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A Causal Analysis of the European Union Emissions Trading System

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To my wonderful wife, the true North Star of my journey! This achievement is as much yours as it is mine.

To my amazing parents, whose endless encouragement and sacrifices laid the foundation for everything I've achieved.

Declaration

I, Hamid Nejadghorban, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I have indicated this within the thesis. Chapters 1 and 4 of this thesis are sole-authored. Chapters 2 and 3 are joint work with Arsham Reisinezhad (University of Essex). I further declare that this thesis has been conducted in accordance with the University's regulations and has not been previously submitted for any other academic qualifications.

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This achievement would not have been possible without each of you.

Abstract

This research examines the EU Emissions Trading System (EU ETS), a key policy aimed at reducing greenhouse gas emissions, revealing its complex effects across sectors and national borders. While prior studies have documented emission reductions, they often leave unanswered questions regarding underlying mechanisms, sustainability of improvements, structural shifts in production, global supply chain adjustments, technological disparities, and evolving carbon and energy flows in international trade. Using robust quasi-experimental methods, including a staggered synthetic difference-in-differences approach, this study demonstrates that EU ETS not only reduces emissions but also promotes increased energy efficiency and the adoption of cleaner technologies within regulated countries. The long-term reduction in carbon intensity appears closely tied to enhanced pollutant energy efficiency. Beyond the EU, this research uncovers how unilateral carbon pricing interacts with global supply chains, indicating that EU ETS can reshape international trade dynamics. The findings suggest that this policy often provides competitive advantages to non-regulated exporters while exacerbating technological gaps related to carbon emissions and energy use. This dual impact underscores the challenges associated with implementing unilateral climate policies within a globally interconnected economy. Moreover, while previous empirical studies have struggled to identify clear evidence of carbon leakage resulting from EU ETS, this study suggests that the scheme may indeed shift emissions-intensive activities to countries with weaker environmental regulations. By integrating sector-level and cross-country trade data, the thesis reveals how unilateral measures can influence comparative advantages, production patterns, global net carbon emissions, and energy consumption. To address these unintended consequences, policymakers should pursue enhanced international coordination, promote domestic investments in clean technologies, and facilitate their broader adoption internationally. Such strategies will enable EU ETS to more effectively contribute to global emissions reductions. Additionally, the study identifies heterogeneous responses across different sectors, highlighting the necessity of more targeted and sector-specific policy measures.

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CHAPTER 1

Thesis Introduction

The unchecked accumulation of greenhouse gas (GHG) emissions represents a significant instance of global market failure. These emissions are by-products of essential economic activities; however, their associated costs, particularly those related to climate change, are not fully accounted for in economic decision-making processes. Market-based regulations are among the most effective mechanisms for mitigating emissions at minimal societal cost. By placing a price on emissions, such regulations discourage the production of emissions-intensive goods and incentivize investments in technologies that reduce abatement costs. Nevertheless, the absence of a global emissions market, combined with the increasing integration of trade and capital flows, raises concerns about the potential impacts of asymmetrical regulations on environmental effectiveness.

The EU Emissions Trading System (EU ETS), established in 2005, is the world's first and largest market-based climate policy. It has served as the cornerstone of Europe's policy framework for achieving its ambitious GHG reduction targets under the 2030 climate and energy framework. Currently, all EU member states, along with Iceland, Liechtenstein, and Norway—members of the European Economic Area (EEA)—participate in the EU ETS. The system operates on the principle of *cap and trade*. Under the *cap*, the European Commission (EC) sets an EU-wide limit on greenhouse gas (GHG) emissions, which is progressively reduced over time. This cap determines the total number of EU Emission Allowances (EUAs) issued, each granting the holder the right to emit one ton of CO_2 or an equivalent amount of another GHG.

The EC systematically lowers the total number of EUAs available in the market to reduce the EU ETS cap. Firms regulated under the EU ETS must cover their emissions with an adequate number of allowances; failure to do so results in substantial fines for each ton of CO_2 emissions not covered. The second component of the system, *trade*, allows firms with insufficient allowances to purchase additional EUAs on a shared market, thereby avoiding non-compliance penalties. This market-based regulation provides firms with the flexibility to determine their preferred methods of compliance.

1.1 Literature Review

The EU ETS can affect carbon-related metrics in two key ways. First, it directly reduces carbon emissions in participating countries by encouraging cleaner and more efficient production processes through technological advancements in carbon mitigation. Second, the policy can alter trade patterns between participating and non-participating countries, potentially outsourcing carbon emissions abroad (i.e., carbon leakage). The first mechanism aligns with the Porter hypothesis, while the second reflects the pollution haven hypothesis.

1.1.1 Direct Effects and the Porter Hypothesis

[86] anticipated that unilateral environmental policies, such as the EU ETS, could reduce carbon emissions at a reasonable cost by fostering the development of new low-carbon technologies. When regulated firms expect to pay a greater price for emissions relative to other production expenses, they are incentivized to make investments and operational changes that reduce the emissions intensity of their output. The development and commercialization of new emissions-reducing technologies will benefit from this increased investment. While lowering emissions is undoubtedly the primary goal of carbon market programs, it is also economically critical to offer incentives for technological advancement, as new technologies have the potential to significantly lower long-term abatement costs. From this perspective, it is expected that the carbon intensity of participating countries will decline.

A substantial body of previous studies has investigated the direct impact of the EU ETS on pollution. Early research utilized aggregated data to assess the policy's impact. [78] offered a comprehensive summary of the existing empirical evidence on the EU ETS, including its effects on emissions and firms' performance. Several studies, such as [30] and [6], have reported reductions in emissions ranging from 2% to 5% during Phase I and/or II. Utilizing a unique dataset of sectoral emissions, [19] estimated counterfactual carbon emissions and determined that the EU ETS resulted in a reduction of approximately 1.2 billion tons of CO_2 between 2008 and 2016, or roughly 3.8% relative to total emissions over these years, compared to a scenario where carbon markets did not exist.

Recent research utilizing Difference in Differences (DiD) designs has primarily focused on assessing the impacts of the EU ETS on individual firms. For instance, [85] analyzed data for German manufacturing firms and found evidence of emissions reductions of 20% during the second phase. [66] evaluated the environmental and economic performance of Lithuanian firms under the EU ETS and found no emissions reductions but a slight improvement in emissions intensity. Similarly, [69] examined the same question for Norwegian firms (plants). While their results suggest weak evidence of emissions reductions among plants during the second phase of the ETS, no significant effects were observed in the other two phases. Additionally, they found no significant effects on emissions intensity during any of the phases. Recently, [37] employed firm-level data for France to estimate the effects of the first two phases of the ETS. Their findings indicate significant emissions reductions of approximately 8–12% in ETS-regulated manufacturing firms compared to a control group of similar but unregulated firms. Lastly, [42] analyzed firm-level data for France, the Netherlands, Norway, and the UK, finding significant emission reductions of around 10% between 2005 and 2012.

A growing body of literature has examined the extent to which the EU ETS has succeeded in stimulating low-carbon development and technological innovation. Using a DiD approach, [33] documented that the EU ETS increased low-carbon patenting by only 2%, suggesting a minimal overall impact on green technological change. Analyzing Swedish companies, [75] found no statistically significant relationship between EU ETS participation and low-carbon technology investments from 2000 to 2008. In contrast, [77], who interviewed approximately 800 manufacturing firms (450 of which were regulated by the EU ETS), reported that anticipated future EU ETS stringency positively influenced innovation.

Furthermore, [68] demonstrated that market-based regulations under the EU ETS encouraged cost-effective renewable energy technologies (e.g., wind rather than solar power), highlighting the role of environmental policies in guiding innovation. Similarly, [5] noted that EU ETS-regulated companies in Ireland adopted new machinery, equipment, and process enhancements, indicating moderate encouragement of technological progress. In Germany's energy sector, [88] observed positive effects on research and development (R&D) for carbon capture systems, though the free allocation of credits was identified as a hindrance to innovation.

In contrast, several studies suggest that the EU ETS has had only a limited impact on innovation. [23] attributed low levels of environmental innovation among Italian businesses to policy volatility. [3] argued that innovation was insufficiently stimulated in the early years of the EU ETS due to low carbon prices and unstable policies.

1.1.2 Indirect Effects and the Pollution Haven Hypothesis

The pollution haven hypothesis predicts that strict environmental policies will ultimately shift pollution-intensive production to regions with lower environmental abatement costs (e.g., [73]). A unilateral environmental policy, such as the EU ETS, raises production costs for domestic firms competing globally with producers from regions with less stringent environmental regulations. As a result, producers may be compelled to mitigate commercial losses by adjusting their pricing strategies, altering market shares, or relocating polluting production facilities to regions with more lenient or no regulations. Consequently, this can reshape the spatial distribution of the industrial value-added chain and influence trade flows. This perspective in the environmental economics literature suggests a potential increase in carbon-relevant metrics in exporting countries not participating in the EU ETS scheme.

Aligned with the pollution haven hypothesis, a body of literature has investigated whether environmental stringency affects trade flows. These studies often use proxies for environmental regulation levels. For example, using U.S. manufacturing industry data from 1978 to 1992, [47] treated pollution abatement and control expenditures (PACE) as an endogenous measure of environmental regulation and found that net imports rose as PACE increased. Similarly, [73], using a fixed-effects model on panel data from 1977 to 1986, documented that a one percent increase in PACE in the United States was associated with a 0.4 percent rise in net imports from Mexico and a 0.6 percent increase from Canada.

As an alternative proxy for environmental regulations, [31] employed the Index of Environmental Stringency Policy (IESP) to analyze changes in trade flows. Their results indicated that higher environmental stringency increases production costs for environmentally sensitive commodities, thereby reducing export values. Examining firm-level data from 2002 to 2009, [93] analyzed how varying environmental regulation stringency across Chinese provinces affected export performance. Using the ventilation coefficient as an instrumental variable for pollution reduction targets, they found that stricter environmental regulations significantly reduced both the probability of exporting and the export volume.[1] Recognizing that rising energy prices influence carbon prices, [91] leveraged cross-country energy price gaps to identify the impact of carbon price differences on trade patterns. Using bilateral trade flows for 42 countries and 62 manufacturing sectors between 1996 and 2011, they found that a 10 percent increase in the energy price gap led to a 0.2 percent increase in bilateral imports.

Another strand of the literature focuses on the impact of global and regional environmental programs on trade flows. [38] applied a sector-level gravity model to analyze manufacturing exports from 15 EU countries to 145 importing partners between 1996 and 2007. Using a binary variable for 2005–2007 to capture the EU ETS period, they concluded that the scheme led to increased exports from medium–low technology sectors targeted by the EU ETS. Similarly, [100], examining the impact of the EU ETS on German manufacturing firms using firm-level panel data (1995–2010) and a DiD approach, found a positive effect on exports during the first three years of Phase II (2008–2010), although this effect became statistically insignificant thereafter.

Several studies have also analyzed this nexus by focusing on the concept of carbon leakage, measured through changes in trade flows as they reflect both market share losses and the relocation of production. A substantial body of literature, primarily utilizing ex-ante computable general equilibrium (CGE) models, has sought to estimate the extent of carbon leakage resulting from existing climate policies (e.g., [26]; [55]; [34]). Additionally, a separate strand of research

[1] They employed a triple-difference (DDD) approach accounting for time variation, differences in provincial policy enforcement, and industry-specific pollution intensity.

has focused on examining the pollution haven effect in the United States. These studies typically explore the relationship between net trade flows and the stringency of environmental regulations, often measured by Pollution Abatement Costs (PAC) using survey data from U.S. manufacturers (e.g., [47]; [73]). However, such approaches frequently rely on theoretical frameworks and may not fully account for real-world complexities.

An ex post study by [4] analyzed bilateral trade flows for 37 countries and 47 industries between 1995 and 2007, finding that Kyoto commitments resulted in approximately 8% higher imports for participating countries from non-Kyoto countries. Several ex ante studies have also investigated carbon leakage, reporting a wide range of leakage rates depending on the modeling approaches and underlying assumptions (e.g., [26], [55], [34]).

In the context of the EU ETS, [29] found that concerns about pollution offshoring in the EU were unfounded, as the relationship between EU manufacturing and imports was opposite to what would be expected if pollution were being offshored. [83] utilized global trade data for 66 source regions in 2004, 2007, and 2011, covering eight sectors regulated by the EU ETS and 17 non-regulated sectors. Following [4] and employing a DiD approach within a gravity model, they found no significant effects of the EU ETS on trade flows and carbon leakage during this period. Similarly, [105], using an extended dataset for five EU ETS-targeted sectors and nine non-targeted sectors across 60 countries from 2000 to 2018, reported statistically significant and robust reductions in carbon intensity and carbon content for ETS countries. Notably, they found a symmetrical 6% decrease in export values and an increase in import values. [41] observed that under the EU ETS, multinational enterprises (MNEs) facing compliance costs that cannot be easily transferred along the value chain are more inclined to shift their international investments to pollution havens outside the EU.

Finally, several sector-specific studies have also been conducted. For instance, [90] examined the aluminum sector, [28] focused on cement and steel, and [74] investigated pulp and paper. These studies generally found limited evidence of the EU ETS exerting a significant influence on trade flows within these specific sectors.

1.2 Study Overview

Although numerous studies have identified modest yet significant emission reductions linked to the EU ETS policy, there are still considerable uncertainties about the actual magnitude and the processes driving these decreases. The existing research does not clearly explain how the policy fosters more substantial structural changes, such as variations in energy intensity, the adoption of low-carbon technologies, and the long-term sustainability of these improvements. To address this gap, in Chapter 2, I investigated the extent to which the EU ETS has lowered carbon emissions and carbon intensity across participating countries and sectors, as well as the mechanisms behind these reductions. Specifically, I examined whether decreases in carbon intensity result from enhanced energy efficiency or the adoption of cleaner energy sources. A major contribution of this study is its focus on analyzing changes in carbon and energy intensity rather than just counting emissions, providing a deeper understanding of the decarbonization process. By integrating Index Decomposition Analysis (IDA) with a novel quasi-experimental method—the staggered design of Synthetic Difference in Differences (SDiD)—this research identifies the pathways through which the EU ETS contributes to reducing carbon intensity, particularly by improving energy intensity and encouraging sector-specific adoption of cleaner production techniques.

Furthermore, I explore whether the observed emission reductions and declines in carbon intensity have been sustained over time and determine if these advancements reflect enduring structural changes or if they are sensitive to economic fluctuations, policy instability, and changes in carbon prices. I stress the importance of understanding how the design, stability, and credibility of policies impact not only immediate emissions reductions but also long-term structural transformations in production processes and global value chains. This research uniquely contributes by specifically analyzing the decomposed carbon intensity of sectors targeted by the EU ETS, providing a more detailed and sector-specific investigation of the factors driving changes in carbon intensity as a result of the EU ETS. The decomposition analysis shows that the reduction in carbon intensity is sustainable and mainly driven by improvements in energy intensity, particularly pollutant energy intensity.

A pivotal gap in existing research pertains to the understanding of the EU ETS policy and its influence on global trade patterns and carbon leakage. The pollution haven hypothesis suggests that stringent environmental regulations may drive emissions-intensive industries to relocate to countries with more lenient standards. Although some studies have attempted to identify such leakage or shifts in trade flows using Computable General Equilibrium (CGE) models or bilateral trade data, their conclusions remain inconclusive. Empirical ex-post analyses have not found substantial evidence of significant carbon leakage associated with the EU ETS, and only a few investigations have addressed the related concept of energy embodied in imports. Furthermore, recent attempts to determine the causal effects of the EU ETS on imports and exports through quasi-experimental methods and gravity models have yielded mixed results. While certain studies report an increase in imports of emissions-intensive goods, others observe no notable changes in trade patterns. Additionally, there is an insufficient understanding of how unilateral carbon pricing interacts with increasingly integrated global supply chains and the potential technological disparities it may create between regulated and unregulated trading partners. This represents another significant gap in the literature.

In Chapters 3 and 4 of this study, I examine the impact of the EU ETS on global trade flows. Specifically, in Chapter 3, I investigate whether unilateral carbon pricing fosters technological gaps related to carbon emissions and energy use between regulated countries and their unregulated trading partners, thereby shaping international comparative advantages and potentially shifting emissions-intensive production abroad. Moreover, I explore whether the EU ETS exacerbates or mitigates disparities in carbon and energy intensities across different countries. Furthermore, by integrating bilateral import data with metrics on carbon and energy intensity, this study clarifies how the EU ETS affects technological disparities between regulated countries and their unregulated trade partners. I defined relative technological gap indicators as follows: (1) relative carbon intensity (the ratio of carbon intensity in the destination country to that of the exporter country); (2) relative energy intensity; and (3) relative carbon-to-energy ratio. The findings indicate that while the EU ETS promotes technological advancements within regulated sectors, it may also widen technological gaps by shifting carbon-intensive production to regions with less stringent regulations.

On the other hand, in Chapter 4, I examine this effect on carbon and energy flows associated with international trade. This research contributes new evidence to the debates on carbon and energy flows associated with international trade by providing both aggregate and sector-specific evaluations. Unlike earlier studies that identified negligible effects, some of my findings suggest that unilateral policies like the EU ETS can alter trade flows and shift emissions-intensive production to other regions, thereby questioning the global environmental efficacy of the EU ETS. This nuanced perspective helps elucidate the conditions under which carbon leakage might occur and underscores the importance of complementary policy measures. In addition to conventional concerns of carbon leakage and energy embodied in imports, I developed a hypothetical "what if" scenario to demonstrate how emissions and energy usage would have differed if exporting countries without regulations had production technologies similar to those of importing countries. By comparing this hypothetical scenario with actual carbon emissions and energy use in unregulated exporters, I show that the policy has led to an increase in global net carbon emissions and net energy use associated with international trade.

Moreover, much of the existing research on the EU ETS policy assesses its impacts either at a broad, aggregate level or focuses narrowly on individual countries at the firm level, which limits the ability to generalize the findings. These studies often overlook the varying responses across different sectors and the diverse effects that policies can have depending on industrial structures. Furthermore, only a few investigations have simultaneously analyzed multiple countries and sectors to determine whether the observed outcomes—such as changes in emissions, production technologies, and trade flows—are widely applicable. Consequently, the literature lacks a detailed, cross-country, and sector-specific understanding of how the EU ETS operates and what results it produces. In this study, I examine which sectors are most responsive to EU ETS regulations in terms of reducing emissions, improving carbon intensity, or altering trade patterns, and explore the implications of these variations for policy design and global climate cooperation. By analyzing a diverse range of sectors and numerous countries, including both those regulated and unregulated by the EU ETS, this research highlights the heterogeneous impacts of the policy. The findings indicate that sectors do not uniformly benefit from cleaner technologies or experience the same trade adjustments. This granular approach allows for more precise policy recommendations, ensuring that the EU ETS remains both environmentally effective and economically sustainable.

The main policy implication of this study is that, while the EU ETS is effective in decreasing emissions and improving carbon intensity and its underlying drivers inside the EU, policymakers should improve its architecture and add supplementary measures to ensure global effectiveness and long-term sustainability. Given the varied responses across different sectors, the implementation of sector-specific benchmarks, allocation of innovation funds, and provision of training programs can aid lagging industries in enhancing their technological capabilities and accelerating the adoption of cleaner production methods. These customized policy tools are essential to guarantee that all industries make progress toward emissions reductions, preventing any sector from being left behind.

Furthermore, sustaining a stable and reliable carbon pricing regime is essential to promoting sustained investments in low-carbon technology. But carbon pricing alone might not be enough to guarantee long-term, sustainable decreases in emissions intensity. It is crucial to combine the EU ETS with other policy instruments, such as targeted R&D grants, low-interest loans for energy-efficient equipment, and incentives for the use of renewable energy sources, in order to increase its efficacy. This combination has the potential to increase the momentum created by the EU ETS and ensure emissions reductions come from long-term structural modifications rather than short-term price signal adjustments.

Addressing potential carbon leakage and the widening of technological disparities requires enhanced international cooperation. Policymakers should explore the adoption of policy tools like border carbon adjustments, bilateral technology transfer agreements, and multilateral climate partnerships to prevent the relocation of emissions-intensive production to regions with less stringent regulations and to improve global energy efficiency. Ensuring that major trading partners implement compatible or complementary environmental policies is vital for maintaining a level playing field and enhancing overall climate outcomes.

CHAPTER 2

On Carbon Emissions, Carbon Intensity, and Its Driving Factors

Emission Reductions, Energy Efficiency, and Beyond: The EU Emissions Trading System and the Path to Sustainable Emission Reductions

Abstract

The uncontrolled accumulation of greenhouse gas (GHG) emissions poses a critical global challenge, stimulating policymakers to seek effective mitigation strategies. The European Union Emissions Trading System (EU ETS) has been a central policy instrument aimed at reducing carbon emissions since 2005. While previous research has mostly focused on single-country or firm-level analyses, questions remain regarding the program's broader cross-country effectiveness, its impact on carbon intensity, and the sustainability of observed reductions. This study uses sector-level data from 32 countries between 1996 and 2012, examining seven EU ETS-targeted sectors. Employing a staggered Synthetic Difference-in-Differences (SDiD) approach, we provide robust causal evidence that the EU ETS reduced aggregated CO_2 emissions by roughly 19%. More importantly, by applying Index Decomposition Analysis (IDA), we assess the policy's effect on carbon intensity and its underlying drivers, and investigate the sustainability of these effects. Our combined use of SDiD and IDA reveals a significant decline in carbon intensity, primarily driven by improvements in energy intensity. Our results also highlight sectoral heterogeneity: while some industries exhibit structural efficiency gains, few lag behind. These findings underscore the EU ETS's scalable efficacy and the need for tailored, sector-specific policy measures.

Keywords: EU ETS, Carbon Intensity, CO_2 Emissions, Sustainability, Index Decomposition Analysis, Synthetic Difference in Differences

JEL Classification: L50, Q54, Q58

2.1 Introduction

The uncontrolled accumulation of greenhouse gas (GHG) emissions is a prime illustration of global market failure. Although GHG emissions arise from economically valuable activities, their unchecked buildup has led to significant environmental issues, including glacier melting, rising sea levels, and ecological imbalances. In recent years, the gravity of these problems has spurred greater global focus on monitoring and mitigating GHG emissions, as well as fostering low-carbon economies. For the past two decades, the European Union (EU) has played a leading role in the global effort to decrease GHG emissions. Since its inception in 2005, the EU Emissions Trading System (EU ETS) has been the cornerstone of the EU's decarbonization strategy and remains the flagship of its environmental policy. Under this program, more than 12,000 power stations and industrial plants in 31 countries receive tradable emissions permits, collectively accounting for over 45% of EU emissions and 5% of global emissions ([37]).[1]

Whether a cap-and-trade scheme effectively safeguards the environment remains a pivotal question for policymakers. Although regulated installations saw a 17% reduction in emissions between 2005 and 2012, it's unclear how much of this decrease can be attributed to the EU ETS itself ([42]). Several factors contribute to this uncertainty. Firstly, the low carbon prices on the EU ETS market have raised concerns about the policy's effectiveness in reducing emissions ([78]).[2] Secondly, the 2008 economic crisis, rising fossil fuel prices, and business-as-usual industrial trends may have influenced emission trends. Thirdly, the potential for carbon leakage and output reduction in targeted sectors may contribute to a reduction in carbon emissions. Fourthly, less attention has been paid to presenting evidence concerning the reduction in carbon intensity and the underlying mechanisms driving these reductions. Finally, the limitations of the quasi-experimental approaches employed in the literature, such as challenges in satisfying parallel trend assumptions, could impact the reliability of the results. Nevertheless, even with confirming the evidence of reduced carbon emissions and carbon intensity obtained through the applied causal methods, the sustainability of these abatements' effects remains an overlooked

[1] [49] is widely recognized as the foremost authoritative reference on the EU ETS. It provides a detailed exploration of the ETS design, offering an intricate examination and a comprehensive analysis of its functioning.

[2] The permit price during the first trading phase (2005-2007) initially rose to $37 but then dropped to below $1 in early 2007. In the second trading phase (2008–2012), permit prices rebounded to around $21.35.

empirical question. Consequently, this paper has two primary objectives: first, to examine the impact of the EU ETS on carbon emissions and carbon intensity, including their underlying factors; and second, to investigate the role of the EU ETS in promoting a sustainable reduction in carbon intensity.

[78] and [98] offer a comprehensive summary of the existing empirical evidence on the EU ETS, including its effects on emissions and firms' performance. A number of studies, such as [30], and [6], have reported reductions in emissions ranging from 2–5% during Phase I and/or II. Utilizing a unique dataset of sectoral emissions, [19] estimate counterfactual carbon emissions and determine that the EU ETS resulted in a reduction of approximately 1.2 billion tons of CO_2 between 2008 and 2016, or roughly 3.8% relative to total emissions over these years, compared to a scenario where carbon markets did not exist.

Recent research utilizing the Difference in Differences (DiD) method has primarily focused on assessing the impacts of the EU ETS on individual firms. For instance, [85] analyzed data for German manufacturing firms and found evidence of emissions reductions of 20% during the second phase. Using firm-level data, [101] suggested that ETS-regulated manufacturing firms in France achieved an average reduction of 15–20% in emissions. [66] evaluated the environmental and economic performance of Lithuanian firms under the EU ETS and found no emissions reductions. Similarly, [69] examined the same question for Norwegian firms (plants), and while their results suggest weak evidence of emissions reductions among plants during the second phase of the ETS, there were no significant effects observed in the other two phases. Additionally, they found no significant effects on emissions intensity during any of the phases. Recently, [37] employed firm-level data for France to estimate the effects of the first two phases of the ETS. Their findings indicate significant emissions reductions of approximately 8–12% in ETS-regulated manufacturing firms compared to a control group of similar but unregulated firms. Last but not least, [42] analyzed firm-level data for France, the Netherlands, Norway, and the UK, and found significant emission reductions of around 10% between 2005 and 2012.

In this paper, we used data from the World Input-Output Database (WIOD) on seven EU ETS-targeted sectors in 32 countries, covering the period from 1996 to 2012. While standard Difference in Differences (DiD) approaches have enriched our understanding of policy impacts (for example, [85]; [101] [66]; [42]), concerns about parallel trends and unobserved heterogeneity are often valid, especially in cross-country panel analyses. By employing the staggered design of the SDiD method ([16], [17]), we reduce dependence on these assumptions and offer a more reliable causal inference strategy that accounts for individual fixed effects, time-varying covariates, and heterogeneous pre-treatment trends. Using this novel quasi-experimental approach, for the first time in the literature to the best of our knowledge, which combines the advantages of DiD and the Synthetic Control Method (SCM), enhances the credibility and robustness of our findings.

The core contribution of this study lies in establishing that the EU ETS not only reduces carbon emissions but does so across a diverse set of countries and sectors. The literature often focused on individual countries or firm-level data (for example, [85]; [66]; [69]; [37]), limiting the capacity to generalize policy effectiveness across broader or more heterogeneous contexts. By examining a panel of 32 countries, including 21 EU ETS-regulated and 11 unregulated countries, and seven targeted sectors spanning the 1996–2012 period, we cover the first two phases of the policy and reveal that the EU ETS regulations led to a statistically significant 19% reduction in CO_2 emissions for these seven targeted sectors aggregated at the country level. This multi-country, sector-level perspective fills an important gap in the existing literature and illustrates that the program's influence is not confined to specific economic environments. From a policy standpoint, this evidence strongly suggests that emissions trading can serve as a globally relevant model for climate policy. Policymakers in regions currently debating the implementation of carbon pricing mechanisms can draw on these results to justify more robust and expansive emission trading frameworks. By demonstrating the EU ETS's scalable efficacy, our findings support efforts to encourage other major economies to adopt similar cap-and-trade systems, potentially fostering a more cohesive global response to climate change.

Furthermore, research on the EU ETS is vital for evaluating its effectiveness in reducing local emissions considering the change in outputs of regulated sectors. However, previous studies have often lacked compelling evidence regarding the reduction in carbon intensity and the mechanisms driving such reductions (for instance, [66]; [32]). To address this gap, it is crucial to provide evidence of changes in carbon intensity. This helps to prevent the misattribution of local reductions to global carbon intensity changes or production variations (such as recessions).

In this study, we went beyond carbon emissions reduction. Our research significantly advances understanding by emphasizing changes in carbon intensity–and crucially, its underlying drivers behind those changes–rather than focusing solely on emission levels. To the best of our knowledge, this paper represents the first comprehensive empirical assessment of the EU ETS's impact on carbon intensity and its underlying factors. While numerous studies document the presence or absence of emission reductions ([85]; [66]; [69]; [37]), fewer investigate whether these improvements stem from deeper structural shifts.

There is extensive literature on decomposition analysis for energy intensity ([76]; [81]; [99]; [67]; [40]), carbon emissions ([84]; [106]; [8]; [35]), and carbon intensity ([106]; [102]; [104]). However, the majority of studies have focused on analyzing changes in environmental indicators and their drivers at the country level across all sectors.

Our paper offers a unique contribution by specifically examining the decomposed carbon intensity of sectors targeted by the EU ETS. This provides a more detailed and sector-specific analysis of the factors influencing changes in carbon intensity as a result of the EU ETS. Our decomposition analysis reveals that the decline in carbon intensity is largely channeled through enhancements in energy intensity, particularly pollutant energy intensity. This represents a meaningful departure from previous work that often lacked evidence on how carbon intensity pathways emerge. Based on the findings of this study, carbon pricing alone can only secure long-term sustainability through improvements in pollutant energy intensity. Complementary policies—such as tax credits for high-efficiency equipment, low-interest loans for energy-saving retrofits, and targeted R&D funding—could reinforce the momentum created by carbon pricing, ensuring that emission reductions will be a more sustainable process.

The sector-specific analysis of this study offers a more granular view of the EU ETS's impact. Prior research frequently treats the economy as a whole, obscuring the substantial heterogeneity in how this policy affects different industries. Our analysis shows that sectors like Chemicals (C20), Non-Metallic Mineral Products (C23), Basic Metal (C24), and Energy (D35) experienced notable reductions in carbon intensity, indicating that in these domains, the EU ETS fosters genuine structural improvements. In contrast, sectors such as Paper and Paper Products (C17) exhibited weaker or even counterintuitive responses, underscoring the need for more finely tuned policy approaches. Our findings suggest that policymakers should not rely solely on uniform, economy-wide regulations, and strategic sector-specific design seems to be necessary. For instance, industries lagging in improvement might benefit from stricter emission benchmarks aligned with their technological processes, dedicated innovation funds that incentivize them to use cleaner production practices, or training initiatives that strengthen workforce capacity in low-carbon technologies. Such calibrated efforts ensure that no sector is left behind, maintaining competitive parity while steering all industries toward decarbonization.

Finally, our focus on carbon intensity rather than merely absolute emission levels highlights a crucial aspect: the decoupling of economic growth from environmental degradation. This decoupling allows economies to continue expanding and innovating without a proportional increase in their carbon footprint, a trend observed in nearly all regulated sectors that have reduced their carbon intensity by enhancing their energy efficiency. However, our analysis revealed that the Basic Metals sector was the only industry to both decrease its carbon intensity through reductions in CO_2 emissions per unit of energy consumed and experience a decline in its output share among all targeted sectors. This finding suggests that while promoting the adoption of cleaner energy sources is essential, policymakers must also consider the potential impact on the market share of regulated industries. Balancing environmental objectives with economic implications is crucial to ensure sustainable growth across all sectors. Additionally, it may be necessary to provide support or transition strategies for sectors that are adversely affected to maintain overall economic stability while pursuing greener initiatives.

The remainder of the paper is organized as follows. Section 2 provides an overview of the data sources and variables utilized in this study. Section 3 presents the stylized facts derived from initial analysis, highlighting key trends and patterns. Section 4 details the methodological approach employed to examine the impact of EU ETS policy on a list of dependent variables. Section 5 showcases the results, including robustness checks to validate our findings and ensure their reliability. Finally, Section 6 concludes the paper by summarizing the main insights and offering policy recommendations based on the study's outcomes.

2.2 Data

The main data source for this analysis is the World Input-Output Database (WIOD), which has been described by [46]. In addition to WIOD, we used the World Development Indicators (WDI) database, Penn World Table (PWT) database, and the KOF Swiss Economic Institute to control for country-time variant covariates.

2.2.1 Dependent Variables

The WIOD is utilized to construct all dependent variables employed in this study. WIOD provides consistent, fully comparable international data, facilitating a detailed examination of efficiency gains at both sectoral and country-specific levels. To comprehensively analyze the first and second phases of the EU ETS policy, this study covers the period from 1996 to 2012 and includes 32 countries, comprising 21 EU ETS member states and 11 non-EU ETS countries.

The dataset is primarily drawn from the WIOD Release 2016, which encompasses data for 42 countries, including 29 EU member states and 13 other major countries, spanning from 2000 to 2014. To extend our analysis back to 1996–1999, data from the WIOD Release 2013, which covers 40 countries (27 EU member states and 13 other major countries) for the period 1995–2011 (with some variables ending in 2009), is integrated. However, data from the year 1995 is excluded due to incomplete information for several countries on variables of interest. Similarly, data on 2013-2014 is omitted to explicitly focus on the initial two phases of the EU ETS. Additionally, certain countries [3] are excluded from our analysis due to incomplete data for essential variables. Additionally, Japan is excluded because it independently established its national ETS programs in 2010, rendering it unsuitable as either a treated or control country within our causal estimation framework. Table A.1 presents the countries covered in our dataset, chosen based on the availability, reliability, and consistency of the data.

