, where σ_Y is the standard deviation of the dependent variable. Thus, the estimated coefficient in Table 3 can be expressed in the original measurement units of the dependent variable using the standard deviation in Table A.3.

While the standard SDiD framework assumes a uniform adoption date for all treated units, it can be modified for staggered adoption scenarios where units receive treatment at different times (Athey and Imbens (2022)). In staggered adoption cases, the average treatment effect on the treated (ATT) is estimated by applying SDiD to data subsets corresponding to each distinct adoption date. For instance, this includes all importers treated by 2005, except Romania and Bulgaria, which are treated starting in 2007. Applying SDiD to each subset produces adoption-specific effect estimates $\hat{\tau}_a$, and the ATT is then computed as:

$$\hat{\tau}_{\text{ATT}} = \sum a \frac{T_a}{T_{\text{post}}} \times \hat{\tau}_a \tag{13}$$

Here, T_a denotes the number of treated unit-periods corresponding to adoption date a, and T_{post} represents the total number of treated unit-periods. This formula calculates a weighted average of the treatment effects, proportionally weighting by the number of treated units in each adoption group.

5 Results

This section presents the estimated effects of the EU ETS policy using Specification 9. First I show the average treatment effect of the EU ETS on carbon leakage, adjusted carbon leakage, and energy leakage under the actual scenario, where the production technology of the origin country (exporter) is used to measure these variables. Then I present the estimated results for the "What if" scenario, where the production technology of the destination country (importer) is used to calculate the carbon and energy flows associated with international trade. Finally, the results of the policy on the net values of carbon emissions and energy usage embodied in trade are discussed.

5.1 Actual Scenario Based on Country of Origin

The first row of Table 1 presents the results of the main model for carbon leakage. The estimates suggest how the EU ETS influences the direct shift of emissions from regulated EU ETS countries to unregulated ones through increased imports from non-EU ETS countries with less stringent environmental regulations. Unlike the empirical literature, which has shown little to no evidence of carbon leakage (Naegele and Zaklan (2019); Wang and Kuusi (2024)), the estimated result for the aggregated sector (column 1) indicates a statistically significant positive effect of the EU ETS on carbon leakage. This implies that the policy led to a shift in carbon-intensive production from EU-regulated regions to non-regulated regions via trade. The results show that, on average, carbon per unit of output transferred through trade from countries under EU ETS regulations to non-treated countries increased by 21% compared to the counterfactual scenario without the EU ETS policy.

The finding implies that while the EU ETS might have been successful in reducing carbon emissions within the regulated area, this success might potentially be due to displacing a proportion of the emissions to non-regulated areas. Hence, in contrast to aus dem Moore et al. (2019)'s claim, the finding suggests that carbon leakage, potentially driven by substantial industrial relocation caused by the EU ETS, does not appear to be overstated. This finding highlights the importance of designing border carbon adjustments or fostering international cooperation on emission reductions as complementary policies to mitigate emission leakage.

The rest of the columns report the carbon leakage due to the EU ETS scheme in sectors that are subjected to EU ETS regulations. The estimated results are statistically significant across all sec-

Table 1: The Effect of the EU ETS Policy on Carbon Emissions and Energy Use Associated with International Trade (Exporter Technology) - 1996–2012

Dependent Variable	(1) $Aggre.$	(2) $C10 - C12$	(3) $C17$	(4) $C20$	(5) $C23$	(6) $C24$
CL	0.193**	0.270*	0.403**	0.001	0.556***	0.762***
	(0.076)	(0.152)	(0.193)	(0.082)	(0.160)	(0.219)
AdjCL^{PE}	0.118*	0.145	0.306*	-0.040	0.410***	0.574***
	(0.064)	(0.120)	(0.171)	(0.071)	(0.139)	(0.170)
AdjCL^{TE}	0.143**	0.141	0.262	-0.024	0.414***	0.572***
	(0.065)	(0.124)	(0.168)	(0.072)	(0.138)	(0.168)
PEL	0.204***	0.299*	0.425**	0.025	0.598***	0.676***
	(0.078)	(0.160)	(0.202)	(0.086)	(0.164)	(0.229)
TEL	0.167**	0.286*	0.453**	-0.044	0.580***	0.669***
	(0.158)	(0.206)	(0.085)	(0.164)	(0.229)	(0.072)
Control variables	YES	YES	YES	YES	YES	YES
Pair-Country-fixed	YES	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES	YES
Observations	5,797	5,797	5,797	5,797	5,797	5,797

Note: The table presents the average treatment effect of the EU ETS on carbon leakage (CL), adjusted carbon leakage based on pollutant energy (AdjCL^{PE}), adjusted carbon leakage based on total energy (AdjCL^{TE}), pollutant energy leakage (PEL), and total energy leakage (TEL), based on the production technology of the exporter countries. As mentioned in the methodology section, all the variables except the binary ones are in logarithm form for this estimation. It reports the estimated results for all sectors combined (Aggre.) along with five regulated manufacturing sectors. The sectors are Food, Beverages, and Tobacco (C10-C12); Paper (C17); Chemicals (C20); Non-Metallic Mineral Products (C23); and Basic Metal (C24). The dataset for each sector and their aggregate includes 5,797 [(21Œ11Œ17)+(11Œ10Œ17)] observations, covering 21 ETS countries and 11 non-ETS countries across five sectors from 1996 to 2012. the staggered design of the SDiD method is employed to evaluate the impact of EU ETS using specification 9. The jackknife approach calculates the estimated coefficients' standard errors, thus determining their statistical significance. All models include time and pair importer-exporter fixed effects. Standard errors report in parentheses, and *** p<0.01, ** p<0.05, * p<0.1.

tors except the chemical sector (C20). These findings indicate an increase of about 31% in the Food, Beverages, and Tobacco sector (C10-C12) and 50% in the Paper sector (C17). This effect is even more pronounced in the Non-Metallic Mineral Products sector (C23) and the Metal sector (C24), where the EU ETS approximately doubled the carbon transferred to non-EU countries through trade flow. This heterogeneity across sectors can be attributed to trade elasticity, energy intensity, and the competitiveness of different industries. Therefore, implementing additional sector-specific complementary policies to address this issue seems necessary.

A unilateral environmental policy affects the carbon embodied in traded goods directly through changes in trade patterns and indirectly through changes in energy efficiency. Traditional carbon leakage analysis overlooks energy efficiency changes. In contrast, adjusted carbon leakage captures energy efficiency variations, providing a more precise assessment of how the EU ETS policy redistributes emissions globally. This metric captures not only the direct effect of this program on carbon embodied in trade but also the spillover effects of the policy on carbon transfer resulting from changes in energy efficiency.

First, I examine the EU ETS effect on adjusted carbon leakage considering pollutant energy efficiency and then for total energy efficiency, which includes both pollutant and clean energy sources. The results for the aggregated sector suggest that following the implementation of the first two phases of the EU ETS policy, adjusted carbon leakage increased by about 12%. However, when the adjustment is conducted considering total energy efficiency, the effect is slightly higher, showing an increase of about 15%. The adjusted carbon leakage metric reflects emission shifts while implicitly considering whether more energy-efficient technologies are being used in the production process. It adjusts the spillover effects of a policy on energy efficiency changes and captures only effects that are not directly related to energy efficiency.

On the other hand, pollutant energy sources, such as coal, oil, and gas, have lower energy efficiency and higher carbon emissions than clean sources, such as renewable and nuclear (Qazi et al. (2019)). Therefore, the estimated lower adjusted carbon leakage for pollutant energy compared to total energy potentially suggests that pollutant sources have a relatively larger impact on adjusted carbon leakage than total energy, which includes clean sources as well. This is because efficiency gains in the usage of clean sources, compared to those in pollutant ones, reduce adjusted carbon leakage for total energy less effectively. One potential reason is that shifting more demand toward foreign suppliers encourages firms in unregulated countries to use more pollutant energy sources or enables firms to use technologies that are less energy efficient to be able to compete in the international market. Hence, the greater dependency of unregulated countries on pollutant energy sources can be adjusted more effectively when I account for variations in energy efficiency across countries.

The sector-specific estimates show statistical significance in the Non-Metallic Mineral Products sector (C23) and the Metal sector (C24). The estimated coefficients of adjusted carbon leakage for both total energy and pollutant energy yield very similar values, indicating a significant share of pollutant energy in the total consumption basket of these two sectors. Moreover, the estimates show that the EU ETS effects on adjusted carbon leakage are smaller compared to the program's effects on carbon leakage. This suggests that carbon leakage is adjusted more effectively when the differences in energy efficiency across countries are taken into account, which may be influenced by the EU ETS scheme through changes in trade patterns.

A potential driving factor of carbon leakage through production relocation is the energy consumption per output. Hence, I investigate the impact of the EU ETS on energy flows associated with international trade to address this issue. The last two rows of Table 1 show the results for energy leakage. The estimated coefficients on energy leakage are statistically significant with positive signs for both cases, which are calculated using total and pollutant energy. These findings suggest a substantial increase in energy usage embodied in imports per unit of output due to the implementation of the EU ETS policy. Notably, the policy led to an increase of about 18% in total (pollutant and non-pollutant) energy leakage and 23% in pollutant energy leakage. The larger estimated effect for pollutant energy leakage might be attributed to shifting the production of pollutant-energy-intensive goods within EU countries to countries with less stringent environmental policies.

The results for sector-specific analysis suggest statistically significant outcomes across sectors except the Chemicals sector (C20). The estimates suggest approximately a 33% increase in energy leakage in the Food, Beverages, and Tobacco sector (C10-C12) due to the implemented policy, while it led to an increase of 55% in the Paper sector (C17). The energy leakage effects of the policy are more pronounced in the Non-Metallic Mineral Products sector (C23) and the Metal sector (C24). The estimated coefficients for the two cases of energy leakage (i.e., total energy and pollutant energy) yield approximately similar results, indicating the substantial share of pollutant energy in the consumption baskets of exporters.

Overall, by focusing on the actual import scenario, in which I considered the production technology of the exporting countries, there is a consistent pattern of higher carbon and energy leakage in the treated group across multiple variables. This suggests the EU ETS may have inadvertently encouraged carbon-intensive imports, leading to carbon leakage. Firms may have shifted production to countries with less stringent environmental regulations to avoid the costs associated with the EU ETS, resulting in increased imports of carbon-intensive goods. Furthermore, the energy leakage and adjusted carbon leakage measures indicate that imports are not only more carbon-intensive but also less energy-efficient compared to domestic production, exacerbating environmental impacts. Additionally, the estimated effects suggest that while the EU ETS aimed to reduce emissions domestically, it may have caused emissions to increase elsewhere.

The results of this study are align with the many ex-ante computable general equilibrium (CGE) and integrated assessment models that have predicted that unilateral climate policies, such as the EU ETS policy, could induce carbon leakage. Studies by Babiker (2005), Böhringer et al. (2010), and Elliott et al. (2010) often forecast notable leakage, particularly if stringent climate policies are imposed unilaterally and without border adjustments. My findings resonate more closely with these CGE-based predictions. While CGE models have frequently been criticized for their strong assumptions and for producing upper-bound leakage estimates, these empirical findings imply that reality may lean closer to these pessimistic projections than previously suggested by empirical studies, such as Martin et al. (2014); Dechezleprêtre and Sato (2017); Dechezleprêtre, Fabre, Kruse, Planterose, Chico and Stantcheva (2022), which found either negligible or non-robust evidence for carbon leakage.

Furthermore, a growing body of literature has emphasized the importance of sector-level differences in responding to climate policies. For instance, Sartor (2012) examined the aluminum sector, and Branger et al. (2016) focused on cement and steel, finding limited leakage but noting that certain characteristics, such as trade elasticity, energy intensity, and cost pass-through, could vary the policys impact across industries. This study shows that the Non-Metallic Mineral Products (C23) and Basic Metals (C24) sectors face stronger leakage effects, illustrating that sectoral heterogeneity can be pronounced. This finding aligns with research that stresses the need for examining disaggregated data and suggests that future studies should avoid generalizing policy impacts across all sectors.

Finally, the inclusion of energy leakage metrics sets this study apart from many that focus solely on embodied carbon. By identifying a shift toward more pollutant-intensive energy sources outside the EU, these results support a dimension sometimes explored by energy-economic studies that assess upstream leakage effects in non-ETS energy markets (e.g., Branger and Quirion (2014*b*); Böhringer et al. (2012)). The evidence that energy efficiency and pollutant-energy use matter underscores the importance of examining not only the location but also the type and intensity of energy sources used abroad. This adds new depth to the leakage debate, suggesting that even modest carbon price differentials can alter the global composition of energy use and technology adoption.

5.2 Hypothetical What-If Scenario Based on Country of Destination

In this part, I analyze the what-if scenario, where the production technology of the importer countries is used to calculate the variables related to carbon and energy flows associated with international trade. This scenario considers the extent to which carbon emissions and energy usage would have occurred if the imported goods had been produced domestically.

The estimated results are reported in Table 2. The findings for the aggregated sectors suggest no significant evidence for any of the dependent variables. This finding might indicate that the EU ETS could have effectively prevented significant leakage if the imported goods had been produced domestically using high-energy-efficient and low-carbon-intensity processes. As EU production processes have relatively low carbon intensity and higher energy efficiency, these non-identical estimates between the real and hypothetical scenarios can most likely be attributed to differences in energy efficiency and carbon intensity between regulated and non-regulated countries. Hence, from another perspective, the EU ETS could have no effect on increasing carbon emissions and energy usage through trade flows if the non-regulated exporters had production technologies similar to those of the regulated countries. Overall, these findings may imply that the main driver of leakage under a unilateral policy such as the EU ETS is the shift in production to areas with less stringent environmental policies, leading to the establishment of a comparative advantage for firms with less energy-efficient production technologies to produce more carbon-intensive goods.

The findings at the sectoral level may suggest that the EU ETS regulations overall improved the production technologies in the regulated countries, but this adjustment may vary across sectors, especially based on the estimated results for the Non-Metallic Mineral Products (C23) and the Basic Metal (C24) sectors.

Under this 'what-if' scenario, the effect of the EU ETS on carbon leakage is statistically significant for the Metal sector (C24). However, this estimated effect is smaller than in the actual import

Table 2: The Effect of the EU ETS Policy on Carbon Emissions and Energy Use Associated with International Trade (Importer Technology/What-If Scenario) - 1996–2012

Dependent Variable	(1) $Aggre.$	(2) $C10-C12$	(3) $C17$	(4) $C20$	(5) $C23$	(6) $C24$
CL	-0.039	-0.141	0.245	0.001	0.375**	0.407*
	(0.069)	(0.126)	(0.179)	(0.079)	(0.149)	(0.216)
AdjCL^{PE}	0.041	0.041	0.384**	0.029	0.396***	0.266
	(0.062)	(0.124)	(0.167)	(0.077)	(0.135)	(0.175)
AdjCL^{TE}	-0.019	-0.137	0.302*	0.00480	0.362***	0.277
	(0.063)	(0.118)	(0.161)	(0.076)	(0.134)	(0.176)
PEL	0.050	0.016	0.197	-0.057	0.409**	0.688***
	(0.071)	(0.134)	(0.190)	(0.079)	(0.163)	(0.223)
TEL	0.111	0.184	0.245	-0.047	0.440***	0.685***
	(0.072)	(0.140)	(0.196)	(0.080)	(0.160)	(0.222)
Control variables	YES	YES	YES	YES	YES	YES
Pair-Country-fixed	YES	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES	YES
Observations	5,797	5,797	5,797	5,797	5,797	5,797

Note: The table presents the average treatment effect of the EU ETS on carbon leakage (CL), adjusted carbon leakage based on pollutant energy (AdjCL^{PE}), adjusted carbon leakage based on total energy (AdjCL^{TE}), pollutant energy leakage (PEL), and total energy leakage (TEL), based on the production technology of the importer countries. As mentioned in the methodology section, all the variables except the binary ones are in logarithm form for this estimation. It reports the estimated results for all sectors combined (Aggre.) along with five regulated manufacturing sectors. The sectors are Food, Beverages, and Tobacco (C10-C12); Paper (C17); Chemicals (C20); Non-Metallic Mineral Products (C23); and Basic Metal (C24). The dataset for each sector and their aggregate includes 5,797 [(21Œ11Œ17)+(11Œ10Œ17)] observations, covering 21 ETS countries and 11 non-ETS countries across five sectors from 1996 to 2012. the staggered design of the SDiD method is employed to evaluate the impact of EU ETS using specification 9. The jackknife approach calculates the estimated coefficients' standard errors, thus determining their statistical significance. All models include time and pair importer-exporter fixed effects. Standard errors report in parentheses, and *** p<0.01, ** p<0.05, * p<0.1.

scenario where I employed the production technology of the exporter countries. Moreover, the results for energy embodied in goods based on pollutant and total energy are almost identical and very close to those in the actual scenario. Additionally, this finding may suggest that mostly pollutant energy sources would have been used even if those goods were produced using technologies similar to those of the regulated importer countries.

Nevertheless, the estimated impacts of the EU ETS on carbon and energy leakage for the Non-Metallic Mineral Products sector (C23) show that both carbon emissions and energy usage would have increased to a lesser extent compared to what I found for the actual import scenario. However, the estimated effects are positive and statistically significant, which may suggest that more carbon and energy embodied in goods would have been generated even using the production technology of the destination countries. Larger domestic demand in these countries may enable firms with lower levels of energy-efficient technology and higher carbon intensity to enter the market and participate in the production process. Moreover, the results show approximately identical coefficient values for both carbon leakage and its adjusted counterpart. These findings may indicate that changes in carbon embodied in goods under this hypothetical scenario can be attributed to increasing imports, with energy efficiency improvement likely playing a negligible role.