The data cover seven selected sectors regulated by the EU ETS, including six manufacturing sectors: Food, Beverages, and Tobacco (ISIC Rev.4, C10-12); Paper (ISIC Rev.4, C17); Coke and refined petroleum (ISIC Rev.4, C19); Chemicals (ISIC Rev.4, C20); Non-Metallic Mineral

[3] Slovenia, Switzerland, Croatia, Norway, Taiwan, Cyprus, Luxembourg, Estonia, and Malta

Products (cement, glass, and ceramic) (ISIC Rev.4, C23); Metal (ISIC Rev.4, C24); and one non-manufacturing sector: Energy (ISIC Rev.4, D35).[4] Table A.2 outlines the industry sectors falling within the scope of the first two phases of the EU ETS along with the number of installations covered by the policy during these phases.

The data on CO_2 equivalent emissions and energy usage are derived from the WIOD environmental accounts at the sectoral level. CO_2 emissions are measured in kilotonnes (kt), while energy use is measured in terajoules (TJ).[5] We considered energy usage from all and pollutant-only sources. The latter refers to an aggregation of energy commodities that emit CO_2, such as fossil fuels, while the former includes both pollutant and non-pollutant energy sources.

Carbon Intensity and its Main Driving Factors

We use WIOD to construct the dependent variables in our main specification. A variable of interest for this study is the carbon emissions of regulated sectors at both country and sectoral levels:

$$CO2_{it} = \sum_{s=1}^{7} CO2_{ist} \tag{2.1}$$

where t denotes the time period from 1996 to 2012, $i = 1,2,\ldots,32$ represents the economy, and $s = 1,2,\ldots,7$ indicates sectors regulated by the EU ETS. Therefore, $CO2_{ist}$ is the carbon emission in sector s of economy i during period t. Additional sectoral level variables of interest include carbon intensity and its driving factors, such as energy intensity and energy to carbon ratio:

$$\frac{CO2_{ist}}{Q_{ist}} = \frac{E_{ist}}{Q_{ist}} \frac{CO2_{ist}}{E_{ist}} \leftrightarrow CI_{ist} = EI_{ist} CE_{ist} \tag{2.2}$$

where CI_{ist} is the carbon intensity of economy i during period t for sector s with gross output of Q_{ist}. Also, E_{ist} is the energy usage and $EI_{ist} = \frac{E_{ist}}{Q_{ist}}$ represents the energy intensity,

[4] The WIOD database (Release 2016) is categorized into 56 sectors, utilizing the International Standard Industrial Classification Revision 4 (ISIC Rev.4). On the other hand, the WIOD database (Release 2013) is classified into 35 sectors based on the International Standard Industrial Classification Revision 3 (ISIC Rev.3). However, for our analysis, we concentrate on 7 sectors that are part of the EU ETS and exclude the other sectors from our study.

[5] We converted the measurements for carbon emissions and energy usage to tonnes (t) and gigajoules (GJ), respectively, for the purpose of this study.

which is calculated for both pollutant (PEI_{ist}) and total (TEI_{ist}) energy sources. Additionally, $CE_{ist} = \frac{CO2_{ist}}{E_{ist}}$ represents the carbon emissions to energy usage. This ratio is also calculated based on the pollutant (CPE_{ist}) and total (CTE_{ist}) energy sources. A higher value of this ratio indicates greater CO_2 emissions for the same amount of energy usage.

At the country level, one can rewrite Equation 2.2 as follows:

$$\frac{CO2_{it}}{Q_{it}} = \sum_{s=1}^{7} \frac{CO2_{ist}}{E_{ist}} \frac{E_{ist}}{Q_{ist}} \frac{Q_{ist}}{Q_{it}} \rightarrow CI_{it} = \sum_{s=1}^{7} EI_{ist} CE_{ist} OS_{ist} \tag{2.3}$$

where CI_{it} is the carbon intensity of economy i during period t and $Q_{it} = \sum_{s=1}^{7} Q_{ist}$ is the aggregated gross output for regulated sectors. The last term, OS_{ist}, is the output share, which is the ratio of gross output of sector s to the aggregated gross output for all regulated sectors ($\frac{Q_{ist}}{Q_{it}}$).

Finally, we considered aggregated values at the country level across regulated sectors as follows:

$$\begin{cases} EI_{it} = \dfrac{\sum_{s=1}^{7} E_{ist}}{\sum_{s=1}^{7} Q_{ist}} \\ CE_{it} = \dfrac{\sum_{s=1}^{7} CO2_{ist}}{\sum_{s=1}^{7} E_{ist}} \end{cases} \tag{2.4}$$

Similar to the sectoral level variables, the above ratios are calculated for both pollutant, PEI_{it} and CPE_{it}, and total, TEI_{it} and CTE_{it}, energy sources.

Decomposed Dependent Variables

We use Index Decomposition Analysis (IDA) to gain a deeper understanding of the relationships between carbon intensity and its driving factors. Widely utilized in the analysis of energy and emission systems, decomposition analysis is an accounting technique that breaks down changes in an aggregate indicator for a system of interest into components related to several predefined factors. These factors, also known as drivers, are responsible for driving changes in the aggregate indicator.

Our main focus is on the carbon intensity across regulated sectors within a given economy i at time t. From Equation 2.3, one can see that carbon intensity can be broken down into a summation across all regulated sectors based on EI_{ist}, CE_{ist}, and OS_{ist} as follows: $CI_{it} = \sum_{s=1}^{7} EI_{ist} CE_{ist} OS_{ist}$.

This equation shows that variations in carbon intensity can be attributed to changes in carbon emissions per unit of energy use, energy intensity, and structural effect of output share.

There are two main categories of methodologies that can be used to separate the effects of different factors on an aggregate indicator. The first category is known as Structural Decomposition Analysis (SDA), which aims to identify the contribution of each factor by breaking down the change in the indicator into several components using Input-Output (I-O) models. The second category is Index Decomposition Analysis (IDA), which uses disaggregation techniques to identify the contribution of each factor to changes in the indicator. Studies by [95] and [103] provide comparisons of more recent methodological developments in SDA and IDA.

One of the key features of the IDA is its flexibility to model an aggregate indicator at either the sectoral or economy-wide level. Therefore, in this paper, we utilize the IDA approach, building on the works of [10]; [15]; [12] and [103] to examine the effect of the EU ETS policy on carbon intensity and its main driving factors across regulated sectors. We rely on the additive decomposition technique and employ the logarithmic mean Divisia index (LMDI-I) approach ([10]).[6] This methodology offers two significant benefits: Firstly, it guarantees perfect decomposition, ensuring that the results obtained do not include a residual term. Secondly, it exhibits consistency in aggregation, enabling the estimates for subgroups to be aggregated in a consistent manner ([10]).

The additive decomposition technique expresses changes in carbon intensity ($\Delta CI_{i,t}$) between two time periods (t and $t-1$) as the sum of various factors contributing to the change, as follows:

$$\Delta CI_{it} = CI_{it} - CI_{i,t-1} = CI_{it}^{CE} + CI_{it}^{EI} + CI_{it}^{OS} \tag{2.5}$$

where CI_{it}^{CE} represents the impact of changes in carbon emissions per unit of energy use on the overall changes in carbon intensity. On the other hand, CI_{it}^{EI} and CI_{it}^{OS} indicate changes in carbon intensity resulting from variations in energy intensity and structural effect on output share, respectively. CI_{it}^{CE}, CI_{it}^{EI} and CI_{it}^{OS} are indicators that show the sensitivity of carbon

[6] Previously, researchers primarily utilized the Laspeyres index to examine variations in energy and emission systems. These studies, however, were associated with a residual term in the decomposition outcomes. Several new IDA decomposition techniques have since been developed and implemented, such as AMDI ([25]), Adaptive Weighting Divisia Method [13]; [11]), LMDI-II ([9]), Shapley/Sun method ([96]), and Fisher index ([14]). A comprehensive comparison of these methods was conducted by [103].

intensity to carbon-to-energy ratio, energy intensity, and output share, respectively. Since the sources of energy use are important, we consider two types of energy sources: total energy sources and pollutant energy sources. Therefore, we use CI_{it}^{CET} and CI_{it}^{TEI}, which account for all energy sources, and CI_{it}^{CEP} and CI_{it}^{PEI}, which specifically account for pollutant energy sources. According to the LMDI-I approach, the decomposition formula for carbon intensity's drivers is shown as Equations (2.6)–(2.10).

$$CI_{it}^{TEI} = \sum_{s=1}^{7} \Delta CI_{ist} \times [\ln \frac{TEI_{ist}}{TEI_{is,t-1}} / \ln \frac{CI_{ist}}{CI_{is,t-1}}] \quad , \tag{2.6}$$

$$CI_{it}^{PEI} = \sum_{s=1}^{7} \Delta CI_{ist} \times [\ln \frac{PEI_{ist}}{PEI_{is,t-1}} / \ln \frac{CI_{ist}}{CI_{is,t-1}}] \quad , \tag{2.7}$$

$$CI_{it}^{CET} = \sum_{s=1}^{7} \Delta CI_{ist} \times [\ln \frac{CET_{ist}}{CET_{is,t-1}} / \ln \frac{CI_{ist}}{CI_{is,t-1}}] \quad , \tag{2.8}$$

$$CI_{it}^{CEP} = \sum_{s=1}^{7} \Delta CI_{ist} \times [\ln \frac{CEP_{ist}}{CEP_{is,t-1}} / \ln \frac{CI_{ist}}{CI_{is,t-1}}] \quad , \tag{2.9}$$

$$CI_{it}^{OS} = \sum_{s=1}^{7} \Delta CI_{ist} \times [\ln \frac{OS_{ist}}{OS_{is,t-1}} / \ln \frac{CI_{ist}}{CI_{is,t-1}}] \quad . \tag{2.10}$$

Table A.7 provides all the dependent variables that are constructed by the author of this study.

2.2.2 Covariates

The main specifications incorporate two groups of covariates. The first group controls for variations between countries. GDP per capita (in constant PPP, log-transformed) is commonly used to capture differences in economic development and purchasing power. We also control for foreign direct investment (% of GDP), as this factor influences production by investing in productive capacity, generating demand for capital goods and intermediate products, and promoting industrial expansion. Moreover, industry value added (% of GDP) and service value added (% of GDP) are included to control for economic structure and sectoral dynamics. We account for coal (% of GDP) as one of the largest sources of carbon emissions to ensure that changes in emissions are not simply due to changes in coal use. Controlling for population allows us to isolate the effects of the EU ETS from demographic factors that can drive emissions independently. These variables are collected from the World Development Indicators (WDI) database.

We also include 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. Additionally, the globalization index, sourced from the KOF Swiss Economic Institute, accounts for the effect of globalization on countries' trade patterns.

Second, we account for variations at the sector level. We control for the capital-to-labor compensation ratio, which represents the relative labor-to-capital intensity in the production process, multiplied by the labor-to-capital ratio:

$$\left.\begin{aligned} R &= (1-\alpha)A\left(\tfrac{L}{K}\right)^{\alpha} \\ W &= \alpha A\left(\tfrac{K}{L}\right)^{1-\alpha} \end{aligned}\right\} \rightarrow \frac{R}{W} = \frac{1-\alpha}{\alpha}\frac{L}{K} \tag{2.11}$$

This allows us to account for potential labor-capital substitution. Higher EU ETS costs may encourage firms in energy-intensive industries to invest in capital (e.g., cleaner technologies) to cut emissions, potentially resulting in capital-labor substitution. Furthermore, this isolates the impact of capital-labor intensity on carbon emissions and energy use. Carbon emissions are increased by capital-intensive industries, such as the energy sector and other manufacturing sectors that frequently depend on heavy machinery and energy usage. On the other hand, labor-intensive sectors may have lower carbon emissions and generally utilize less energy per unit of output. Even if the EU ETS policy stays the same, a sector's carbon emissions may vary if it becomes capital-intensive rather than labor-intensive.

Table A.3 presents summary statistics of all the variables that are used in this study.

2.3 Stylized Facts

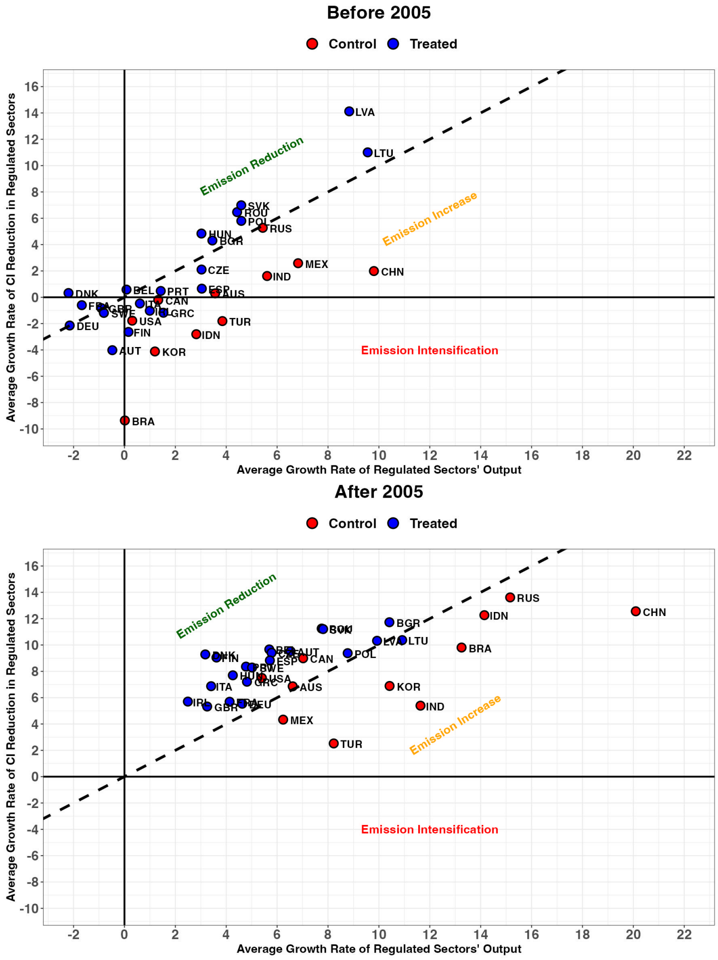
This section presents stylized facts regarding the impact of the EU ETS policy on various variables discussed in the previous section. Figure 2.1 provides an intuitive illustration of the effectiveness of the EU ETS decarbonization strategy. This figure illustrates the average annual growth rate of carbon intensity reduction (i.e., the reduction in CO_2 emissions per unit of output) relative to the average annual growth rate of output in the seven aggregated sectors during both the pre-treatment and post-treatment periods of the EU ETS (see Table A.2). Blue circles denote regulated countries, while red circles represent countries not under EU ETS regulations.

On the positive side of the output average growth rate axis, countries are categorized into three domains during both the pre-treatment and post-treatment periods: (1) Countries located above the dashed 45-degree line, with positive output growth and positive carbon intensity (CI) reduction growth rates (Emission Reduction), where the reduction in carbon intensity exceeds output growth. In this domain, CO_2 emissions decrease despite economic growth, indicating successful decoupling of emissions from economic output; (2) Countries located below the dashed line but with positive output growth and positive CI reduction growth rates (Emission Increase). In this domain, output growth exceeds the reduction in carbon intensity, leading to an overall increase in CO_2 emissions, although carbon intensity is improving; and (3) Countries with positive output growth but negative CI reduction growth rates (Emission Intensification), indicating that both output and carbon intensity are increasing. This leads to a significant rise in CO_2 emissions, reflecting a coupling of emissions with economic growth.

Similarly, on the negative side of the output growth rate axis, countries can be categorized into three domains: (1) Countries with negative output growth rates but positive CI reduction growth rates, Emission Reduction with Economic Contraction, indicating that emissions are decreasing due to both reduced economic activity and improvements in carbon intensity; (2) Countries with negative output growth rates and negative CI reduction growth rates (Emission Increase with Economic Contraction), but located above the dashed 45-degree line. Here, carbon intensity is increasing, but the reduction in output is greater than the increase in carbon intensity, possibly leading to a net decrease in emissions; and (3) Countries with negative output growth rates and negative CI reduction growth rates, but located below the dashed line, Severe Emission Increase with Economic Contraction. In this domain, the increase in carbon intensity outpaces the decrease in output, resulting in a net increase in CO_2 emissions despite economic contraction.

It is evident from Figure 2.1 that both EU ETS regulated and unregulated countries experienced an improvement in their carbon emissions and carbon intensity, while they improved their output growth among the regulated sectors. However, this shift is sharper among regulated countries, where almost all of them, in targeted sectors, experienced a reduction in their carbon

Figure 2.1: Carbon Intensity Improvement Against Output Growth Among Targeted Sectors - EU vs non-EU Countries



Note: This figure plots the average decarbonization growth (reverse change of CO_2 per output) of the aggregated seven regulated sectors in each country, along with the average economic growth of those sectors, during the pre-treatment and post-treatment periods of the EU ETS. The list of countries is presented in Table A.1. Furthermore, Table A.2 presents the list of targeted sectors in EU ETS.

intensity greater than the increase in their output. Among the countries under EU ETS regulations in the pre-treatment period, one can see some experienced a slight emission reduction with economic contraction, such as Denmark; emission increase with economic contraction, such as France and Germany; and severe emission increase with economic contraction, such as Sweden and Austria. Nevertheless, all these countries were placed in the emission reduction domain in the post-treatment period, where the reduction in carbon intensity exceeds output growth.

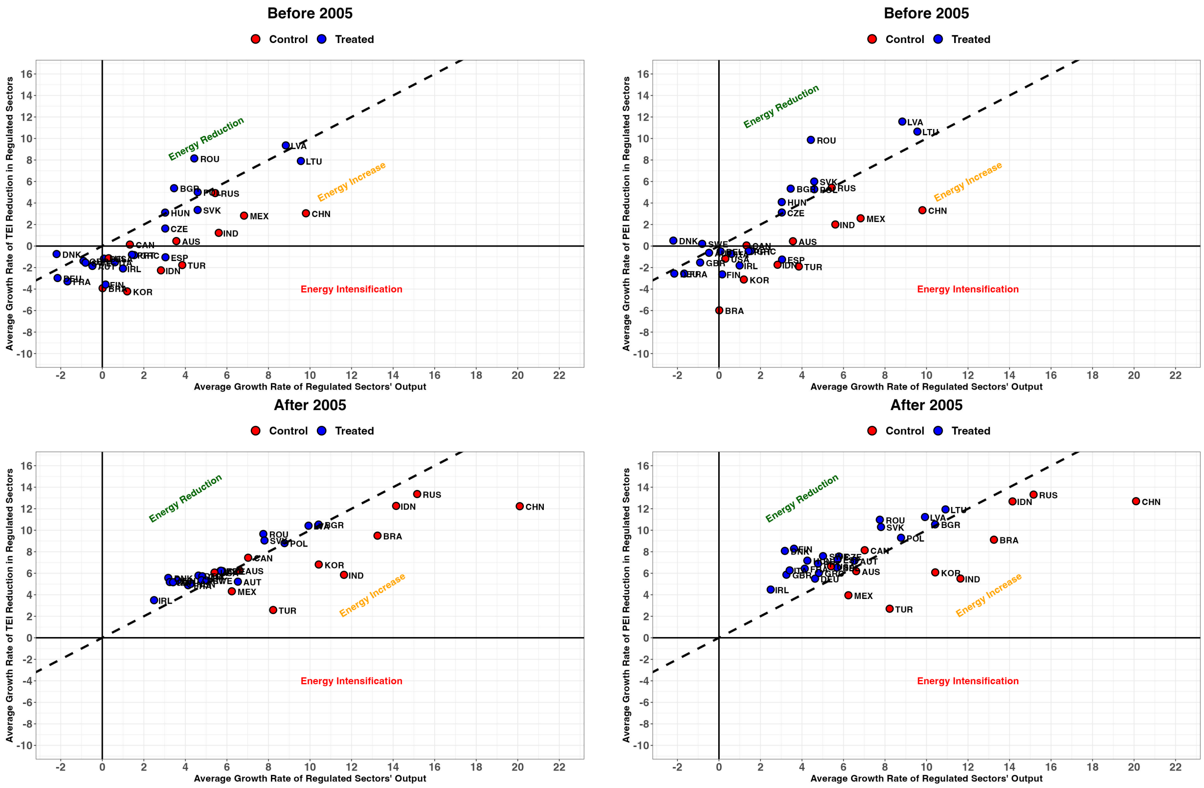
EU ETS revenues are mainly allocated to national budgets, and the members are required to utilize these funds to invest in renewable energy, enhance energy efficiency, and develop low-carbon technologies that contribute to emission reductions and lower carbon costs for companies. Additionally, a portion of the EU ETS revenue is directed towards supporting low-carbon innovation and advancing the EU's energy transition through the Innovation Fund and the Modernisation Fund. Hence, the EU ETS can influence both energy consumption per unit of output (PEI and TEI in this study) and carbon emissions per unit of energy (CPE and CTE in this study) in addition to carbon intensity (CI). We demonstrate the same concept as what is presented in Figure 2.1 for energy intensity from all (TEI) and pollutant (PEI) sources and carbon to energy ratio from all (CTE) and pollutant (CPE) sources in Figure 2.2 and Figure 2.3, respectively.

The logic in interpreting Figure 2.2 is similar to Figure 2.1, but using energy intensity—TEI in Part (a) and PEI in Part (b) of this figure—instead of carbon intensity. This figure aims to break the link between economic growth and the reliance on energy consumption. The underlying idea is that technological innovation and adjustments in the industrial structure can foster energy conservation and diminish dependence on pollutant energy sources, such as fossil fuels. In theory, EU ETS establishes a cap on the overall carbon emissions and increases the cost of such emissions, compelling covered sectors to actively reduce their energy consumption ([62]). Economically, these sectors may find it more viable to improve energy efficiency through innovations in green technology, thereby facilitating transitions in the energy system ([63]).

Despite the mixed rates among EU ETS regulated and unregulated countries in the pre-treatment period, one can see in Part (a) of Figure 2.2 that all countries experienced improvement in the energy usage per unit of output. Notwithstanding, almost all the regulated countries shift upward towards the energy reduction domain, where they experienced output growth with a greater improvement in their energy intensity from all sources (TEI). This improvement is even sharper based on Part (b) of this figure, where we observe the improvement in energy intensity from pollutant sources (PEI). One can see even the few exceptions among regulated countries for Part (a), such as Austria, are placed in the energy reduction domain when it comes to the improvement in energy usage per unit of output from pollutant sources (PEI).

To illustrate the countries' performance in improving their carbon emissions and energy usage, we compared the carbon emission per unit of energy with energy usage per unit of output in Figure 2.3. Part (a) of this figure focuses on energy from all sources (so, CTE versus TEI)

Figure 2.2: Energy Intensity Improvement Against Output Growth Among Targeted Sectors - EU vs non-EU Countries



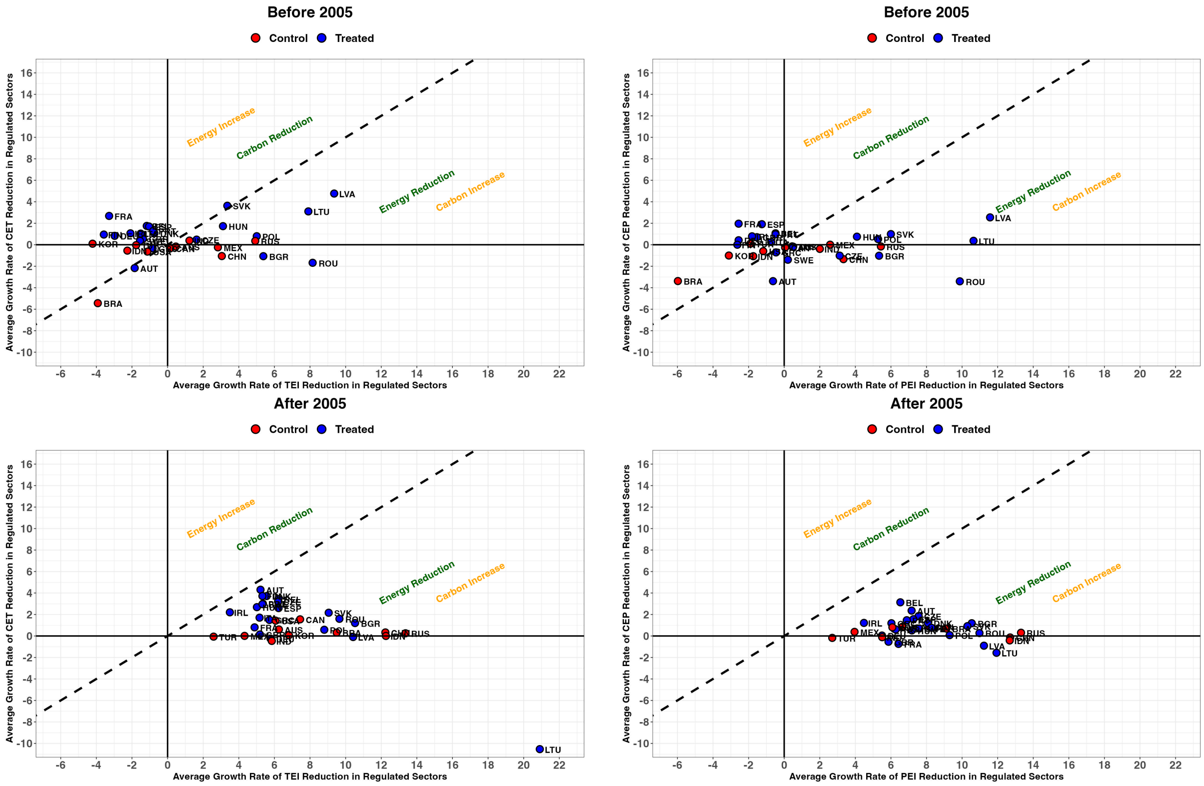
(a) Total Energy deintensification

(b) Pollutant Energy deintensification

Note: This figure shows the average total energy deintensification growth (reverse change of total energy per output) (plot a) and the average pollutant energy deintensification growth (reverse change of pollutant energy per output) (plot b) for the aggregated seven targeted sectors in each country, along with the average economic growth of those sectors, during the pre-treatment and post-treatment periods of the EU ETS. The list of countries is presented in Table A.1. Furthermore, Table A.2 presents the list of targeted sectors in EU ETS.

and Part (b) demonstrates the relation between the same concepts but from pollutant energy sources (hence, CPE against PEI). All the positive side of this figure represents improvement in either energy intensity or carbon emission per unit of output. However, it depicts whether the improvement is more toward more efficient use of energy or cleaner use of energy (less emission). It shows that almost all the countries in this study experienced improvement in both energy intensity and emissions per unit of energy, with some exceptions for pollutant energy sources in Part (b), such as France, Indonesia, Latvia, and Lithuania, where their emission to energy usage ratio worsened in the post-treatment period. However, France and Indonesia perform very differently than the other two in terms of improvement in their energy intensity, as their energy intensity shifted from negative values in the pre-treatment period to high positive amounts in the post-treatment period. Based on this figure, one can assume the improvement in carbon intensity is mostly driven by the improvement in energy intensity rather than the cleaner use of energy to emit less CO_2.

Figure 2.3: Carbon-to-Energy Ratio Against Energy Intensity Improvements Among Targeted Sectors - EU vs non-EU Countries



(a) Total Energy deintensification (b) Pollutant Energy deintensification

Note: This figure shows the average growth of carbon to total energy reduction (plot a) and the average growth of carbon to pollutant energy reduction (plot b) for the aggregated seven targeted sectors in each country, along with their average energy deintensification growth, during the pre-treatment and post-treatment periods of the EU ETS. The list of countries is presented in Table A.1. Furthermore, Table A.2 presents the list of targeted sectors in EU ETS.

While the above figures are averaged for the pre- and post-treatment periods for different countries, Figure 2.4 demonstrates the trend of this study's outcome variables for all regulated sectors combined, averaged among countries under EU ETS regulations (Treated, blue) and those that are not subjected to the policy (Control, red). The changes in decomposed variables are shown by dashed lines with values represented on the right vertical axis, and the intensity ratios are depicted by solid lines with values represented on the left vertical axis. The first and second phases of the EU ETS policy are displayed by vertical dashed black and green lines in

2005 and 2008, respectively.

Unlike what we showed in the previous figures—that countries in the treated group (under EU ETS regulations) perform much better than those in the control group (not subjected to the EU ETS policy) in terms of reducing the carbon intensity and energy intensity—one can see in Figure 2.4 that the average trends among treated and control groups are almost identical for these values (the top and middle parts of this figure).

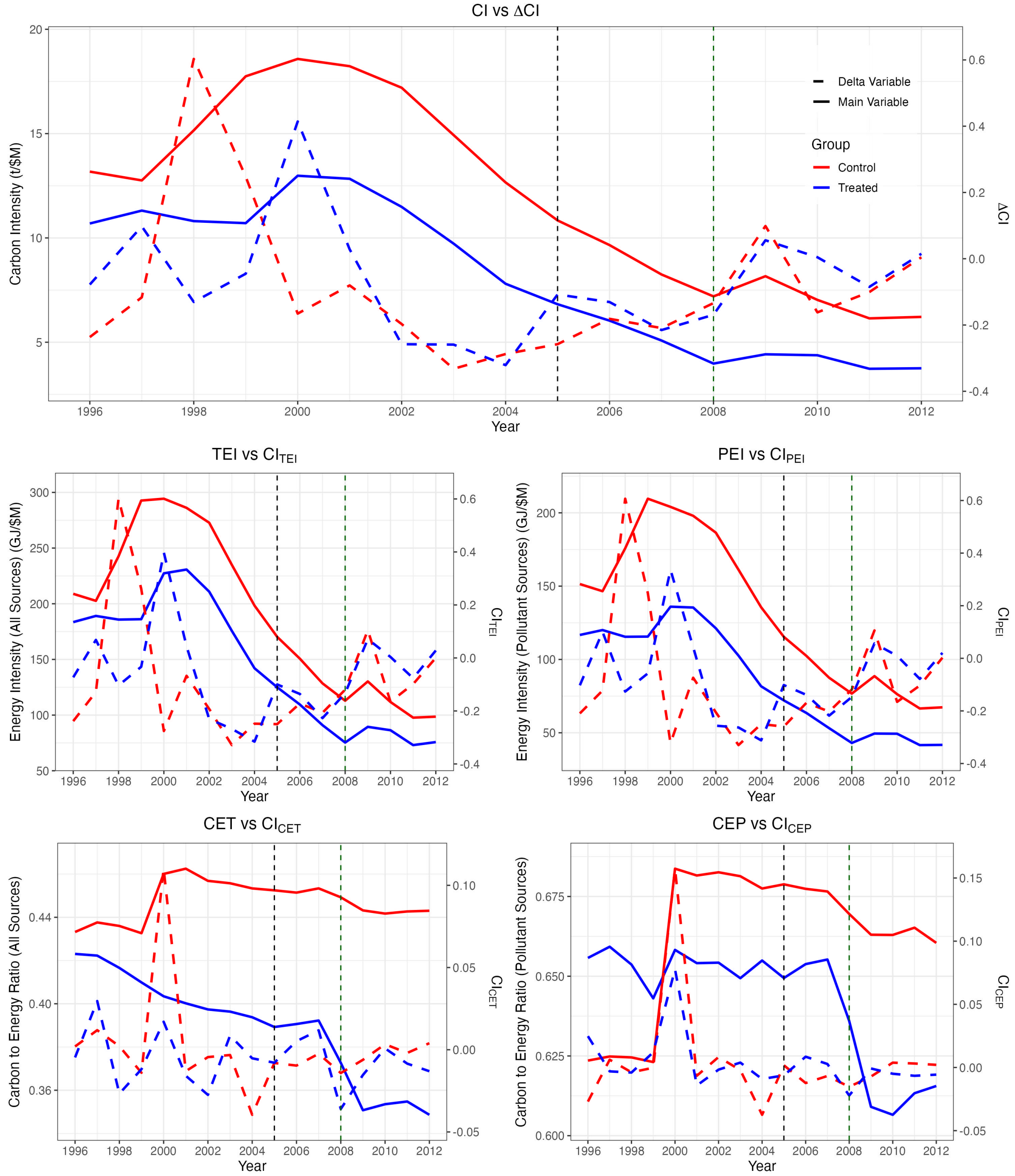
On the other hand, the lower part of Figure 2.4 demonstrates that this difference in trends is very sharp for carbon to energy ratio in the post-treatment period, especially for carbon emissions to energy use ratio from pollutant energy sources. This change in the trend is clearer after the second phase of the program. Additionally, the trend in all decomposed variables seems to have fewer fluctuations in the post-treatment period, with a slightly better performance among the countries under the EU ETS regulations (treated countries).

2.4 Methodology

In this study, we employ the staggered design of the Synthetic Difference in Differences (SDiD) approach to evaluate the causal impact of the EU ETS on carbon intensity and its underlying driving factors. The SDiD approach, developed by [16], combines elements of the Difference in Differences (DiD) and Synthetic Control Method (SCM). The DiD approach offers a useful framework for estimating the causal effect of treatment if pre-treatment trends are parallel. However, achieving parallel trends in practice can be challenging and may result in biased estimates, especially in the context of cross-country panel analysis. In contrast, the SCM approach constructs a synthetic control group that approximates the counterfactual trend in the absence of treatment. Nevertheless, SCM has its limitations, including the inability to control for unit fixed effects, the requirement for parallel trends in covariates, and the potential for underestimating the uncertainty of the estimates.

The SDiD method overcomes the limitations of DiD and SCM by reweighting and matching pre-exposure trends, reducing the reliance on parallel trend-type assumptions. Similar to DiD, SDiD is invariant to additive unit-level shifts and enables valid large-panel inference, allowing for individual fixed effects to be controlled. Incorporating unit fixed effects provides flexibility,

Figure 2.4: Carbon Intensity and Its Underlying Driving Factors Trend Among Targeted Sectors - EU vs non-EU Countries



Note: This figure depicts the average carbon intensity, energy intensity (for both total and pollutant energies), and carbon-to-energy ratio (for both total and pollutant energies), along with the average ΔCI (change in carbon intensity), CI^{TEI} (change in total energy intensity), CI^{PEI} (change in pollutant energy intensity), CI^{CET} (change in carbon-to-energy ratio from all energy sources), and CI^{CEP} (change in carbon-to-energy ratio from pollutant energy sources). The green lines and red lines represent participating and non-participating countries in EU ETS, respectively.

while incorporating time weights ensures that the weighted periods align more closely with the periods assigned to the counterfactual. This approach can be viewed as a doubly weighted version of DiD, encompassing time-invariant and time-varying covariates.

The main specification of this study is presented as follows:

$$Y_{it} = \mu + \alpha_i + \delta_t + X_{it}'\beta + \tau W_{it} + \varepsilon_{it} \tag{2.12}$$

Here, the index i refers to a country, totaling $N = 32$ countries, while t represents time across $T = 17$ years, from 1996 to 2012. Y_{it} is two sets of dependent variables for country i at time t as follows:

1. Log Variables: Carbon emissions (CO_2), carbon intensity (CI), total energy intensity (TEI), pollutant energy intensity (PEI), carbon-to-total energy (CTE), carbon-to-pollutant energy ratio (CPE), and output share of all selected sectors aggregated (OS);

2. Decomposed Variables: Change in carbon intensity (ΔCI), change in carbon intensity through: (i) changes in total energy intensity (CI^{TEI}), (ii) changes in pollutant energy intensity (CI^{PEI}), (iii) changes in carbon-to-total energy ratio (CI^{CET}), (iv) changes in carbon-to-pollutant energy ratio (CI^{CEP}), and (v) changes in output share (CI^{OS}).

The treatment indicator $W_{it} \in \{0,1\}$ equals one for countries under the EU ETS regulations during the period after the program's implementation year (2005 for most countries, except for Romania and Bulgaria, where it began in 2007), and zero otherwise. The primary parameter of interest is the SDiD estimator τ, representing the causal effect of the EU ETS policy on carbon emissions, carbon intensity, and its underlying factors (both log and decomposed variables). X_{it} is a vector of covariates detailed in Section 2.2, and β is a vector of coefficients corresponding to it. α_i denotes the country fixed effects, capturing unobserved heterogeneity between countries, and δ_t captures the year fixed effects, controlling for global shocks affecting all output variables equally in a given year. ε_{it} is the error term, and is assumed to be uncorrelated with the treatment assignment once we condition on fixed effects and observed covariates..

Following [16], the first step of the SDiD estimation with covariates is as follows:

First, we proceed by applying the SDiD algorithm to the residuals calculated as:

$$Y_{it} = \mu + X_{it}'\beta + e_{it} \tag{2.13}$$

Then the residual outcome variable is calculated as follows:

$$Y_{it}^{\text{res}} = Y_{it} - X_{it}'\hat{\beta} \tag{2.14}$$

Next, the optimal weights ω_i and λ_t are computed such that they 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. The details of this optimization procedure can be found in Appendix B. Finally, utilizing these weights, we conduct a weighted two-way fixed effects regression of Y_{it}^{res} on W_{it} to estimate τ, with the weights enhancing the credibility of the control comparisons:

$$\left(\hat{\mu}, \hat{\alpha}, \hat{\delta}, \hat{\tau}^{\text{sdid}}\right) = \arg\min_{\mu,\alpha,\delta,\tau} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it}^{\text{res}} - \mu - \alpha_i - \delta_t - W_{it}\tau\right)^2 \hat{\omega}_i \hat{\lambda}_t \tag{2.15}$$

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

When evaluating the impact of the EU ETS policy on carbon emissions, carbon intensity, and its underlying factors, the dependent and independent variables in Specification 2.12 (except for W_{it} and the binary variables) are in logarithmic terms. This means the effect of the EU ETS on these variables, which are presented in Table 2.1, can be calculated using the estimated value of $\hat{\tau}$ as follows: $[\exp(\hat{\tau}) - 1] \times 100\%$. However, because the decomposed values contain negative values and their scale could be different from the rest of the covariates, to avoid bias due to the linearity of the model, we employ standardized values for all the variables, except for W_{it} and the binary variables in this specification. To interpret the estimated coefficient of the policy effect on the decomposed variables, the estimated effect can be expressed in the original units of Y_{it} as follows: $\hat{\tau} \times \sigma_Y$, where σ_Y is the standard deviation of the dependent variable. Thus, the estimated coefficient in Table 2.2 can be expressed in the original measurement units of the dependent variable using the standard deviation in Table A.3.

Finally, following ([17]), we employ the staggered adoption of the SDiD method, where units receive treatment at different times. In this case, the average treatment effect on the treated (ATT) is estimated by applying SDiD to data subsets corresponding to each distinct adoption date—2005 for all treated countries except Bulgaria and Romania, which are regulated post-2007. Applying SDiD to each subset produces adoption-specific effect estimates $\hat{\tau}_a$, and the ATT is then computed as:

$$\hat{\tau}_{\text{ATT}} = \sum_a \frac{T_a}{T_{\text{post}}} \times \hat{\tau}_a \tag{2.16}$$

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. We also considered the literature on SDiD's theoretical and practical limitations, and implemented mitigation strategies accordingly to reduce the associated risks (see Appendix C).

2.5 Results

In this section, we first examine the overall impact of the EU ETS on carbon emissions, carbon intensity, and its driving factors at the country level. Next, we narrow our focus to explore the effects of the EU ETS on changes in carbon intensity and its primary determinants, utilizing a decomposition method to evaluate the program's long-term sustainability.

2.5.1 Carbon Emissions, Carbon Intensity, and Their Underlying Factors

We begin by estimating the average treatment effect of the EU ETS policy on the logarithm of carbon emissions (CO_2), carbon intensity (CI), total energy intensity (TEI), pollutant energy intensity (PEI), carbon-to-total energy (CTE), carbon-to-pollutant energy ratio (CPE), and output share of an individual sector (OS) using Specification 2.12 at both the sectoral and aggregated (all regulated sectors combined) levels.[7] We employ the staggered design of the SDiD method as discussed in Section 4.

[7] The list of regulated sectors considered in this study can be found in Table A.2, along with the number of installations covered by the first two phases of the EU ETS policy.

Table 2.1 presents the results. The first column shows the effectiveness of the EU ETS in mitigating CO_2 emissions. The estimated coefficient in the first row, for all regulated sectors aggregated at the country level, indicates a significant impact of the EU ETS on CO_2 emissions. Holding other variables constant, countries that joined the EU ETS emitted about 19% less CO_2 due to the program's influence, compared to countries that did not participate. Figure 2.5 shows this relative carbon emission reduction in treated groups compared to control groups, which is more pronounced in the second phase of the program. Our findings are in line with recent studies such as [85], [101], [37], and [42].[8]

Table 2.1: The Effect of the EU ETS Policy on Carbon Emissions, Carbon Intensity, and Its Underlying Driving Factors - 1996–2012

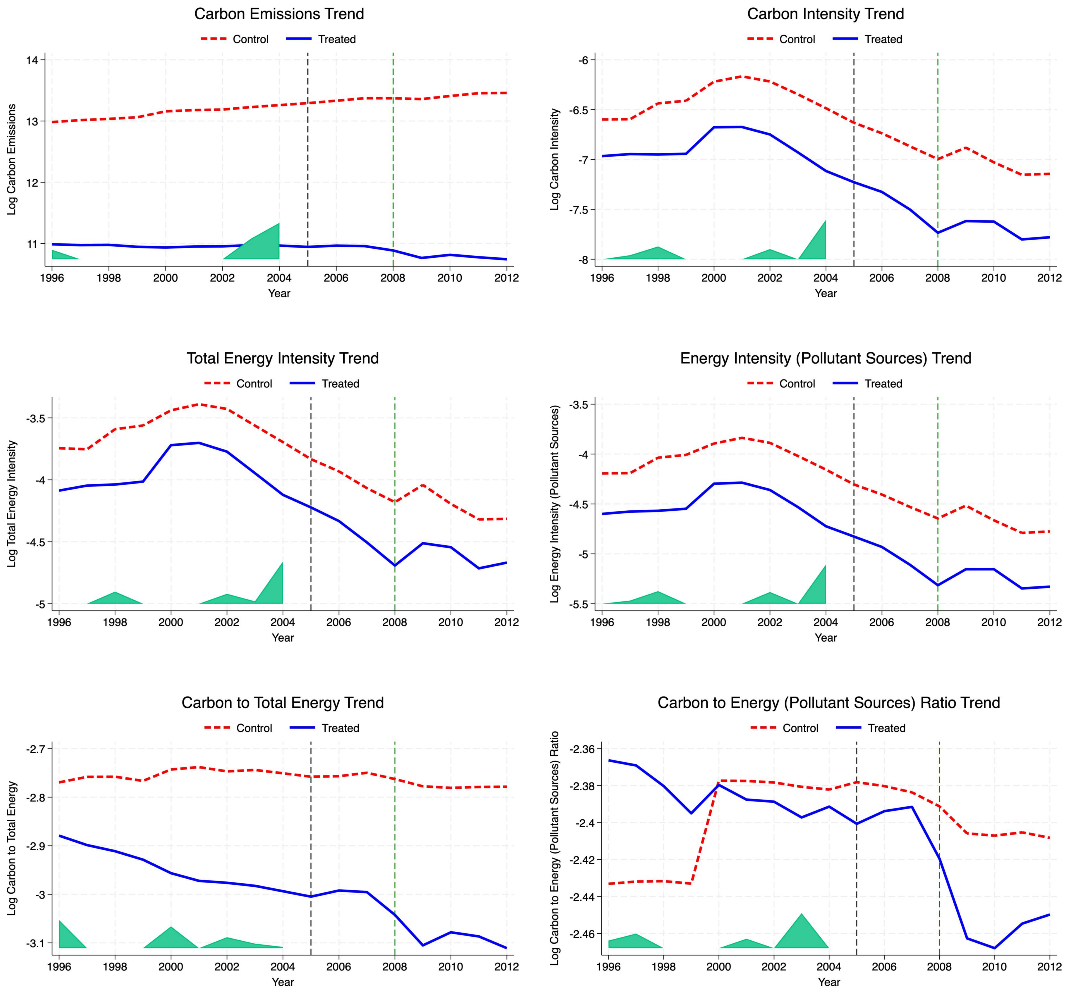
Sectors	(1) CO_2	(2) CI	(3) TEI	(4) PEI	(5) CTE	(6) CPE	(7) OS
All Sectors	-0.206**	-0.209**	-0.142*	-0.177**	-0.085**	-0.026	—-
	(0.088)	(0.082)	(0.073)	(0.076)	(0.036)	(0.023)	—-
C10-C12	-0.133	0.031	-0.087	-0.021	0.012	-0.057	-0.012
	(0.099)	(0.142)	(0.103)	(0.124)	(0.096)	(0.092)	(0.035)
C17	-0.021	0.283**	0.076	0.280**	0.026	0.023	-0.040
	(0.161)	(0.124)	(0.140)	(0.121)	(0.164)	(0.093)	(0.053)
C19	-0.142	0.127	0.137	0.037	0.068	0.048	-0.152
	(0.116)	(0.650)	(0.135)	(0.116)	(0.141)	(0.870)	(0.171)
C20	-0.150	-0.240**	-0.125	-0.152	0.045	0.106	0.077
	(0.136)	(0.122)	(0.104)	(0.127)	(0.119)	(0.185)	(0.053)
C23	-0.233**	-0.203*	-0.371***	-0.443***	0.079	0.117*	0.006
	(0.103)	(0.117)	(0.121)	(0.106)	(0.067)	(0.067)	(0.084)
C24	-0.511***	-0.262**	-0.045	-0.093	-0.193***	-0.165**	-0.141**
	(0.125)	(0.129)	(0.127)	(0.122)	(0.058)	(0.066)	(0.063)
D35	-0.135	-0.222**	-0.221*	-0.194*	-0.031	-0.030	0.140
	(0.121)	(0.102)	(0.119)	(0.110)	(0.053)	(0.020)	(0.089)
Observations	544	544	544	544	544	544	544

Note: This table presents the EU ETS average treatment effect on carbon emissions (CO_2), carbon intensity (CI), total energy intensity (TEI), pollutant energy intensity (PEI), carbon-to-total energy (CTE), carbon-to-pollutant energy ratio (CPE), and output share of an individual sector over all selected sector aggregated (OS) using Specification 2.12. We analyze 21 treated countries and 11 control countries over the period 1996-2012 (see Tables A.1 and A.2). The Jackknife approach is used to calculate the standard errors of the estimated coefficients. All regressions include time and country fixed effects. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[8] [85] report a 25-28% reduction in firm-level emissions in Germany during phase II of the EU ETS. [101] and [37] show similar reductions for French manufacturing firms. [42] find an approximately 10% reduction using firm-level data from four countries. Our distinct findings can be attributed to differences in methodology, model specification, and datasets used.

To evaluate the EU ETS effects at the sectoral level, we use the same specification (Specification 2.12). The results show that the coefficients for carbon emissions are statistically significant and negative only for the Non-Metallic Mineral Products (C23) and Basic Metal (C24) sectors. For sector C23, regulated countries achieved around a 21% reduction in CO_2 emissions due to the EU ETS. In sector C24, the EU ETS program led to a 40% reduction in CO_2 emissions. These findings align with [1], confirming that the metal sector made the most substantial contribution to emission reductions during the second phase of the EU ETS.

Figure 2.5: The Adjusted Outcome Trends Among Treated and Control Groups



Note: This figure illustrates the trends in carbon emissions, carbon intensity, and its underlying driving factors from 1996 to 2012, comparing the average outcomes of treated units with the weighted average outcomes of control units. The first and second phases of the EU ETS policy are marked by vertical black and green dashed lines, respectively. Green triangles indicate the time weights. Both unit and time weights are determined through an optimization procedure, as described in [16] and briefly outlined in the Methodology section.

The second column of Table 2.1 shows the estimated impact of the EU ETS on carbon intensity. The results indicate a statistically significant coefficient for all regulated sectors aggregated at the country level, revealing a reduction in carbon intensity by around 19% in the countries under the EU ETS regulations. Furthermore, Figure 2.5 illustrates a steeper reduction in carbon intensity in the treated group compared to the control group during the first phase of the program. It appears that the EU ETS has been successful not only in curbing carbon emissions but also in lowering carbon intensity in the regulated countries.

At the sectoral level, we found heterogeneous impacts. While the policy seems effective for Chemicals (C20), Non-Metallic Mineral Products (C23), Basic Metal (C24), and Energy (D35) sectors—reducing carbon intensity by 21%, 18%, 23%, and 20%, respectively—it has no statistically significant impact on the Food, Beverages, and Tobacco (C10-12) and Coke and Petroleum (C19) sectors. Moreover, it counterintuitively increased the carbon intensity for the Paper and Paper Products (C17) sector. Examining the driving factors of carbon intensity suggests that this counterintuitive result may be linked to energy intensity. These findings imply that policymakers should consider sector-specific regulations. Not only did the EU ETS fail to significantly affect carbon emissions in these three sectors, but production technologies also did not improve during the first two phases of the policy, resulting in no effect (or a counterintuitive effect in the case of C17) on carbon intensity and its underlying driving factors.

Table 2.1 also presents the impact of the EU ETS on the drivers of carbon intensity: energy intensity (TEI and PEI for all and pollutant energy sources, respectively), carbon-to-energy ratio (CTE and CPE for all and pollutant energy sources), and output share (relative to the aggregated output of all targeted sectors). Columns (3) and (5) display the results using total energy, while columns (4) and (6) show the results when pollutant energy is considered. The estimates reveal a substantial impact of the program on energy intensity across the entire sample for both pollutant and total energy sources, with more pronounced effects observed in the pollutant energy case. On average, the EU ETS led to approximately a 13% reduction in total energy intensity. The effect is even more pronounced for pollutant energy intensity, with about a 16% reduction for all sectors aggregated at the country level. Furthermore, Figure 2.5 shows a pattern for energy intensity (both total and pollutant) similar to that observed for carbon intensity, highlighting the role of energy efficiency improvements as a key driver of carbon intensity reduction.

A larger average treatment effect on pollutant energy intensity compared to total energy intensity may indicate that EU firms focused more on improving fossil fuel energy use rather than making a comprehensive shift toward clean energy sources. First, enhancing fossil fuel efficiency often requires a lower initial investment than installing clean energy sources. Second, improving fossil fuel efficiency delivers immediate cost savings that can offset rising carbon allowance costs, incentivizing firms to focus on pollutant energy improvements. Third, a 'lock-in' effect may have occurred during the early phases of the EU ETS, as pre-existing investments in fossil fuel-based infrastructure and technologies (e.g., CHP) were more readily available than renewable energy solutions.

The sector-specific results show larger average treatment effects in the Non-Metallic Minerals and Energy sectors, with a 31% and 20% decrease in energy intensity from all energy sources (TEI), and a 36% and 18% decrease in pollutant energy intensity (PEI), respectively. While the effect is greater for PEI in the Non-Metallic Minerals sector, it is lower in the Energy sector. This discrepancy, seemingly inconsistent with the aggregated sample estimates, may reflect a simultaneous shift toward cleaner energy use alongside fossil fuel efficiency improvements in the Energy sector.

The estimated coefficients for the carbon-to-energy ratio show a negative effect for all sectors combined, although it is statistically significant only for CTE (where all energy sources are considered). The estimation suggests approximately an 8% reduction in carbon emissions per unit of energy use in countries under the EU ETS. Figure 2.5 shows a change in the carbon-to-energy ratio trend of treated countries relative to control countries starting in the middle of the first phase of the EU ETS.

At the sectoral level, the coefficient for carbon-to-energy ratio of pollutant energy is statistically significant and positive in the Non-Metallic Minerals sector. This suggests that firms in this sector produce more carbon per unit of energy use, but due to improvements in their energy intensity, their overall carbon emissions and carbon intensity still decreased after the implementation of the EU ETS. One plausible explanation is that, faced with higher production costs, firms prioritized improving energy use per unit of production rather than investing in more expensive technology to reduce carbon emissions per unit of energy use. This finding underscores the need for policymakers to focus more on promoting cleaner energy technologies that emit lower CO_2 per unit of energy consumption.

The sector-specific results also show that the Basic Metals sector experienced approximately an 18% decrease in CTE and a 15% decrease in CPE. The smaller reduction in the carbon-to-energy ratio for pollutant energy compared to total energy sources may reflect a shift in the energy mix toward cleaner energy. Notably, the Basic Metals sector, which improved its CO_2 emission per unit of energy use, is also the only sector that experienced a decrease in its output share among all targeted sectors. In contrast, sectors that either were not influenced by the policy or reduced their CO_2 emissions and carbon intensity mainly through energy intensity improvements did not experience similar changes in their output share. Therefore, while incentivizing the use of cleaner energy is crucial, policymakers should also consider that it might reduce the output share of regulated sectors.

2.5.2 Sustainability of the EU ETS Impact

The results from the previous section demonstrate that the EU ETS had a substantial impact on reducing carbon intensity, primarily through improvements in energy intensity. It is now important to determine whether this effect led to sustained changes in carbon intensity or whether it diminished over time. In this section, we combine the decomposition method with a causal inference strategy, a distinctive aspect of our study, allowing us to estimate the causal impact of the EU ETS on changes in carbon intensity and identify the specific channels through which these sustained changes occur.

Since the decomposed variables are constructed based on Equation 2.5 and then computed using Equations 2.6, 2.7, 2.8, 2.9, and 2.10, we can estimate the effect on all targeted sectors combined (sectoral variations are embedded in the formulas). Therefore, Table 2.2 only presents the estimated impacts of the decomposed variables for all targeted sectors aggregated at the country level. As mentioned in the Methodology section, the variables in this part are standardized because the scale of the decomposed variables differs substantially from that of the covariates used in Specification 2.12. Moreover, since these variables include negative values, a log transformation was not feasible. Hence, we standardized all variables except for the binary variables.

The estimated coefficients indicate that the EU ETS had a significant impact on the change in carbon intensity for all targeted sectors combined at the country level. Specifically, the EU ETS led to a 0.12 standard deviation decrease in the change in carbon intensity, corresponding to approximately 0.4 tons of change in carbon emissions per one million dollars of output. In other words, compared to the average value of carbon intensity, the rate of change in carbon intensity accelerated by about 30%. Furthermore, Figure 2.6 shows an immediate reduction in the change in carbon intensity of treated countries compared to control countries following the implementation of the first phase of the EU ETS. These findings suggest a progressive and sustained reduction in carbon intensity for the overall sample of sectors due to the EU ETS. In summary, the reduction in carbon intensity indicates that sectors in EU ETS countries are making faster progress toward emission reduction, supporting a sustainable green development path.

Table 2.2: The Effect of the EU ETS Policy on the Change in Carbon Intensity and its Drivers - 1996–2012

Variable	(1) ΔCI	(2) CI^{TEI}	(3) CI^{PEI}	(4) CI^{CTE}	(5) CI^{CPE}	(6) CI^{OS}
EU ETS Effect	0.119*	0.119	0.147*	-0.026	0.230	0.017
	(0.067)	(0.074)	(0.077)	(0.172)	(0.193)	(0.150)
Observations	544	544	544	544	544	544

Note: This table presents the EU ETS average treatment effect on the following decomposed variables: change in carbon intensity (ΔCI) and change in carbon intensity through: (1) changes in total energy intensity (CI^{TEI}), (2) changes in pollutant energy intensity (CI^{PEI}), (3) changes in carbon-to-total energy ratio (CI^{CET}), changes in carbon-to-pollutant energy ratio (CI^{CEP}), and changes in output share (CI^{OS}) using Specification 2.12. We analyze 21 treated countries and 11 control countries over the period 1996-2012 (see Tables A.1 and A.2). The Jackknife approach is used to calculate the standard errors of the estimated coefficients. All regressions include time and country fixed effects. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Columns (2) through (6) represent the change in carbon intensity through changes in energy intensity (CI^{TEI} and CI^{PEI} for all and pollutant energy sources), changes in carbon-to-energy ratio (CI^{CET} and CI^{CEP} for all and pollutant energy sources), and changes in output share (CI^{OS}). From Equations 2.6, 2.7, 2.8, 2.9, and 2.10, we see that these decomposed values reflect the change in carbon intensity (ΔCI) multiplied by the elasticity between carbon intensity and its underlying factors. Thus, these columns capture the contribution of each driving factor to changes in carbon intensity.

Columns (2) to (6) generally do not show statistically significant results, except for column (3), which corresponds to CI^{PEI}. This implies that we did not find sufficient statistical evidence that the EU ETS sustainably reduces carbon intensity through improvements in the carbon-to-energy ratio or structural changes in output share. However, the program did accelerate the reduction in carbon intensity through improvements in pollutant energy intensity. The results show that the EU ETS led to a 0.15 standard deviation increase in the change in carbon intensity via this channel, equivalent to approximately 0.49 tons of change in carbon emissions per one million dollars of output. In other words, compared to the average carbon intensity value, this corresponds to a 36% acceleration in the rate of change in carbon intensity.

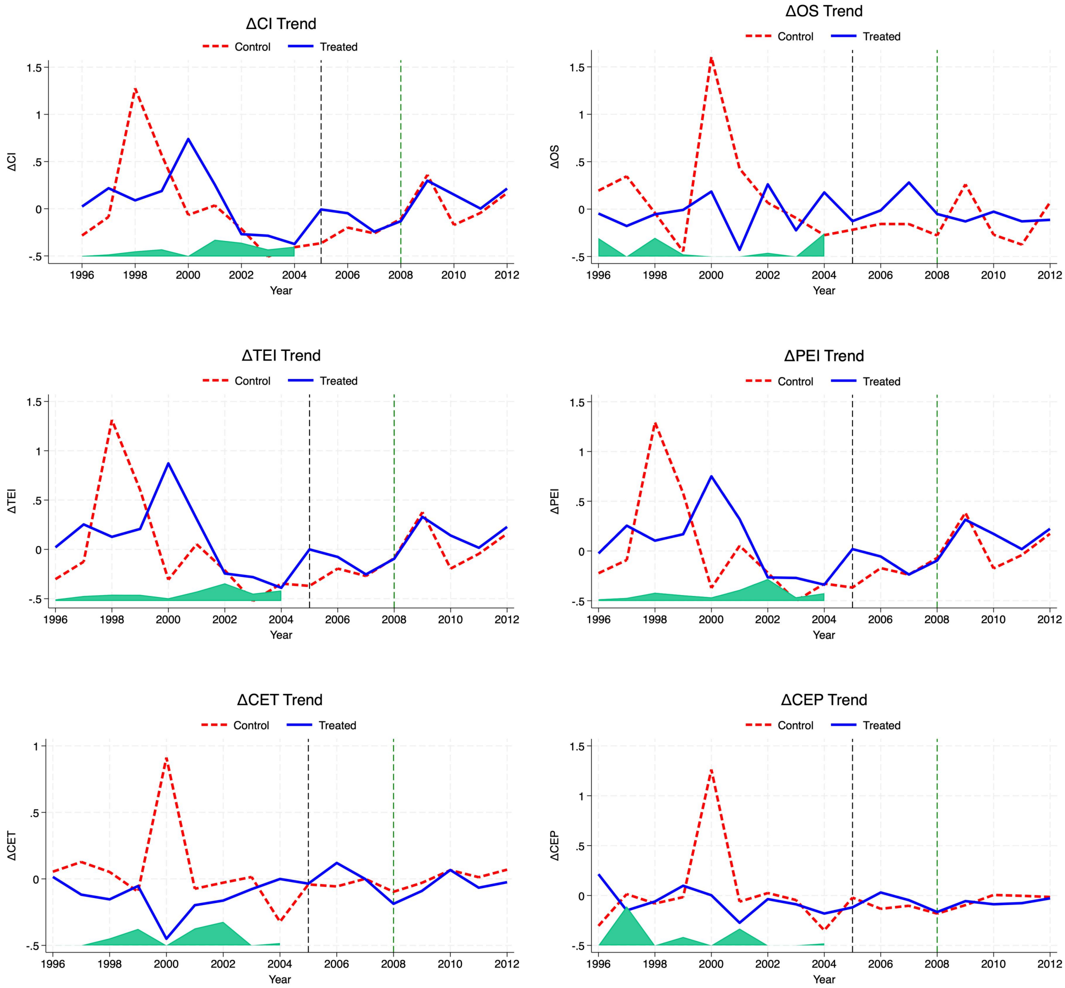
In summary, our study suggests that the EU ETS successfully achieved a sustainable reduction in carbon intensity through improvements in energy intensity from pollutant energy sources.

2.5.3 Robustness Checks

To verify the reliability of the main findings, we conducted a placebo-based robustness assessment. In particular, a permutation test is employed to determine whether the observed effects of the EU ETS differ meaningfully from what one would expect if treatment were assigned at random. This approach involves generating a reference distribution of estimated effects by repeatedly and randomly reallocating treatment status. Under the null hypothesis, the EU ETS exerts no influence on the examined dependent variables—carbon emissions, carbon intensity, and its underlying driving factors—implying that any detected pattern arises by chance. The alternative hypothesis posits that the EU ETS indeed affects these outcomes among treated countries, indicating that the observed results are not merely random fluctuations.

This permutation test serves as a non-parametric tool to evaluate the statistical importance of the EU ETS impacts identified through the SDiD framework. In each iteration of the test, it randomly selects a new set of treated countries while keeping their total number fixed (21 treated countries), mirroring the original treatment assignment. This selection is carried out without replacement from the full sample of countries, ensuring each nation's equal probability of being treated in every iteration. By maintaining a constant number of treated units, we control for

Figure 2.6: The Trends of Adjusted Outcome, Change in Carbon Intensity and Its Underlying Drivers, Among Treated and Control Groups



Note: This figure illustrates the trends of the change in carbon intensity and its underlying driving factors from 1996 to 2012, comparing the average outcomes of treated units with the weighted average outcomes of control units. The first and second phases of the EU ETS policy are marked by vertical black and green dashed lines, respectively. Green triangles indicate the time weights. Both unit and time weights are determined through an optimization procedure, as described in [16] and briefly outlined in the Methodology section.

potential confounders related to group size, ensuring that differences in estimated effects arise from treatment assignment rather than changes in sample composition.

To form an empirical null distribution of EU ETS effects, the code is executed over 1,000 such permutations for each dependent variable. After generating this distribution, the extremity of the originally estimated effect relative to what might be expected purely by chance is evaluated . We expect that the EU ETS policy decrease carbon emissions, carbon intensity and its main driving factors, hence, we implemented a one-tailed test. In this context, the p-value is defined as the share of permuted outcomes that equal or less than the observed effect.[9]

To further ensure that the inference does not depend on assumptions regarding the directionality of the effect, a two-tailed permutation test is also conducted. Here, the p-value is determined by the fraction of permuted outcomes whose absolute value matches or surpasses that of the observed estimate, effectively considering deviations in both positive and negative directions.[10] This approach enhances the rigor of the statistical inference by accounting for potential bias in the initial expectations.

In summary, by applying both one-tailed and two-tailed permutation tests, we validated the robustness of the SDiD-based results. These tests confirm that the estimated effects of the EU ETS on all dependent variables are not driven by random factors, thereby lending further credibility to the conclusion that the EU ETS has a substantive and sustained influence on carbon emissions, carbon intensity and it underlying driving factors.

2.6 Conclusion and Policy Remarks

This paper examines the effectiveness of the EU ETS in mitigating carbon emissions, lowering carbon intensity, and influencing its key determinants at both the country and sectoral levels. It also evaluates the program's contribution to facilitating a sustainable decrease in carbon intensity. Employing data from seven targeted sectors across 32 countries over the period 1996–2012, and using a staggered Synthetic Difference in Differences (SDiD) framework alongside a decomposition analysis, we find that the EU ETS not only reduced overall emissions but also affected the underlying factors driving carbon intensity throughout the first two phases of the policy.

Our results show that, on average, regulated countries achieved a statistically significant 19% reduction in CO_2 emissions at the aggregate level, consistent with earlier studies that highlight the EU ETS's effectiveness in reducing carbon emissions over time. Furthermore, we observe a substantial decrease in carbon intensity among EU ETS-regulated countries, indicating that

[9] If this p-value is low, it suggests that achieving the estimated ATT by random chance is unlikely, reinforcing the conclusion that the EU ETS meaningfully affects the outcome variables.

[10] A low p-value in the two-tailed test indicates that the observed effect is not easily attributable to random variation in either direction, thereby confirming that the EU ETS has a genuine, statistically significant impact on the dependent variables.

the policy's influence extends beyond simple emission cuts to structural improvements in the emissions efficiency of production. Notably, these impacts vary across sectors: Chemicals (C20), Non-Metallic Mineral Products (C23), Basic Metal (C24), and Energy (D35) demonstrated significant reductions in carbon intensity.

Our decomposition analysis reveals that enhancements in energy intensity—especially regarding pollutant energy sources—served as a principal channel for reducing carbon intensity. This underscores the importance of improving energy efficiency within existing fossil-based infrastructures and highlights the role of incremental technological upgrades and operational optimizations. Moreover, the sectors that achieved the most pronounced and sustained decreases in carbon intensity were often those that realized the greatest reductions in pollutant energy intensity.

A key insight from our study is that improvements in carbon intensity are persistent rather than transient. The EU ETS appears to have prompted a trajectory of sustained efficiency gains, evidenced by accelerated changes in carbon intensity well beyond the early implementation phases. This suggests that market-based instruments can stimulate long-term structural transformations rather than delivering only short-term emission reductions.

Nevertheless, the heterogeneous responses across sectors suggest that a one-size-fits-all approach may not suffice. While the EU ETS has been effective on average, sectors like Paper and Paper Products, which did not show the expected improvements, may require more tailored measures—such as targeted subsidies for low-carbon technologies, stricter emissions benchmarks, or capacity-building initiatives—to overcome specific structural barriers. In contrast, improvements in the Basic Metals sector, achieved through better carbon-to-energy ratios, also influenced output shares, indicating that even successful strategies can carry economic trade-offs. Policymakers must be mindful of these distributional and competitiveness effects when shaping complementary measures.

Our findings also show that firms have tended to optimize fossil fuel usage rather than fully transition to clean energy alternatives. Policymakers could consider reinforcing the EU ETS with stronger incentives for renewable energy adoption. Such measures might include increasing the stringency of emission caps, adjusting allowance allocations to favor cleaner energy inputs, and introducing complementary policies—such as renewable energy mandates and innovation funds—designed to encourage the gradual replacement of pollutant energy sources with cleaner options.

Moreover, the sustained reduction in carbon intensity linked to pollutant energy efficiency improvements underscores the crucial role of continuous technological progress. Governments and the European Commission could strengthen research and development incentives, bolster support for energy audits, and finance pilot projects that showcase advanced efficiency measures. Such actions would not only consolidate the gains already realized but also expedite the shift toward more sustainable industrial processes.

Finally, while this study has focused on the direct effects of the EU ETS on participating countries, future research might examine the policy's indirect impacts on non-regulated trade partners. By exploring potential influences on production patterns, trade flows, and emission trajectories elsewhere, scholars could ascertain whether this unilateral policy induces carbon leakage, stimulates cleaner technologies abroad, or reshapes the global emissions landscape. Understanding these indirect consequences would provide valuable insights for designing more effective international climate policies and fostering deeper alignment in global sustainability initiatives.