5.3 Net Carbon Emissions and Energy Usage Associated with Trade

The consequences of carbon and energy leakage are more related to the characteristics of exporters rather than importers. This raises a crucial question for policymaking: how does a unilateral environmental policy affect emissions globally rather than only in regulated areas? Hence, I examine the impact of the EU ETS on the net carbon emissions and energy flows associated with international trade. First, I measure the difference in carbon leakage between the actual and what-if scenarios, calculated as the difference in carbon intensity between the exporters and importers multiplied by the bilateral import value. Then I evaluate the impact of the EU ETS on this variable to determine whether the difference in carbon and energy intensity between exporter and importer countries influences net carbon emissions and energy consumption.

Table 3 reports the results related to these net values. The estimated coefficient for the aggregated sectors shows an increase of about 0.161 standard deviations in net carbon leakage due to the EU ETS effect. This means that the net global carbon emissions associated with international trade increased by approximately 315kt on average in each non-EU exporter that participated in trade with a regulated country as a result of the programs effect. Additionally, the sector-level analysis reveals that the global net carbon emissions associated with international trade in the Basic Metal (C24) sector increased, on average, by about 175kt.

By comparing actual and hypothetical scenarios (based on exporter vs. importer technology), I underscore the significance of technological differences in explaining leakage. Few empirical studies have explicitly accounted for the disparity in production technologies between regulated and unregulated regions. My approach aligns with a strand of literature in environmental economics that increasingly looks at the role of technological diffusion and efficiency improvements (Fischer and Newell (2008); Acemoglu et al. (2012)). These works argue that bridging technology gaps and encouraging cleaner production methods in other countries can reduce leakage risks, a perspective my findings strongly support.

Overall, the findings suggest that while emissions were reduced within the EU, net carbon emissions increased globally through the trade channel due to the EU ETS effect. This provides strong evidence that unilateral policies such as the EU ETS may not effectively support international efforts to reduce global emissions. One possible explanation is that the EU ETS led to a shift of carbon-intensive production toward unregulated countries with less stringent environmental policies. This shift can be attributed to the EU ETS policy, making domestic production more costly,

Table 3: The Effect of the EU ETS Policy on Global Net Carbon Emissions and Net Energy Use Associated with International Trade - 1996–2012

Dependent Variable	(1) $Aggre.$	(2) $C10 - C12$	(3) $C17$	(4) $C20$	(5) $C23$	(6) $C24$
NetCL	0.161*	0.140	0.126	0.066	0.041	0.179*
	(0.085)	(0.121)	(0.133)	(0.077)	(0.091)	(0.102)
NetPEL	0.171*	0.241	0.144	0.045	0.116*	0.117
	(0.093)	(0.154)	(0.116)	(0.079)	(0.069)	(0.081)
NetTEL	0.182**	0.226**	0.0597	0.031	0.118	0.127
	(0.086)	(0.113)	(0.084)	(0.075)	(0.078)	(0.081)
Control variables	YES	YES	YES	YES	YES	YES
Pair-Country-fixed	YES	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES	YES
Observations	5,797	5,797	5,797	5,797	5,797	5,797

Note: The table presents the average treatment effect of the EU ETS on global net carbon emissions (NetCL, global net pollutant energy use (NetPEL), and global net total energy use (NetPEL) associated with international trade. As mentioned in the methodology section, all the variables except the binary ones are standardized for this estimation. So, the coefficients are expressed in terms of standard deviations. It reports the estimated results for all sectors combined (Aggre.) along with five regulated manufacturing sectors. The sectors are Food, Beverages, and Tobacco (C10-C12); Paper (C17); Chemicals (C20); Non-Metallic Mineral Products (C23); and Basic Metal (C24). The dataset for each sector and their aggregate includes 5,797 [(21Œ11Œ17)+(11Œ10Œ17)] observations, covering 21 ETS countries and 11 non-ETS countries across five sectors from 1996 to 2012. the staggered design of the SDiD method is employed to evaluate the impact of EU ETS using specification 9. The jackknife approach calculates the estimated coefficients' standard errors, thus determining their statistical significance. All models include time and pair importer-exporter fixed effects. Standard errors report in parentheses, and *** $p<0.01$, ** $p<0.05$, * $p<0.1$..

which, in turn, redirects more demand to unregulated countries. Consequently, this leads to higher carbon emissions per unit of output, as firms in these unregulated countries have less incentive to use low-carbon processes and invest in green technologies.

On the other hand, the estimated net energy leakage of the aggregated sectors for both pollutant and total energy cases indicates statistically significant and positive effects of the EU ETS in increasing the global energy embodied in imported goods. It reveals that, on average, approximately 2,166TJ and 4,104TJ more pollutant energy and energy from all sources are consumed by each non-EU exporter participating in trade with regulated countries, respectively, compared to a scenario where the exporter countries had similar production technologies to the regulated countries. This higher energy usage may be the main driving factor behind the increased carbon emissions associated with international trade. Furthermore, the sector-level analysis shows that the EU ETS increases the energy usage from pollutant sources in the Non-Metallic Mineral Products (C23) sector by about 501TJ through trade flows. For the Food, Beverages, and Tobacco (C10-C12) sector, there is a 270TJ increase in total energy usage associated with trade.

In summary, the findings of this part show that the EU ETS policy alone could not reduce global carbon emissions and may unintentionally worsen the situation. As can be seen from the results, net emissions increased due to the first two phases of the policy, which could be mainly attributed to shifting carbon-intensive products to unregulated countries. Additionally, net energy usage also increased, which may have resulted from the use of less energy-efficient technology in those countries. This increase in energy usage may lead to another unintentional effect of this policy. For instance, the annual real price of a barrel of imported crude oil rose from approximately $40 before 2004 to over $100 after 2008. This is highly correlated with the implementation of the EU ETS policy, which I show led to an increase in energy demand and could suggest one of the potential drivers of rising oil prices that was previously unrecognized.

5.4 Robustness Checks

To examine the robustness of the estimated results, I implemented a placebo-style methodology. Specifically, I utilized a permutation test to evaluate the statistical significance of the estimated impact of the EU ETS by contrasting it with a distribution of effects derived from random permutations of the treatment assignments. The null hypothesis posits that the EU ETS does not influence dependent variables, including (1) carbon embodied in the import, (2) the energy embodied in the import, (3) carbon embodied in the import adjusted by energy usage, and (4) net emission, and any observed effect is due to random variation. Conversely, the alternative hypothesis suggests that the EU ETS policy does affect the dependent variables mentioned above among the treated countries, indicating that the results are not due to chance.

This permutation test, a non-parametric approach, aims to assess the statistical significance of the EU ETS effect as evaluated by the SDiD analysis. In each iteration of the test, I randomly assign countries to form a new treated group, while keeping the number of treated countries identical to the original analysis (21 countries). The selection is performed without replacement from the pool of all available countries, guaranteeing that each country has an equal probability of selection in every iteration. By maintaining the same number of treated units, I control for potential confounding effects related to group size, ensuring that any differences in estimated effects are attributable to the treatment assignment rather than variations in sample size.

For this method, a substantial number of permutations (more than 1,000 iterations) is necessary to obtain an empirical distribution of the EU ETS effects expected under the null hypothesis of no effect. After completing all iterations, I compare the estimated effect to this distribution to evaluate how extreme the result is relative to what might occur by chance. Anticipating a positive impact of the EU ETS on EU importers due to the programs regulations, I performed a one-tailed test. The p-value is computed by determining the proportion of permuted EU ETS effects that are greater than or equal to the observed effect.[7]

To remove any bias from my prior assumptions on the test results, I also conducted a two-tailed permutation test. In this case, the p-value is calculated by determining the proportion of permuted effects where the absolute value is equal to or exceeds that of the estimated effect. This approach effectively doubles the area of interest in the permutation distribution, accounting for extreme effects in both positive and negative directions.[8] This methodological rigor enhances the validity of the statistical inference, providing a robust assessment of the programs impact.

I confirm all results obtained through the SDiD approach by conducting permutation tests as a robustness check. Both the one-tailed and two-tailed tests offer strong evidence that the estimated effects of the EU ETS policy on all of the dependent variables, including (1) carbon embodied in the import, (2) the energy embodied in the import, (3) carbon embodied in the import adjusted by energy usage, and (4) net emission are causal and not due to random factors.

6 Conclusion and Policy Suggestions

The EU ETS has been implemented to reduce carbon emissions in regulated countries since 2005. Yet, there is limited evidence in the literature about how it affects carbon embodied in imports (carbon leakage) and no evidence on how it changes the energy flows associated with international trade (energy leakage). In this paper, I introduced three new aspects of environmental leakage: (1) conventional carbon leakage adjusted for energy efficiency (adjusted carbon leakage), (2) the energy embodied in imports, and (3) net values for both energy and carbon leakage using a hypothetical 'what-if' scenario. I then examined the effects of the EU ETS policy on these variables alongside the conventional carbon leakage phenomenon.