CHAPTER 3

On Trade Flow and Relative Technological Gaps

Does the EU Emissions Trading System Affect Trade Flow and Relative Technological Gaps?

Abstract

This study examines the impact of the European Union Emission Trading System (EU ETS) on international trade flows and technological gaps, focusing on five manufacturing sectors directly regulated by the policy. Employing a dataset spanning 1996–2012, the analysis is conducted using quasi-experimental techniques, such as a staggered Synthetic Difference in Differences (SDiD) approach, to establish a credible counterfactual and address methodological challenges commonly encountered in cross-country empirical analyses. The results reveal that, contrary to prior inconclusive evidence, the EU ETS led to a significant 14% increase in imports from non-EU ETS countries. This effect is heterogeneous across sectors, with Food, Non-Metallic Mineral Products, and Metals experiencing more substantial increases in import values, while Paper and Chemicals show negligible changes. Further analysis indicates that unilateral carbon pricing not only influences trade patterns but also widens cross-country technological gaps, particularly related to carbon emissions and energy use. These findings underscore the complexity of unilateral climate policies. While the EU ETS may foster low-carbon innovation and efficiency improvements in regulated countries, it may also shift carbon-intensive production abroad. The study's insights highlight the need for complementary policies to ensure global emissions reductions and support more balanced, sustainable technological progress.

Keywords: EU ETS, Import, Trade flow, Synthetic Difference in Differences, Technological Gap, Carbon Intensity

JEL Classification: F14, Q54, Q58

3.1 Introduction

Environmental protection against climate change caused by carbon emissions has grown into a critical global concern in recent decades. Heightened public awareness of environmental harm has spurred a range of policy interventions, among which Emission Trading Systems (ETS) have emerged as a popular carbon pricing strategy. The European Union Emission Trading System (EU ETS), a key component of Europe's decarbonization efforts, is frequently regarded as the most influential unilateral and cost-effective mechanism to curb climate change ([94]). Nonetheless, the absence of a comprehensive international carbon market—combined with increasing trade and capital flows—raises vital questions about how asymmetric environmental policies influence technological disparities across countries, particularly in terms of carbon emissions and energy efficiency. This study explores how the EU ETS affects these technological gaps between EU ETS-regulated nations and their unregulated trading partners, with a focus on the role of international trade as a transmission channel.

Existing research provides mixed evidence regarding the EU ETS's performance, including its effects on emissions, innovation, and trade patterns. A substantial body of literature considers how environmental policy stringency influences international trade flows, often framed through the lens of the pollution haven hypothesis. Using proxies like pollution abatement and control expenditures (PACE), [47] and [73] demonstrate that stricter regulations can lead to increases in net imports from less regulated regions. Other researchers have employed alternative indices of environmental stringency, such as [31], or instrumental variables, like the ventilation coefficient in Chinese provinces ([93]), consistently finding that tightening regulations drives trade patterns toward countries with lower compliance costs. Energy prices, too, matter: [91] show that cross-country energy price gaps influence trade flows. Studies focusing on global and regional climate programs, like [38], reveal that even while some regulated sectors (e.g., medium-low technology EU manufacturing sectors) saw increased exports post-EU ETS, others experienced shifts indicative of carbon leakage ([100]), [4]).

On the other hand, a unilateral environmental policy like the EU ETS can directly reduce carbon intensity in regulated countries by fostering technological advancements in carbon mitigation within production processes, which refers to the Porter hypothesis ([86]) in the literature. The Porter hypothesis anticipated that the EU ETS would promote the creation of new low-carbon technology in addition to reducing carbon emissions at a reasonable cost. When regulated firms expect to pay a greater price for emissions relative to other production expenses, they are incentivized to make investments and operational changes that reduce the emissions intensity of their output. The development and commercialization of new emissions-reducing technology will receive a portion of this increased investment. While lowering emissions is undoubtedly the main goal of carbon market programs, it is also critical from an economic standpoint to offer incentives for technical advancement, as new technologies have the potential to significantly lower the long-term abatement cost. From this angle, it is expected that the carbon intensity of the participating countries will decline.

When it comes to low-carbon innovation, a concept central to the Porter hypothesis, the evidence is somewhat inconclusive. Some studies highlight minimal impacts on low-carbon patenting ([33]) or no statistically significant relationship between EU ETS participation and low-carbon investments ([75]), while others suggest that anticipation of future stringency and stable carbon pricing fosters some degree of innovation and technological investment ([77]). Research examining how the EU ETS affects low-carbon technology development draws on a range of empirical and theoretical frameworks. For example, market-based environmental policies can guide renewable energy technology adoption, as shown by [68], while case studies in Ireland ([5]) and Germany ([88]) indicate that regulated firms do respond by improving equipment and R&D, although outcomes are hampered by factors like free allocation of credits. Other authors found limited environmental innovation due to policy volatility ([23]) and low carbon prices ([3]), suggesting that clear and stable policy signals are essential to mobilize meaningful technological transformation. These disparate results highlight the gap in understanding the nuanced ways in which the EU ETS shapes both innovation trajectories and the structural composition of production across sectors.

In contrast, the policy can indirectly affect the carbon intensity of countries that are not under the program's regulations through shifts in trade patterns among partners, which corresponds to the pollution haven hypothesis ([73]; [26]; [58]). The pollution haven hypothesis predicts that strict environmental policies will ultimately shift pollution-intensive production toward regions with lower environmental abatement costs (e.g. [73]). A unilateral environmental policy such as the EU ETS will raise production costs for domestic firms who compete globally with producers from regions with less stringent environmental regulations. Producers may therefore be compelled to reduce their commercial losses by adjusting their pricing strategy, changing their market shares, or moving their polluting production facilities to regions with laxer or no regulations. Consequently, this may shift the spatial distribution of the industrial value-added chain and subsequently influence trade flows. The pollution haven hypothesis perspective in the environmental economics literature ([73]; [26]; [58]) may predict a worsening in the relative carbon intensity in the exporter countries that are not part of the EU ETS scheme compared to their regulated partners.

Variations in emissions per unit of output (i.e., carbon intensity) of manufacturing firms are more likely to reflect technological changes rather than fuel switching ([97]).[1] On emissions reduction, numerous early works relied on aggregate data, indicating modest but meaningful declines during the initial phases of the EU ETS ([30]; [6]), while more recent analyses using counterfactual estimates confirm that the policy effectively curbed carbon emissions (see Chapter 1), though the magnitude of these reductions varies ([19]). Firm-level investigations similarly find that emissions declined, albeit heterogeneously ([85]; [66]; [69]; [37]; [42]).

In the context of the EU ETS, both channels, innovations and international trade flows, are likely to decrease the relative carbon intensity (i.e., the carbon intensity of regulated countries over the carbon intensity of their unregulated trade partner) and relative energy intensity (i.e., the energy intensity of regulated countries over the energy intensity of their unregulated trade partner) of non-EU countries compared to their EU trade partners that are under the program's regulations. Since these relative intensities can effectively represent the cross-country technological gaps, particularly those related to carbon emissions and energy use, this decreasing in relative carbon and energy intensity can be interpreted as a widening of the technological gaps between these countries.

The stringent environmental regulations may stimulate innovation, improve productivity, and

[1] We focus on carbon intensity in the manufacturing sector, as empirical studies on electricity generation highlight the effectiveness of the EU ETS in reducing emissions through fuel switching (from coal to gas). See e.g., [50].

ultimately enhance competitiveness by spurring the development and commercialization of low-carbon technologies as suggested by the Porter hypothesis ([86]). In contrast, the pollution haven hypothesis ([73]; [26]; [58]) posits that such stringent regulations could shift carbon-intensive production and trade flows toward countries with less stringent environmental standards. Further complicating this picture, some studies suggest that the additional emission costs introduced by the EU ETS are not substantial enough to meaningfully alter trade patterns or technological incentives. The reason is that such costs are relatively marginal compared to existing labor cost disparities ([83]). Also, they pointed out that the generous free allocations of emissions permits in this policy may dampen innovation signals ([59]; [54]; [92]). Therefore, a crucial gap remains in understanding how the EU ETS influences both trade flows and technological disparities, especially across key manufacturing sectors most affected by the policy.

By highlighting how the EU ETS has the potential to affect both the cross-border flow of carbon-intensive products and the production technology of trading partners, this study contributes to the evolving discussion on how carbon pricing mechanisms shape international comparative advantages. Our findings extend beyond the established debates framed by the Porter and pollution haven hypotheses. While much of the literature focuses on static outcomes such as emissions reductions and cost pass-through, the results of this study suggest that policy-induced changes penetrate more deeply into global value chains, influencing the speed, direction, and degree of technological changes in both regulated and non-regulated regions.

In this study, we construct a balanced panel dataset containing five manufacturing sectors targeted by the EU ETS program, covering 21 countries subjected to the EU ETS regulations and 11 non-EU countries on: (1) bilateral import values from UNCTAD-COMTRADE to study the impact of the policy on trade flows; and (2) carbon emission, energy usage, and output from World Input-Output Database (WIOD) to construct technological gap indicators related to carbon emissions and energy use, to capture how the EU ETS may have influenced relative underlying production technologies and environmental efficiency across EU ETS-regulated and -unregulated countries. This dataset spans the period from 1996 to 2012 which includes the first two phases of the EU ETS program. We employed two quasi-experimental frameworks, first, the DiD Gravity method, which broadly used in the literature ([4]; [83]; [105]); and second, the staggered design of the SDiD approach ([16]; [17]; [72]). We suggested that while the DiD Gravity approach, employed by the literature, estimated significant effects on trade flow, they could be biased due to major issues of counterfactual robustness and violation of pre-treatment parallel trend assumption. To the best of our knowledge, this is the first study in the literature that conducted a causal inference analysis using the SDiD approach along with re-defining the counterfactual scenario to mitigate the effects of these issues.

Within the EU ETS context, recent empirical works remain inconclusive. While [83] find no significant effects on trade flow using a DiD Gravity approach, [105] report symmetric reductions in export values and increases in import values for EU ETS regulated countries. Using the same approach, but with a different dataset and treated and control groups, we found an overall 58% increase in import values for all selected sectors aggregated at the country level due to the implementation of this program across EU ETS-regulated countries. Nevertheless, the estimated results using the SDiD approach with a modified identification strategy present a different scale of effect and show that imports from non-EU countries increased by about 14% under EU ETS regulations among regulated countries.

Additionally, sector-level analysis of products such as aluminum ([90]), cement and steel ([28]), and pulp and paper ([74]) yielded limited or mixed results in the literature. However, not only with the DiD Gravity model, which may estimate a biased effect, but also with a more robust SDiD approach we found heterogeneous sectoral effects. In the Food (C10-C12), Non-Metallic Mineral Products (C23), and Basic Metals (C24) sectors the imports among EU ETS-regulated countries have increased from non-EU exporters. While the results for the Paper (C17) and Chemicals (C20) sectors were significant and positive with the DiD Gravity model, we could not find enough statistical evidence to show EU ETS affected the trade flow in these sectors using the SDiD approach. This sectoral heterogeneity highlights that not all regulated industries are equally affected by carbon pricing, and that sectoral production structures, technological flexibility, and adaptation capacities play essential roles in shaping trade responses.

Moreover, beyond its effect on trade flows, the literature shows variations in carbon intensity are often attributed more to technological changes within manufacturing processes than to mere fuel switching ([97]), suggesting that a more granular, sector-specific understanding of how

ETS-regulated countries adapt, and how this adaptation affects their unregulated trade partners, is essential. Against this complex backdrop, our research, drawing upon comprehensive bilateral import data, in addition to the relative carbon intensity, relative energy intensity, and relative carbon-to-energy ratio-as technological gap indicators-aims to fill this gap by analyzing the EU ETS's role in shaping international trade patterns and, for the first time in the literature (to the best of our knowledge), technological disparities. We find that the program has contributed to widening technological gaps between regulated countries and their unregulated trade partners, which appears consistent with a combination of the Porter and pollution haven hypotheses. Literature exploring distributional outcomes increasingly recognizes that carbon pricing must integrate with other social, labor, and industrial policies to ensure equity ([70]). If unilateral carbon markets lead to a net shift in high-carbon production activities abroad, then the environmental gains in the regulating country may come at the expense of emissions growth and potentially less sustainable working conditions elsewhere. The widening technological gap uncovered here suggests that without deliberate policies to encourage global diffusion of clean technologies, the full decarbonization potential of carbon markets may remain unrealized.

The sectoral analysis of the EU ETS effect on these technological gaps is more divergent, ranging from widening the gaps in some indicators to shrinking them in others, while some sectors were not affected by the policy. Our findings suggest that technology gaps can expand as regulated countries pursue cleaner production while less regulated partners capitalize on trade opportunities without commensurate upgrades. Consistent with [70], our results underscore the need for integrated policy frameworks. Without mechanisms to encourage low-carbon technology diffusion globally—through financial support, capability-building, or easing access to green technology—carbon pricing risks yielding only partial climate benefits and uneven socio-economic outcomes.

Finally, as another contribution to the literature, examining growth rates rather than just static levels offers nuanced insights into the temporal dimension of policy effects. According to growth-based analysis, imports into particular industries (including food) increased faster after the EU ETS, possibly due to difficulties faced by domestic producers in adapting quickly to compliance costs. In contrast, sectors like Non-Metallic Mineral Products and Basic Metals showed slower import growth rates, suggesting that regulated firms may be undertaking a gradual restructuring and investing in cleaner technologies over time. Similarly, growth-based indicators of the technological gap underscore that the EU ETS not only affects the current level of environmental performance but also influences its trajectory, with regulated countries' decarbonization efforts accelerating relative to their non-regulated counterparts. These findings on acceleration in technical advancements and decarbonization trends suggests that climate policy can produce long-term, dynamic gains. Policymakers should consider long-term benefits in addition to the immediate costs of compliance. Policy frameworks that are stable and predictable can incentivize businesses to invest in greener technologies, innovate their processes, and acquire new skills. The long-term goals of climate policy are strengthened in such an environment, which promotes consistent increases in energy efficiency and emissions reductions.

This study presents findings that are partly discussed for the first time in the literature, particularly regarding the impact on technological gap indicators. These results underscore the challenges of implementing unilateral climate policies within an interdependent global economy. While the EU ETS might promote advancements in low-carbon technologies and energy efficiency within regulated entities, it risks encouraging increased carbon-intensive production in other regions. To ensure that global emissions are truly reduced rather than merely shifted, these dynamics highlight the need for complementary policies. These could include precisely calibrated border carbon adjustments, multilateral climate agreements, and enhanced international coordination to curb carbon emissions. Policymakers might also consider providing targeted support to sectors that are struggling to adapt, investing in stable policy frameworks that encourage long-term innovation, and motivating unregulated partners to improve their technological capabilities. Ultimately, our findings that the EU ETS affects trade flows, drives dynamic decarbonization efforts domestically, and exacerbates cross-country technological disparities highlight the pressing need for more comprehensive policy designs that address both local and global environmental outcomes.

The remainder of this paper proceeds as follows. Section 2 details the dataset. Section 3 presents stylized facts, and Section 4 outlines the econometric models. Section 5 discusses the empirical results and robustness checks. Finally, Section 6 concludes with policy implications.

3.2 Data

The primary data sources for this study are the World Input-Output Database (WIOD) and the UNCTAD-COMTRADE database. The WIOD, described in detail by [46], provides a comprehensive set of harmonized input-output tables and associated environmental and socio-economic indicators. The UNCTAD-COMTRADE database supplies data on bilateral international trade flows. In addition, we draw upon the World Development Indicators (WDI) database, the Penn World Table (PWT) database, the KOF Swiss Economic Institute database, and the CEPII Gravity Database to incorporate a rich set of time-varying control variables at the importer-exporter-sector level.

3.2.1 Dependent Variables

We consider two sets of dependent variables to examine the effects of the EU ETS policy. First, we use bilateral import values to study the impact of the policy on trade flows. Second, we employ WIOD to construct technological gap indicators related to carbon emissions and energy use, to capture how the EU ETS may have influenced relative underlying production technologies and environmental efficiency across EU ETS-regulated and -unregulated countries.

WIOD offers consistent and fully comparable international data, enabling an in-depth evaluation of efficiency improvements at both the sector and country levels. To thoroughly assess the first two phases of the EU ETS policy, the analysis spans from 1996 to 2012, encompassing 32 OECD and key partner countries (e.g., India and Indonesia), 21 participants in the EU ETS and 11 non-participating countries. Table A.1 lists the countries included in our dataset. These countries are selected based on data availability, reliability, and consistency.

The primary dataset originates from the WIOD Release 2016, covering 42 countries (29 EU member states and 13 other major economies) from 2000 to 2014. To extend the analysis backward to the 1996–1999 period, data from the WIOD Release 2013 are integrated, which includes 40 countries (27 EU member states and 13 additional major economies) for the years 1995–2011, although some variables conclude in 2009. Data from 1995 are excluded due to incomplete records for key variables across several countries. Likewise, data for 2013–2014 are omitted to concentrate explicitly on the EU ETS's first two phases. Moreover, the analysis excludes certain countries[2] due to incomplete essential variables. Japan is also excluded, as it implemented its own national ETS in 2010, making it inappropriate as either a treatment or control country in this causal framework.

We focus on 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 (ISIC Rev.4 C23); and Basic Metals (ISIC Rev.4 C24).[3] By restricting the analysis to sectors directly targeted by the EU ETS, we reduce the risk of mixing sectors with fundamentally different carbon intensities and energy usage patterns, thus minimizing selection bias.

From UNCTAD-COMTRADE, we extract bilateral import values at the 2-digit industry level in ISIC Rev.3 format and convert them to ISIC Rev.4 using a concordance table from the World Bank's WITS page. These data cover the same 32 countries and the 1996–2012 period, ensuring consistency and comparability with the WIOD-based variables.

International Trade Flow

Changes in trade competitiveness are often gauged using trade volumes. However, collecting consistent volume data can be challenging due to missing observations and inconsistent measurement units across products. Instead, we rely on bilateral import values to approximate trade competitiveness, consistent with approaches in the literature ([74]). Although values may reflect price and exchange rate fluctuations, they remain widely used in empirical studies and are more readily available.

We used the logarithm of bilateral import values to reduces variance, mitigates the influence of outliers, and improves model performance. Additionally, by focusing on import growth, we capture the relative sensitivity of trade flows to the environmental policy, shedding light on whether the EU ETS has altered the global competitive landscape.

[2] Slovenia, Switzerland, Croatia, Norway, Taiwan, Cyprus, Luxembourg, Estonia, and Malta

[3] We identified the manufacturing sectors covered by the EU ETS using the EUTL Database and the EU ETS Handbook. Initially, we mapped installations to their ISIC Rev.3 activities and selected manufacturing sectors representing more than 3% of the total installations. We excluded sector C19 (Coke and Refined Petroleum) due to its atypically large number of zero observations to avoid introducing bias in our estimates.

Technological Gap Indicators

In addition to examining changes in trade flows, we investigate how differences in carbon intensity, energy intensity, and carbon-to-energy ratios evolve between treated (EU) and control (non-EU) countries. We construct a set of technological gap indicators using both WIOD and UNCTAD-COMTRADE data. These indicators serve as proxies for disparities in technological sophistication and environmental performance across trading partners, reflecting differences in production processes, resource efficiency, and the adoption of clean technologies.

Following Equation 3.1, we define three types of ratios at the importer-exporter level, where d denotes the destination/importer country and o denotes the origin/exporter country:

$$\begin{cases} \mathrm{TG}^{\mathrm{CI}} = \dfrac{\mathrm{CI}^d}{\mathrm{CI}^o} \\ \mathrm{TG}^{\mathrm{EI}} = \dfrac{\mathrm{EI}^d}{\mathrm{EI}^o} \\ \mathrm{TG}^{\mathrm{CE}} = \dfrac{\mathrm{CE}^d}{\mathrm{CE}^o} \end{cases} \tag{3.1}$$

where CI is the carbon intensity (carbon emissions per unit of output), EI is the energy intensity (energy use per unit of output), and CE is the carbon-to-energy ratio (carbon emissions per unit of energy consumed). These ratios allow us to assess how much cleaner or more efficient an importer's production technology is relative to its exporter counterpart.

We refine these indicators further by distinguishing between pollutant-specific and total energy use. For energy intensity, we construct pollutant energy intensity ($\mathrm{TG}^{\mathrm{PEI}}$) and total energy intensity ($\mathrm{TG}^{\mathrm{TEI}}$) measures. Similarly, for carbon-to-energy ratios, we derive carbon-to-energy from pollutant ($\mathrm{TG}^{\mathrm{CPE}}$) and total ($\mathrm{TG}^{\mathrm{CTE}}$) energy sources.

A lower relative carbon intensity ($\mathrm{TG}^{\mathrm{CI}}$) suggests that the importer's production technology is relatively less carbon-intensive compared to the exporter, indicating a technological gap in terms of environmental performance. Similar to the carbon intensity, the relative energy intensity ($\mathrm{TG}^{\mathrm{PEI}}$ and $\mathrm{TG}^{\mathrm{TEI}}$) indicate whether an importer's production processes are more or less energy-efficient than those of its trading partners. Disparities in these ratios suggest differences in the adoption of energy-saving technologies and energy management practices. Finally, a lower relative carbon-to-energy ratio ($\mathrm{TG}^{\mathrm{CPE}}$ and $\mathrm{TG}^{\mathrm{CTE}}$) suggests that the importer's energy portfolio leans more heavily toward low-carbon technologies or energy sources, thereby indicating a greater technology gap related to cleaner energy utilization and decarbonization strategies, including technologies like Carbon Capture and Storage (CCS) and other low-carbon solutions.

3.2.2 Covariates

We incorporate a comprehensive set of covariates, tailored for each set of dependent variables, to control for confounding factors and ensure robust identification of the EU ETS's impact. These covariates fall into four main categories.

The first group controls for variations among pairs of importer and exporter countries. Most trade studies include GDP per capita (constant PPP in log form) in the model to control for differences in economic development and purchasing power in importer and exporter countries. However, unilateral dimensions often lose statistical robustness. Hence, we propose a country level and sector-specific (s) country-pair time variant measure of relative size rather than double unilateral ones. We compute the similarity index of the GDPs and outputs of two trading partners, Sim_{ijt} and Sim^s_{ijt} respectively, calculated as in [48]:

$$\text{Sim}^s_{ijt} = \ln\left[1 - \left|\left(\frac{\text{Output}^s_{it}}{\text{Output}^s_{it} + \text{Output}^s_{jt}}\right)^2 - \left(\frac{\text{Output}^s_{jt}}{\text{Output}^S_{it} + \text{Output}^s_{jt}}\right)^2\right|\right] \tag{3.2}$$

And similarly at the country level:

$$\text{Sim}_{ijt} = \ln\left[1 - \left|\left(\frac{\text{GDP}_{it}}{\text{GDP}_{it} + \text{GDP}_{jt}}\right)^2 - \left(\frac{\text{GDP}_{jt}}{\text{GDP}_{it} + \text{GDP}_{jt}}\right)^2\right|\right] \tag{3.3}$$

The intra- and inter-industry trades are often approximated by the relative endowment of domestic assets. We use differences in GDP per capita and output per capita as a proxy for the relative capital-labor ratio between countries, as in [38]. The greater value of these variables, (Endw_{ijt}) and (Endw^s_{ijt}), represents the lower share of intra-industry trade and the higher volume of inter-industry trade.

$$\text{Endw}_{ijt}^{s} = \left| \ln\left(\frac{\text{Output}_{it}^{s}}{\text{Pop}_{it}}\right) - \ln\left(\frac{\text{Output}_{jt}^{s}}{\text{Pop}_{jt}}\right) \right| \tag{3.4}$$

And similarly at the country level:

$$\text{Endw}_{ijt} = \left| \ln\left(\frac{\text{GDP}_{it}}{\text{Pop}_{it}}\right) - \ln\left(\frac{\text{GDP}_{jt}}{\text{Pop}_{jt}}\right) \right| \tag{3.5}$$

We also measure the impact of country-sector-pair size and country-pair size as given in [38]:

$$\text{Mass}_{ijt}^{s} = \ln\left(\text{Output}_{it}^{s} + \text{Output}_{jt}^{s}\right) \tag{3.6}$$

and the same for country-pair:

$$\text{Mass}_{ijt} = \ln\left(\text{GDP}_{it} + \text{GDP}_{jt}\right) \tag{3.7}$$

Second, we consider time-varying country-level variables for both the exporter and importer countries. We control for foreign direct investment (FDI) as % of GDP, and trade share (% of GDP), as these factors affect trade flows by fostering industrial growth, creating demand for capital goods and intermediate products, investing in productive capacity, and accounting for trade policies or openness. Additionally, we include oil rent (% of GDP) to account for resource dependency, which affects trade patterns of more or less energy-intensive products. All variables are sourced from the World Development Indicators (WDI) database. In addition, the Human Capital Index and Total Factor Productivity (TFP) are also included in the model specifications to control for skill levels and productivity differences. These data are collected from the Penn World Table (*PWT*) database. Furthermore, we control for the effect of the degree of globalization on countries' trade patterns by including the globalization index, sourced from the *KOF* Swiss Economic Institute. Finally, in the DiD Gravity model, the EU control variable is defined as 1 for EU country pairs in which at least one member of the pair joined the EU after 1996, starting from the year when both were members. For example, the Bulgaria-France pair is set to 1 starting from 2007, when Bulgaria joined the EU, while Germany-France remains 0, as both countries joined the EU before 1996.

Additionally, since capital and intermediate inputs directly influence production within a sector, we included these factor inputs to avoid confounding the observed effects with structural differences. We also incorporated measures of labor compensation and capital compensation (as a share of value-added) to capture the structural composition of income, reflecting changes in the relative roles of labor and capital in the production process. Furthermore, our specification accounts for energy usage from both pollutant clean sources, allowing us to consider variations related to price differentials between clean energy and pollutant ones, such as fossil fuels, as well as differences in relative energy prices across countries. All these data originate from the World Input-Output Database (WIOD), provided at the sector-importer-exporter-year level.

Finally, following the literature (e.g., [7]), it is generally assumed that trade costs can be controlled through groups of dummies alongside bilateral distance. We use the population-weighted distance between the most populated cities, sourced from the *CEPII* Gravity Database. The dummies are as follows. First, using Mario Larch's Regional Trade Agreements Database, we consider dummies for regional trade agreements, customs unions, free trade agreements, partial scope agreements, economic integration agreements, and combined free-trade & economic integration agreements. Second, using the *CEPII* Gravity Database, we include 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. Third, we control whether the two countries have a common border (either land or sea border) and whether at least one of the two countries is a landlocked country (no access to high sea).

Table A.6 presents all variables and their data sources and Table A.4 shows summary statistics of all variables.

3.3 Stylized Facts

3.3.1 International Trade Flow

Figure 3.1 presents the distribution of import values (on a logarithmic scale) before and after the implementation year of the EU ETS policy (2005). One notable observation from the figure is the emergence of additional trading links across countries and sectors in the post-2005 period, which would remain undetected if we were not to utilize a fully balanced panel of potential trade relationships. By constructing a fully balanced dataset, we include not only observed trade flows but also potential trade links that may not have materialized in certain periods. In other words, in addition to the observed non-zero trade flows recorded by the UNCTAD-COMTRADE database, we consider zero trade values to account for latent but unrealized trade opportunities. This approach mitigates the risk of selection bias and enhances the credibility of the empirical analysis, ensuring that the estimated policy impacts are not confounded by the exclusion of these unrealized trade links.

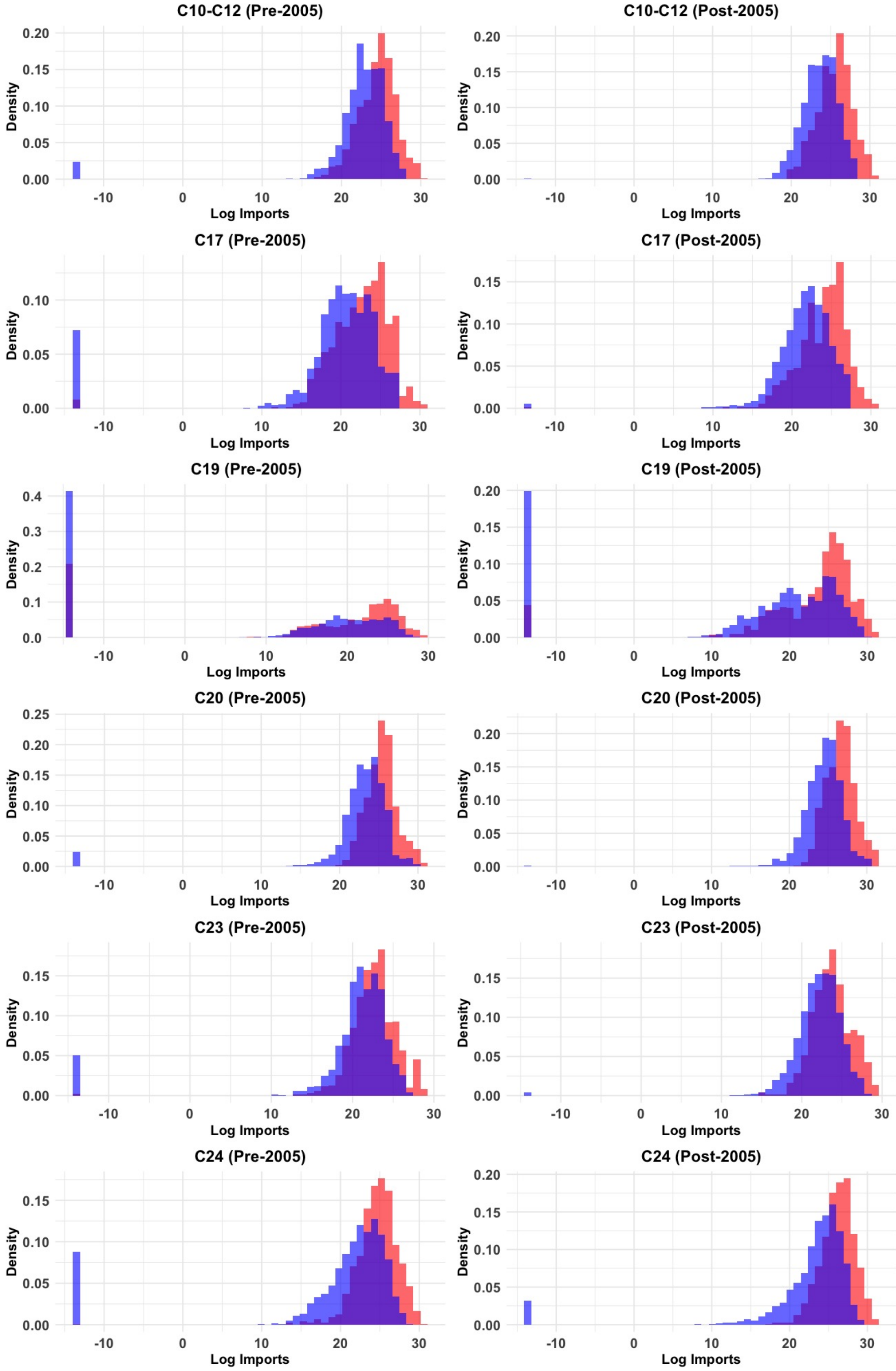
To achieve this, we compiled a balanced dataset that includes every potential trade pair across all selected manufacturing sectors for the years 1996–2012. This approach yields 101,184 observations in total (16,864 per sector), representing 21 countries under EU ETS regulation and 11 non-EU ETS countries. Incorporating zero trade flows ensures that we capture both the initiation and cessation of potential trade relationships over time, providing a more reliable foundation for causal inference.

These newly observed link formations appear in both the control and treatment groups. While this phenomenon could be partially attributed to the EU ETS policy, it is important to emphasize that the patterns described here are presented as stylized facts derived directly from the raw data. At this stage, we do not control for confounding variables or employ robust econometric techniques. The identification of these patterns merely highlights the complexity of the underlying data and motivates the need for rigorous econometric modeling in subsequent sections.

It is also evident from Figure 3.1 that one particular sector, C19 (Coke and Refined Petroleum), substantially differs from other sectors due to a disproportionately large number of zero trade values. Although the incidence of zero values decreases after treatment, C19 still exhibits many more zeros than other sectors. To prevent this atypical pattern from biasing our estimates and influencing the robustness of the empirical strategy, we exclude sector C19 from our main analysis.