Using the staggered design of the SDiD method, I found that the EU ETS led to an increase in carbon embodied in imported goods, mainly by transferring the energy usage of produced goods abroad. I showed that the increased energy leakage is associated not only with higher imports but also with production technologies that have lower energy efficiency among exporters. These effects are more pronounced for pollutant energy sources, revealing that unregulated firms not only use less energy-efficient technology but also employ more polluting energy sources. Moreover, based on the mostly insignificant results for the what-if scenarioassessing the extent to which carbon emissions and energy consumption would have occurred if the imported goods had been produced using the production technology of the importer countriesI suggest that the EU ETS could have prevented leakage or led to a smaller leakage if the production processes were similar to those of the importer countries. Finally, by examining the gap between what has actually occurred and

[7] A low p-value suggests that the estimated effect is unlikely to be due to random chance, indicating that the EU ETS policy has a statistically significant impact on the outcome variables.

[8] A low p-value indicates that the estimated effect significantly differs from zero, reinforcing the conclusion that the EU ETS has a real effect on the outcome variables, whether it increases or decreases the measured variable.

the hypothetical 'what-if' scenario, I found that the policy led to an increase in global carbon emissions and energy consumption associated with international trade.

Overall, the analysis reveals that, while the EU ETS has been instrumental in reducing emissions within the regulated countries, it may have led to unintended consequences, such as increased carbon and energy leakage through imports. The significant carbon and energy leakages suggest that policies must account for global supply chains and the shifting of emissions across borders. These findings indicate that comprehensive and collaborative policies are necessary to mitigate carbon leakage and achieve more effective global emissions reductions.

The findings related to adjusted carbon leakage and energy usage embodied in trade suggest that collaboration with trading partners to establish common environmental standards, which reduce the incentive to outsource production to countries with less stringent environmental policies, is necessary. Furthermore, as I found that the policy impact on carbon leakage diminishes when energy efficiency is considered, investing in these technologies domestically and promoting their adoption internationally to reduce the overall carbon footprint appears to be a potential solution for the elevated carbon and energy flows associated with international trade.

Last but not least, finding heterogeneous effects on regulated sectors for both carbon and energy flows associated with international trade suggests implementing complementary sector-specific policies to address the unique challenges of each sector, specifically focusing on those with the highest leakage rates.

To deepen the understanding gained from this study, future research should examine how the technological diffusion and the adoption of low-carbon innovations in countries with less stringent regulations affect leakage dynamics. Long-term studies that extend beyond the initial phases of the EU ETS would shed light on the persistence and evolution of leakage effects over time. Moreover, a targeted analysis of key sectors, such as Non-Metallic Mineral Products and Basic Metals, which are particularly vulnerable to leakage, could aid in designing more focused and effective regulatory measures to address the specific challenges these industries face.

References

Acemoglu, D., Aghion, P., Bursztyn, L. and Hemous, D. (2012), 'The environment and directed technical change', *American economic review* **102**(1), 131–166.

Aichele, R. and 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.

Anderson, J. E. and Van Wincoop, E. (2004), 'Trade costs', *Journal of Economic literature* **42**(3), 691–751.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W. and Wager, S. (2021), 'Synthetic difference-in-differences', *American Economic Review* **111**(12), 4088–4118.

Athey, S. and Imbens, G. W. (2022), 'Design-based analysis in difference-in-differences settings with staggered adoption', *Journal of Econometrics* **226**(1), 62–79.

aus dem Moore, N., Großkurth, P. and Themann, M. (2019), 'Multinational corporations and the eu emissions trading system: The specter of asset erosion and creeping deindustrialization', *Journal of Environmental Economics and Management* **94**, 1–26.

Babiker, M. H. (2005), 'Climate change policy, market structure, and carbon leakage', *Journal of international Economics* **65**(2), 421–445.

Böhringer, C., Balistreri, E. J. and Rutherford, T. F. (2012), 'The role of border carbon adjustment in unilateral climate policy: Overview of an energy modeling forum study (emf 29)', *Energy Economics* **34**, S97–S110.

Böhringer, C., Fischer, C. and Rosendahl, K. E. (2010), 'The global effects of subglobal climate policies', *The BE Journal of Economic Analysis & Policy* **10**(2).

Borghesi, S., Franco, C. and Marin, G. (2020), 'Outward foreign direct investment patterns of italian firms in the european union's emission trading scheme', *The Scandinavian journal of economics* **122**(1), 219–256.

Branger, F. and Quirion, P. (2014*a*), 'Climate policy and the carbon haveneffect', *Wiley Interdisciplinary Reviews: Climate Change* **5**(1), 53–71.

Branger, F. and Quirion, P. (2014*b*), 'Would border carbon adjustments prevent carbon leakage and heavy industry competitiveness losses? insights from a meta-analysis of recent economic studies', *Ecological Economics* **99**, 29–39.

Branger, F., Quirion, P. and Chevallier, J. (2016), 'Carbon leakage and competitiveness of cement and steel industries under the eu ets: much ado about nothing', *The Energy Journal* **37**(3), 109–136.

Calel, R. and Dechezleprêtre, A. (2016), 'Environmental policy and directed technological change: evidence from the european carbon market', *Review of economics and statistics* **98**(1), 173–191.

Carbone, J. C. and Rivers, N. (2017), 'The impacts of unilateral climate policy on competitiveness: evidence from computable general equilibrium models', *Review of Environmental Economics and Policy* .

Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Chico, A. S. and Stantcheva, S. (2022), Fighting climate change: International attitudes toward climate policies, Technical report, National Bureau of Economic Research.

Dechezleprêtre, A., Gennaioli, C., Martin, R., Muûls, M. and Stoerk, T. (2022), 'Searching for carbon leaks in multinational companies', *Journal of Environmental Economics and Management* **112**, 102601.

Dechezleprêtre, A. and Sato, M. (2017), 'The impacts of environmental regulations on competitiveness', *Review of environmental economics and policy* .

Ederington, J. and Minier, J. (2003), 'Is environmental policy a secondary trade barrier? an empirical analysis', *Canadian Journal of Economics/Revue canadienne d'économique* **36**(1), 137–154.

Egger, P. (2000), 'A note on the proper econometric specification of the gravity equation', *Economics letters* **66**(1), 25–31.

Elliott, J., Foster, I., Kortum, S., Munson, T., Cervantes, F. P. and Weisbach, D. (2010), 'Trade and carbon taxes', *American Economic Review* **100**(2), 465–469.

Fischer, C. and Newell, R. G. (2008), 'Environmental and technology policies for climate mitigation', *Journal of environmental economics and management* **55**(2), 142–162.

Gerlagh, R. and Kuik, O. (2014), 'Spill or leak? carbon leakage with international technology spillovers: A cge analysis', *Energy Economics* **45**, 381–388.

Grether, J.-M., Mathys, N. A. and De Melo, J. (2012), 'Unravelling the worldwide pollution haven effect', *The Journal of International Trade & Economic Development* **21**(1), 131–162.

ICAP, C. (2022), 'Emissions trading worldwide: status report 2022'.

Koch, N. and Mama, H. B. (2019), 'Does the eu emissions trading system induce investment leakage? evidence from german multinational firms', *Energy Economics* **81**, 479–492.

Kranz (2022), 'Synthetic difference-in-differences with time-varying covariates', *GitHub* .

Levinson, A. and Taylor, M. S. (2008), 'Unmasking the pollution haven effect', *International economic review* **49**(1), 223–254.

Lin, W., Chen, J., Zheng, Y. and Dai, Y. (2019), 'Effects of the eu emission trading scheme on the international competitiveness of pulp-and-paper industry', *Forest Policy and Economics* **109**, 102021.

Martin, R., Muûls, M., De Preux, L. B. and Wagner, U. J. (2014), 'On the empirical content of carbon leakage criteria in the eu emissions trading scheme', *Ecological Economics* **105**, 78–88.

Naegele, H. and Zaklan, A. (2019), 'Does the eu ets cause carbon leakage in european manufacturing?', *Journal of Environmental Economics and Management* **93**, 125–147.

Porter, M. E. and Linde, C. v. d. (1995), 'Toward a new conception of the environment-competitiveness relationship', *Journal of economic perspectives* **9**(4), 97–118.

Qazi, A., Hussain, F., Rahim, N. A., Hardaker, G., Alghazzawi, D., Shaban, K. and Haruna, K. (2019), 'Towards sustainable energy: a systematic review of renewable energy sources, technologies, and public opinions', *IEEE access* **7**, 63837–63851.

Sartor, O. (2012), Carbon leakage in the primary aluminium sector: What evidence after 6 1/2 years of the eu ets?-working paper no. 2012-12, Technical report, CDC Climat.

Sartor, O. (2013), 'Carbon leakage in the primary aluminium sector: What evidence after 6.5 years of the eu ets?'.

Schmidt, R. C. and Heitzig, J. (2014), 'Carbon leakage: Grandfathering as an incentive device to avert firm relocation', *Journal of Environmental Economics and Management* **67**(2), 209–223.

Wang, M. and Kuusi, T. (2024), 'Trade flows, carbon leakage, and the eu emissions trading system', *Energy Economics* **134**, 107556.

Appendix A: Additional Tables

Table A.1: List of Countries Included in the Sample

EU ETS member	EU ETS member	non EU ETS member
Austria	Italy	Australia
Belgium	Latvia	Brazil
Bulgaria *	Lithuania	Canada
Czech Republic	Poland	China
Denmark	Portugal	India
Finland	Romania *	Indonesia
France	Slovakia	Russia
Germany	Spain	Mexico
Greece	Sweden	South Korea
Hungary	United Kingdom	Turkey
Ireland		USA

Note: * represents countries that joined the EU ETS in 2007, while other countries joined from the first date of the EU ETS implementation in 2005.

Table A.2: List of the EU ETS Targeted Sectors in This Study

Sector name	ISIC code Rev 4	ISIC code Rev 3	Number of Installations
Food, beverages, and tobacco	C10-C12	15	1193
Paper	C17	21	985
Chemicals	C20	24	541
Non-metallic mineral products (Cement, glass, and ceramic)	C23	26	2868
Metal	C24	27	373

Note: I considered manufacturing sectors that account for more than 1.5% of total installations, according to the EUTL database and EU ETS handbook, in addition to the Energy sector.

Table A.3: Summary Statistics

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
Scenario-Sector Specific Variables					
All					
$Mass_{ijt}$	5797	12.946	0.946	10.767	15.775
$Endow_{ijt}$	5797	1.201	0.926	0	4.551
Total Energy (d) ($\ln$)	5797	13.122	1.528	9.544	17.311
Total Energy (o) ($\ln$)	5797	14.568	1.051	12.819	17.311
Intermediate Input (d) ($\ln$)	5797	10.937	1.541	6.762	15.203
Intermediate Input (o) ($\ln$)	5797	12.085	1.008	10.305	15.203
Capital Formation (d) ($\ln$)	5797	3.172	0.248	0.146	3.843
Capital Formation (d) ($\ln$)	5797	3.243	0.246	2.697	3.843
Capital Compensation (d) ($\ln$)	5797	9.259	1.546	5.018	13.417
Capital Compensation (o) ($\ln$)	5797	10.579	1.013	8.973	13.417
Labor Compensation (d) ($\ln$)	5797	9.276	1.543	5.426	12.839
Labor Compensation (o) ($\ln$)	5797	10.26	0.995	8.635	12.839
$Mass_{ijt}$ *(stdd)*	5797	0	1	-2.304	2.991
$Endow_{ijt}$ *(stdd)*	5797	0	1	-1.297	3.616
Total Energy (d) (stdd)	5797	0	1	-0.429	8.461
Total Energy (o) (stdd)	5797	0	1	-0.626	5
Intermediate Input (d) (stdd)	5797	0	1	-0.471	11.149
Intermediate Input (o) (stdd)	5797	0	1	-0.564	6.707
Capital Formation (d) (stdd)	5797	0	1	-4.209	3.997
Capital Formation (d) (stdd)	5797	0	1	-1.678	2.926
Capital Compensation (d) (stdd)	5797	0	1	-0.448	8.943
Capital Compensation (o) (stdd)	5797	0	1	-0.596	5.289
Labor Compensation (d) (stdd)	5797	0	1	-0.557	6.462
Labor Compensation (o) (stdd)	5797	0	1	-0.603	4.026
importer technology scenario					
CL ($\ln$)	5797	4.196	2.856	-18.421	10.537
AdjCL (All Sources) ($\ln$)	5797	-0.966	2.27	-18.421	4.541
AdjCL (Pollutant Sources) ($\ln$)	5797	-0.471	2.293	-18.421	5.294
EL (All Sources) ($\ln$)	5797	6.768	2.973	-18.421	13.057
EL (Pollutant Sources) ($\ln$)	5797	6.273	2.95	-18.421	12.466
exporter technology scenario					
CL ($\ln$)	5797	6.104	3.314	-18.421	13.54

Table A.3 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
AdjCL (All Sources) (ln)	5797	-0.963	2.286	-18.421	4.695
AdjCL (Pollutant Sources) (ln)	5797	-0.44	2.315	-18.421	5.155
EL (All Sources) (ln)	5797	8.673	3.408	-18.421	15.708
EL (Pollutant Sources) (ln)	5797	8.15	3.381	-18.421	15.449
net values					
NetCL (stdd)	5797	0	1	-13.4	15.938
NetEL (All Sources) (stdd)	5797	0	1	-10.615	15.107
NetEL (Pollutant Sources) (stdd)	5797	0	1	-14.775	15.818
NetCL	5797	155.863	1954.483	-26000	31300
NetEL (All Sources)	5797	2565.596	24000	-252000	365000
NetEL (Pollutant Sources)	5797	1076.394	11900	-175000	189000
C10-C12					
$Mass_{ijt}$	5797	11.995	0.885	10.161	14.684
$Endow_{ijt}$	5797	1.184	0.933	0.001	4.509
Total Energy (d) (ln)	5797	11.166	1.455	8.332	14.46
Total Energy (o) (ln)	5797	12.608	1.062	10.94	14.46
Intermediate Input (d) (ln)	5797	10.089	1.457	6.179	13.928
Intermediate Input (o) (ln)	5797	11.172	0.919	9.779	13.928
Capital Formation (d) (ln)	5797	3.172	0.248	0.146	3.843
Capital Formation (d) (ln)	5797	3.243	0.246	2.697	3.843
Capital Compensation (d) (ln)	5797	8.288	1.481	4.405	12.369
Capital Compensation (o) (ln)	5797	9.536	1.055	7.939	12.369
Labor Compensation (d) (ln)	5797	8.326	1.433	4.962	11.716
Labor Compensation (o) (ln)	5797	9.214	0.931	7.607	11.716
$Mass_{ijt}$ *(stdd)*	5797	0	1	-2.074	3.039
$Endow_{ijt}$ *(stdd)*	5797	0	1	-1.268	3.563
Total Energy (d) (stdd)	5797	0	1	-0.575	4.869
Total Energy (o) (stdd)	5797	0	1	-0.921	2.885
Intermediate Input (d) (stdd)	5797	0	1	-0.549	9.409
Intermediate Input (o) (stdd)	5797	0	1	-0.607	5.774
Capital Formation (d) (stdd)	5797	0	1	-4.209	3.997
Capital Formation (d) (stdd)	5797	0	1	-1.678	2.926
Capital Compensation (d) (stdd)	5797	0	1	-0.474	9.221
Capital Compensation (o) (stdd)	5797	0	1	-0.625	5.515
Labor Compensation (d) (stdd)	5797	0	1	-0.611	6.724
Labor Compensation (o) (stdd)	5797	0	1	-0.637	4.332

Table A.3 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
importer technology scenario					
*CL (*ln*)*	5797	0.436	2.893	-18.421	7.034
*AdjCL (All Sources) (*ln*)*	5797	-3.648	2.721	-18.421	2.887
*AdjCL (Pollutant Sources) (*ln*)*	5797	-3.021	2.569	-18.421	3.132
*EL (All Sources) (*ln*)*	5797	3.702	3.036	-18.421	10.268
*EL (Pollutant Sources) (*ln*)*	5797	3.076	2.996	-18.421	9.813
exporter technology scenario					
*CL (*ln*)*	5797	2.108	3.447	-18.421	9.528
*AdjCL (All Sources) (*ln*)*	5797	-3.938	2.552	-18.421	2.966
*AdjCL (Pollutant Sources) (*ln*)*	5797	-2.985	2.534	-18.421	3.262
*EL (All Sources) (*ln*)*	5797	5.663	3.742	-18.421	12.165
*EL (Pollutant Sources) (*ln*)*	5797	4.711	3.543	-18.421	11.891
net values					
NetCL (stdd)	5797	0	1	-9.954	14.53
NetEL (All Sources) (stdd)	5797	0	1	-16.313	9.212
NetEL (Pollutant Sources) (stdd)	5797	0	1	-11.233	12.352
NetCL	5797	1.053	51.959	-516.164	755.999
NetEL (All Sources)	5797	226.460	1195.919	-19282.580	11242.880
NetEL (Pollutant Sources)	5797	16.910	634.177	-7106.829	7850.544
C17					
$Mass_{ijt}$	5797	10.399	1.008	8.18	13.092
$Endow_{ijt}$	5797	1.519	1.172	0	6.521
*Total Energy (d) (*ln*)*	5797	10.666	2.006	5.102	14.778
*Total Energy (o) (*ln*)*	5797	12.1	1.356	9.748	14.778
*Intermediate Input (d) (*ln*)*	5797	8.335	1.718	3.865	12.36
*Intermediate Input (o) (*ln*)*	5797	9.425	1.073	7.574	12.36
*Capital Formation (d) (*ln*)*	5797	3.172	0.248	0.146	3.843
*Capital Formation (d) (*ln*)*	5797	3.243	0.246	2.697	3.843
*Capital Compensation (d) (*ln*)*	5797	6.57	2.544	-18.421	11.178
*Capital Compensation (o) (*ln*)*	5797	7.912	1.062	6.115	11.178
*Labor Compensation (d) (*ln*)*	5797	6.876	1.762	2.138	11.505
*Labor Compensation (o) (*ln*)*	5797	7.875	1.176	5.924	11.505
$Mass_{ijt}$ *(stdd)*	5797	0	1	-2.201	2.673
$Endow_{ijt}$ *(stdd)*	5797	0	1	-1.295	4.267
Total Energy (d) (stdd)	5797	0	1	-0.477	6.194
Total Energy (o) (stdd)	5797	0	1	-0.681	3.587