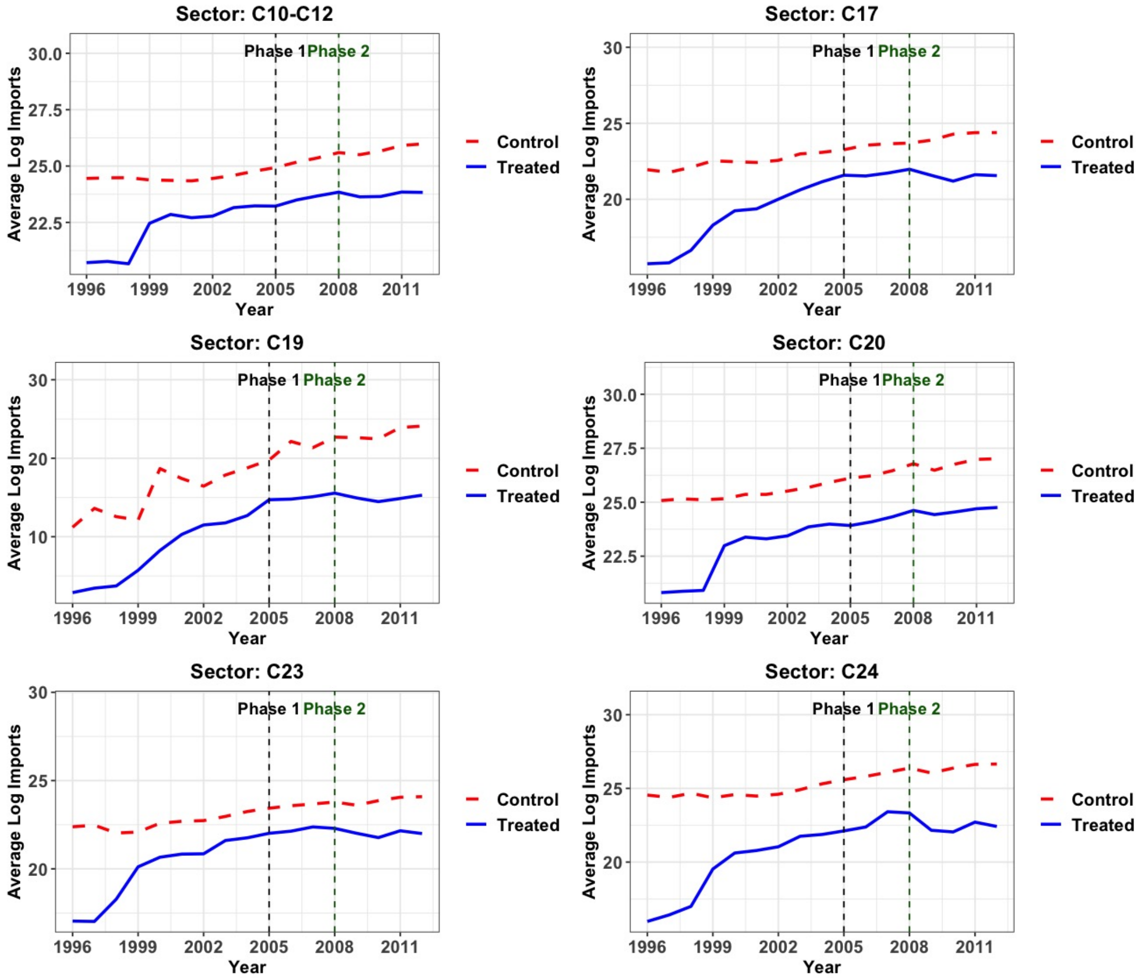
Figure 3.2 further illustrates the temporal evolution of average log-transformed import values for treated and control groups. Despite the smoothing effect of aggregation, distinct pre-treatment

Figure 3.1: Distribution of Log-Transformed Import Values for Manufacturing Sectors Under EU ETS Regulations



Note: This figure displays the distribution of log-transformed import values at the sectoral level for manufacturing sectors subject to the EU ETS Phase I and Phase II policies. The figure differentiates between control and treated units using red and blue colors, respectively. The left graphs are related to the pre-treatment period, while the right ones are for post-2005.

Figure 3.2: Sectoral Trends in Average Log-Transformed Import Values for Manufacturing Sectors under EU ETS Regulations

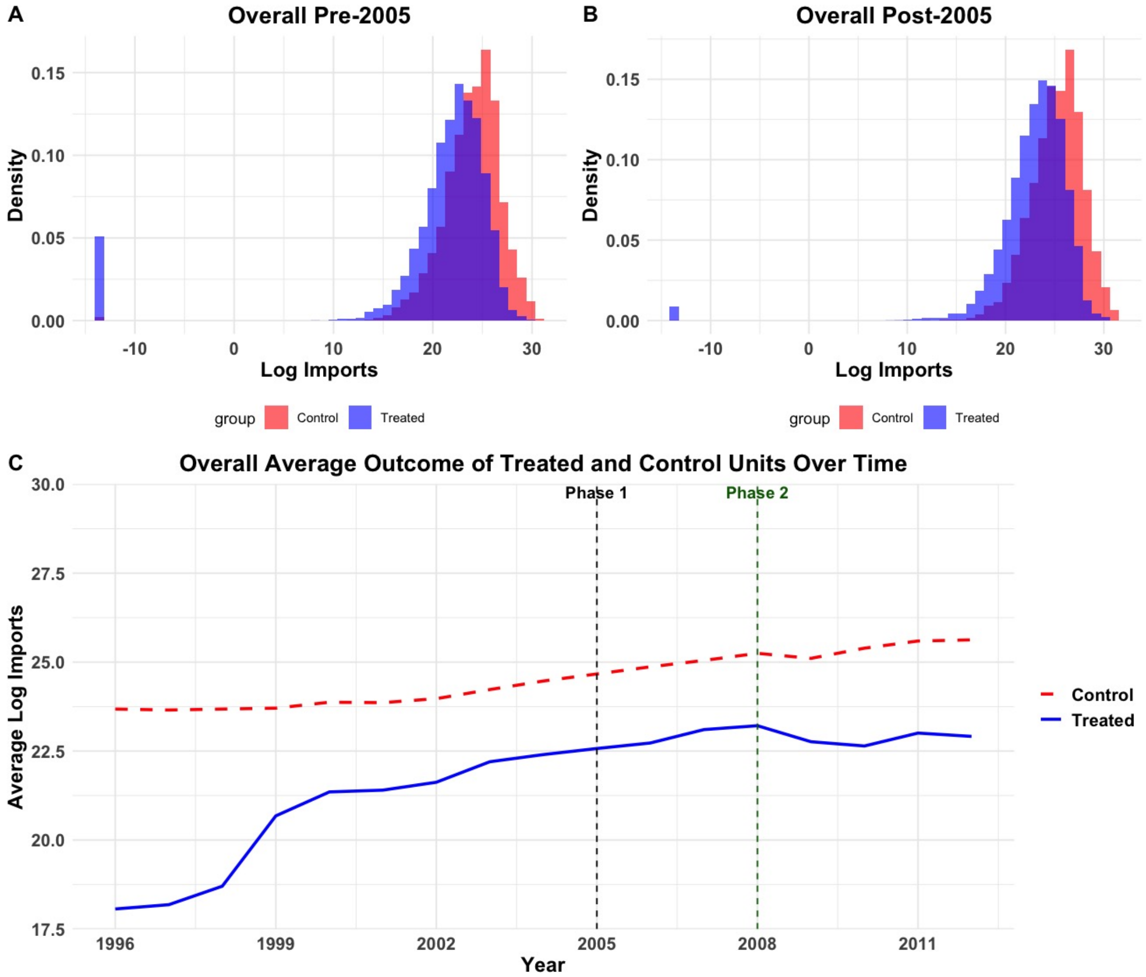


Note: This figure plots the evolution of average log-transformed import values over time (1996–2012) for both treated and control groups across the selected manufacturing sectors.

trends remain visible, highlighting a key concern for causal inference. When applying quasi-experimental methods, it is crucial to ensure that pre-treatment trends are adequately controlled for or accounted for in the identification strategy. In the Methodology section, we discuss how we address this issue.

Figure 3.3 provides a broader perspective by showing both the aggregated distribution and trends of import values across all selected sectors. The divergence between treated and control groups becomes more pronounced after 2008, aligning with the EU ETS Phase II period. This increasing gap suggests that the policy may have had heterogeneous impacts over time. Yet, as with previous figures, the presence of divergent pre-treatment trends for the aggregated data further stresses the importance of careful methodological handling to draw credible inferences.

Figure 3.3: Log-Transformed of Aggregated Import Values (Trend and Distribution) Across All Selected Manufacturing Sectors

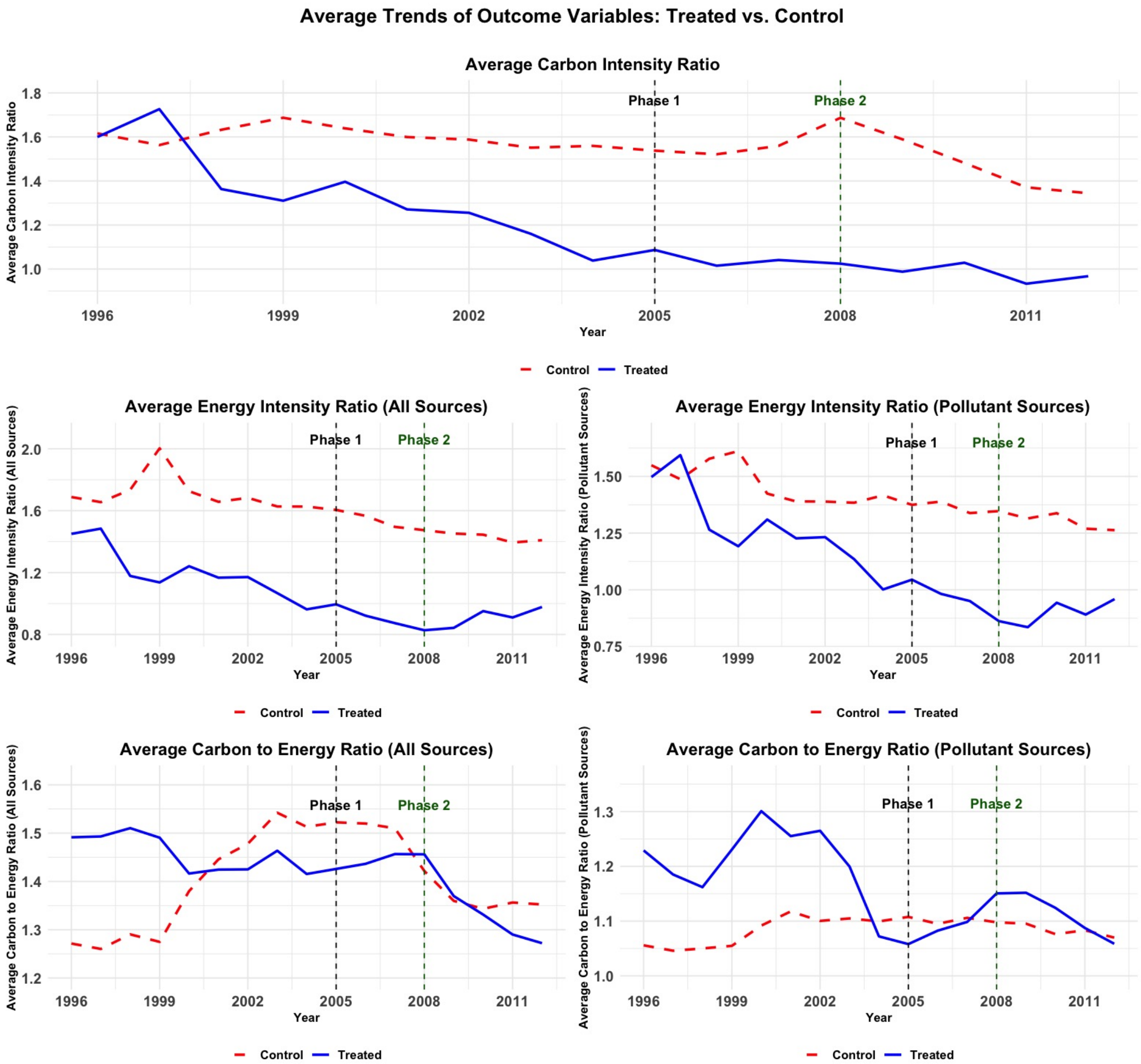


Note: The lower panel shows the temporal trend in average log-transformed import values for both treated and control groups from 1996 to 2012 for five selected, targeted, manufacturing sectors aggregated at the country level. The upper panel presents the corresponding distribution of these values.

3.3.2 Technological Gap Indicators

In addition to trade flows, we analyze how technological gaps evolve between treated and control countries using the indicators introduced earlier. Figure 3.4 presents the temporal trends of relative carbon intensity, relative energy intensity, and relative carbon-to-energy ratio from 1996 to 2012 between EU ETS-regulated countries and their major unregulated trade partners. The top graph depicts the trend in relative carbon intensity, while the middle and bottom panels represent relative energy intensity and relative carbon-to-energy ratio, respectively, highlighting the use of both pollutants and all energy sources.

Figure 3.4: Average Technological Gap Indicators' Trends Across Treated and Control Groups



Note: This figure shows the evolution of relative carbon intensity, relative energy intensity, and relative carbon to energy ratio as indicators for technological gaps between treated and control groups over the period 1996–2012.

During the first phase of the EU ETS, the technology gap related to the relative carbon intensity indicator increased in the treated group. As the indicator diminished in the post-treatment period and was compared with the control group's trend, it appears that this gap widened, predominantly driven by disparities in relative energy intensity measures. Moving into the second phase, the gap in the relative carbon-to-energy ratio indicator becomes more pronounced, while the gap in the relative energy intensity indicator declines. This shift suggests that policy-induced adjustments, such as enhanced energy efficiency and improved carbon management strategies, may be influencing competitive dynamics and, ultimately, trade patterns.

As with the trade-related stylized facts, these technological gap indicators offer descriptive insights rather than definitive conclusions. In subsequent sections, we employ rigorous econometric frameworks to formally test these hypotheses and disentangle the policy effects from other potential confounding factors.

3.4 Methodology

In this section, we outline the empirical strategies employed to examine the causal effect of the EU ETS on bilateral import values (in log form) and technological gap indicators. Our objective is to rigorously identify whether and to what extent the implementation of the EU ETS policy impacted trade flows and as a results technological gaps between regulated and unregulated parties, particularly among the sectors subject to the emissions trading scheme. To achieve this, we proceed in two steps. First, we implement a Difference in Differences (DiD) Gravity model framework to estimate the policy effect. Second, we apply the staggered design of the Synthetic Difference in Differences (SDiD) method, which improves upon standard DiD approaches by combining aspects of the Synthetic Control Method (SCM) and DiD estimators.

3.4.1 The Gravity Model

We begin by analyzing bilateral import data (in value per capita) to test for potential competitiveness effects of the EU ETS policy on trade and as its results technological gaps. Following the existing literature on carbon-related policy impacts on trade (e.g., [83]; [4]), we specify a DiD gravity model. This allows us to capture time-varying and pair-specific heterogeneity and to identify changes in trade flows associated with the onset of the EU ETS.

For each sector targeted by the EU ETS, as well as for aggregated ETS-targeted sectors, we estimate the following model:

$$Y_{mxt} = \mu + \tau W_{mt} + X'_{mxt}\beta + Z'_{mt}\gamma_1 + Z'_{xt}\gamma_2 + K'_{mt}\zeta_1 + K'_{xt}\zeta_2 + L'_{mxt}\kappa + \alpha_{mx} + \delta_t + \varepsilon_{mxt} \tag{3.8}$$

where indices x and m represent the exporter and importer parties, respectively, and year is shown by index t. Y_{mxt} is a dependent variable from the following list:

1. International Trade Flow: logarithm of import values and import growth,

2. Technological Gap Indicators: the relative carbon intensity ($\mathrm{TG^{CI}}$), relative total energy intensity($\mathrm{TG^{TEI}}$), relative pollutant energy intensity ($\mathrm{TG^{PEI}}$), relative carbon-to-total energy ratio ($\mathrm{TG^{CET}}$), and relative carbon-to-pollutant energy ratio ($\mathrm{TG^{CEP}}$) along with their growth rates.

The variable W_{mt} is a policy indicator that takes the value of one if the importer country m is regulated under the EU ETS in year t (post-2005 for most member states, with adjustments for countries that joined later) and zero otherwise.[4]

The vector X_{mxt} contains pair-specific control variables (e.g., bilateral exchange rates and trade agreements), while Z_{mt} and Z_{xt} capture importer- and exporter-specific controls such as GDP and population. The vectors K_{mt} and K_{xt} incorporate sector-specific controls (e.g., sectoral productivity) for importer and exporter countries, and L_{mxt} includes variables capturing trade costs (e.g., tariffs, transportation costs). Together, these variables, discussed in Section 2.2, ensure a comprehensive set of controls to account for confounding factors. The terms α_{mx} and δ_t represent importer-exporter pair and year fixed effects, respectively. The parameter of interest, τ, measures the average treatment effect of the EU ETS policy on import values. The error term ε_{mxt} is assumed to be uncorrelated with the treatment assignment once we condition on fixed effects and observed covariates.

While the DiD gravity model is a common approach, it may not guarantee causal identification under certain conditions. Two main issues arise: (1) Zero trade flows and model specification bias. Previous studies often relied on databases with limited accounting for zero trade flows. Omitting country pairs that do not trade can lead to biased estimates. However, the presence of zeros raises statistical challenges, primarily due to heteroscedasticity rather than sample selection ([61]). Using the Poisson Pseudo-Maximum Likelihood (PPML) estimator, as [105] does, can mitigate heteroscedasticity issues. Still, a non-linear Poisson specification is not directly compatible with the standard DiD linear framework ([20]); and (2) Sectoral heterogeneity and confounding

[4] Previous studies, such as [105] and [83], included sectors not subjected to the EU ETS. In contrast, we focus solely on the manufacturing sectors directly covered by the EU ETS, thus avoiding potential biases introduced by mixing ETS and non-ETS sectors.

Effects. EU ETS-targeted sectors tend to be more energy-intensive than non-targeted sectors. Mixing these heterogeneous sectors with all unregulated sectors can confound the estimated treatment effect. By focusing exclusively on manufacturing sectors that fall under EU ETS regulations, we minimize this confounding and limit the influence of sectoral differences.

This study exploits a detailed and high-resolution dataset for 32 countries, concentrating on EU ETS-targeted manufacturing sectors. This approach yields a relatively low incidence of zero trade flows, reducing the need for complex nonlinear specifications. We further implement a High-Dimensional Fixed Effects (HDFE) estimation technique. This approach provides several benefits over conventional OLS, as highlighted by [60]: (i) it flexibly accounts for multiple high-dimensional fixed effects, mitigating unobserved heterogeneity; (ii) it reduces omitted variable bias; (iii) it addresses potential multicollinearity; and (iv) allows for more robust standard errors through multi-dimensional clustering.

3.4.2 The Synthetic Difference in Differences Approach

While the DiD gravity model is informative, it relies on the parallel trends assumption—i.e., that in the absence of the EU ETS, treated and control units would have followed the same trends over time. When this assumption is questionable, more flexible methods can enhance credibility.

The SDiD methodology, introduced by [16], combines features of the DiD and the SCM. It constructs a weighted comparison group that better approximates the counterfactual trend that treated units would have followed in the absence of treatment. By estimating both unit (importer-exporter pair) and time weights, SDiD relaxes the strict parallel trends assumption and improves the quality of the counterfactual, resulting in potentially more credible causal inference.

Specifically, [16] recast the SCM as a weighted least squares estimator with unit-specific weights and time fixed effects. By adding unit fixed effects and time weights, we obtain the SDiD estimator. Unit fixed effects allow for baseline differences between units, and time weights ensure that the weighted pre-treatment periods resemble those of the treated units. The details of the optimization procedures to find these weights are available in Appendix B.

The model specification for the SDiD approach is:

$$Y_{pt} = \mu + \tau W_{pt} + X'_{pt}\beta + \alpha_p + \delta_t + \varepsilon_{pt} \tag{3.9}$$

Here, the index p refers to the pair contains importer i and exporter j, totalling $N = 341$ units, while t represents time across $T = 17$ years, from 1996 to 2012. Y_{pt} is a dependent variable for pair p at time t from the same list of variables as above (see Specification 3.8). 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 program's 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 and is assumed to be uncorrelated with the treatment assignment once we condition on fixed effects and observed covariates.

To identify the EU ETS policy effect on import values and growth, as mentioned in the Data section, we employ a logarithmic transformation of all the variables in Specifications 3.9 and 3.8, except for the binary ones. Hence, the results in Tables 3.1, 3.2, and 3.4 can be calculated using the estimated value of $\hat{\tau}$ as follows: $[\exp(\hat{\tau}) - 1] \times 100\%$. On the other hand, because the ratio indicators contain many values between zero and one, applying a logarithmic transformation to these indicators makes the interpretation of the results challenging. Therefore, when examining the program's effect on relative carbon intensity, relative energy intensity, and relative carbon-to-energy ratio indicators, we employ standardized values for all dependent and independent variables in this specification, except for the binary ones. 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 3.3 can be expressed in the original measurement units of the dependent variable using the standard deviation provided in Table A.4

Following [16] and [72], we implement SDiD by first partialling out covariates and fixed effects to obtain adjusted outcomes. We then select unit and time weights $\hat{\omega}_p$ and $\hat{\lambda}_t$ that minimize discrepancies in pre-treatment trends between treated and control groups. These weights localize comparisons to more comparable controls and relevant time periods, mitigating bias.

The optimization problems to determine weights ensure that the weighted control units closely track the treated units' pre-treatment outcomes, thereby producing a more reliable counterfactual. Once the weights are determined, we run a weighted two-way fixed effects regression of adjusted outcomes on the treatment indicator to estimate τ^{sdid}, the causal impact of the EU ETS in Specification 3.9.

As with the DiD approach, inference is performed using methods, such as bootstrap and jackknife procedures to construct robust confidence intervals. Here we used jackknife approach, 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.

Moreover, SDiD can handle staggered treatment adoption designs. In our case, most EU countries adopt the EU ETS post-2005, except for Romania and Bulgaria, which join post-2007. By applying SDiD separately for each adoption cohort and then aggregating the results, we obtain an overall average treatment effect, weighting by the number of treated unit-periods corresponding to each cohort. This allows us to capture dynamic treatment effects and incorporate the temporal dimension of policy adoption more flexibly.

Finally, Informed by the literature on SDiD's theoretical and practical limitations, we implemented mitigation strategies to address potential risks (see Appendix C).

3.5 Results

3.5.1 Trade Flow

In this section, we first explore the overall impact of the EU ETS on bilateral import values using a standard DiD Gravity model suggested by the literature. Subsequently, we re-examine this relationship using the SDiD approach, which addresses potential biases arising from the assumptions and specifications of the DiD Gravity method. Given that the SDiD approach yields results that we consider more credible and robust, we do not employ the DiD Gravity method for assessing the effects on technological gap indicators. Instead, we rely solely on the SDiD estimates to evaluate the impact of the EU ETS on relative carbon intensity, energy intensity, and carbon-to-energy ratios between trading partners and the growth rates of international trade and technological gap indicators.

DiD Gravity Results

We begin by estimating Specification 3.8 using aggregated import values for all selected sectors combined. Column (1) of Table 3.1 reports the results. The estimated coefficient on the EU ETS variable is both statistically significant and economically sizable, suggesting that import values from non-ETS exporters to ETS-regulated countries increased by approximately 58% due to the implementation of the EU ETS. This sizeable effect highlights the potential role of the EU ETS in reshaping international trade patterns. Our finding is consistent with [105], albeit they report smaller magnitudes, potentially due to their use of non-linear estimations and level specifications. Whereas we adopt a linear DiD Gravity model, because DiD relies on a linear model and nonlinear specification should not be combined with it ([20]; [36]). We also apply log transformations to reduce skewness and variance, which could be the source of the difference between the results of this study and them.

Columns (2)–(6) in Table 3.1 present sector-specific estimates for the five targeted manufacturing sectors. The coefficients remain statistically significant and positive across all sectors, although the magnitudes vary. Specifically, import values rise by approximately 34% in the Food, Beverages, and Tobacco sector (C10-C12), 45% in Paper (C17), 31% in Chemicals (C20), 44% in Non-Metallic Mineral Products (C23), and 57% in Basic Metals (C24). These consistent positive effects suggest that the EU ETS, through various direct and indirect channels, may have contributed to shifting trade patterns in the regulated sectors of the treated countries.

The estimated results of the Gravity model show the large impact of EU ETS on import value. However, the results of this empirical strategy suggested by the literature could be biased. There are two potential major issues with this approach. First, the counterfactual scenario which should represent no EU ETS policy, contains countries under the EU ETS regulations as the exporters.

Table 3.1: The Effect of the EU ETS Policy on International Trade Flow (the DiD Gravity Results) - 1996–2012

Variable	(1) *Aggre.*	(2) $C10-C12$	(3) $C17$	(4) $C20$	(5) $C23$	(6) $C24$
EU ETS Effect	0.456***	0.292**	0.375**	0.270*	0.367**	0.453***
	(0.147)	(0.144)	(0.175)	(0.143)	(0.145)	(0.151)
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	16,864	16,864	16,864	16,864	16,864	16,864
R-squared	0.617	0.712	0.755	0.639	0.728	0.707

Note: This table presents the EU ETS average treatment effect on the log of bilateral import value using the DiD Gravity model and Specification 3.8. It reports the estimated results for all selected sectors aggregated at the importer-exporter pair level and five individual sectors. The sectors are Food, Beverages, and Tobacco (C10-C12); Paper (C17); Chemicals (C20); Non-Metallic Mineral Products (cement, glass, and ceramic) (C23); and Metal (C24). The dataset for each sector and their aggregate includes 16,864 (32×31×17) observations, covering 21 ETS countries and 11 non-ETS countries across five sectors from 1996 to 2012. Note that the estimation results for control variables are not provided in the table but can be provided upon request. All regressions include time and pair importer-exporter fixed effects. Standard errors report in parentheses, and *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

These countries are under the influence of the program and it affects their export. This influence on export could be due (1) directly through emissions constraints, carbon costs, and potential competition, and (2) indirectly through spillover effects that distort trade behaviors, such as supply chain adjustments, pricing changes, or shifts in market demand and competitiveness. For instance, if the carbon-intensive products become costly as firms adjust to the EU ETS scheme, the EU exporters shift their production processes to mitigate EU ETS compliance costs which might lead to increasing export prices or reducing production. Therefore, the exporters that are under EU ETS regulations should be excluded from the control group.

Additionally, in this type of cross-country panel analysis, the pre-treatment parallel trend assumption among the treatment and control units is challenging. Using the average trend of outcomes for the treatment and control groups at the sectoral level presented in Figure 3.2 and at the country level for all five regulated manufacturing sectors illustrated in Figure 3.3 one can see that even for the average values which contains less fluctuation, the parallel trend assumption in the pre-treatment period could be violated.

SDiD Results

To mitigate the aforementioned potential biases, we implement two key modifications. First, we refine the control group by selecting non-EU importers that import exclusively from exporters not subject to EU ETS regulations. This ensures that our counterfactual units are less likely to be influenced by the EU ETS. Second, we employ the SDiD approach to construct a synthetic control group whose pre-treatment trends more closely match those of the treated units, thereby addressing potential violations of the parallel trend assumption.

Table 3.2 reports the estimated average treatment effects of the EU ETS on import values for both the aggregate of all selected sectors and each individual regulated sector, following Specification 3.9. In contrast to the DiD Gravity results, the SDiD estimates are generally smaller but are more methodologically defensible. For the aggregated sample (column 1), the estimated effect is statistically significant and indicates that import values rose by about 14% from non-ETS exporters after the EU ETS implementation. This positive shift suggests that unilateral environmental regulation in ETS countries may have elevated production costs domestically, thereby inducing a relative competitiveness advantage for producers in countries with less stringent environmental regimes. This outcome aligns with the literature suggesting that stringent environmental policies can lead to pollution haven dynamics, as documented by [73], [26], and [58].

Examining the results by sector reveals heterogeneous responses to the EU ETS. While the Food (C10-C12), Non-Metallic Mineral Products (C23), and Basic Metals (C24) sectors exhibit statistically significant and positive import responses (24%, 47%, and 40%, respectively), the Paper (C17) and Chemicals (C20) sectors show statistically insignificant effects. These sectoral differences could reflect varying degrees of adaptability, technological flexibility, and market structure. For instance, the Paper and Chemicals sectors may have more readily adjusted their production processes or sought cost-effective compliance strategies, mitigating the EU ETS-driven cost disadvantage. In contrast, sectors such as Non-Metallic Minerals and Basic Metals, which are generally more emissions-intensive and less flexible in their production processes, may have experienced greater cost escalation, prompting importers to source more from non-ETS countries.

Table 3.2: The Effect of the EU ETS Policy on International Trade Flow (the SDiD Results) - 1996–2012

Dependent Variable	(1) $Aggre.$	(2) $C10-C12$	(3) $C17$	(4) $C20$	(5) $C23$	(6) $C24$
Import Value	0.131*	0.215*	0.247	-0.110	0.384***	0.338*
	(0.073)	(0.126)	(0.195)	(0.081)	(0.118)	(0.180)
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: This table presents the EU ETS average treatment effect on the log of bilateral import value using the SDiD model and Specification 3.9. It reports the estimated results for all selected sectors aggregated at the importer-exporter pair level and five individual sectors. The sectors are Food, Beverages, and Tobacco (C10-C12); Paper (C17); Chemicals (C20); Non-Metallic Mineral Products (C23); and Basic Metals (C24). The dataset for each sector and their aggregation includes $[(21 \times 11) + (11 \times 10)] \times 17 = 5,797$ observations, covering 21 ETS countries and 11 non-ETS countries across five sectors from 1996 to 2012. We used the Jackknife approach to calculate the standard errors of the estimated coefficients, thus determining their statistical significance. All regressions include time and pair importer-exporter fixed effects. Standard errors report in parentheses, and *** p<0.01, ** p<0.05, * p<0.1.

The estimated effects from the SDiD framework are up to three times smaller than those obtained from the DiD Gravity model. This suggests that the earlier approach may have overestimated the effect due to violations of the parallel trend assumption or the inclusion of exporters under EU ETS regulations within the counterfactual group. Additionally, sectoral heterogeneity plays a role in this difference. Paper (C17) and Chemical (C20) sectors, which do not show a significant import shift under the SDiD approach, may have inflated the aggregate estimates in the DiD Gravity model. When we exclude these two sectors and focus only on C10-C12, C23, and C24, the difference between SDiD and DiD Gravity estimates becomes smaller, lending credence to the view that sectoral composition and methodological robustness both matter significantly for accurate inference.

Overall, our SDiD results indicate that the EU ETS had a positive and statistically significant impact on imports from non-ETS countries to ETS-regulated importers, although these effects vary substantially by sector. This is an important finding that reveals the effect of a unilateral policy on international trade flows.

3.5.2 Technological Gap Indicators

Having established that the unilateral EU ETS policy can influence international trade flows, the next step is to investigate whether these trade-induced adjustments translate into changes in relative technological gaps between regulated and unregulated countries. In particular, we focus on three sets of technological gap indicators: (i) relative carbon intensity, (ii) relative energy intensity (including both total and pollutant-based energy use), and (iii) the relative carbon-to-energy ratio (which we cosider both total and pollutant-based energy sources). By examining these indicators, we aim to determine if the EU ETS has facilitated a divergence in technological standards and practices concerning carbon abatement and energy efficiency.

Table 3.3 presents the SDiD estimation results for the technological gap indicators. The estimates for all selected sectors aggregated at the importer-exporter pair level (column (1)) and across individual sectors (columns (2)–(6)) generally show a statistically significant and negative effect of the EU ETS on the standardized values of these relative technological measures. A negative coefficient indicates that, over time, the gap in technological performance, measured in terms of aforementioned indicators, has widened between ETS-regulated importers and their unregulated counterparts, with regulated countries moving toward cleaner, more energy-efficient production technologies relative to their trading partners.

The estimated coefficient for relative carbon intensity, when considering all selected sectors combined, suggests a statistically significant reduction of approximately 0.13 standard deviations due to the EU ETS. Interpreting a decrease in this standardized measure as a widening gap, we infer that regulated countries have effectively reduced their carbon intensity relative to unregulated countries. This result can emerge through two key channels. First, consistent with the intended objectives of the EU ETS, there may have been meaningful technological progress and adoption of low-carbon production processes within regulated countries. Such progress is often associated with the Porter Hypothesis, which posits that well-designed environmental policies can induce innovation and enhance productivity over the long run ([86]; [56]). Second, from an international trade perspective, the increased demand in ETS-regulated markets may have incentivized producers in non-regulated countries to scale up output using relatively less efficient, more carbon-intensive technologies. In other words, while regulated countries progress toward cleaner methods, non-regulated exporters may meet heightened demand with technologies that remain relatively carbon-intensive, thus widening the cross-border technological gap.

Turning to energy-related measures, our results also show statistically significant and negative coefficients for relative energy intensity. Specifically, we find a reduction (the gap has widened) of about 0.10 standard deviations in the relative total energy intensity and approximately 0.16 standard deviations in the relative pollutant-based energy intensity. These findings suggest that regulated countries have not only improved their overall energy efficiency but have done so more markedly in terms of pollutant-based energy sources, such as fossil fuels. This aligns with previous research indicating that stringent climate policies can accelerate investments in cleaner technologies, energy-efficient equipment, and process optimization ([39]). The more pronounced effect on pollutant-based energy intensity likely reflects direct compliance strategies, such as substituting away from coal and oil toward cleaner fuels and renewables, as well as indirect effects related to innovation and structural shifts in production. Meanwhile, as non-regulated countries expand their export volumes to ETS-regulated markets, they may rely on existing, less efficient and more pollutant-intensive production techniques, thereby reinforcing and widening the technological gap.

We also observe a negative effect of the EU ETS on the relative carbon-to-energy ratio. For the aggregated sample, the ratio decreases by about 0.27 standard deviations for total energy sources and 0.15 standard deviations for pollutant-based energy sources (the gap increased). These results are consistent with a scenario where ETS-regulated countries are not only reducing emissions intensity at the source but also enhancing the carbon efficiency of their overall energy mix. By transitioning to cleaner energy carriers, such as natural gas and renewables, and optimizing industrial processes, regulated countries can achieve substantial improvements in carbon-to-energy efficiency. In contrast, non-regulated partners, facing no equivalent environmental constraints, may respond to increased export opportunities with no mandate on the parallel investment in cleaner technologies, thus broadening the cross-border gap.