Table A.3 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
Intermediate Input (d) (stdd)	5797	0	1	-0.487	8.004
Intermediate Input (o) (stdd)	5797	0	1	-0.556	4.76
Capital Formation (d) (stdd)	5797	0	1	-4.209	3.997
Capital Formation (d) (stdd)	5797	0	1	-1.678	2.926
Capital Compensation (d) (stdd)	5797	0	1	-0.426	10.716
Capital Compensation (o) (stdd)	5797	0	1	-0.513	6.36
Labor Compensation (d) (stdd)	5797	0	1	-0.401	10.567
Labor Compensation (o) (stdd)	5797	0	1	-0.439	6.434
importer technology scenario					
*CL (*ln*)*	5797	-0.968	4.407	-18.421	8.349
*AdjCL (All Sources) (*ln*)*	5797	-6.156	3.534	-19.111	0.517
*AdjCL (Pollutant Sources) (*ln*)*	5797	-5.175	3.593	-18.421	2.142
*EL (All Sources) (*ln*)*	5797	2.599	4.767	-18.421	12.156
*EL (Pollutant Sources) (*ln*)*	5797	1.618	4.658	-18.421	11.114
exporter technology scenario					
*CL (*ln*)*	5797	0.931	4.698	-18.421	9.418
*AdjCL (All Sources) (*ln*)*	5797	-6.157	3.429	-18.754	1.185
*AdjCL (Pollutant Sources) (*ln*)*	5797	-5.173	3.59	-18.421	2.343
*EL (All Sources) (*ln*)*	5797	4.499	5.136	-18.421	13.197
*EL (Pollutant Sources) (*ln*)*	5797	3.515	4.94	-18.421	12.147
net values					
NetCL (stdd)	5797	0	1	-8.793	31.087
NetEL (All Sources) (stdd)	5797	0	1	-8.143	26.401
NetEL (Pollutant Sources) (stdd)	5797	0	1	-9.773	34.427
NetCL	5797	1.630	100.795	-884.697	3135.002
NetEL (All Sources)	5797	898.978	13897.790	-112271.300	367820.200
NetEL (Pollutant Sources)	5797	70.093	1564.555	-15219.820	53932.750
C20					
$Mass_{ijt}$	5797	11.309	1.117	8.842	14.355
$Endow_{ijt}$	5797	1.318	0.948	0.001	5.049
*Total Energy (d) (*ln*)*	5797	11.435	1.703	6.478	15.842
*Total Energy (o) (*ln*)*	5797	12.853	1.275	10.811	15.842
*Intermediate Input (d) (*ln*)*	5797	9.085	1.839	3.212	13.745
*Intermediate Input (o) (*ln*)*	5797	10.402	1.201	8.395	13.745
*Capital Formation (d) (*ln*)*	5797	3.172	0.248	0.146	3.843
*Capital Formation (d) (*ln*)*	5797	3.243	0.246	2.697	3.843

Table A.3 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
Capital Compensation (d) (ln)	5797	7.502	1.906	1.274	12.124
Capital Compensation (o) (ln)	5797	8.917	1.305	6.534	12.124
Labor Compensation (d) (ln)	5797	7.355	1.775	2.437	11.108
Labor Compensation (o) (ln)	5797	8.46	1.128	6.723	11.108
$Mass_{ijt}$ *(stdd)*	5797	0	1	-2.208	2.727
$Endow_{ijt}$ *(stdd)*	5797	0	1	-1.39	3.937
Total Energy (d) (stdd)	5797	0	1	-0.403	7.837
Total Energy (o) (stdd)	5797	0	1	-0.602	4.563
Intermediate Input (d) (stdd)	5797	0	1	-0.437	11.169
Intermediate Input (o) (stdd)	5797	0	1	-0.552	6.697
Capital Formation (d) (stdd)	5797	0	1	-4.209	3.997
Capital Formation (d) (stdd)	5797	0	1	-1.678	2.926
Capital Compensation (d) (stdd)	5797	0	1	-0.38	7.78
Capital Compensation (o) (stdd)	5797	0	1	-0.537	4.492
Labor Compensation (d) (stdd)	5797	0	1	-0.506	5.328
Labor Compensation (o) (stdd)	5797	0	1	-0.567	3.277
importer technology scenario					
CL (ln)	5797	2.903	3.145	-18.421	9.975
AdjCL (All Sources) (ln)	5797	-2.392	2.478	-18.421	4.115
AdjCL (Pollutant Sources) (ln)	5797	-1.864	2.531	-18.421	4.603
EL (All Sources) (ln)	5797	5.655	3.198	-18.421	12.575
EL (Pollutant Sources) (ln)	5797	5.126	3.247	-18.421	12.195
exporter technology scenario					
CL (ln)	5797	4.772	3.632	-18.421	11.89
AdjCL (All Sources) (ln)	5797	-2.256	2.462	-18.421	4.072
AdjCL (Pollutant Sources) (ln)	5797	-1.879	2.529	-18.421	4.415
EL (All Sources) (ln)	5797	7.387	3.74	-18.421	14.325
EL (Pollutant Sources) (ln)	5797	7.01	3.67	-18.421	13.998
net values					
NetCL (stdd)	5797	0	1	-17.87	8.607
NetEL (All Sources) (stdd)	5797	0	1	-13.568	12.45
NetEL (Pollutant Sources) (stdd)	5797	0	1	-16.548	12.309
NetCL	5797	33.605	1017.566	-18150.680	8792.154
NetEL (All Sources)	5797	851.567	13786.630	-186206.800	172490
NetEL (Pollutant Sources)	5797	362.303	8689.878	-143440.200	107322.800
C23					

Table A.3 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
$Mass_{ijt}$	5797	10.448	1.022	7.631	13.603
$Endow_{ijt}$	5797	1.212	0.918	0	4.247
Total Energy (d) (ln)	5797	11.353	1.483	7.928	15.998
Total Energy (o) (ln)	5797	12.699	1.164	10.912	15.998
Intermediate Input (d) (ln)	5797	8.396	1.535	3.802	13.164
Intermediate Input (o) (ln)	5797	9.378	1.121	7.023	13.164
Capital Formation (d) (ln)	5797	3.172	0.248	0.146	3.843
Capital Formation (d) (ln)	5797	3.243	0.246	2.697	3.843
Capital Compensation (d) (ln)	5797	6.728	3.114	-18.421	11.569
Capital Compensation (o) (ln)	5797	8.222	1.052	6.233	11.569
Labor Compensation (d) (ln)	5797	7.263	1.537	2.703	11.323
Labor Compensation (o) (ln)	5797	8.103	1.095	5.797	11.323
$Mass_{ijt}$ *(stdd)*	5797	0	1	-2.757	3.087
$Endow_{ijt}$ *(stdd)*	5797	0	1	-1.32	3.306
Total Energy (d) (stdd)	5797	0	1	-0.32	8.744
Total Energy (o) (stdd)	5797	0	1	-0.464	5.006
Intermediate Input (d) (stdd)	5797	0	1	-0.355	12.979
Intermediate Input (o) (stdd)	5797	0	1	-0.421	7.577
Capital Formation (d) (stdd)	5797	0	1	-4.209	3.997
Capital Formation (d) (stdd)	5797	0	1	-1.678	2.926
Capital Compensation (d) (stdd)	5797	0	1	-0.387	11.845
Capital Compensation (o) (stdd)	5797	0	1	-0.498	6.95
Labor Compensation (d) (stdd)	5797	0	1	-0.527	10.428
Labor Compensation (o) (stdd)	5797	0	1	-0.57	6.459
importer technology scenario					
CL (ln)	5797	1.639	3.669	-18.421	8.932
AdjCL (All Sources) (ln)	5797	-4.101	3.112	-18.421	2.834
AdjCL (Pollutant Sources) (ln)	5797	-3.895	3.135	-18.421	3.199
EL (All Sources) (ln)	5797	3.598	3.833	-18.421	10.893
EL (Pollutant Sources) (ln)	5797	3.392	3.814	-18.421	10.757
exporter technology scenario					
CL (ln)	5797	3.678	4.484	-18.421	12.37
AdjCL (All Sources) (ln)	5797	-3.999	3.174	-18.421	2.587
AdjCL (Pollutant Sources) (ln)	5797	-3.787	3.174	-18.421	2.768
EL (All Sources) (ln)	5797	5.535	4.614	-18.421	14.138
EL (Pollutant Sources) (ln)	5797	5.323	4.621	-18.421	14.049