One reason the effect appears larger on the total carbon-to-energy ratio relative to the pollutant-specific ratio could be that regulated countries improve their carbon efficiency across a broad range of energy inputs. These improvements may reflect a host of adaptive strategies,

Table 3.3: The Effect of the EU ETS Policy on Technological Gap Indicators - 1996–2012

Dependent Variable	(1) *Aggre.*	(2) $C10-C12$	(3) $C17$	(4) $C20$	(5) $C23$	(6) $C24$
TG^{CI}	-0.127***	-0.184**	-0.0973	-0.112	-0.00683	-0.104*
	(0.0474)	(0.0805)	(0.0741)	(0.132)	(0.0544)	(0.0568)
TG^{TEI}	-0.104**	-0.212***	-0.130	-0.209**	-0.0845	-0.0433
	(0.0482)	(0.0739)	(0.132)	(0.102)	(0.0743)	(0.0485)
TG^{PEI}	-0.158***	-0.637***	-0.114	-0.186*	-0.0883	-0.0104
	(0.0562)	(0.212)	(0.0694)	(0.103)	(0.0837)	(0.0490)
TG^{CET}	-0.266***	-0.165	-0.210***	0.0290	0.173**	-0.331***
	(0.0419)	(0.105)	(0.0810)	(0.0917)	(0.0734)	(0.0794)
TG^{CEP}	-0.148**	-0.588***	0.0926	-0.188**	0.275***	-0.381***
	(0.0616)	(0.129)	(0.103)	(0.0932)	(0.0732)	(0.0703)
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: This table presents the EU ETS average treatment effect on the relative carbon intensity (TG^{CI}), relative total energy intensity(TG^{TEI}), relative pollutant energy intensity (TG^{PEI}), relative carbon-to-total energy ratio (TG^{CET}), and relative carbon-2-pollutant energy ratio (TG^{CEP}) using the SDiD model and Specification 3.9. It reports the estimated results for all selected sectors aggregated at the importer-exporter pair level and five individual sectors. The sectors are Food, Beverages, and Tobacco (C10-C12); Paper (C17); Chemicals (C20); Non-Metallic Mineral Products (C23); and Basic Metals (C24). The dataset for each sector and their aggregation includes $[(21\times 11)+(11\times 10)]\times 17 = 5,797$ observations, covering 21 ETS countries and 11 non-ETS countries across five sectors from 1996 to 2012. We used the Jackknife approach to calculate the standard errors of the estimated coefficients, thus determining their statistical significance. All regressions include time and pair importer-exporter fixed effects. Standard errors report in parentheses, and *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

including process innovation, adoption of best-available technologies, and compliance-driven retrofitting of production lines ([33]; [79]). Non-regulated firms, by contrast, are not compelled to follow similar paths, especially if their comparative advantage lies in cost-competitive but carbon-intensive production processes.

Taken together, the results of the first column of Table 3.3 lend empirical support to a composite narrative involving both the Porter and pollution haven hypotheses. On the one hand, the EU ETS spurs cleaner technological changes and energizes carbon abatement innovations in regulated markets, showcasing the potency of climate policies to enhance environmental performance domestically. On the other hand, the ensuing trade dynamics may lead to increased importation of carbon-intensive goods from non-regulated partners, effectively contributing to a divergence in technological standards. This divergence ultimately manifests as a widened technological gap between regulated and unregulated countries. Such a pattern highlights the complexity of unilateral climate policy instruments within a globalized economy and underscores the importance of complementary measures, such as carbon border adjustments or multinational climate agreements, to prevent policy-induced carbon leakage and ensure more uniform progress toward cleaner, more energy-efficient global production standards.

The sector-specific estimates (reported in columns (2)–(6) of Table 3.3) reveal important heterogeneities. For the Food, Beverages, and Tobacco sector (C10-C12) sector, we observe a 0.18 standard deviation decrease in relative carbon intensity (the gap increased), along with more pronounced improvements in pollutant energy intensity. This suggests that regulated countries in this sector have achieved greater optimization in fossil fuel use and a more rapid transition to cleaner energy sources. Meanwhile, non-regulated countries appear to be increasingly reliant on carbon-intensive fuels, investing less in pollutant energy efficiency and making slower progress toward renewables. The large 0.59 standard deviation decrease in the relative carbon-to-energy ratio in the Food sector suggests that technological improvements, potentially including Carbon Capture and Storage (CCS) and low-carbon technologies, play a significant role in this widening gap.

In the Paper sector (C17), we do not find strong evidence of a significant EU ETS effect on relative carbon and energy intensity measures. This may be attributed to characteristics of the paper industry, where existing technologies and energy sources are already relatively optimized or where the costs and benefits of transitioning to cleaner processes differ compared to other sectors. However, we do observe a 0.21 standard deviation decrease in the relative carbon-to-total energy ratio (the gap increased), implying that regulated countries may still be making progress toward cleaner energy mixes or marginal improvements in process efficiencies. The lack of strong carbon intensity changes is consistent with findings by [74], who found limited evidence of EU ETS impact in the pulp and paper sector.

For the Chemical sector (C20), the reductions in relative energy intensity (the gap increased) are more pronounced for total energy than for pollutant energy, suggesting a broad-based improvement in energy efficiency among regulated producers. Additionally, we find a significant reduction in the relative pollutant carbon-to-energy ratio, indicating that regulated countries are likely making targeted improvements in fossil fuel efficiency or transitioning to cleaner technologies and energy sources. These outcomes align with the notion that compliance costs under the ETS encourage a shift away from high-carbon inputs and an investment in cleaner technologies ([33]).

The Non-Metallic Mineral Products (C23) sector shows an increase in the relative carbon-to-energy ratio for both total and pollutant-based energy (the gap decreased), albeit more pronounced for pollutant energy. One possible explanation is that firms in regulated countries may be focusing on broad-based energy efficiency measures and cleaner input mixes, while some non-regulated countries respond by adopting carbon absorption or other mitigation strategies that do not necessarily enhance overall energy efficiency. Sectoral nuances are also consistent with earlier studies that report limited or mixed evidence of the EU ETS's effects on specific industries ([28]; [90]).

Finally, in the Metal sector (C24), we observe a 0.10 standard deviation decrease in relative carbon intensity (the gap increased), indicating a widening carbon-related technological gap. This gap likely stems from greater reliance on high-efficiency, low-emission production processes and improved low-carbon technologies in regulated countries more pronounced than their non-regulated counterparts. The key driver here appears to be the relative carbon-to-energy ratio, which captures the efficiency and cleanliness of energy use. The Metal sector findings align with the broader narrative that the EU ETS, while directly incentivizing innovation and cleaner energy use within regulated countries, may indirectly encourage non-regulated exporters to meet growing demand without adopting cleaner technologies, thus reinforcing technological divergence.

Overall, these sector-specific results highlight that while the EU ETS can drive innovation, energy efficiency, and carbon reduction efforts within regulated markets, the interplay with international trade may create avenues for carbon-intensive production to persist or even expand in non-regulated regions. This reinforces the complexity of unilateral climate policies and underscores the importance of integrating climate and trade policies to ensure that environmental gains in one region are not undermined by carbon-intensive responses in another.

3.5.3 Growth Rate and Adjustment

Having identified that the EU ETS can influence the level of international trade flows and the carbon emissions and energy use related technological gap indicators, it is equally important to understand its dynamic, time-dependent effects. In other words, rather than focusing solely on static comparisons before and after the policy implementation, we assess how the rates of change (growth rates) in both trade and technological indicators evolve under the EU ETS regime. This approach allows us to capture short-term adjustments, the pace of convergence or divergence, and the potential path-dependent effects of climate policies.

Specifically, we consider the bilateral import growth (expressed as log differences) and the growth rates of the technological gap measures. Examining growth rates has several advantages. First, using growth-based measures helps uncover short-run responses and transitional dynamics that static analyses may overlook ([73]). For instance, even if absolute levels of trade or technology gap indicators differ substantially across countries, their growth patterns can reveal the speed and direction of adjustments that the EU ETS triggers. Second, growth-based approaches allow us to disentangle the policy's impact from general secular trends in global trade, such as increasing integration driven by economic development or reductions in trade barriers ([53]). Third, focusing on growth rates can illuminate how policy-induced changes in competitiveness unfold over time, highlighting whether certain sectors adapt faster or slower to carbon pricing than others. Finally, growth-based models can capture variation in sectoral dynamics, innovation trajectories, and trade expansion more effectively than level-based measures ([64]). This perspective is especially important given the evolving technological environment spurred by environmental regulations, where green innovations and process optimizations may take time to diffuse ([33]; [56]; [2]).

Applying a growth-based analysis to the carbon- and energy-relevant technological gap (relative carbon intensity, relative energy intensity, and relative carbon-to-energy ratio) yields insights into the trajectory of decarbonization efforts over time. Policies like the EU ETS may initially face barriers—such as learning curves, capital investment cycles, and entrenched production technologies—that slow the short-term response. Over time, however, regulatory pressure could stimulate a steeper rate of improvement in emissions efficiency, especially if firms invest in cleaner technologies, adopt best-available technologies, and improve energy management practices ([86]; [56]; [52]). Growth-based measures can reveal these accelerating effects, indicating whether regulated countries experience a sustained improvement in their environmental performance relative to non-regulated counterparts. In contrast, if non-regulated countries respond to increased export opportunities without upgrading their energy efficiency or abatement technologies, this discrepancy in growth rates can further widen the technological gap.

Table 3.4 presents the estimated results for both the aggregated sample and the individual sectors found to be significantly affected in the level-based analysis. For import growth, we find that the Food (C10-C12) sector experiences a marked increase in growth rates (approximately 52%), while the Non-Metallic Mineral Products (C23) and Basic Metals (C24) sectors show a reduction in their import growth rates by about 17% and 19%, respectively. These patterns hint at sector-specific dynamics of adjustment. The Food sector's accelerated growth may reflect difficulties in coping with elevated carbon costs among domestic producers, thereby creating room for non-regulated exporters to gain market share. In contrast, the deceleration in Non-Metallic Mineral Products and Metals may indicate a restructuring process as regulated firms progressively invest in cleaner technologies and realign their production mix, partially offsetting initial competitive disadvantages.

For the carbon-relevant technological gap, we observe that for the aggregated sample, the EU ETS induces a statistically significant and positive effect on the growth of relative carbon intensity improvements. Specifically, regulated countries accelerate their rate of reducing carbon intensity by about 4% relative to non-regulated nations compared to the control group which we have the same indicators but using values for non-EU importer-exporter pairs to construct the relative ratios. This suggests that the cumulative effects of the EU ETS—such as ongoing investments in emissions-reducing technologies, learning-by-doing, and incremental innovations—strengthen over time, pushing regulated firms to continuously improve their environmental performance at a faster pace than their counterparts. These findings are consistent with research showing that environmental policies, when stable and credible, foster long-term innovation and cleaner production methods ([79]).

Table 3.4: The Effect of the EU ETS Policy on Import and Technological Gap Indicators Growth Rates - 1996–2012

Dependent Variable	(1) *Aggre.*	(2) $C10-C12$	(3) $C17$	(4) $C20$	(5) $C23$	(6) $C24$
Import Growth	0.0626	0.422***	-	-	-0.187**	-0.216*
	(0.114)	(0.144)	-	-	(0.0912)	(0.112)
TG^{CI} Growth	0.0419**	0.0504	-	-	-	-0.0169
	(0.0178)	(0.0428)	-	-	-	(0.0201)
TG^{TEI} Growth	0.0305***	0.0179	-	0.0357**	-	-
	(0.0111)	(0.0176)	-	(0.0139)	-	-
TG^{PEI} Growth	0.00824	-0.0200	-	0.0500***	-	-
	(0.0103)	(0.0193)	-	(0.0194)	-	-
TG^{CET} Growth	0.0180***	-	0.0175	-	-0.0538***	-0.0173
	(0.00618)	-	(0.0266)	-	(0.0157)	(0.0106)
TG^{CEP} Growth	-0.00483	-0.0438***	-	-0.00987	-0.0412***	0.00585
	(0.00474)	(0.0129)	-	(0.0105)	(0.0128)	(0.0127)
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: This table presents the EU ETS average treatment effect on the growth rates of import, relative carbon intensity (TG^{CI}), relative total energy intensity(TG^{TEI}), relative pollutant energy intensity (TG^{PEI}), relative carbon-to-total energy ratio (TG^{CET}), and relative carbon-2-pollutant energy ratio (TG^{CEP}) using the SDiD model and Specification 3.9. It reports the estimated results for all selected sectors aggregated at the importer-exporter pair level and five individual sectors. The sectors are Food, Beverages, and Tobacco (C10-C12); Paper (C17); Chemicals (C20); Non-Metallic Mineral Products (C23); and Basic Metals (C24). The dataset for each sector and their aggregation includes $[(21 \times 11) + (11 \times 10)] \times 17 = 5,797$ observations, covering 21 ETS countries and 11 non-ETS countries across five sectors from 1996 to 2012. We used the Jackknife approach to calculate the standard errors of the estimated coefficients, thus determining their statistical significance. All regressions include time and pair importer-exporter fixed effects. Standard errors report in parentheses, and *** p<0.01, ** p<0.05, * p<0.1.

Regarding technological gap represented by relative energy intensity indicator, we find that all selected sectors combined and the Chemicals sector (C20) exhibit positive and significant effects on the growth rates of energy-related technological improvements. For instance, the Chemical sector shows significant positive effects for both total and pollutant energy intensities, indicating that the EU ETS not only motivates immediate changes in energy efficiency but also fosters continuous and potentially accelerating improvements over time. This aligns with the notion that industries with higher technological complexity and potential for innovation may respond more dynamically to regulatory signals by progressively refining their energy management and abatement strategies ([33]; [2]).

For the relative carbon-to-energy ratios, we find a nuanced picture. The aggregated sectors show a positive growth-based improvement for the total carbon-to-energy ratio, signaling a persistent and accelerating divergence as regulated countries continue to optimize their energy mix and carbon management. Meanwhile, for some sectors like Food (C10–C12) and Non-Metallic Mineral Products (C23), negative and significant effects emerge, indicating a deceleration in the widening of the gap for pollutant-based carbon-to-energy ratios over time. These sectoral differences highlight the importance of considering the heterogeneity in industrial structure, technological opportunities, and adaptation strategies when assessing the dynamic impacts of climate policies.

In sum, the growth-based analysis reveals that the EU ETS can have varying dynamic effects on different sectors. Some sectors experience accelerated divergence as regulated countries continuously improve their environmental performance at a faster pace, while others show signs of convergence or deceleration in the widening gap as cleaner technologies and energy-efficient practices diffuse. These results underscore the complexity of environmental policy impacts and the importance of analyzing not only whether a policy affects trade and technological gaps, but also how quickly and persistently those effects materialize.

By focusing on growth rates rather than static levels, we gain a clearer understanding of how environmental policies shape the evolution of global trade patterns and technological standards over time. This perspective emphasizes that policy assessments should consider long-run trajectories and dynamic responses, rather than relying solely on cross-sectional snapshots. Ultimately, integrating dynamic considerations into environmental and trade policy evaluations can help inform better policy design to ensure both environmental effectiveness and economic sustainability in the long term ([57]; [91]; [105]).

3.5.4 Robustness checks

We designed a placebo-like approach to test the robustness of our findings. We employ a permutation test which assesses the statistical significance of the estimated EU ETS effect by comparing it to a distribution of effects obtained under random permutations of the treatment assignment. The null hypothesis of this test is that EU ETS has no impact on the list of dependent variables, including trade flow and technological gap indicators, and any estimated effect is due to random chance. The alternative hypothesis is that the EU ETS policy affects the dependent variables across treated countries and the results are not random.

The permutation test we conducted is a non-parametric method aimed at assessing the statistical significance of the evaluated EU ETS effect from the SDiD analysis. In each iteration, we randomly select countries to form a new "treated" group while keeping the number of treated countries exactly the same as in the original analysis, i.e., 21 countries. The selection procedure is done without replacement from the pool of all available countries, ensuring that each country's chance of being selected is equal in every iteration. By maintaining the same number of treated units, we control for potential confounding effects related to group size and ensure that differences in estimated effects are due to the treatment assignment rather than variations in sample size.

A large number of permutations (e.g., 1,000 iterations) is needed for this approach, and we obtain an empirical distribution of the EU ETS effects that could be expected under the null hypothesis of no effect after completion of all iterations. Then we compare the estimated effect to this distribution, and assess how extreme our result is relative to what might occur by chance. As we expect the impact of EU ETS on EU importers under the program's regulations would be positive we attempted a one-tailed test. The p-value is calculated by determining the proportion of permuted EU ETS effects that are greater than or equal to the actual observed effect.[5]

However, to eliminate the effect of our ex-ante judgment on the test results, we also considered a two-tailed permutation test. The p-value is then calculated by finding the proportion of permuted effects where the absolute value is equal to or greater than that of the estimated effect. This approach effectively doubles the area of interest in the permutation distribution, accounting for extreme effects in both directions.[6] This methodological rigor enhances the validity of our

[5] A low p-value indicates that the estimated effect is unlikely to have occurred by random chance, which suggests that the EU ETS policy has a statistically significant impact on the outcome variables.

[6] A low p-value signifies that the estimated effect is significantly different from zero, which strengthens the conclusion that the EU ETS has a real effect on the outcome variables, whether it increases or decreases the measured variable.

statistical inference, providing a robust assessment of the program's impact.

We validate all results obtained using the SDiD approach by conducting the permutation tests as a robustness check. Both tests provide strong evidence that the estimated effects of the EU ETS policy on the list of dependent variables, such as trade flow, relative carbon intensity, relative energy intensity, and relative carbon-to-energy ratio, where we found significant results, are causal and not attributable to random factors.

3.6 Conclusion and Policy Remarks

This study examines the impact of the EU ETS on international trade flows and technological gaps, between EU ETS-regulated countries and their non-EU partners, providing both static and dynamic perspectives. Drawing on a comprehensive dataset covering five regulated manufacturing sectors and employing a robust methodological framework that combines DiD Gravity and the staggered design of SDiD approaches, we find that the EU ETS has had a significant influence on bilateral import flows and associated technological gaps.

This analysis reveals several key findings. First, the more robust SDiD estimates indicate that the EU ETS led to approximately a 14% increase in imports from non-regulated exporters. Examining sector-specific outcomes, we observe heterogeneous responses: while Food, Non-Metallic Mineral Products, and Basic Metals sectors experienced substantial increases in imports, the Paper and Chemicals sectors displayed more muted or insignificant responses. This sectoral heterogeneity highlights that not all regulated industries are equally affected by carbon pricing, and that sectoral production structures, technological flexibility, and adaptation capacities play essential roles in shaping trade responses.

Second, beyond its effect on trade flows, the EU ETS has contributed to widening technological gaps related to emissions and energy use. The results show that the relative technological gap between countries under EU ETS regulations and their non-EU partners widened, resulting in greater divergence in relative carbon intensity, relative energy intensity, and relative carbon-to-energy ratio. This divergence appears consistent with a combination of the Porter and pollution haven hypotheses.

Third, examining growth rates rather than just static levels offers nuanced insights into the temporal dimension of policy effects. Growth-based analyses reveal that some sectors (e.g., Food) saw an accelerated increase in imports following the EU ETS, possibly due to difficulties faced by domestic producers in adapting quickly to compliance costs. In contrast, sectors like Non-Metallic Mineral Products and Basic Metals showed slower import growth rates, suggesting that regulated firms may be undertaking a gradual restructuring and investing in cleaner technologies over time. Similarly, growth-based indicators of the technological gap underscore that the EU ETS not only affects the current level of environmental performance but also influences its trajectory, with regulated countries' decarbonization efforts accelerating relative to their non-regulated counterparts.

In conclusion, the EU ETS has substantially influenced international trade patterns, often favoring non-regulated exporters, while simultaneously widening the technological gaps, particularly related to carbon emissions and energy use, between regulated countries and their trade partners. This duality emphasizes the complexity of implementing unilateral climate policies in a globalized world. To capitalize on the environmental benefits and mitigate unintended consequences, we suggest the couple of actions based on the finding of this study:

First, sectoral heterogeneity in policy responses suggests that one-size-fits-all regulations may be insufficient. Policymakers might consider sector-specific guidelines, support for technological upgrading, and targeted measures to help industries that face greater adaptation challenges. For instance, providing research and development incentives, improving access to low-carbon technologies, or facilitating knowledge transfer could enhance the competitiveness of regulated sectors.

Second, the observed acceleration in technological improvements and decarbonization trajectories signals that climate policies can yield dynamic benefits over time. Policymakers should focus not only on immediate compliance costs but also on long-run gains. Stable and predictable policy frameworks can encourage firms to invest in cleaner technologies, undertake process innovations, and develop new capabilities. Such an environment fosters sustained improvements in energy efficiency and emissions reductions, reinforcing the long-term objectives of climate policy.

Finally, the future research could build on these findings in several important directions. First, given our evidence that the EU ETS influences the technological gap and trade patterns, a natural extension would be to investigate how the policy affects the embodied carbon and energy content of traded goods. Second, examining the net global emissions consequences of the EU ETS, beyond the borders of regulated countries, could illuminate whether the program truly fosters global emissions reductions or mainly increased the overall emissions by shifting it towards less regulated regions. This line of inquiry would benefit from integrating detailed energy balance data with international trade flows. Last but not least, exploring the dynamic interplay between climate policies like the EU ETS and emerging low-carbon technologies, such as carbon capture, hydrogen fuels, and electrification of industrial processes, could provide deeper insights into long-term structural transformations, which could minimize leakage and so net emissions and energy use.

CHAPTER 4

On Carbon Leakage and Net Global Emissions

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

Abstract

The European Union Emissions Trading System (EU ETS) is central to the EU's 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 ETS's 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

4.1 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 ([43]).

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 ([58]). Additionally, according to the Porter hypothesis, the negative effects of the EU ETS on firms' competitiveness may be mitigated or

[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 ([65]).

[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., [73]).

even offset by improvements in productivity, driven by innovation in low-carbon technologies and products ([86]; [33]). Moreover, although emission costs are typically zero in the EU's 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 ([83]). 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 operations abroad. Finally, European firms have been granted substantial free emissions allowances under the EU ETS, which may be sufficient to prevent carbon leakage ([92]).

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., [26]; [55]; [34]). Considerable number of these studies have predicted that unilateral climate policies, such as the EU ETS, could induce carbon leakage. Research by [18], [22], and [51] 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., [47]; [73]). 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 [4], 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 [80], [43], and [83], as well as more recent papers by [44], generally find either insignificant or non-robust evidence for carbon leakage. [83] 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 [4]'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, [105] 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. [90] for the aluminum sector, [28] for the cement and steel sectors, and [74] for pulp and paper found limited evidence of a statistically significant impact of the EU ETS on carbon leakage.[3]

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, [82], using European firm data from 2002-2012; [45], using European firm data from 2007-2014; [71], using data from German multinational firms (1999-2013); and [24], 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 program's 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

[3] [74] 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.

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 program's 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., ([83]; [105]). 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 [83] and [105] 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 ([83]; [105]). 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., [27]; [21]) 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 ([90]; [28]; [74]), 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 policy's 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 ([2]; [52]). 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 ETS's effectiveness in contributing to global emissions reductions.

The remainder of this paper is organized as follows. Section 2 details the data. Section 3 presents stylized facts, and Section 4 outlines the empirical strategy. Section 5 presents and discusses the empirical results. Conclusions and policy suggestions are provided in Section 6.

4.2 Data

4.2.1 Dependent variables

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. 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. 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. The data represent carbon dioxide emissions in kilotons (kt) and total fossil fuel energy use in terajoules (TJ).

WIOD offers internationally consistent data, ideal for examining efficiency improvements at the sectoral and national levels. The period of analysis covers 1996 through 2012, enabling a comprehensive evaluation of the EU ETS policy's initial two phases. In total, 32 OECD countries and key partners, such as India and Indonesia, are studied, including 21 EU ETS participants and 11 non-participants.

The core dataset is obtained from WIOD Release 2016, encompassing 42 countries (29 EU member states plus 13 major international economies) for 2000–2014. To broaden the analysis to include 1996–1999, data from WIOD Release 2013 are used, covering 40 countries (27 EU members and 13 other significant economies) from 1995–2011, with some variables available only up to 2009. Data from the year 1995 are excluded due to incomplete information, and data for 2013–2014 are omitted to maintain a clear focus on the EU ETS's first and second phases. Furthermore, specific countries[4] are excluded from the study due to missing critical data. Japan is also excluded since it launched an independent national ETS in 2010, making its inclusion inappropriate for causal analysis as either treated or control units. Table A.1 outlines 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).[5] 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.

Table A.9 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] Slovenia, Switzerland, Croatia, Norway, Taiwan, Cyprus, Luxembourg, Estonia, and Malta

[5] 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. The analysis in the previous chapter shows that sector C19 (Coke and Refined Petroleum) significantly differs from other sectors, primarily due to a high number of zeros. Therefore, I excluded sector C19 from the study to mitigate potential bias in the estimates.

dependent variables in the main specification (i.e., specification 4.9). The main variable of interest is the carbon leakage which measures the amount of carbon emissions embedded in imports per unit of output:

$$\mathrm{CL}_{ijt}^{s} = \mathrm{M}_{ijt}^{s} \times \frac{\mathrm{C}_{jt}^{s}}{\mathrm{Q}_{jt}^{s}} \tag{4.1}$$

where M_{ijt}^{s} 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_{jt}^{s}/Q_{jt}^{s} 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:

$$\mathrm{AdjCL}_{ijt}^{s} = \mathrm{CL}_{ijt}^{s} \times \frac{\mathrm{Q}_{jt}^{s}}{\mathrm{E}_{jt}^{s}} \tag{4.2}$$

where E_{jt}^{s} 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:

$$\mathrm{EL}_{ijt}^{s} = \mathrm{M}_{ijt}^{s} \times \frac{\mathrm{E}_{jt}^{s}}{\mathrm{Q}_{jt}^{s}} \tag{4.3}$$

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:

$$\mathrm{NetCL}_{ijt}^{s} = \left(\frac{\mathrm{C}_{jt}^{s}}{\mathrm{Q}_{jt}^{s}} - \frac{\mathrm{C}_{it}^{s}}{\mathrm{Q}_{it}^{s}} \right) \times \mathrm{M}_{ijt}^{s} \tag{4.4}$$

and

$$\mathrm{NetEL}_{ijt}^{s} = \left(\frac{\mathrm{E}_{jt}^{s}}{\mathrm{Q}_{jt}^{s}} - \frac{\mathrm{E}_{it}^{s}}{\mathrm{Q}_{it}^{s}} \right) \times \mathrm{M}_{ijt}^{s} \tag{4.5}$$

where $\frac{\mathrm{C}_{jt}^{s}}{\mathrm{Q}_{jt}^{s}}$ is the carbon intensity of the exporter j at time t in sector s and $\frac{\mathrm{C}_{it}^{s}}{\mathrm{Q}_{it}^{s}}$ 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, $\frac{\mathrm{E}_{jt}^{s}}{\mathrm{Q}_{jt}^{s}}$ and $\frac{\mathrm{E}_{it}^{s}}{\mathrm{Q}_{it}^{s}}$, 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.

4.2.2 Covariates

The main specifications (i.e., Equation 4.9) 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 [48]:

$$\text{Sim}_{ijt} = \ln\left[1 - \left|\left(\frac{\text{GDP}_{it}}{\text{GDP}_{it} + \text{GDP}_{jt}}\right)^2 - \left(\frac{\text{GDP}_{jt}}{\text{GDP}_{it} + \text{GDP}_{jt}}\right)^2\right|\right] \tag{4.6}$$

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)

$$\text{endw}^s_{ijt} = \left|\ln\left(\frac{\text{Output}^s_{it}}{\text{POP}_{it}}\right) - \ln\left(\frac{\text{Output}^s_{jt}}{\text{POP}_{jt}}\right)\right| \tag{4.7}$$

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

$$\text{Mass}^s_{ijt} = ln\left(\text{Output}^s_{it} + \text{Output}^s_{jt}\right) \tag{4.8}$$

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., [7]), I assume that trade costs can be controlled through groups of dummies alongside bilateral distance ([7]). 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 Larch's 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.6 presents all variables and their data sources. Summary statistics of all variables are available in Table A.5.

4.3 Stylized Facts

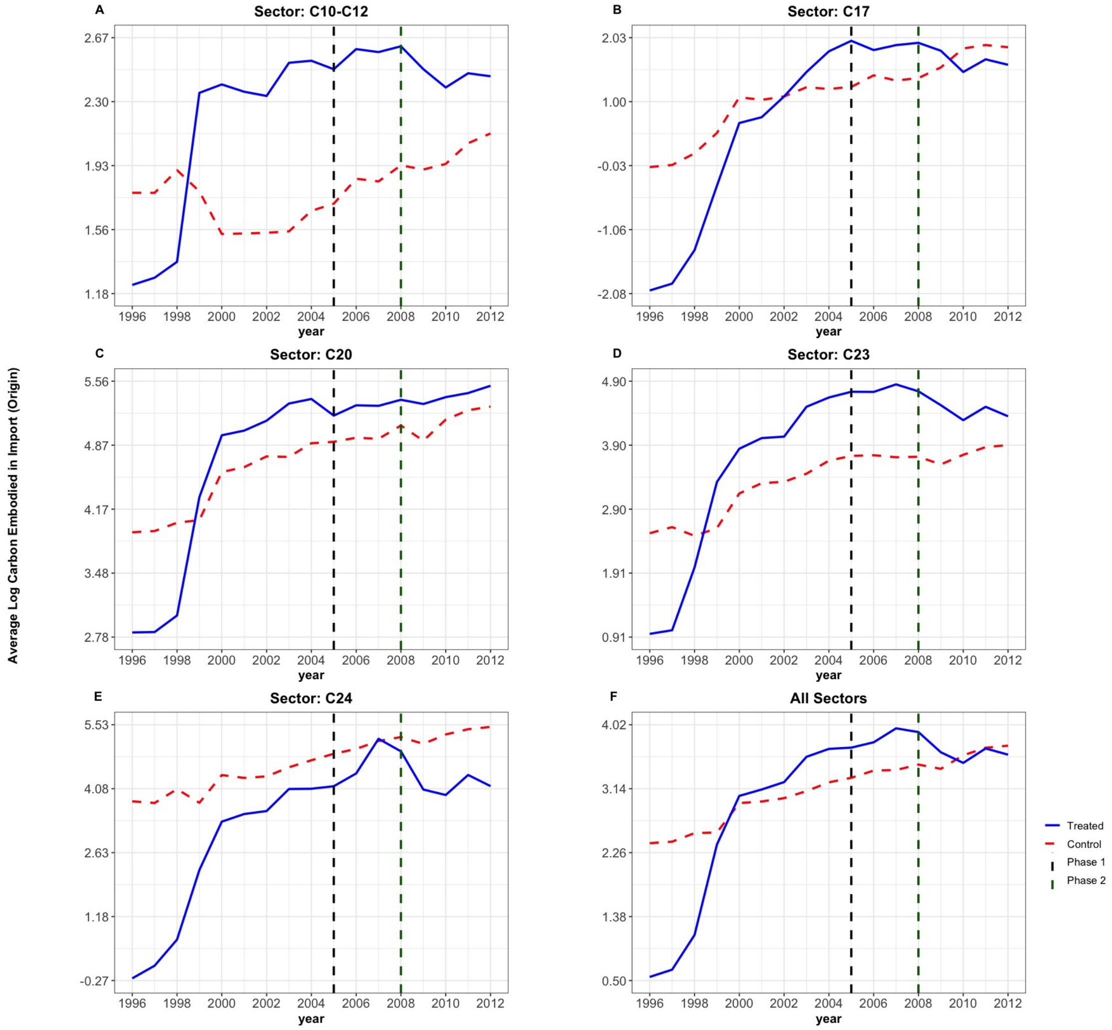
This section presents a set of stylized facts concerning the influence of the EU ETS policy on multiple measures of carbon and energy embodied in imports across five key industrial sectors. These sectors are subject to the EU ETS, and the goal here is to shed light on how policy implementation and subsequent phases of the EU ETS may have affected the carbon and energy content of their traded goods. The variables examined—ranging from carbon emissions embodied in imports to net energy flows—are 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.9.

Figure 4.1 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 policy's 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 4.2 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.