Table A.3 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
net values					
NetCL (stdd)	5797	0	1	-2.533	28.698
NetEL (All Sources) (stdd)	5797	0	1	-3.074	30.615
NetEL (Pollutant Sources) (stdd)	5797	0	1	-2.722	30.962
NetCL	5797	108.493	943.414	-2281.497	27182.410
NetEL (All Sources)	5797	533.266	4672.328	-13827.540	143575.500
NetEL (Pollutant Sources)	5797	492.095	4319.333	-11266.240	134229.200
C24					
$Mass_{ijt}$	5797	11.409	1.029	7.881	14.409
$Endow_{ijt}$	5797	1.361	1.019	0	5.73
Total Energy (d) (ln)	5797	11.668	2.016	4.648	16.42
Total Energy (o) (ln)	5797	13.387	1.129	11.162	16.42
Intermediate Input (d) (ln)	5797	9.179	1.893	2.694	14.059
Intermediate Input (o) (ln)	5797	10.562	1.15	7.431	14.059
Capital Formation (d) (ln)	5797	3.172	0.248	0.146	3.843
Capital Formation (d) (ln)	5797	3.243	0.246	2.697	3.843
Capital Compensation (d) (ln)	5797	6.73	3.727	-18.421	12.097
Capital Compensation (o) (ln)	5797	8.917	1.075	6.287	12.097
Labor Compensation (d) (ln)	5797	7.424	1.858	1.82	11.606
Labor Compensation (o) (ln)	5797	8.672	1.176	5.647	11.606
$Mass_{ijt}$ *(stdd)*	5797	0	1	-3.429	2.916
$Endow_{ijt}$ *(stdd)*	5797	0	1	-1.336	4.288
Total Energy (d) (stdd)	5797	0	1	-0.384	9.54
Total Energy (o) (stdd)	5797	0	1	-0.579	5.614
Intermediate Input (d) (stdd)	5797	0	1	-0.373	12.068
Intermediate Input (o) (stdd)	5797	0	1	-0.502	7.095
Capital Formation (d) (stdd)	5797	0	1	-4.209	3.997
Capital Formation (d) (stdd)	5797	0	1	-1.678	2.926
Capital Compensation (d) (stdd)	5797	0	1	-0.36	10.531
Capital Compensation (o) (stdd)	5797	0	1	-0.542	6.186
Labor Compensation (d) (stdd)	5797	0	1	-0.484	7.885
Labor Compensation (o) (stdd)	5797	0	1	-0.615	5.014
importer technology scenario					
CL (ln)	5797	1.901	5.127	-18.421	9.528
AdjCL (All Sources) (ln)	5797	-3.482	3.982	-18.421	3.526
AdjCL (Pollutant Sources) (ln)	5797	-3.07	4.036	-18.421	4.183

Table A.3 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
EL (All Sources) (ln)	5797	4.35	5.455	-18.421	11.869
EL (Pollutant Sources) (ln)	5797	3.938	5.419	-18.421	11.559
exporter technology scenario					
CL (ln)	5797	3.758	5.442	-18.421	12.923
AdjCL (All Sources) (ln)	5797	-3.433	3.981	-18.421	3.628
AdjCL (Pollutant Sources) (ln)	5797	-3.016	4.062	-18.421	4.115
EL (All Sources) (ln)	5797	6.158	5.805	-18.421	15.296
EL (Pollutant Sources) (ln)	5797	5.741	5.741	-18.421	14.984
net values					
NetCL (stdd)	5797	0	1	-3.519	26.139
NetEL (All Sources) (stdd)	5797	0	1	-4.789	26.657
NetEL (Pollutant Sources) (stdd)	5797	0	1	-5.696	25.971
NetCL	5797	164.319	976.785	-3272.556	25696.900
NetEL (All Sources)	5797	2037.443	12834.580	-59422.140	344171.300
NetEL (Pollutant Sources)	5797	934.609	6030.056	-33411.570	157541.500
Rest of the Variables					
Sim_{ijt} *(ln)*	5797	-0.64	0.562	-2.356	0
Foreign Direct (d) (ln)	5797	0.279	3.831	-18.421	3.92
Foreign Direct (o) (ln)	5797	0.015	3.436	-18.421	2.216
Trade Share (d) (ln)	5797	4.209	0.473	2.75	5.253
Trade Share (o) (ln)	5797	3.813	0.394	2.75	4.659
Global Index (d) (ln)	5797	4.181	0.244	3.047	4.509
Global Index (o) (ln)	5797	3.938	0.232	3.047	4.258
Human Capital (d) (ln)	5797	1.079	0.175	0.495	1.313
Human Capital (o) (ln)	5797	0.989	0.24	0.495	1.312
TFP (d)	5797	-0.301	0.315	-1.319	0.355
TFP (o)	5797	-0.474	0.394	-1.319	0.066
Distance	5797	8.876	0.658	6.368	9.789
Sim_{ijt} *(stdd)*	5797	0	1	-3.054	1.14
Foreign Direct (d) (stdd)	5797	0	1	-0.725	7.363
Foreign Direct (o) (stdd)	5797	0	1	-1.521	4.627
Trade Share (d) (stdd)	5797	0	1	-1.663	3.249
Trade Share (o) (stdd)	5797	0	1	-1.866	3.213
Global Index (d) (stdd)	5797	0	1	-3.234	1.657
Global Index (o) (stdd)	5797	0	1	-2.87	1.639

Table A.3 continued from previous page

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
Human Capital (d) (stdd)	5797	0	1	-2.803	1.534
Human Capital (o) (stdd)	5797	0	1	-1.741	1.465
TFP (d) (stdd)	5797	0	1	-2.351	3.031
TFP (o) (stdd)	5797	0	1	-1.67	1.656
Distance (stdd)	5797	0	1	-1.961	2.343
RTA	5797	0.223	0.416	0	1
comlang_off	5797	0.07	0.256	0	1
col45	5797	0.009	0.093	0	1
WTO (d)	5797	0.949	0.221	0	1
WTO (o)	5797	0.888	0.316	0	1
Land Border	5797	0.041	0.198	0	1
Sea Border	5797	0.018	0.131	0	1
Landlock	5797	0.129	0.335	0	1

Note: This table presents the summary statistics of all variables used in Specification 9. $\ln$ in parentheses indicates that the values are in logarithmic terms. For standardized values, stdd is used in parentheses. The unilateral variables for importer and exporter countries are also indicated in parentheses by "d" and "o", respectively. The dependent variables are categorized under three scenarios: the Importer Technology Scenario, the Exporter Technology Scenario, and Net Values, which correspond to the hypothetical, actual, and net global scenarios, respectively. Moreover, variables are provided in their original measurement units in addition to the standardized ones in the Net Values to calculate the estimated effects in those original units.

Table A.4: Variables and Their Data Sources

Variables	***Data Sources***
Sectoral CO_2 Emissions	World Input-Output Database (WIOD)
Sectoral Output	WIOD
Sectoral Energy Use (Total)	WIOD
Sectoral Energy Use (Pollutant)	WIOD
Sectoral Energy Use (Clean)	WIOD
Intermediate Inputs	WIOD
Capital Input	WIOD
Labor Compensation to Value Added	WIOD
Capital Compensation to Value Added	WIOD
Import Value	UNCTAD-COMTRADE
GDP PPP	World Development Indicators (WDI)
Industrial GVA	WDI
Services GVA	WDI
Coal Rent (% of GDP)	WDI
FDI (% of GDP)	WDI
Trade (% of GDP)	WDI
KOF Globalization Index	KOF Swiss Economic Institute
Human Capital Index	Penn World Table (PWT)
Total Factor Productivity	PWT
Population	PWT
Population-weighted Distance	CEPII Gravity Database
Colonial Relationship	CEPII Gravity Database
Common Official Language	CEPII Gravity Database
WTO	CEPII Gravity Database
Regional Trade Agreements	Mario Larchs Regional Trade Agreements Database
Customs Unions	Mario Larchs Regional Trade Agreements Database
Free Trade Agreements	Mario Larchs Regional Trade Agreements Database
Partial Scope Agreements	Mario Larchs Regional Trade Agreements Database
Economic Integration Agreements	Mario Larchs Regional Trade Agreements Database
Free-trade and Econ. Integ. Agre.	Mario Larchs Regional Trade Agreements Database
Carbon Intensity	Constructed by Author
Energy Intensity (Total)	Constructed by Author
Energy Intensity (Pollutant)	Constructed by Author
Carbon-to-Energy Ratio (Total)	Constructed by Author
Carbon-to-Energy Ratio (Pollutant)	Constructed by Author
Output Share	Constructed by Author

Table A.4 continued from previous page

Variables	***Data Sources***
Carbon Leakage	Constructed by Author
Adjusted Carbon Leakage (Pollutant)	Constructed by Author
Adjusted Carbon Leakage (Total)	Constructed by Author
Energy Leakage (Pollutant)	Constructed by Author
Energy Leakage (Total)	Constructed by Author
Net Carbon Leakage	Constructed by Author
Net Energy Leakage (Pollutant)	Constructed by Author
Net Energy Leakage (Total)	Constructed by Author
Similarity Index	Constructed by Author
Endowment of Domestic Assets	Constructed by Author
Mass Index	Constructed by Author
Land Border	Constructed by Author
Sea Border	Constructed by Author
Landlock	Constructed by Author

Note: This table demonstrates the variables used in this study along with their data sources.