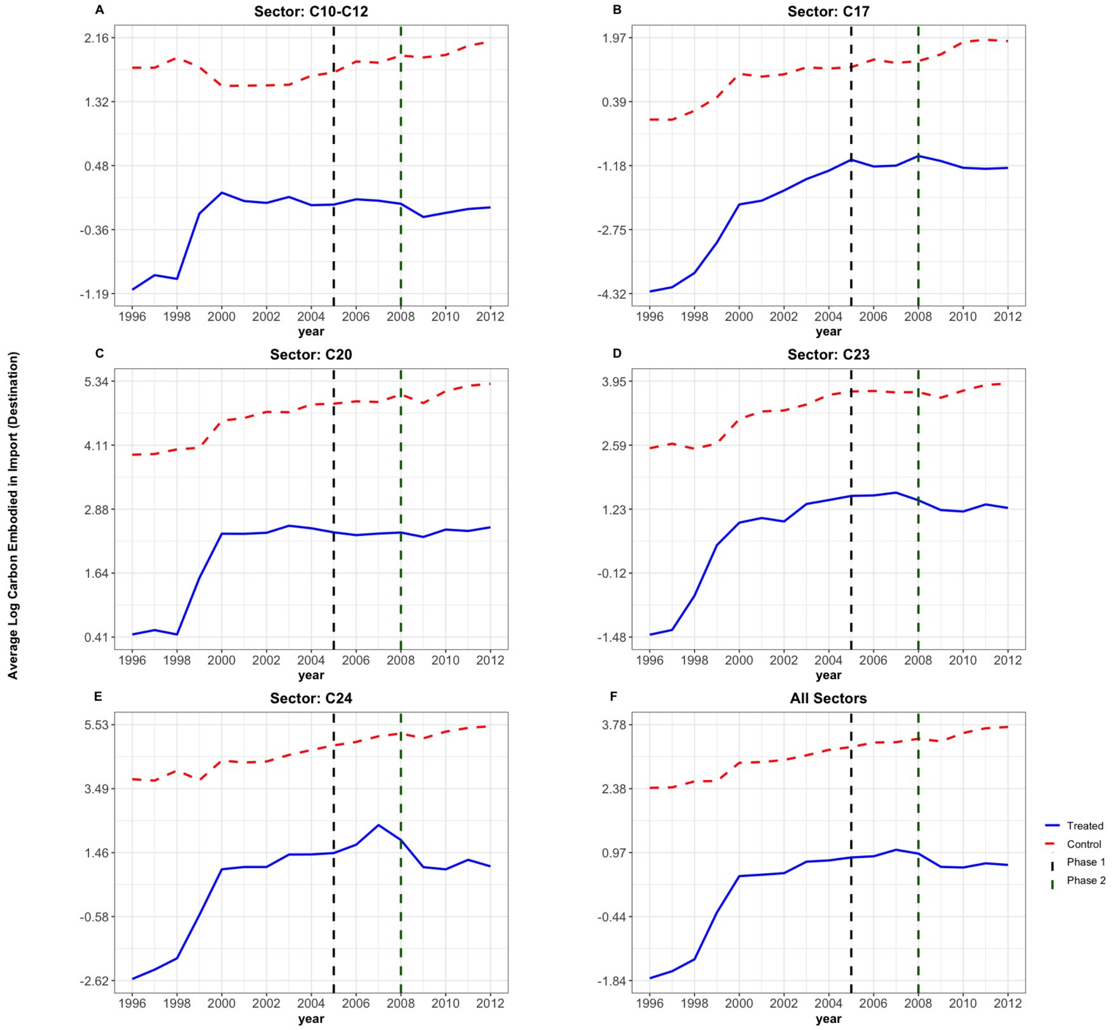
Figure 4.1: Trends in Log Carbon Embodied in Imports (1996-2012) by Sector (Exporter Production Technology)



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.

Figure 4.3 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

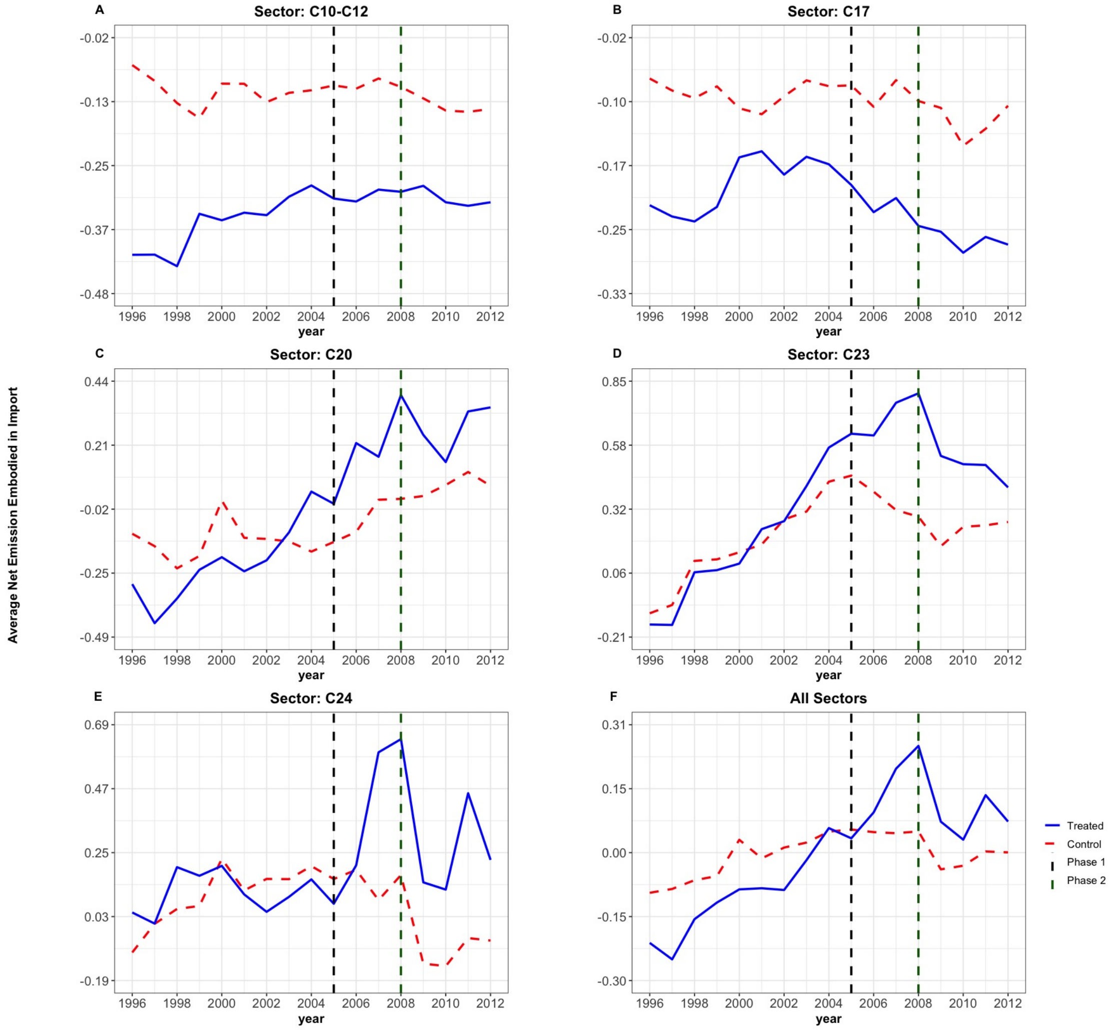
Figure 4.2: Trends in Log Carbon Embodied in Imports (1996-2012) by Sector (Importer Production Technology)



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.

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

Figure 4.3: Trends in Net Carbon Embodied in Imports (1996-2012) by Sector

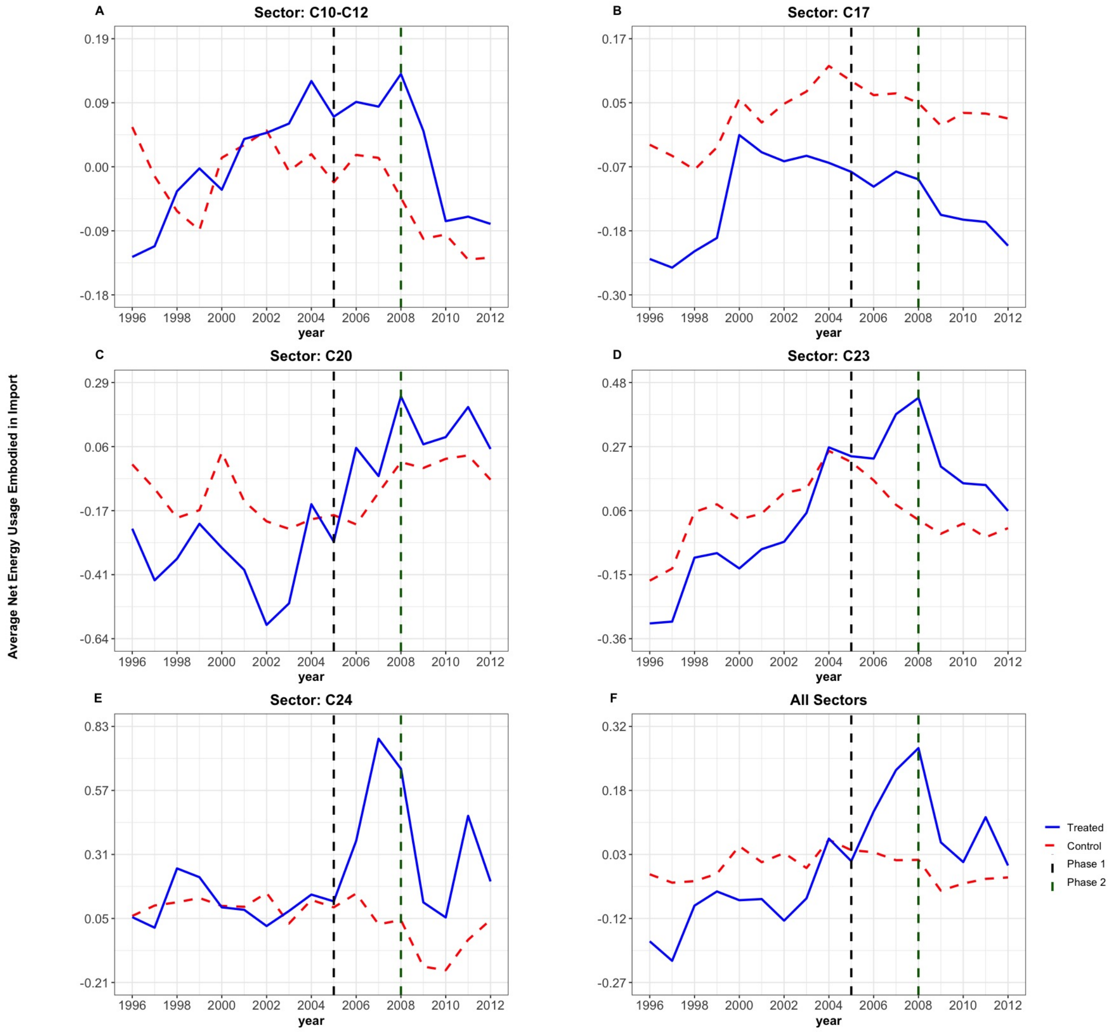


Note: This figure illustrates the changes in net carbon leakage across various industrial sectors, comparing the trends between the treatment (blue) and control (red) groups, based on differences in exporter and importer production technologies. Each panel represents a different sector, Panels A-E, alongside 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.

as all selected sectors at the country level.

Figures 4.4 and 4.5 provide additional insights by demonstrating energy usage embodied in international trade flows. Figure 4.4 displays the trends in net energy consumption from all energy sources, whereas Figure 4.5 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.

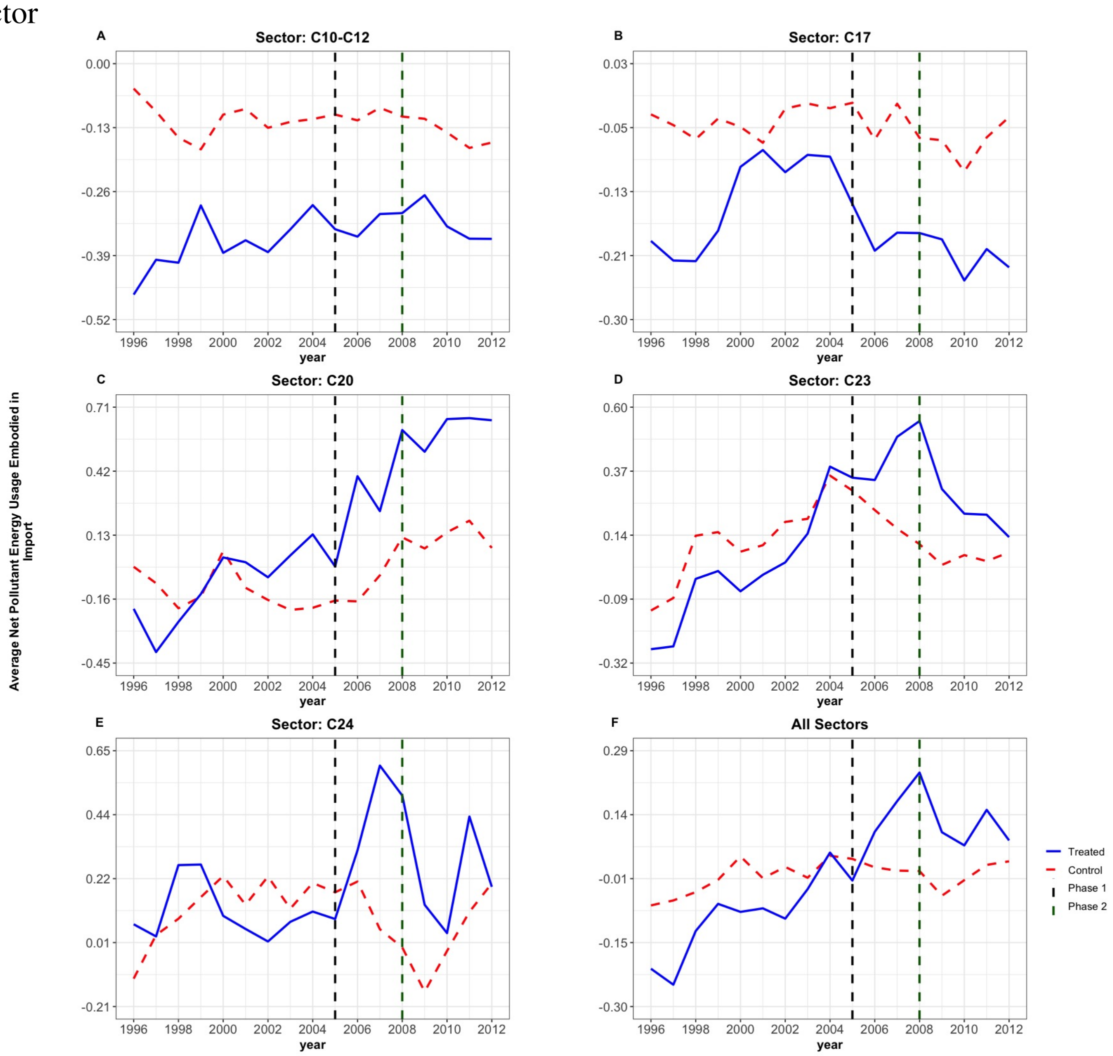
Figure 4.4: Trends in Net Energy Consumption Embodied in Imports (1996-2012) by Sector



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.

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 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.

Figure 4.5: 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.

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 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.

4.4 Methodology

The DiD Gravity model that is broadly used and suggested by the literature ([4], [83], [105]) 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 4.1, Figure 4.2, and Figure 4.3 for the carbon leakage based on the exporter production technology, importer 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 ([16]). 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.

[16] 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. The details of the optimization procedure to find unit and time weights can be found in Appendix B. The 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 approach—applied here for the first time in the literature, to the best of my knowledge, with the following specification:

$$Y_{pt} = \mu + \tau W_{pt} + X'_{pt}\beta + \alpha_p + \delta_t + \varepsilon_{pt} \tag{4.9}$$

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.9. 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 program's 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, and is assumed to be uncorrelated with the treatment assignment once we condition on fixed effects and observed covariates.

In line with [16] and [72], I outline the SDiD estimation via the following optimization process :

First, as per [72], I estimate the fixed-effects regression:

$$Y_{pt} = \mu + X'_{pt}\beta + \alpha_p + \delta_t + e_{pt} \tag{4.10}$$

I then compute the adjusted outcome variable using:

$$Y_{pt}^{\text{adj}} = Y_{pt} - X'_{pt}\hat{\beta} \tag{4.11}$$

Next, following [16], 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:

$$\left(\hat{\mu}, \hat{\alpha}, \hat{\delta}, \hat{\tau}^{\text{sdid}}\right) = \arg\min_{\mu,\alpha,\delta,\tau} \sum_{p=1}^{N}\sum_{t=1}^{T}\left(Y_{pt}^{\text{adj}} - \mu - \alpha_p - \delta_t - W_{pt}\tau\right)^2 \hat{\omega}_p\hat{\lambda}_t \tag{4.12}$$

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 4.9 (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 program's 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 4.3 can be expressed in the original measurement units of the dependent variable using the standard deviation in Table A.5.

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 ([17]). 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:

$$\hat{\tau}_{\text{ATT}} = \sum a \frac{T_a}{T_{\text{post}}} \times \hat{\tau}_a \tag{4.13}$$

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. I also considered mitigation strategies to address the potential risks associated with SDiD, drawing on relevant theoretical and empirical studies (see Appendix C).

4.5 Results

This section presents the estimated effects of the EU ETS policy using Specification 4.9. 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.

4.5.1 Actual Scenario Based on Country of Origin

The first row of Table 4.1 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 ([83]; [105]), 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 (see Chapter 1), this success might potentially be due to displacing a proportion of the emissions to non-regulated areas. Hence, in contrast to [82]'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 sectors 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

Table 4.1: 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***
	(0.058)	(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 aggregation includes $[(21 \times 11) + (11 \times 10)] \times 17 = 5,797$ 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 4.9. 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.

(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 ([87]). 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 4.1 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 (see Chapter 1), 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 [18], [22], and [51] 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 [80]; [43]; [44], 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, [89] examined the aluminum sector, and [28] 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 policy's 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., [27]; [21]). 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.

4.5.2 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 4.2. 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 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

Table 4.2: 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 aggregation includes $[(21\times 11)+(11\times 10)]\times 17 = 5,797$ 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 4.9. 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 *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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.

4.5.3 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 4.3 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 program's 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

Table 4.3: 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 [(21×11×17)+(11×10×17)] 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 4.9. 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..

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 ([52]; [2]). 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 (see Chapter 1), 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, 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.

4.5.4 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 program's 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.[6]

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

[6] 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.

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.[7] This methodological rigor enhances the validity of the statistical inference, providing a robust assessment of the program's 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.

4.6 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' scenario—assessing the extent to which carbon emissions and energy consumption would have occurred if the imported

[7] 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.

goods had been produced using the production technology of the importer countries—I 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 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.

Thesis Conclusion

The European Union Emissions Trading System (EU ETS) has demonstrated substantial effectiveness in carbon abatement and improving carbon intensity across targeted sectors in regulated countries, as examined in the first chapter of this thesis. Analyzing data from seven targeted sectors across 32 countries between 1996 and 2012, covering the first two phases of the program, using a Synthetic Difference in Differences (SDiD) framework and index decomposition analysis, the study found that the EU ETS achieved an average reduction of 19% in CO_2 emissions among regulated countries. Furthermore, the carbon intensity significantly decreased, particularly in the Chemicals, Non-Metallic Mineral Products, Basic Metals, and Energy sectors. These reductions were primarily driven by improvements in energy efficiency, especially from pollutant energy sources, such as fossil fuels, and these efficiency gains were sustained over time. However, the varied responses across different sectors indicate the need for more tailored approaches to address specific industrial challenges effectively.

Expanding on these findings, the second chapter investigates the EU ETS's impact on international trade flows and the technological disparities between EU-regulated countries and their non-EU trade partners. Utilizing a robust quasi-experimental technique, the study focused on five regulated manufacturing sectors. The results show a 14% increase in imports from non-regulated exporters, with heterogeneous effects across targeted sectors. The Food, Non-Metallic Mineral Products, and Basic Metals sectors experienced a substantial increase in import values, whereas sectors like Paper and Chemicals showed no significant effects. Most importantly, the findings, which were consistent with the Porter hypothesis and the pollution haven hypothesis, revealed that the EU ETS contributed to widening technological gaps related to carbon emissions and energy use. Growth-based analyses suggested while some sectors experienced an accelerated increase in imports, possibly due to difficulties faced by domestic producers in adapting quickly to compliance costs, others may gradually restructured and invested in cleaner technologies as they faced decelerated growth. Similarly, the analysis of the growth rate of technological gap indicators revealed that the EU ETS not only affects the current level of environmental performance but also influences its trajectory. This highlights the complex interplay between environmental policies and international trade dynamics.

In the third chapter, the focus shifts to the often-overlooked aspects of carbon and energy leakage associated with the EU ETS, specifically how the policy influences the carbon embodied in imports and the energy flows related to international trade. By introducing new metrics such as adjusted carbon leakage and energy embodied in imports and employing a hypothetical 'what-if' scenario, the study found that the EU ETS inadvertently increased carbon and energy leakage by shifting energy-intensive production abroad. This shift was particularly pronounced in regions utilizing less efficient and more polluting energy sources, leading to a rise in global carbon emissions and energy consumption linked to international trade. These findings suggest that while the EU ETS effectively reduces emissions within regulated countries, it may contribute to higher overall emissions globally. The research underscores the importance of considering global supply chains and the interconnectedness of international markets when designing and implementing climate policies to avoid unintended environmental consequences.

Drawing on the thorough analyses conducted in this thesis, several policy recommendations are presented that could improve the effectiveness of the EU ETS in mitigating its unintended effects. For instance, introducing sector-specific regulations can address the diverse responses observed, ensuring that industries with higher leakage rates receive focused support, such as subsidies for low-carbon technologies. Incentivizing the adoption of renewable energy is also crucial, which could be achieved through the preferential allocation of allowances to less polluting energy sources. Furthermore, encouraging international collaboration to establish unified environmental standards can disincentivize the targeted entities from relocating carbon-intensive production, thereby decreasing global carbon emissions. Encouraging investments in continuous technological innovations and boosting energy efficiency both domestically and internationally will also aid in maintaining long-term emissions reductions. Lastly, establishing stable and predictable policy frameworks can foster long-term investments in cleaner technologies, ensuring that the EU ETS not only achieves immediate emission reductions but also supports enduring structural changes toward sustainability.

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APPENDIX A

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
Coke and refined petroleum	C19	23	199
Chemicals	C20	24	541
Non-metallic mineral products (Cement, glass, and ceramic)	C23	26	2868
Metal	C24	27	373
Energy	D35	40	5361

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 - Chapter 1

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
Decomposed Variables					
ΔCI	544	-0.533	3.378	-16.291	41.148
CI^{TEI}	544	-0.509	3.241	-17.747	40.767
CI^{PEI}	544	-0.556	3.326	-21.96	40.444
CI^{CTE}	544	-0.024	0.729	-6.295	7.448
CI^{CPE}	544	0.023	0.748	-5.541	7.585
CI^{OS}	544	0.081	1.38	-11.966	13.975
All					
CO_2 (ln)	544	11.637	1.544	7.954	15.881
Carbon Intensity (ln)	544	-6.935	0.772	-8.66	-4.422
Total Energy Intensity (ln)	544	-4.022	0.646	-5.231	-1.54
Pollutant Energy Intensity (ln)	544	-4.548	0.763	-6.335	-1.855
Carbon to Total Energy (ln)	544	-2.913	0.418	-4.435	-2.237
Carbon to Pollutant Energy (ln)	544	-2.387	0.136	-2.779	-2.047
Energy (All sources)	544	6203885	12400000	74465.78	84200000
Energy (Pollutant sources)	544	4317694	9532995	45414.4	68200000
CO_2	544	411019.1	983037.9	2848.063	7887839
Output	544	325741.8	653456.5	1871.455	6599675
Capital Compensations	544	53209.64	114763.9	309.52	852622.5
Labor Compensations	544	38330.91	67815.12	327.96	447537.6
Labor to Capital Ratio	544	1.421	0.67	0.422	4.614
C10-C12					
CO_2 (ln)	544	7.915	1.43	3.882	11.829
Carbon Intensity (ln)	544	-9.425	0.767	-12.089	-6.976

Table A.3 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
Total Energy Intensity (ln)	544	-6.129	0.72	-7.589	-3.635
Pollutant Energy Intensity (ln)	544	-6.769	0.68	-8.245	-4.427
Carbon to Total Energy (ln)	544	-3.296	0.68	-6.59	-0.905
Carbon to Pollutant Energy (ln)	544	-2.655	0.427	-6.346	-0.36
Output Share (ln)	544	-1.233	0.31	-2.08	-0.365
Energy (All sources)	544	214226.9	358187.2	4156.625	1904418
Energy (Pollutant sources)	544	112574	242835.4	2666.978	1440144
CO_2	544	8567.184	19838.44	48.51	137161.3
Output	544	86613.63	155506.5	744.893	1476981
Capital Compensations	544	12045.9	24975.39	81.847	235460.3
Labor Compensations	544	10568.36	17037.37	142.85	122568.2
Labor to Capital Ratio	544	1.191	0.888	0.253	6.186
C17					
CO_2 (ln)	544	7.063	1.977	1.5	11.111
Carbon Intensity (ln)	544	-8.593	0.863	-12.155	-6.29
Total Energy Intensity (ln)	544	-4.946	0.876	-8.356	-3.09
Pollutant Energy Intensity (ln)	544	-5.947	0.788	-8.808	-3.752
Carbon to Total Energy (ln)	544	-3.648	0.693	-5.534	-1.821
Carbon to Pollutant Energy (ln)	544	-2.646	0.382	-4.44	-1.353
Output Share (ln)	544	-2.916	0.671	-5.158	-1.02
Energy (All sources)	544	195080.9	403624.1	164.414	2618277
Energy (Pollutant sources)	544	69430.93	158545.4	56.332	1104889
CO_2	544	5193.417	11618.53	4.483	66870.57
Output	544	20378.14	43435.11	72.743	400363.7
Capital Compensations	544	2827.806	6602.994	0	71512.84

Table A.3 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
Labor Compensations	544	3733.49	9284.696	8.485	99249.12
Labor to Capital Ratio	544	1.031	0.647	0	3.713
C19					
CO_2 (ln)	544	8.343	2.837	-18.421	12.319
Carbon Intensity (ln)	544	-7.779	1.43	-24.967	-4.117
Total Energy Intensity (ln)	544	-4.875	1.07	-11.353	-1.091
Pollutant Energy Intensity (ln)	544	-5.03	1.088	-11.372	-1.182
Carbon to Total Energy (ln)	544	-2.904	1.089	-16.598	2.137
Carbon to Pollutant Energy (ln)	544	-2.75	1.064	-16.581	2.154
Output Share (ln)	544	-2.45	1.241	-10.612	-0.897
Energy (All sources)	544	319721.5	614005.6	0.002	3446550
Energy (Pollutant sources)	544	277644.3	550147.1	0.002	3240628
CO_2	544	18743.18	36590.15	0	224008.3
Output	544	42761.77	99357.99	0.126	829045
Capital Compensations	544	5848.458	18465.85	0	154869.2
Labor Compensations	544	1619.789	3380.898	0	24897.41
Labor to Capital Ratio	544	3.342	4.735	0	58.058
C20					
CO_2 (ln)	544	8.711	1.886	2.678	13.402
Carbon Intensity (ln)	544	-7.68	1.11	-11.534	-4.63
Total Energy Intensity (ln)	544	-4.912	0.915	-7.211	-2.017
Pollutant Energy Intensity (ln)	544	-5.442	0.965	-7.595	-2.406
Carbon to Total Energy (ln)	544	-2.768	0.541	-4.938	-1.451
Carbon to Pollutant Energy (ln)	544	-2.239	0.646	-4.338	1.155
Output Share (ln)	544	-2.18	0.457	-3.982	-0.99

Table A.3 continued from previous page

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
Energy (All sources)	544	388617.7	947728.8	650.39	7584944
Energy (Pollutant sources)	544	257190.9	657251.4	351.009	5212011
CO_2	544	28152.33	77501.93	14.558	661073.1
Output	544	51269.9	113127.9	43.507	1124971
Capital Compensations	544	8939.645	23246.47	3.574	184211.7
Labor Compensations	544	5944.011	11696.05	11.44	66726.84
Labor to Capital Ratio	544	1.432	1.005	0.041	8.68
C23					
CO_2 (ln)	544	9.404	1.567	5.741	14.284
Carbon Intensity (ln)	544	-6.4	0.72	-7.915	-4.388
Total Energy Intensity (ln)	544	-4.408	0.708	-5.87	-2.043
Pollutant Energy Intensity (ln)	544	-4.617	0.737	-6.127	-2.143
Carbon to Total Energy (ln)	544	-1.991	0.284	-3.331	-1.095
Carbon to Pollutant Energy (ln)	544	-1.782	0.291	-3.196	-0.707
Output Share (ln)	544	-2.769	0.351	-3.875	-1.862
Energy (All sources)	544	330777.8	1008450	2773.714	8869092
Energy (Pollutant sources)	544	284797.4	904740.2	2417.376	7804509
CO_2	544	52079.53	178770.6	311.249	1597149
Output	544	21960.31	56290.81	67.407	709930
Capital Compensations	544	3482.298	8910.793	0	105811.8
Labor Compensations	544	4088.312	7736.612	14.922	82698.66
Labor to Capital Ratio	544	0.91	0.601	0	3.965
C24					
CO_2 (ln)	544	9.175	2.215	1.291	14.04
Carbon Intensity (ln)	544	-7.252	1.008	-10.557	-4.883

Table A.3 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
Total Energy Intensity (ln)	544	-4.706	0.766	-6.9	-2.236
Pollutant Energy Intensity (ln)	544	-5.135	0.888	-8.141	-2.992
Carbon to Total Energy (ln)	544	-2.547	0.425	-3.831	-1.691
Carbon to Pollutant Energy (ln)	544	-2.117	0.395	-3.52	-1.122
Output Share (ln)	544	-2.145	0.742	-5.875	-1.244
Energy (All sources)	544	549337.9	1403671	104.338	13500000
Energy (Pollutant sources)	544	382831.1	1025264	22.988	9874002
CO_2	544	49091.46	130025.6	3.637	1251760
Output	544	52531.58	132754.7	23.119	1543116
Capital Compensations	544	6199.781	16955.18	0	179269.7
Labor Compensations	544	6534.047	13409.57	6.17	109768.9
Labor to Capital Ratio	544	1.049	1.167	0	9.434
D35					
CO_2 (ln)	544	11.004	1.633	7.537	15.206
Carbon Intensity (ln)	544	-5.731	1.064	-8.384	-3.05
Total Energy Intensity (ln)	544	-2.577	0.733	-4.447	-0.156
Pollutant Energy Intensity (ln)	544	-3.195	0.996	-6.141	-0.337
Carbon to Total Energy (ln)	544	-3.154	0.661	-5.193	-2.135
Carbon to Pollutant Energy (ln)	544	-2.536	0.17	-2.957	-2.018
Output Share (ln)	544	-1.836	0.425	-3.469	-0.763
Energy (All sources)	544	4206123	8404026	60506.25	48300000
Energy (Pollutant sources)	544	2933225	6493839	34716.03	41200000
CO_2	544	249192	580675.3	1875.831	4016883
Output	544	50226.47	94218.81	491.171	776784.2
Capital Compensations	544	14007.48	27915.11	107.132	194601.6

Table A.3 continued from previous page

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
Labor Compensations	544	5842.902	10817.17	93.012	68980.59
Labor to Capital Ratio	544	2.614	1.274	0.335	7.797
Rest of the Variables					
Coal Rent	544	0.231	0.542	0	4.956
Foreign Direct	544	4.446	6.155	0	50.384
GDP PPP	544	29581.87	14832.75	2220.893	59530.89
Global Index	544	66.747	14.421	21.044	90.859
Human Capital	544	2.977	0.487	1.64	3.719
TFP	544	0.771	0.217	0.267	1.427
Industry GVA	544	27.639	6.527	14.377	48.061
Services GVA	544	58.135	8.143	33.369	76.514
Population	544	125000000	290000000	2034319	1350000000

Note: This table shows the summary statistics of all variables used in Specification 2.12. 'ln' in parentheses indicates that the values are in logarithmic terms.