Table A.5: Dependent Variables Constructed by the Author

Dependent Variable	Description	Formula
Carbon Leakage (based on actual import scenario)	Measures the carbon emissions embodied in imports from the exporting country (j) to the importing country (i) in the sector (s) at the time (t).	$\mathrm{CL}^s_{ijt} = \frac{\mathrm{C}^s_{jt}}{\mathrm{Q}^s_{jt}} \times \mathrm{M}^s_{ijt}$
Carbon Leakage (based on domestic production scenario)	Estimates the carbon emissions that would have been produced if the importing country had produced the goods domestically.	$\mathrm{CL}^s_{ijt} = \frac{\mathrm{C}^s_{it}}{\mathrm{Q}^s_{it}} \times \mathrm{M}^s_{ijt}$
Net Carbon Leakage	Represents the difference in carbon intensity between the exporter and importer, multiplied by the import volume, indicating the net impact of trade on emissions.	$\mathrm{NetCL}^s_{ijt} = \frac{\mathrm{C}^s_{jt}}{\mathrm{Q}^s_{jt}} - \frac{\mathrm{C}^s_{it}}{\mathrm{Q}^s_{it}} \times \mathrm{M}^s_{ijt}$
Adjusted Carbon Leakage by Energy (based on actual import scenario)	Adjusted carbon leakage by considering the energy efficiency of the exporting country.	$\mathrm{AdjCL}^s_{ijt} = \mathrm{CL}^s_{ijt} \times \frac{\mathrm{Q}^s_{jt}}{\mathrm{E}^s_{jt}}$
Adjusted Carbon Leakage by Energy (based on domestic production scenario)	Reflects the adjusted carbon leakage if the goods were produced domestically, accounting for the importers energy efficiency.	$\mathrm{AdjCL}^s_{ijt} = \mathrm{CL}^s_{ijt} \times \frac{\mathrm{Q}^s_{it}}{\mathrm{E}^s_{it}}$
Energy Leakage (based on the actual import scenario)	Measures the total energy embodied in imports from the exporter.	$\mathrm{EL}^s_{ijt} = \frac{\mathrm{E}^s_{jt}}{\mathrm{Q}^s_{jt}} \times \mathrm{M}^s_{ijt}$
Energy Leakage (based on the domestic production scenario)	Measures the energy that would have been embodied if the importer produced the goods domestically.	$\mathrm{EL}^s_{ijt} = \frac{\mathrm{E}^s_{it}}{\mathrm{Q}^s_{it}} \times \mathrm{M}^s_{ijt}$

Table A.5 continued from previous page

Dependent Variable	**Description**	**Formula**
Net Energy Leakage	Represents the difference in energy intensity between the exporter and importer, multiplied by the import volume, indicating the net impact of trade on energy use.	$\mathrm{NetEL}^s_{ijt} = \left(\frac{\mathrm{E}^s_{jt}}{\mathrm{Q}^s_{jt}} - \frac{\mathrm{E}^s_{it}}{\mathrm{Q}^s_{it}}\right) \times \mathrm{M}^s_{ijt}$

Note: This table presents all the dependent variables constructed by the author in this study, along with a brief description and the corresponding formula.

Appendix B: Synthetic Differece in Differences Optimization Procedure

In this part, I present the optimization procedure for time and unit weights for the SDiD approach.

Considering the following specification:

$$Y_{it} = \mu + \tau W_{it} + X'_{it}\beta + \alpha_i + \delta_t + \varepsilon_{it} \tag{B.1}$$

where Y_{it} represents the dependent variable for unit "i" at time "t". The treatment exposure is denoted by $W_{it} \in \{0, 1\}$, where $W_{it} = 1$ for the treated units post-intervention and $W_{it} = 0$ otherwise. The SDiD estimator, the variable of interest, is "τ", which is the causal impact of an intervention, such as the EU ETS policy. X_{it} is a vector of all potential covariates. Finally, δ_t and α_i are the time and unit fixed effects, respectively.

In the first step, following Kranz (2022), the outcome variable is regressed on all the variables in Equation B.1, except the treatment variable, in a fixed-effect regression as below:

$$Y_{it} = \mu + X'_{it}\beta + \alpha_i + \delta_t + e_{it} \tag{B.2}$$

Then the adjusted outcome variable is obtained as follows:

$$Y^{adj}_{it} = Y_{it} - X'_{it}\hat{\beta} \tag{B.3}$$

In the second step, following Arkhangelsky et al. (2021), the optimal weights ω_i and λ_t that balance pre-treatment outcomes and trends across treated and control units are calculated. This is done by minimizing the discrepancy between the weighted average of control outcomes and the simple average of the treated outcomes prior to treatment adoption through the following optimization procedures:

$$(\hat{\omega}_0, \hat{\omega}) = \arg\min \left\{ \sum_{t \leq T_{pre}} \left(\omega_0 + \sum_{i \leq N_c} \omega_i Y^{adj}_{it} - \bar{Y}^{adj}_{N_c+1:N_T} \right)^2 + \zeta^2 T_{pre} \|\omega\|_2^2 \right\} \tag{B.4}$$

subject to $\omega_0 \in \mathbf{R}_+$, $\omega_1, \ldots, \omega_{N_c} \geq 0$, and $\sum_{i \leq N_c} \omega_i = 1$.

$$\left(\hat{\lambda}_0, \hat{\lambda}\right) = \arg\min \left\{ \sum_{i \leq N_c} \left(\lambda_0 + \sum_{t \leq T_{pre}} \lambda_t Y^{adj}_{it} - \bar{Y}^{adj}_{i,T_{pre}+1:T} \right)^2 + \zeta^2 N_c \|\lambda\|^2 \right\} \tag{B.5}$$

subject to $\lambda_0 \in \mathbf{R}_+$, $\lambda_1, \ldots, \lambda_{T_{pre}} \geq 0$, and $\sum_{t \leq T_{pre}} \lambda_t = 1$.

In Equations B.4 and B.5, ζ is the regularization parameter calculated as follows:

$$\zeta = (N_{tr} T_{post})^{1/4} \hat{\sigma} \tag{B.6}$$

where:

$$\hat{\sigma}^2 = \frac{1}{N_c(T_{pre}-1)} \sum_{i \leq N_c} \sum_{t \leq T_{pre}-1} (\Delta_{it} - \bar{\Delta})^2 \tag{B.7}$$

and:

$$\Delta_{it} = Y_{i(t+1)} - Y_{it} \tag{B.8}$$

and:

$$\bar{\Delta} = \frac{1}{N_c(T_{pre}-1)} \sum_{i \leq N_c} \sum_{t \leq T_{pre}-1} \Delta_{it} \tag{B.9}$$

In addition, ω_i and λ_t are unit and time weights, respectively. N_c and N_T are the number of control and the total number of units, respectively, and T_{pre} is the pre-treatment period.

Next, with these weights, a weighted two-way fixed effects regression of Y_{it}^{adj} on W_{it} is conducted to estimate τ. The weights localize comparisons to more credible controls:

$$\left(\widehat{\mu}, \hat{\alpha}, \hat{\beta}, \hat{\tau}^{\text{sdid}}\right) = \arg\min_{\mu,\alpha,\beta,\tau} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it}^{adj} - \mu - \alpha_i - \delta_t - W_{it}\tau\right)^2 \hat{\omega}_i \hat{\lambda}_t \tag{B.10}$$

In other words, the SDiD estimator incorporates both unit and time fixed effects as well as weights. The time weights (λ_t) are chosen such that within a unit, the weighted average outcomes across the period are close to the target period. Overall, SDiD differs from the DiD by including unit and time weights and differs from the SCM by incorporating unit fixed effects as well as allowing for time weights.

Finally, the standard SDiD method assumes a single adoption date, with all treated units adopting the treatment simultaneously. However, SDiD can be adapted to scenarios where treated units adopt the treatment at different times in a staggered adoption design (Athey and Imbens (2022)). In cases of staggered adoption, the average treatment effect on the treated (ATT) can be estimated by repeatedly applying SDiD to subsets of the data, each corresponding to a different adoption date. Applying SDiD to each subset yields adoption-specific effect estimates $\hat{\tau}_a$. The ATT combines these as:

$$\hat{\tau}_{\text{ATT}} = \sum_{a} \frac{T_a}{T_{\text{post}}} \times \hat{\tau}_a \tag{B.11}$$

where T_a is the number of treated unit-periods for adoption date "a", and T_{post} is the total number of treated unit-periods. This averages treatment effects, weighting by the share of treated units in each adoption group.