Table A.4: Summary Statistics - Chapter 2

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
All					
Import (ln)	5797	1.606	2.401	-18.421	7.507
TG^{CI} (ln)	5797	-1.927	2.512	-8.3	5.521
TG^{TEI} (ln)	5797	-1.926	2.421	-8.187	5.13
TG^{PEI} (ln)	5797	-1.898	2.451	-8.247	5.363
TG^{CET} (ln)	5797	-0.001	0.454	-1.611	1.289
TG^{CEP} (ln)	5797	-0.029	0.25	-0.956	0.738
Import Growth	5797	0.2	1.578	-19.819	24.517
TG^{CI} *Growth*	5797	-0.017	0.179	-0.997	1.153
TG^{TEI} *Growth*	5797	-0.006	0.17	-0.972	1.207
TG^{PEI} *Growth*	5797	-0.013	0.181	-1.027	1.186
TG^{CET} *Growth*	5797	-0.011	0.094	-0.792	0.739
TG^{CEP} *Growth*	5797	-0.004	0.094	-0.724	0.696
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
Total Pollutant Energy (d) (ln)	5797	12.624	1.525	9.256	17.026
Total Pollutant Energy (o) (ln)	5797	14.041	1.079	12.535	17.026
Total Clean Energy (d) (ln)	5797	12.066	1.61	7.976	15.945
Total Clean Energy (o) (ln)	5797	13.567	1.097	11.421	15.945
Intermediate Output (d) (ln)	5797	10.937	1.541	6.762	15.203
Intermediate Output (o) (ln)	5797	12.085	1.008	10.305	15.203
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

Table A.4 continued from previous page

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
Labor Compensation (o) (ln)	5797	10.26	0.995	8.635	12.839
Sim^{s}_{ijt}	5797	-1.232	1.136	-6.433	0
$Mass^{s}_{ijt}$	5797	12.946	0.946	10.767	15.775
$Endw^{s}_{ijt}$	5797	1.201	0.926	0	4.551
TG^{CI} *(stdd)*	5797	0	1	-0.211	14.688
TG^{CI}	5797	3.539	16.772	0	249.884
TG^{TEI} *(stdd)*	5797	0	1	-0.237	13.921
TG^{TEI}	5797	2.827	11.934	0	168.963
TG^{PEI} *(stdd)*	5797	0	1	-0.223	14.969
TG^{PEI}	5797	3.134	14.052	0	213.465
TG^{CET} *(stdd)*	5797	0	1	-1.846	5.167
TG^{CET}	5797	1.102	0.489	0.2	3.628
TG^{CEP} *(stdd)*	5797	0	1	-2.444	4.313
TG^{CEP}	5797	1.002	0.253	0.384	2.092
Total Energy (d) (stdd)	5797	0	1	-0.429	8.461
Total Energy (o) (stdd)	5797	0	1	-0.626	5
Total Pollutant Energy (d) (stdd)	5797	0	1	-0.378	8.561
Total Pollutant Energy (o) (stdd)	5797	0	1	-0.531	4.975
Total Clean Energy (d) (stdd)	5797	0	1	-0.54	7.818
Total Clean Energy (o) (stdd)	5797	0	1	-0.868	4.849
Intermediate Output (d) (stdd)	5797	0	1	-0.471	11.149
Intermediate Output (o) (stdd)	5797	0	1	-0.564	6.707
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

Table A.4 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
Labor Compensation (o) (stdd)	5797	0	1	-0.603	4.026
Sim^{s}_{ijt} *(stdd)*	5797	0	1	-4.577	1.084
$Mass^{s}_{ijt}$ *(stdd)*	5797	0	1	-2.304	2.991
$Endw^{s}_{ijt}$ *(stdd)*	5797	0	1	-1.297	3.616
C10-C12					
Import (ln)	5797	-0.382	2.665	-18.421	6.078
TG^{CI} (ln)	5797	-1.694	2.415	-8.838	6.307
TG^{TEI} (ln)	5797	-1.989	2.648	-8.329	5.953
TG^{PEI} (ln)	5797	-1.661	2.318	-7.834	6.219
TG^{CET} (ln)	5797	0.296	1.072	-4.016	3.77
TG^{CEP} (ln)	5797	-0.033	0.484	-3.973	2.511
Import Growth	5797	0.184	1.627	-18.83	22.051
TG^{CI} *Growth*	5797	0.001	0.363	-2.753	5.671
TG^{TEI} *Growth*	5797	-0.004	0.203	-1.074	0.863
TG^{PEI} *Growth*	5797	-0.002	0.324	-2.793	2.999
TG^{CET} *Growth*	5797	0.005	0.32	-2.431	5.216
TG^{CEP} *Growth*	5797	0.003	0.23	-2.409	3.128
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
Total Pollutant Energy (d) (ln)	5797	10.535	1.347	7.889	14.18
Total Pollutant Energy (o) (ln)	5797	11.649	1.094	10.373	14.18
Total Clean Energy (d) (ln)	5797	10.186	1.589	7.284	13.76
Total Clean Energy (o) (ln)	5797	11.77	1.325	9.285	13.76
Intermediate Output (d) (ln)	5797	10.089	1.457	6.179	13.928

Table A.4 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
Intermediate Output (o) (ln)	5797	11.172	0.919	9.779	13.928
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
Sim^s_{ijt}	5797	-1.135	1.04	-5.818	0
$Mass^s_{ijt}$	5797	11.995	0.885	10.161	14.684
$Endw^s_{ijt}$	5797	1.184	0.933	0.001	4.509
TG^{CI} *(stdd)*	5797	0	1	-0.173	22.058
TG^{CI}	5797	4.272	24.665	0	548.331
TG^{TEI} *(stdd)*	5797	0	1	-0.192	14.323
TG^{TEI}	5797	5.101	26.528	0	385.074
TG^{PEI} *(stdd)*	5797	0	1	-0.177	25.214
TG^{PEI}	5797	3.492	19.776	0	502.132
TG^{CET} *(stdd)*	5797	0	1	-0.721	12.641
TG^{CET}	5797	2.358	3.244	0.018	43.372
TG^{CEP} *(stdd)*	5797	0	1	-1.332	14.055
TG^{CEP}	5797	1.083	0.799	0.019	12.316
Total Energy (d) (stdd)	5797	0	1	-0.575	4.869
Total Energy (o) (stdd)	5797	0	1	-0.921	2.885
Total Pollutant Energy (d) (stdd)	5797	0	1	-0.447	5.645
Total Pollutant Energy (o) (stdd)	5797	0	1	-0.582	3.199
Total Clean Energy (d) (stdd)	5797	0	1	-0.52	4.637
Total Clean Energy (o) (stdd)	5797	0	1	-0.949	2.69
Intermediate Output (d) (stdd)	5797	0	1	-0.549	9.409

Table A.4 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
Intermediate Output (o) (stdd)	5797	0	1	-0.607	5.774
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
Sim^s_{ijt} *(stdd)*	5797	0	1	-4.504	1.091
$Mass^s_{ijt}$ *(stdd)*	5797	0	1	-2.074	3.039
$Endw^s_{ijt}$ *(stdd)*	5797	0	1	-1.268	3.563
C17					
Import (ln)	5797	-2.589	3.849	-18.421	5.003
TG^{CI} (ln)	5797	-1.965	2.751	-10.321	6.06
TG^{TEI} (ln)	5797	-1.978	2.545	-9.755	5.931
TG^{PEI} (ln)	5797	-1.973	2.577	-9.574	5.656
TG^{CET} (ln)	5797	0.012	0.982	-2.835	2.777
TG^{CEP} (ln)	5797	0.008	0.453	-2.102	1.838
Import Growth	5797	0.234	2.257	-15.724	21.209
TG^{CI} *Growth*	5797	-0.01	0.358	-2.822	2.282
TG^{TEI} *Growth*	5797	-0.001	0.3	-1.859	3.052
TG^{PEI} *Growth*	5797	-0.009	0.317	-1.722	2.405
TG^{CET} *Growth*	5797	-0.009	0.306	-2.738	1.909
TG^{CEP} *Growth*	5797	-0.001	0.225	-2.094	1.64
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
Total Pollutant Energy (d) (ln)	5797	9.665	1.89	4.031	13.915

Table A.4 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
Total Pollutant Energy (o) (ln)	5797	11.094	1.241	8.829	13.915
Total Clean Energy (d) (ln)	5797	10.032	2.149	4.537	14.301
Total Clean Energy (o) (ln)	5797	11.428	1.606	8.591	14.301
Intermediate Output (d) (ln)	5797	8.335	1.718	3.865	12.36
Intermediate Output (o) (ln)	5797	9.425	1.073	7.574	12.36
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
Sim^s_{ijt}	5797	-1.315	1.279	-7.025	0
$Mass^s_{ijt}$	5797	10.399	1.008	8.18	13.092
$Endw^s_{ijt}$	5797	1.519	1.172	0	6.521
TG^{CI} *(stdd)*	5797	0	1	-0.197	17.214
TG^{CI}	5797	4.853	24.603	0	428.369
TG^{TEI} *(stdd)*	5797	0	1	-0.202	24.617
TG^{TEI}	5797	3.057	15.164	0	376.345
TG^{PEI} *(stdd)*	5797	0	1	-0.219	18.884
TG^{PEI}	5797	3.279	14.969	0	285.945
TG^{CET} *(stdd)*	5797	0	1	-0.866	8.037
TG^{CET}	5797	1.617	1.799	0.059	16.072
TG^{CEP} *(stdd)*	5797	0	1	-1.789	9.286
TG^{CEP}	5797	1.118	0.556	0.122	6.284
Total Energy (d) (stdd)	5797	0	1	-0.477	6.194
Total Energy (o) (stdd)	5797	0	1	-0.681	3.587
Total Pollutant Energy (d) (stdd)	5797	0	1	-0.432	6.739

Table A.4 continued from previous page

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
Total Pollutant Energy (o) (stdd)	5797	0	1	-0.617	3.896
Total Clean Energy (d) (stdd)	5797	0	1	-0.474	5.91
Total Clean Energy (o) (stdd)	5797	0	1	-0.686	3.434
Intermediate Output (d) (stdd)	5797	0	1	-0.487	8.004
Intermediate Output (o) (stdd)	5797	0	1	-0.556	4.76
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
Sim^{s}_{ijt} *(stdd)*	5797	0	1	-4.464	1.028
$Mass^{s}_{ijt}$ *(stdd)*	5797	0	1	-2.201	2.673
$Endw^{s}_{ijt}$ *(stdd)*	5797	0	1	-1.295	4.267
C20					
Import (ln)	5797	0.359	2.611	-18.421	6.815
TG^{CI} (ln)	5797	-1.892	2.718	-10.162	5.981
TG^{TEI} (ln)	5797	-1.758	2.472	-9.24	5.891
TG^{PEI} (ln)	5797	-1.912	2.552	-9.35	5.875
TG^{CET} (ln)	5797	-0.135	0.653	-2.879	1.939
TG^{CEP} (ln)	5797	0.019	0.73	-2.46	3.731
Import Growth	5797	0.213	1.571	-18.077	24.341
TG^{CI} *Growth*	5797	-0.021	0.348	-2.623	3.211
TG^{TEI} *Growth*	5797	-0.015	0.279	-1.401	2.288
TG^{PEI} *Growth*	5797	-0.028	0.359	-2.593	2.324
TG^{CET} *Growth*	5797	-0.005	0.243	-1.79	1.707

Table A.4 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
TG^{CEP} *Growth*	5797	0.008	0.292	-1.727	1.727
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
Total Pollutant Energy (d) (ln)	5797	10.901	1.843	5.861	15.466
Total Pollutant Energy (o) (ln)	5797	12.474	1.203	10.45	15.466
Total Clean Energy (d) (ln)	5797	10.36	1.663	5.667	14.757
Total Clean Energy (o) (ln)	5797	11.492	1.588	8.874	14.757
Intermediate Output (d) (ln)	5797	9.085	1.839	3.212	13.745
Intermediate Output (o) (ln)	5797	10.402	1.201	8.395	13.745
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
Sim^{s}_{ijt}	5797	-1.517	1.35	-8.227	0
$Mass^{s}_{ijt}$	5797	11.309	1.117	8.842	14.355
$Endw^{s}_{ijt}$	5797	1.318	0.948	0.001	5.049
TG^{CI} *(stdd)*	5797	0	1	-0.215	20.162
TG^{CI}	5797	4.184	19.42	0	395.742
TG^{TEI} *(stdd)*	5797	0	1	-0.224	24.419
TG^{TEI}	5797	3.295	14.682	0	361.822
TG^{PEI} *(stdd)*	5797	0	1	-0.213	23.548
TG^{PEI}	5797	3.185	14.983	0	356.011
TG^{CET} *(stdd)*	5797	0	1	-1.467	8.598
TG^{CET}	5797	1.061	0.685	0.056	6.95
TG^{CEP} *(stdd)*	5797	0	1	-0.537	15.944

Table A.4 continued from previous page

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
TG^{CEP}	5797	1.442	2.525	0.085	41.704
Total Energy (d) (stdd)	5797	0	1	-0.403	7.837
Total Energy (o) (stdd)	5797	0	1	-0.602	4.563
Total Pollutant Energy (d) (stdd)	5797	0	1	-0.384	7.782
Total Pollutant Energy (o) (stdd)	5797	0	1	-0.577	4.509
Total Clean Energy (d) (stdd)	5797	0	1	-0.424	8.236
Total Clean Energy (o) (stdd)	5797	0	1	-0.641	4.836
Intermediate Output (d) (stdd)	5797	0	1	-0.437	11.169
Intermediate Output (o) (stdd)	5797	0	1	-0.552	6.697
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
Sim^{s}_{ijt} *(stdd)*	5797	0	1	-4.97	1.124
$Mass^{s}_{ijt}$ *(stdd)*	5797	0	1	-2.208	2.727
$Endw^{s}_{ijt}$ *(stdd)*	5797	0	1	-1.39	3.937
C23					
Import (ln)	5797	-2.142	3.265	-18.421	4.579
TG^{CI} (ln)	5797	-2.079	2.58	-8.069	6.132
TG^{TEI} (ln)	5797	-1.977	2.539	-7.648	5.915
TG^{PEI} (ln)	5797	-1.97	2.575	-7.798	6.194
TG^{CET} (ln)	5797	-0.102	0.409	-2.235	1.498
TG^{CEP} (ln)	5797	-0.109	0.41	-2.489	1.385
Import Growth	5797	0.211	1.832	-18.737	20.888

Table A.4 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
TG^{CI} *Growth*	5797	-0.018	0.253	-1.648	2.043
TG^{TEI} *Growth*	5797	-0.022	0.256	-1.843	1.843
TG^{PEI} *Growth*	5797	-0.023	0.274	-1.919	1.919
TG^{CET} *Growth*	5797	0.005	0.153	-1.009	1.706
TG^{CEP} *Growth*	5797	0.005	0.171	-1.109	1.909
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
Total Pollutant Energy (d) (ln)	5797	11.144	1.487	7.79	15.87
Total Pollutant Energy (o) (ln)	5797	12.483	1.207	10.547	15.87
Total Clean Energy (d) (ln)	5797	9.588	1.488	5.864	13.888
Total Clean Energy (o) (ln)	5797	10.874	1.101	8.866	13.888
Intermediate Output (d) (ln)	5797	8.396	1.535	3.802	13.164
Intermediate Output (o) (ln)	5797	9.378	1.121	7.023	13.164
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
Sim^{s}_{ijt}	5797	-1.197	1.134	-6.567	0
$Mass^{s}_{ijt}$	5797	10.448	1.022	7.631	13.603
$Endw^{s}_{ijt}$	5797	1.212	0.918	0	4.247
TG^{CI} *(stdd)*	5797	0	1	-0.176	19.669
TG^{CI}	5797	4.077	23.203	0	460.46
TG^{TEI} *(stdd)*	5797	0	1	-0.198	18.875
TG^{TEI}	5797	3.851	19.431	0	370.605
TG^{PEI} *(stdd)*	5797	0	1	-0.192	21.905

Table A.4 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
TG^{PEI}	5797	4.251	22.171	0	489.924
TG^{CET} *(stdd)*	5797	0	1	-2.155	8.628
TG^{CET}	5797	0.979	0.405	0.107	4.472
TG^{CEP} *(stdd)*	5797	0	1	-2.19	7.443
TG^{CEP}	5797	0.972	0.406	0.083	3.995
Total Energy (d) (stdd)	5797	0	1	-0.32	8.744
Total Energy (o) (stdd)	5797	0	1	-0.464	5.006
Total Pollutant Energy (d) (stdd)	5797	0	1	-0.307	8.585
Total Pollutant Energy (o) (stdd)	5797	0	1	-0.455	4.898
Total Clean Energy (d) (stdd)	5797	0	1	-0.418	9.851
Total Clean Energy (o) (stdd)	5797	0	1	-0.582	5.803
Intermediate Output (d) (stdd)	5797	0	1	-0.355	12.979
Intermediate Output (o) (stdd)	5797	0	1	-0.421	7.577
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
Sim^{s}_{ijt} *(stdd)*	5797	0	1	-4.737	1.056
$Mass^{s}_{ijt}$ *(stdd)*	5797	0	1	-2.757	3.087
$Endw^{s}_{ijt}$ *(stdd)*	5797	0	1	-1.32	3.306
C24					
Import (ln)	5797	-1.034	4.329	-18.421	5.913
TG^{CI} (ln)	5797	-1.991	2.543	-9.763	4.75
TG^{TEI} (ln)	5797	-1.938	2.364	-8.495	4.555

Table A.4 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
TG^{PEI} (ln)	5797	-1.938	2.475	-9.514	5.053
TG^{CET} (ln)	5797	-0.054	0.491	-1.628	1.698
TG^{CEP} (ln)	5797	-0.054	0.486	-1.519	1.443
Import Growth	5797	0.244	2.527	-20.182	21.55
TG^{CI} *Growth*	5797	-0.015	0.327	-2.114	2.6
TG^{TEI} *Growth*	5797	0.003	0.253	-1.336	1.645
TG^{PEI} *Growth*	5797	-0.002	0.281	-1.499	1.694
TG^{CET} *Growth*	5797	-0.018	0.198	-1.692	1.696
TG^{CEP} *Growth*	5797	-0.013	0.205	-1.527	1.806
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
Total Pollutant Energy (d) (ln)	5797	11.238	2.124	3.135	16.105
Total Pollutant Energy (o) (ln)	5797	12.957	1.144	10.962	16.105
Total Clean Energy (d) (ln)	5797	10.437	2.002	4.284	15.111
Total Clean Energy (o) (ln)	5797	12.183	1.272	9.049	15.111
Intermediate Output (d) (ln)	5797	9.179	1.893	2.694	14.059
Intermediate Output (o) (ln)	5797	10.562	1.15	7.431	14.059
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
Sim^{s}_{ijt}	5797	-1.519	1.478	-9.014	0
$Mass^{s}_{ijt}$	5797	11.409	1.029	7.881	14.409
$Endw^{s}_{ijt}$	5797	1.361	1.019	0	5.73
TG^{CI} *(stdd)*	5797	0	1	-0.259	11.883

Table A.4 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
TG^{CI}	5797	2.466	9.522	0	115.611
TG^{TEI} *(stdd)*	5797	0	1	-0.265	11.806
TG^{TEI}	5797	2.089	7.879	0	95.106
TG^{PEI} *(stdd)*	5797	0	1	-0.24	14.749
TG^{PEI}	5797	2.504	10.441	0	156.491
TG^{CET} *(stdd)*	5797	0	1	-1.684	8.556
TG^{CET}	5797	1.062	0.514	0.196	5.461
TG^{CEP} *(stdd)*	5797	0	1	-1.636	6.153
TG^{CEP}	5797	1.062	0.515	0.219	4.234
Total Energy (d) (stdd)	5797	0	1	-0.384	9.54
Total Energy (o) (stdd)	5797	0	1	-0.579	5.614
Total Pollutant Energy (d) (stdd)	5797	0	1	-0.367	9.553
Total Pollutant Energy (o) (stdd)	5797	0	1	-0.535	5.584
Total Clean Energy (d) (stdd)	5797	0	1	-0.415	9.145
Total Clean Energy (o) (stdd)	5797	0	1	-0.681	5.454
Intermediate Output (d) (stdd)	5797	0	1	-0.373	12.068
Intermediate Output (o) (stdd)	5797	0	1	-0.502	7.095
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
Sim^{s}_{ijt} *(stdd)*	5797	0	1	-5.07	1.028
$Mass^{s}_{ijt}$ *(stdd)*	5797	0	1	-3.429	2.916
$Endw^{s}_{ijt}$ *(stdd)*	5797	0	1	-1.336	4.288

Table A.4 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
Rest of the Variables					
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) (ln)	5797	-0.301	0.315	-1.319	0.355
TFP (o) (ln)	5797	-0.474	0.394	-1.319	0.066
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
Capital Formation (d) (ln)	5797	3.172	0.248	0.146	3.843
Capital Formation (o) (ln)	5797	3.243	0.246	2.697	3.843
Oil Rent (d) (ln)	5797	-5.362	7.001	-18.421	2.674
Oil Rent (o) (ln)	5797	-0.978	4.171	-18.421	2.674
Distance (ln)	5797	8.876	0.658	6.368	9.789
Sim_{ijt}	5797	-0.64	0.562	-2.356	0
$Mass_{ijt}$	5797	10.753	0.492	8.481	11.656
$Endw_{ijt}$	5797	2.947	2.016	0.001	8.582
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
Foreign Direct (d) (stdd)	5797	0	1	-0.725	7.363
Foreign Direct (o) (stdd)	5797	0	1	-1.521	4.627

Table A.4 continued from previous page

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
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
Capital Formation (d) (stdd)	5797	0	1	-4.209	3.997
Capital Formation (o) (stdd)	5797	0	1	-1.678	2.926
Oil Rent (d) (stdd)	5797	0	1	-0.42	7.137
Oil Rent (o) (stdd)	5797	0	1	-0.748	4.249
Distance (stdd)	5797	0	1	-1.961	2.343
Sim_{ijt} *(stdd)*	5797	0	1	-3.054	1.14
$Mass_{ijt}$ *(stdd)*	5797	0	1	-4.613	1.835
$Endw_{ijt}$ *(stdd)*	5797	0	1	-1.461	2.795
RTA	5797	0.223	0.416	0	1
CU	5797	0.05	0.217	0	1
FTA	5797	0.011	0.102	0	1
PSA	5797	0.096	0.294	0	1
EIA	5797	0	0.019	0	1
FTAEIA	5797	0.073	0.26	0	1
comlang_off	5797	0.07	0.256	0	1
col45	5797	0.009	0.093	0	1
WTO (o)	5797	0.888	0.316	0	1
WTO (d)	5797	0.949	0.221	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 Specifications 3.8 and 3.9. ‘ln’ in parentheses indicates that the values are in logarithmic terms and ‘stdd’ in parentheses represents standardized values. The unilateral variables for importer and exporter countries are also indicated in parentheses by "d" and "o", respectively.

Table A.5: Summary Statistics - Chapter 3

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

Table A.5 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
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
*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

Table A.5 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
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
'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

Table A.5 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
*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

Table A.5 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
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
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

Table A.5 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
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
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

Table A.5 continued from previous page

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
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

Table A.5 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
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					
$Mass_{ijt}$	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

Table A.5 continued from previous page

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
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
'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

Table A.5 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
$Endow_{ijt}$	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

Table A.5 continued from previous page

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
*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
*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
<u>Rest of the Variables</u>					
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

Table A.5 continued from previous page

Variables	*Obs.*	*Mean*	*Standard Deviation*	*Min*	*Max*
*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
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

Table A.5 continued from previous page

Variables	***Obs.***	***Mean***	***Standard Deviation***	***Min***	***Max***
Landlock	5797	0.129	0.335	0	1

Note: This table presents the summary statistics of all variables used in Specification 4.9. ‘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.6: Data Sources

Variables	***Variables and Their 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
Oil Rent (% of GDP)	World Development Indicators (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 Larch's Regional Trade Agreements Database
Customs Unions	Mario Larch's Regional Trade Agreements Database
Free Trade Agreements	Mario Larch's Regional Trade Agreements Database
Partial Scope Agreements	Mario Larch's Regional Trade Agreements Database
Economic Integration Agreements	Mario Larch's Regional Trade Agreements Database

Table A.6 continued from previous page

Variables	***Data Sources***
Free-trade and Econ. Integ. Agre.	Mario Larch's Regional Trade Agreements Database
ΔCI	Constructed by Author
CI^{TEI}	Constructed by Author
CI^{PEI}	Constructed by Author
CI^{CET}	Constructed by Author
CI^{CEP}	Constructed by Author
CI^{OS}	Constructed by Author
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
Import Growth	Constructed by Author
Relative Carbon Intensity	Constructed by Author
Relative Energy Intensity (Total)	Constructed by Author
Relative Energy Intensity (Pollutant)	Constructed by Author
Relative Carbon-to-Energy Ratio (Total)	Constructed by Author
Relative Carbon-to-Energy Ratio (Pollutant)	Constructed by Author
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

Table A.6 continued from previous page

Variables	***Data Sources***
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.7: Dependent Variables Constructed by the Author in Chapter 1

Dependent Variable	**Description**	**Formula**
Carbon Intensity	Measures the carbon emissions per unit of output.	$\mathrm{CI}_{it}^{s} = \frac{\mathrm{C}_{it}^{s}}{\mathrm{Q}_{it}^{s}}$
Total Energy Intensity	Measures the energy use from all energy sources per unit of output.	$\mathrm{TEI}_{it}^{s} = \frac{\mathrm{TE}_{it}^{s}}{\mathrm{Q}_{it}^{s}}$
Pollutant Energy Intensity	Measures the energy use from pollutant energy sources per unit of output.	$\mathrm{PEI}_{it}^{s} = \frac{\mathrm{PE}_{it}^{s}}{\mathrm{Q}_{it}^{s}}$
Carbon-to-Energy Ratio (Total)	Measures the carbon emission per unit of energy use from all energy sources.	$\mathrm{CET}_{it}^{s} = \frac{\mathrm{C}_{it}^{s}}{\mathrm{TE}_{it}^{s}}$
Carbon-to-Energy Ratio (Pollutant)	Measures the carbon emission per unit of energy use from pollutant energy sources.	$\mathrm{CEP}_{it}^{s} = \frac{\mathrm{C}_{it}^{s}}{\mathrm{PE}_{it}^{s}}$
Output Share	Measures the output for an individual sector s over all selected sectors aggregated.	$\mathrm{OS}_{it}^{s} = \frac{\mathrm{Q}_{it}^{s}}{\mathrm{Q}_{it}}$
Change in Carbon Intensity	Measures the changes in carbon intensity.	$\Delta CI_{it} = CI_{it} - CI_{i,t-1}$

Table A.7 continued from previous page

Dependent Variable	Description	Formula
Change in Carbon Intensity Through Total Energy Intensity	Measures the changes in carbon intensity through the changes in energy use from all energy sources per unit of output. This is an indicator that shows the sensitivity of carbon intensity to total energy intensity.	$CI_{it}^{TEI} = \sum_{s=1}^{7} \Delta CI_{it} \times \left[\ln \frac{TEI_{ist}}{TEI_{is,t-1}} / \ln \frac{CI_{ist}}{CI_{is,t-1}}\right]$
Change in Carbon Intensity Through Pollutant Energy Intensity	Measures the changes in carbon intensity through the changes in energy use from pollutant energy sources per unit of output. This is an indicator that shows the sensitivity of carbon intensity to pollutant energy intensity.	$CI_{it}^{PEI} = \sum_{s=1}^{7} \Delta CI_{it} \times \left[\ln \frac{PEI_{ist}}{PEI_{is,t-1}} / \ln \frac{CI_{ist}}{CI_{is,t-1}}\right]$
Change in Carbon Intensity Through Carbon-to-Energy Ratio (Total)	Measures the changes in carbon intensity through the changes in carbon emissions per unit of energy use from all energy sources. This is an indicator that shows the sensitivity of carbon intensity to carbon-to-total energy ratio.	$CI_{it}^{CET} = \sum_{s=1}^{7} \Delta CI_{it} \times \left[\ln \frac{CET_{ist}}{CET_{is,t-1}} / \ln \frac{CI_{ist}}{CI_{is,t-1}}\right]$

Table A.7 continued from previous page

Dependent Variable	Description	Formula
Change in Carbon Intensity Through Carbon-to-Energy Ratio (Pollutant)	Measures the changes in carbon intensity through the changes in carbon emissions per unit of energy use from pollutant energy sources. This is an indicator that shows the sensitivity of carbon intensity to carbon-to-pollutant energy ratio.	$CI_{it}^{CEP} = \sum_{s=1}^{7} \Delta CI_{it} \times \left[\ln \frac{CEP_{ist}}{CEP_{is,t-1}} / \ln \frac{CI_{ist}}{CI_{is,t-1}} \right]$
Change in Carbon Intensity Through Output Share	Measures the changes in carbon intensity through the structural changes in output share. This is an indicator that shows the sensitivity of carbon intensity to output share.	$CI_{it}^{OS} = \sum_{s=1}^{7} \Delta CI_{it} \times \left[\ln \frac{OS_{ist}}{OS_{is,t-1}} / \ln \frac{CI_{ist}}{CI_{is,t-1}} \right]$

Note: This table presents all the dependent variables constructed by the author in chapter 1 of this study, along with a brief description and the corresponding formula.

Table A.8: Dependent Variables Constructed by the Author in Chapter 2

Dependent Variable	**Description**	**Formula**
Relative Carbon Intensity	Measures the ratio of carbon intensity of importer country (i) over carbon intensity of the exporter (j), which is a proxy of relative technological gap between importer and exporter countries.	$\mathrm{TG}^{\mathrm{CI}} = \frac{\mathrm{CI}^{s}_{it}}{\mathrm{CI}^{s}_{jt}}$
Relative Energy Intensity (Total)	Measures the ratio of energy intensity of importer country (i) over energy intensity of the exporter (j) from all sources of energy use, which is a proxy of relative technological gap between importer and exporter countries.	$\mathrm{TG}^{\mathrm{TEI}} = \frac{\mathrm{TEI}^{s}_{it}}{\mathrm{TEI}^{s}_{jt}}$
Relative Energy Intensity (Pollutant)	Measures the ratio of energy intensity of importer country (i) over energy intensity of the exporter (j) from pollutant sources of energy use, which is a proxy of relative technological gap between importer and exporter countries.	$\mathrm{TG}^{\mathrm{PEI}} = \frac{\mathrm{PEI}^{s}_{it}}{\mathrm{PEI}^{s}_{jt}}$

Table A.8 continued from previous page

Dependent Variable	Description	Formula
Relative Carbon-to-Energy Ratio (Total)	Measures the relative carbon-to-energy ratio of importer country (i) and exporter (j) countries from all sources of energy use, which is a proxy of relative technological gap between them.	$\mathrm{TG}^{\mathrm{CET}} = \frac{\mathrm{CET}^s_{it}}{\mathrm{CET}^s_{jt}}$
Relative Carbon-to-Energy Ratio (Pollutant)	Measures the relative carbon-to-energy ratio of importer country (i) and exporter (j) countries from pollutant sources of energy use, which is a proxy of relative technological gap between them.	$\mathrm{TG}^{\mathrm{CEP}} = \frac{\mathrm{CEP}^s_{it}}{\mathrm{CEP}^s_{jt}}$

Note: This table presents all the dependent variables constructed by the author in chapter 2 of this study, along with a brief description and the corresponding formula.

Table A.9: Dependent Variables Constructed by the Author in Chapter 3

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).	$CL_{ijt}^{s} = \frac{C_{jt}^{s}}{Q_{jt}^{s}} \times M_{ijt}^{s}$
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.	$CL_{ijt}^{s} = \frac{C_{it}^{s}}{Q_{it}^{s}} \times M_{ijt}^{s}$
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.	$NetCL_{ijt}^{s} = \frac{C_{jt}^{s}}{Q_{jt}^{s}} - \frac{C_{it}^{s}}{Q_{it}^{s}} \times M_{ijt}^{s}$
Adjusted Carbon Leakage by Energy (based on actual import scenario)	Adjusted carbon leakage by considering the energy efficiency of the exporting country.	$AdjCL_{ijt}^{s} = CL_{ijt}^{s} \times \frac{Q_{jt}^{s}}{E_{jt}^{s}}$
Adjusted Carbon Leakage by Energy (based on domestic production scenario)	Reflects the adjusted carbon leakage if the goods were produced domestically, accounting for the importer's energy efficiency.	$AdjCL_{ijt}^{s} = CL_{ijt}^{s} \times \frac{Q_{it}^{s}}{E_{it}^{s}}$

Table A.9 continued from previous page

Dependent Variable	Description	Formula
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.	$\mathrm{EL}^{s}_{ijt} = \frac{\mathrm{E}^{s}_{it}}{\mathrm{Q}^{s}_{it}} \times \mathrm{M}^{s}_{ijt}$
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 chapter 3 of this study, along with a brief description and the corresponding formula.

Appendix B

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. ε_{it} is the onobserved error term and is assumed to be uncorrelated with the treatment assignment once we condition on fixed effects and observed covariates.

In the first step, following [72], 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:

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

In the second step, following [16], 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:

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

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

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

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 ([17]). 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.

Appendix C

In this appendix, I outline the main limitations of the SDiD approach and describe the measures employed in this causal analysis to mitigate potential biases.

First, because SDiD relies on a latent factor structure to account for unobserved confounders, there is a risk that the outcome trajectories of treated units may not be accurately replicated if control units differ significantly. To mitigate this, I carefully selected countries in the control group based on their similarity to the treated units (EU countries), thus enhancing the likelihood that latent factors influencing emissions and economic trends are properly captured. Additionally, I included an extensive set of covariates and fixed effects in the model to account for further sources of variation, thereby minimizing residual confounding that could otherwise bias the estimates.

Second, SDiD assumes that treatment effects do not spill over between units and generally posits a uniform treatment effect across all treated units. Although incorporating covariates, as well as time and unit fixed effects, does not entirely eliminate the potential for spillovers, it helps isolate changes driven by observable factors and common shocks, making the no-interference assumption more plausible. To address heterogeneity more explicitly, I conducted analyses at two levels: an aggregated level (combining all regulated sectors) and a sector-specific level (examining individual regulated sectors). This disaggregated approach reduces the likelihood that national-level dynamics obscure genuine sectoral differences. While this does not entirely rule out cross-sector or cross-border interference, it directs the analysis toward capturing the most direct policy effects.

Third, concerns about the sensitivity of the SDiD fitting procedure to data availability and the computational burden associated with bootstrap-based inference are addressed by both our sample design and chosen inference methods. By analyzing data from the period 1996-2012, I obtained nine full pre-treatment years to accurately calibrate counterfactual trajectories.

Furthermore, our sample comprises 32 countries, ensuring a panel size sufficient for stable SDiD weighting and robust inference. Additionally, multiple treated units enhance statistical inference power, and I adopted a jackknife resampling procedure, which is computationally less intensive than repeated bootstrap methods, mitigating practical concerns associated with large-scale bootstrapping.

Finally, evaluating a major policy initiative such as the EU ETS inevitably introduces additional complexities, including the risk of spillovers and varying data quality across sectors. To minimize spillover-related confounding, I specifically selected control countries that do not participate in comparable emissions trading systems. Moreover, conducting sector-specific estimations allowed us to capture differentiated policy effects clearly, rather than masking them at the national aggregate level. These methodological steps collectively reduce the potential for over- or underestimating the causal impacts of the EU ETS and reflect a cautious and nuanced approach to analyzing such a complex policy intervention.